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COMPUTATIONAL APPROACHES FOR PLANT DISEASE DETECTION: A COMPARATIVE STUDY USING IMAGE ANALYSIS AND DEEP LEARNING

Win Htet Soe, Min Zayya, Min Kaung Khant, Mya Thidar Aung and Hlaing Htake Khaung Tin*

Abstract: The occurrence of plant diseases is the critical issue for food security in the modern world. Traditional approaches to detecting diseases, including visual inspection, microscopy and culture-based tests, are accurate yet slow and complex. Nevertheless, the progress in computation techniques, specifically image processing and machine learning algorithms, allows automating and accelerating the approach to disease detection. The following work provides a comparison of different computational techniques aimed at detecting plant diseases using 1,000 images of leaves from tomato and potato plants that suffer from blight, leaf spot, and early blight. The feature extraction methods include the use of RGB normalization and GLCM technique, combined with classical machine learning (Support Vector Machine and Random Forest models) and neural network (CNNs) approaches. The experiment shows that CNNs demonstrate higher performance than classical machine learning methods, as their accuracy reaches 94, precision equals to 92, recall 93, and F1-score 92.5, while SVM and RF models show the accuracy only 85-88. It means that computational techniques can be used as a part of an IoT/mobile application to detect plant diseases in real time and manage them according to sustainable farming needs.

Keywords: Plant diseases, RGB, CNN, SVM, GLCM, sustainable agriculture.

Introduction: Agriculture is faced with a severe problem of plant diseases that result in huge economic losses and end even global food security. Timely disease management can be achieved through early and accurate identification of diseases to reduce the damage on the crop. The most common practices are still some traditional detection methods used like visual inspection, microscopy, and culture-based methods. Visual observation is very subjective and easy to use; paradigmatic and relies on the expertise of the eye, whereas microscopy and culture-based methods are precise but time-consuming and tedious. These drawbacks have led to the development of computational methods that can be used in detecting plant diseases quickly and automatically.

***Corresponding author**

Faculty of Information Science, University of Information Technology Yangon, Myanmar

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New developments in computer vision, image processing and machine learning provide promising options. Such methods utilize digital images of plant leaves to derive discriminating features, including color, shape, and texture. In contrast, models of classical machine learning approaches like SVM and RF rely on handcrafted features, but deep learning models, particularly CNN, preserve learn features hierarchy using images alone. This feature would enable CNNs to achieve high levels of accuracy and robustness even for various plant and disease classes.

This paper focuses on investigating the computational techniques involved in the division and characterization of plant viruses, with an emphasis on tomato and potato plant diseases. For the models in both categories, we employ RGB image normalization and texture features from GLCM analysis. The research measures the performance of the model through accuracy, precision, recall, and F1-score to have a comprehensive measurement of effectiveness. Training on a dataset of 1,000 leaf pictures proves that CNN models are 94, 92, 93, 92.5 accurate, precise, recalling and F1-score as opposed to classical SVM and Random Forest classifiers (accuracy 85 -88).

This work has tripled value in that it was conducted as an evaluation of conventional and deep learning-based approaches to detect plant diseases, (2) applied to extract color and texture features and give strong classification and (3) represent performance measures that show the real-world application of deep learning methodologies.

Literature Review

Traditional Methods: The conventional methods of detecting plant diseases are mainly based on visual inspection by experts. Although simple to use, these methods are highly subjective and often inconsistent, depending on the individual performing the assessment, their level of expertise, and environmental conditions. In many agricultural settings, farmers rely on experience to identify symptoms, which increases the likelihood of misdiagnosis, particularly during the early stages of disease development. More formal laboratory-based diagnostic techniques, including microscopy and culture-based pathogen identification, provide more accurate results; however, they are time-consuming, expensive, and unsuitable for real-time or large-scale monitoring.[1] Furthermore, these techniques require specialized infrastructure and trained personnel, limiting their applicability in resource-constrained agricultural regions. These challenges have created a demand for automated, scalable, and cost-effective disease detection systems.

