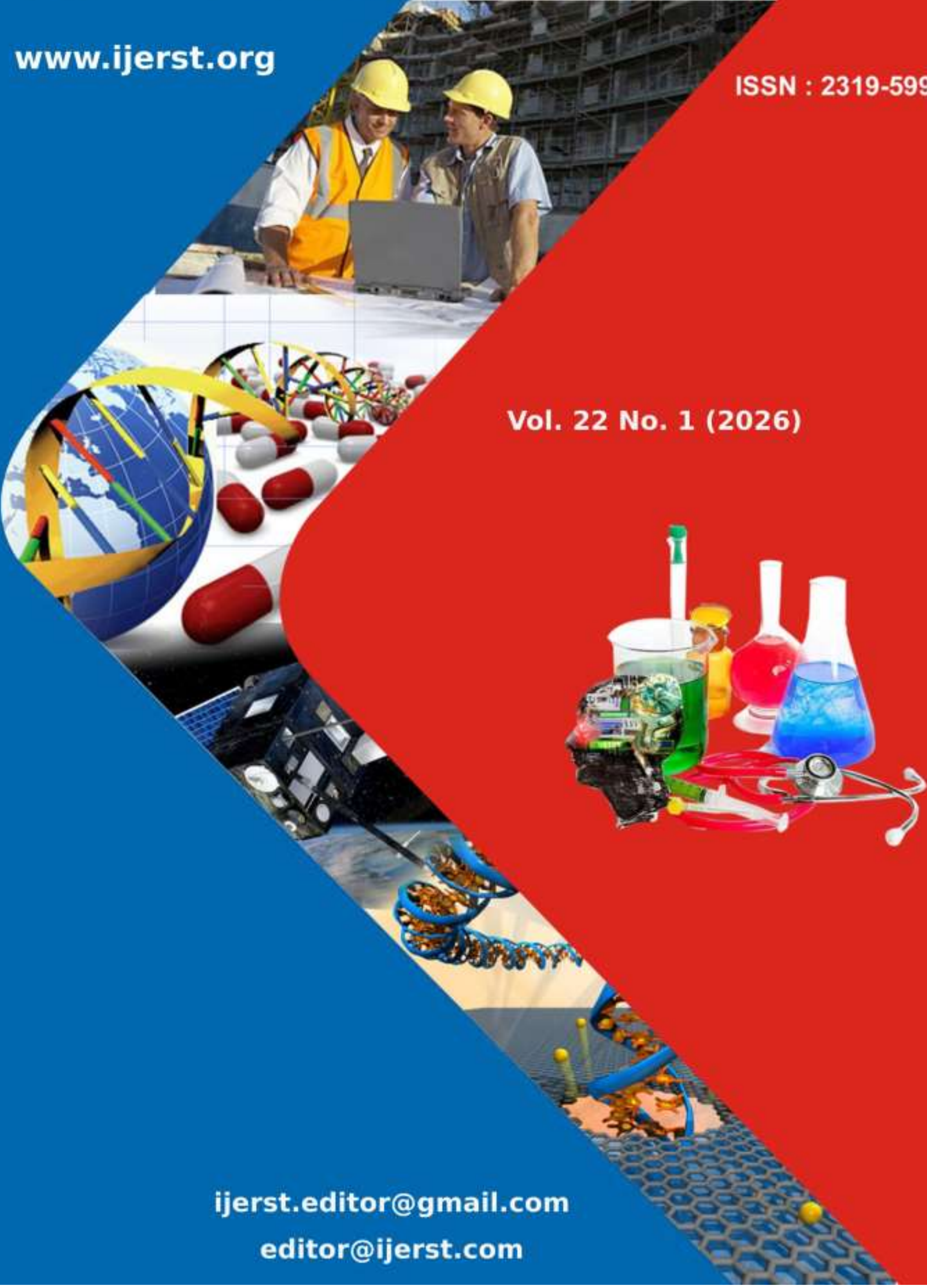
International Journal of Engineering Research and Science & Technology

