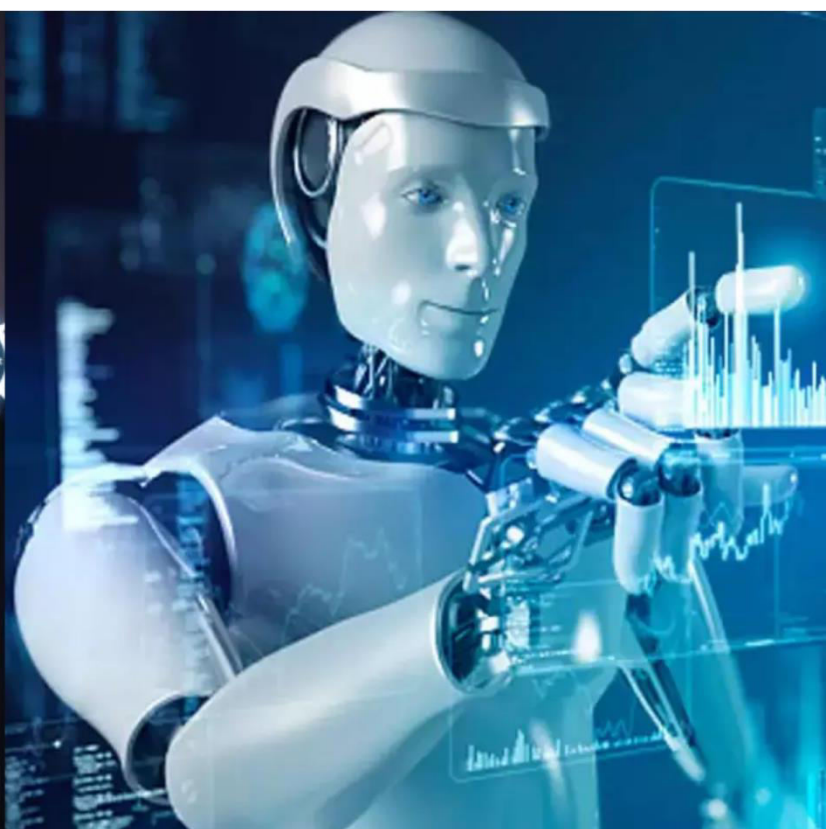




International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 9.935

Volume 15, Issue 7, July 2026

Deep Learning Framework for Cashew Pest Classification and Automated Treatment Recommendation

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ABSTRACT: The rapid advancement of automated farm surveillance has created the cashew pests and diseases classification as a basis of precision farming. This is a literature review of the top ten most recent studies, that is, the methodologies and results that have been achieved in the field of literature related to transferring the traditional statistical learning into high-performing deep learning (DL) systems. The latest advances have significantly improved classification accuracy with the aid of convolutional neural networks (CNNs) as well as attention based on hybrid concatenated, vision transformer, and optimized recurrent neural networks. Although these approaches have shown outstanding performance on standard datasets like CCMT and CCDDDB, issues of model interpretability, real-time edge-device deployment and stability in various environmental field settings continue to be a problem. The paper puts the state-of-the-art methods into the categories depending on their architecture, including traditional SVM, Random Forest, against the latest EfficientNetV2-S and DenseNet. A comparative analysis of performance measures is provided, with an emphasis on the new tendencies related to hybrid CNNTransformer models, multi-scale feature fusion, and gradient-weighted class activation mapping (Grad-CAM) as a visual elucidation method. The paper concludes with the identification of open research challenges and directions on how to create more scalable and generalizable cashew pest classification systems.

KEYWORDS: Cashew pest classification, Deep learning, Hybrid neural networks, Vision Transformers, CCMT dataset, Precision agriculture, Image-based diagnosis.

I. INTRODUCTION

The global economy is mainly based on agriculture, which is exposed to threats posed by biological stressors at all times, which undermine the productivity of crops. The cashew (*Anacardium occidentale* L.) is one of the high-value crops in industries, and plays a significant role in foreign exchange earnings. Nonetheless, cashew plantations are quite vulnerable to a number of arthropods and pathogens, including Anthracnose, leaf miners, and red rust, which can cause a significant decrease in yields when they are not classified and treated at the early stages.