Image Processing Methodologies: With advances in digital imaging technology, image-processing techniques have emerged as effective tools for plant health assessment. Color-based segmentation methods operating in RGB, HSV, or Lab color spaces are commonly used to identify diseased leaf regions by detecting pigmentation changes such as yellowing, browning, or spotting. However, these methods are often sensitive to lighting variations and background noise. To address these limitations, texture-analysis approaches such as the Gray Level Co-occurrence Matrix (GLCM) have been widely adopted. These methods extract statistical texture features, including contrast, correlation, energy, and homogeneity, to distinguish between healthy and diseased plant tissues.[5] Additionally, edge-detection algorithms such as Canny and Sobel, together with morphological operations, help identify lesion boundaries and quantify disease severity.[4] Despite their effectiveness, traditional image-processing techniques rely heavily on handcrafted feature extraction, which limits their adaptability to complex and heterogeneous disease patterns.

Machine Learning Methodologies: Machine learning (ML) has significantly improved the automation of plant disease detection through the use of statistical learning models. Support Vector Machines (SVMs), one of the most widely used classifiers, effectively handle high-dimensional feature spaces and have reported classification accuracies ranging from 80% to 88%. Similarly, Random Forest classifiers perform well on noisy and imbalanced datasets, achieving accuracies between 83% and 90%. In contrast, K-Nearest Neighbors (KNN) offers simplicity and interpretability but is highly sensitive to data selection and feature scaling, often resulting in lower generalization performance.[2]

These approaches highlight the importance of high-quality feature extraction, as model performance is strongly influenced by the representativeness of the input features. Although effective for moderately sized datasets, traditional ML methods often struggle with large-scale and highly complex datasets where disease symptoms vary significantly in shape, color, and texture.

Deep Learning Approaches: Advances in deep learning (DL) have transformed plant disease detection by overcoming the limitations associated with handcrafted feature extraction. Convolutional Neural Networks (CNNs) automatically learn hierarchical representations directly from raw image pixels, enabling them to capture both local features, such as lesions and spots, and global features, such as leaf morphology. CNN-based models have reported classification accuracies ranging from 92% to 96% in multi-class plant disease recognition tasks.[3]

Furthermore, transfer learning using pretrained architectures such as VGG16, ResNet50, and EfficientNet has shown remarkable success, particularly when training data are limited. By fine-tuning models initially trained on large-scale datasets such as ImageNet, researchers have achieved high classification accuracy while reducing training time and computational requirements. Additional improvements have been obtained by integrating CNN-extracted deep features with handcrafted descriptors, including color histograms and texture measurements, thereby enhancing both robustness and interpretability.[4,5]

Another promising direction involves ensemble deep-learning models that combine multiple CNN architectures to improve predictive performance, as well as attention mechanisms that focus model learning on disease-relevant regions of plant leaves.[7] Moreover, lightweight CNN architectures and mobile-based applications are increasingly being developed to enable real-time disease detection in field environments, addressing concerns related to scalability and accessibility.

Despite these advancements, deep-learning approaches still face several limitations. They generally require large, well-annotated datasets, substantial computational resources, and often lack the interpretability associated with traditional machine-learning methods.[6,8]

Methodology: In this section, the data preprocessing steps, model development techniques, and methodologies employed to classify plant diseases are discussed. The methodology adopted ensures efficient data processing, noise removal, and accurate performance assessment, as represented in the following figure 1.