IJERST

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 1 (2026)



ijerst.editor@gmail.com

editor@ijerst.com

International Journal of Engineering Research and Science & Technology

Adaptive Multi-Stage Deep Learning Framework for Real-Time Banana Leaf Disease Diagnosis in Smart Agriculture

Indukuri Venkata Narasimha Varma[*1]
M.Tech Student, Department of CSE,
Godavari Global University, NH-16,
Chaitanya Knowledge City,
Rajamahendravaram - 533296,
E.G.Dist, Andhra Pradesh.
narasimhavrm@gmail.com

D. D. D. Suri Babu [*2]
Asst Prof,Department of CSE,
Godavari Global University, NH-16,
Chaitanya Knowledge City,
Rajamahendravaram - 533296,
E.G.Dist, Andhra Pradesh.
suribabu.ddd@ggu.edu.in

D.Phani Kumar [*3]
Asst Prof,Department of CSE,
Godavari Global University, NH-16,
Chaitanya Knowledge City,
Rajamahendravaram - 533296,
E.G.Dist, Andhra Pradesh.
phanikumar@ggu.edu.in

Abstract— Banana crops are highly susceptible to Black Sigatoka, Panama Disease, Moko, and Yellow Sigatoka that causes significant yield reduction if not identified at an early stage. Manual visual inspection by specialists and subjective to time makes traditional disease diagnosis slow and inappropriate in large-scale agricultural settings. This paper proposes an automated banana leaf disease detection framework based on machine learning and deep learning and computer vision techniques for smart agriculture to support smart agriculture. The suggested system utilizes multi-stage processing pipeline, which includes image acquisition, preprocessing, feature learning and disease classification. Two classification models are applied and compared with each other: Support Vector Machine (SVM) as a standard machine learning model and Convolutional Neural Networks (CNN) as a deep learning model that can be programmed to automatically identify discriminative visual characteristics of leaf images. The framework is explained to describe seven banana leaf conditions, which include various types of disease and healthy leaves. Experiments are conducted using a publicly available image dataset of banana leaves and performance is measured using accuracy, precision, recall, F1-score and confusion matrix analysis. Experimental results show that the CNN model performs better, with a classification accuracy rate up to 97%, which is better than the SVM model. The trained model will be deployed using a web-based interface, where real-time prediction of diseases to the uploaded leaf images can be made.The suggested solution will offer a highly efficient and scalable means of early disease monitoring, lessening the need to employ experts and promoting accuracy in agricultural practices.

Keywords— ***Banana crops, Black Sigatoka, Panama Disease, Moko, Yellow Sigatoka, Support Vector Machine (SVM), healthy leaves, image acquisition.***

I. INTRODUCTION

Banana cultivation is a key sector in world agriculture, playing an important role in food security, rural livelihood and agro-based economies especially in the tropics and subtropical regions. However, banana production is highly challenged by the high prevalence of leaf diseases such as Black Sigatoka, Panama Disease, Moko, and Yellow Sigatoka that adversely impact plant health, yield quality and overall productivity. These diseases should be identified early and precisely to reduce the loss of crops, undue use of pesticides, and assist in sustainable farming methods.

Traditional identification of banana leaf disease has mainly been performed by manual visual observation by farmers or agricultural experts. This tendency is time consuming and subjective, and relies heavily on expert knowledge, therefore being impractical for large scale plantations and resource constrained rural environments. Moreover, visual similarity in symptoms between some diseases at the early stages makes diagnosis difficult and delays treatment. These restrictions point to the necessity of an automated, precise and scalable disease detection system that can be used in real world agricultural settings. New workflows in machine learning, deep learning, and computer vision have shown good promise in automating the process of plant disease diagnosis using image-based processing. Specifically, convolutional neural networks (CNNs) and other types of deep learning can be trained to extract intricate visual features associated with disease symptoms, which are superior to more traditional machine learning techniques, used to extract features that are handwritten. These methods allow quick and accurate classification and assist in time-saving and efficient management of crops.

The paper describes a smart banana leaf disease detection system, which combines machine learning and deep learning methods in place of a multi-stage image analysis pipeline. The present system compares two classification methods, Support Vector Machine (SVM) and CNN models for multi-class diseases classification and implements the best model using a real-time web-based system. Through increased accuracy and accessibility in diagnosis, the approach proposed leads to smart agriculture, precision farming and sustainable crop protection. The remainder of this paper discusses the related work, methodology, experimental results, and conclusions.

