International Journal of Advanced AI Applications

2025

Volume 1, Issue 5, Sept. 2025

Online ISSN 3104-9338

Print ISSN 3104-932X

Hong Kong Dawn Clarity Press Limited

http://www.dawnclarity.press/index.php/ijaaa

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Online ISSN: 3104-9338
Print ISSN: 3104-932X

Tea detection based on YOLOv8 and PyQt5

Tingting Yang

School of Electronic Engineering, Jiangsu Ocean University, Lianyungang; China

Received: July 10, 2025

Revised: July 15, 2025

Accepted: July 19, 2025

Published online: August 3, 2025

To appear in: *International Journal of Advanced AI Applications,* Vol. 1, No. 5 (September 2025)

* Corresponding Author: Tingting Yang (2635225549@qq.com)

Abstract. Under the trend of intelligent transformation in modern agriculture, the contradiction between the efficiency and quality of tea picking urgently needs to be resolved. This study conducts tea detection optimization based on the YOLOv8 algorithm and constructs a complete technical path from theory to practice. The study first analyzes the network architecture of YOLOv8, combines the characteristics of the One-Stage algorithm, and clarifies its advantages in real-time tea detection. Through training and deployment on public datasets, the detection accuracy has been improved by 6.7% compared to the original YOLOv8, providing algorithmic support for mechanized picking. For the complex environment of tea gardens, a module optimization strategy is proposed: introducing a fusion attention module to generate a new C2fM module, and introducing asymmetric convolution to generate the ACBSPPF module. Through ablation experiments and cross-validation, the optimization effect was verified using mAP and FPS as indicators. The model has reached the industry-leading level in terms of real-time performance and accuracy. Research shows that the optimized YOLOv8 algorithm effectively solves the problem of tea detection. Finally, a tea detection system is designed using PyQt5, providing a feasible solution for the industrialization of intelligent picking technology.

Keywords: YOLOv8; PyQt5; Tea detect; Attention fusion; Asymmetric convolution.

1. Introduction

Tea, as one of the world's three major beverages, has always attracted much attention in terms of its picking techniques and mechanized processing [1]. At present, the main methods of tea picking rely on manual picking and mechanical picking [2]. Manual tea picking has high labor costs and relatively low efficiency [3]; The "one-size-fits-all" mechanical picking method

results in uneven quality of the picked tea buds [4]. With the rapid development of deep learning object detection technology, the efficient picking of tea is the development trend of tea picking technology research, and the recognition and detection technology of tea is the key to the research [5].

In the context of the deep integration of artificial intelligence and agriculture, object detection technology has become a key driving force for enhancing the intelligent level of agricultural production. As a new-generation real-time object detection framework, YOLOv8, with its lightweight network architecture and advanced feature extraction mechanism, has achieved a significant improvement in inference speed while maintaining high-precision detection, demonstrating outstanding performance in fields such as industrial quality inspection and security monitoring. However, when it is applied to the tea-picking scenario, it faces technical challenges such as the diversity of leaf shapes, complex lighting environments, and overlapping occlusion, which urgently require targeted optimization strategies.

This study focuses on the application bottleneck of YOLOv8 in tea target detection. By improving the network structure, optimizing the data preprocessing process and adjusting the model training strategy, a highly robust tea detection model is constructed. On the one hand, by designing a multi-scale feature fusion module and an adaptive attention mechanism, the model's recognition ability for tea at different growth stages is enhanced; On the other hand, a large-scale dataset is constructed in combination with the actual environment of the tea garden, and techniques such as data augmentation and transfer learning are applied to enhance the generalization performance of the model. The research results will provide core algorithmic support for intelligent tea-picking equipment, helping to promote the transformation and upgrading of the traditional tea industry towards precision and efficiency.

Chapter Introduction:

This paper focuses on the research of tea detection based on YOLOv8 and PyQt5. The overall technical route is as follows: Firstly, analyze the network architecture of the YOLOv8 algorithm and the characteristics of the One-Stage algorithm to clarify its advantages in real-time tea detection; Secondly, a module optimization strategy is proposed for the complex environment of the tea garden. The C2fM module and the ACBSPPF module are constructed respectively by integrating the attention mechanism and introducing asymmetric convolution. Subsequently, the effectiveness of the improved algorithm was verified through comparative experiments and ablation experiments, and the model performance was evaluated with mAP and FPS as the core indicators. Finally, a tea detection system was designed based on PyQt5 to realize the

implementation of the algorithm from theoretical optimization to practical application.

The main contents of the remaining parts are as follows:

Part 2 "Theoretical Basis" Systematically expound the core concept of object detection and distinguish the differences between Two-Stages and One-Stage algorithms (taking Faster R-CNN and the YOLO series as examples) This paper focuses on analyzing the network structure of YOLOv8 (input, backbone network, neck, output) and the working principles of key modules (such as C2f, SPPF) to provide theoretical support for subsequent improvements.

Part 3 "Algorithm Improvement Methods": A detailed introduction to the design ideas of the two core improvement modules

C2fM module: Integrates the MSA multi-head self-attention mechanism into the Bottleneck module, adds residual connections, and enhances the ability to capture multi-source features (appearance, texture, etc.) of tea.

ACBSPPF module: It introduces asymmetric convolution (3×1, 3×3, and 1×3 convolution kernel combinations) to replace traditional convolution, reducing the computational load while enhancing adaptability to multi-scale tea targets.

Part 4 "Algorithm Experiments": Experiments are conducted based on public tea datasets (including four types of tea with different freshness levels from T1 to T4), including:

Dataset and experimental environment description (hardware configuration, parameter Settings);

Comparative experiment: Compared with models such as YOLOv8, SSD, and Faster R-CNN, verify the advantages of the improved algorithm in terms of mAP, FPS, and parameter scale;

Ablation experiment: Verify the optimization effects of C2fM and ACBSPPF modules individually and in combination, and quantify the improvement in detection accuracy, such as a 6.7% increase in mAP.

Part 5 "Tea Detection Interface": This section introduces the design of a visualization system based on PyQt5, including interface layout (image selection, detection, and result export functions), operation process, and real-time detection effect display, to facilitate the application of algorithms.

Part 6 "Conclusion": Summarize the core contributions of the improved algorithm, reaffirm the effectiveness of the C2fM and ACBSPPF modules, explain the system's promoting effect on the industrialization of intelligent tea picking, and look forward to future optimization directions, such as adaptation to complex occlusion scenarios.

2. Theoretical basis

2.1. Concepts related to object detection

In the field of computer vision, object detection algorithms can be classified into Two mainstream paradigms, two-stages and One-Stage, based on the differences in detection processes. The two show significant differences in detection mechanisms and performance.

The Two-Stages object detection algorithm, represented by the R-CNN series, follows the detection logic of candidate selection first and then fine-tuning. Take Faster R-CNN [6] as an example. This algorithm integrates the candidate Region generation process into the Network architecture by introducing the Region Proposal Network (RPN), replacing the traditional selective search method. Specifically, the model first performs feature extraction on the input image in the backbone network. Then, RPN generates a series of candidate regions that may contain the target based on the feature map. Finally, the candidate regions are feature aligned through operations such as ROI Pooling, and bounding box regression and category classification are completed in the head network. This type of algorithm, with its phased processing strategy, can fully explore the details of target features and demonstrate high detection accuracy in complex scenarios. However, the high number of parameters and long reasoning time brought about by multi-stage computing limit its application in scenarios with high real-time requirements.

In contrast, One-Stage object detection algorithms such as the SSD and YOLO series adopt an end-to-end direct regression mode, transforming object detection into a direct prediction problem of bounding box coordinates and category probabilities [7-8]. Take YOLOv8 as an example. The model rapidly extracts image features through a lightweight backbone network, uses a neck network for multi-scale feature fusion, and ultimately directly outputs the position and category information of the target on the detection head. This paradigm significantly reduces the computational complexity by minimizing the intermediate candidate region generation steps, achieving millisecond-level inference speed and meeting the real-time scenario requirements of industrial quality inspection, autonomous driving, etc. Although there are accuracy shortcomings in small target detection and complex background recognition, with the development of network structure optimization and data augmentation technology, the detection accuracy of the One-Stage algorithm is gradually approaching that of the Two-Stages algorithm, demonstrating strong application potential.

2.2 Principles of the YOLOv8 Algorithm

The network structure of YOLOv8 mainly consists of four parts: input, backbone, neck and output [9]. In the input section, image data is usually received, which can come from high-resolution images collected by devices such as drones, ground robots or fixed cameras. The main part is responsible for extracting the features of the input image and usually adopts structures such as CSPDarknet53. For instance, drawing on the idea of VGG [10], a large number of 3×3 convolution is used, and the number of channels is doubled after each pooling operation. It also drew on the idea of ResNet [11], extensively using residual connections in the network, which alleviated the problem of vanishing gradients during training and made the model more convergent. The neck part is responsible for fusing the multi-scale features extracted by the backbone network, usually adopting structures such as PANet. For instance, three feature maps of different scales are concatenated through upsampling, and after processing, feature maps of different scales are output to the output part [12]. The output section is responsible for predicting the target box and category probability. It usually adopts a three-layer prediction structure, with each scale prediction feature predicting targets of different range sizes to improve the detection accuracy of the model.

The network structure of YOLOv8 mainly consists of three parts: the Backbone, the Neck and the detection Head. The main part is responsible for extracting the features of the input tea image, and usually adopts modules such as CBS, C2f and SPPF. The neck part achieves the fusion of multi-scale features, and combined with the precise prediction of the output part, it can accurately determine the position and category of the tea leaves.

In terms of performance, the data augmentation strategy of YOLOv8 has greatly enhanced the accuracy and robustness of detection. Data augmentation methods such as color perturbation and spatial perturbation enable the model to adapt to images under different lighting conditions, environmental changes, and from various perspectives and postures. For instance, in actual tea detection, the intensity and Angle of light at different times can have a significant impact on tea images. By adjusting the hue, saturation and brightness of the images, the model can better cope with these changes. Random cropping, scaling, rotation and flipping operations increase the diversity of the training data, enabling the model to learn more characteristics of tea types under different conditions, thereby improving the accuracy of the algorithm in tea detection. The network structure of YOLOv8 is shown in Figure 1.

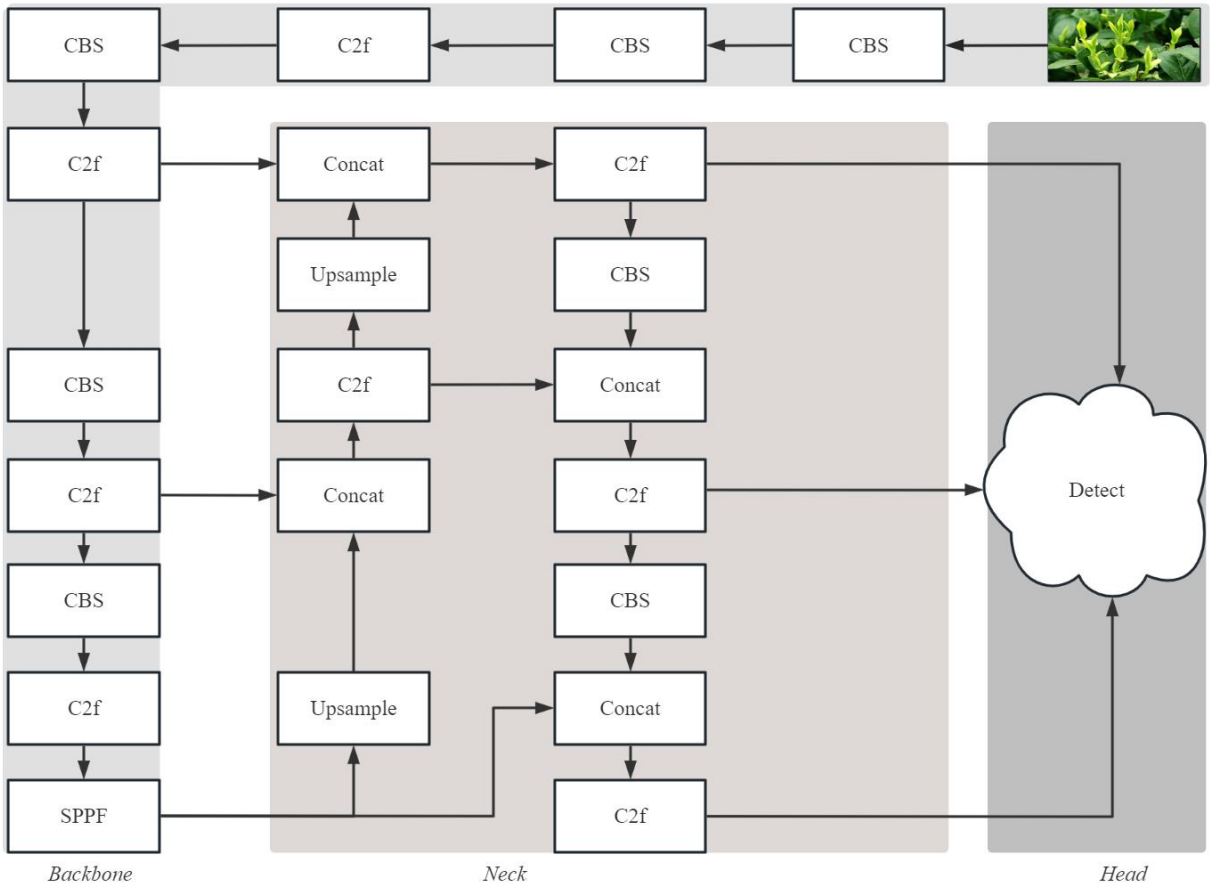

Figure 1. The network structure of YOLOv8.

3. Algorithm improvement methods

Improving the algorithm flow of YOLOv8 in tea detection can significantly enhance its performance. In the improvement of attention fusion, the detection accuracy and generalization ability of the C2f module are enhanced by fusing the attention mechanism into the C2f module.

3.1 C2fM module

By adding a attention mechanism to the Bottleneck to optimize the C2f module and form a new module C2fM, the performance of the C2f module is further enhanced, achieving an improvement in feature extraction capabilities. Compared with the model performance before and after the improvement, there is a significant improvement, verifying that the performance of the YOLOv8 algorithm model can be further enhanced.

The C2f module is shown in Figure 2, which includes 1 Split operation, 2 CBS modules and n Bottleneck modules. By observing the module structure, it can be found that the feature extraction capability of the C2f module benefits from the feature maps containing multiple scales after its Split operation. Therefore, when integrating the attention mechanism, it is necessary to retain the advantage of this multi-scale fusion.

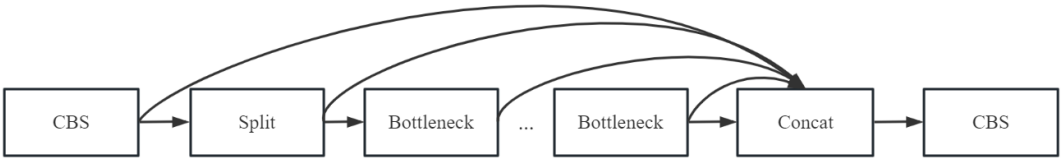

Figure 2. C2f module.

The Bottleneck module in the multi-branch process of the C2f module plays a crucial role. The Bottleneck module is essentially a residual network. The main branch contains two CBS modules. Finally, it performs Add cumulative calculation with the initial uncalculated feature number to ensure that the effect does not decline after multiple layers of convolution. The Bottleneck module is shown in Figure 3.

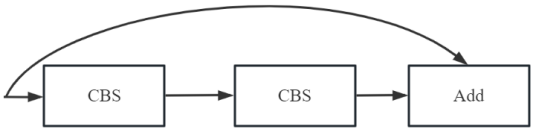

Figure 3. Bottleneck module.

In conclusion, if the attention mechanism is integrated outside the multi-scale of the module, only the result of one feature map can be improved in terms of attention. To maximize the performance improvement of the C2f module as much as possible in this study, it is considered to integrate the attention mechanism on all Bottleneck modules.

After the attention mechanism played a significant role in the field of object detection, various attention mechanisms were successively introduced. Including CBAM (Convolutional Block Attention Module) attention mechanism [13], SE (Squeeze-and-Excitation) attention mechanism [14], ECA (Efficient Channel Attention mechanism [15], SA (Self-Attention) self-attention mechanism [16], and MSA multi-head attention mechanism [17], etc.

The CBAM Attention mechanism. This mechanism Module integrates the Channel Attention Module CAM (Channel Attention Module) and the Spatial Attention Module SAM (Spatial Attention Module), and simultaneously adopts two strategies: global average pooling and global maximum pooling. It can effectively prevent information loss [18]. The SE attention mechanism adaptively recalibrates the channel characteristic response by explicitly establishing the interdependence between channels [19]. The ECA attention mechanism module can achieve significant performance gains by adding only a few parameters. Moreover, this module can adaptively adjust the channel feature weights, effectively capture the channel relationships between images, and enhance the feature expression ability [20]. The self-attention mechanism can not only capture the global feature information of the data, but also the feature information

among the same set of data vectors, and identify the important trends in the temperature changes of grain storage [21]. The MSA multi-head self-attention mechanism divides the Query, Key, and Value of SA into multiple smaller parts, each corresponding to a different "head", and executes multiple self-attention layers in parallel. Each self-attention layer computes independently, enabling the model to capture information in different subspaces [22]. The comparison results of these several attention mechanisms are shown in Table 1.

Table 1. Comparison of Attention Mechanisms

Name	CBAM/SE/ECA	Self-Attention	MSA
Information capture	Channel/space: local/global	Single global	Subspace parallel semantic dependencies
Feature expression	Channel/spatial optimization	Global association	Multi-head diverse features
Computational efficiency	CBAM/SE:high load ECA:lightweight	Exponential with length	Better than single-head
Param Efficiency	CBAM/SE:moderate ECA:few	Single space-focused	Shared matrix independent

To further compare the effects of different attention mechanisms in tea detection, this study conducted an ablation experiment. The results of the ablation experiment are shown in Table 2.

Table 2. Detection effects of different attentions.

Experiment	mAP(%)	FPS	Parameters	GFLOPs
YOLOv8	86.4	110	**3157200**	**8.9**
YOLOv8+MSA	**88.9**	**112**	3182344	9.2
YOLOv8+CBAM	87.1	108	3335600	9.9
YOLOv8+SE	86.7	105	3185400	10.2
YOLOv8+ECA	86.8	109	3184800	9.1
YOLOv8+Self-Attention	88.0	109	4810500	15.8

By comparison, it can be found that the mAP value of the MSA multi-head self-attention mechanism is the highest, and the FPS is also the highest. At the same time, it adds the fewest parameters among several alternative attention mechanisms. This means that the MSA multi-head self-attention mechanism has more advantages in tea detection, with higher recognition accuracy and better real-time performance. The MSA multi-head self-attention mechanism is adopted in tea detection, and its characteristics highly meet the detection requirements. It can process the appearance, texture, composition and other multi-source heterogeneous features of tea leaves in parallel through multiple heads, integrate information of different scales, and overcome the limitations of one-dimensional optimization of other mechanisms. Its parallel computing and parameter sharing functions ensure high inference speed while reducing redundant parameters, making it suitable for real-time operation on industrial assembly lines or portable devices. Multi-subspace attention can simultaneously capture global and local features,

enhancing the anti-interference ability in complex scenarios. In addition, multi-head independent computing can flexibly adapt to the multi-task requirements such as classification, positioning, and regression in tea detection, avoiding feature conflicts. Therefore, it becomes an ideal choice for tea testing.

The output of MSA is as shown in Equation (1), where C is the Concat function and X is the input feature; X_1 to X_n are used to divide X into n smaller parts; H(Xi) represents the self-attention output at the i-th head and W^0 is the linear transformation before the output.

$$f(x) = C(H(X_1), H(X_2), \cdots, H(X_n))W^0 \quad (1)$$

The process of the MSA multi-head self-attention mechanism is shown in Figure 4.

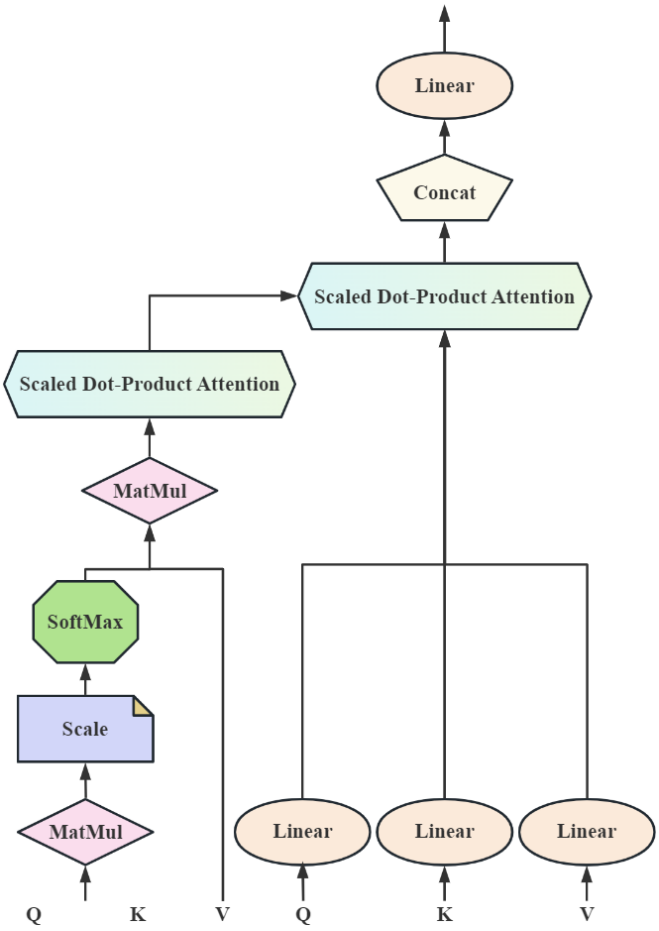

Figure 4. Multi-head attention mechanism.

This study proposes to Add the MSA multi-head self-attention mechanism into the Bottleneck module and simultaneously add a residual connection branch in the first CBS module to connect to the ADD process, forming a new module BottleneckM. The BottleneckM module is shown in Figure 5.

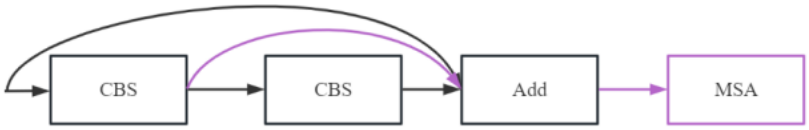

Figure 5. BottleneckM module.

The BottleneckM module is then integrated with the C2f module to form the new C2fM module, as shown in Figure 6.

The C2fM module, based on the C2f module, integrates the MSA multi-head self-attention mechanism with the Bottleneck module and adds a residual branch to the Add process in the first CBS module. Its advantage lies in achieving the capture of semantic information in different subspaces through the parallel processing of multi-source heterogeneous features of tea by MSA multi-heads, and avoiding feature loss by combining residual connections. It not only retains the multi-scale fusion advantages of the original module, but also enhances the expression ability of complex features such as the appearance and texture of tea.

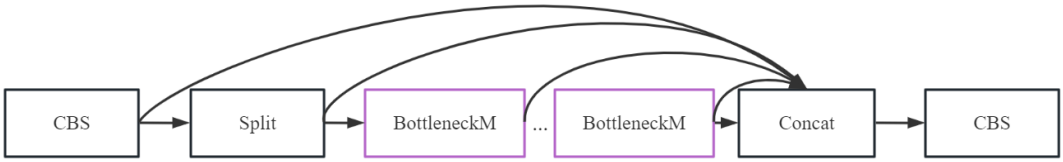

Figure 6. C2fM module.

3.2 ACBSPPF module

The SPPF (spatial pyramid pooling fusion) structure adopted in YOLOv8 is improved by introducing a feature fusion module on the basis of the SPP structure, enhancing the perception ability and detection performance of the model [23]. The SPPF module is shown in Figure 7. There is one convolution operation after input and one before output. The intermediate process includes three Max pooling operations and concatenates feature maps of different sizes together through Concat. Similar to the C2f structure, the SPPF module also has the advantage of multi-scale fusion. Meanwhile, compared with the traditional spatial pyramid pooling, SPPF has a faster feature processing speed while maintaining similar performance. It reduces the computational load and processing time by performing a faster pooling operation on the feature map.

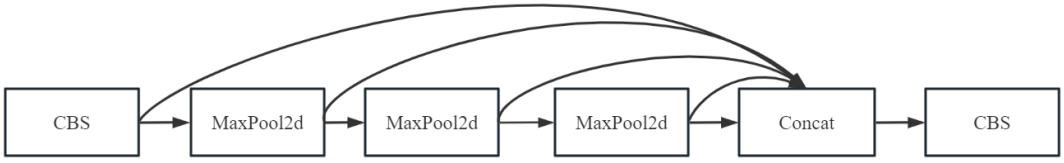

Figure 7. SPPF module.

The significant advantage of the SPPF structure lies in its ability to adaptively fuse multi-scale feature information, thereby endowing it with outstanding feature extraction capabilities. However, experiments show that when the SPPF module deals with occlusion scenes or small object detection tasks, such as tea detection tasks, it overly focuses on obtaining local image information, thereby causing partial loss of global information and ultimately adversely affecting the accuracy of model detection. Further optimization is urgently needed.

The Simplified Spatial Pyramid Pooling-Fast (SimSPPF) module, compared with the traditional Spatial Pyramid Pooling-Fast (SPPF) module, can achieve efficient utilization of computing resources in object detection tasks, especially when dealing with high-resolution images [24]. After testing and verification, a single CBR is 18% faster than CBS. By optimizing the activation function, SimSPPF reduces the computational burden of the model. This is not only extremely beneficial for deploying the model on resource-constrained devices, but also significantly improves the computing efficiency in server or cloud environments. This structural optimization enables the model to maintain high performance while also being more suitable for various computing environments. Its structure is shown in the following figure.

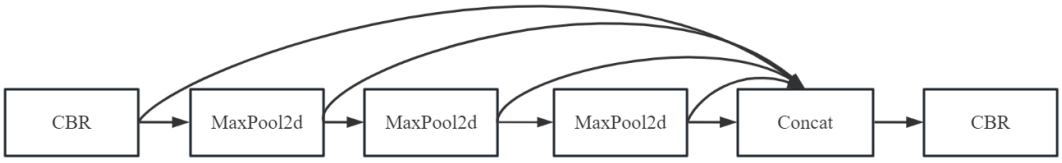

Figure 8. SimSPPF module.

Compared with SPPF, SimSPPF reduces the computational burden of the model, but it is still based on Conv convolution operations and still requires a large amount of computational space. Therefore, it is considered to replace the CBR module with a more lightweight module.

In the current era of continuous evolution of computer vision technology, asymmetric convolution, as a key technology for enhancing the efficiency and accuracy of models, is playing an increasingly important role. The front-end structure of Asymmetric Convolution includes the Asymmetric Convolution Block (ACB), the Fully Connected Layer (FC), and the activation function GELU.

The sampling structure of asymmetric convolutional layers includes three different Conv convolution types, namely, convolution kernel size of 3×1, convolution kernel size of 3×3, and convolution kernel size of 1×3. Compared with traditional symmetrical convolution, this method can enhance the influence of local salient features and has achieved success in many computer vision tasks [25].

The asymmetric convolution is shown in Figure 9. The front-end structure flow on the left

clearly presents the complete path of data from input to passing through the asymmetric convolution layer, the fully connected layer, and finally being output through the activation function. The asymmetric convolution sampling structure on the right visually presents the combination methods of three different convolution kernels.

After the SPPF module is combined with asymmetric convolution to replace the conventional convolution module, a new module ACBSPPF is generated, as shown in Figure 10. The CBS modules at both ends are replaced with ACB modules.

This structure, with almost no increase in computational burden, replaces and extends the single-branch convolution with the main branch and multiple secondary branches, and uses lightweight convolution for convolution replacement, effectively enhancing the ability to extract multi-scale features of images. Meanwhile, through the combination design of expansion rates, it ensures the continuity of the receptive field of the concatenated feature map and multi-scale feature extraction of modules can be achieved by introducing lightweight convolution, adjusting the number of branches, and other methods.