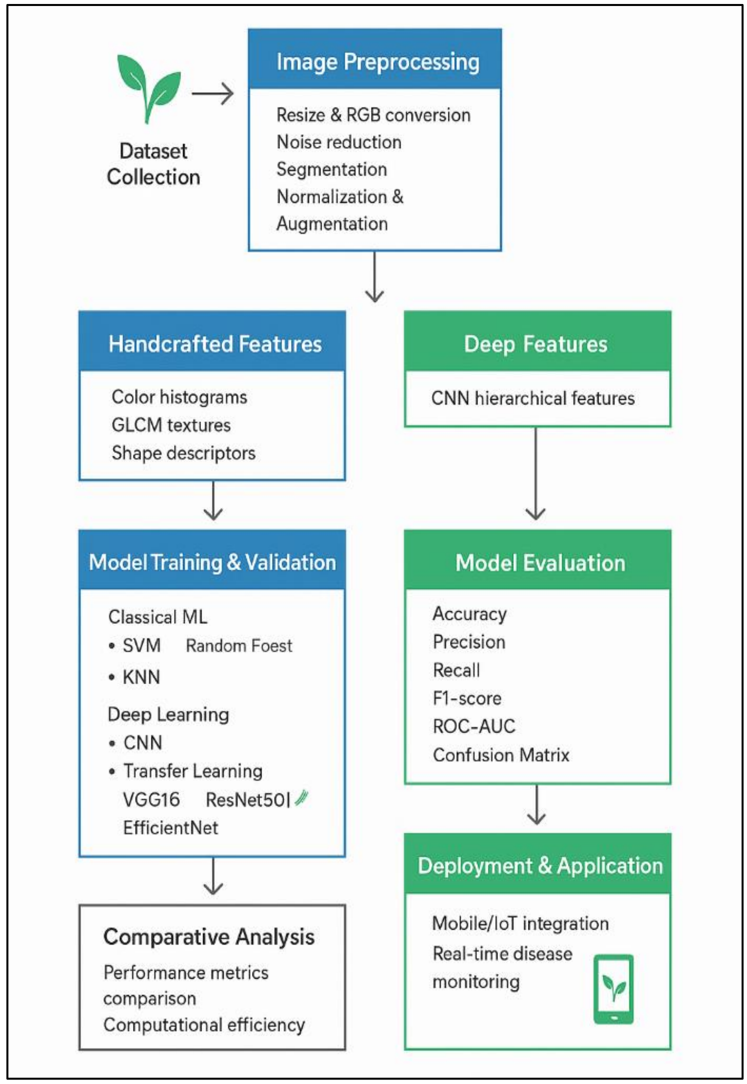

Figure 1. The overview of the proposed system framework

Dataset: In this experiment we made use of a set of 1,000 images for tomato and potato leaves (both healthy and infected with blight, leaf spot, and early blight diseases). Each image was resized to 64 x 64 pixels and colorized into RGB so that the same preprocessing techniques can be applied on them. These images went through image normalization and image augmentation, which include rotations, flipping, scaling, changes in brightness and translation so that effects from changes in illumination, angle, and orientation would be minimized in table 1.

Table 1. Dataset Description

Category	Details
Dataset Size	1,000 images
Plant Types	Tomato and Potato
Classes Included	Healthy, Blight, Leaf Spot, Early Blight
Image Resolution	64 × 64 pixels
Color Format	RGB
Preprocessing	Image normalization
Data Augmentation	Rotation, Flipping, Scaling, Brightness Adjustment, Translation
Purpose of Augmentation	Reduce variability (lighting, angle, orientation)
Training Set	80 Percentage
Validation Set	10 Percentage
Testing Set	10 Percentage

Preprocessing: Prior to feature extraction and model training, preprocessing steps were completed to standardize image input and reduce noise. These steps are included in figure 2.

