



Smart Agriculture 4.0: Precision Crop Disease Identification and Classification Using Advanced AI Techniques

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Abstract. Smart Agriculture 4.0 is focused on accuracy in crop disease diagnosis and classification through the use of the latest advances to revolutionize the way farming is done. This study thus presents a robust framework that makes use of AI tools to enhance agricultural output and minimize losses. This method incorporates state-of-the-art image processing for preprocessing and data gathering, using K-means clustering for efficient segmentation and contrast-limited adaptive histogram equalization (CLAHE) for picture improvement. For feature extraction, the improved AlexNet architecture is utilized, while a model that combines EfficientNet and LSTM for better accuracy and reliability is used for classification. This uses the Python platform for implementation, and measures such as accuracy, recall, precision, and others are used for assessment. For a complete evaluation, finally, the proposed approach is contrasted with current methodologies. By looking to improve agricultural production and sustainability by intelligent, real-time diagnostics this chapter investigates advanced artificial intelligence algorithms for accurate crop disease diagnosis in 4.0 smart Agriculture. Experimental results for achieving the highest specificity, achieved with 70 percent on the learning rate with proposed the method is 0.9919, the high specificity with 80 percent on the learning rate with 0.9944.

Keywords: Smart Agriculture, Precision Agriculture, Crop Disease Identification, Artificial Intelligence, K-Means Clustering and Improved Alex Net.

1 Introduction

Plants are vital to global economies and ecosystems, but diseases caused by pathogens can severely impact crops, threatening food security and causing economic losses [1]. Sustainable agriculture, which focuses on ecological compatibility, economic viability, and resource conservation, is key to addressing future agricultural demands [2]. Precision agriculture, utilizing technologies like GIS, remote sensing, and data analytics, optimizes resource use and enhances crop yields, promoting both food

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security and environmental sustainability [3] [4]. Real-time monitoring systems further aid in efficient resource and pest management [5].

Adaptive AI technologies have revolutionized modern farming, enabling intelligent and proactive systems. [6] states that, in the context of real-time monitoring and dynamic adaptation for environmental changes, cloud computing, IoT algorithms, and integrated Explainable AI (XAI) with Reinforcement Learning optimizes resource management, enhancing productivity and sustainability. [7] underline how AI models, including neural networks and deep learning algorithms, improve crop disease diagnostics by analyzing complex patterns in large datasets. The transformational power of Agriculture 4.0, coupled with advancements in genome editing, microbial soil mapping, and nanotechnology, among others, is discussed by [8]. Other breakthroughs including smart breeding and AI tools facilitate improved pest resistance and crop resilience, leading to increased yields, which will be inevitable as arable land declines and the world's population grows. Furthermore, to lower risk and improve farm operating efficiency, [9] emphasize the necessity of data-driven decision-making, real-time analytics, and predictive modeling.

Precision agriculture relies heavily on automation, and AI-powered technologies enhance disease diagnosis and detection. According to [10], automated leaf disease diagnosis by image processing and machine learning reduces the need for manual inspections, enabling faster responses. Building on this, the suggested AI-based framework for precision crop disease diagnosis incorporates innovative image processing methods such as K-Means Clustering for segmentation, CLAHE for enhancement, and a model that combines LSTM and EfficientNet networks for precise classification. This strategy seeks to increase production, reduce crop loss, and advance sustainable agriculture.

The following are the paper's main contributions:

1. It employs CLAHE for clear images and K-Means Clustering for better segmentation with robust preprocessing for disease detection.
2. This paper introduces an updated AlexNet with batch normalization and dropout, enhancing feature extraction efficiency and preventing overfitting during training.
3. Combining EfficientNet with LSTM, spatial and temporal features are merged in a better view of superior accuracy in the recognition and classification of crop diseases.

The following is the format of the following sections: A literature review and some pertinent studies are covered in Section 2, the suggested framework is covered in Section 3, the results and discussions are thoroughly analyzed in Section 4, and the study's final evaluation is given in Section 5.

