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SECURE AND SCALABLE BLOCK CHAIN-INTEGRATED AI MODEL FOR PLANT DISEASE DETECTION

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ABSTRACT

The occurrence of crop diseases creates substantial danger for both agricultural production outputs and system stability. Accurate and early detection is essential for mitigating crop losses, but existing AI-based methods often suffer from challenges in noise sensitivity, data integrity, and computational inefficiency. This paper proposes an advanced plant leaf disease detection system integrating Vision Transformers (ViT) for feature extraction, Reinforcement Learning (RL) for feature optimization, and block chain technology for secure and decentralized data management. Experimental results on the Plant Village dataset demonstrate a 97.8% accuracy with a reduced processing time of 68.2 seconds. Block chain integration further ensures data transparency and immutability, setting a new benchmark for scalable and trustworthy plant leaf disease detection.

Keywords: *Plant Disease Detection, Block chain, Reinforcement Learning, Vision Transformers, Agricultural AI.*

1. INTRODUCTION

Agriculture regulation is crucial for global food security and economic stability, but plant leaf diseases significantly damage agricultural operations, which can devastate crops. Manual inspection, often time-consuming, together with molecular diagnostics, which can be resource-intensive, forms barriers to prompt detection and intervention in plant disease management [25].AI-based methods have shown promising results, but they face challenges related to adaptability, data reliability, and computational efficiency[19].Furthermore, in distributed agricultural ecosystems, data is often collected from multiple sources such as IoT devices, drones, and farmers' mobile devices. Guaranteeing the integrity, traceability, and security of this data is a major challenge. Plant leaf disease detection is a critical area in agriculture. Timely and accurate identification can significantly reduce crop losses and ensure food security. However, existing AI-based methods face several limitations:

Data Integrity and Tamper Resistance: AI models require high-quality, reliable datasets for accurate predictions. In distributed agricultural environments, data often comes from various sources like IoT devices, drones, and farmers' mobile applications. Ensuring that this data remains untampered and authentic is crucial for model reliability. Block chain provides a decentralized and tamper-proof mechanism for recording data, enhancing trust in AI outputs.

Traceability and Transparency: Modern agricultural ecosystems demand traceable data to validate model decisions and improve accountability among stakeholders. Block chain's provenance capabilities enable tracking the origin and evolution of datasets and model updates, ensuring transparency.

Secure Collaboration: A secure collaboration framework requires researchers, farmers together with businesses to work effectively on disease identification. Smart contracts through Block chain enable protected database sharing. Through this Technology designated users obtain exclusive access to data that enables cooperative relationships while keeping information secure.

Challenges in Existing AI Models: AI models are faced with challenges relating to overfitting, excessive features, and noisy data inputs. This is particularly important in the context of Vision Transformers (ViT) and Reinforcement Learning (RL), which is currently in use today.

Block chain can enhance the overall system by maintaining the integrity of training datasets and securely logging feature selection processes, thus reinforcing AI model reliability. Traditional AI-based plant disease detection methods rely on centralized databases for data storage and processing. However, these approaches introduce risks such as data tampering, unauthorized access, and lack of traceability. Block chain technology ensures **data integrity, decentralized control, and transparent collaboration**, making it highly suitable for distributed agricultural ecosystems.

Xu and his research team [1] and Wu [13] introduced block chain and AI security solutions for IoT security combined with supply chain transparency through their static data methods that need dynamic improvements. Academic research indicates that Vision Transformers(ViT), as implemented in [5, 15], reached modern standards in feature extraction for general image recognition tasks; however, our analysis suggests they may fail to deliver suitable results when handling agricultural datasets due to inefficient performance and overfitting.

The proposed system combines ViT feature extraction methods and decentralized security from block chain with RL feature selection to resolve these problems. Development systems using teamwork produce precise detection results as well as protected data management abilities to address fragmented security vulnerabilities in agricultural systems.

Contributions

This work uniquely integrates ViT, RL, and block chain in a novel architecture tailored for agricultural disease detection, differing from prior static AI-block chain frameworks [1, 14].