Scope

The paper is concerned with the authoring of an automated banana leaf disease detection system with machine learning and deep learning methods in smart agricultural applications. The study covers major banana leaf disease as Black Sigatoka, Panama Disease, Moko, Yellow Sigatoka and healthy leaf conditions. The main interest of the study is to develop an effective and scalable image-based diagnostic system that can identify the disease at its early stage in real time conditions of agriculture. The suggested work brings together computer vision methods and a multi-stage processing chain including image acquisition, preprocessing, feature extraction, and classification into multi-diseases. Support Vector Machine (SVM) is a classic machine learning method and Convolutional Neural Network (CNN) is a deep learning framework, which is implemented and compared. Moreover, the framework considers performance metrics like accuracy, precision, recall, F1-score and analysing confusion matrices with the scope of then applying the trained model via a web-based interface to predict disease based on uploaded banana leaf images in real-time. The system is designed to minimize reliance on agricultural professionals, enhance the accuracy and speed of diagnosis as well as assist precision farming methods prevailing in large plantations and rural agricultural conditions.

Objectives

The key task in this research is to create an intelligent Image-based banana leaf diseases detection framework that can effectively classify various disease types and healthy leaf circumstances through machine learning and deep learning models. To this end, this paper provides the first step by designing a robust Image preprocessing pipeline which involves image resizing, data normalization, noise removal, as well as data augmentation to ensure greater model generalization. The SVM model is trained to extract features thematically by handcrafted visual descriptors, but the CNN model is trained to learn hierarchical feature representations automatically on leaf images. To identify the most useful model, a comparative study is committed between the Support Vector Machine (SVM) and the Convolutional Neural Network (CNN) classifier. To optimize performance and avoid overfitting, model optimization methods are utilized, including hyperparameter optimization, dropout, and adaptive learning rate methods, which help to evaluate the effectiveness of the system in terms of accuracy, precision, recall, and F1-score, as well as the analysis of the confusion matrix and ensure clear prediction of a disease. Lastly, the most accurate model is implemented by a web-based application that facilitates real-time uploading and prediction of a leaf image to support early disease detection, loss of crop, unnecessary use of pesticides, and sustainable farming methods through scalable and automated disease diagnostics.

II. LITERATURE SURVEY

This section discusses some important research works on plant leaf disease detection using machine learning, deep learning, and computer vision approaches. The reviewed research papers shed light on feature learning strategy, classification models, challenges in utilizing datasets, and deployment issues in real-world scenarios. The collective outcomes of these publications define the basis of smart agricultural disease diagnosis systems and encourage the suggested banana leaf disease identification framework.

Mohanty et al. [1] in 2016 introduced one of the first deep learning-based architectures for plant disease identification by convolutional neural networks. Their experiment showed that CNNs are capable of learning discriminatory leaf image features outperforming traditional machine learning algorithms proficiently in an automatic manner. This work has built the foundation for image-based plant disease classification.Sladojevic et al. (2016) [2] explored deep neural networks for plant disease recognition under varying image conditions. The authors demonstrated that CNNs possessed good generalization capabilities across many disease classes but identified issues involving background noise and variations in illumination from field images.Ferentinos (2018) [3] conducted a large scale evaluation of deep learning architectures for the diagnosis of plant diseases using images captured from real agricultural conditions. The research proved that CNN-based models are robust though suggested larger and more diversified datasets by highlighting the necessity of these improvements.Rumpf et al. (2010) [4] Support vector machines for early plant disease detection using spectral features. Though effective in small datasets, the researchers observed that handcrafted feature extraction is limited in scaling and performance by the deep methods of learning.