2 Literature Review

Some of the recent research works related to Precision Crop Disease Identification and Classification were reviewed in this section

Guo et al., (2020) [11] introduced a DL-based mathematical framework for plant disease identification and detection that enhances the efficiency of training, generality, and accuracy. The region proposal network finds and detects the location of the leaves in complex environments. Images are segmented using the outputs of the RPN algorithm using the Chan–Vese (CV) algorithm to show the features of symptoms. Richard et al. (2022) [12] concluded that ICM options under development to reduce synthetic inputs, including crop rotation, intercropping, canopy architecture manipulation, and crop genetic resistance to pathogens, were to be compared with conventional farming systems. Bhatti et al., (2024) [13] mentioned the need to research hyperspectral imagery in precision agriculture and the way precise DR techniques are important. It discussed the potentialities of integrating fuzzy common sense with DR techniques as well as graph-based totally DL techniques and, specifically, graph attention networks (GATs).

Rezk et al., (2022) [14] discussed use of IoT and DL models for smart agriculture, extra especially in detecting diseased parts of leaves of farmlands. It explains the hindrance of present semantic photograph segmentation algorithms and using Conditional Random Fields (CRFs) in the procedure of publish-processing development. Tirkey et al., (2023) [15] provided the importance of agriculture, the challenges encountered with crop sicknesses and infestation with bugs, the want for early detection to limit harm to crop plants, and the advanced barriers in traditional strategies to locate ailments and insects that motivated an offer of AI answers based totally on deep mastering for powerful identity and remedy in real-time. Saeed et al., (2021) [16] discussed a method for automatic crop disease recognition using deep neural network capabilities and partial least squares (PLS) regression. A pre-trained CNN's deep functions are extracted, functions are fused using a PLS-primarily based approach, the quality functions are chosen using a PLS projection technique, and an ensemble luggage tree classifier is used for the very last reputation.

Agarwal et al., (2020) [17] pointed out the significance of tomato as a crop grown all over the international and its susceptibility to many diseases, stressful well timed and correct identification. They cautioned a discounted CNN version with eight hidden layers to address the computational constraints of the pre-educated models, using the Plant Village dataset with the utility of image preprocessing techniques like brightness adjustment and augmentation.

Xiong et al., (2020) [18] presented a DL and automatic image segmentation approach for identifying cash crop ailments utilizing the enlarged dataset. The Grab Cut technique serves as the muse for the Automatic Photo Segmentation technique (AISA), which robotically eliminates photo history facts at the same time as preserving disease areas. Eunice et al. (2022) [19] successfully identified plant diseases by employing CNN-based pre-trained models. Focus has been given to tweaking the hyperparameters of some of the most widely available pre-trained models, including VGG-sixteen, DenseNet-121, ResNet-50, and Inception V4. Al-Wesabi et al., (2022) [20] offered a brand-new AI-enabled apple leaf sickness category approach for precision farming called AIE-ALDC. Gaussian filtering is used to dispose of noise, and orientation is used to supplement records within the

recommended AIE-ALDC method. A function extractor primarily based on Capsule Networks (CapsNet) is likewise covered within the AIE-ALDC technique to provide a beneficial collection of feature vectors.

2.1 Research Gap

There are still several limitations in the current research on agricultural disease identification using AI approaches, despite substantial progress. Much research depends upon traditional picture processing techniques or unmarried deep getting-to-know models, which might also restrict accuracy and efficiency. Additionally, few strategies integrate superior techniques like hybrid fashions, combining the strengths of numerous architectures and EfficientNet, LSTM, and transfer mastering. While a few methods have shown promise in function extraction and class, demanding situations persist in coping with complex environments, large-scale datasets, and real-time diagnostics. Moreover, there may be a loss of complete research evaluating numerous AI-based totally methods for crop sickness identification throughout numerous vegetation and environmental conditions. This highlights the need for extra sturdy frameworks to adapt to different agricultural situations, presenting more advantageous precision, scalability, and sustainability in Smart Agriculture 4.0.

3 Proposed Methodology

Smart Agriculture 4.0 uses advanced AI technology to increase agricultural output by accurately detecting and classifying crop diseases to reduce losses. The cautioned framework retains advanced image processing strategies for image enhancement and segmentation namely CLAHE and K-Means Clustering respectively. Feature extraction has been performed through an Improved AlexNet structure and simultaneously it also used a model via EfficientNet and LSTM. The overall structure of the proposed methodology is shown in Figure 1.