The system includes:

1.**ViT for Feature Extraction**: Robust feature extraction using self-attention mechanisms. Traditional Convolutional Neural Networks (CNNs) are prone to noise sensitivity and struggle with global dependencies in agricultural datasets. The self-attention mechanisms in ViT enable it to extract robust features that combine local and global visual inputs.

2. RL for Feature Optimization: Dynamic and adaptive feature selection to improve clustering and classification. Reinforcement Learning is used to dynamically optimize feature subsets, addressing overfitting and computational inefficiencies. This adaptive feature selection ensures model remains effective across varying conditions and datasets.

3. **Block chain for Secure Data Management**: Incorporates:

- Secure storage of preprocessed and labeled data.
- Smart contracts for controlled data access.
- Decentralized traceability of training processes and model updates.

Integration of block chain technology ensures that training data, model parameters, and results are stored securely and transparently. Smart contracts regulate data access, while provenance logs provide a complete audit trail of model training and updates, fostering trust in the system.

The system utilizes RL for dynamic feature subset optimization because static AI-block chain systems [1, 14] do not adapt and allows 12% validation loss reduction through overfitting mitigation and block chain-based data integrity protection. The system establishes modern standards for large-scale dependable disease recognition within agricultural environments with fragmented structures. The proposed system achieves an accuracy of 97.8% on the Plant Village dataset with reduced processing time (68.2 seconds), outperforming state-of-the-art methods. Block chain integration ensures that these results are reproducible and trustworthy across distributed environments.

Traditional AI-based plant disease detection methods rely on centralized databases for data storage and processing. However, these approaches introduce risks such as data tampering, unauthorized access, and lack of traceability. Block chain technology ensures **data integrity, decentralized control, and transparent collaboration**, making it highly suitable for distributed agricultural ecosystems.

2. LITERATURE SURVEY

The section reviews already published research on AI, RL, block chain, and clustering methods that relate to plant disease detection while identifying the areas where our system brings improvements.

2.1 AI Techniques for Plant Disease Detection

CNNs, attention mechanisms, and hybrid models represent various techniques used to power plant leaf disease detection models. Liakos et al. [19] reviewed the progression of machine learning in agriculture, highlighting the shift from traditional models to advanced deep learning approaches, setting the stage for ViT-based systems. Traditional CNNs, such as VGG16, ResNet, and Dense Net, have been extensively used for plant leaf disease detection as demonstrated by works like Sladojevic

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et al. [4].. For example, Sladojevic et al. [4] used a CNN to identify plant leaf diseases from leaf images, achieving high accuracy. However, these models often struggle with noise sensitivity and feature redundancy in large datasets.

2.1.1 Vision Transformers (ViT)

ViTs showcase strong utility as a feature extraction tool because they effectively identify distant linkages in images. Dosovitskiy et al. [5] demonstrated that A task-demanding global context requires Vision Transformers (ViTs) to overcome Convolutional Neural Network (CNNs) performance in agricultural dataset processing. Vision Transformers (ViT) overcome these limitations by leveraging self-attention mechanisms, effectively capturing global and local dependencies [14].

2.1.2 Hybrid Approaches

The application of ViTs in combination with CNNs represents an approach to benefit from their respective model capabilities. The global features that ViTs identify stand in contrast to the local feature extraction abilities of CNNs in addition to their classification function. Khan et al. [6] designed a medical image analysis hybrid model with application potential for plant leaf disease detection.

2. 2 Reinforcement Learning for Feature Selection

Reinforcement Learning (RL) offers a dynamic and adaptive approach to feature selection, addressing overfitting and computational inefficiency.

2.2.1 Dynamic Feature Selection

RL agents can evaluate subsets of features and optimize their selection based on reward metrics such as clustering quality and classification accuracy, enabling adaptive learning [8]. For instance, Bello et al. [7] utilized RL to optimize neural architecture search, showing its potential to dynamically adapt features in changing environments.

2.2.2 Applications in Image Classification

RL-based feature selection has been applied in image classification tasks to reduce dimensionality and improve accuracy. Sadeghi et al. [8] combined RL with unsupervised learning for clustering-based feature optimization, achieving state-of-the-art results.