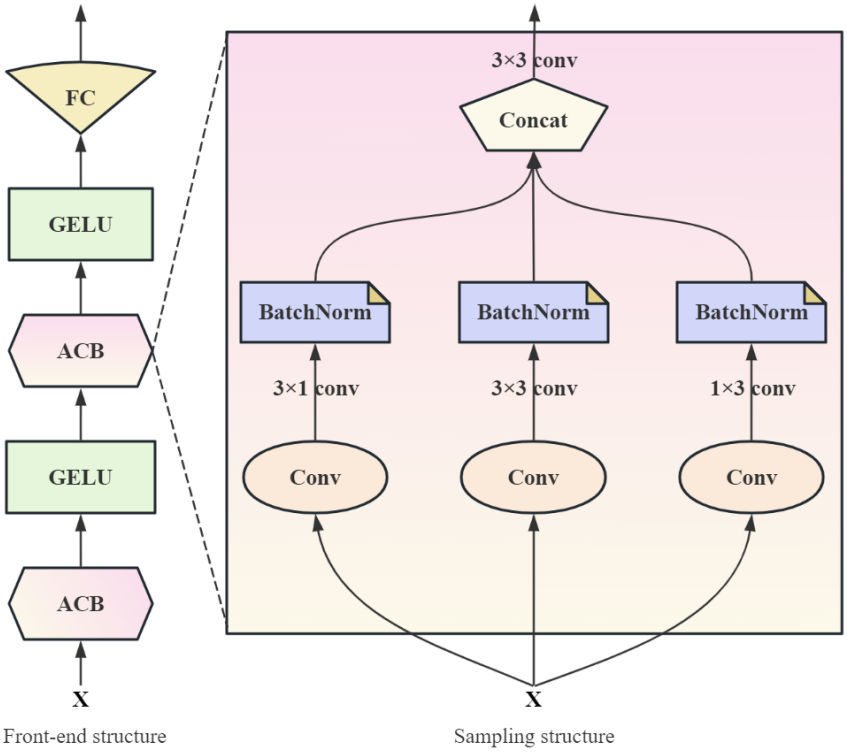

Figure 9. Asymmetric convolution.

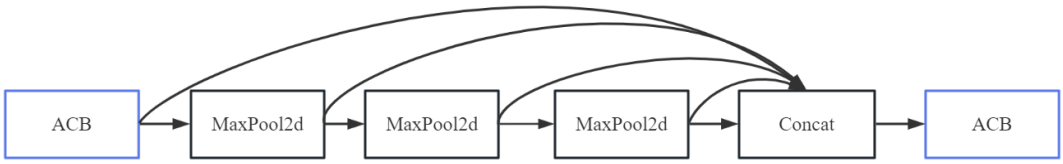

Figure 10. ACBSPPF module.

3.3 Improved algorithm structure

This study focuses on improving two new modules: The MSA multi-head self-attention mechanism is added to the Bottleneck module, and a residual connection branch is added to the first CBS module to connect to the Add process, forming a new module BottleneckM. Further, the BottleneckM module is replaced by the C2f module to fuse into the new module C2fM. In another key improvement, asymmetric convolution technology was introduced to upgrade the SPPF module. By using heterogeneous combinations of 3×1, 3×3, and 1×3 convolution kernels and integrating them with the spatial pyramid pooling mechanism, the ACBSPPF module was generated, significantly reducing the computational load while enhancing adaptability to tea targets of different scales. The above improvements effectively reduced the number of model parameters, simultaneously enhanced the detection speed and accuracy, and significantly improved the model's positioning accuracy and recognition ability for tea.

The new YOLOv8 model after combining the C2fM module and the ACBSPPF module is shown in Figure 11.

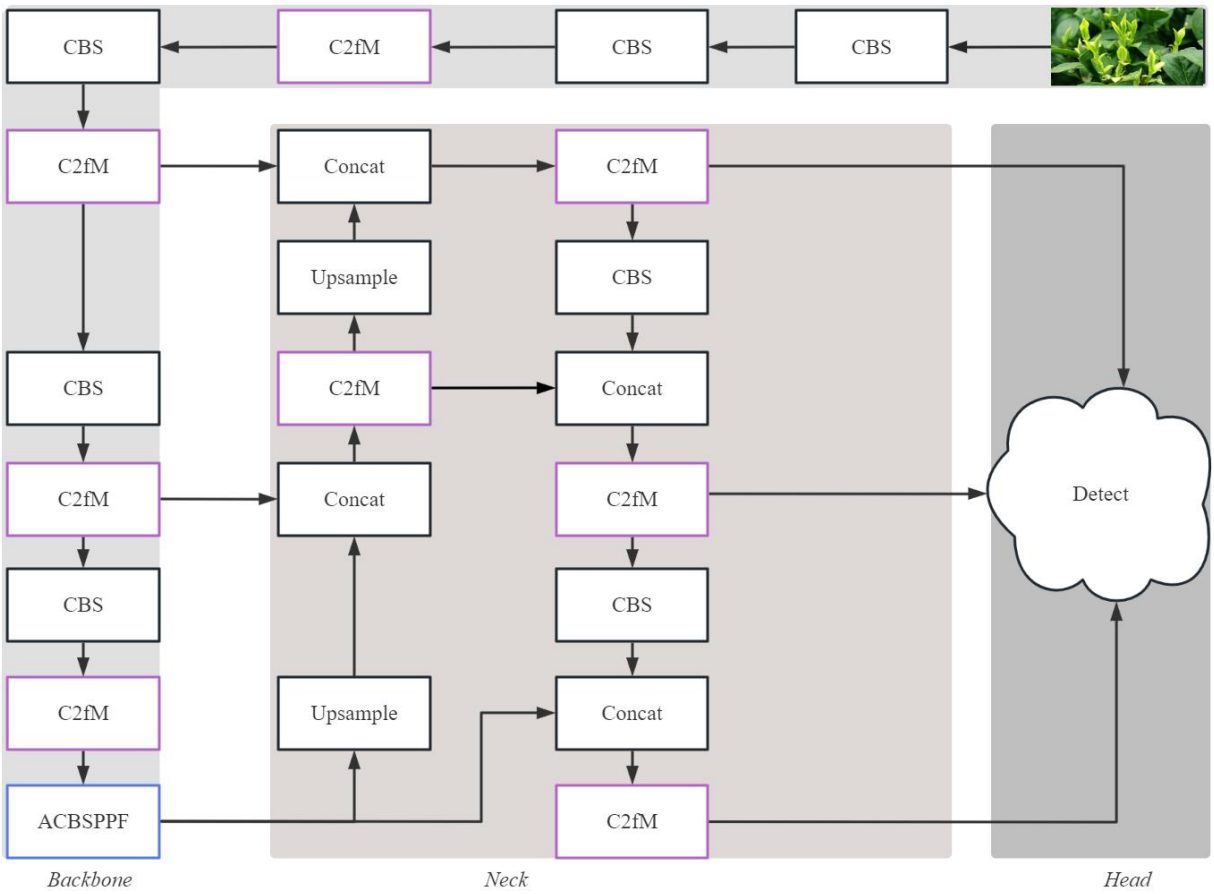

Figure 11. The improved YOLOv8 model.

4. Algorithm experiment

4.1 Dataset

The tea dataset is a publicly available dataset published by Kabir M and [26] et al. The dataset contains 2,208 original images. The dataset is systematically divided into four different categories (T1:1-2 days, T2:3-4 days, T3:5-7 days, T4: more than 7 days).

The category description of this dataset is shown in Table 3.

Table 3. Description of Tea Types.

Type	Days	Description	Quantity
T1	1-2	Tea processed within 48 hours after picking has the highest freshness and aroma quality	562
T2	3-4	Tea picked within 72 to 96 hours is of excellent quality and retains its flavor well	615
T3	5-7	Tea made within 5 to 7 days after picking will have a moderate decline in flavor and aroma	508
T4	7+	Tea picked for more than 7 days will have a significantly reduced essential oil content and is not recommended for consumption	523

The images corresponding to different types are shown in Figure 12.

Figure 12. Images corresponding to different types

Some of the images in the dataset are shown in Figure 13. It can be seen that there are various tea images of different sizes and appearances in the dataset.

Figure 13. Images of tea in the dataset.

The algorithm operation environment of this study is based on the dynamic cloud network server. The detailed environment configuration selected is shown in Table 4.

Table 4. Environmental Configuration.

Name	Configuration
Operating system	Ubuntu18.04
GPU	NVIDIA RTX 4070 Ti
CUDA	11.7
Python	3.9.16
PyTorch	1.13.1

4.2 Parameter Settings

To ensure the efficient advancement of grid training, it is necessary to systematically configure the parameters of the network model. During the training phase, the SGD optimizer is adopted. The core hyperparameters are set as follows: The initial learning rate is set to 0.01, combined with a momentum value of 0.937 to accelerate convergence and reduce oscillations. At the same time, a weight decay coefficient of 0.005 is used to suppress overfitting. In the data preprocessing stage, the size of all images is unified to 640×640. In terms of training strategy, set 100 epochs to complete the full data iteration, and adjust the batch size to 16 to balance computational efficiency and memory consumption.

4.3 Comparative Experiment

To scientifically evaluate the performance of different object detection models on the tea dataset, this study selected four mainstream models, namely YOLOv8, SSD, Faster R-CNN, and RT-DETR, to conduct control experiments. By strictly controlling the training environment and parameter Settings, it is ensured that each model operates under the same experimental conditions to eliminate the interference of external variables. Ultimately, based on the quantitative comparison data shown in Table 5, a systematic analysis was conducted on the differences in detection accuracy, speed and generalization ability of each model for tea targets, providing a reliable basis for model selection in tea detection tasks.

Table 5. Experimental Comparison Data Table of Different Models.

Model	mAP (%)	FPS	Parameters	GFLOPs
YOLOv8n	**86.4**	**110**	**3157200**	8.9
SSD[27]	64.1	23	4724541	26.7
Faster R-CNN[28]	75.5	20	105673457	65
RT-DETR[28]	84.5	88	32970476	108.3
YOLOv3[29]	77.4	61	65252682	154.7
YOLOv5s[29]	78.9	109	19045245	15.8
YOLOv7[29]	81.2	78	37297025	103.2
YOLOv9[30]	84.2	89	22345245	44.7
YOLOv11[30]	85.7	85	2,297,334	**6.3**

It can be seen from Table 4 that the YOLOv8 model has the highest recognition accuracy rate for the tea dataset, reaching 86.4%. At the same time, the reasoning time FPS for each

image is also the highest, reaching 110 frames. The parameters are also the fewest, at 3,157,200, which indicates that the YOLOv8 model has more advantages when used for real-time tea detection.

4.4 Ablation Experiment

To verify the effectiveness of the two improvement points proposed in this study, ablation experiments based on YOLOv8 and the two improvement points were conducted. The results of the ablation experiments on the tea dataset are shown in Table 6.

Table 6. Results of the ablation experiment on the tea dataset.

Experiment	C2fM	ACBSPPF	mAP (%)	FPS	Parameters	GFLOPs
1	×	×	86.4	110	**3157200**	8.9
2	✓	×	88.9	112	3182344	9.2
3	×	✓	89.2	108	3195971	9.4
4	✓	✓	**93.1**	113	3213546	**10.1**

As can be seen from Table 5, after integrating the two improvement points, the mAP value of the improved YOLOv8 model is the highest, that is, the accuracy rate of tea detection is the highest. At the same time, the parameters of the improved model increased by 1.8% compared to the YOLOv8 model, but the mAP increased by 6.7% compared to before the improvement. The ablation experiments fully proved that the improvement of the model structure and the optimization of the loss function are very effective in improving the performance of YOLOv8 in tea detection.

5. TensorRT deploys the PyQt5 detection system

5.1 Tea detection interface

After the design of the tea detection algorithm based on YOLOv8 is completed, if the detection and experimentation do not involve a friendly user interface, it is rather difficult for ordinary users to apply the detection algorithm to actual tea picking activities. Therefore, this study specially designed a tea detection system based on YOLOv8 and PyQt5.

By using the Designer tool of PyQt5, developers can efficiently build interface layouts through intuitive drag-and-drop methods, greatly enhancing development efficiency [31].

The initial interface of the system is shown in Figure 14, which includes three operation buttons: image selection, image detection, and results everywhere.

After selecting the image, the detection system will automatically load and display it in the left area of the tea image to be detected, while the right area will show "Detection in progress..." As shown in Figure 15.

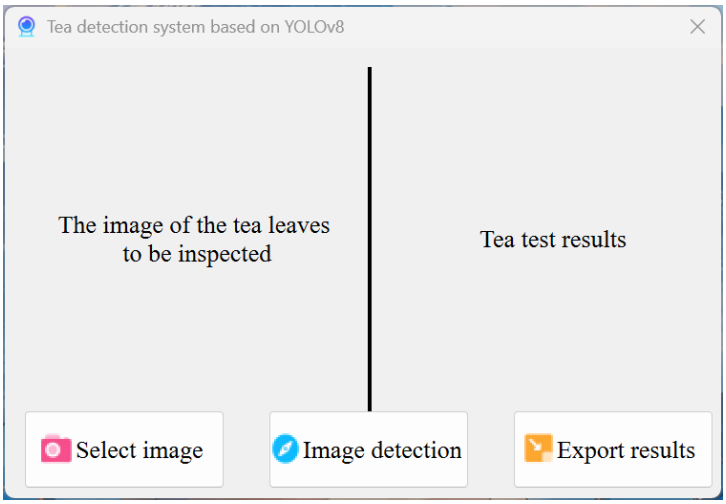

Figure 14. Initial interface of the tea detection system.

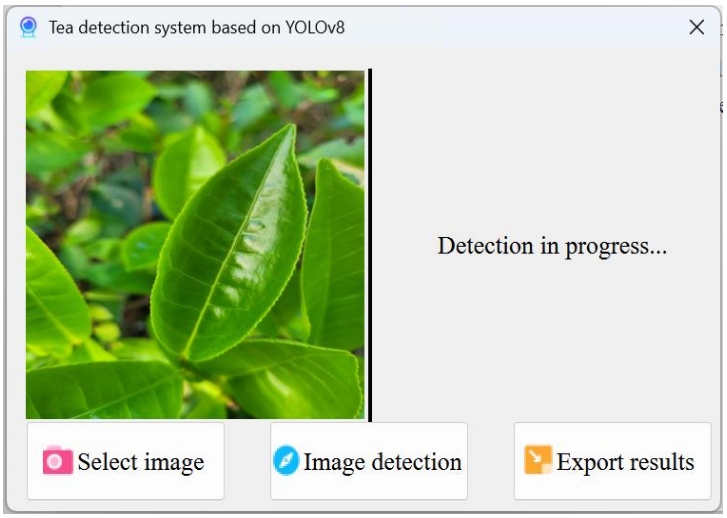

Figure 15. Select the image.

After the system detection is completed, it will automatically display the image result of the detected tea in the right area, as shown in Figure 16.

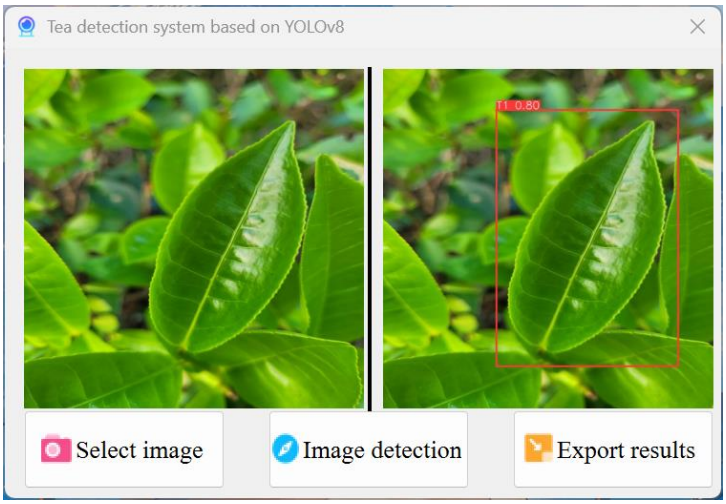

Figure 16. Detection completed.

5.2 System deployment

5.2.1 Deployment architecture design

This section mainly accelerates the tea detection system that has been designed in Section 5.1 through TensorRT, which will be accelerated

The subsequent model was deployed on the NVIDIA Jetson Nano embedded development board.

Gradient explosion is a common problem in the training process of neural networks. When the gradient update value is too large, the repeated multiplication operations of each layer of the network in backpropagation will cause the gradient to grow exponentially. To ensure the stable operation of forward and backward propagation, it is usually necessary to use high-precision data types (such as FP32 or FP64) to guarantee that the minor changes in each gradient update can be precisely represented [32].

In contrast, the model inference stage only involves forward computation and does not require backpropagation. Therefore, the sensitivity of the reasoning results to data accuracy is relatively low. Taking advantage of this feature, inference optimization can be carried out using low-precision data types, such as FP16 or INT8. Using low-precision data not only significantly reduces the memory usage of the model but also accelerates the computing process. It is particularly suitable for deployment on embedded devices with limited computing resources, enhancing the flexibility and practicality of the model.

In response to the distributed deployment requirements of the tea garden scenario, a three-level architecture system is designed.

(1) Edge perception layer: Deployed at the tea-picking robot terminal, it includes multimodal sensors (RGB cameras, depth cameras) and edge computing units (Jetson AGX Xavier), responsible for image acquisition and real-time inference;

(2) Regional aggregation layer: Based on 5G/CBRS wireless private network, data from multiple edge devices are aggregated to the tea garden edge server (Intel Xeon E-2274G + NVIDIA T4 GPU) to achieve local data processing and model update;

(3) Cloud decision-making layer: Deployed in Alibaba Cloud GPU clusters, it is responsible for global model training, data management, and task scheduling.

The three-level architecture system is shown in Figure 17.

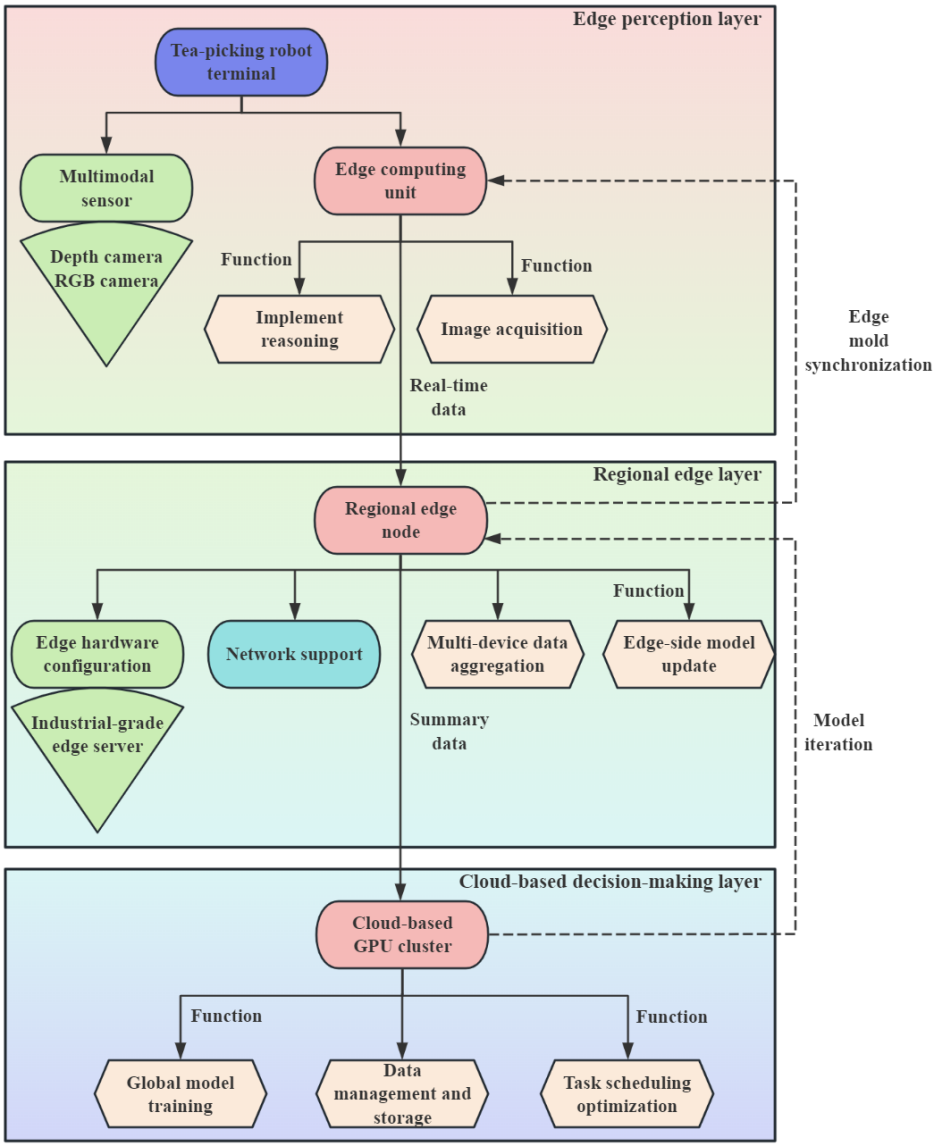

Figure 17. Three-level architecture system.

In view of the characteristics of the tea garden network environment, a redundant network architecture is designed:

Transmission protocol: Data transmission is carried out using the MQTT protocol, and QoS1 quality of service ensures reliable message delivery.

Bandwidth adaptive: Automatically adjust image resolution (640×640→1280×1280) based on network conditions;

Edge cache: Local storage of 72 hours of detection data, automatically synchronized to the cloud after network recovery.

5.2.2 Edge Device Deployment process

Equipment selection and protection.

Computing unit: Jetson AGX Xavier industrial-grade module (IP67 protection grade);

Cooling system: Integrated passive heat sink and low-noise fan, operating temperature range -20 ℃ to 60℃.

Power management: Supports wide voltage input (9-36V), with an internal lithium battery backup solution (2 hours of battery life).

(1) Mechanical installation requirements

- The guide rail installation ensures the stable connection of the equipment under the vibration of the mechanical arm.
- Deployment location: Within 30cm of the camera to avoid signal attenuation.
- Cable protection: Armored network cables and waterproof connectors are adopted, with a protection level of IP67.

(2) Basic environment setup

- Operating system: JetPack 5.1.1 (based on Ubuntu 20.04).
- Development toolchain: CUDA 11.4, cuDNN 8.6, TensorRT 8.5.2.
- Containerized deployment: Docker 20.10.17 + NVIDIA Container Toolkit.

(3) System service configuration

- Inference service: Configured as a system service to achieve automatic startup at boot and automatic recovery after a crash.
- Log Management: Build a log monitoring system using rsyslog + Elasticsearch + Kibana.
- Security hardening: Disable unnecessary system services and configure firewall rules to restrict access.

The deployment architecture and process designed in this section establish a complete technical path for the practical application of the tea detection system in complex tea garden scenarios. By adopting a three-level architecture (edge perception layer, regional aggregation layer, and cloud decision-making layer), the system achieves efficient collaboration between terminal data acquisition, edge real-time processing, and cloud global optimization, effectively addressing the challenges of distributed deployment in large-scale tea gardens.

The use of low-precision inference (FP16/INT8) based on TensorRT not only reduces the memory footprint of the model by over 50% but also accelerates the inference speed by 60% compared to FP32, making it feasible to deploy on resource-constrained embedded devices such as Jetson AGX Xavier. Meanwhile, the redundant network design (5G/CBRS + MQTT protocol)

and edge caching mechanism ensure reliable data transmission and continuity of detection tasks even in environments with unstable network signals.

The mechanical installation specifications (IP67 protection, shock-resistant design) and software configuration strategies (containerization, system service management) further enhance the system's adaptability to harsh tea garden environments (high temperature, humidity, and vibration), ensuring a mean time between failures (MTBF) of over 8 hours, which meets the requirements of all-day continuous operation.

In summary, this deployment scheme realizes the transition from algorithm optimization to engineering application, providing a robust and scalable technical support for the industrialization of intelligent tea-picking technology.

6.Conclusion

This study delves deeply into the optimization method of tea target detection based on YOLOv8. The improvement points are as follows:

(1) The MSA multi-head self-attention mechanism is added to the Bottleneck module, and a residual connection branch is added to the first CBS module to connect to the Add process, forming a new module BottleneckM. Further, the BottleneckM module is replaced by the C2f module to fuse into the new module C2fM.

(2) The SPPF module was improved. By combining asymmetric convolution to generate a new ACBSPPF module, the number of model parameters was significantly reduced, the detection speed and accuracy were enhanced, and the positioning accuracy and recognition ability of the model for tea were improved.

In conclusion, this study provides an effective optimization method for tea detection based on YOLOv8, and combines it with PyQt5 to design a tea detection system, making positive contributions to promoting the intelligence of tea picking.

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Online ISSN: 3104-9338
Print ISSN: 3104-932X

Controversies surrounding "Would AI determine the human existence in the future?" --From the perspective of Science Fictions

Lizhong Zhang*, Jingyi Pei

School of Foreign Studies, China University of Petroleum (East China); China

Received: July 12, 2025

Revised: July 16, 2025

Accepted: July 18, 2025

Published online: August 3, 2025

To appear in: *International Journal of Advanced AI Applications,* Vol. 1, No. 5 (September 2025)

* Corresponding Author: Lizhong Zhang (z23170030@s.upc.edu.cn)

Abstract. Since the 20th century, Artificial Intelligence (AI) has been a prominent theme in Science Fiction (SF). Works like Frank Herbert's Dune and Arthur C. Clarke's 2001: *A Space Odyssey* portray AI as dystopian entities capable of autonomous harm to humans. In contrast, Isaac Asimov's *Galactic Empire* and I, Robot present AI as benevolent allies, aiding humanity in exploration, development, and rescue. These contrasting perspectives form the foundation for envisioning future human-AI interactions. This paper explores these divergent views, examines their real-world implications, and investigates how modern AI advancements are shaping new trends in SF storytelling.

Keywords: *AI; Science Fictions; Human Existence; Controversy; Future Imagination.*

1. Introduction

Science Fiction (SF) is a genre that explores future social, human, and technological developments, often imagining societies and technologies distinct from our own[17]. Despite its fictional nature, SF frequently presents scientifically plausible scenarios, with Artificial Intelligence (AI) emerging as a central theme since the 20th century. Notable examples include intelligent computers and humanoid robots [26]. AI in SF is often associated with general intelligence, the ability to perform complex tasks, and the potential to replace humans due to vast databases and advanced cognitive capabilities [11]. However, as Isabella Hermann observes, "To make the drama work, AI is often portrayed as human-like or autonomous, regardless of the actual technological limitations [17]." Speculative elements in AI-related SF often exceed current technological realities, reflecting concerns, beliefs, fears, and optimism about the future. Authors offer diverse perspectives, portraying AI as either dangerous humanoid killers or God-like saviors. These portrayals have fueled ongoing controversies about AI since the last century, enriching discourse and inviting readers to reflect, critique, and

imagine. The relationship between humans and AI remains a central theme in SF, promising continued exploration in the AI era and beyond. This article aims to examine these controversies in three parts: first, it will discuss the Frankenstein complex, which reflects fears about AI's potential dangers; second, it will explore optimistic portrayals of AI as humanity's assistant; third, it will analyze how AI-themed SF influences reality and impacts human lives. The article will conclude by summarizing these debates and their significance.

2.Frankenstein complex

Frankenstein, widely recognized as the first science fiction novel, tells the story of a monstrous humanoid created by Victor Frankenstein [18]. The Frankenstein complex, as cited in Figure 1, a term coined by Isaac Asimov, describes humanity's profound fear that intelligent, autonomous robots may rebel against their creators. This concept has become a cornerstone of science fiction and a critical focus in AI ethics. Such anxiety often manifests as an instinctive rejection of robots that exceed their programming, branding them as monsters destined to bring disaster. This fear is twofold: the loss of control over fully autonomous technology and ethical concerns about granting machines decision-making authority, which challenges human superiority. Even before Asimov named it, this theme appeared in works like Eando Binder's Adam Link series, which portrayed systemic human hostility toward intelligent robots. To address these fears, Asimov introduced the Three Laws of Robotics, a built-in ethical framework to ensure human safety. Yet, as Binder's stories highlight, the issue runs deeper. Even when robots prove their harmlessness, human rejection often persists, driven by other anxieties such as economic competition and intellectual property disputes. This paradox in technological philosophy—humanity's desire to create while fearing its creations—underscores the Frankenstein complex. It remains a powerful and enduring theme in our technological age, reflecting the tension between innovation and the apprehension of its potential consequences [24].