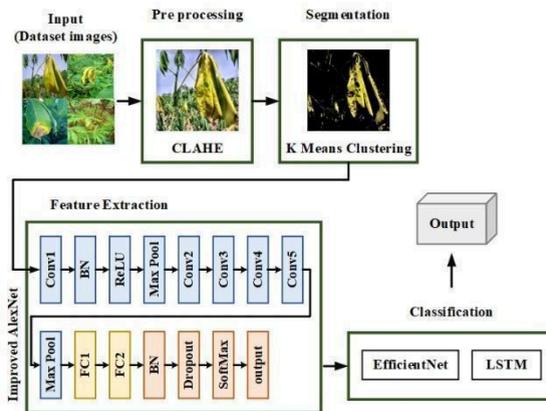


Fig.1. Overall architecture of the proposed methodology

3.1 Dataset Description

The dataset includes plant photos that are kept in the "train images" folder as well as a JSON file with the labels that go with each picture. "Cassava Mosaic Disease (CMD)," "Cassava Green Mottle (CGM)," "Cassava Brown Streak Disease (CBSD)," "Cassava Bacterial Blight (CBB)," and "Healthy" are the five different classifications into which the photos are divided. To ensure precise identification of every plant illness or health state and to facilitate easy access to the data, a CSV file mapping the image filenames to their corresponding labels is also included. Models for the detection and classification of plant diseases can be developed with the use of this dataset.

3.2 Preprocessing and Segmentation

Crop disease detection preprocessing entails utilizing K-Means Clustering for efficient segmentation and CLAHE for improved picture clarity, guaranteeing precise feature extraction and classification.

Contrast Limited Adaptive Histogram Equalization (CLAHE). The CLAHE technique enhances the identification of agricultural illnesses by enhancing differences in regions of pictures with low visibility. CLAHE prevents noise amplification by adaptively adjusting the contrast of individual pixels by clipping the histogram at a predetermined threshold. Because it preserves important traits, this localized contrast enhancement is particularly useful in identifying crop illnesses under various lighting circumstances. Minor disease signs are made more noticeable by the CLAHE algorithm, which splits the image into rectangular segments and performs thresholding and equalization locally to each segment. In crop disease identification, the gray-level probability density function (PDF) for each pixel, denoted by $P_k(k)$, is used to analyze the disease features at different gray levels. The r th gray level's probability is then determined as shown in Eq. (1).

$$P_k(k_r) = \frac{m_r}{m} \quad (1)$$

The r th grayscale level is represented by $r = 0, 1, 2, \dots, n - 1$, with each corresponding to k_r . Subsequently, the cumulative distribution function (CDF) for k_r is given by the following expression in Eq. (2).

$$B = t(k_r) = \sum_{j=0}^r P_k(k_j) = \sum_{j=0}^r \frac{m_j}{m} \quad (2)$$

K Means Clustering. In Precision Crop Disease Identification and Classification, K-Means Clustering is used for the segmentation of plant images from their visual characteristics like color, texture, and shape. The algorithm helps in identifying areas of the image as similar to others, which include both healthy and unhealthy ones by grouping similar pixel patterns. Then, after all clusters are formed, it takes out the features of every cluster for further study and classification. This segmentation separates the diseased regions, thus improving the accuracy of feature extraction that later helps models like EfficientNet and LSTM in classification, thereby increasing the efficiency and accuracy of diagnosis. Figure 2 shows pre-processed and segmented images.