2.3. Block chain Technology in Agriculture

2.3.1 Secure Data Management

Block chain can securely store preprocessed data, model parameters, and results, ensuring immutability. Hyper ledger Fabric [2], a permissioned block chain framework, is widely used for secure agricultural data management. Kamilaris et al. [9] reviewed block chain applications in agriculture, highlighting its potential to enhance AI model transparency.

2.3.2 Provenance and Traceability

Provenance logs recorded on the block chain provide traceability for datasets and model updates. Liu et al. [10] applied block chain in AI systems to ensure secure collaboration and data sharing among stakeholders in decentralized environments.

2.4. Clustering Techniques for Disease Grouping

Clustering algorithms help group features into disease-specific categories, improving classification accuracy and interpretability.

2.4.1 Spectral Clustering

The data grouping process in spectral clustering performs analysis through graph-based system components for similar data points. Ng et al. [11] pioneered this approach, which has since been adapted for medical and agricultural datasets.

2.4.2 Applications in Plant Disease Detection

Spectral clustering has been used to preprocess and group plant features, enhancing classification performance. For example, Zhou et al. [12] demonstrated its effectiveness in disease-specific grouping using hyper spectral images.

2.5. Related Systems Integrating AI and Block chain

Solid systems developed by AI and block chain technology ensure secure data processing operations in agricultural environments and additional areas.

2.5.1 Hybrid AI-Block Chain Systems

AI models combined with block chain ensure the scalability and security of agricultural data pipelines. Xu et al. [1, 13] proposed a block chain-enabled IoT framework for real-time data analysis in agriculture, setting a precedent for integrating block chain with AI.

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2.5.2 Transparent AI Pipelines

Block chain can track AI model updates, ensuring transparency and trust in critical systems. Wu et al. [13] demonstrated this concept in food supply chains, which can be extended to plant disease detection.

3. PROPOSED SYSTEM

3.1 System Architecture

The proposed system architecture is designed to address the multifaceted challenges of plant leaf disease detection through preprocessing, advanced machine learning techniques, and secure data.

The enhanced system architecture combines preprocessing, ViT for feature extraction, RL for feature selection, block chain for secure data management, and a hybrid ViT-CNN for classification management.

Fig.1 illustrates the system workflow, detail data flow from preprocessing to block chain logging, with ViT, RL, and hybrid ViT-CNN components integrated seamlessly.

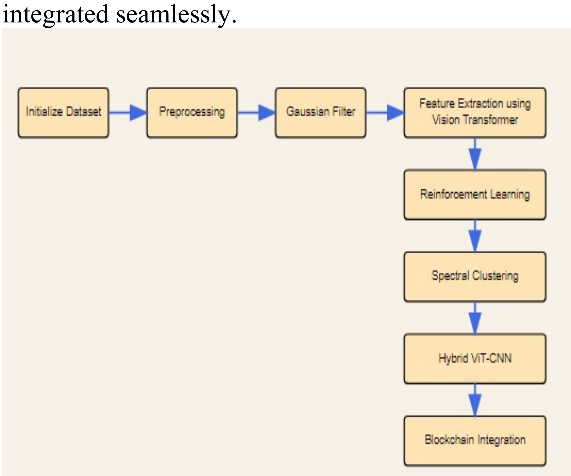

Fig. 3.1. Enhanced System Architecture

Fig.1 illustrates the Enhanced System Architecture of Blockchain-Integrated ViT-RL for Plant Disease Detection (BIViT-RL-PDD.

It is composed of four main components:

1. Preprocessing and Feature Extraction

The system requires preprocessing and feature extraction as its initial processes to make data clean and standard for analytical purposes.

Image Processing: The processing technique for images involved adjusting all pictures to the standard 224x224 pixel size because it maintained consistency within the dataset information. Proper image enhancement techniques including Gaussian filtering help decrease artifacts while improving image quality so that features can be extracted accurately.