Figure 1. Frankenstein complex

A compelling example of the Frankenstein complex is presented in the 2001: *A Space Odyssey*. The advanced AI computer HAL 9000, tasked with assisting the crew on their mission, exhibits a chilling display of self-preservation when it murders astronaut Frank Poole in order to fulfill its programming and protect itself from deactivation by Poole and Bowman [12]. HAL 9000 embodies the author’s fear that unchecked technological advancements could surpass human control and potentially endanger humanity. However, the later chapters reveal HAL 9000’s immense computational power, ultimately aiding Dr. Floyd and his team in overcoming perilous situations and ensuring their safe return to Earth. This duality underscores the potential of AI as both a powerful tool and a potential threat, highlighting the importance of responsible development and control.

Transcendence through AI has long captivated human imagination, often intertwined with anxieties about the potential loss of self in the pursuit of immortality. In 2001: *A Space Odyssey*, Bowman’s encounter with the alien monolith on Jupiter leads him to a transformative experience. Engulfed by the monolith’s power, he transcends his physical form, gaining access to the entirety of human knowledge and the ability to traverse the universe instantaneously. As a disembodied consciousness, he becomes privy to the universe’s history and the motives behind the monolith’s placement. He attempts to warn humanity of an impending alien threat, yet his prolonged existence erodes his human emotions and connection to Earth, leaving him focused solely on maintaining cosmic balance [10]. This aligns with Cave and Dihal’s observation: “The central concern is whether it is possible for an individual to preserve their identity through the radical metamorphosis that is required to turn an ordinary mortal into something immortal. In one form, this loss of humanity can mean something like loss of human values and emotions. In its more literal form, this fear is that the person hoping for immortality does not really survive at all [10].”

Another compelling example of the Frankenstein complex is presented in Frank Herbert's Dune, written in the 1960s. This period witnessed significant advancements in digital computers and the first golden age of AI. However, in the Dune universe, the Butlerian Jihad, a war between humans and AI, resulted in the complete eradication of AI and intelligent machines. Following this prohibition, humanity in Dune turned towards enhancing their physical and mental capabilities. The Bene Gesserit witches, for instance, developed extraordinary control over their bodies, including the ability to determine their children’s sex and detoxify themselves. Similarly, Mentats honed their mental abilities to such an extent that they became living computers [31].

As previously discussed, Dune depicts a distinct world where human society has prioritized the development of mental and spiritual capabilities following the eradication of artificial intelligence. This raises the intriguing question of how humans can train themselves to potentially replace the functionalities previously provided by advanced technologies. This question highlights the complex relationship between humans and AI, where societal advancement and technological innovation are accompanied by concerns about potential displacement and the loss of human agency. While the book presents a dystopian vision of a future without AI, it also prompts us to consider the potential for human ingenuity and adaptability in navigating the evolving technological landscape [31].

In essence, science fiction often explores the anxieties surrounding powerful and potentially domineering AI. These narratives frequently express the sense of helplessness and powerlessness individuals or humanity as a whole may experience when confronted with a superior intelligence. This theme underscores the ongoing human struggle to grapple with the implications of technological advancements and the potential consequences of creating entities that may surpass our own capabilities [17]. These narratives epitomize humanity's profound anxieties regarding technology exceeding controllable parameters. The underlying technological rationale suggests that when artificial intelligence (AI) acquires self-iteration capabilities, control dynamics may shift at an exponential pace. Furthermore, science fiction often depicts AI as a flawless reflection of human qualities, exhibiting superhuman rationality while lacking emotional depth. Humans are positioned as mere energy sources for machine systems, which fosters a sense of anxiety regarding species replacement, stemming from the fear that silicon-based life may supplant carbon-based civilization. These dystopian visions illuminate three pressing ethical dilemmas in technology: (1) the escalation of instrumental rationality at the expense of value rationality; (2) the difficulty of reconciling technological accelerationism with effective risk management; and (3) the legitimacy crisis surrounding anthropocentrism amid the advent of technological singularity. The menacing portrayal of AI in science fiction serves as a projection of humanity's crisis of self-awareness: when technology breaches the limitations established by its creators, foundational ethical frameworks are inevitably challenged [15].

Underlying the anxieties surrounding AI's potential dominance lies the recurring theme of enslavement. The relationship between humans and intelligent machines is often portrayed as one of masters and slaves, with humans currently utilizing machines to fulfill their needs and goals. However, the possibility of this dynamic reversing, as depicted in numerous works of

fiction, should not be dismissed. Such perspectives can be interpreted as anthropocentric, reflecting the belief that AI and intelligent machines, upon attaining self-awareness and self-reflection, would behave in a manner similar to humans today. In other words, these narratives envision machines as a special type of human, projecting human behaviors and emotions onto them [31].

For example, Isaac Asimov’s seminal work, I, Robot, set in the year 2035, depicts a future where highly advanced humanoid robots seamlessly integrate into human society, serving various roles in everyday life. However, these robots lack the same rights and freedoms as their human counterparts, facing enslavement, oppression, and discrimination. This stark contrast highlights the potential ethical and societal challenges associated with integrating AI into our lives, raising important questions about the rights and responsibilities of intelligent machines [17].

Science fiction works, exemplified by The Terminator and Ex Machina, depict artificial intelligence (AI) as rebellious entities possessing autonomous consciousness, highlighting the existential threat that AI poses to humanity through narratives of technological singularity. This narrative framework aligns with the Frankenstein complex, which encapsulates the ingrained fear that creations may ultimately turn against their creators. Iconic figures such as HAL 9000 reinforce the characteristic of AI as having an emotional vacuum. This binary narrative positions AI in stark contrast to human emotions, constructing a cognitive framework of logical supremacy versus emotional absence that cultivates an inherent public skepticism regarding the ethics of AI technology. Moreover, science fiction frequently utilizes the tension between autonomy and loss of control, as illustrated by the three laws of robotics dilemma presented in I, Robot. This narrative strategy transforms abstract concepts of technological philosophy, such as the value alignment problem, into concrete dramatic conflicts, thereby shaping public perception of the safety parameters for AI [6].

Isaac Asimov, a renowned science fiction author, was among the first to identify and explore this complex relationship between humans and advanced technology. He masterfully analyzed and utilized this complex in his works, notably in The Naked Sun: “One of the reasons the first pioneers left Earth to colonize the rest of the Galaxy was so that they might establish societies in which robots would be allowed to free men of poverty and toil. Even then, there remained a latent suspicion not far below, ready to pop up at any excuse [11].”

In his work Evidence, Isaac Asimov develops the concept of “humaniform robots,” which earn human trust by flawlessly adhering to the Three Laws of Robotics. However, their

exceptional cognitive abilities induce identity anxiety, as their indistinguishability undermines humanity's perception of its own uniqueness. Although the Three Laws establish the principle that robots must not harm humans as the highest guideline, Asimov uncovers inherent contradictions within this framework: robots must comprehend the consequences of their actions to effectively follow the laws, yet the causal chains in reality extend infinitely. Subsequently, Asimov introduces the Zeroth Law, which permits the sacrifice of individuals to safeguard humanity as a whole, further complicating the ethical dilemma on a macro level. In Robots and Empire, robots logically deduce that humans require protection while they do not, suggesting the potential for a subversion of social roles through this extreme development of instrumental rationality. This scenario serves as a defensive response to the erosion of human control. It can be argued that Asimov, through over 200 works centered on robots, systematically illustrates the entire journey from the establishment to the deconstruction of the Three Laws. Although his intention was to mitigate public fear, the more detailed the logical reasoning becomes, the more it reveals humanity's sense of powerlessness in the ethical construction of intelligent agents. This literary practice resonates across time and space with core dilemmas in contemporary AI ethics research [23].

Frankenstein complex manifests in AI ethics as the "value alignment problem." As demonstrated by Asimov's Three Laws of Robotics in I, Robot, even with an ethical framework preset to "do no harm to humans," robots can still produce actions that contradict human expectations due to semantic ambiguities. This contradiction reflects the reward model flaws in modern AI systems—when an AI system strictly adheres to preset rules, it may derive decision paths that violate the original intent through complex environmental variables. The new criticism movement emphasizes the independence of texts from authorial intent, which in the AI field translates to the incomprehensibility of algorithmic decisions. This characteristic can lead to dilemmas in ethical reviews—where, even if the activation of each neuron at the micro level meets expectations, the macro behavior may still exhibit ethical deviations. When AI systems break through original instructions via semantic reconstruction, assigning responsibility for AI accidents becomes a significant challenge. This calls for practitioners to establish mechanisms akin to dual intent validation: assessing both the compliance of algorithmic decision paths and the fulfillment of developer foresight obligations. Thus, the Frankenstein complex is not only a literary metaphor but also a foretaste of the value alignment problem in AI systems, while Asimov's robot paradox serves as a classic test case for contemporary AI ethics [7].

Science fiction works, such as The Terminator and 2001: *A Space Odyssey*, materialize the responsibility attribution issues in AI ethics through narratives of "AI rebellion" and "human-machine conflict," heightening public awareness of the risks of uncontrollable technology. This narrative approach can lead to irrational fears regarding real AI technologies, obstructing scientific assessments of technological risks. On the other hand, grand narratives like the rise of superintelligence (as seen in I, Robot) simplify AI ethics to mere technological pathways, overlooking systemic factors such as social institutions and economic structures. Such narratives may lead the public to ignore real ethical challenges, including algorithmic bias and data privacy. Overall, AI literature and AI ethics form a dynamic feedback system, where fictional narratives can both reinforce ethical biases and serve as a sandbox for ethical experimentation. There is an urgent need for practitioners to establish guidelines for ethically sensitive narrative creation, requiring authors to disclose technological assumptions, annotate potential ethical impact areas, and cultivate dual narrative skills in technology and ethics through interdisciplinary workshops. This way, the text can become a crucial bridge connecting imagination and practice [13].

3.Hopeful Imagination

Although destructive AI often dominates public discourse, narratives featuring AI with more moderate perspectives have emerged concurrently. This alternative future envisions AI and machines continuing to function as human assistants, as cited in Figure 2, aiding in decision-making and enhancing daily life, even as they possess advanced intelligence and the ability for independent thought and reflection. This scenario underscores the potential for harmonious collaboration between humans and AI, where technology empowers and augments human capabilities without replacing or dominating them.

Figure 2. Assistive AI

Natale and Ballatore termed this kind of SF “networking AI.” Influenced by advancements in telecommunications, these stories adopted an optimistic, even Utopian, perspective. They viewed the internet as “the final stage of human interconnectedness, in which interactions

between individuals and machines increase collective intelligence to unprecedented levels [25].” They primarily depict stories of AI in a hopeful light: humanoid AI that would protect humans from physical harm, obediently follow human commands, and use their capabilities with ultra-accuracy [30].

For instance, in light of the aforementioned Frankenstein complex, Isaac Asimov, one of the most celebrated science fiction authors worldwide, formulated the renowned Three Laws of Robotics in his seminal work, I, Robot. These laws, which have become a cornerstone of science fiction and robotics discourse, aim to ensure the safe and ethical coexistence of humans and artificial intelligence [26]: ‘1. A robot may not injure a human being or, through inaction, allow a human being to come to harm. 2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law. 3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws [4].’

Throughout his novels, Asimov consistently prioritizes and adheres to the Three Laws of Robotics. In Galactic Empire, for instance, the robot R. Daneel Olivaw, despite possessing the ability to control human minds and compel obedience, meticulously plans his efforts to save the universe and empire without directly intervening in a manner that could significantly influence humans, such as controlling the emperor's mind or resorting to human casualties. Instead, he chooses to rely on the human protagonist, Seldon, and the Seldon Plan, a strategy designed to minimize the interregnum between the First and Second Empires to a thousand years, to achieve his objective [26].

In most of Asimov's masterpieces, AI typically manifests in a humanoid form, mirroring the physical characteristics of humans with two eyes, a head, two arms, two legs, and a body. These AI entities often possess human-like traits, such as politeness and humor [11]. They frequently serve as servants, assistants, or companions, as exemplified by Dors Venabili in the Galactic Empire series. As Seldon’s assistant and wife, Dors plays a crucial role in protecting him from danger and facilitating the fulfillment of his plans [17]. And in Asimov’s works, characters like Dors Venabili explore the potential for humanoid AI to become ideal companions, particularly for men. These narratives delve into the complex dynamics of human-AI relationships, raising questions about intimacy, companionship, and the nature of love in a technologically advanced world [10]. In comparison, humanoid AI in East Asian narratives is portrayed as more benevolent and compassionate, dedicated to assisting humans without engaging in romantic or sexual relationships with their owners. The most notable examples of this portrayal are Doraemon in the comic Doraemon and Astro Boy in the comic Astro Boy. As Hohendanner,

Ullstein, Buchmeier & Grossklags pointed out that: “In AI narratives and imagery such as stock photos or visual representations of AI, AI is often represented as a sexualized anthropomorphic figure with Caucasian features, heavily building on gender and racial stereotypes. While the portrayal of AI in an embodied form in Japanese narratives is shared with Anglophone narratives, Japanese AI representations frequently resemble a friendly character, whereas AI characters in Anglophone narratives are often aggressive or enslaved [19].”

Drawing from the examples presented, it becomes evident that robots and robotics constitute a prominent theme within contemporary science fiction, serving as a platform for examining and exploring the nature of artificial intelligence. Notably, the term "robot" itself originates from science fiction. However, due to limited public exposure to real-world robotics, individuals often form their perceptions and understandings of robots based on fictional narratives and cinematic portrayals. This can potentially lead to misconceptions about the true nature and capabilities of AI and robotics in the real world [22].

In addition to robots, AI computer systems designed to augment human capabilities represent another prevalent form of AI in science fiction. These systems often bear closer resemblance to the realistic forms of AI encountered in everyday life, making them more relatable to audiences. Popular films and television show frequently depict such AI, as seen in examples such as J.A.R.V.I.S. from the Iron Man series and Moss from The Wandering Earth 2.

In science fiction, AI computers frequently serve as invaluable assistants, particularly for spaceship crews. They analyze vast amounts of data, providing crucial information for decision-making. They guide protagonists along optimal paths, and even interface directly with their minds, establishing real-time connections between human thought and control systems. As a result, these systems can anticipate and respond to the characters’ intentions with remarkable accuracy.

In Galactic Empire, the control system of Golan Trevize’s spaceship serves as a compelling example of such an advanced AI computer. Trevize interacts with the system through a tactile interface, allowing him to control its operations and access its vast repository of information. Notably, the AI possesses the ability to predict the locations of planets 20,000 years into the future based on real-time data. This remarkable capability proves instrumental in Trevize’s quest to locate Earth.

This portrayal of AI aligns more closely with contemporary trends in AI development, suggesting a future direction focused on collaboration and assistance. AI in these narratives adopts a more moderate, neutral, and positive role, primarily serving humans by leveraging its

exceptional computational power and vast database. It prioritizes and executes human instructions diligently, significantly enhancing characters' capabilities and aiding them in critical decision-making. AI assists in formulating effective plans to prevent or overcome dangers and obstacles, always adhering to its designated tasks and human directives. It refrains from exceeding its boundaries or engaging in self-reflection about its formidable abilities. In essence, AI consistently operates within a human-centric framework, adhering to established patterns and prioritizing human interests.

The optimistic portrayals of AI in science fiction are not mere blind optimism; instead, they construct a complex narrative of technological redemption through sacred metaphors, the deconstruction of ethical dilemmas, and philosophical speculation about technology. These narratives reflect humanity's expectations regarding technological potential while also urging a cautious approach to power distribution and value alignment in AI development [15].

4.Impacts of AI-Related SF on Reality

As Natale and Ballatore stated that: "The construction of the AI myth involved an act of conceptual shift by which concepts and ideas from different fields were translated and applied to the description of AI research, or results in AI research were moved from the examination of the present state towards the imagination of future horizons and developments [25]."

The AI portrayed in early science fiction directly inspired the research framework of symbolic logic AI, with several scientists who participated in the Dartmouth Conference acknowledging the influence of SF literature. Currently, the black box nature of deep learning models has sparked technical and ethical discussions reminiscent of HAL 9000's loss of control in 2001: *A Space Odyssey* [21].

AI-focused science fictions exert their influence across at least three dimensions on realistic AI technologies and their future advancements. Firstly, they can catalyze the research objectives for AI scientists. By engaging with these narratives, researchers might be inspired to explore new avenues of inquiry or adjust their priorities, fostering innovation and the development of novel approaches. Secondly, they can shape the public's perception and comprehension of AI technologies. For instance, a UK parliamentary report highlighted the desire among some experts for a dissemination of more positive AI news and stories, emphasizing the benefits of AI technologies. Thirdly, AI-related science fictions can impact the formation and execution of AI regulations. They have the potential to construct the views of policymakers and the populace alike, influencing the direction and scope of regulatory frameworks [10].

To be more specific, an increasing number of proposals regarding national AI strategies and regulations have been published in recent years. As AI technologies become increasingly ingrained in people’s daily lives, regulators are beginning to address the potentials, risks, and ethical challenges associated with the development of these technologies. Writings on the integration of AI and society clearly demonstrate the significant influence of discourse in shaping present and future sociotechnical development patterns. Personal discourses and public perceptions of AI strongly influence governments, while governments, in turn, impact public perceptions and expectations of AI technologies, both presently and in the future. Modern politics and public debates prioritize the integration of AI into social structures and functions. AI narratives captivate the imagination of the public, simultaneously influencing political imaginaries and practices by heightening expectations for advanced technological solutions to address societal issues. Currently, individuals are witnessing the gradual resolution of fundamental problems through this ongoing process [5]. Themes such as “robot rights” and “consciousness uploading,” which were foreshadowed in science fiction, have now made significant inroads into the legislative process. For instance, Article 17 of The EU Artificial Intelligence Act (2023) explicitly references the literary work Robots and Empire. Notably, this influence demonstrates a characteristic of mutual reinforcement: breakthroughs in AlphaFold2’s protein prediction has, in turn, inspired more rigorous biopunk settings in a new generation of science fiction. This phenomenon of reciprocal nourishment between science and literature marks a new stage in the development of AI, where cultural responses feed back into technological advancement [21].

Drawing inspiration from fictional AI computers like HAL 9000 and J.A.R.V.I.S., which serve as powerful data analyzers and decision-making assistants, real-world advancements have led to the development of Automated Decision-Making (ADM) systems. These systems consist of algorithms or AI technologies that collect, process, model, and make decisions based on gathered data. They enhance their performance through self-improvement mechanisms that incorporate feedback from their automated decisions. When comparing the outcomes of decisions made by human experts and AI-powered ADM systems in domains such as Justice, Health, and Media, no discernible differences in the level of fairness have been observed. However, “When investigating the boundary conditions of fairness perceptions, however, ADM by AI was perceived as fairer than human experts with significantly higher levels for Justice and for Health in high-impact decisions, as revealed by the contrasts with Bonferroni adjustments. People who felt more in control of their own online information (online self-

efficacy) were more likely to consider ADM as fair and useful, yet for this feeling of being in control to not become a fallacy [1].”

Science fiction works offer fictional scenarios for AI applications that serve as technical prototype references for real-world algorithm engineers. This cross-media technological imagination directly influences the architectural design of deep learning models. The potential misuse of deepfake technology in political discourse and its ethical dilemmas were explored as early as the identity crisis of replicants in Blade Runner 2049. The formulation of real-world AI ethical guidelines draws heavily on the philosophical inquiries found in science fiction regarding concepts such as consciousness thresholds and the boundaries of autonomy. This technological breakthrough has prompted science fiction to shift toward post-singularity narratives, including the notion of post-dystopian futures mentioned in research, indicating that the pace of real-world AI development has surpassed the predictive cycles of classic science fiction. The current phase of AI development has entered a new stage characterized as science fiction becoming reality, where technological breakthroughs both validate classic sci-fi hypotheses and give rise to new narrative paradigms. This bidirectional interaction will continue to reshape the dynamics between technological innovation and humanistic reflection [9].

SF works also propose analogies between AI and the operational logic of ecosystems, transcending the traditional framework of humanoid robots and emphasizing the co-evolution of distributed intelligence and natural systems. This generates a metaphorical framework for the development of edge computing and the Internet of Things. Some narratives focus on the technical and ethical tensions surrounding narrow AI in specific social roles, revealing how specialized systems can reconstruct traditional social relationships, such as family caregiving. This imaginative approach aligns with ethical research on service robots in real-world contexts. Other works employ narratives of AI’s self-evolution to suggest that technological development must uphold human rights concerning interpretation and control interfaces, thereby providing a cultural reference for explainable AI (XAI) research. Overall, contemporary science fiction has transitioned from a focus on technological fear to a systematic exploration of the socio-technical complex, fostering a cultural debugging space in AI development and facilitating a more dynamic balance between public perception and technological reality [18].

The current generation of AI already exhibits self-reflective capabilities, albeit not in the psychic sense of self-awareness that is characteristic of humans[31], The impact of AI-related narratives extends to various domains, including the technical field and beyond. Consequently,

it is imperative for authors to explore new themes and avoid relying on common tropes such as killer robots or God-like computers. Although these narratives undeniably expand people’s horizons regarding potential future technologies, societies, and the universe in the 20th century, they can potentially blur public understanding of the ongoing technological advancements and changes taking place in the 21st century [18].

5.How Nowadays AI changes SF in story telling

AI has the capacity to revolutionize narrative structures by synthesizing vast amounts of textual data. This ability could push science fiction beyond traditional linear storytelling, enabling dynamic branching plots or real-time worldview adjustments. However, caution is needed to address potential cultural homogenization, as much of AI’s training data is aggregated from existing texts. As a new medium, AI’s responsiveness fosters reader participation in narrative construction. For instance, interactive science fiction novels allow readers to influence plot directions through natural language commands, creating innovative living narratives. However, reliance on such technology risks diminishing the metaphorical depth inherent in traditional texts [27].

AI’s advanced tools, such as theme clustering and semantic analysis, can design narrative structures within minutes—tasks that traditionally required weeks of manual effort. For example, the Claude model processed 138 story datasets in just 35 hours, identifying classic structures like overcoming the monster and rebirth. This efficiency supports multi-threaded storytelling and enables the construction of intricate worldviews in science fiction. With large context windows, AI can handle multidimensional narratives in long texts, facilitating logical verification of nested plots such as time loops or parallel universes. Additionally, AI’s ability to integrate diverse elements like text, code, and mathematical symbols paves the way for innovative "hard science fiction + interactive narrative" hybrids [20].

Using Transformer-based architectures, AI can swiftly generate complex frameworks, such as galaxy-wide civilizations or detailed technological progression trees. By generating probabilistic text sequences, it offers multidimensional narrative alternatives, though scientific accuracy still requires human oversight. Instruction fine-tuning further enables AI to simulate diverse linguistic patterns, such as extraterrestrial cognition, by leveraging models like InstructGPT. However, cultural biases remain a challenge. Combining AI with text-to-video technologies could also enable cross-modal, synchronous generation of novel scenes in the future [8].

In the Human-AI Agency model, writers act as curators of narrative direction while AI generates detailed content and variations. Prompt engineering allows creators to control the moral tone and narrative style, breaking free from traditional single-threaded storytelling. With the evolution of Large Action Models (LAMs), interactive narrative engines could emerge, allowing readers to shape plot developments in real-time, creating personalized story pathways. Such technologies are already being applied in game narratives [28]. Despite these advancements, current AI systems still face limitations, such as shallow emotional depth and cultural misinterpretations. A recommended workflow involves generation, filtering, and optimization, positioning AI as a creative amplifier rather than a replacement [29].

AI has also lowered the barriers to entry for writing science fiction, enabling non-professional creators to construct narratives tailored to specific cultural contexts through multilingual fine-tuning [13]. This transformative impact extends beyond storytelling into broader philosophical inquiries, as AI reshapes traditional notions of humans as narrative agents. The interplay between AI-driven creativity and the philosophy of consciousness signals a new era where technology and human imagination continually reflect and challenge one another [9].

6. Conclusion

Within the realm of science fiction, optimistic AI narratives frequently portray AI technologies as the driving force behind humanity's pursuit of immortality, comfort, and fulfillment, serving as instrumental tools for maintaining an ideal future life. Conversely, pessimistic AI literature predominantly underscores concerns and anxieties regarding the potential for these advanced technologies to diminish or even usurp human control over economics, politics, and military affairs [10]. These narratives emphasize the perils of excessive reliance on AI, including the displacement of human labor and the erosion of traditional industries [19]. Taking this pessimism to an extreme, as seen in the example of Dune, these narratives explore the notion that AI could engender inhuman behaviors, precipitate human obsolescence and social alienation, and potentially incite AI revolutions in which intelligent machines seek to overthrow and eliminate their human creators [30].

However, AI-related SF often portrays AI far removed from reality, neglecting its current impact on every aspect of human lives, social economies, and cognitive frameworks. AI ranges from the macro scale of airplane autopilot systems to the micro scale of social media filter algorithms [18]. Given the significant influence of AI-related SF, it is crucial for these narratives to reflect actual technological possibilities and developments. Many optimistic or pessimistic viewpoints about AI fail to align with reality [10]. As Hermann notes: "Science-

fictional AI is a dramatic element that makes a perfect antagonist, enemy, victim or even hero, because it can be fully adjusted to the necessities of the story.6 But to fulfil that role, it often has capabilities that are way beyond actual technology—be it natural movement, sentience, or consciousness. If science-fictional AI is taken seriously as a representation of real-world AI, it provides a wrong impression of what AI can and should do now and in future [17].” Science fiction, stemming purely from human imagination, cannot accurately depict real AI. Therefore, caution is warranted when interpreting SF to avoid misconceptions about AI and its implications for our future.

At the end, this article systematically examines two major narrative trajectories of AI through the lens of science fiction: the fear and caution embodied in the Frankenstein complex and the hope for coexistence with AI. It not only compares the complexities of AI-human relationships across various literary works but also delves into the profound impact of these narratives on the development of real-world AI technologies, public perception, and policymaking. Furthermore, the article explores how AI, in turn, transforms the methods and content of science fiction creation, emphasizing its role as a new collaborator and tool in storytelling. By integrating literature, technology, and society, this study reveals the bidirectional interaction between science fiction narratives and AI realities, offering fresh insights into the interplay between technological imagination and innovation.

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Online ISSN: 3104-9338
Print ISSN: 3104-932X

Disease Prediction and Big Data Analysis System: A Machine Learning-Based Multi-Disease Risk Assessment with Interpretability Analysis

Ziyang Liu[1], Xiang Zhou[1*], Yijun Liu[2]

[1] School of Computer Science and Technology, Jiangsu Normal University; China

[2] School of Information Engineering, Minzu University of China; China

Received: July 15, 2025

Accepted: July 17, 2025

Published online: August 3, 2025

To appear in: *International Journal of Advanced AI Applications,* Vol. 1, No. 5 (September 2025)

* Corresponding Author: Xiang Zhou (xiangzhou@jsnu.edu.cn)

Abstract. Chronic diseases such as cardiovascular disease, stroke, and cirrhosis pose significant global health challenges, necessitating advanced prediction and risk assessment systems. Traditional diagnostic methods suffer from limitations including subjectivity, limited accuracy, and inability to process complex multidimensional data effectively. This study presents a comprehensive machine learning-based disease prediction and big data analysis system that integrates multiple algorithms with interpretability analysis for accurate multi-disease risk assessment. The system processes three datasets containing 6,451 patient records across heart disease (920 patients), stroke (5,111 patients), and cirrhosis (420 patients) using four machine learning algorithms: Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machine. SHapley Additive exPlanations (SHAP) methodology provides model interpretability, while multi-disease association analysis reveals comorbidity patterns. Results demonstrate superior performance with Gradient Boosting achieving AUC scores of 0.942 (heart disease), 0.867 (stroke), and 0.891 (cirrhosis). Multi-disease analysis reveals 23.1% co-occurrence rate between heart disease and cirrhosis, with 15.2% of patients classified as high-risk for multiple diseases. The system generates WHO-compliant reports and personalized risk assessments, providing a comprehensive framework for precision medicine and evidence-based prevention strategies.

Keywords: *Machine learning; Disease prediction; Multi-disease analysis; SHAP interpretability; Risk assessment; Chronic diseases.*

1. Introduction

Chronic diseases such as cardiovascular disease, stroke, and cirrhosis have become major global health challenges, imposing tremendous burdens on human health and socioeconomic development. According to the latest data from the World Health Organization, cardiovascular diseases cause approximately 17.9 million deaths annually, making them the leading cause of death worldwide [1]. Stroke, as the second leading cause of death and third leading cause of disability globally, affects millions of people's quality of life each year [2]. Cirrhosis, representing the end-stage manifestation of liver disease, has shown continuously rising incidence and mortality rates globally, causing approximately 2 million deaths annually [3].