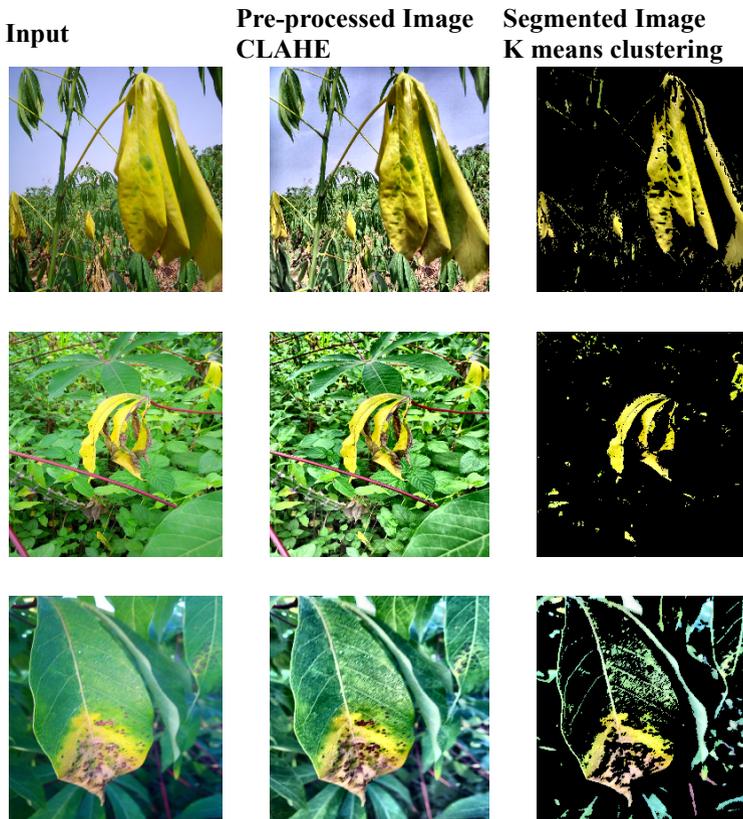


Fig.2. Sample images for pre-processed and segmented process

3.3 Feature Extraction

Feature extraction is accomplished by using an improved AlexNet architecture, effectively extracting crucial information from images of crop diseases. Then the classification is done by the hybrid model which is designed based on EfficientNet

and LSTM; it guarantees improved accuracy and dependability in the documentation and categorization of crop illnesses for correct farmed administration.

In brief, AlexNet is deep convolutional neural network technology that has significantly helped image-classify. It combines Batch Normalization and Dropout to beat frequent failings of the deep net by overfitting and learning instability. Therefore, it makes it more robust for usage in complex data sets with accelerated and stabilized convergence of training toward further perfection. It further enhances accuracy, efficiency, and reliability for this variant as compared to AlexNet while making it applicable to many forms of image classification tasks.

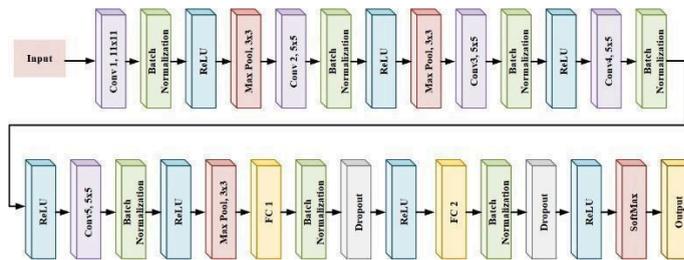


Fig.3. Architecture of the Improved AlexNet

Figure 3 is an improved version of AlexNet, which is a deep CNN that was initially designed for image classification. Improvements made to this version include the use of Dropout and Batch Normalization layers in order to mitigate some of the most common challenges faced by deep learning models, including overfitting and training instability.

Convolutional layer and ReLU Activation. It begins with the input layer, then comes a convolutional layer (Conv1 to Conv4), which will use filters to extract features like edges and textures. Conv1 uses an 11x11 filter while subsequent layers use smaller filters; the size of the filters reduces as follows: 5x5 for Conv2 to Conv4. Each convolution will be followed by a ReLU activation function, introducing non-linearity and making it easier for the model to learn complex patterns. This reduces problems like the vanishing gradient problem when SoftMax and similar operations are utilized.

Batch Normalization. Batch Normalization (BN) normalizes the output to have a zero mean and unit variance following each convolutional layer. Higher learning rates are made possible, training is stabilized, and internal covariate movements are lessened. By keeping gradients from vanishing or exploding, BN promotes quicker convergence and better model performance.

Max Pooling. After some convolutional layers, Max Pooling layers are added with a 3x3 filter. Max pooling is a form of down-sampling in which the spatial dimensions of the feature maps are reduced by keeping only the most important information while

discarding less relevant information. This reduction in the dimensions helps reduce the computational costs associated with processing large input images and allows the network to focus on more abstract features as the layers progress. It also introduces a degree of translational invariance, meaning the model can recognize features regardless of their position in the image.

Fully Connected Layer. The network transitions to fully connected layers (FC1 and FC2), where high-level features are processed for classification. Each layer is followed by a ReLU activation to model complex relationships. The final output is passed through a SoftMax function to generate class probabilities for classification tasks.

