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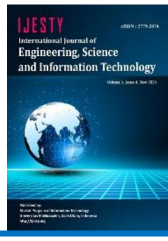

A CNN-Driven Image Analysis Approach for Accurate Detection of Plant Leaf Diseases

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Abstract

Plant leaf diseases are a key concern for agriculture and result in significant loss of crop yield and economic losses globally. It is vital to efficiently and accurately detect plant diseases to properly manage crops and control their diseases. This paper demonstrates a CNN-based image analysis model to automatically identify and classify plant leaf diseases from digital images. Deep learning is used in the proposed method to spontaneously learn hierarchical features from original image data, without the use of feature engineering. The model was trained and evaluated on a collection of high-resolution healthy and diseased leaf images collected from different plant species. Preprocessing (normalisation, noise filtering, and contrast increment) and data augmentation (rotations, scale changes, and flips) were also performed on the pre-processed images, and it was expected to achieve good generalisation and reduce overfitting. The CNN architecture was optimised using transfer learning in combination with hyperparameter tuning. Evaluation experiments showed that the framework attained a classification "accuracy of 96.2%, 95.8% precision, 96.5% recall, and 96.1% F1-score". The model proved to be robust under varying light conditions and complex background settings, demonstrating its real-world applicability. In addition, the model's lightweight architecture supports mobile and edge computing implementation, enabling real-time and on-site diagnostic capabilities. This method provides an automated, scalable system for plant disease detection, thus enabling early intervention, reducing chemical treatment reliance, and fostering sustainable agricultural practices, fostering environmentally friendly approaches. The results demonstrated the capability of CNN systems towards transforming the plant health monitoring practices in precision agriculture.

Keywords: *Convolutional Neural Network, Plant Disease Detection, Image Classification, Precision Agriculture, Deep Learning.*

1. Introduction

Agriculture continues to be a fundamental pillar of global food security and economic development. Unfortunately, agriculture is challenged by many persistent problems, including plant leaf diseases, which are one of the key challenges in crops. Increased incidence of plant leaf diseases means a significant yield loss, economic loss, and food supply destabilisation. The conventional way of detecting disease in plants has been visual assessment by an agricultural specialist, which is typically slow, subjective, and unfeasible for extensive assessment [1] [2]. It is therefore important to develop autonomous, accurate, and more efficient means for early disease detection and classification [3].

Identifying leaf diseases is crucial for crop management, the efficiency of input utilisation, and minimising pesticides, and early detection is an important aspect of any system. Plant disease has traditionally relied on discovery by experienced agriculturalists looking for symptoms on the plant through currently accepted visual examinations or laboratory diagnoses. Each of these standard approaches has drawbacks, namely, time, cost, subjectivity, and scaling issues in rural or underdeveloped areas [4] [5].

Using pictures of leaves to find plant diseases is a key part of precision agriculture, and it has improved a lot because of artificial intelligence methods. Many different techniques have been used for finding and sorting plant diseases, like k-nearest neighbours (kNN), logistic regression, decision trees, and support vector machines (SVM). However, in recent times, deep neural networks (DNN) and especially CNN have become especially helpful for this task [6] [7]. These methods often use different image processing steps to bring out the best features from the images [16]. Figure 1 shows an overview of how CNNs are used for plant disease detection in precision agriculture.