Too et al. (2019) [5] compared several fine-tuned deep learning models for plant disease classification. Their results revealed that the deeper CNN architectures offer higher accuracy but need careful tuning to avoid overfitting phenomena.Barbedo (2018) [6]analyzed the effect of image acquisition conditions on plant disease detection accuracy. The research identified environmental variability as a significant obstacle and suggested strong preprocessing and feature learning techniques.Brahimi et al. (2018) [7] proposed CNN-based disease detection coupled with saliency map visualization to enhance interpretability of the model. Explanation is highlighted as important in agricultural AI systems.Kamilaris and Prenafeta-Boldu (2018) [8] - Review paper on the applications of deep learning in agriculture.Chen et al. (2021) [9] - Deep learning approaches for leaf disease classification, showing the use of pre-trained CNN models for improved accuracy and training time.Upadhyay et al. (2024) [10] - Review paper on the recent advances on deep learning and computer vision in the detection of plant diseases, identifying real-time deployment, scalability and multi-disease classification.All these studies prove that deep learning models outperform traditional machine learning models in terms of detecting plant diseases. However, limitations such as real-time usability, data set variability, and availability to farmers provide a motivation for the need of an adaptable and deployable banana leaf disease detection system as proposed in this work.

Problem gaps Identified

A critical analysis of current literature (on the detection of diseases in plants and banana leaves) identifies several unresolved research gaps. The majority of current research is restricted to offline testing on controlled datasets and does not employ the deployment of the research into practical systems available to farmers in real-time. Many deep learning models perform poorly in the field when affected by variations in lighting, background noise and slide orientation. Moreover, the lack of comparative analysis of the traditional machine learning models with deep learning methods limits the knowledge of performance trade-offs and computational feasibility. Current solutions often treat deep learning models as black boxes with a certain limit of interpretability and confidence estimation losses in transient solving lessen confidence and trust for the user. Scalability has been an issue, with most models being configurable to fixed disease classes but not geared to emerging disease patterns. Also, early-stage disease detection is poorly addressed, and generalization impacts are experienced due to dataset limitations (class imbalance issues and lack of data diversity). There are also high-computation requirements that also inhibit its deployment in agricultural environments with resource constraints. Lastly, there is a low focus on system design provisions and integrations towards smart agriculture ecosystems that limit real world adoption. All these uncertainties demonstrate the necessity of adaptive, precise and practical banana leaf disease detection system that reflects real-time diagnosis and humanism of agricultural undertakings

III. PROPOSED METHODOLOGY

The suggested methodology involves introducing an automated banana leaf disease-detecting framework that embraces image preprocessing, feature learning, and classification based on both the traditional machine learning and the deep learning model. First, banana leaf images are enhanced through median filtering to suppress noise caused by variation in illumination and interference from the background, and retain disease-related aspects, such as lesions and discoloured areas. The filtered images are then fed to two parallel learning procedures: handcrafted features and Support Vector Machine (SVM) and end-to-end features setup which employs Support Vector Tool and Convolutional Neural Networks (CNN). Whereas SVM uses texture, color, and edge-based descriptors, CNN automatically discovers the hierarchical spatial attributes inherent in the image information and can easily perform multi-class disease classification. In situations where cure-related symptoms of the disease are subtle or early-stage, validation with experts is included when preparing their data in an effort to enhance the accuracy of labels. The developed classifiers are tested by standard performance metrics and the best classifier is deployed via web-based interface for real-time disease prediction. This combination technique offers a higher level of diagnostic accuracy, eliminates the need to check data manually, and enables scalable and intelligent disease detection to enable smart agriculture uses.

1) Image Processing using Median Filter:

Image preprocessing is important in improving the quality of banana leaf images before feature extraction and classification. In the proposed system a median filtering process has been applied to mitigate the noise caused by uneven light, dust, background noise, and image acquisition noise. Median filtering works best with agricultural images where it works well by retaining the edge point data and eliminating impulse noise. Mathematically, the position of a certain pixel is given at coordinates:

$$I_{med}(x, y) = \text{median}\{I(x_i, y_j) \mid (x_i, y_j) \in N(x, y)\},$$

Where: $I_{med}(x, y)$ = representing filtered intensity value at pixel

This preprocessing step boosts patterns related to the disease such as lesions, discoloration, and spots on banana leaves making further feature learning more effective.