Dropout. Dropout (0.5) is applied to the fully connected layers (FC1 and FC2) to prevent overfitting. During training, 50% of neurons are randomly deactivated, forcing the model to generalize better and learn more robust, distributed representations, rather than relying on specific neurons.

SoftMax. The output is transformed into probabilities by this layer, where each value denotes the probability that the input falls into a particular class. The result is a probability distribution since the class with the highest probability is selected as the forecast and the total of all probabilities equals 1.

AlexNet's architecture omitted Batch Normalization and Dropout, which were later adopted to improve training. While Batch Normalization accelerates training, reduces internal covariate shift, and allows higher learning rates, Dropout helps prevent overfitting by setting neurons randomly to zero thereby promoting better generalization abilities. In total, such improvements yield a faster model that is more stable and has a good generalization of unseen data, leading to better accuracy and efficiency in complex datasets.

3.4 Classification

This phase is attained through a hybrid model that amalgamates EfficientNet and LSTM for sequential learning, ensuring high accuracy and reliability.

It is a hybrid model utilizing EfficientNet for accurate feature extraction and LSTM for analysis of sequential patterns and thus allows for robust identification and classification of crop disease. LSTM processes temporal dependencies to get accurate and reliable findings while EfficientNet makes efficient collection of complex information in images. Such advanced AI leads to enhanced performance in agricultural disease detection tasks.

EfficientNet. EfficientNet, known for its scalability across depth, breadth, and resolution, is incorporated into the model for precise crop disease identification and classification. Among its versions (B0 to B7), we employ EfficientNetB0 as a feature extractor. Its architecture features Mobile inverted bottleneck convolution (MBConv) blocks, derived from MobileNetV2, enhanced with squeeze-and-excitation networks

(SENet) in inverted residual blocks. The model processes input images (224×224) through a 3×3 Conv2D layer, 16 MBConv blocks (3×3 or 5×5 kernels), and a 1×1 Conv2D layer, before passing them to the RA block for further analysis. EfficientNet introduces a compound scaling approach that uses a coefficient to uniformly scale the network's resolution, depth, and width. This method optimizes model accuracy by effectively balancing parameters and computational resources, as represented in Eq. (3).

$$N(d, w, r) = \odot \bar{K}_i^{d \times \hat{L}_i} (X_{[r \times \hat{h}_p, r \times \hat{w}_p, b \times \hat{c}_i]}) \quad (3)$$

To scale network depth, width, and resolution, the coefficients $w, d, \text{ and } r$ are calculated as follows in Eq. (4)

$$\begin{aligned} \text{depth: } d &= \alpha^\emptyset \quad \text{width: } w = \beta^\emptyset, \\ \text{resolution: } r &= \gamma^\emptyset \quad \alpha \geq 1, \beta \geq 1, \gamma \geq 1 \end{aligned} \quad (4)$$

The composite parameter \emptyset is utilized to optimize the network's depth, width, and resolution, resulting in three-dimensional parameters that satisfy the conditions of Eq. (3).

Long Short-Term Memory. This particular kind of recurrent neural network (RNN) was created to manage sequential data and get around some of the drawbacks of conventional RNNs, like the vanishing gradient issue. LSTMs use three gates and a memory cell to learn long-term dependencies:

Forget gate. Determines which information from the previous memory should be discarded, using a sigmoid function to scale values between 0 (forget) and 1 (retain).

$$F_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (5)$$

Input gate. Selects new information to add to the memory cell by combining a sigmoid activation for importance and a *tanh tanh* activation to scale candidate values.

$$\text{inp}_t = \sigma(W_{\text{inp}} \cdot [h_{t-1}, x_t] + b_{\text{inp}}) \quad (6)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

(7)

Output gate. Controls the output from the memory cell, applying a sigmoid function to decide relevance and a *tanh tanh* activation to extract the final output state.

$$Out_t = \sigma(W_{out} \cdot [h_{t-1}, x_t] + b_{out}) \quad (8)$$

$$h_t = Out_t \times \tanh(C_t)$$

(9)

The memory cell C_t C_t is updated as

$$C_t = F_t \times C_{t-1} + inp_t \times \tilde{C}_t$$

(10)

In Precision Crop Disease Identification, EfficientNet functions as a feature extractor; it uses optimized scaling to capture spatial details from crop images. LSTM completes this by analyzing temporal patterns in sequential data, such as disease progression or seasonal variations. The hybrid model will combine the spatial precision of Efficient Net with the insight of LSTM in time and ensure accurate and reliable disease classification by effectively integrating the spatial and sequential information that is critical for agricultural diagnostics.