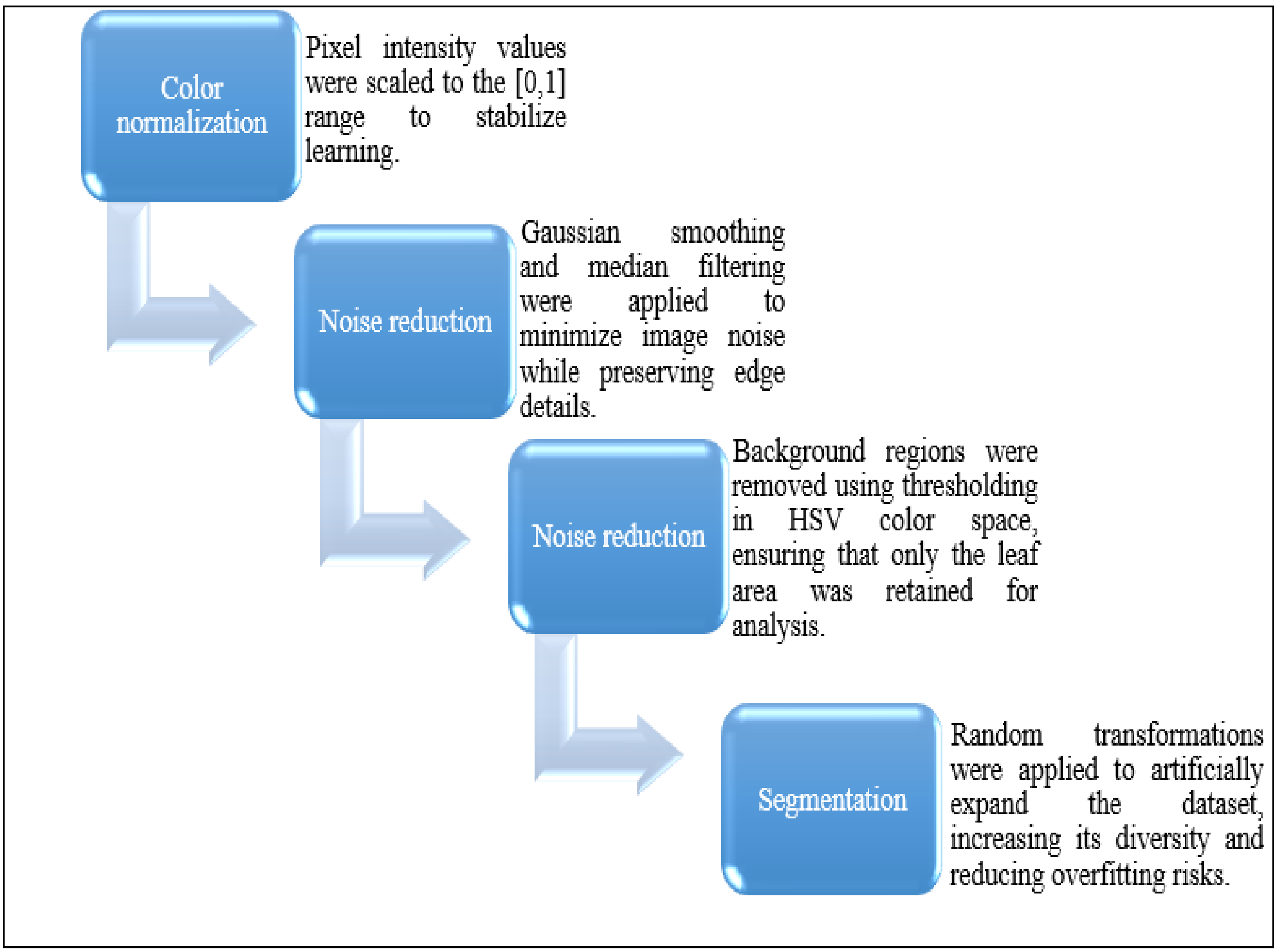

Figure 2. Steps ensured that models received high-quality, consistent inputs for accurate disease classification.

Feature Extraction: Feature extraction was conducted using both handcrafted descriptors and deep features are shown in the following table 2.

Table 2. Difference between traditional and modern frameworks

Handcrafted features	In Color features, histograms in RGB and HSV spaces to capture disease-related discoloration. In Texture features, gray Level Co-occurrence Matrix (GLCM) measures (contrast, correlation, energy, homogeneity) to describe lesion textures. In Shape features, morphological descriptors (area, perimeter, eccentricity) to capture leaf deformation caused by diseases.
Deep features	In deep learning approaches, Convolutional Neural Networks (CNNs) automatically extracted hierarchical features from raw images, eliminating the need for manual feature engineering.