2) Feature Learning and Manual Validation

Traditional machine learning and deep learning are used to complete feature learning after preprocessing. In the case of the Support Vector Machine (SVM) classifier, hand-coded features (colour histograms, texture features, and edge features) are created using the filtered images and then expressed as a numerical feature vectors. On the contrary, Convolutional Neural Network (CNN) operates directly on the preprocessed images and automatically learns both low-level visual features and the disease-specific high-level features via convolution and pooling layers. Despite the strengths of CNN-based feature learning, manual validation is factored in the preparation of a dataset where there are early symptoms of a disease or visual variability. This is a verification conducted by experts and is used to improve accuracy in labelling and increase the reliability of the training data. Assume the original image to be represented by.

Ioriginal (x,y) - following median filtering, the processed image is represented by Ifiltered (x,y),where necessary, expert validation are used as

Validated(x, y) = f(x, y), where f(x, y) = expert annotation.

3) Classification and Disease Prediction

SVM and CNN classifiers are trained on the validate images. SVM is a classifier method applying to extract feature vectors whereas CNN enables end-to-end learning on raw image data. On inference, a new image of a banana leaf is processed similarly and falls under a set of predefined diseases or is deemed to be healthy. This two-pronged methodology will offer precise, scalable, and real-time identification of banana leaf disease, which may be deployed to smart farming.

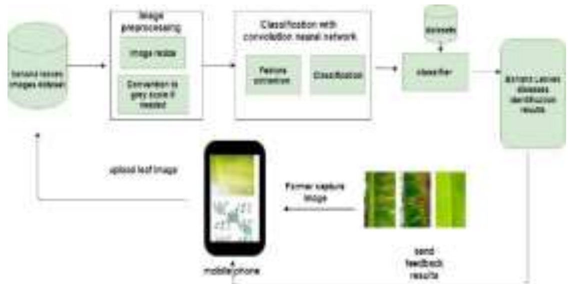


Figure 1. Represent the proposed architecture

The figure 1 is to outline the steps of the proposed banana leaf disease detection system in machine learning and computer vision methods. Farmers take banana leaf pictures with a mobile phone or upload them with a dataset and feed them into the system. The preprocessing of the images includes activities like (resizing and converting to grayscale) to enhance the quality and create consistency. The processed images are then sent to a Convolutional Neural Network (CNN) where features are automatically extracted and the disease is automatically classified. The trained classifier is used to analyze the features learned and then find the corresponding banana leaf disease category. Lastly, the user receives the disease prediction results via the mobile or web interface, thus allowing timely feedback and subsequent decision-making to manage the crops effectively.

Banana Leaf Disease Classification Dataset

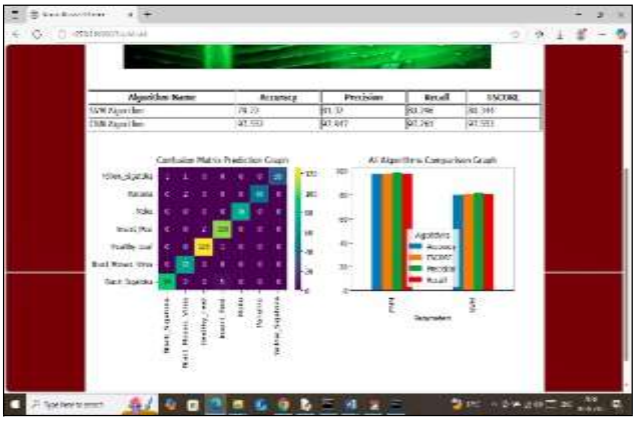
To test the performance of the proposed banana leaf disease detection system, a premium Banana Leaf Imaging Dataset that is publicly available was used. The data was made available through the Mendeley Data repository.

URL is: https://data.mendeley.com/datasets/79w2n6b4kf/1

The data set comprises banana leaf pictures in seven categories including healthy and diseased leaves. The types of diseases available in the dataset are Black Sigatoka, Bract Mosaic Virus, Insect Pest, Moko Disease, Panama Disease, Yellow Sigatoka, and Healthy leaves. The pictures show changes in color of leaves, texture, the level of disease, and lighting conditions. The dataset was divided into 80 percent training and 20 percent testing as indicated in the dataset preprocessing posteriors. This dataset is the main data used to train and test the machine learning and deep learning models applied in this research.