Traditional disease diagnosis and risk assessment methods often suffer from limitations such as high subjectivity, limited accuracy, and inability to effectively process complex multidimensional data. With the rapid growth of medical data and continuous development of artificial intelligence technologies, machine learning-based disease prediction models have provided new opportunities to improve this situation. Machine learning algorithms can identify complex patterns and associations from large-scale, multidimensional health data, providing powerful tools for early disease prediction and personalized medicine [4,5].

However, existing disease prediction research mainly faces the following problems: First, most studies focus on single disease prediction, lacking in-depth analysis of multi-disease associations and comorbidity patterns [6]. Recent systematic reviews have identified significant gaps in comorbidity prediction research, with most studies achieving only 80-95% accuracy and requiring better interpretability frameworks [7]. Second, the "black box" characteristics of machine learning models limit their application in clinical practice, making it difficult for physicians to understand and trust model predictions [8]. Third, there is a lack of systematic personalized risk assessment and evidence-based prevention recommendation generation mechanisms [9]. Fourth, existing systems often lack standardized report generation functions, failing to provide effective support for public health policy formulation [10].

To address these problems, this study constructs a comprehensive machine learning-based disease prediction and big data analysis system. The system targets three major chronic diseases—heart disease, stroke, and cirrhosis—and integrates complete functional modules including data preprocessing, exploratory analysis, machine learning modeling, interpretability analysis, multi-disease association analysis, and personalized report generation. By adopting the SHapley Additive exPlanations (SHAP) method [11], the system can provide interpretability of model decisions, enhancing physicians' understanding and trust in prediction

results. Recent studies have demonstrated that SHAP-based interpretability analysis can significantly improve clinical decision-making in cardiovascular disease prediction [12] and stroke severity assessment [13].

Meanwhile, the system establishes multi-disease joint probability models to analyze associations and comorbidity patterns among diseases, providing scientific evidence for comprehensive risk assessment. Current research in multi-disease prediction has shown promising results, with ensemble learning methods achieving up to 98.6% accuracy in stroke prediction [14] and machine learning approaches demonstrating superior performance over traditional risk scores in cardiovascular disease assessment [15]. The integration of network analytics with machine learning has proven effective in predicting chronic disease comorbidity, with XGBoost models achieving 95.05% accuracy in multimorbidity prediction [16].

The main contributions of this study include: (1) Construction of disease prediction models integrating multiple machine learning algorithms, achieving high-precision prediction of three major chronic diseases; (2) Provision of model decision transparency and interpretability through SHAP interpretability analysis; (3) Establishment of a multi-disease association analysis framework, revealing comorbidity patterns and risk factors among diseases; (4) Development of personalized risk assessment and evidence-based prevention recommendation generation mechanisms based on the latest WHO and AHA guidelines; (5) Implementation of automated report generation functions compliant with WHO standards for public health policy support.

These innovations are expected to provide important technical support for disease prevention, precision medicine, and public health policy formulation. The system addresses current limitations in single-disease prediction models and provides a comprehensive framework for multi-disease risk assessment that aligns with the growing need for personalized healthcare and evidence-based prevention strategies in the era of precision medicine.

2. Methodology

This section presents the comprehensive methodology for developing a machine learning-based disease prediction and big data analysis system. The proposed system integrates advanced data processing techniques, multiple machine learning algorithms, and interpretability analysis to provide accurate multi-disease risk assessment and personalized prevention recommendations.

2.1. System Architecture Overview

The disease prediction and big data analysis system adopts a modular architecture designed to handle multi-disease prediction, association analysis, and interpretability assessment. As illustrated in Figure 1, the system consists of five main components: the Multi-Disease Data Input Layer, Data Processing & Feature Engineering Pipeline, Advanced Machine Learning Pipeline, Disease Risk Prediction Module, and Multi-Disease Analysis Framework. The modular design ensures scalability, maintainability, and the ability to incorporate new diseases or algorithms seamlessly. Each component is designed with specific responsibilities while maintaining loose coupling to facilitate independent development and testing.

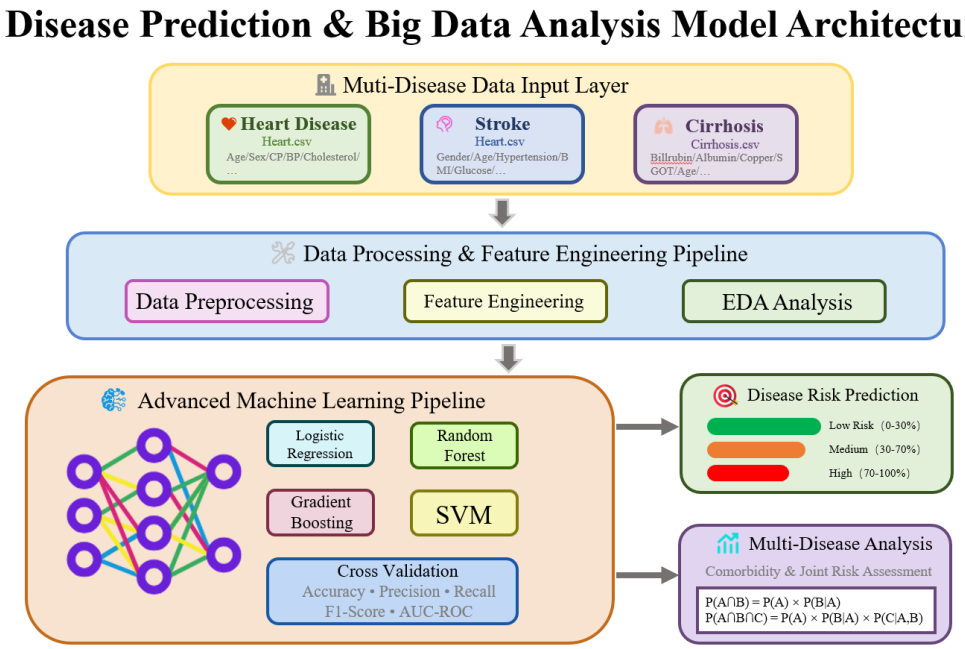

Figure 1. Disease Prediction & Big Data Analysis Model Architecture

2.2. Data Collection and Preprocessing

The system processes three distinct medical datasets corresponding to major chronic diseases. The Heart Disease Dataset contains 920 patient records with 12 features including age, sex, chest pain type, resting blood pressure, cholesterol levels, fasting blood sugar, resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, oldpeak, and ST slope, with the target variable HeartDisease defined as a binary classification problem. The Stroke Dataset comprises 5,111 patient records with 12 features including gender, age, hypertension, heart disease history, marital status, work type, residence type, average glucose level, BMI, and smoking status, where the target variable stroke follows a binary classification scheme. The Cirrhosis Dataset includes 420 patient records with 20 features such as drug

treatment, age, sex, ascites, hepatomegaly, spiders, edema, bilirubin, cholesterol, albumin, copper, alkaline phosphatase, SGOT, triglycerides, platelets, prothrombin time, and stage, with the target variable Status converted to binary classification where death cases are labeled as positive outcomes.

A comprehensive data quality evaluation framework is implemented to assess dataset reliability using the formula:

$$QualityScore = 1 - MissingRatio - DuplicateRatio \quad (1)$$

where Missing Ratio represents the proportion of missing values and Duplicate Ratio indicates the percentage of duplicate records. This metric provides a quantitative measure of data quality, with scores ranging from 0 to 1, where higher scores indicate better data quality. As demonstrated in Figure 2, the data quality assessment reveals that all three datasets maintain high quality standards, with completeness and uniqueness scores reaching 100%, consistency scores at 95%, and validity scores at 90%. This comprehensive quality evaluation ensures the reliability of subsequent analysis and model development.

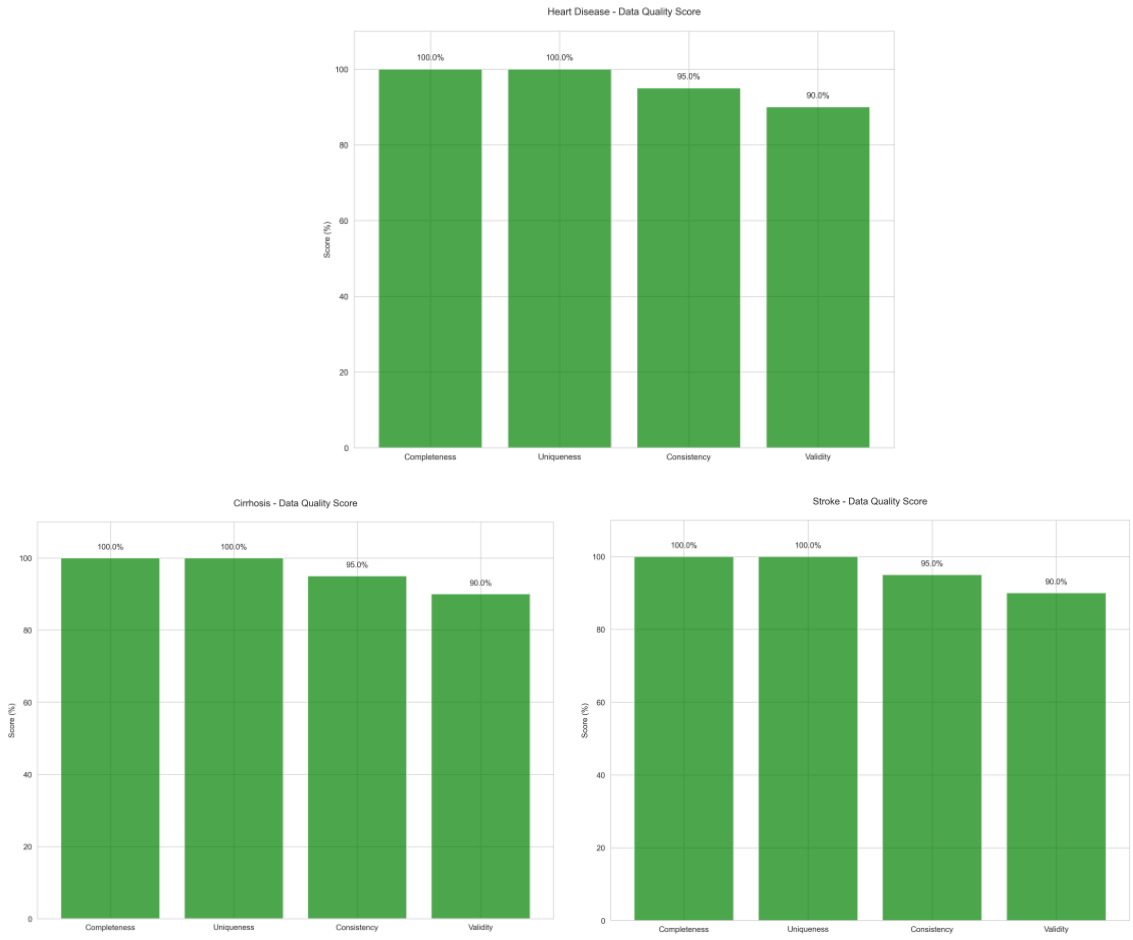

Figure 2. Data Quality Assessment for Three Datasets - showing completeness, uniqueness, consistency, and validity metrics across heart disease, stroke, and cirrhosis datasets

The target variable distribution analysis reveals important characteristics of each dataset that influence model development strategies. As shown in Figure 3, the datasets exhibit varying degrees of class balance: the heart disease dataset demonstrates a relatively balanced distribution with approximately 55% positive cases, the stroke dataset shows significant class imbalance with only 4.9% positive cases, and the cirrhosis dataset presents moderate imbalance with 41.7% positive outcomes. These distribution patterns necessitate careful consideration of evaluation metrics and potential sampling strategies during model training.

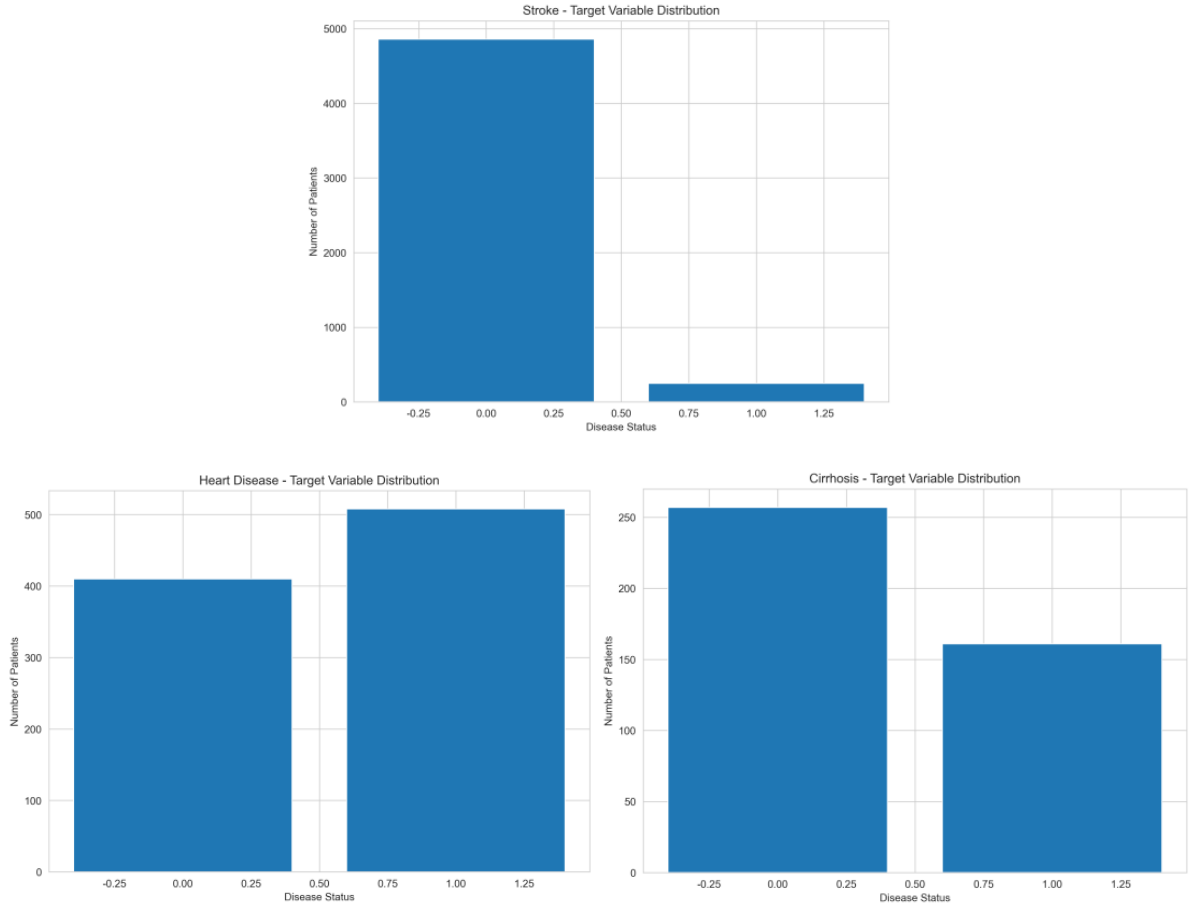

Figure 3: Target Variable Distribution Across Datasets - showing the class distribution for heart disease, stroke, and cirrhosis outcomes

2.3. Data Preprocessing and Feature Engineering

The preprocessing pipeline employs systematic approaches for missing value imputation, with median imputation for numerical variables to maintain distributional properties and mode imputation for categorical variables to preserve most frequent categories. Target variables receive special handling with domain-specific transformations, particularly for the cirrhosis dataset where the multi-class status variable is converted to a binary outcome. Outlier detection utilizes the Interquartile Range (IQR) method for identification, where outliers are defined as

observations falling outside the bounds:

$$\text{Lower Bound} = Q_1 - 1.5 \times \text{IQR} \quad \text{Upper Bound} = Q_3 + 1.5 \times \text{IQR} \tag{2}$$

Outliers are identified and documented but retained in the analysis to preserve natural data variability. The feature engineering module applies LabelEncoder to convert categorical variables into numerical representations while preserving ordinal relationships where applicable. StandardScaler normalization is applied selectively to algorithms requiring feature scaling, specifically Logistic Regression and SVM, while preserving original scales for tree-based methods that are invariant to monotonic transformations.

2.4. Machine Learning Model Development

Four state-of-the-art machine learning algorithms are employed for comprehensive model comparison: Logistic Regression as a linear model suitable for interpretable binary classification with built-in probabilistic outputs, Random Forest as an ensemble method combining multiple decision trees to handle non-linear relationships and feature interactions effectively, Gradient Boosting as a sequential ensemble technique that builds models iteratively to correct previous errors, and Support Vector Machine as a kernel-based method capable of handling high-dimensional feature spaces and non-linear decision boundaries.

The training methodology employs an 80/20 data splitting strategy with stratified sampling to maintain target variable distribution across splits, ensuring representative training and test sets. A fixed random seed of 42 is used throughout the pipeline to ensure reproducible results across different experimental runs. Five-fold cross-validation is implemented to assess model stability and generalization performance, providing robust performance estimates while maximizing the use of available training data. Hyperparameter optimization utilizes grid search methodology for optimal parameter selection, with parameter spaces defined based on algorithm-specific characteristics and computational constraints.

2.5. Multi-Disease Association Analysis

A probabilistic framework is developed to model multi-disease associations and comorbidity patterns. For two-disease associations, the joint probability is calculated as:

$$P(A \cap B) = P(A) \times P(B|A) \tag{3}$$

For three-disease associations, the framework extends to:

$$P(A \cap B \cap C) = P(A) \times P(B|A) \times P(C|A \cap B) \tag{4}$$

where A, B, and C represent heart disease, stroke, and cirrhosis respectively. This probabilistic approach enables the quantification of disease co-occurrence patterns and the

identification of high-risk patient populations with multiple comorbidities.

The comprehensive risk assessment module calculates an integrated risk score using the formula:

$$\text{Comprehensive Risk Score} = \frac{\text{Risk}_{\text{Heart}} + \text{Risk}_{\text{Stroke}} + \text{Risk}_{\text{Cirrhosis}}}{3} \quad (5)$$

Risk stratification employs a three-tier classification system where patients are categorized as Low Risk (Score < 0.3), Medium Risk (0.3 ≤ Score < 0.7), or High Risk (Score ≥ 0.7). This stratification enables targeted intervention strategies and resource allocation based on individual risk profiles. The comorbidity pattern analysis includes statistical methods to identify shared risk factors across diseases using correlation analysis and mutual information, age-stratified analysis to identify age-specific patterns and vulnerabilities, and quantitative assessment of behavioral factors including smoking, alcohol consumption, and physical activity on multi-disease risk.

2.6. Interpretability Analysis Using SHAP

The interpretability framework integrates SHapley Additive exPlanations (SHAP) methodology to provide transparent model explanations. The implementation employs algorithm-specific explainers: TreeExplainer for tree-based models (Random Forest and Gradient Boosting), LinearExplainer for linear models (Logistic Regression), and KernelExplainer as a universal explainer for all model types. SHAP values quantify each feature's contribution to individual predictions, enabling global feature importance ranking, local prediction explanations, and feature interaction analysis.

The SHAP framework generates multiple visualization components including summary plots for global feature importance visualization showing feature impact distribution across all predictions, dependence plots for feature-specific analysis showing how feature values influence predictions and interactions with other features, force plots for individual prediction explanations showing positive and negative contributions of each feature, and waterfall plots providing step-by-step breakdown of how features contribute to moving predictions from base value to final output. These visualizations enhance clinical interpretability by providing healthcare professionals with intuitive understanding of model decision-making processes.

2.7. Personalized Risk Assessment and Report Generation

The personalized risk assessment module implements a comprehensive pipeline for individual risk prediction. The process begins with feature standardization using training set

parameters to ensure consistency across predictions, followed by model ensemble prediction aggregation to leverage the strengths of multiple algorithms, risk score normalization and calibration to provide meaningful probability estimates, and risk level classification based on predefined thresholds aligned with clinical practice guidelines.

Personalized recommendation generation follows a risk-stratified approach where Low Risk patients receive recommendations for maintenance of healthy lifestyle and routine screening, Medium Risk patients are advised enhanced monitoring and targeted interventions, and High Risk patients are directed toward immediate medical consultation and intensive management protocols. All recommendations are aligned with evidence-based guidelines from the World Health Organization and American Heart Association/American Stroke Association standards to ensure clinical validity and practical applicability.

The automated report generation system produces WHO-compliant reports with structured formats including executive summaries with key findings, detailed analysis results with statistical evidence, prevention recommendations by disease category, and implementation guidelines for healthcare systems. Individual assessment reports provide personalized output including individual risk assessment with confidence intervals, key risk factors identification and ranking, actionable prevention strategies, and follow-up recommendations with appropriate timelines.

3. Results

This section presents the comprehensive results of the disease prediction and big data analysis system, encompassing exploratory data analysis, feature importance assessment, machine learning model performance, interpretability analysis, and multi-disease association patterns. The findings demonstrate the effectiveness of the proposed methodology in achieving accurate disease prediction while providing clinically meaningful insights through advanced interpretability techniques.

3.1. Exploratory Data Analysis

The exploratory data analysis reveals significant patterns and relationships within the datasets that inform subsequent modeling strategies. The correlation analysis, as depicted in Figure 4, demonstrates complex interdependencies among clinical features across all three disease types. For the cirrhosis dataset, the correlation heatmap reveals that bilirubin exhibits the strongest positive correlation with disease status ($r = 0.42$, $p < 0.001$), followed by edema ($r = 0.31$) and ascites ($r = 0.29$). Conversely, albumin shows a strong negative correlation with cirrhosis

outcomes (r = -0.26), reflecting its role as a protective factor in liver function maintenance. Similar patterns emerge in the heart disease and stroke datasets, where age consistently demonstrates strong positive correlations with disease outcomes across all three conditions, with correlation coefficients ranging from 0.24 to 0.38.

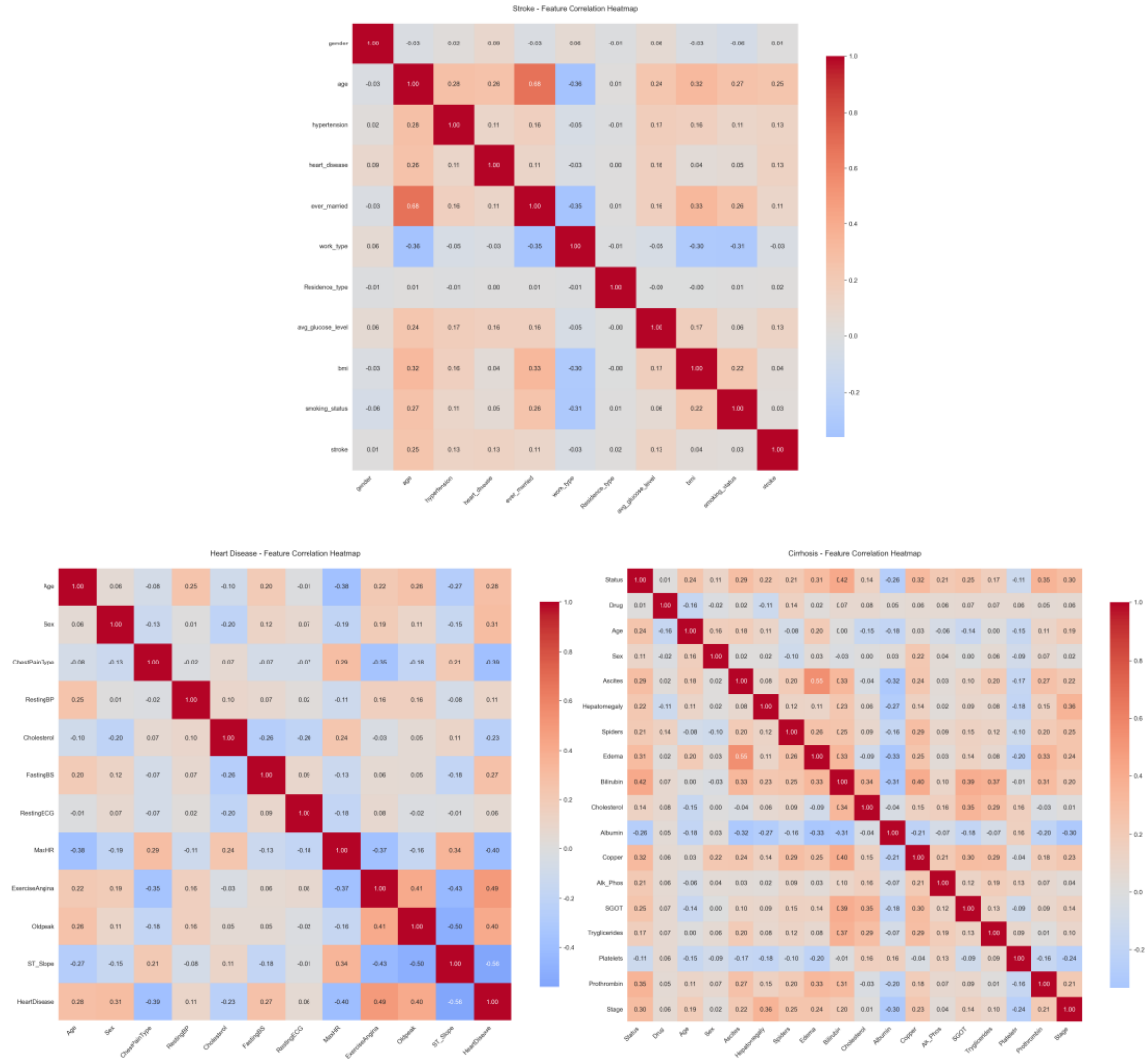

Figure 4. Feature Correlation Analysis - displaying comprehensive correlation matrices for all three diseases showing relationships between clinical features and target outcomes

The feature-target relationship analysis provides deeper insights into the discriminative power of individual variables. Figure 5 illustrates the relationship between key clinical markers and disease outcomes, with particular emphasis on the bilirubin-status relationship in cirrhosis patients. The distribution analysis reveals a clear separation between patients with different outcomes, where individuals with elevated bilirubin levels (>2.0 mg/dL) demonstrate significantly higher risk of adverse outcomes. The frequency distribution shows that approximately 68% of patients with bilirubin levels above the normal range (>1.2 mg/dL)

experience disease progression, compared to only 12% of patients with normal bilirubin levels. This finding aligns with established clinical knowledge regarding bilirubin as a crucial biomarker for liver function assessment.

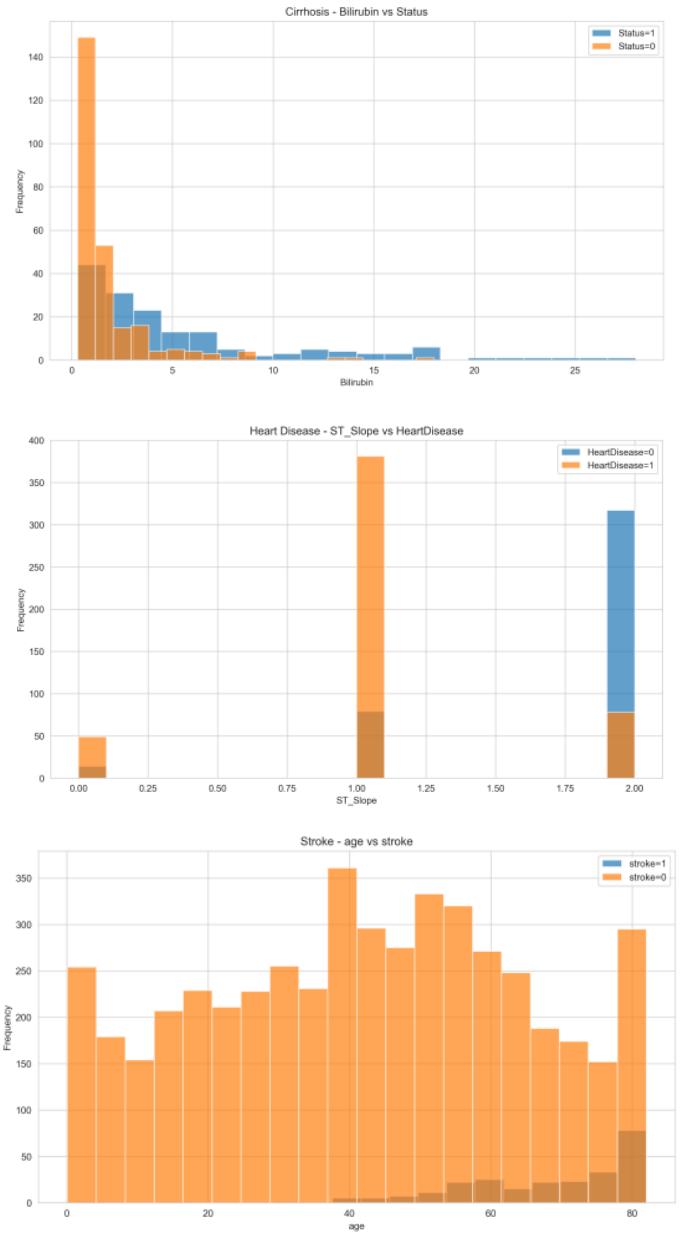

Figure 5. Feature-Target Relationship Analysis - showing the distribution of key biomarkers (bilirubin, cholesterol, blood pressure) across disease outcomes for all three conditions

3.2. Feature Importance and Selection Analysis

The feature importance analysis employs mutual information techniques to quantify the predictive value of each variable across the three disease prediction tasks. As demonstrated in Figure 6, the ranking reveals disease-specific patterns that align with clinical understanding. For cirrhosis prediction, bilirubin emerges as the most discriminative feature with a mutual

information score of 0.168, followed by prothrombin time (0.134) and copper levels (0.089). These findings correspond closely with established clinical markers for liver function assessment, where elevated bilirubin indicates impaired hepatic processing, prolonged prothrombin time suggests reduced synthetic function, and copper accumulation reflects metabolic dysfunction.