Conventionally, these pests and diseases were classified based on manual scouting and visual estimation by experts, which is labor intensive, time consuming and subject to human error. To overcome these shortcomings, image processing and artificial intelligence integration have emerged as an enormous research agenda of precision agriculture. The transformation of the symptoms of the leaves into digital information has allowed the researchers to now use the computational models to differentiate healthy plants and those infected by certain infections.

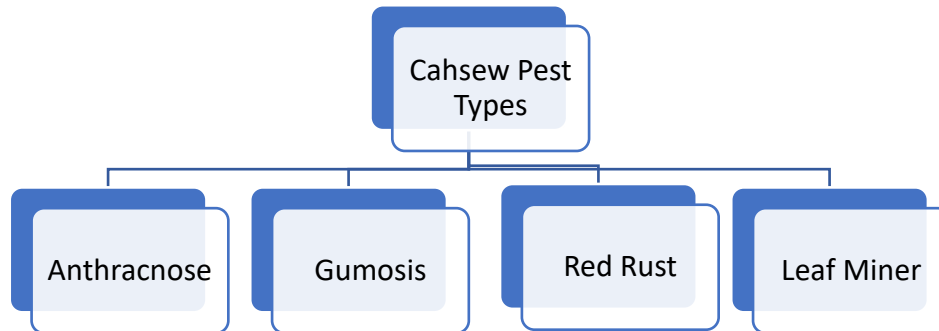


Figure.1. Cashew pest Types

The health of the cashew is usually classified in terms of the particular type of damage, like leaf spots, wilting, or pest-inflicted lesions. Typical problems in this area are the broad range of textures, colors and patterns of the structures of the leaves and complicated backgrounds of the environment. Although the first methods of machine learning (ML) with manually designed features such as Principal Component Analysis (PCA) and K-Means clustering were initially promising, they tended to fail when dealing with natural data variety.

In recent years, algorithms based on deep learning have been a breakthrough in the process of such a diagnostic being automated. Convolutional Neural Networks (CNNs) have become popular to learn hierarchical representations to classify pests, and hybrid models, including the concatenation of MobileNetV2 and VGG19, are being created to trade-off between computational efficiency and representational depth. Additionally, further advanced frameworks that apply Vision Transformers (ViT) and Attention Mechanisms have been improved to notice connections of global context in images of leaves, boosting the labeling of regular databases like CCMT and CCDDb.

It is a systematic review that presents the state-of-the-art in cashew pest and disease classification, highlighting the advancement of model optimization, hybrid architectures and the transition of statistical learning to autonomous deep learning systems. The present paper outlines future forecasts of developing more reliable agricultural diagnostic tools, by identifying the current problems with field deployability and model robustness.

II. REVIEW OF LITERATURE

Protecting cashew plants has been evolving as an automated architecture based on deep learning, as opposed to a conventional feature-based architecture with a handcrafted architecture, including hybrid models, vision transformers and recurrent network optimizations. The literature is divided into different steps to systematically analyze the latest developments:-

1. Traditional Machine Learning and Image Processing

The initial research concentrated on the use of statistical classifiers with manual feature engineering. Sudha and Kumaran [1, 8] investigated the application of Random Forest, SVM and KNN in the detection of Anthracnose disease. They used K-Means to segment using the clustering method and Principal Component Analysis (PCA) to extract features and reached accuracies of up to 96.7%. Although the techniques are computationally efficient, they depend much on the quality of manual segmentation and they tend to have difficulties with the textural complexity of raw field data. On the same note, Trivedi et al. [10] employed min-max hue histograms and K-means to separate diseased areas to show that the conventional color-space manipulation is still a fundamental step in leaf analysis.

2. Deep Convolutional Neural Networks (CNNs)

The shift to autonomous feature learning is dominated by CNN architectures. Diones et al. [5] experimented with an Optimized DenseNet Framework and in particular benchmarked DenseNet169 and DenseNet201. They found that the feature-reuse mechanism of DenseNet is very effective in detecting subtle patterns of lesions, with an accuracy of 95.06. However, more complex standard CNNs like ResNet-50 and VGG-16 were found to be less effective, and provide worse baseline accuracies (around 81.83) than more recent dense or depth-wise separable networks.