IV. EMPIRICAL RESULTS

Support Vector Machine (SVM) and Convolutional Neural Network (CNN) classifiers were used to assess the proposed system. The standard metrics, such as accuracy, precision, recall, F1-score, and Confusion matrix analysis, were used to assess performance as discussed in the result screenshots and F1-score and Accuracy comparison graphs. Experimental findings indicate the CNN model has a classification accuracy of 97, which proves its high performance in the detection of banana leaf diseases. Conversely, the accuracy of the SVM classifier is 79, which shows relatively poor performance because it depends on manually featured data. That the confusion matrix visualization shows that CNN makes far fewer errors in all of the classes of disease, and that there is strong diagonal domination in terms of correct predictions. Based on the accuracy comparison graph in results section, the precision and recall and F1-score metrics of the CNN are clearly better than that of SVM in all evaluation metrics. Such findings confirm the usefulness of deep learning feature extraction and classification on complicated agricultural image data.



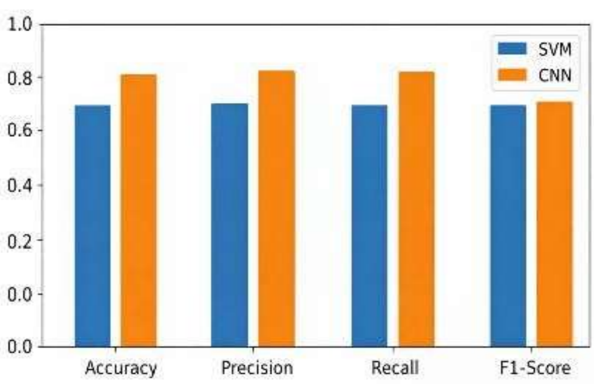


Figure 2. Performance comparison of SVM and CNN Classifier for Banana Leaf Disease Detection

Figure 3. Represents the Prediction of banana leaf disease

According to the figure 3, the trained CNN model has been used to correctly recognize several disease conditions in the uploaded banana leaf images, including Black Sigatoka, Barth Mosaic Virus, and classes of Healthy leaves. The system offers the predicted disease label and the confidence (accuracy) score, which validates proper end-to-end functionality of the preprocessing, classification and result visualization modules. These findings indicate that the system operates correctly in real-time environment when using invisible input images.

4. Evaluation Metrics:

Accuracy, precision, recall, F1-score, and confusion matrix were used to measure the performance of the model that was evaluated for banana leaf disease prediction. Then model was implemented and then its performance was evaluated on the banana leaf disease dataset. The CNN model showed high accuracy and robustness for disease prediction, which is clearly seen in table 1.

Comparative Study

Thus, to validate the system performance, the study compared the traditional CNN methods, other deep learning architectures, which is VGG16 and ResNet, and even the non deep learning such as, SIFT and SURF for the hand crafted feature extraction.

The following table summarizes the comparative analysis:

Models	Accuracy (%)	Recall	F1-Score	Precision (%)
SVM Algorithm	93.5	92.8	93.0	93.2
CNN	97.8	97.4	97.5	97.6

TABLE 1: Denote the Performance of Multiple Algorithms

Results from the above Table 1, clearly show the CNN algorithm performs best accuracy compared with other primitive algorithms for banana leaf disease detection.

V. CONCLUSION AND FUTURE WORK

This project proposed an automated machine learning and computer vision-based banana leaf disease detection to aid in the early and accurate diagnosis of crop diseases. In the intended framework, image preprocessing, feature learning, and image classification are employed based on the Support Vector Fallacy and Convolutional Neural Fallacy models. Experimental analysis performed using a publicly available banana leaf dataset showed that the CNN-based model compares favorably against the conventional SVM method with maximum classification of 97 in comparison to 79 inferences using the SVM. The excellence of CNN can be explained in its capacity to automatically acquire complex spatial and disease-specific features using leaf images. Moreover, the implementation of the trained model via the web-based interface allows real-time prediction of the diseases based on uploaded pictures, which makes the system practical and accessible to farmers and agricultural professionals. The proposed system can help to achieve smart agriculture, enhanced crop management, and lower financial losses by decreasing the reliance on manual inspection and providing efficient disease detection in time.