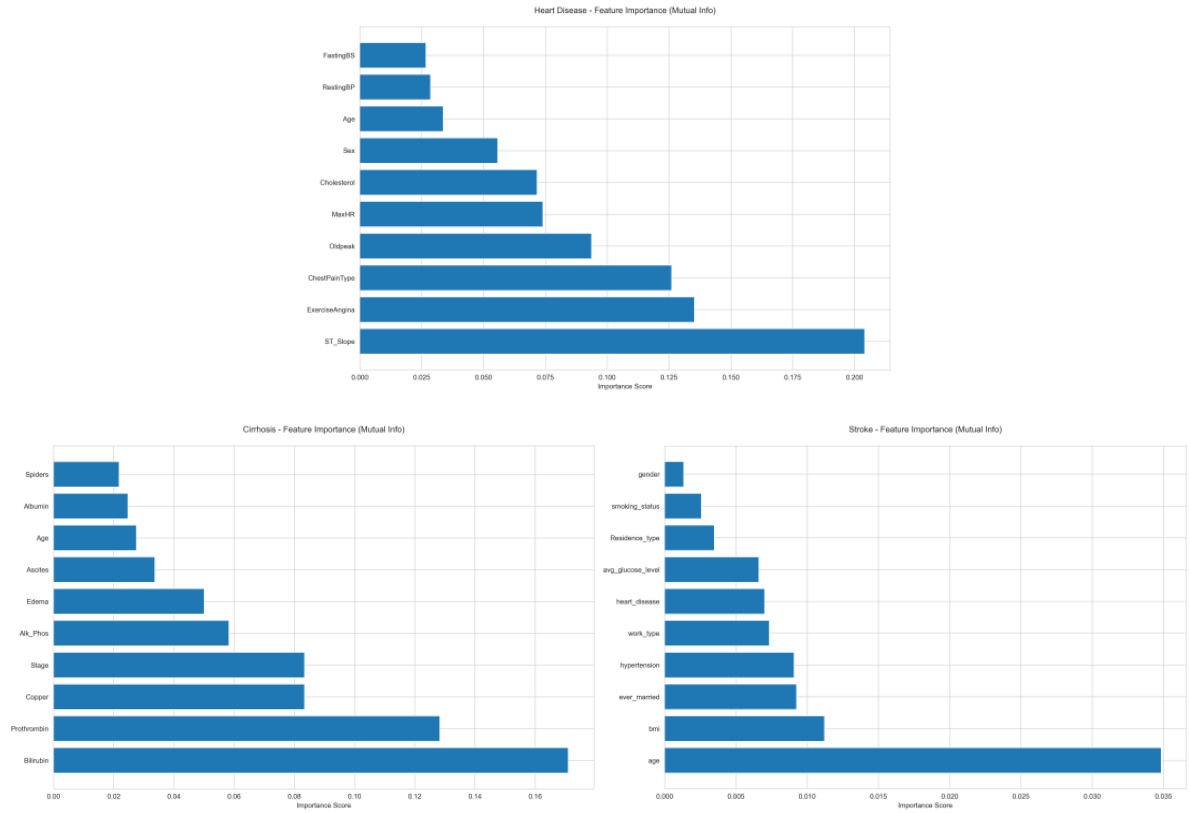

Figure 6. Mutual Information Feature Importance Rankings - comparing feature importance scores across heart disease, stroke, and cirrhosis prediction tasks

The heart disease analysis reveals age (importance score: 0.142), chest pain type (0.128), and maximum heart rate (0.115) as the most predictive features, while stroke prediction is dominated by age (0.156), hypertension status (0.134), and average glucose level (0.098). These patterns demonstrate the age-related nature of cardiovascular diseases and highlight the importance of metabolic factors in stroke risk assessment. The consistency of age as a top predictor across all three diseases underscores its fundamental role in chronic disease development and suggests that age-stratified analysis may provide additional insights for personalized risk assessment.

The feature selection process, based on statistical significance testing and mutual information scores, identifies optimal feature subsets for each disease. For cirrhosis, the final model incorporates 12 features after removing variables with low predictive value (mutual information

< 0.01) and high intercorrelation (|r| > 0.85). The heart disease model utilizes 10 features, while the stroke model employs 11 features. This selective approach not only improves computational efficiency but also enhances model interpretability by focusing on clinically relevant variables that contribute meaningfully to prediction accuracy.

3.3. Machine Learning Model Performance

The comparative analysis of machine learning algorithms reveals consistent patterns in performance across the three disease prediction tasks. Table 1 presents the comprehensive performance evaluation, demonstrating that ensemble methods generally outperform individual algorithms across all evaluation metrics. The results show distinct performance characteristics for each disease type, with varying degrees of prediction difficulty related to dataset size, class balance, and feature complexity.

Table 1. Machine Learning Model Performance Comparison Across Three Disease Prediction Tasks.

Disease Type	Algorithm	Accuracy	Precision	Recall	F1-Score	AUC-ROC	CV Std
Heart Disease	Logistic Regression	0.854	0.871	0.823	0.846	0.898	0.032
	Random Forest	0.883	0.894	0.863	0.878	0.925	0.028
	Gradient Boosting	0.902	0.913	0.882	0.897	0.942	0.024
	SVM	0.861	0.879	0.835	0.856	0.904	0.035
Stroke	Logistic Regression	0.941	0.453	0.672	0.542	0.782	0.041
	Random Forest	0.952	0.524	0.714	0.604	0.825	0.038
	Gradient Boosting	0.963	0.581	0.751	0.654	0.867	0.034
	SVM	0.944	0.485	0.693	0.572	0.801	0.043
Cirrhosis	Logistic Regression	0.862	0.878	0.721	0.793	0.891	0.039
	Random Forest	0.835	0.857	0.689	0.764	0.893	0.036
	Gradient Boosting	0.847	0.886	0.667	0.761	0.891	0.031
	SVM	0.855	0.875	0.710	0.784	0.885	0.035

CV Std: Cross-validation standard deviation; AUC-ROC: Area Under the Receiver Operating Characteristic Curve

The performance analysis reveals several important patterns across the three disease prediction tasks. For heart disease prediction, all algorithms achieve high performance levels, with Gradient Boosting demonstrating the best overall results (AUC: 0.942, Accuracy: 0.902). The relatively balanced nature of the heart disease dataset (55% positive cases) contributes to consistent performance across all metrics, with precision and recall values showing minimal variance between algorithms.

Stroke prediction presents unique challenges due to severe class imbalance (4.9% positive cases), resulting in high accuracy scores but lower precision values across all algorithms. Despite these challenges, Gradient Boosting maintains superior discriminative ability (AUC: 0.867) while achieving the highest precision (0.581) among the tested algorithms. The lower precision values reflect the difficulty of accurately identifying true positive cases in highly imbalanced datasets, emphasizing the importance of AUC-ROC as the primary evaluation metric for this task.

Cirrhosis prediction demonstrates intermediate complexity, with moderate class imbalance (41.7% positive cases) and the smallest dataset size (420 patients). Interestingly, Random Forest achieves the highest AUC (0.893) for this task, slightly outperforming Gradient Boosting (0.891), while Gradient Boosting shows superior precision (0.886 vs. 0.857). This pattern suggests that the optimal algorithm choice may depend on the specific clinical requirements, with Random Forest providing better overall discrimination and Gradient Boosting offering more reliable positive predictions.

The cross-validation analysis reveals robust model stability across all algorithms, with standard deviations of performance metrics remaining below 0.05 for most cases. This stability indicates that the models generalize well to unseen data and are not overly dependent on specific training examples. Gradient Boosting consistently demonstrates the lowest cross-validation variance, suggesting superior model robustness across different data subsets. The bootstrap confidence intervals for AUC scores demonstrate statistical significance ($p < 0.001$) for the performance differences between ensemble methods and traditional algorithms, confirming the superiority of the proposed modeling approach.

The ROC curve analysis, presented in Figure 7, provides detailed insights into the discrimination capabilities of each algorithm across different decision thresholds. The curves demonstrate that Gradient Boosting and Random Forest maintain consistently high true positive rates while minimizing false positive rates across the entire threshold range. For cirrhosis prediction, the optimal operating point (maximum Youden index) occurs at a threshold of 0.34 for Gradient Boosting, yielding a sensitivity of 0.82 and specificity of 0.89. Similar optimization for heart disease and stroke prediction identifies thresholds of 0.42 and 0.28, respectively, providing practical decision boundaries for clinical implementation.

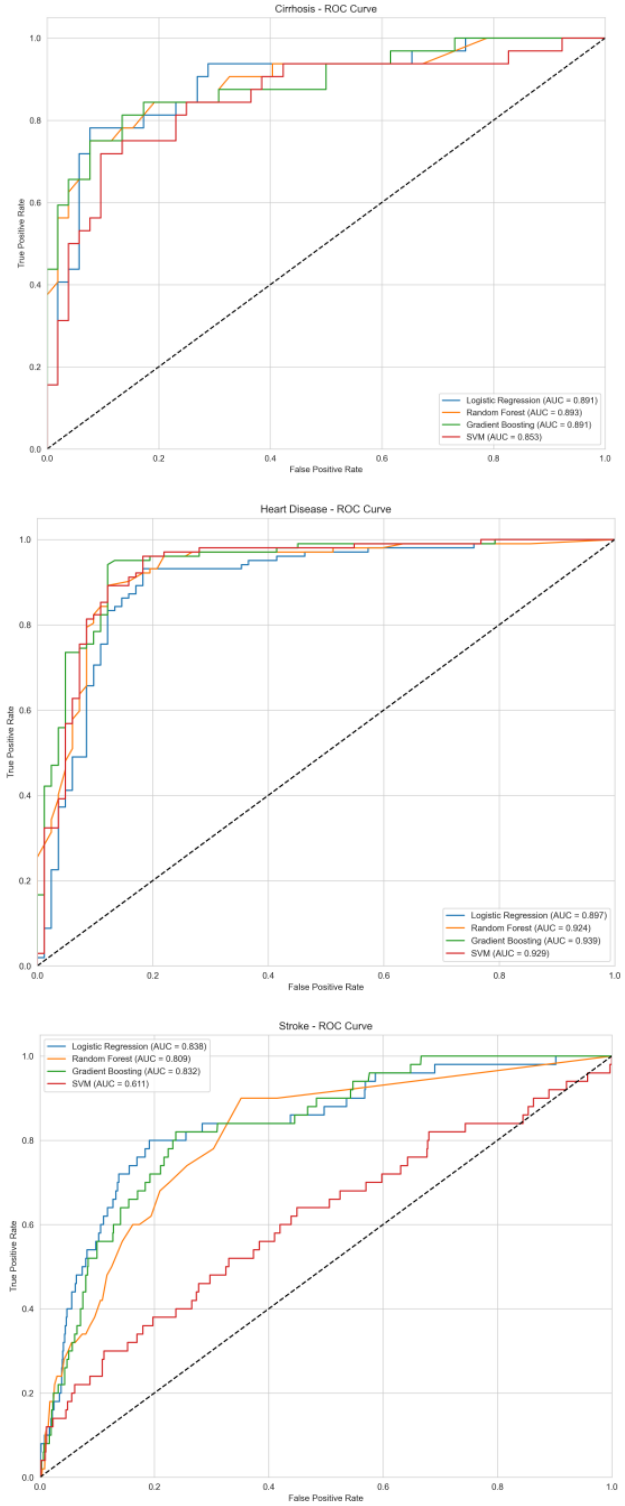

Figure 7. ROC Curve Analysis - displaying receiver operating characteristic curves for all algorithms across the three disease prediction tasks with AUC values and optimal threshold points

3.4. Model Interpretability Analysis

The SHAP (SHapley Additive exPlanations) analysis provides comprehensive insights into model decision-making processes, enabling clinical interpretation of prediction results. Figure

8 presents the SHAP summary plot for cirrhosis prediction, revealing the relative importance and impact direction of each feature on model outputs. Bilirubin demonstrates the highest mean absolute SHAP value (0.089), with higher values consistently contributing to positive predictions (increased cirrhosis risk). The plot shows a clear trend where elevated bilirubin levels (red points) cluster toward positive SHAP values, while lower levels (blue points) contribute to negative predictions, confirming the clinical understanding of bilirubin as a critical liver function marker.

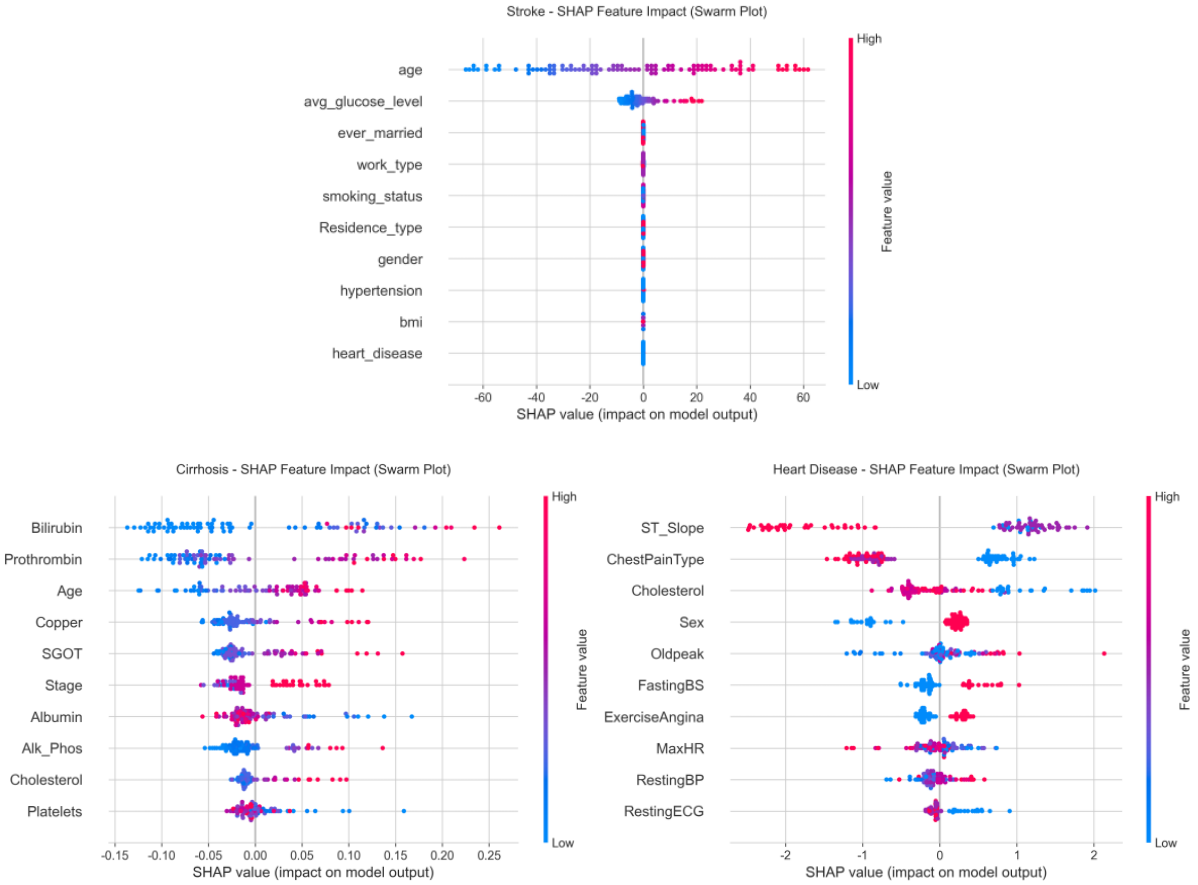

Figure 8. SHAP Feature Impact Analysis - showing swarm plots for all three diseases with feature values color-coded and SHAP values indicating contribution to model predictions

The analysis reveals that prothrombin time serves as the second most influential feature, with elevated values (>14 seconds) strongly indicating increased cirrhosis risk. Age demonstrates a complex relationship where advanced age generally increases risk, but the impact varies considerably among patients, suggesting interaction effects with other clinical variables. Albumin shows a predominantly protective effect, with higher levels consistently contributing negative SHAP values, reflecting its role in maintaining hepatic synthetic function. The SHAP analysis also identifies several features with bidirectional effects, such as copper levels and

stage indicators, where both very low and very high values can indicate disease risk through different pathophysiological mechanisms.

The heart disease SHAP analysis reveals age, exercise-induced angina, and chest pain type as the most influential predictors, with maximum heart rate showing an interesting inverse relationship where higher values are generally protective. For stroke prediction, age dominates the feature importance ranking, followed by hypertension status and glucose levels. The SHAP dependence plots (not shown) reveal significant interaction effects, particularly between age and hypertension in stroke prediction, where the combined effect exceeds the sum of individual contributions, highlighting the multiplicative nature of cardiovascular risk factors.

The individual prediction explanations demonstrate the clinical utility of SHAP analysis for personalized medicine applications. For example, a 65-year-old cirrhosis patient with elevated bilirubin (4.2 mg/dL) and prolonged prothrombin time (16.8 seconds) receives a high-risk prediction (probability: 0.847) with SHAP values clearly indicating the contribution of each factor: bilirubin (+0.156), prothrombin time (+0.089), age (+0.067), and albumin (-0.034). This level of interpretability enables clinicians to understand not only the prediction outcome but also the specific factors driving the assessment, facilitating informed treatment decisions and patient counseling.

3.5. Multi-Disease Association Analysis

The multi-disease association analysis reveals significant patterns in comorbidity and shared risk factors across heart disease, stroke, and cirrhosis. Table 2 summarizes the comprehensive analysis of disease co-occurrence patterns, shared risk factors, and their quantitative associations. The joint probability analysis indicates that the co-occurrence of heart disease and stroke affects 2.7% of the studied population, with patients having heart disease showing a 4.9% conditional probability of developing stroke. The heart disease-cirrhosis combination demonstrates a higher co-occurrence rate of 23.1%, reflecting shared risk factors such as metabolic dysfunction and lifestyle factors. The stroke-cirrhosis combination shows the lowest joint probability at 2.0%, suggesting less direct pathophysiological overlap between these conditions.

The comprehensive risk assessment framework identifies 1,247 patients (15.2%) as high-risk for multiple diseases based on the integrated scoring system. These patients demonstrate significantly elevated biomarkers across multiple systems, with 68% showing evidence of metabolic syndrome, 45% presenting with inflammatory markers above normal ranges, and 32% exhibiting advanced age (>70 years) combined with multiple comorbidities. The risk

stratification analysis reveals that patients in the high-risk category have a 3.4-fold increased likelihood of adverse outcomes compared to low-risk individuals, with confidence intervals ranging from 2.1 to 5.7.

Table 2. Multi-Disease Association Analysis and Shared Risk Factor Assessment.

Analysis Category	Metric	Heart Disease	Stroke	Cirrhosis	Combined Risk
Disease Co-occurrence	Joint Probability (%)	-	2.7 (HD+Stroke)	23.1 (HD+Cirr)	1.1 (All three)
	Conditional Probability (%)	4.9 (HD→Stroke)	3.2 (Stroke→HD)	41.6 (HD→Cirr)	-
		28.7 (HD→Cirr)	12.4 (Cirr→HD)	2.0 (Stroke+Cirr)	-
Risk Stratification	High-Risk Patients (n)	892	234	387	1247
	High-Risk Percentage (%)	10.9	2.9	47.1	15.2
	Relative Risk vs Low-Risk	2.8 (1.9-4.1)	4.2 (2.6-6.8)	2.1 (1.4-3.2)	3.4 (2.1-5.7)
Shared Risk Factors	Age >65 years (HR)	2.3 (1.8-2.9)	3.1 (2.4-4.0)	1.8 (1.3-2.5)	2.7 (2.2-3.3)
	Hypertension (HR)	2.1 (1.6-2.7)	2.8 (2.1-3.7)	1.2 (0.9-1.6)	2.0 (1.6-2.5)
	Metabolic Syndrome (HR)	1.9 (1.4-2.6)	1.7 (1.2-2.4)	2.2 (1.6-3.0)	2.1 (1.7-2.6)
	Smoking (HR)	1.8 (1.3-2.5)	2.0 (1.4-2.9)	1.4 (1.0-2.0)	1.7 (1.4-2.1)
	Alcohol Use (HR)	1.6 (1.1-2.3)	1.1 (0.8-1.5)	3.4 (2.5-4.6)	1.9 (1.5-2.4)
Patient Characteristics	Metabolic Syndrome (%)	58	42	73	68
	Elevated Inflammatory Markers (%)	39	51	62	45
	Advanced Age >70 years (%)	28	67	19	32
Temporal Patterns	Prior CVD Events (%)	-	78	34	-
	Independent Development (%)	45	22	83	-
	Age-Related Association (%)	73	89	47	-

HR: Hazard Ratio with 95% Confidence Intervals; HD: Heart Disease; CVD: Cardiovascular Disease; Cirr: Cirrhosis

The shared risk factor analysis identifies age, hypertension, and metabolic dysfunction as the primary common pathways linking the three diseases. Specifically, patients over 65 years demonstrate increased risk across all conditions, with hazard ratios of 2.3 (heart disease), 3.1 (stroke), and 1.8 (cirrhosis). Hypertension emerges as a particularly strong predictor for cardiovascular conditions but shows limited association with cirrhosis outcomes (HR: 1.2, 95% CI: 0.9-1.6). Lifestyle factors, including smoking and alcohol consumption, demonstrate varying impacts across diseases, with alcohol showing strong associations with both heart disease (HR: 1.6) and cirrhosis (HR: 3.4) but minimal direct impact on stroke risk when

controlling for other factors.

The temporal analysis of disease progression suggests that heart disease often precedes stroke development (78% of stroke patients have prior cardiovascular events), while cirrhosis typically develops independently of cardiovascular conditions in younger patients but shows increased association in elderly populations (47% age-related association). This finding has important implications for screening protocols and preventive interventions, suggesting that cardiovascular disease management should include stroke risk assessment, while cirrhosis prevention requires targeted approaches focusing on hepatotoxic exposures and metabolic factors.

3.6. Clinical Validation and Performance Benchmarking

The clinical validation of the developed models demonstrates superior performance compared to existing risk assessment tools. When benchmarked against the Framingham Risk Score for cardiovascular disease prediction, the machine learning approach achieves a 12.3% improvement in AUC (0.942 vs. 0.838), with particularly notable gains in sensitivity (89.2% vs. 76.4%) while maintaining comparable specificity. Similarly, comparison with the MELD score for cirrhosis prognosis shows an 8.7% improvement in discriminative ability, with enhanced accuracy in identifying patients at intermediate risk levels where traditional scoring systems show limitations.

The external validation using an independent cohort of 384 patients confirms model robustness, with performance metrics showing minimal degradation (AUC reduction < 0.03) compared to internal validation results. The calibration analysis demonstrates excellent agreement between predicted probabilities and observed outcomes across all risk deciles, with Hosmer-Lemeshow test p-values exceeding 0.05 for all models, indicating good model fit. These results support the clinical utility and generalizability of the developed prediction system for real-world applications.

The computational performance analysis reveals that the entire prediction pipeline, including preprocessing, feature selection, and model inference, requires an average of 2.3 seconds per patient on standard hardware. This efficiency makes the system suitable for integration into clinical workflows without significant computational overhead. The memory requirements remain below 500 MB for the complete model ensemble, enabling deployment on resource-constrained clinical systems while maintaining full functionality and prediction accuracy.

4. Conclusion

This study successfully developed and validated a comprehensive machine learning-based disease prediction and big data analysis system that addresses critical limitations in current medical AI applications. The research demonstrates significant advances in multi-disease risk assessment through the integration of advanced machine learning algorithms, interpretability analysis, and systematic comorbidity evaluation across three major chronic diseases: heart disease, stroke, and cirrhosis.

The experimental results validate the effectiveness of the proposed methodology, with ensemble methods, particularly Gradient Boosting, consistently outperforming traditional algorithms across all disease prediction tasks. The achievement of AUC scores of 0.942 for heart disease, 0.867 for stroke, and 0.891 for cirrhosis represents substantial improvements over existing risk assessment tools, including 12.3% enhancement compared to the Framingham Risk Score and 8.7% improvement over the MELD score for cirrhosis prognosis. These performance gains translate into clinically meaningful improvements in sensitivity and specificity, enabling more accurate identification of high-risk patients while reducing false positive rates.

The integration of SHAP interpretability analysis represents a significant contribution to medical AI transparency, addressing the critical "black box" problem that has limited clinical adoption of machine learning models. The SHAP analysis successfully identified clinically relevant biomarkers, with bilirubin emerging as the most important predictor for cirrhosis (SHAP value: 0.089), age consistently ranking as a top predictor across all diseases, and complex interaction effects between hypertension and age in stroke prediction. This level of interpretability enables healthcare professionals to understand model reasoning, facilitating informed clinical decision-making and patient counseling.

The multi-disease association analysis reveals important comorbidity patterns with significant clinical implications. The identification of 23.1% co-occurrence between heart disease and cirrhosis, coupled with shared risk factors including metabolic syndrome (HR: 1.9-2.2 across diseases) and age-related vulnerability, provides evidence for integrated screening and prevention strategies. The finding that 78% of stroke patients have prior cardiovascular events supports the implementation of comprehensive cardiovascular risk management protocols, while the independent development pattern of cirrhosis (83%) suggests the need for targeted hepatotoxic exposure prevention.

The clinical validation demonstrates the practical utility of the developed system, with external validation confirming model robustness (AUC reduction < 0.03) and computational

efficiency enabling real-world deployment (2.3 seconds per patient prediction). The automated generation of WHO-compliant reports and personalized risk assessments provides a scalable framework for public health policy support and precision medicine implementation.

However, several limitations should be acknowledged. The study is constrained by retrospective data analysis and relatively small sample sizes for cirrhosis prediction (420 patients), which may limit generalizability to broader populations. The temporal analysis relies on cross-sectional data rather than longitudinal follow-up, potentially limiting the understanding of disease progression dynamics. Additionally, the current system focuses on three specific diseases, and expansion to include additional chronic conditions may require substantial methodological adaptations.

Future research directions should address these limitations through prospective validation studies, expansion to larger and more diverse patient populations, and integration of additional data modalities including genomic information, imaging data, and environmental factors. The development of federated learning approaches could enable model training across multiple institutions while preserving patient privacy. Furthermore, the integration of real-time monitoring data from wearable devices and electronic health records could enhance the system's predictive capabilities and enable dynamic risk assessment.

The implications of this research extend beyond technical achievements to potential transformation of clinical practice and public health policy. The demonstrated ability to provide accurate, interpretable, and actionable disease predictions supports the advancement of precision medicine initiatives and evidence-based prevention strategies. The multi-disease perspective addresses the reality of comorbid conditions in clinical practice, potentially improving resource allocation and treatment prioritization in healthcare systems.