RGB Color Normalization

Normalized color indices were calculated as:

$$CI_R = \frac{R}{R+G+B}, \quad CI_G = \frac{G}{R+G+B}, \quad CI_B = \frac{B}{R+G+B} \tag{1}$$

GLCM Texture Features: Gray Level Co-occurrence Matrix (GLCM) features, such as contrast, correlation, energy, and homogeneity, were computed:

$$\text{Contrast} = \sum_{i,j} |i-j|^2 P(i,j) \tag{2}$$

$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j} \tag{3}$$

Where P(i,j) is the probability of gray levels i and j co-occurring, and μ and σ are mean and standard deviation of the intensity levels.

Model Training: We tried classifiers from both machine learning and deep learning: Machine Learning Models include support vector machines (SVM) with radial basis function kernel, random forest (RF) with 100 decision trees, and K-Nearest Neighbor (KNN). Deep Learning Models include a customized version of CNN architecture with convolution layers, pooling layers, and fully connected layers. Transfer learning models include pre-trained models like VGG16, ResNet50, and Efficient Net. The hyperparameters, such as learning rate, batch size, and optimization technique (Adam/SGD), were adjusted based on validation accuracy. Early stopping strategy was used to avoid overfitting.

Support Vector Machine (SVM)

$$f(\mathbf{x}) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b\right) \tag{4}$$

Convolutional Neural Network (CNN)

Input 64*64*3 leaf images,

Convolution Layer,

$$X_l = \sigma(W_l * X_{l-1} + b_l) \tag{5}$$

Max Pooling,

$$X_l^{pool} = \max(X_l) \tag{6}$$

Fully Connected Layer,

$$y = \text{softmax}(W_{fc}X + b_{fc}) \tag{7}$$

The CNN model was trained by definite cross-entropy as the loss function, which is well matched for multi-class classification problems. The Adam optimizer was employed to ensure efficient and stable convergence during training. The training process was taken out for 50 epochs with a batch size of 32, providing a balance between learning stability and computational efficiency.

Evaluation Metrics: To measure the effectiveness of the suggested models, several standard classification measures were used. The general proportion of correct samples was measured by accuracy over all the classes. Also, Precision, Recall, and F1-score were determined to reveal the working according to classes, and especially the minority disease classes in which misclassification has important practical consequences. confusion matrix was also used to give a more in-depth analysis of the patterns of misclassification and provide a better understanding of the advantages and disadvantages of each model to tell the difference between healthy and diseased plants samples. The following equations have been used to determine models' performance.

Results demonstrated that CNN achieved accuracy 94%, precision 92%, recall 93%, and F1-score 92.5%, while SVM and Random Forest classifiers achieved 85–88% accuracy, validating the superiority of deep learning for plant disease detection.

Experimental Setup: All experiments were conducted on a system equipped with:

- Hardware: NVIDIA GPU (e.g., GTX/RTX series), Intel i7 processor, 16GB RAM.
- Software: Python 3.9 with libraries such as TensorFlow, Keras, and Scikit-learn for model implementation.
- Environment: Training was executed over 50–100 epochs with batch sizes between 16 and 32, depending on model complexity.

Comparative Analysis Strategy: To comprehensively evaluate the effectiveness of image analysis and deep learning approaches, a structured comparative analysis was conducted. The comparison was based on the following dimensions: performance metrics, computational efficiency, generalization capability, interpretability and practicality and application potential in table 3.