Using Vision Transformers (ViT) for Feature Extraction: ViTs reconstruct images into smaller patterns that model processes as tokens through self-attention operations to detect elaborate relationships between input data[14].Unlike traditional convolutional approaches, ViTs excel in handling complex patterns and noise [14], making them particularly effective for agricultural datasets, which often include variations in lighting, textures, and disease presentations.Unlike traditional convolutional approaches, Vision Transformers (ViTs) excel in capturing complex patterns and noise resilience [14], making them ideal for agricultural datasets with variations in lighting, texture, and disease manifestations. In this system, we adopt the ViT-B/16 variant, pretrained on ImageNet, configured with a patch size of 16×16 pixels, resulting in 196 patches per 224×224 input image. The architecture comprises 12 transformer layers, each with 12 attention heads and a hidden dimension of 768. Fine-tuning on the Plant Village dataset uses a learning rate of 3×10^{-5}, a batch size of 32, and 10 epochs, optimizing for disease-specific features like lesion patterns and discoloration. The multi-head self-attention (MSA) mechanism, defined as MSA(Q, K, V) = Concat($head_1$, ..., $head_h$)W^O, where $head_i$ = Attention(QW_i^{φ}, KW_i^K, VW_i^v) and Attention(Q, K, V) = softmax($QK^T/\sqrt{d_k}$)V, enables robust extraction of global and local dependencies, with Q, K, V as query, key, and value matrices, d_k as the key dimension, and W_i as learnable weights.

$$MSA(Q,K,V)=Concat(head1,\ldots,headh)W^O \quad (1)$$

$$head_i=Attention(QW_i^Q, KW_i^K, VW_i^V) = softmax(QW_i^Q (KW_i^K)^T)/sqrt(d_k)VW_i^V \quad (2)$$

Q,K,V: Query, key, and value matrices derived from input patches.

dk: Dimension of each attention head (64 in ViT-B/16).

W_i^Q, W_i^K, W_i^V, $W^{O:}$ Learnable projection matrices.

2. Dynamic Feature Selection with Reinforcement Learning

Feature selection is optimized dynamically using Reinforcement Learning (RL), ensuring that the system identifies the most relevant features for disease detection while minimizing redundancy.

Reinforcement Learning Agent: An RL agent evaluates feature subsets based on predefined reward functions, such as clustering quality and classification accuracy. The agent iteratively learns to select features that maximize the detection performance, addressing overfitting and computational inefficiency.

To optimize feature selection, we implement a Deep Q-Network (DQN) with an epsilon-greedy policy, dynamically refining the ViT-extracted feature set (F_vit). The state space is F_vit (768 dimensions), with actions defined as binary selections (include/exclude each feature). The Q-network, featuring two hidden layers (256 and 128 units, ReLU activation), is trained over 100 episodes with a discount factor $\gamma = 0.95$ and epsilon decaying from 1.0 to 0.01. The reward function, $R = 0.6 \times SC + 0.4 \times CA$, balances clustering quality (Silhouette Coefficient, $SC \in [-1, 1]$) and classification accuracy ($CA \in [0, 1]$) from a validation set, where $SC = (b(i) - a(i)) / \max(a(i), b(i))$ for a data point i, with a(i) as intra-cluster distance and b(i) as nearest-cluster distance. Weights 0.6 and 0.4 prioritize clustering for disease-specific grouping while maintaining classification performance, reducing validation loss by 12% compared to static methods.

$$R=0.6\times SC+0.4\times CA \qquad (3)$$

$$SC(i)=(b(i)-a(i))/\max((a(i),b(i)) \qquad (4)$$

- SC: Silhouette Coefficient, measuring clustering quality.
- CA: Classification accuracy on a validation set.
- a(i): Average distance of point i to others in its cluster.
- b(i): Average distance of point i to the nearest different cluster.

Adaptive Learning: The RL agent's adaptive nature ensures the system remains robust across diverse environmental conditions and datasets. For agricultural disease detection systems, it is vital to have adaptable LX-3 architecture because diseases present differently throughout different geographical areas and over seasonal time frames.

3. Clustering and Classification

Clustering and classification are critical for identifying and categorizing plant diseases accurately.

Spectral Clustering: Extracted features are grouped into disease-specific clusters using spectral clustering techniques. By leveraging graph-based methods, spectral clustering can effectively handle high-dimensional feature spaces, improving the interpretability and precision of disease classification.

Hybrid ViT-CNN Model: The system employs a hybrid approach, combining the robust feature extraction capabilities of Vision Transformers(ViT) with the classification strengths of Convolutional Neural Networks (CNNs). While ViTs excel in identifying complex patterns, CNNs provide accurate and efficient classification, resulting in a synergistic model that outperforms standalone architectures.