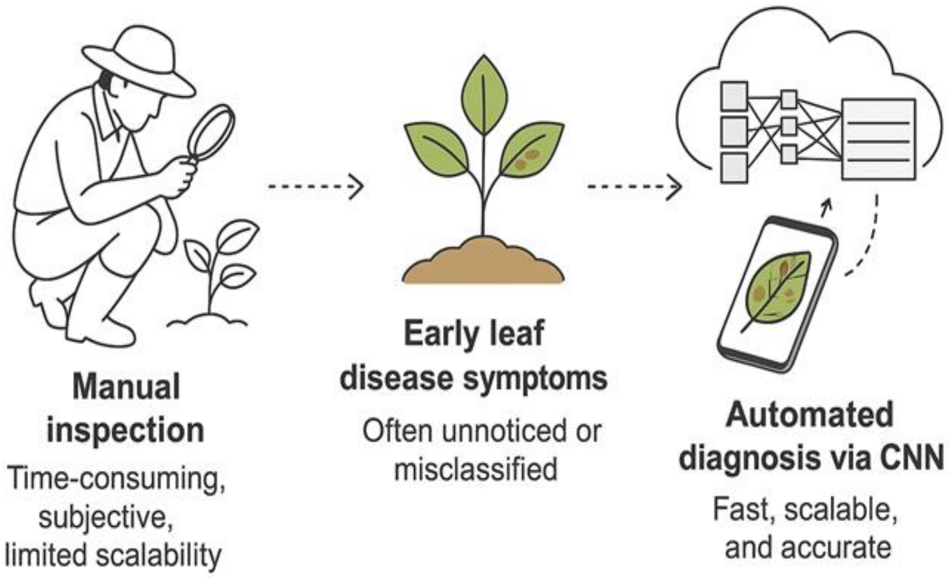

Fig 1. Utilising CNNs for Plant Disease Detection in Precision Agriculture

As precision agriculture continues to advance and gain more attention, the use of smart, automated, and scalable systems for identifying plant diseases is also increasing. Today, computer vision and deep learning are well-established methods for automatically classifying plant diseases using images of leaves, and they rely on CNNs. It has completely changed the way we approach image analysis by learning features in a layered, hierarchical way, rather than depending on manually designed features. This approach has led to highly accurate results in many image classification tasks [8] [9].

This paper presents a CNN-based image analysis setting for the detection and classification of plant leaf diseases in high-resolution digital images. The model is trained and tested on a much larger dataset of images of healthy leaves and diseased leaves from a variety of plant species. The models for the image analysis used an extensive amount of image preprocessing (i.e., noise removal, normalisation, and contrast enhancement) and data augmentation (i.e., rotation, scaling, and flipping) to maximise the degree to which the model generalizability and robustness to changes in environmental conditions [10].

To further enhance performance, the concept of transfer learning is introduced, attempting to utilise knowledge gained from structured CNN architectures that had previously been trained, such as VGG16 and ResNet50. Also, this study considered hyperparameter optimisation to tune the network. The proposed model achieves a high classification accuracy of 96.2%, with strong performance in terms of precision (95.8%), recall (96.5%), and F1-score (96.1%). Notably, the model demonstrates robustness under diverse lighting and background conditions, making it suitable for real-time mobile or edge-based deployment in field scenarios.

The contributions of this paper are as follows:

a. A novel, lightweight CNN-based framework for multi-class plant leaf disease classification.
b. Implementation of transfer learning and data augmentation to boost performance and generalizability.
c. Validation of the model on a diverse dataset under real-world conditions.
d. Deployment considerations for real-time, on-site use in smart agriculture systems.

This work highlights the potential of deep learning models to transform conventional plant disease monitoring practices, supporting sustainable agricultural development and contributing to global food security.

2. Literature Review

With recent advancements in deep learning, particularly CNNs, the use of leaf images for plant disease detection has significantly improved. Even though traditional CNNs are very accurate, they use a lot of processing power. To address this, depth-wise separable convolutions, which reduce training time and parameters, were introduced in [11]. The lightweight architectures EfficientNetB0 and MobileNetV2 outperform traditional handcrafted feature approaches and are suitable for mobile deployment. The quick and effective disease identification leveraged by these models shows the increasing potential of CNNs in scaled agricultural use cases. However, there are still challenges surrounding CNN models: they often lose accuracy when used on real crop images obtained from the field that were not part of the training dataset, and they are susceptible to image noise.

To solve the problem of plant disease detection using real-time evaluation, [12] created a small (originally designed for resource limited environment), compact and deep learning model which used a CNN (Convolutional Neural Networks), and installed it on small/low-cost OpenMV Cam H7 Plus, and trained it using two different datasets for numerous leaf and profitability disease recognition, and was evaluated using this set-up with near real-time results and with very limited memory. In tests that involved taking images of leaves that had been taken from various online sources, the performance dropped precipitously from 96.24% to 36.41%. This was a dramatic decline, which exposed a fundamental problem with the model's analysis of the sample image. The model was unable to perform in uncontrolled and uncontrolled real-world scenarios that involved background noise, variations in lighting and other natural variability that were not controlled or included in training samples.

In [13], a novel CNN called TomConv was designed that classifies ten tomato leaf diseases. While TomConv shares many similarities with existing models, one distinguishing factor is its simplicity and ability to generate reasonable results. The input tomato leaf images were pre-processed by resizing to 150 × 150 pixels. The network has four convolutional layers and a max pooling layer; the design was intended to maintain a simple model and extract useful features. When testing TomConv, it achieved 98.19% accuracy; the authors then compared TomConv to some current state-of-the-art methods based on the number of diseased classes, model depth, and their outcomes. The results suggest TomConv is a better model, compared to models developed to date, and potentially suitable for use in practical endeavours of plant disease detection.