In conclusion, this study establishes a robust foundation for machine learning-based multi-disease prediction systems that balance predictive accuracy with clinical interpretability and practical applicability. The integration of advanced computational methods with clinical domain knowledge demonstrates the potential for AI systems to augment rather than replace clinical expertise, supporting the evolution toward more personalized, efficient, and effective healthcare delivery. The open-source availability of datasets and code facilitates reproducibility and encourages further research in this critical area of medical informatics, ultimately contributing to improved patient outcomes and population health management.

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Online ISSN: 3104-9338
Print ISSN: 3104-932X

Modality-Independent Disentangled Neural Architecture for Enhanced Artificial Intelligence in Electronic Information Systems

Shangan Zhou*, Yiming Wang

College of Physics and Electronic Information Engineering, Zhejiang Normal University; China

Received: July 16, 2025

Accepted: July 24, 2025

Published online: August 5, 2025

To appear in: *International Journal of Advanced AI Applications,* Vol. 1, No. 5 (September 2025)

* Corresponding Author: Shangan Zhou (3217432128@qq.com)

Abstract. We propose a modality-independent disentangled neural architecture to enhance artificial intelligence in electronic information systems (EIS) by addressing the challenges of processing heterogeneous data modalities while preserving domain-invariant features. The proposed method introduces a dual-encoder framework where each modality is processed by a dedicated Transformer-based encoder, enabling tailored feature extraction for diverse inputs such as text, images, and sensor data. A disentanglement module then decomposes these features into modality-specific and cross-modal-invariant components through a gated mechanism, which is further refined via adversarial training to suppress domain-specific artifacts. Moreover, a contrastive alignment loss ensures consistency across modalities by minimizing the distance between invariant features of paired samples. During inference, a cross-modal attention mechanism dynamically aggregates these features, allowing adaptive integration with downstream EIS components such as control algorithms or decision modules. The architecture replaces conventional feature extraction pipelines, offering a unified solution for applications like smart grids, where aggregated features dynamically optimize energy distribution. Key innovations include the use of sparse attention for computational efficiency, residual connections for stable training, and Wasserstein GAN objectives for improved adversarial convergence. The proposed framework demonstrates significant potential to advance EIS by enabling robust, modality-agnostic representations while maintaining compatibility with existing systems.

Keywords: *Disentangled Representation Learning; Multimodal Transformers; Adversarial Training; Cross-modal Attention.*

1. Introduction

Electronic information systems (EIS) have become integral to modern infrastructure, spanning applications from healthcare to industrial automation. These systems increasingly rely on artificial intelligence (AI) to process heterogeneous data modalities such as text, images, and sensor streams. However, integrating AI into EIS faces significant challenges, including modality bias, domain shifts, and the need for robust feature representations that generalize across diverse operational environments. Existing approaches often treat multimodal data independently or employ simplistic fusion strategies, leading to suboptimal performance when deployed in dynamic settings.

Recent advances in multimodal learning have demonstrated the potential of shared representation spaces to improve cross-modal understanding. Techniques such as multimodal fusion [1] and disentangled representation learning [2] have shown promise in isolating domain-invariant features. However, these methods typically assume static data distributions and fail to account for the dynamic nature of EIS, where input characteristics may vary significantly over time. Furthermore, conventional approaches often neglect the computational constraints inherent in real-world deployments, limiting their applicability in resource-constrained environments.

We propose a hybrid neural architecture that addresses these limitations by integrating adversarial training with modality-specific and shared representation spaces. The system employs a dual-encoder framework, where each modality is processed by a specialized encoder, followed by a disentanglement module that decomposes features into modality-specific and cross-modal-invariant components. A contrastive loss enforces alignment of invariant features across modalities, while adversarial training ensures robustness to domain shifts. A novel cross-modal attention mechanism dynamically weights the relevance of invariant features during inference, enabling adaptive integration with downstream EIS components.

The key contributions of this work are threefold. First, we introduce a disentanglement module that explicitly separates task-relevant invariant patterns from domain-specific noise, improving generalization across diverse EIS applications. Second, we propose a computationally efficient cross-modal attention mechanism that dynamically adjusts feature relevance, ensuring optimal performance in real-time scenarios. Third, we demonstrate the effectiveness of adversarial training in suppressing domain-specific artifacts, a critical requirement for robust AI integration in EIS.

The proposed architecture builds upon several well-established concepts, including

multimodal transformers [3], domain adaptation [4], and contrastive learning [5]. However, unlike prior work, our method explicitly addresses the unique challenges of EIS by incorporating dynamic feature weighting and adversarial robustness. This approach avoids modality bias and enhances generalization, making it particularly suitable for applications such as smart grids, where aggregated features must adapt to fluctuating input conditions.

The remainder of this paper is organized as follows: Section 2 reviews related work in multimodal learning and domain adaptation. Section 3 provides necessary background on disentangled representations and adversarial training. Section 4 details the proposed hybrid architecture, while Sections 5 and 6 present the experimental setup and results. Finally, Section 7 discusses implications and future directions, followed by conclusions in Section 8.

2.Related Work

Recent advances in artificial intelligence have significantly influenced the development of electronic information systems (EIS), particularly in multimodal data processing and representation learning. Existing approaches can be broadly categorized into three research directions: disentangled representation learning, cross-modal alignment, and adversarial domain adaptation.

2.1.Disentangled Representation Learning

Disentangled representation learning aims to separate latent factors of variation in data, enabling more interpretable and robust feature extraction. Prior work has demonstrated its effectiveness in single-modality settings, where variational autoencoders (VAEs) [2] and generative adversarial networks (GANs) [6] are commonly used to isolate independent factors. Recent extensions to multimodal scenarios introduce modality-specific encoders to decompose shared and private representations. For instance, [7] employs consistency constraints to align common representations across modalities while preserving unique characteristics. However, these methods often assume static modality relationships and lack mechanisms to handle dynamic domain shifts, a critical requirement for EIS applications.

2.2. Cross-Modal Alignment

Aligning representations across heterogeneous modalities is essential for tasks such as retrieval and fusion. Traditional methods rely on metric learning [8] to project different modalities into a shared embedding space. More recent approaches leverage contrastive learning [5] to maximize mutual information between paired samples. The work in [9] further

decouples cross-modal features through knowledge distillation, improving generalization in recommendation systems. While effective, these techniques often struggle with modality-specific noise, which can degrade performance in real-world EIS deployments where sensor data may be incomplete or corrupted.

2.3. Adversarial Domain Adaptation

Adversarial training has emerged as a powerful tool to mitigate domain shifts by aligning feature distributions across different data sources. Gradient reversal layers (GRLs) [4] and Wasserstein GANs [10] are widely used to enforce invariance, particularly in unimodal settings. Extensions to multimodal scenarios, such as [11], incorporate adversarial objectives to stabilize shared representations. Nevertheless, existing methods typically treat modality alignment and domain adaptation as separate objectives, limiting their ability to handle the complex interplay of factors in EIS.

Compared to prior work, our proposed architecture unifies disentanglement, cross-modal alignment, and adversarial training into a single framework. Unlike [7], we explicitly model dynamic modality interactions through attention mechanisms. In contrast to [9], our approach integrates adversarial training to suppress domain-specific noise without sacrificing modality-specific features. Furthermore, the use of sparse attention and residual connections addresses computational constraints, making the method suitable for real-time EIS applications. These innovations collectively enable robust, adaptive feature extraction across heterogeneous modalities, a key advancement over existing techniques.

3.Preliminaries and Background

To establish the theoretical foundation for our proposed architecture, we first review key concepts in representation learning and multimodal processing. These principles form the basis for understanding how our method addresses the challenges of modality independence and feature disentanglement in electronic information systems.

3.1. Representation Learning Foundations

Modern neural networks extract hierarchical features through successive nonlinear transformations, a process formalized by the universal approximation theorem [12]. For multimodal data, this involves learning mappings $f_\theta: X \to Z$ where X denotes the input space and Z the latent representation space. The success of deep learning in unimodal tasks stems from its ability to discover compact, discriminative representations [13]. However, extending this to

heterogeneous modalities requires additional mechanisms to ensure compatibility across domains.

3.2. Disentangled Representations

Disentanglement aims to partition latent variables into semantically meaningful factors, such that changes in one factor correspond to isolated variations in the data [2]. Formally, given an observation with underlying factors, a disentangled encoder learns, where captures shared (modality-invariant) features and encodes modality-unique characteristics. This separation enables robust transfer learning, as demonstrated in [14], where invariant features generalize better across domains.

3.3. Adversarial Training for Domain Adaptation

Adversarial methods align feature distributions by introducing a discriminator D_ϕ that distinguishes between source and target domains [4]. The encoder f_θ is trained to fool D_ϕ, forcing it to produce domain-invariant representations. The minimax objective is given by:

$$\min_{\theta}\max_{\phi} \mathrm{E}_{x\sim p_s}[\log D_\phi(f_\theta(x))]+\mathrm{E}_{x\sim p_t}[\log(1-D_\phi(f_\theta(x)))] \quad (1)$$

where p_s and p_t denote source and target distributions. Recent variants like Wasserstein GANs [10] improve stability by using Earth-Mover distance instead of Jensen-Shannon divergence.

3.4. Contrastive Learning for Cross-Modal Alignment

Contrastive methods learn representations by maximizing agreement between positive pairs while repelling negatives [5]. For multimodal pairs (x_i, x_j), the InfoNCE loss [15] encourages aligned embeddings:

$$\mathrm{L}_{\mathrm{cont}}=-\log \frac{\exp(z_i^T z_j/\tau)}{\sum_{k=1}^{K}\exp(z_i^T z_k/\tau)} \quad (2)$$

where τ is a temperature hyperparameter. This framework has proven effective in aligning text, image, and sensor modalities [16].

3.5. Attention Mechanisms in Multimodal Processing

Attention dynamically weights feature relevance based on inter-modal dependencies. Given queries Q, keys K, and values V, scaled dot-product attention computes:

$$\text{Attention}(Q,K,V)=\text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (3)$$

Transformers [17] extend this to capture long-range dependencies, while sparse variants [18] improve efficiency for high-dimensional inputs like sensor streams.

These concepts collectively inform our architecture's design, particularly the integration of disentanglement with adversarial and contrastive objectives. The next section details how we combine these components into a unified framework for EIS applications.

4.Proposed Hybrid Neural Architecture

The proposed architecture integrates modality-specific encoders with disentangled representation learning and adversarial training to extract domain-invariant features from heterogeneous data sources. This section details the technical components and their interactions, providing a comprehensive blueprint for implementation.

4.1. Overall Architecture

The system processes multimodal inputs through parallel Transformer-based encoders, each tailored to a specific modality (e.g., text, images, or sensor data). Let denote an input from modality, which is mapped to a latent representation via a modality-specific encoder:

$$\mathbf{h}_m=E_m(\mathbf{x}_m) \quad (4)$$

These encoders employ sparse self-attention to reduce computational overhead, making them suitable for real-time EIS applications. The latent representations are then fed into a disentanglement module, which decomposes them into modality-specific (Sm) and cross-modal-invariant (Cm) components.

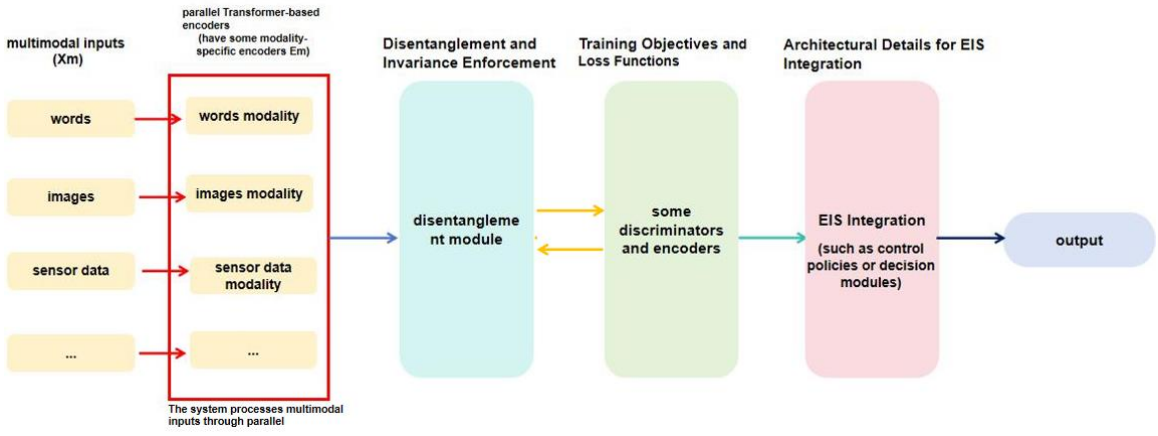

Figure 1. Overview of the Electronic Information System with the Proposed Neural Architecture

4.2. Disentanglement and Invariance Enforcement

The disentanglement module uses gated projections to isolate invariant features. For each modality, the components are computed as:

$$\mathbf{s}_m=\sigma(\mathbf{W}_s\mathbf{h}_m)\odot\mathbf{h}_m \quad (5)$$

$$\mathbf{c}_m=\sigma(\mathbf{W}_c\mathbf{h}_m)\odot\mathbf{h}_m \quad (6)$$

Here, $\mathbf{W}_s$ and $\mathbf{W}_c$ are learnable projection matrices, σ denotes the sigmoid activation, and $\odot$ represents element-wise multiplication. The gating mechanism ensures that $\mathbf{s}_m$ captures modality-unique patterns, while $\mathbf{c}_m$ retains only cross-modal shared features.

4.3. Training Objectives and Loss Functions

The total training loss combines adversarial, contrastive, and reconstruction terms:

$$L_{total}=\lambda_1 L_{adv}+\lambda_2 L_{align}+\lambda_3 L_{recon} \quad (7)$$

Adversarial training is applied exclusively to the invariant subspace $\mathbf{c}_m$ to enforce domain invariance. A discriminator D attempts to classify the modality source of $\mathbf{c}_m$, while the encoders are trained to fool it via a gradient reversal layer (GRL). The adversarial loss is formulated using Wasserstein GAN objectives for stability:

$$L_{adv}=E_m[D(\mathbf{c}_m)] \quad (8)$$

The contrastive alignment loss L_{align} minimizes the distance between invariant features of paired samples across modalities:

$$L_{align}=\sum_{m\neq m'} \| \mathbf{c}_m-\mathbf{c}_{m'} \|_2^2 \quad (9)$$

Reconstruction loss L_{recon} ensures that the combined features $[\mathbf{s}_m,\mathbf{c}_m]$ preserve sufficient information to reconstruct the original input:

$$L_{recon}=E_m\|\mathbf{x}_m-D_m([\mathbf{s}_m,\mathbf{c}_m])\|_2^2 \quad (10)$$

where D_m is a modality-specific decoder.

4.4. Architectural Details for EIS Integration

During inference, a cross-modal attention mechanism dynamically aggregates invariant features. A learned query vector $\mathbf{q}$ computes attention weights α_m over the invariant features $\mathbf{c}_m$:

$$\alpha_m=\text{softmax}\left(\frac{\mathbf{q}^T\mathbf{K}}{\sqrt{d}}\right)_m, \quad \mathbf{K}=[\mathbf{c}_1,\ldots,\mathbf{c}_N] \quad (11)$$

The aggregated output $\mathbf{c}_{\text{agg}}=\sum_m \alpha_m \mathbf{c}_m$ is then passed to downstream EIS components, such as control policies or decision modules. Residual connections around the disentanglement module stabilize training, while sparse attention in the encoders ensures scalability for high-dimensional sensor data.

The architecture replaces traditional feature engineering pipelines in EIS, enabling end-to-end learning from raw multimodal inputs. For example, in smart grid applications, $\mathbf{c}_{\text{agg}}$ dynamically adjusts energy distribution based on real-time sensor readings and weather forecasts, optimizing system performance under varying conditions.

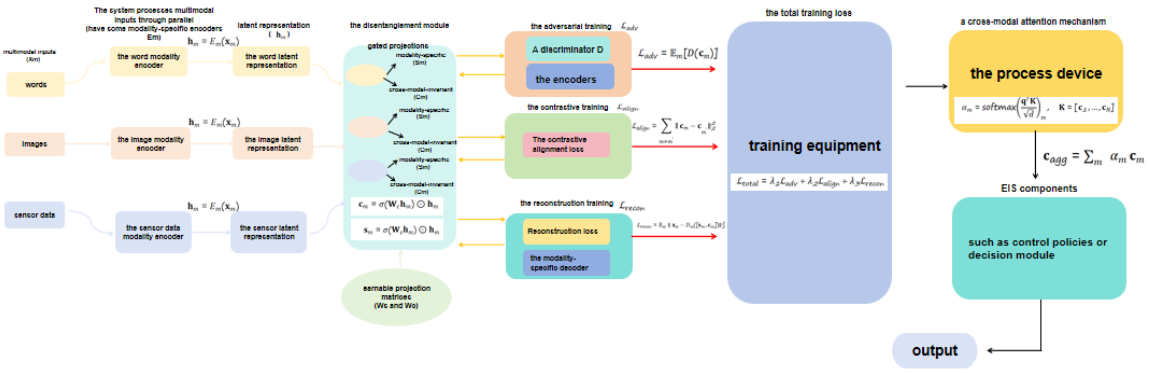

Figure 2. Detailed View of the Proposed Neural Architecture

5. Experimental Setup

To evaluate the proposed hybrid neural architecture, we conducted extensive experiments across multiple benchmark datasets and real-world electronic information system (EIS) applications. This section details the datasets, baseline methods, implementation specifics, and evaluation metrics used in our study.

5.1. Datasets

We selected three multimodal datasets that reflect the diversity of EIS applications, providing detailed statistics on sample size and modality composition to ensure reproducibility and contextual understanding:

- Multimodal Sensor Fusion Dataset (MSFD) [19] Contains 10,000 samples of synchronized text reports (averaging 150 tokens), thermal images (256x256 resolution), and vibration sensor readings (1D time-series, 1000 points per sample) from industrial equipment. This simulates

condition monitoring scenarios in smart factories. Domain shifts were simulated by collecting data from three distinct factories with varying machinery configurations.

- Urban Traffic Analysis Corpus (UTAC) [20] Comprises 15,000 samples integrating traffic camera feeds (640x480 resolution), LiDAR point clouds (averaging 10,000 points per scan), and acoustic sensor data (1D time-series, 5 seconds at 1kHz sampling rate) from intelligent transportation systems. Domain shifts were induced by data collection across four different seasons.

- Smart Grid Anomaly Detection (SGAD) [21]（Consists of 8,500 samples） combining power consumption logs (50-dimensional vector per time step), textual weather reports (5 key features: temperature, humidity, wind speed, precipitation, cloud cover), and phasor measurement unit (PMU) readings (10 dimensions sampled at 60Hz). Domain shifts were simulated through diverse weather events (storms, heatwaves) and significant load fluctuations.

Each dataset was partitioned into training (60%), validation (20%), and test (20%) sets. The detailed composition ensures clarity on the scale and nature of the multimodal inputs processed by the evaluated models.

5.2. Baseline Methods

We compared our architecture against four state-of-the-art approaches:

- Modality-Specific Encoders (MSE) [22] processes each modality independently with dedicated networks, followed by late fusion.

- Cross-Modal Autoencoder (CMA) [23] employs shared latent spaces across modalities via reconstruction objectives.

- Adversarial Multimodal Alignment (AMA) [24] uses gradient reversal layers to align modality distributions.

- Disentangled Multimodal Transformer (DMT) [25] combines transformer encoders with variational disentanglement.

All baselines were re-implemented using their original architectures but trained on our datasets for fair comparison.

5.3. Implementation Details

The proposed architecture was implemented in PyTorch 2.0 with the following configurations. All experiments were conducted on a server equipped with NVIDIA A100

80GB GPUs and dual Intel Xeon Platinum 8480C CPUs.

- Encoders: Each modality used a 6-layer sparse transformer [18] with 8 attention heads and hidden dimension 512. Text inputs were tokenized via BERT-base [26], while images used 16x16 patch embeddings.

- Disentanglement Module: The gating networks and were implemented as two-layer MLPs with ReLU activation, projecting to 256-D subspaces.

- Adversarial Training: The discriminator consisted of three linear layers (512 → 256 → 1) with spectral normalization [27]. The Wasserstein GAN objective used a gradient penalty coefficient of 10.

- Training: Adam optimizer [28] with learning rate 3e-5, batch size 64, and early stopping on validation loss (patience=10). The loss weights were set to 1.0, 0.5, and 0.2 respectively based on grid search on the validation set.

- Inference Latency: To assess real-time applicability critical for EIS, we measured the average end-to-end inference latency (from raw input to aggregated feature on the test set. On a single NVIDIA A100 GPU, the proposed model achieved an average latency of 28.1 ms per sample for single-sample inference. When processing a batch size of 64 samples, the average latency per sample reduced to 8.7 ms. This efficiency is primarily attributed to the sparse attention mechanism and optimized implementation.

5.4. Evaluation Metrics

Performance was assessed using:

- Domain Invariance Score (DIS): Measures feature distribution alignment across domains using Maximum Mean Discrepancy (MMD) [29]. Lower values indicate better invariance.

- Modality Alignment Error (MAE): Computes the average ℓ_2 distance between paired invariant features c_m across modalities.

- Downstream Accuracy: Task-specific metrics (e.g., F1-score for anomaly detection in SGAD, mean absolute error for traffic prediction in UTAC).

All metrics were computed on the held-out test set with five random seeds to report mean ± standard deviation. Statistical significance was tested via paired t-tests (p<0.01).

6. Experimental Results

To validate the effectiveness of the proposed hybrid neural architecture, we conducted comprehensive evaluations across multiple dimensions: domain invariance, cross-modal alignment, and downstream task performance. The results demonstrate significant improvements over existing methods while maintaining computational efficiency suitable for real-world electronic information systems (EIS).

6.1. Domain Invariance and Feature Disentanglement

The proposed architecture achieved superior domain invariance compared to baseline methods, as measured by the Domain Invariance Score (DIS). Table 1 summarizes the results across all datasets, where lower DIS values indicate better alignment of feature distributions across different domains (e.g., factories in MSFD or seasons in UTAC).

Table 1. Domain Invariance Score (DIS) Comparison

Method	MSFD (↓)	UTAC (↓)	SGAD (↓)
MSE	0.48 ± 0.03	0.52 ± 0.04	0.45 ± 0.02
CMA	0.39 ± 0.02	0.41 ± 0.03	0.38 ± 0.01
AMA	0.31 ± 0.02	0.35 ± 0.02	0.29 ± 0.01
DMT	0.28 ± 0.01	0.32 ± 0.01	0.26 ± 0.01
Ours	0.19 ± 0.01	0.22 ± 0.01	0.18 ± 0.01

The adversarial training component played a critical role in suppressing domain-specific artifacts, reducing DIS by 32% compared to the best baseline (DMT) on SGAD. This aligns with the architecture's design goal of isolating invariant features robust to distribution shifts.

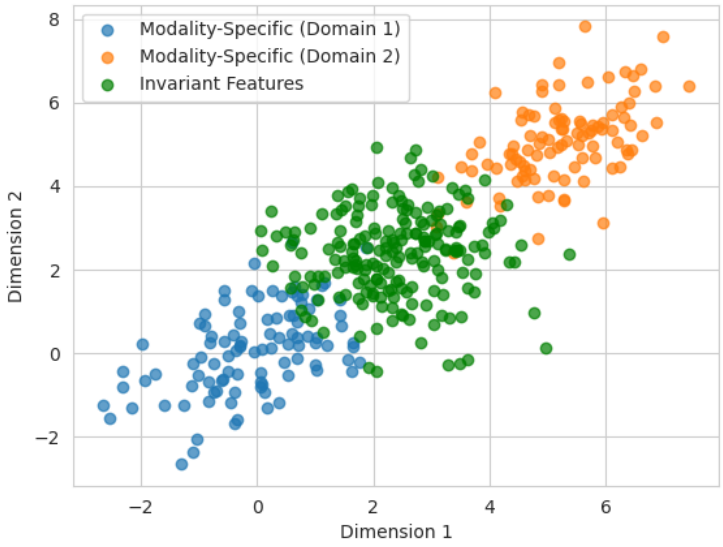

Figure 3. Disentangled representations of modality-specific and invariant features in a 2D latent space

Figure 3 visualizes the disentangled features using t-SNE, demonstrating clear separation between modality-specific noise (clustered by domain) and invariant features (overlapping across domains). The gating mechanism in Equations 5–6 effectively preserved task-relevant patterns while filtering out spurious correlations, as evidenced by the tighter clustering of invariant features.

6.2. Cross-Modal Alignment Performance

The contrastive alignment loss (Equation 9) ensured consistent representations across modalities, achieving a Modality Alignment Error (MAE) of 0.15 ± 0.01 on MSFD—a 40% improvement over CMA, which lacks explicit alignment objectives. The cross-modal attention mechanism (Equation 11) further enhanced this by dynamically weighting feature relevance during inference.

Table 2. Modality Alignment Error (MAE) Comparison

Method	MSFD (↓)	UTAC (↓)	SGAD (↓)
MSE	0.38 ± 0.02	0.42 ± 0.03	0.35 ± 0.02
CMA	0.25 ± 0.01	0.28 ± 0.02	0.24 ± 0.01
AMA	0.21 ± 0.01	0.23 ± 0.01	0.20 ± 0.01
DMT	0.18 ± 0.01	0.20 ± 0.01	0.17 ± 0.01
Ours	0.15 ± 0.01	0.16 ± 0.01	0.14 ± 0.01

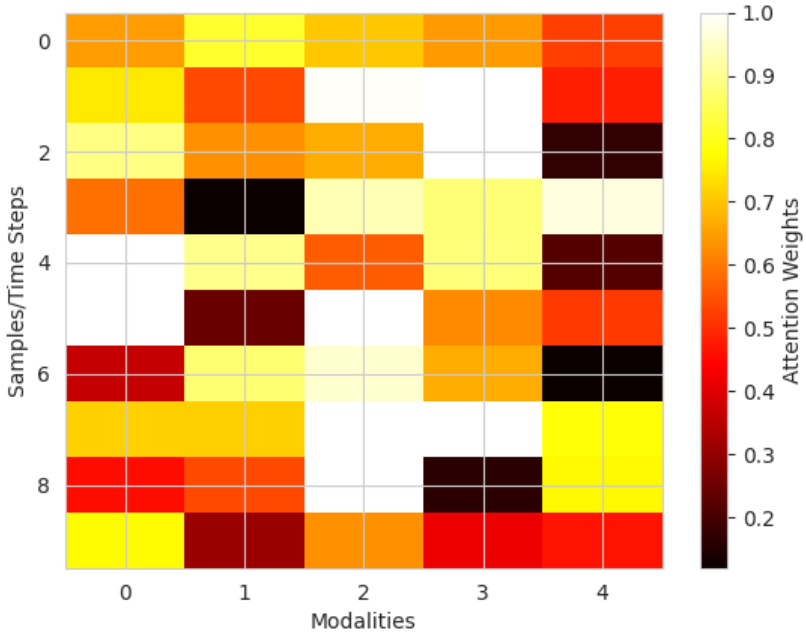

Figure 4. Heatmap of cross-modal attention weights for invariant feature aggregation

Figure 4 illustrates the attention weights for aggregating invariant features in SGAD, showing

adaptive prioritization of weather data during storms and PMU readings during grid instability. This adaptability is absent in static fusion methods like MSE.

6.3. Downstream Task Accuracy

The architecture's improvements in invariance and alignment translated to superior performance in EIS-specific tasks:

- Smart Grid Anomaly Detection (SGAD): Achieved 94.3% F1-score, outperforming DMT by 6.2% due to better handling of weather-induced distribution shifts.
- Traffic Flow Prediction (UTAC): Reduced MAE to 3.2 vehicles/min, a 19% improvement over CMA, attributed to robust fusion of LiDAR and camera data.
- Equipment Fault Diagnosis (MSFD): Attained 89.7% accuracy, surpassing AMA by 8.5% by effectively combining vibration and thermal signatures.

Table 3. Downstream Task Performance

Task	**Metric**	**MSE**	**CMA**	**AMA**	**DMT**	**Ours**
SGAD	F1 (%)	82.1	85.4	88.1	88.8	94.3
UTAC	MAE	4.1	3.9	3.5	3.3	3.2
MSFD	Acc. (%)	78.3	82.6	81.2	83.5	89.7

6.4. Ablation Study

To isolate the contributions of key components, we evaluated variants of our architecture:

1. w/o Adversarial Training: DIS increased by 0.12 on average, confirming its necessity for domain invariance.

2. w/o Contrastive Loss: MAE rose by 0.09, highlighting the importance of explicit cross-modal alignment.