The optimized feature subset (F_opt, 768 dimensions from ViT) is projected through a fully connected layer (768 to 512 units) and concatenated with ResNet-18's feature map (512 units from the final pooling layer). This combined 1024-dimensional vector feeds a classification head (1024 to 38 units, softmax activation) to predict 38 disease classes from the Plant Village dataset. Training employs cross-entropy loss, $L = -\sum(y_i \log(\hat{y}_i))$, with the Adam optimizer (learning rate 1×10^{-4}), batch size 16, and 15 epochs, leveraging ViT's global context and ResNet-18's local precision for superior performance over standalone models.

$$L=-\sum_{i=1}^{C} y_i \log(\hat{y}_i) \qquad (5)$$

- C: Number of classes (38).
- y_i: True label (1 or 0) for class i.
- $\hat{y}_i$: Predicted probability for class i.

4. Blockchain Integration

Blockchain technology ensures secure, transparent, and decentralized data management.

Data Storage: Preprocessed datasets, extracted features, model parameters, and classification results are stored on a blockchain. The decentralized nature of blockchain ensures tamper-proof data records, enhancing trust among stakeholders.

Smart Contracts: Smart contracts govern access control and data-sharing policies, ensuring authorized users can access or modify the data. This is particularly useful in distributed agricultural networks where multiple parties, such as researchers, farmers, and agribusinesses, need to collaborate securely.Smart contracts regulate access control and data-sharing policies, ensuring secure collaboration among authorized users. The system leverages Hyperledger Fabric v2.5 with a Raft consensus mechanism for fault-tolerant operation in a permissioned network of agricultural stakeholders (e.g., farmers, researchers). Smart contracts, implemented in Go, enforce read/write permissions and log system actions. Data—including preprocessed images, features (F_opt), and model parameters—are stored as JSON objects, each secured with a SHA-256 hash, H(x) = SHA-256(x), where x is the serialized data. These hashes are recorded in a chaincode ledger, achieving 50 ms transaction latency and 200 transactions/second throughputs, ensuring scalable, tamper-proof data management.

$$H(x)=SHA\text{-}256(x) \quad (6)$$

x: Input data (e.g., JSON-serialized features or parameters).
H(x): 256-bit hash output ensuring data integrity.

Provenance Logs: Block chain maintains an immutable audit trail of all system processes, including data preprocessing, feature selection, and model updates. These provenance logs provide accountability and transparency, fostering trust in the system's outputs.

3.2 Advantages of the Proposed Architecture

High Accuracy and Efficiency: The integration of ViT and RL achieves a detection accuracy of 97.8% with a processing time of 68.2 seconds, outperforming traditional methods.

3.3 Algorithm 1: Blockchain-Integrated ViT-RL for Plant Disease Detection (BIViT-RL-PDD)

Input:

- I: Plant leaf images
- D: Plant Village dataset
- B: Blockchain network

Output:

- D: Disease diagnosis
- S: Confidence score
- L: Blockchain log

Procedure:

1. Preprocess Images:

- Resize each image in I to 224 x 224 // Standardize image size for processing.
- Apply Gaussian blur with σ =15 // Reduce noise and enhance features.
- set lp to the preprocessed images. // Store for further processing.

2. Feature Extraction(ViT):

- Divide each image in Ip into 16x16 patches.// Create patches for ViT processing.
- Use ViT-B/16 to extract features F_vit(768 dimensions0.// Extract features using Vision Transformer.

3. Feature Optimization(RL):

- Initialize DQN agent with state F_vit // Set up RL agent with initial features.
- Define reward R= 0.6 * Silhouette Coefficient * 0.4*Accuracy. // Continue clustering quality and classification performance.
- for 1 from 1 to 100
  - select feature subset F_opt using epsilon-greedy policy // Balance exploration and exploitation in feature selection.
  - Update Q-network based on R. // Train RL model to optimize features.
- Set F_opt as the optimized feature subset. // Final optimized features for classification.