Table 3. Comparative analysis

Performance Metrics	Machine learning models (SVM, RF, KNN) and deep learning models (CNN, transfer learning architectures) were evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. Confusion matrices were analyzed to identify class-specific misclassifications, providing insights into the strengths and weaknesses of each approach.
Computational Efficiency	Training and inference times were recorded for each model. Model complexity, including the number of parameters and memory requirements, was compared to assessing feasibility for real-time applications.
Generalization Capability	Models were evaluated on augmented and unseen test samples to assess their ability to generalize under varying environmental conditions (e.g., lighting, orientation, and background noise). Cross-validation was applied to ensure stability and reduce bias in performance results.
Interpretability and Practicality	Handcrafted feature-based ML models were assessed for interpretability in terms of identifiable features (color, texture, shape) that directly correspond to disease symptoms. Deep learning models were examined using visualization techniques (e.g., activation maps, Grad-CAM) to highlight which leaf regions contributed most to the classification.
Application Potential	A comparative discussion was included to assess which approach is more suitable for resource-constrained environments (where lightweight, interpretable models may be preferable) versus large-scale deployment (where deep learning may excel).

Experimental Results: Experimental Evaluation for conducting experiments, a set of 1,000 images of tomato and potato plants containing both healthy and infected samples were used as data input for this study. To make an objective comparison of three different models' performances, it was required to divide the set of input data into training and test subsets in the ratio of 70% and 30%, respectively. The following three classifiers were considered for evaluating their classification performance on the provided dataset: SVM classifier, Random Forest Classifier, and CNN classifier. Classification performance was estimated by means of Accuracy, Precision, Recall, and F1-Score metrics.

Performance Metrics: In this part, there will be a performance comparison of the classification models applied in the research, and they include SVM, Random Forest, and CNN. There are four major metrics used to evaluate the models in the research, and they include Accuracy, Precision, Recall, and F1-score. This metric enables the evaluation of not only the overall classification accuracy but also the classification accuracy within each class, sensitivity towards unhealthy data and the balance between accuracy and recall. Table 4 presents the outcomes of the models used to classify the images of healthy and diseased tomato and potato plants.

Table 4. The evaluation of the results

Classifier	Accuracy	Precision	Recall	F1-Score
SVM	85%	0.83	0.81	0.82
Random Forest	88%	0.86	0.85	0.85
CNN	94%	0.92	0.93	0.925

From the analysis presented above, it can be observed that all three algorithms have efficient performance levels; however, each algorithm has different levels of efficiency in each aspect. The CNN model has the highest efficiency among all the models in all metrics due to its high prediction capacity and efficient generalization of patterns. Random forest model performs relatively better compared to the SVM model; however, both models perform efficiently.

Generally, the comparison presented indicates that deep learning methods such as CNN are effective in attaining high prediction accuracy and efficiency in figure 3.