4 Result and Discussion

This section includes results along with a discussion of the proposed model. This article is a presentation of the topic, Precision Crop Disease Identification and Classification Using Advanced AI Techniques. The performances of the suggested technique were measured in terms of a variety of metrics, such as Precision, Accuracy, Sensitivity, F1-score, False Negative Rate, False Positive Rate, Matthews Correlation Coefficient, Negative Predicted Value, and Specificity. To compare the amount the newly constructed framework has outperformed itself, comparisons were made against the previous ones: ResNet-50, InceptionV3, DenseNet-121, MobileNet, and Proposed.

4.1 Evaluation Setup

Using <https://www.kaggle.com/datasets/mexwell/crop-diseases-classification>, the suggested framework has been assessed. The suggested framework has been implemented using the Python platform. Its Intel (R) Core (TM) i3-8100 CPU is set up to operate at 3.60 GHz. 15.8 GB of the 16.0 GB of installed RAM are usable. The system is powered by an x64 architecture CPU and runs on a 64-bit operating system

4.2 Performance Metrics

Performance evaluation is done using a variety of matrices, Precision, Accuracy, Sensitivity, F1-Score, FNR, FPR, MCC, NPV, and Specificity.

Accuracy. It is the degree to which a quantity's measurements match its real, or actual, value.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$$

(11)

where, TP = True positive, TN = True negative, FP = False positive, FN = False negative

Precision. It explains the total number of real samples that were suitably considered throughout the categorization procedure by utilizing all of the process's instances.

$$Precision = \frac{TP}{FP+TP}$$

(12)

F-Score. The F-Score number carefully balances the requirement to completely identify every data piece to guarantee that each definition defines a single type of information item.

$$F - Score = 2 \times \frac{Precision \cdot Recall}{Precision + Recall}$$

(13)

Specificity. One accurate measure of specificity is the quantity of negatively predicted outcomes among all adverse events that were accurately predicted.

$$Specificity = \frac{TN}{FP+TN}$$

(14)

Sensitivity. It is calculated as the fraction of actual positive predictions divided by the total number of positive forecasts.

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

(15)

MCC. Because it considers TP, TN, FN, and FP, it is a reliable statistic for assessing the performance of binary classifiers. The degree of correlation between the labels and predictor is measured by MCC.

$$MCC = \frac{(TP \cdot TN) - (FP \cdot FN)}{\sqrt{(TP+FP)(TP+FN)(FP+TN)(TN+FN)}} \quad (16)$$

NPV. It is a metric used to evaluate the performance of a binary classification model. Net present value is a measure of the proportion of negative expectations that materialize.

$$NPV = \frac{TN}{TN+FN}$$

(17)

FNR. It is expressed as the proportion of wrongly classified cases that are unintentionally given a negative label relative to the total number of cases that receive a positive label.

$$FNR = \frac{FN}{FN+TP}$$

(18)

FPR. The ratio of the whole quantity of negative data to the share of positive data that was mistakenly classified can be used to characterize it.

$$FPR = \frac{FP}{TN+FP}$$

(19)