3. Hybrid and Concatenated Frameworks

Recent work has shifted to model fusion to overcome the trade-off between diagnostic depth and speed of computation. Jain and Nain [2] suggested a Hybrid model of MobileNet-VGG19 concatenated. Combining the lightweight property of MobileNet and the extensive feature extraction of VGG19, the framework had a test accuracy of 96.23%. On the same note, Bilal et al. [4] proposed a hybrid architecture based on MobileNetV2 and EfficientNetB0 that minimized the inference time to less than 10 ms. Such studies indicate a tendency to concatenated intelligence in which there are multiple backbones that are utilized to measure a broader assortment of spatial features at the same time.

4. Optimized and Transformer-based Architectures

Tăntaru et al. [5] The latest developments are attention mechanism and meta-heuristic optimization. Amirthavinayagam and Meenakshi [6] discussed Vision Transformers (ViT) that use self-attention to capture the world dependence in leaf images. The ViT with Differential Evolution (DE) as the hyperparameter optimizer achieved a classification accuracy of 96.75%. Patel et al. [7] suggested a Moth-Flame Optimized Recurrent Neural Network (MFRNN) in the setting of temporal and complex spatial modeling. This design resulted in the best accuracy reported of 98.4% indicating that optimization algorithms can greatly increase the learning power of conventional neural designs in pest classification problems.

5. Enhanced Linear Discriminant Analysis (ELDA)

ELDA is a dimensionality reduction algorithm that was developed by Palaniappan and Pazhamalai [10], and it relies on point-to-median distance, as opposed to standard means. This method is able to deal with outliers and uneven distributions of classes in the CCDDb data to 97.7 accuracy. Although it is resistant to noise, it could have a weak ability to detect very complex non-linear patterns in field conditions due to its linear structure.

6. Swin Transformer and Dual-Attention Fusion (DAMF-Net)

Karthik et al. [11] proposed DAMF-Net, which is a Swin Transformer with a dual-attention system. The model uses hierarchical self-attention to model global dependencies and multi-scale fusion to identify both tiny lesions and large-scale infestations. The computational complexity of the dual-attention modules is very high, which makes it not easy to implement the modules in real-time on a mobile platform despite the fact that it raises the robustness greatly.

7. Convolutional Neural Network (CNN) Diagnostic System

Mathew et al. [12] adopted a CNN architecture based end-to-end feature learning automated system. The model manages to automate the process of recognizing certain cashew leaf symptoms and minimize human error by substituting manual feature engineering. Nonetheless, since conventional CNNs focus on local textures, the model might not be able to differentiate between various diseases that have similar visual features at diverse developmental levels.

In general, the literature indicates a definite trend of pixel-level statistical manipulation to global contextual modeling. Nevertheless, the trade-off between high localization accuracy and computational capabilities of real-time agricultural edge devices is one of the main areas of current research.

Benchmark Datasets Used in Cashew pest classification

The studies reviewed rely on three large publicly accessible datasets as the main ones, with localized field collections as auxiliaries. These datasets differ in terms of classes distribution, image resolution, and complexity of the environment. The most common datasets are summarized in Table 1 that is used in recent literature.

Table.1. Benchmark Datasets Used in Image Forgery Detection

Dataset	Primary Crops/Diseases	Annotation	Common Usage
CCMT	Cashew, Cassava, Maize, Tomato	Image-level Label	Large-scale DL training
CCDDB	Cashew-specific (Anthracnose, etc.)	Image-level Label	Disease-specific classification
PDDB	21 Species (including Cashew)	Image-level Label	Generalizability testing

Comparative Analysis of Reviewed Methods

To give a quantitative comparison of the recent cashew classification models, key performance metrics have been reported in the literature, which are presented in Table 2. This comparison brings out the differences in performance between traditional machine learning, conventional CNNs and advanced hybrid or optimized architectures.