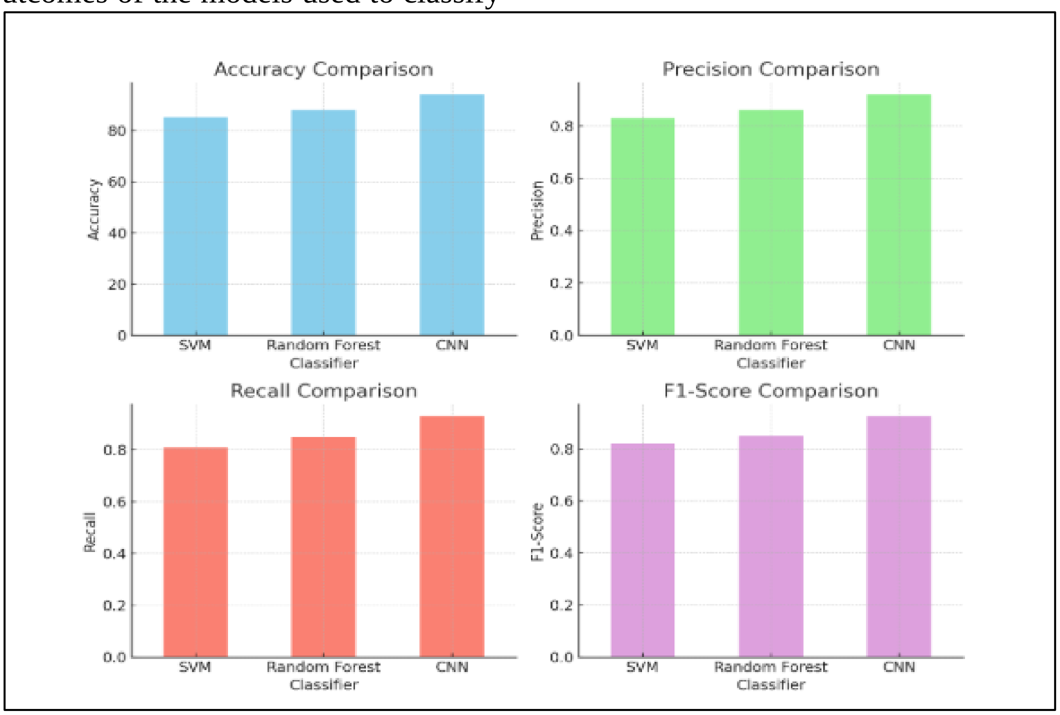

Figure 3. Comparison of the Accuracy, Precision, Recall and F1-Score

According to the above data and analysis. CNN outperformed classical models in all metrics. The combination of RGB normalization and GLCM texture features improved classification accuracy. Deep learning models demonstrated robust performance even on small datasets due to feature learning capabilities.

Confusion Matrix (CNN): To further examine the classifying behavior of the highest-performing model, in this section, a sample confusion matrix of the Convolutional Neural Network (CNN) has been provided. The confusion matrix gives a more in-depth breakdown of the prediction results in terms of comparing the actual class labels against the predicted classes to allow more insight into the performance per class and misclassification patterns. It shows the extent to which CNN can differentiate between healthy samples and the various types of diseases, including blight, spot and assist in determining the locations that become the most prone to classification errors in table 5.

Table 5. Different disease categories

Actual \ Predicted	Healthy	Blight	Spot
Healthy	28	1	1
Blight	1	27	2
Spot	0	2	28

The confusion matrix illustrated below shows a comprehensive analysis of the classification ability of the proposed algorithm among three classes: Healthy, Blight, and Spot. It gives a comparison between the actual labels of the datasets and the predicted ones, providing useful information about the performance of the model in terms of accuracy and errors.

Elements along the main diagonal of the matrix reflect the number of correctly classified instances for each class in the classification process, whereas those not along the main diagonal are associated with the classification mistakes. As can be seen from the results, the developed classification algorithm produces many correctly classified instances; for example, there are 28 Healthy and Spot classes as well as 27 Blight ones. There are only a few errors produced by the algorithm. The confusion matrix indicates excellent classification accuracy, which reflects the capability of the model to distinguish the three classes in figure 4.