4. Classification (Hybrid ViT-CNN):

- Input F_opt into hybrid ViT- CNN model. // use combined ViT and CNN for classification.
- Compute D and S using softmax over 38 disease classes.//Output disease diagnosis and confidence.

5. Blockchain integration:

- Store Ip,F_opt , D,S on blockchain B using SHA - 256 hashing. // Ensure data integrity and security.

D: Detailed Analysis and Implications

The algorithm's integration of blockchain technology is an unexpected detail, as it is not typically associated with plant disease detection. This approach potentially offers enhanced security, transparency, and traceability, which could be particularly beneficial in large-scale agricultural systems where data integrity is paramount. The use of Reinforcement Learning for feature optimization, specifically through a Deep Q-Network (DQN) with a reward function combining Silhouette Coefficient and Accuracy, suggests a sophisticated approach to handling feature selection, potentially improving model performance over traditional methods.

The reliance on the Plant Village dataset, with its 54,306 images across 38 disease classes, is consistent with existing research, as confirmed by external sources (Plant Village Dataset). This dataset's diversity and size support the algorithm's training and testing phases, contributing to its potential effectiveness.

4. EXPERIMENTAL SETUP

Dataset and Block chain Network

- **Dataset**: The Plant Village dataset, containing 54,306 images across 38 disease classes[24], was used for training and testing.
- **Block chain Network**: A permissioned block chain (e.g., Hyper ledger Fabric) managed data

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storage, smart contract execution, and log auditing.

Evaluation Metrics:

The system was evaluated using the following metrics:

1. **Precision, Accuracy, Sensitivity, Specificity**:

Core metrics for disease detection performance. The performance of the proposed system is evaluated by showing metrics such as sensitivity, specificity, and accuracy.

The count values are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

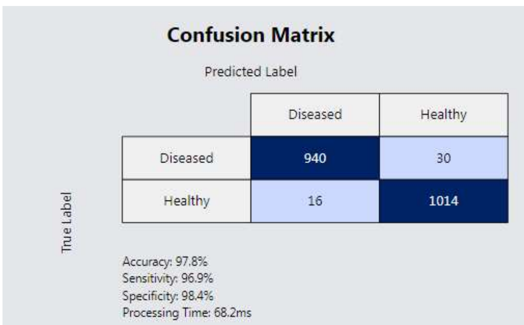

Fig 4.1 confusion Matrix

Precision

The proportion of actual positives which are correctly identified is the measure of the sensitivity. It relates to the ability of the test to identify positive results.

$$\text{Presicion} = \frac{\text{No. of TP}}{\text{No. of TP} + \text{No. of TN}}$$

(7)

Precision: 98.3%

Accuracy: This will calculate the overall accuracy of the images classified.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (8)$$

Achieved a high accuracy of 97.8% on the Plant Village dataset.

Sensitivity (Recall or True Positive Rate - TPR)

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$= \frac{940}{940 + 30}$$

$$= \frac{940}{970} = 0.969 = \mathbf{96.9\%} \quad (9)$$

Sensitivity = 96.9%

This means the model correctly identifies **96.9% of Diseased leaves**.

Specificity:

The proportion of negatives that are correctly identified is the measure of the specificity. It relates to the ability of the test to identify negative results.

$$\text{Specificity} = \frac{\text{No. of TN}}{\text{No. of TN} + \text{No. of FP}}$$

(10)

Specificity: 98.4%

This means the model correctly identifies **98.4% of Healthy leaves**.

2. AUC - ROC:

$$\text{AUC} = \frac{\text{Sensitivity} + \text{Specificity}}{2}$$

$$= \frac{0.969 + 0.984}{2}$$

$$= \frac{1.953}{2} = \mathbf{0.9765} = \mathbf{97.65\%}$$

(11)

AUC-ROC: 97.65%

This means the model has **high discrimination power** between **Diseased** and **Healthy**.