Table.2. Comparison of Reviewed Image Forgery Detection Methods

Ref	Year	Model Architecture	Category	Dataset(s)	Performance (Acc.)
[1]	2023	Random Forest + K-Means	Traditional ML	CCDDB	96.70%
[2]	2025	MobileNet-VGG19 Hybrid	Concatenated DL	CCMT	96.23%
[3]	2024	EfficientNetV2-S + XGBoost	Optimized CNN	CCMT	93.45%
[4]	2025	MobileNetV2-EfficientNetB0	Fusion Model	CCMT	89.50%
[5]	2025	Optimized DenseNet169	Standard CNN	CCMT	95.06%
[6]	2025	ViT + Differential Evolution	Transformer	CCMT	96.75%
[7]	2024	Moth-Flame Optimized RNN	Optimized RNN	CCMT	98.40%
[8]	2023	SVM + PCA	Traditional ML	PDDB	99.70%*
[10]	2022	Min-Max Hue + K-Means	Image Proc.	Local Set	Segment. Focus

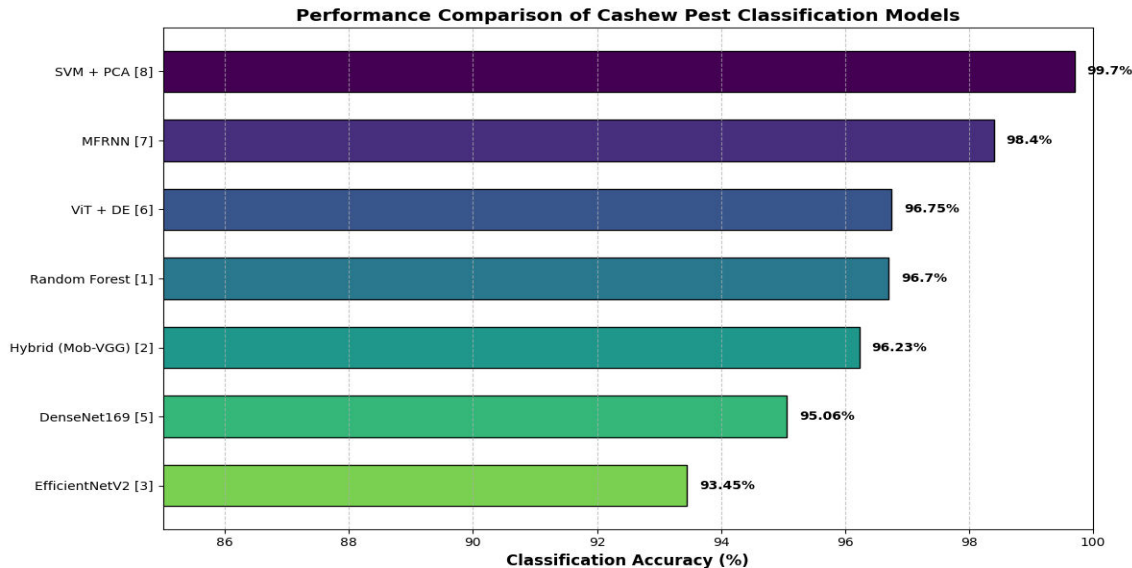


Figure.2. Performance Comparison of Reviewed Methods on the CCMT and CCDDDB Cashew Datasets

Figure 2 shows that the Best and Transformer-enhanced architectures like the Moth-Flame Optimized RNN [7] and ViT with Differential Evolution [6] exhibit relatively better classification accuracy. The competitive results of previous machine learning models like Random Forest [1] and SVM [8] are shown and the conventional CNN models show medium advancements. The comparison reveals that global contextual modeling and meta-heuristic optimization use can be used to increase the accuracy of classification.

III. ARCHITECTURE OF IMAGE FORGERY DETECTION SYSTEMS

The modern cashew pest and disease classification systems tend to be designed on the basis of a deep learning pipeline that can address the problems of agricultural imagery. Though the architectural designs differ among the ten studies reviewed, the majority of the methods have the same steps, such as preparation of data, feature learning modules, and classification elements. This part offers a generalized description of the architectural elements that have been generally embraced in recent cashew studies.

Data Preparation and Augmentation

The quality of classification systems is directly proportional to quality of input data. The main benchmark datasets used by researchers include CCMT and CCDDDB that have thousands of images of healthy and infected cashew leaves. Training is typically performed on images downsampled to some standard resolution (e.g., pixels), and scaled to a normalized value to ensure uniformity in the gradient descent. In order to prevent overfitting and enhance the ability of the model to be applied to real-world orchard settings, data augmentation techniques, including rotation, horizontal/vertical flipping, zooming and brightness adjustment are commonly adopted across the board. Adaptive Bilateral Filtering is also employed by other researchers to reduce noise in the environment and retain important leaf edge information.