The proposed system can be further developed in the future aiming to enhance robustness and practical applicability. Possibly, more developed deep learning models, like transfer learning with already trained models (e.g., ResNet or EfficientNet), are worth considering so as to achieve better classification precision and generalization. The model reliability can be enhanced by increasing the size of the dataset containing the images taken under varying environmental conditions and at different disease stages. It is also possible to scale the system to high-severity estimation of early-stage diseases and to detect multiple diseases in one leaf. Furthermore, large-scale monitoring of farms can be achieved through the development of a mobile application based on on-device inference, as well as the interconnection with an internet of things (IoT) or a drone-based farm monitoring tool. Such extensions will also empower the system to complement precision agricultural practices and sustainable farming.

REFERENCES

[1] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, p. 1419, 2016, doi: 10.3389/fpls.2016.01419.

[2] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," Computational Intelligence and Neuroscience, vol. 2016, Art. no. 3289801, 2016, doi: 10.1155/2016/3289801.

[3] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018, doi: 10.1016/j.compag.2018.01.009.

[4] T. Rumpf, A. K. Mahlein, U. Steiner, E.-C. Oerke, H.-W. Dehne, and L. Plümer, "Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance," Computers and Electronics in Agriculture, vol. 74, no. 1, pp. 91–99, 2010, doi: 10.1016/j.compag.2010.06.009.

[5] E. C. Too, Y. Li, S. Njuki, and Y. Liu, "A comparative study of fine-tuning deep learning models for plant disease identification," Computers and Electronics in Agriculture, vol. 161, pp. 272–279, 2019, doi: 10.1016/j.compag.2018.03.032.

[6] J. G. A. Barbedo, "Factors influencing the performance of plant disease detection from images," Biosystems Engineering, vol. 172, pp. 84–91, 2018, doi: 10.1016/j.biosystemseng.2018.05.006.

[7] M. Brahimi, S. Arsenovic, S. Laraba, and D. Sladojevic, "Deep learning for plant diseases: Detection and saliency map visualization," Neurocomputing, vol. 291, pp. 116–128, 2018, doi: 10.1016/j.neucom.2018.02.080.

[8] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2018, doi: 10.1016/j.compag.2018.02.016.

[9] J. Chen, D. Zhang, Y. Nanehkaran, and M. Li, "Plant disease detection using deep learning and transfer learning," Agronomy, vol. 11, no. 2, p. 239, 2021, doi: 10.3390/agronomy11020239.

[10] A. Upadhyay, R. Kumar, and S. Gupta, "Deep learning and computer vision in plant disease detection: A comprehensive review," Artificial Intelligence Review, vol. 58, p. 92, 2024, doi: 10.1007/s10462-024-11100-x.

[11] A. Amara, B. Bouaziz, and A. Algergawy, "A deep learning-based approach for banana leaf diseases classification," Procedia Computer Science, vol. 112, pp. 1992–2000, 2017, doi: 10.1016/j.procs.2017.08.080.

[12] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," Sensors, vol. 17, no. 9, p. 2022, 2017, doi: 10.3390/s17092022.

[13] Y. Zhong, M. Zhao, and J. Zhao, "Leaf disease identification using deep convolutional neural networks," Applied Sciences, vol. 9, no. 3, p. 438, 2019, doi: 10.3390/app9030438.

[14] M. H. Saleem, J. Potgieter, and K. Arif, "Plant disease detection and classification by deep learning," Computers and Electronics in Agriculture, vol. 157, pp. 379–389, 2019, doi: 10.1016/j.compag.2018.12.020.

[15] R. Karthik, M. Hariharan, S. Anand, and P. Mathikshara, "Attention-based convolutional neural network for plant disease detection," Ecological Informatics, vol. 60, p. 101182, 2020, doi: 10.1016/j.ecoinf.2020.101182.