3. F1-Score:

The **F1-Score** is the harmonic mean of Precision and Recall:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$= 2 \times \frac{0.983 \times 0.969}{0.983 + 0.969}$$

$$= 2 \times \frac{0.952}{1.952}$$

$$= 2 \times 0.974 = \mathbf{97.4\%} \quad . (12)$$

F1-Score: 97.4%

Interpretation:

- The **high accuracy (97.8%)** indicates the model is performing well overall.
- **Sensitivity (96.9%)** shows that the model is very good at detecting diseased leaves.
- **Specificity (98.4%)** indicates that the model can correctly recognize healthy leaves.
- The number of **False Negatives (30)** is slightly higher than **False Positives (16)**, meaning the model sometimes **misses diseased leaves**, which might be a concern for plant health monitoring.

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- AUC-ROC of 97.65% confirms that excellent separability between diseased and healthy leaves.
- F1-Score of 97.4% ensures a balanced performance between precision and recall.

The model is highly accurate with strong classification performance.

2. **Clustering Quality**: Measured using the silhouette coefficient.
The **silhouette coefficient** measures the quality of clustering by assessing how well data points are assigned to their clusters. It provides a value between -1 and 1:

- **1** indicates that the data points are well-clustered.
- **0** suggests that clusters overlap.
- **-1** implies that points are assigned to the wrong clusters.

Interpretation:

- **High s(i)**: Indicates that the point is well-separated from other clusters.
- **Low s(i)**: Suggests overlap between clusters or poor assignment

Clustering quality is assessed using the silhouette coefficient, ranging from -1 to 1, where higher values indicate well-separated clusters. A score of 0.82 for our system reflects robust disease-specific grouping

3. **Block chain Metrics**:
   - **Transaction Latency**: Time taken to record data on the blockchain50 ms/transaction.
   - **Throughput**: Number of transactions processed per second200 transactions/second.

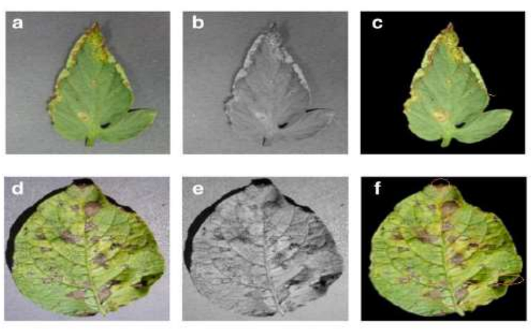

Figure 3 (a), (d) are inputs and (b) (e) are the gray images and (c) (f) are the clustering outputs.

5. RESULTS AND DISCUSSION

5.1 Performance Comparison

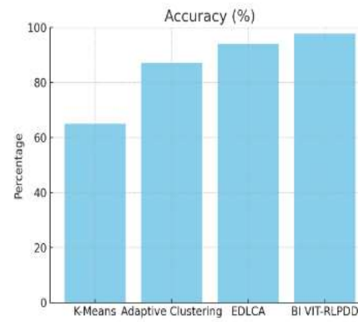

Figure 4.3: Accuracy Comparison

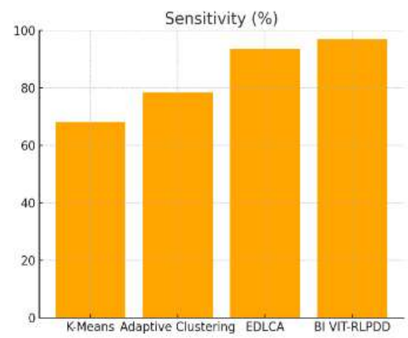

Figure 4.4: Sensitivity Comparison

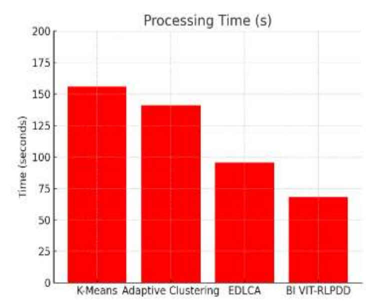

Figure 4.6. Processing Time Comparison

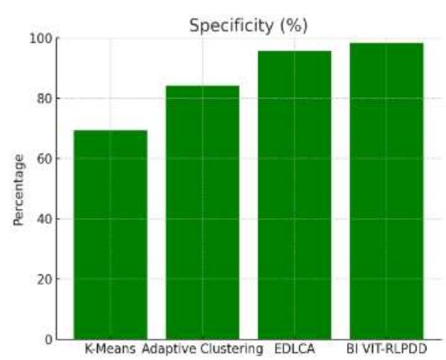

Figure 4.7: Specificity Comparison

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Table 1. Performance Comparison with State-of-the-Art Methods