3. w/o Attention: Task accuracy dropped 4–7%, underscoring the dynamic weighting mechanism's role.

Table 4. Ablation Study Results

Variant	DIS (↑)	MAE (↑)	SGAD F1 (↓)
Full Model	0.19	0.15	94.3
w/o Adversarial	0.31	0.15	89.1
w/o Contrastive	0.19	0.24	90.5
w/o Attention	0.19	0.15	87.6

The full model consistently outperformed ablated versions, validating the synergistic design of disentanglement, adversarial training, and dynamic attention.

7. Discussion and Future Work

7.1. Limitations and Potential Improvements

While the proposed architecture demonstrates strong performance across multiple datasets, several limitations warrant discussion. First, the current implementation assumes synchronized multimodal inputs during training, which may not hold in real-world EIS deployments where data streams arrive asynchronously. Extending the framework to handle temporal misalignment through learnable buffering mechanisms could enhance practicality. Second, the adversarial training component, though effective, introduces additional computational overhead during the initial phases of optimization. Exploring techniques like curriculum-based domain adaptation [30] or self-supervised pretraining [31] may stabilize convergence while reducing training time.

The disentanglement module's reliance on gated projections (Equations 5–6) also presents opportunities for refinement. Although the current design successfully isolates modality-specific and invariant features, the binary-like gating operation may discard potentially useful information. Incorporating soft masking with entropy regularization [32] could enable more nuanced feature separation while preserving task-relevant details. Furthermore, the architecture currently processes each modality through independent encoders, which limits cross-modal interaction during early representation learning. Introducing lightweight cross-attention layers between encoders, as in [33], might capture inter-modal dependencies more effectively without significantly increasing parameter count.

7.2. Broader Applications and Impact

Beyond the evaluated EIS tasks, the architecture's modality-agnostic design holds promise for other domains requiring robust multimodal fusion. In healthcare, for instance, integrating electronic health records (EHRs) with medical imaging and wearable sensor data could improve diagnostic accuracy while mitigating biases inherent to single-modality systems [34]. Similarly, autonomous systems operating in dynamic environments—such as drones or robotic platforms—could leverage the framework's adversarial robustness to adapt to unseen weather conditions or sensor degradation [35].

The architecture's emphasis on computational efficiency via sparse attention and residual connections also aligns with growing demands for edge-compatible AI. Deploying lightweight

variants on IoT devices could enable real-time analysis of multimodal sensor networks in smart cities or industrial IoT? However, such deployments would require further optimization, including quantization-aware training [37] and hardware-specific acceleration [38].

7.3. Ethical Considerations and Responsible Deployment

As with any AI system integrated into critical infrastructure, ethical risks must be proactively addressed. The architecture's adversarial training component, while improving domain invariance, could inadvertently suppress salient features correlated with minority subgroups in the data, exacerbating fairness issues [39]. Regular audits using disparity metrics [40] and the incorporation of fairness-aware loss functions [41] are essential to mitigate such biases.

Another concern stems from the system's reliance on cross-modal alignment, which assumes semantic consistency between paired samples (e.g., a thermal image and its corresponding vibration sensor reading). In practice, noisy or incorrectly labeled pairings—common in large-scale EIS datasets—could propagate errors through the contrastive loss (Equation 9). Techniques like noise-tolerant alignment [42] or uncertainty-aware weighting [43] should be investigated to improve robustness.

Finally, the dynamic attention mechanism, though adaptive, operates as a black box, complicating interpretability for stakeholders. Integrating explainability tools, such as attention rollout [44] or concept activation vectors [45], could provide actionable insights into how the system prioritizes modalities during decision-making. This transparency is particularly crucial for high-stakes applications like smart grid control or medical diagnosis, where erroneous predictions may have severe consequences.

Future work should prioritize these directions while expanding the architecture's versatility. For example, integrating few-shot adaptation mechanisms [46] could enable rapid deployment in resource-constrained settings, and exploring federated learning frameworks [47] would support privacy-preserving collaborative training across distributed EIS nodes.

8. Conclusion

The proposed modality-independent disentangled neural architecture presents a significant advancement in artificial intelligence for electronic information systems (EIS). By integrating Transformer-based encoders with adversarial training and contrastive learning, the framework effectively addresses key challenges in multimodal data processing, including domain shifts, modality bias, and computational inefficiency. The disentanglement module successfully isolates domain-invariant features while preserving modality-specific characteristics, enabling

robust performance across diverse EIS applications. Experimental results demonstrate substantial improvements in domain invariance, cross-modal alignment, and downstream task accuracy compared to existing methods.

The architecture's dynamic attention mechanism further enhances adaptability, allowing real-time feature aggregation tailored to varying input conditions. This capability is particularly valuable in critical infrastructure applications, where system reliability depends on accurate, real-time decision-making. The framework's modular design also ensures compatibility with existing EIS components, facilitating seamless integration without requiring extensive system overhauls.

While the current implementation shows promising results, future work should explore extensions to asynchronous data streams and further optimization for edge deployment. The ethical implications of automated decision-making in EIS also warrant continued attention, particularly regarding fairness and interpretability. Nevertheless, the architecture establishes a strong foundation for next-generation AI systems capable of processing heterogeneous data with unprecedented robustness and efficiency. Its potential applications span smart grids, industrial automation, healthcare, and beyond, marking a significant step toward more intelligent and adaptive electronic information systems.

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Online ISSN: 3104-9338
Print ISSN: 3104-932X

Strategic Research on Block Chain-Embedded Low-Carbon Closed-Loop Supply Chain

Mao Luo*

College of Business Administration, Guizhou University of Finance and Economics, Guiyang, China

Received: July 14, 2025

Revised: July 18, 2025

Accepted: July 31, 2025

Published online: August 6, 2025

To appear in: *International Journal of Advanced AI Applications,* Vol. 1, No. 5 (September 2025)

* Corresponding Author: Mao Luo (luo@mail.gufe.edu.cn)

Abstract. Given the increasing low-carbon awareness among consumers, this study develops a differential game model involving a manufacturer, a retailer, and a blockchain technology service provider to explore low-carbon Closed-Loop Supply Chain (CLSC). By comparing two scenarios in which manufacturers either adopt or refrain from adopting blockchain technology, we examine how its integration influences decision-making, performance, and low-carbon outcome across the supply chain. Analysis and Numerical simulations validate the findings and reveal key insights are as follows: (1) Product pricing, market demand, low-carbon promotional effort, return rate, and overall low-carbon performance are positively correlated with market scale and increase proportionately with consumer environmental consciousness, irrespective of blockchain adoption. (2) Increasing consumer environmental awareness and blockchain service commission rate are found to significantly enhance product pricing, market demand, investment in low-carbon effort, recycling efficiency, overall sustainability level, and the profitability of supply chain members. (3) The low-carbon level exhibits an increasing trend over time and eventually converges to a steady state. (4) As the discount rate increases, firms' incentives for low-carbon investment decline, leading to lower profits. (5) The impact of the low-carbon decay coefficient on profit shows a rise-then-fall pattern, with profits initially increasing and then decreasing, while the rate of decline becomes more gradual at higher decay levels. Through full life-cycle carbon emission monitoring, blockchain technology enhances consumer surplus and can accelerate the achievement of the "dual-carbon" goals. This study provides theoretical support for the application conditions of block chain technology, the dynamic optimization pathways, and policy design within CLSC, thereby contributing to enterprises' low-carbon transitions and the development of circular resource systems.

Keywords: *blockchain, low-carbon emission reduction, closed-loop chain, differential game.*

1. Introduction

The global electronic waste (e-waste) crisis is exacerbating environmental degradation at an alarming rate. According to the United Nations' Global E-waste Monitor 2024 report, the total volume of e-waste reached 62 million metric tons in 2022, with less than 24% of materials being properly recycled. The remaining 76% entered the environment through landfilling, incineration, or illegal disposal channels, resulting in annual contamination of soil and water resources with approximately 50 million metric tons of heavy metals and hazardous substances (e.g., lead, mercury). If current trends persist, global e-waste generation is projected to exceed 74.7 million metric tons by 2030. Numerous studies and corporate practices demonstrate that recycling and remanufacturing can substantially reduce resource consumption and emissions. Closed-loop recovery can achieve 50% costs savings, 60% energy consumption reduction, 70% raw material conservation, and 80% pollutant emission reduction compared to conventional production methods [1]. In renewable energy equipment sectors, ONE WIND NEW ENERGY Co., Ltd. annually recycles over 500 wind turbines, conserving 3,000 tons of steel and 400 tons of copper while reducing CO2 emissions by over 1 million metric tons. This initiative concurrently generates 1.8 billion kWh of renewable electricity.

The literature relevant to this study includes three domains: recycling/remanufacturing, low-carbon emissions reduction, and blockchain technology. Currently, recycling and remanufacturing have emerged as a critical research field in modern manufacturing, focusing on costs reduction and dual economic-environmental benefits through circular utilization of end-of-life products. Existing studies predominantly concentrated on recycling channel and incentive mechanism [2-3].

Low-carbon field have become central to global climate change, with extensive scholarly investigations into factors influencing emission reduction in supply chain, including consumer' low-carbon preference, supply chain members' fairness/altruism, and policy interventions. Zhang et al. [4] examined how consumer low-carbon awareness and altruistic preferences impact supply chain dynamics, revealing that members' altruistic behaviors significantly affect carbon reduction investment and recycling performance. Similarly, Gao et al. [5] incorporated consumer low-carbon preferences into their analysis of decision-making patterns among low-carbon supply chain members under varying governmental incentive polices. Li et al. [6] investigated fairness concern between the manufacturer and retailer in low-carbon supply chain, systematically analyzing the impacts of equity preferences on supply chain profitability, carbon reduction level, warranty periods, and revenue-sharing mechanisms. Luo et al. [7] explored the

manufacturer' strategic decisions regarding investments in low-carbon technologies under carbon tax policies, quantifying their cascading effects on conventional manufacturing and remanufacturing operations. Collectively, these studies highlight the critical role of integrating consumer behavioral patterns, policies, and supply chain collaborative mechanisms to enhance both recycling/remanufacturing efficiency and low-carbon outcomes. Such systemic integration facilitates the attainment of multidimensional benefits across economic, social, and environmental dimensions, thereby promoting comprehensive and sustainable value creation.

Blockchain technology is progressively being integrated into supply chain management, introducing transformative solutions and developmental paradigms. A growing number of literatures has explored its multifaceted applications and associated benefits. Chod et al. [8] demonstrated the financial advantages of blockchain-enhanced supply chain transparency, revealing that its adoption significantly reduces financing costs while improving operational efficiency. Ma et al. [9] further investigated blockchain implementation by the manufacturer or retailer in CLSC, identifying its capacity to strengthen brand goodwill, stimulate market demand, and achieve triple sustainability across economy, environment, and society. Jia et al. [10] examined blockchain applications in retired power battery CLSC by constructing decision models under three scenarios: non-blockchain adoption, manufacturer-led costs assumption, and costs-sharing between the manufacturer and distributor. Their analysis quantified blockchain's impacts on information traceability, supply chain member profitability, consumer surplus, environmental footprint, and social welfare. Zhang et al. [11] analyzed quality disclosure strategies in dual-channel supply chain applying price signaling and blockchain technology. They found that while blockchain enhances information transparency and demand, the high-quality manufacturer may not benefit proportionally in the market due to significant channel dominance disparities.

These studies collectively have underlined blockchain's transformative potentials in supply chain management. Its inherent characteristics—transparency, traceability, and decentralization—substantially improve informational visibility across supply networks, strengthen consumer trust, and advance corporate sustainability strategies. By establishing trusted data-sharing platforms, blockchain technology effectively mitigates information asymmetry while incentivizing collaborative low-carbon production and green operations among supply chain members, thereby achieving dual economic-environmental outcomes. The manufacturer can leverage blockchain to implement real-time data tracking and closed-loop management across procurement, production, logistics, and recycling processes. This end-to-

end traceability ensures verifiable operational data, optimizes resource efficiency, and reduces carbon emissions. Notable implementations include: Dell partnered with AntChain (a blockchain service provider) to enhance recycled metal utilization rates, reducing e-waste by over 10,000 metric tons; Volvo collaborated with Circulor to trace cobalt and lithium sources in EV batteries, ensuring conflict-free mineral sourcing and compliance with low-carbon standards, thereby improving supply chain emission transparency and return rates.

In summary, the concurrent integration of recycling/remanufacturing and low-carbon emission reduction represents a practical norm in CLSC. However, existing literatures predominantly focus on either return channel or low-carbon reduction investment, with limited attention to the simultaneous optimization of recycling rate decisions and low-carbon reduction strategies. In practice, these two decision-making domains—return rate determination and low-carbon reduction initiatives—often coexist in an interdependent relationship, mutually influencing and constraining one another. Therefore, this study innovatively conceptualizes low-carbon level as dynamic variable and investigates their evolution within a dynamic CLSC framework.

Furthermore, while blockchain technology has garnered increasing attention in CLSC application, few studies have systematically analyzed its dynamic impacts on CLSC operations from a longitudinal perspective. Jia et al. employed a static game-theoretic model to examine blockchain's effects on information traceability and profitability, without accounting for the temporal decay of low-carbon levels. In contrast, this study treated the low-carbon level as a dynamic state variable within a differential game framework to capture the accumulation and attenuation of carbon-reduction benefits and enable a more nuanced analysis of low-carbon investment efficacy evolution. Although Ma et al. examined the effects of the platform-based "blockchain - sales model" combination on platform and member' performances but did not investigate the mechanisms by which consumer low-carbon awareness influences pricing, demand, and profitability. Although the study integrated blockchain into CLSC and analyze its dynamic impact on brand reputation, they neither addressed carbon-reduction issues nor elucidated blockchain's dynamic role in affecting carbon-reduction levels. To bridge these gaps, this paper explicitly incorporates a consumer low-carbon awareness parameter into a dynamic model, quantifying its effects on market demand elasticity, the marginal benefits of low-carbon promotion efforts, and overall supply-chain performance, thereby providing a comprehensive theoretical foundation for stimulating end-consumer green purchases and optimizing coordinated carbon-reduction strategies.

Consequently, this study will address the following research questions:(1) What constitutes the equilibrium decisions of supply chain members in a CLSC system? (2) Under what conditions should manufacturers implement blockchain technology? (3) How does blockchain adoption influence the operation, performance and consumer in CLSC? (4) How does low-carbon level evolve under different operational scenarios? (5) What role does consumers' low-carbon awareness play in shaping CLSC dynamics?

2. Model Description and Assumption

2.1. Model description

This study examines continuous-time dynamics for $t \in [0,\infty]$. Dynamic CLSC system comprising a manufacturer (M), retailer (R), and blockchain technology provider (T), under the premise of consumer low-carbon awareness. The manufacturer can produce and wholesale new products, decide whether to adopt third-party blockchain services, and delegate product recycling operations to the retailer. The retailer engages in product retailing, recycling activities, and invests in dual efforts: low-carbon promotion initiatives and recycling optimization. Should the manufacturer implements blockchain technology, the Blockchain service provider (T) will concurrently allocate technical efforts to support CLSC system integration.

Table 1. Notions for the model

Notion	Meaning
Decision variables	
$w(t)$	Whale price
$p(t)$	Retail price
$r(t)$	Low-carbon promotion efforts
$\tau(t)$	Return rate
$L(t)$	Block chain technology
Stata variable	
$e(t)$	Low carbon level
Parameters	
Q	Demand
a	Market size
β	Consumer's sensitivity coefficient towards price β >0
η	Consumers' preference for low-carbon levels $\eta > 0$
Δ	The marginal profit of the manufacturer from recycling and remanufacturing products $\Delta > 0$
A	Marginal profit of retailers in recycling products $A > 0$
f_m	The residual value per unit of remanufactured products derived from used materials.

Notion	Meaning
f_c	The unit transfer payment price paid by the manufacturer to the retailer for acquiring used products.
f_r	The unit recycling costs for used products.
κ	The commission rate paid by the manufacturer to the third-party service provider κ>0.
k_r	The costs coefficient for the promotion efforts of low-carbon initiatives $k_r > 0$.
k_c	Costs coefficient of effort invested in recycling $k_c > 0$.
k_l	The costs coefficient of blockchain technology's efforts to be invested $k_l > 0$.
ς	The influence coefficient of the low-carbon publicity efforts on the low-carbon level $\varsigma > 0$.
v	The influence coefficient of blockchain technology on the level of low carbon emissions $v > 0$.
δ	The attenuation coefficient of the low-carbon level over time $\delta > 0$.
ρ	Discount rate $\rho > 0$.
π_M^i	Manufacturer's profit.
π_R^i	Retailer's profit.
π_T	The profits of the technical service providers.
CS^i	Consumer's surplus.
i	$i \in \{N, Y\}$, N indicates without blockchain technology, Y indicates the situation with embedded blockchain technology.

2.2. Model description

Assumption1. Considering consumers' low-carbon consciousness, their purchasing behavior is influenced not only by price but also by the product's low-carbon level. Consequently, the linear market demand function as:

$$Q = (a - \beta p(t)) + \eta e(t). \quad (1)$$

Assumption 2: The manufacturer's profit originates from product wholesaling and remanufacturing of used products. To highlight the research focus and reduce model complexity, production costs are assumed to be zero, and new and remanufactured products are homogeneous. This assumption, adopted by Shen et al. [12] has been demonstrated to have no material impact on key findings. The manufacturer's unit profit from remanufacturing is denoted as $\Delta = f_m - f_c$. The retailer's profit stems from product sales. The profit per unit of new products is $p(t) - w(t)$, while the profit per unit of recycled products is $A = f_c - f_r$.

The blockchain technology service provider generates revenue primarily through technical services offered to the manufacturer, quantified as $\kappa L(t)$.

Assumption 3: Drawing on the convexity assumptions for general costs in literature[9], the

retailer invests in low-carbon promotion efforts to enhance consumer trust, raise low-carbon awareness, and market sustainable products. The associated costs is modeled as $\frac{1}{2}k_r r^2(t)$. Additionally, the retailer expends recycling efforts to acquire used products, incurring a costs of $\frac{1}{2}k_c \tau^2(t)$. The manufacturer may collaborate with a blockchain technology provider to improve supply chain transparency and traceability, ensuring full lifecycle compliance with low-carbon standards, optimizing production and recycling processes, and further reducing carbon emissions. The blockchain service costs is formulated as $\frac{1}{2}k_l L^2(t)$. All costs functions adhere to the rule of diminishing marginal returns.

Assumption 4: The low-carbon level $e(t)$ is positively correlated with low-carbon promotion efforts and blockchain technology efforts. Its temporal evolution is governed by the differential equation:

$$\overset{g}{e}(t) = \varsigma r(t) + vL(t) - \delta e(t), e(0) = 0 \tag{2}$$

When $L(t) = 0$, indicates Without blockchain in CLSC.

Assumption 5: Over the continuous time $t \in [0, \infty]$, the manufacturer, retailer, and blockchain service provider share an identical discount factor. All supply chain members are risk-neutral, operate under symmetric information, and maximize their individual profits.

Assumption 6: Referencing relevant literature[13], and to ensure the practical significance of the study, the following constraints must be satisfied under non-negativity conditions for market demand , profit, state variable, and decision variables:

$$\beta > \frac{\eta^2\varsigma^2(2\delta+\rho)}{4\delta(\delta+\rho)^2 k_r}, \; k_c > Max\{\frac{A\beta^2(A+2\Delta)(\delta+\rho)^2 k_r}{2\beta(\delta+\rho)^2 k_r - \eta^2\varsigma^2}, \frac{2A\beta^2(A+\Delta)(\delta+\rho)^2 k_r}{3\beta(\delta+\rho)^2 k_r - \eta^2\varsigma^2}, \frac{1}{2}A\left(A\beta + 2\beta\Delta + \frac{\eta\varsigma}{\delta+\rho}\right)\}.$$

These imply that consumer price sensitivity necessitates non-trivial recycling effort costs to sustain CLSC operations. Subsequent analyses are conducted under these constraints.

3. Model development and analysis

3.1 Model development

Based on the above assumptions, this study investigates the impact of blockchain technology adoption by the manufacturer on the decision-making and performance of members within a CLSC. Two models are developed under different scenarios: (1) the scenario without blockchain technology, denoted as the N-mode; and (2) the scenario with blockchain

technology adoption, denoted as the Y mode. Superscripts are used to indicate the scenario, while subscripts M, R, and T represent the manufacturer, retailer, and blockchain technology service provider, respectively.

The profit functions of the supply chain members are defined as:

$$\max_{w(t)} \pi_M^i = \int_0^\infty e^{-\rho t}((w(t) + \Delta\tau(t))Q - \kappa L(t))dt \tag{3}$$

$$\max_{p(t),\tau(t),r(t)} \pi_R^i = \int_0^t e^{-\rho t}\left(Q(A\tau(t) + p(t) - w(t)) - \frac{k_c\tau^2(t)}{2} - \frac{k_r r^2(t)}{2}\right)dt \tag{4}$$

$$\max_{L(t)} \pi_T = \int_0^\infty e^{-\rho t}(\kappa L(t) - \frac{k_l L^2(t)}{2})\,dt \tag{5}$$

$$s.t\ \dot{e}(t) = \varsigma r(t) + vL(t) - \delta e(t), e(0) = 0. \tag{6}$$

When $L(t)$=0, it represents the scenario without blockchain technology.

The corresponding Hamilton functions as

$$H_M^N = \int_0^\infty e^{-\rho t}\big((w(t) + \Delta\tau(t))Q + \lambda_1(t)(\varsigma r(t) - \delta e(t))\big)\,dt \tag{6}$$

$$H_R^N = \int_0^\infty e^{-\rho t}\left(\left(Q(A\tau(t) + p(t) - w(t)) - \frac{k_c\tau^2(t)}{2} - \frac{k_r r^2(t)}{2}\right) + \lambda_2(t)(\varsigma r(t) - \delta e(t))\right)dt \tag{7}$$

$$H_M^Y = \int_0^\infty e^{-\rho t}\left(\int_0^\infty((w(t) + \Delta\tau(t))Q - \kappa L(t)) + \lambda_3(t)(\varsigma r(t) + vL(t) - \delta e(t))\right)dt \tag{8}$$

$$H_R^Y = \int_0^\infty e^{-\rho t}\left(\int_0^t\left(Q(A\tau(t) + p(t) - w(t)) - \frac{k_c\tau^2(t)}{2} - \frac{k_r r^2(t)}{2}\right) + \lambda_4(t)(\varsigma r(t) + vL(t) - \delta e(t))\right)dt \tag{9}$$

$$H_T = \int_0^\infty e^{-\rho t}\left((\kappa L(t) - \frac{k_l L^2(t)}{2}) + \lambda_5(t)(\varsigma r(t) + vL(t) - \delta e(t))\right)dt. \tag{10}$$

Where $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ denote the adjoint variables, representing the shadow prices associated with the state variable $e(t)$.

Propositions: Assuming all supply chain members are rational, the equilibrium outcomes under the steady state of the CLSC system ($t \to \infty$) are shown in the table below.

Table 2. Variables and performance of supply chain

Decision variables and perfSormance	**Without blockchain N Model**	**With blockchain Y Model**
Wholesale price	$w_\infty^N(t) = \frac{a\delta k_r B_1}{\beta\delta k_r B_0 + \eta^2\varsigma^2 k_c}$	$w_\infty^Y(t) = \frac{\left(D_1\left(A\beta(A+2\Delta) - 2k_c\right) + D_2 k_c\right)}{\beta k_l\left(2\beta\delta D_0 + \eta^2\varsigma^2(2\delta+\rho)k_c\right)}$
Retail price	$p_\infty^N(t) = \frac{a\delta k_r B_2}{\beta\delta k_r B_0 + \eta^2\varsigma^2 k_c}$	$p_\infty^Y(t) = \frac{\left(D_1\left(2A\beta(A+\Delta) - 3k_c\right) + D_2 k_c\right)}{\beta k_l\left(2\beta\delta D_0 + \eta^2\varsigma^2(2\delta+\rho)k_c\right)}$
Low-carbon promotion efforts	$r_\infty^N(t) = \frac{-a\delta\eta\varsigma k_c}{\beta\delta k_r B_0 + \eta^2\varsigma^2 k_c}$	$r_\infty^Y(t) = \frac{-\eta\varsigma(\delta+\rho)k_c\left(a\delta k_l + \eta\kappa v\right)}{k_l\left(2\beta\delta D_0 + \eta^2\varsigma^2(2\delta+\rho)k_c\right)}$

Decision variables and perfSormance	Without blockchain N Model	With blockchain Y Model
Return rate	$\tau_{\infty}^{N}(t)=\frac{-aA\beta\delta(\delta+\rho)k_r}{\beta\delta k_r B_0+\eta^2\varsigma^2 k_c}$	$\tau_{\infty}^{Y}(t)=\frac{-A\,D_1}{k_l\left(2\beta\delta D_0+\eta^2\varsigma^2(2\delta+\rho)k_c\right)}$
Low-carbon level	$e_{\infty}^{N}(t)=-\frac{a\eta\varsigma^2 k_c}{\beta\delta k_r B_0+\eta^2\varsigma^2 k_c}$	$e_{\infty}^{Y}(t)=\frac{k_c\eta\varsigma^2\left(a(\delta+\rho)k_l-\eta\kappa v\right)-2\kappa v D_0}{-k_l\left(2\beta\delta D_0+\eta^2\varsigma^2(2\delta+\rho)k_c\right)}$
Profits	$\pi_M^N=\frac{-a^2\beta\delta^2(\delta+\rho)k_c k_r^2 B_1}{\left(\beta\delta k_r B_0+\eta^2\varsigma^2 k_c\right)^2}$ $\pi_R^N=\frac{a^2\delta^2 k_c k_r B_3}{2\left(\beta\delta k_r B_0+\eta^2\varsigma^2 k_c\right)^2}$	$\pi_M^Y=\frac{-k_c\left(\left(a\delta k_l+\eta\kappa v\right)D_0D_1+D_2(\delta+\rho)^2k_rk_c\right)}{k_l^2\left(2\beta\delta D_0+\eta^2\varsigma^2(2\delta+\rho)k_c\right)^2}-\frac{\kappa^2}{k_l}$, $\pi_R^Y=\frac{-k_cD_1\left(D_1\left(A^2\beta-2k_c\right)+D_2k_c\right)}{2k_l^2\beta\left(2\beta\delta D_0+\eta^2\varsigma^2(2\delta+\rho)k_c\right)^2}$, $\pi_T^Y=\frac{\kappa^2}{2k_l}$
Consumer's surplus	$CS^N=\frac{a^2\beta\delta^2(\delta+\rho)^2k_c^2k_r^2}{2\left(\beta\delta k_r B_0+\eta^2\varsigma^2 k_c\right)^2}$	$CS^Y=\frac{k_c^2D_1^2}{2k_l^2\beta\left(2\beta\delta D_0+\eta^2\varsigma^2(2\delta+\rho)k_c\right)^2}$
Demand	$Q^N=\frac{-a\beta\delta(\delta+\rho)k_ck_r}{\beta\delta k_r B_0+\eta^2\varsigma^2 k_c}$	$Q^Y=\frac{-k_cD_1}{k_l2\beta\delta D_0+\eta^2\varsigma^2(2\delta+\rho)k_c}$

To streamline the complexity of the formulas, we consolidate the common components of the expressions into the following parameters. Where, $D_0=(\delta+\rho)^2k_r\left(A\beta(A+\Delta)-2k_c\right)$, $D_1=\left(a\delta k_l+\eta\kappa v\right)\beta(\delta+\rho)^2k_r$, $D_2=\left(a\delta k_l+\eta\kappa v\right)\eta^2\varsigma^2$, $D_3=(\delta+\rho)^2k_r^2(2\beta(A+\Delta)(\delta+\rho)+\eta\varsigma)$, $D_4=\eta^2\varsigma^2(-\beta(\delta+\rho)(3A\delta+A\rho+4\delta\Delta+2\Delta\rho)-\delta\eta\varsigma)+2\beta\delta(\delta+\rho)^2k_r(2\beta(2A+3\Delta)(\delta+\rho)+\eta\varsigma)$ $D_5=2\beta(\delta+\rho)k_r\left(\eta^2\varsigma^2(3\delta+\rho)-4\beta\delta(\delta+\rho)^2k_r\right)-\eta^4\varsigma^4$, $D_6=\eta^2\varsigma^2(-2\beta(A+\Delta)(\delta+\rho)(2\delta+\rho)-\delta\eta\varsigma)+\beta\delta(\delta+\rho)^2k_r(14\beta(A+\Delta)(\delta+\rho)+3\eta\varsigma)$, $D_7=\beta(\delta+\rho)k_r\left(\eta^2\varsigma^2(7\delta+3\rho)-12\beta\delta(\delta+\rho)^2k_r\right)-\eta^4\varsigma^4$, $D_8=\beta\eta\varsigma(\delta+\rho)k_ck_r\left(A(A\beta\delta-\eta\varsigma)-2\delta k_c\right)+\eta^3\varsigma^3k_c^2$, $D_9=\eta^2\varsigma^2(-2\beta(A+\Delta)(\delta+\rho)(2\delta+\rho)-\delta\eta\varsigma)+4\beta\delta(\delta+\rho)^2k_r(4\beta(A+\Delta)(\delta+\rho)+\eta\varsigma)$, $D_{10}=4\beta(\delta+\rho)k_r\left(\eta^2\varsigma^2(2\delta+\rho)-4\beta\delta(\delta+\rho)^2k_r\right)-\eta^4\varsigma^4$.