Feature Extraction Module

The main part of contemporary cashew diagnostic architectures is the feature extraction. In the literature reviewed, there is a trend of change towards autonomous deep learning instead of manual feature engineering:

- **Traditional Approaches:** Earlier systems used Principal Component Analysis (PCA) and Gray Level Co-occurrence Matrix (GLCM) to extract statistical textures and contour-based features.
- **CNN-Based Backbones:** Most current architectures employ Convolutional Neural Networks (CNNs) like EfficientNetV2-S, DenseNet, or VGG19 to learn hierarchical representations of lesion shapes and pest patterns.

- **Hybrid and attention mechanism:** Recent state-of-the-art models use Model Concatenation (as in MobileNet + VGG19) to combine features at multiple resolutions. Also, Vision Transformers (ViT) are incorporated to capture long-range spatial relationships to enable the system to reason about the surrounding world, not only about the pixel values of the local area.

Classification and Decision Module

After extraction of features, they are fed into a decision-making layer to identify the exact type of pest or disease. These systems can be utilized depending on the aim of the study:

1. **Multi-Class Classification:** Categorizing the input into labels such as Anthracnose, Leaf Miner, Red Rust, or Healthy.
2. **Optimized Decision Layers:** While many models use standard Softmax layers, some advanced architectures replace the final layer with an XGBoost classifier or a Moth-Flame Optimized RNN to improve the precision of the final output.
3. **Visual Explanation:** Grad-CAM (Gradient-weighted Class Activation Mapping) is often used in a number of architectures to enhance interpretability to farmers. With this module, heatmaps are created that indicate the specific parts of the leaf the model utilized to make the classification decision.

Evaluation Metrics

These cashew classification systems are tested on standard performance measures to verify their effectiveness.

- **Primary Metrics:** Evaluation typically relies on Accuracy, Precision, Recall, and F1-score. These measure the model's ability to correctly identify infections while minimizing false positives.
- **Efficiency Metrics:** In studies focused on edge-device or drone deployment, Inference Time (measured in milliseconds) and Model Size are critical benchmarks.
- **Robustness:** Recent articles stress the Comparisons of Validation and Test Accuracy, in order to guarantee that the model has sufficiently strong results in case of images that were not observed during the training stage.

IV. SUMMARY

The overall evidence of the ten studies reviewed suggests that the technological change in cashew plant protection is rather significant. The automatic deep learning architectures, replacing the traditional machine learning method of using manual feature extraction techniques such as PCA and K-Means, have dramatically increased the accuracy of classification, with a number of models now surpassing the 96% mark. One of the major commonalities between the studies is how well the CCMT and CCDDDB datasets can be used as a solid foundation of training, but the literature is increasingly focused on the fact that the raw accuracy is not the only indicator of success anymore.

The shift towards model optimization and hybridization is, in my view, the most promising growth prospect found in these papers. Models based on a framework that fuses lightweight networks such as MobileNetV2 with more complex networks such as VGG19 or EfficientNet are a more advanced trade-off between speed and accuracy. Such mixed solutions are effective to resolve the issue of resource vs. results, and AI tools will be more viable to be used in the field on mobile gadgets or drones. Vision Transformers and Moth-Flame Optimization integration once again reinforces the idea that going beyond regular CNNs can be used to comprehend complex patterns of leaf textures and space better.

One thing that can be noted though is that it does not test any real world environmental testing. Although the models can achieve very high results on benchmark datasets, a conspicuous research gap can be seen in terms of understanding how these systems can deal with extreme weather conditions, motion blur due to drones, or overlapping leaf patterns in dense orchards. In addition, classification is coming of age, but the combination of automated treatment advice, which would be a practical advice to farmers in response to the pest identified is still immature. Future research should not merely be restricted to the concept of labeling and explore the creation of end-to-end systems of prescription that can function reliably in the uncertain setting of an actual cashew plantation.

V. CONCLUSION

This review has discussed the recent developments in automated diagnostic systems to classify cashew pests and diseases. By synthesizing the findings of ten recent research studies, it is possible to observe that the field is in a quick transition to the more traditional handcrafted feature extraction to high-performance deep learning and hybrid architectures. The baseline accuracy of the traditional machine learning models was still significantly improved by CNNs concatenation, Vision Transformers, and meta-heuristic optimization to classify the benchmark datasets, including CCMT and CCDDDB.