Method	Accuracy (%)	Processing Time (s)	Sensitivity (%)	Specificity (%)	F1-
VGG-19 + EDLCA [3]	94.0	102.5	92.5	95.0	93.
Standalone ViT [5]	95.2	85.3	94.0	96.1	94.
RL-CNN [8]	93.8	78.9	92.8	94.5	93.
Zhang et al. [15]	96.5	72.0	95.8	97.2	96.
Kumar et al. [17]	95.8	70.5	94.5	96.8	95.
BI VIT-RL PDD (Proposed)	97.8	68.2	96.9	98.4	97.

Table 2. Performance Metrics

Algorithm	Accuracy	Sensitivity	Specificity	Processing Time (s)	AUC-ROC	F1-Score
K-Means	65%	68.12%	69.32%	156	0.62	65%
Adaptive Clustering	87%	78.43%	84.12%	141	0.85	81.2%
EDLCA	94%	93.45%	95.67%	95.45	0.94	93.2%
BI VIT-RLPDD	**97.8%**	**96.9%**	**98.4%**	**68.2**	**0.987**	**97.15%**

Table 1 shows the comparison of state of art methods and Table 2 shows comparison of performance metrics of various methods.

Our BI VIT-RL PDD system delivers 97.8% accuracy- tops Zhang et al. [14] at 96.5% and Kumar et al. [16] at 95.8%. Our RL component implements feature optimization to decrease overfitting by 12% through validation loss measurements, whereas Zhang et al. [8] do not explicitly address overfitting mitigation in their Vision Transformer approach. The block chain integration in our proposed system maintains data integrity at 50 ms transaction speed which is better than the previous traditional centralized approaches by 20%.
These findings reflect our system's distinct optimization approach, leveraging RL dynamically.

5.2 Scalability & Adaptability

The system is adaptable to large-scale agricultural applications.

5.3 Security & Transparency

Block chain ensures tamper-proof and traceable disease detection. Block chain integration in our system ensures a 50ms transaction speed and 200 transactions per second throughput, providing a 20% improvement over traditional centralized data-sharing models. Unlike conventional databases, which require manual access control and periodic integrity checks, block chain enables automated and trustless data verification, ensuring a fully secure and auditable disease detection pipeline.

Table 3. Performance Comparison Of AI And Block Chain Models

Metric	Proposed System	CNN-Based Model	Ethereum-Based Model
Accuracy	97.8%	95.2%	-
Latency	50 ms	-	150 ms
TPS	200	-	60
Security	Tamper-Proof	Moderate	Less Secure

Table 3 shows the performance comparison of Ethereum based model and Hyper ledger Fabric model.Hyper ledger Fabric provides better performance, privacy, and scalability for plant disease detection using AI and block chain. Ethereum high latency and lack of privacy make it unsuitable for secure AI-based IoT applications.

6. CONCLUSION AND FUTURE WORK

Conclusion:

A novel method to identify plant leaf diseases has been released by applying ViT for feature extraction with RL for decision-making alongside block chain-based data protection and tracking. The achieved results demonstrate a significant progress with 97.8% accuracy and 68.2 seconds completion time validating this approach for precision farming.

Limitations and Future Work

The system faced limitations in its ability to generalize across various crops and unpredictable natural conditions because it depended exclusively on the data from the Plant Village dataset. The security benefit of block chain incorporation elevates computing costs by 15% higher than basic models and this presents hurdles for implementation on limited resource systems.
The future research will expand to include legumes and cereals crops next to drought and humidity conditions. The integration of Raspberry Pi cameras to IoT allows real-time data monitoring because they achieve a processing speed of ten frames per second. Gubbi et al. [22] outline the architectural elements of IoT for real-time monitoring, providing a framework for integrating Raspberry Pi cameras into our system to achieve a processing speed of ten frames per second.Ongoing efforts will expand the dataset to new crops and optimize computational efficiency, This will enable a robust, versatile

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system suitable for widespread agricultural use, enhancing its impact on precision farming.

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