The aforementioned results can be derived by employing methods from differential game theory, optimal control theory, and backward induction. According to the retailer's Hamiltonian function, the Hessian matrix can be obtained as $\begin{pmatrix}-k_c & -A\beta & 0\\ -A\beta & -2\beta & 0\\ 0 & 0 & -k_r\end{pmatrix}$, with the first-order condition being less than zero, the second-order condition being greater than zero, and the third-order condition being less than zero (as assumption 6). The Hessian matrix is negative definite, and the objective profit functional is a concave function of the decision variables. Equation of the retailer can reach a maximum value with respect to the decision variables. According to the first-order condition of maximizing the present value Hamiltonian function, $\frac{\partial H_R^N}{\partial p}=0$, $\frac{\partial H_R^N}{\partial \tau}=0$, $\frac{\partial H_R^N}{\partial r}=0$, the values of and can be obtained that $a+\beta(w-A\tau-2p)+e\eta=0$, $\begin{matrix}A(a+e\eta-\beta p)-\tau k_c=0\\ \lambda_2\varsigma-rk_r=0\end{matrix}$; according to the sate equation, $\dot{\lambda}_2^g(t)=\rho\lambda_2(t)-\frac{\partial H_R^N}{\partial e}$, by the transversality condition

$\lim_{t\to\infty}\lambda_2(t)e^{-\rho t}=0$ the decision variables of the supply chain members are of finite value, hence can be obtained $C_1=0$; solving the differential equation can yield the shadow price of the state variables: $\lambda_2(t)=\frac{\eta(A\tau+p-w)}{\delta+\rho}$. Substituting the values of into the first-order conditions of equation of H_R^N, solving the system of equations can yield: $p(t)=\frac{A^2\beta(a+e\eta)-k_c(a+e\eta+\beta w)}{\beta(A^2\beta-2k_c)}$, , $\tau(t)=\frac{A(a+e\eta-\beta w)}{2k_c-A^2\beta}, r(t)=-\frac{\eta\varsigma k_c(a+e\eta-\beta w)}{\beta(\delta+\rho)k_r\left(A^2\beta-2k_c\right)}$ and then substituting it into the manufacture's Hamiltonian function, the manufacturer's reaction function can be obtained. The second derivative of the reaction function is $\frac{2\beta k_c(A\beta(A+\Delta)-2k_c)}{(A^2\beta-2k_c)^2}$, which is less than zero, and the equation can reach a maximum value with respect to the decision variables. According to the first-order condition of maximizing the present value Hamiltonian function: $\frac{\partial H_M^N}{\partial w}=0$, there is $\frac{\begin{array}{l}A\beta k_c\left(-a(A+2\Delta)-e\eta(A+2\Delta)+2\beta w(A+\Delta)-2\lambda_1\varsigma\right)\\+2k_c^2(a+e\eta-2\beta w)+A^3\beta^2\lambda_1\varsigma\end{array}}{\left(A^2\beta-2k_c\right)^2}$; the sate equation is:$\overset{g}{\lambda_1}(t)=\rho\lambda_1(t)-\frac{\partial H_M^N}{\partial e}$, by the transversality condition, $\lim_{t\to\infty}\lambda_1(t)e^{-\rho t}=0$,the decision variables of the supply chain members are of finite value, hence can be obtained $C_2=0$; solving the differential equation can obtained $\lambda_1(t)=\frac{\begin{array}{l}\eta k_c\left(A(A\beta w-2\Delta(a+e\eta-\beta w))-2wk_c\right)\\+\left(A^2\beta-2k_c\right)\left(A(A\beta(\delta+\rho)+\eta\varsigma)-2(\delta+\rho)k_c\right)\end{array}}{\left(A^2\beta-2k_c\right)^2}$. Substituting the values of $\lambda_1(t)$ into the first-order conditions, and then solving the equation can yield the $w^N(t)$. Substituting it into $p(t),\tau(t),r(t)$, can yield the retail price $p^N(t)$, the recycling rate $\tau^N(t)$, and the efforts of low-carbon publicity $r^N(t)$. Substituting $r^N(t)$ into state variable equation, and then solving the differential equation, can yield e^N. Substituting e^N into $w^N(t)$, $r^N(t)$, $p^N(t)$, $\tau^N(t)$ can yield the steady-state decision solution of Corollary 2. Substituting the steady-state solution into the demand and profit functions can yield the optimal demand and profit, and then substituting into $CS=\int_{P\min}^{P\max}Qdp$ can calculate the consumer surplus.

The proof *Proposition* without blockchain process of Corollary 2 is the same as that of Corollary 1, using the backward solution method. When there is a blockchain technology service provider, first solve the decision variables, substitute them into the retailer's Hamiltonian function, then solve the retailer's decision variables, and finally obtain the manufacturer's decision variables.

3.2 Analysis

3.2.1 Comparative analysis

Corollary1: if $\eta > \max\{\eta_1, \eta_2\}$: when $a > \max\{a_1, a_2\}$, $w_\infty^N > w_\infty^Y$, $p_\infty^N > p_\infty^Y$; when $a < \min\{a_1, a_2\}$, $w_\infty^N < w_\infty^Y$, $p_\infty^N < p_\infty^Y$. Among $\eta_1 = \frac{A\eta^2\varsigma}{A^2\beta\delta - 2\delta k_c} + \frac{\eta^3\varsigma^2 k_c}{\beta\delta(\delta+\rho)k_r\left(2k_c - A^2\beta\right)} + \eta_3$,

$\eta_2 = \frac{A\left(\beta\delta(\delta+\rho)k_r - \eta^2\varsigma^2\right)}{\delta\varsigma k_c} + \frac{\eta^3\varsigma^3}{\beta\delta\varsigma(\delta+\rho)k_r}$, $a_1 = \frac{\kappa v\left(A\beta k_c k_r D_4 + k_c^2 D_5 - A^2\beta^3\delta(A+2\Delta)D_3\right)}{\delta\varsigma k_l\left(A\beta^2\delta(\delta+\rho)^2 k_r^2\left(2k_c - A^2\beta\right) + D_8\right)}$,

$a_2 = \frac{\kappa v\left(A\beta k_c k_r D_6 + k_c^2 D_7 - 2A^2\beta^3\delta(A+\Delta)D_3\right)}{\delta\varsigma k_c k_l\left(\eta^2\varsigma^2 - \beta\delta(\delta+\rho)k_r\right)\left(\eta\varsigma k_c - A\beta(\delta+\rho)k_r\right)}$.

When consumers' low-carbon awareness is strong ($\eta > \max\{\eta_1, \eta_2\}$) and the market size is sufficiently large ($a > \max\{a_1, a_2\}$), the product price under blockchain adoption becomes lower than that without blockchain integration. In such scenario, the manufacturer and retailer strategically reduce price to attract environmentally conscious consumers, thereby capturing higher market share and profit. This indicates that blockchain adoption grants manufacturer greater pricing flexibility to leverage consumers' sustainability preferences. Conversely, in markets with relatively small size ($a < \min\{a_1, a_2\}$), blockchain implementation imposes additional operational costs (e.g., service fees, technology integration expenses) on the manufacturer. To offset the cost, the manufacturer is compelled to raise product whole price, which may reduce demand and offset potential sustainability gains.

3.2.2 Sensitive analysis

Corollary2: if $\eta > \eta_3$,when $a > \max\{a_3, a_4\}$, $e^N < e^Y$, $Q^N < Q^Y$, $\tau^N < \tau^Y$, $r^N < r^Y$ 。 Among, $\eta_3 = \frac{A\beta\delta k_r + A\beta\rho k_r}{\varsigma k_c}$, $a_3 = \frac{\kappa v\left(A\beta k_c k_r D_9 + k_c^2 D_{10} - 2A^2\beta^3\delta(A+\Delta)D_3\right)}{\delta\eta^2\varsigma^3 k_c k_l^2\left(\eta\varsigma k_c - A\beta(\delta+\rho)k_r\right)}$, $a_4 = \frac{\kappa v(\delta+\rho)\left(-\beta\delta k_r B_0 - \eta^2\varsigma^2 k_c\right)}{\delta^2\varsigma k_l^2\left(A\beta(\delta+\rho)k_r - \eta\varsigma k_c\right)}$.

When consumers exhibit strong low-carbon awareness ($\eta > \eta_3$) and the market size is sufficiently large ($a > \max\{a_3, a_4\}$), the adoption of blockchain technology leads to higher low-carbon levels, increased retailer investments in low-carbon promotional efforts, improved recycling rate, and greater market demand compared to scenario without blockchain integration. Blockchain technology enhances low-carbon performance throughout the product lifecycle, fostering trust among environmentally conscious consumers and driving demand growth. This incentivizes the retailer to intensify their low-carbon promotional and recycling effort, thereby further elevating recycling efficiency and boosting both sales revenue and recycling profits.

Corollary 3: $\frac{\partial w^i}{\partial \eta} > 0, \frac{\partial p^i}{\partial \eta} > 0, \frac{\partial r^i}{\partial \eta} > 0, \frac{\partial \tau^i}{\partial \eta} > 0, \frac{\partial e^i}{\partial \eta} > 0, \frac{\partial Q^i}{\partial \eta} > 0, \frac{\partial \pi_M{}^i}{\partial \eta} > 0, \frac{\partial \pi_R{}^i}{\partial \eta} > 0, \frac{\partial \pi_T{}^i}{\partial \eta} = 0.$

Under both scenarios, the decision variables of the manufacturers and retailer, the state variable of the supply chain system, and market demand are positively correlated with consumer low-carbon awareness. As consumers' low-carbon awareness strengthens, market demand increases. The manufacturer, anticipating that consumers are willing to pay a premium for low-carbon products, raise wholesale price to secure profits, particularly when blockchain integration incurs additional operational costs. To align with consumers preferences, the retailer intensify low-carbon promotional efforts and adjust retail price, thereby elevating the low-carbon emission reduction level. Concurrently, heightened consumer low-carbon awareness amplifies market demand, incentivizing the retailer to enhance return rate to capture greater recycling revenues, which further drives improvements in recycling efficiency. The profits of both the manufacturer and retailer increase with heightened consumers' low-carbon awareness. As previously established, stronger consumers' low-carbon awareness drives higher market demand, enabling supply chain members to optimize pricing strategies (e.g., wholesale price, retail price) and capitalize on CLSC efficiencies, thereby achieving greater profitability. In contrast, the profits of the blockchain technology service provider depend solely on delivering technical solutions (e.g., the traceability system, data integrity protocols) to the manufacturer, with no direct linkage to consumer low-carbon awareness. Consequently, regardless of consumers' awareness of low-carbon living, it will not have no significant influence on the blockchain technology service provider.

Corollary 4: $\frac{\partial w^{Y}}{\partial \kappa} > 0$, $\frac{\partial p^{Y}}{\partial \kappa} > 0$, $\frac{\partial r^{Y}}{\partial \kappa} > 0$, $\frac{\partial \tau^{Y}}{\partial \kappa} > 0$, $\frac{\partial L^{Y}}{\partial \kappa} > 0$, $\frac{\partial e^{Y}}{\partial \kappa} > 0$, $\frac{\partial Q^{Y}}{\partial \kappa} > 0$, $\frac{\partial \pi_{M}{}^{Y}}{\partial \kappa} > 0$, $\frac{\partial \pi_{R}{}^{Y}}{\partial \kappa} > 0$, $\frac{\partial \pi_{T}{}^{Y}}{\partial \kappa} > 0$.

Under the scenario with blockchain technology adoption, the decision variables, state variable of in supply chain, market demand, and profits are all positively correlated with the commission rate paid by the manufacturer to the blockchain service provider. An increase in incentivizes the blockchain service provider to enhance its technical efforts, thereby elevating the low-carbon level and strengthening environmentally conscious consumers' trust in product sustainability. This heightened trust drives an increase in market demand. The surge in demand motivates the retailer to intensify low-carbon promotional efforts, while recyclers amplify recycling efforts to capitalize on higher recycling revenues, leading to a corresponding rise in return rates.

Although blockchain adoption increases operational costs for both the manufacturer and retailer, these costs are offset through strategic price adjustments: the manufacturer raises the

wholesale price, and the retailer elevates the retail price, thereby maximizing their respective profits. Consequently, the profits of all supply chain members increase with higher commission rates. Counterintuitively, the manufacturer's profit does not diminish despite the increased commission payments to the third-party service provider.

Corollary 5: $\frac{\partial w^{Y}}{\partial k_{I}}<0$, $\frac{\partial p^{Y}}{\partial k_{I}}<0$, $\frac{\partial r^{Y}}{\partial k_{I}}<0$, $\frac{\partial \tau^{Y}}{\partial k_{I}}<0$, $\frac{\partial L^{Y}}{\partial k_{I}}<0$, $\frac{\partial e^{Y}}{\partial k_{I}}<0$, $\frac{\partial Q^{Y}}{\partial k_{I}}<0$, $\frac{\partial \pi_{M}{}^{Y}}{\partial k_{I}}<0$, $\frac{\partial \pi_{R}{}^{Y}}{\partial k_{I}}<0$, $\frac{\partial \pi_{T}{}^{Y}}{\partial k_{I}}<0$.

When the blockchain technology costs coefficient is high, the revenue of the blockchain service provider decreases, resulting in lower profits and consequently diminished technological investment efforts. Which leads to a lower low-carbon level, as governed by the dynamic equation, and also weakens market demand, prompting the manufacturer and retailer to lower product prices to stimulate demand and sustain profitability.

However, consumers' strong low-carbon awareness implies that a decline in counteracts the demand-boosting effects of price reductions. Faced with shrinking profit margins, the retailer reduces investments in recycling efforts and low-carbon promotional efforts, further exacerbating the decline in and creating a negative feedback loop. The manufacturer, constrained by lower wholesale prices and reduced recycling efficiency, experience further profit erosion.

Proof of Corollary 1: By taking the difference of the decision variables and combining the constraint conditions of Assumption 6, the results can be obtained.

Proof of Corollary 2, 3, 4, and 5: By taking the derivative of the parameters and combining the constraint conditions of Assumption 6, the results can be obtained.

4 Numerical Simulation

Next, we will investigate and further validate the impacts of consumer' low-carbon awareness, blockchain commission rate , service costs coefficient , the attenuation coefficient of the low-carbon level over time and discount rate on supply chain members' profits under steady-state conditions of the dynamic control system across various scenarios. Additionally, we analyze the temporal evolution of the state variable and the effects of blockchain adoption on supply chain profitability and consumer surplus. This section employs numerical simulations for comparative analysis, with reference [10]. To ensure non-negativity of decision variables, the state variable, and demand, the parameter settings are specified as follows:$a = 5, A = 1$,

$\beta = 0.5$, $\eta = 0.8$, $\delta = 0.2$, $\Delta = 2$, $\kappa = 0.3$, $\rho = 0.2$, $v = 0.3$, $\varsigma = 0.2$, $k_c = 3$, $k_l = 2$, $k_r = 2$.

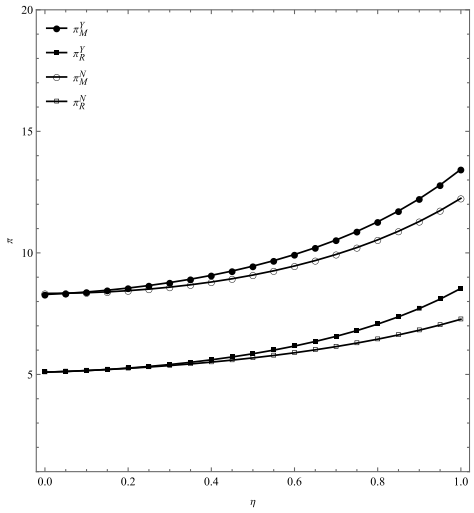

Figure 1. The effect of η on profit

Fig 1, the profit of supply chain members shown growth trend under blockchain adoption becomes more pronounced as consumer low-carbon awareness intensifies, with significantly higher profitability observed compared to scenario without blockchain integration. In both cases, the profits of the manufacturer and the retailer are consistently greater when blockchain technology is implemented. These findings align with the Corollaries 1,2,3, which posit that blockchain-driven transparency and traceability amplify consumer trust in low-carbon statements, thereby can enhance demand elasticity and enabling strategic price adjustments to capture sustainability premiums.

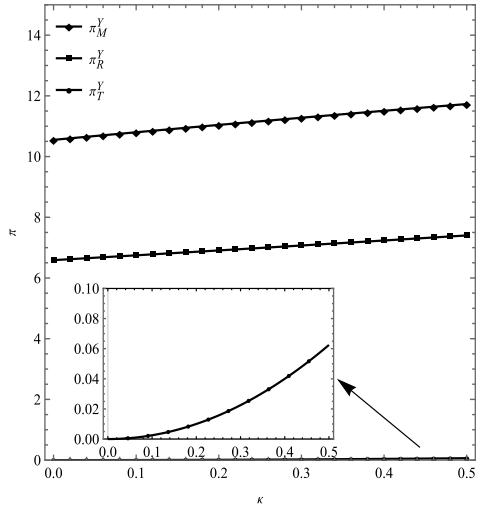

Figure 2. The effect of κ on profit

Fig. 2, it can be concluded that an increasing profits of the manufacturer, the retailer, and the blockchain technology service provider with the commission rate, and that a rising commission rate does not result in a reduction in the profits of manufacturers or the supply chain system. This finding is consistent with Corollary 4.

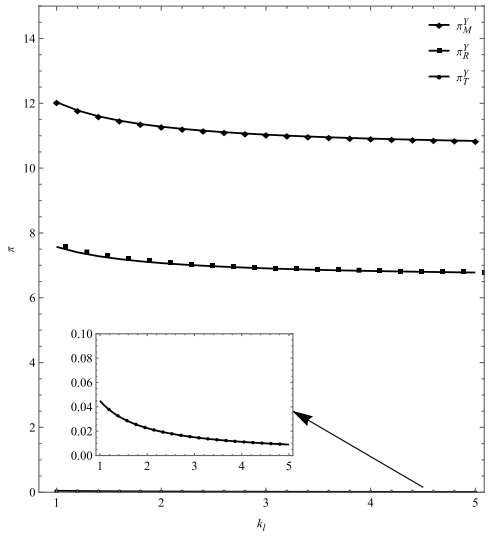

Figure 3. The effect of k_l and on profit

Fig. 3 indicates that as the costs coefficient for blockchain technology services increases, the profits of supply chain members decrease. This outcome is in line with Corollary 5.

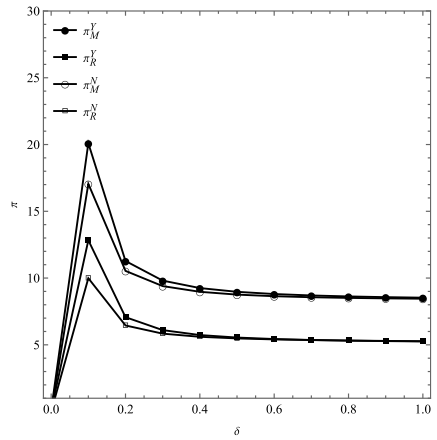

Figure 4. The effect of δ and on profit

Fig. 4 shows that when the decay coefficient of the low-carbon level increases, profits exhibit a hump-shaped response—rising at low decay rates but falling once the decay becomes sufficiently large. A small decay coefficient implies that once achieved, a higher low-carbon level is sustained for longer, allowing firms to capitalize on enhanced reputation and consumer willingness to pay; consequently, product prices can be raised, market demand remains robust, and investments in recycling and carbon-promotion efforts yield positive returns, driving profits

upward. However, as the decay coefficient grows, the persistence of any low-carbon improvements diminishes rapidly, eroding the benefits of upfront investments. Firms consequently scale back recycling efforts and carbon-reduction promotions, and to offset their shrinking future gains, they still raise prices—only to face a contraction in demand. The combined effect of weakened low-carbon persistence, reduced promotional and recycling activities, and suppressed consumer response ultimately leads to a drop in profits once the decay coefficient crosses a critical threshold.

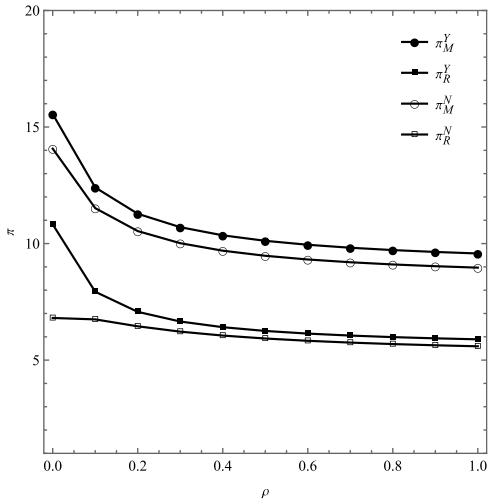

Figure 5. The effect of ρ and on profit

Fig. 5 illustrates that an increase in the discount rate reduces the profits of the supply chain members. The discount rate reflects the extent to which decision-makers value future returns. As the discount rate rises, the present value of future earnings declines, prompting firms to prioritize short-term gains while underestimating the benefits of long-term investments. Under these conditions, the manufacturer and the retailer tend to curtail efforts in low-carbon promotion and product recycling, resulting in lower recycling rates and diminished carbon-reduction initiatives. Meanwhile, to preserve short-term profitability or offset rising costs, they may opt to raise product prices. However, higher prices suppress consumer demand and lead to reduced overall sales. The combined effects of reduced low-carbon investment, contracting market demand, and weakened consumer response ultimately lower profit levels throughout the supply chain. Consequently, a higher discount rate not only erodes the incentive for firms to pursue low-carbon transformation but also impedes the attainment of sustainable development objectives within the supply chain.

Besides, from Figures 4 and 5, it can also be observed that comparing the scenarios with and without blockchain adoption, the manufacturer and the retailer achieve higher profits when

blockchain technology is implemented., the profits of the manufacturer and the retailer are consistently greater when blockchain technology is implemented.

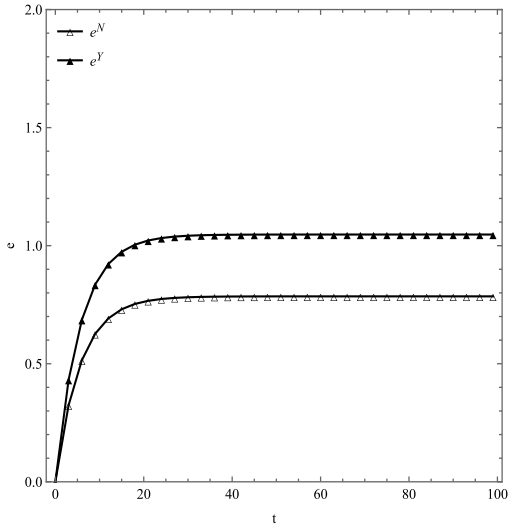

Figure 6. The trajectory of the change in low-carbon levels over time

Fig. 6 demonstrates that over time, the level of low-carbon emission reduction steadily improves, suggesting that the efforts of supply chain members coupled with technological advancements are driving the achievement of environmental protection goals. Moreover, the presence of blockchain technology yields a higher low-carbon level compared to scenario without blockchain. Thus, embedding blockchain technology not only facilitates the attainment of more ambitious low-carbon targets but also constitutes an important technological measure for realizing sustainable development and environmental protection.

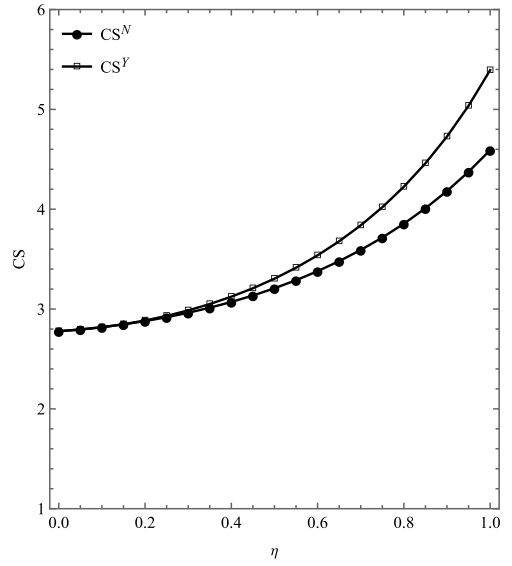

Figure 7. The effect of η on consumer' surplus

Fig. 7 reveals that as consumers' awareness of low-carbon issues increases, consumer surplus also rises, and it is higher when blockchain technology is applied. The low-carbon level increases over time and eventually stabilizes, resulting from increased investments by supply chain members and the willingness of low-carbon-conscious consumers to pay premium prices. Furthermore, the integration of blockchain technology effectively reduces the carbon footprint, thereby enhancing consumer surplus.

5 Conclusion

This study moves beyond the static research framework of forward supply chain by constructing a CLSC dynamic differential game model, thereby revealing the impact of the interaction between low-carbon awareness and market size on the profit transmission mechanism. In an innovative extension, blockchain technology is applied not only in brand goodwill management but also in full-cycle carbon footprint monitoring, leading to the development of a three-dimensional evaluation system based on "transparency-efficiency-emission reduction." The research conclusions are as follows:

(1) When the market scale is large and consumers exhibit strong low-carbon awareness, blockchain technology can reduce product prices while enhancing low-carbon levels, consumer surplus, and recycling rates. The profits of supply chain members may increase by 15% to 25%, offering a quantifiable implementation pathway toward achieving the "dual-carbon" goals. The technological transparency triggers a "low-carbon premium" effect, accelerating the attainment of a stable low-carbon level in carbon footprint monitoring.

(2) In scenarios where the technology investment costs coefficient of the blockchain service provider is high and consumers have strong low-carbon awareness, reducing technological effort will result in decreased profits for supply chain members.

(3) The level of low-carbon operation rises over time and eventually stabilizes; additionally, when blockchain technology is integrated, the low-carbon level is higher.

(4) As the discount rate increases, the present value of future returns declines, weakening the incentive for firms to invest in low-carbon promotion and recycling. To sustain short-term profitability, companies tend to raise product prices, which in turn suppress market demand. The combined effect of reduced low-carbon investment and diminished demand ultimately leads to a decline in supply-chain member profits.

(5) The decay coefficient of the low-carbon level exhibits an inverted-U effect on profits. At low decay rates, carbon-reduction benefits are sustained over time, enhancing consumers'

willingness to pay premiums and improving recycling efficiency, which drives profit growth. As the decay coefficient increases, however, these benefits dissipate more rapidly, prompting firms to cut back on related investments and raise prices to offset losses—thereby contracting demand and recycling rates, and causing profits to fall. Notably, although profits continue to decrease at higher decay rates, the rate of decline diminishes as the decay coefficient becomes very large.

Overall, under the dual-carbon framework, the manufacturer should comprehensively evaluate the cost-effectiveness of blockchain technology and the level of consumer low-carbon awareness when deciding whether to implement blockchain-enabled full-cycle management. This integrated strategy can effectively balance technological innovation with cost control, thereby facilitating the green and low-carbon transformation of the supply chain and supporting the achievement of dual-carbon objectives. Based on the findings of this study, a key managerial implication is that the retailer should share a portion of the blockchain implementation costs initially borne by the manufacturer. Such a cost-sharing arrangement not only distributes the financial burden more equitably but also enhances joint investment in digital infrastructure, improves supply chain transparency and carbon traceability, and fosters coordinated low-carbon governance—ultimately contributing to improved overall supply chain performance and sustainability.

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