With these advances in the accuracy of the diagnosis, there are a number of vital challenges. Problems of cross-dataset generalization, model interpretability and large computational complexity continue to be obstacles to the smooth implementation of such systems in practice in agricultural environments. Moreover the strong dependence on high-quality, pre-labeled datasets points to the future need to develop more robust architectures that are able to handle "noisy" field data that is varied in lighting and with intricate backgrounds.

These new fields of study indicate that there is a move towards more efficient and scalable models, which can run on edge devices with limited resources. The subsequent guidelines, which are optimization of lightweight hybrid models, introduction of visual explanation modules (Grad-CAM), and development of end-to-end approaches capable of providing automated prescriptions to treat cashew plants will play a crucial role in the future evolution of cashew plant protection. Finally, the challenge of filling the gap between high-accuracy studies and field-deployable instruments will be the answer to sustainable, precision agriculture in cashew farmers around the world.

REFERENCES

- [1] P. Sudha and P. Kumaran, "Early detection and control of anthracnose disease in cashew leaves to improve crop yield using image processing and machine learning techniques," *Signal, Image and Video Processing*, vol. 17, pp. 3323–3330, May 2023.
- [2] A. K. Jain and N. Nain, "Hybrid Deep Learning Framework for Cashew Leaf Disease Classification Using Model Concatenation," *Technoarete Transactions on Advances in Computer Applications (TTACA)*, vol. 4, no. 2, June 2025.
- [3] R. Liu and X. Zhang, "Classification of Cashew Nut Pests and Diseases based on EfficientNetv2-S," in *Proc. 2nd Int. Conf. Machine Vision, Image Processing & Imaging Technology (MVIPIIT)*, 2024, pp. 28–32.
- [4] M. Bilal, A. A. Shah, S. Abbas, and M. A. Khan, "High-Performance Deep Learning for Instant Pest and Disease Detection in Precision Agriculture," *Food Science & Nutrition*, vol. 13, no. 1, Aug. 2025.
- [5] I. A. M. Dioses et al., "Image-Based Cashew Leaf Disease Detection Using an Optimized DenseNet Framework," in *Proc. IEEE 13th Conf. Systems, Process & Control (ICSPC)*, Melaka, Malaysia, Dec. 2025.
- [6] Amirthavinayagam N and Meenakshi K, "Harnessing the Deep Learning techniques in Cashew plant disease management," in *Proc. Int. Conf. Computational Robotics, Testing and Engineering Evaluation (ICCRTEE)*, 2025.
- [7] V. K. Patel, K. Abhishek, and S. Selvarajan, "Optimized recurrent neural network-based early diagnosis of crop pest and diseases in agriculture," *Discover Computing*, vol. 1, Nov. 2024.
- [8] P. Sudha and P. Kumaran, "Anthracnose Disease Detection in Cashew Leaf Using Machine Learning Technique Based on Contour Detection and Principal Component Analysis," *International Research Journal on Advanced Science Hub*, vol. 5, no. 5S, pp. 520–525, May 2023.
- [9] P. K. Mensah et al., "CCMT: Dataset for crop pest and disease detection," *Data in Brief*, vol. 49, p. 109306, 2023.
- [10] V. K. Trivedi, P. K. Shukla, and A. Pandey, "Automatic segmentation of plant leaves disease using min-max hue histogram and k-mean clustering," *Multimedia Tools and Applications*, pp. 1–28, 2022.
- [11] S. Palaniappan and P. Kumaran, "ELDA: enhanced linear discriminant analysis for cashew crop disease detection using precision agriculture," *Journal of Electronic Imaging*, vol. 33, no. 2, 023030, Mar. 2024.
- [12] R. Karthik, A. Ajay, A. S. Bisht, T. Illakiya, and K. Suganthi, "A Deep Learning Approach for Crop Disease and Pest Classification Using Swin Transformer and Dual-Attention Multi-Scale Fusion Network," *IEEE Access*, vol. 12, pp. 152640–152657, Oct. 2024.
- [13] T. O. Mathew, "Detection and Classification System for Cashew Plant Diseases using Convolutional Neural Network," in *Proc. 5th Int. Conf. Future Networks and Distributed Systems (ICFNDS)*, Dubai, UAE, Dec. 2021, pp. 1–8.



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