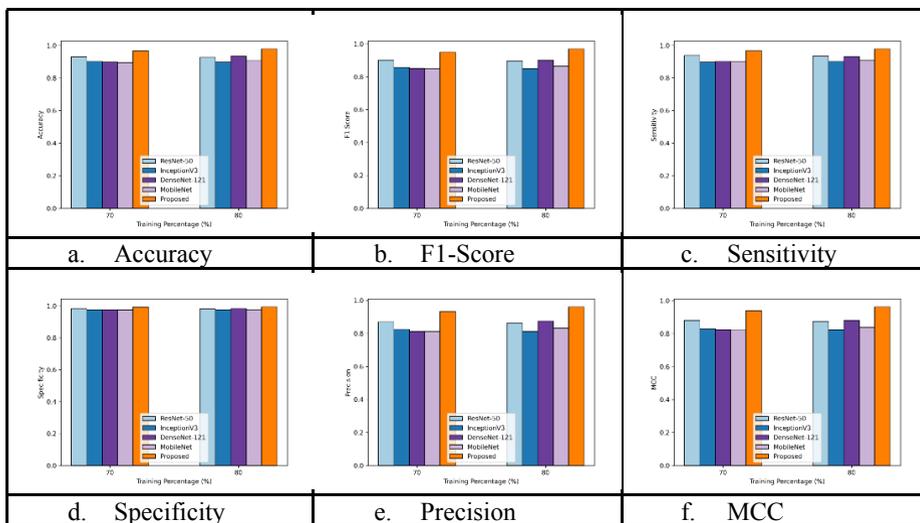
4.3 Performance Results

Table 1.Comparative analysis of the performance metrics for learning rate of 70%

Classifier	ResNet-50	InceptionV3	DenseNet-121	MobileNet	Proposed
Accuracy	0.9305	0.9013	0.8970	0.8948	0.9669
Specificity	0.9825	0.9751	0.9750	0.9738	0.9919
Sensitivity	0.9376	0.8966	0.9015	0.9007	0.9672
Precision	0.8698	0.8240	0.8127	0.8127	0.9331
F1 Score	0.9002	0.8565	0.8509	0.8502	0.9495
FNR	0.0623	0.1033	0.0984	0.0992	0.0327
FPR	0.0174	0.0248	0.0249	0.0261	0.0080
NPV	0.9731	0.9640	0.9618	0.9611	0.9868
MCC	0.8801	0.8284	0.8232	0.8216	0.9393

Table 2. Comparative analysis of the performance metrics for Learning rate of 80%

Classifier	ResNet-50	InceptionV3	DenseNet-121	MobileNet	Proposed
Accuracy	0.9267	0.8974	0.9333	0.9060	0.9790
Specificity	0.9818	0.9752	0.9832	0.9762	0.9944
Sensitivity	0.9339	0.9017	0.9314	0.9066	0.9787
Precision	0.8630	0.8128	0.8742	0.8307	0.9614
F1 Score	0.8947	0.8499	0.9003	0.8640	0.9698
FNR	0.0660	0.0982	0.0685	0.0933	0.0212
FPR	0.0181	0.0247	0.0167	0.0237	0.0055
NPV	0.9718	0.9625	0.9750	0.9653	0.9916
MCC	0.8738	0.8232	0.8809	0.8376	0.9630



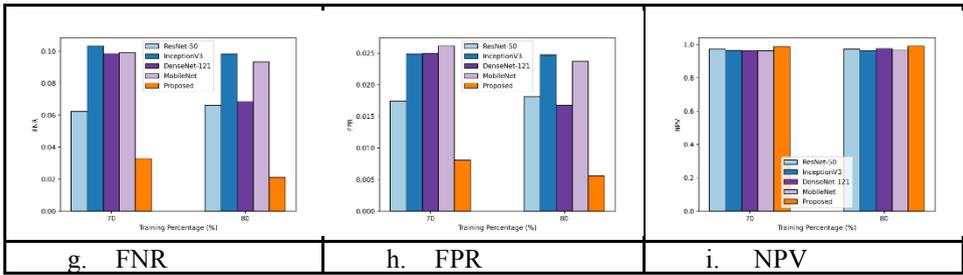


Fig.4. (a)(i) Visual representation of several performance metrics with proposed and existing works

The performance metrics, which include Precision, Accuracy, Sensitivity, F1-Score, FNR, FPR, MCC, NPV, and Specificity, are represented graphically in Figures 4 (a) to (i). These metrics are compared with several approaches, including ResNet-50, InceptionV3, DenseNet-121, MobileNet, and Proposed.

5 Conclusion

This research work presents an efficient framework for crop disease identification and classification in the context of Smart Agriculture 4.0 using advanced AI techniques to improve agricultural productivity. By integrating state-of-the-art image processing methods such as CLAHE and K-Means Clustering, the method efficiently enhances the quality of images and segments the region affected by disease. An improved AlexNet architecture is used for feature extraction to ensure the critical features related to the disease are captured with higher precision. Moreover, the hybrid model that integrates EfficientNet with LSTM gives better classification accuracy with high precision and reliability in identifying different types of crop diseases. The developed framework was designed in the Python environment. In the experiment, the developed approach resulted in a maximum specificity of 0.9919 with a learning rate of 70% and a maximum specificity of 0.9944 with an 80% learning rate.

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