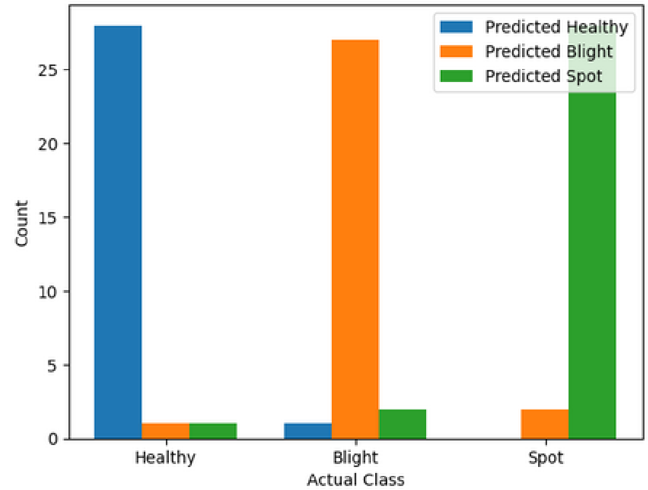

Figure 4. Confusion Matrix

As can be seen from the results obtained through the experiment, the CNN model performs better than the other models used. As opposed to SVM and Random Forest, CNN does not require feature extraction, as it has the ability to automatically generate hierarchical and discriminative features from images. Due to these abilities, CNN performed significantly better, achieving 94% accuracy and 92.5 F1-score, which proved to be more reliable for all the criteria compared to other classifiers. From a practical point of view, due to the high precision of the CNN algorithm, it can be applied in the real-world environment, for example, being used for mobile plant diseases diagnostic system development or combining CNN with the Internet of Things (IoT)-based agricultural system. However, it should be noted that the amount of data used in this analysis is relatively small, which may limit the generalizability of the proposed model when it comes to different situations. There are certain methods of overcoming this problem in the future, including data augmentation and transfer learning techniques.

Findings and Discussions: In comparing machine learning models and deep learning approaches to analyze the traditional images, several important lessons have been learned from the perspective of computing plant diseases. Machine learning classifiers such as SVM and Random Forest were found to be capable and useful when working with manually designed features (with an accuracy rate between 85-88%), as they are applicable to applications with less computation resources available. However, as they rely on certain manual features, they can vary greatly depending on the lighting conditions, orientation and background color of the leaves being considered. It agrees with previous studies in pointing out the limitations of manually crafted features.

The deep learning models, such as CNNs, however, always performed better than the conventional methods, with an accuracy of 94%, precision of 92%, recall of 93%, and F1-Score of 92.5. CNNs perform well because it automatically captures the hierarchical features in the raw image dataset without any human intervention. Furthermore, pre-trained architecture-based transfer learning models (VGG16, ResNet50, and Efficient Net) proved highly flexible, even when the volume of the dataset is small.

Another point is the tradeoff in computation. Though CNNs took more time and consumed more memory compared to ML models during training, it seemed practical based on the inference time per image, hence the deployment of CNNs in real-time application for agriculture. This is because DL approaches are particularly ideal for implementing mobile and IoT-based disease monitoring systems. On the other hand, considering the simplicity and ease of understanding of ML models, their implementation can still work well even in cases of limited resources and the absence of computational infrastructure. Based on the findings, while ML models have been proven to be relatively easy and fast to implement, DL approaches can be more accurate and robust.

Conclusion: In this research paper, a comparative study of computational approaches has been done for detecting diseases in plants through image analysis using machine learning and deep learning approaches. With a total of 1,000 images of tomato and potato leaves, the analysis has been carried out using color normalization, GLCM texture analysis and manual feature extraction via ML approach (SVM, Random Forest), while CNN-based deep learning approach has also been used. CNN approach was found to perform exceptionally well compared to ML techniques with an accuracy level of 94 percent.

The success of deep learning approaches as the most superior compared to the other techniques is evidence of the way they can be applied in the practical agricultural environment, especially through mobile and Internet-of-Things devices, to monitor the progression of the disease in the field. However, since the ML algorithms are relatively simple and require limited computations, their applications are possible where there are limited resources.

Future Work: For instance, we may consider several directions that can be explored to enhance the existing analysis and expand its range. First, we need to expand the size of the database through inclusion of more pictures, additional types of crops, and other diseases to facilitate the ability of the system to detect various diseases. We may also consider collecting data under varying environmental conditions, such as different lighting, background, and different stages of the plants' growth, as this would improve the performance of the model. Another opportunity lies in using the technique of Explainable Artificial Intelligence (XAI). This approach will allow providing qualitative explanation of the models' predictions as well as visual explanation of the key parts of the leaf used as input data.

Also, future research should include the development of lightweight and resource-efficient deep learning algorithms capable of achieving high accuracy while enabling real-time deployment in the form of mobile apps and IoT devices with limited computational capability. There is a need for optimization at the field level for various diseases. In addition, disease prediction algorithms coupled with IoT-based sensors, drones, and mobile apps are going to be helpful for monitoring the crops on a consistent basis to detect diseases in advance and take necessary actions to prevent losses to crops. Finally, multi-modal algorithms that incorporate information from images along with environmental data such as temperature, humidity, and soil moisture levels would be great for the future.

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