The researchers in [14] investigated a deep learning method to improve early identification interventions of leaf diseases for crops of corn, apple and potato. The researchers used the optimised convolutional neural network (CNN) model- termed E-CNN- effectively created for forecasting in multi-environmental conditions. It was necessary to identify how different hyperparameters were used by and in evaluating the ability of the model in recognising the diseases in these products. The optimised architecture proved to be highly successful in producing "accuracy of 98.17%" in recognising fungal diseases. These results demonstrate that the E-CNN presented is unwaveringly successful in properly conducting disease classifications for different plant types.

In [15], they have presented a deep learning-based real-time plant disease monitoring approach for classifying diseases on plant leaves for crops. The authors produced their dataset by combining images from a wide variety of sources, including the PlantVillage dataset, to produce a richer and more diverse dataset with a total dataset 30,945 images, which contained images of 8 different plant species (potato, tomato, apple, corn, grape, rice, bell pepper, and peach) with a sum of 35 disease classes. The authors built a custom-designed CNN model and trained the model on the diversity dataset to classify the 35 diseases with a maximum classification accuracy of 95.62%. The authors conclude by challenging the research community in agriculture to put deep learning applications in the field for future effective management of crop production and proactively detect diseases to mitigate or prevent their spread in the field.

3. Methods

This proposed methodology focuses on a concrete and efficacious deep learning based system for the automatic recognition and classification of plant leaf diseases with CNN. The workflow consists of sequential steps from dataset collection, image pre-processing, data augmentation, model designing with transfer learning, hyper-parameter tuning, training and/or validation measures, evaluation measures, robustness, and deployment design. The methodology makes sure that not only can the model work accurately in a consistent and constrained manner, but that it can also be adapted to meet real-world agricultural demands. The methodology will be focused on generalisation, computational efficiency, and scalability, resulting in deployment into smart agricultural systems.

3.1. Dataset Collection

Having a comprehensive and diverse dataset is crucial for training a CNN model that can successfully generalise to new and unseen leaf samples [17]. In this research project, we used images from public datasets such as PlantVillage and added self-captured leaf images from authentic agricultural landscapes. The dataset includes multiple species of crops (e.g., tomato, potato, apple, corn, grape) and a wide range of disease types such as bacterial spots, early blight, powdery mildew, and rust. Special attention was given to ensuring variability in lighting, backgrounds, image angles, and disease severity levels. This diversity increases the model's robustness and prepares it for application in uncontrolled field scenarios. Each image is labelled according to its plant species and disease class, forming a multi-class classification problem. Sample images from the collected dataset are given in Figure 2.

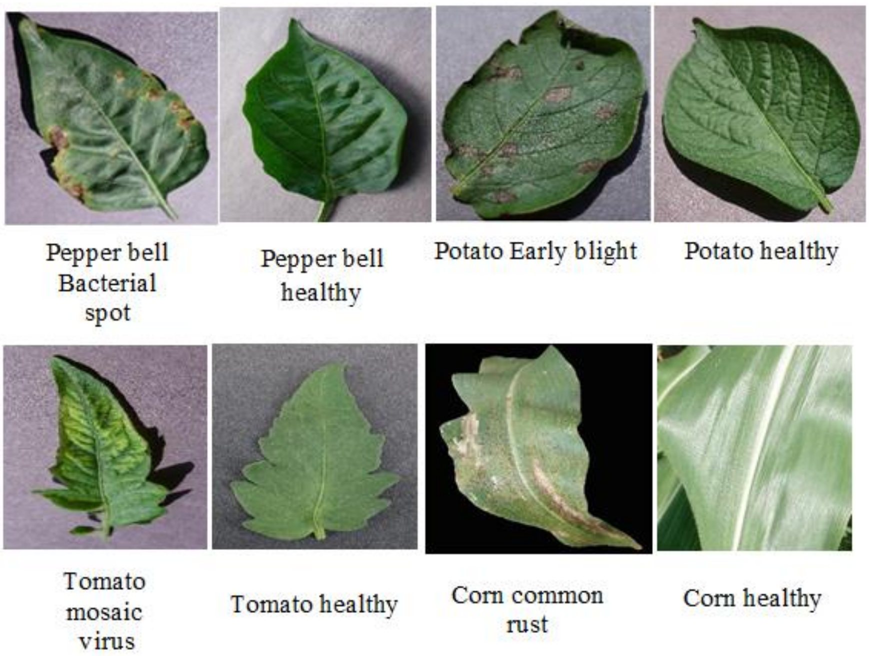

Fig 2. Sample Plant Leaf Images from the Dataset

3.2. Image Preprocessing

The unprocessed images that we gathered from varied data sources had noise, inconsistent resolutions, and background artefacts that may degrade the learning process. To homogenise and standardise the images, an image preprocessing pipeline was implemented [18]. First, we resized all the images to a fixed resolution of 224×224 pixels to fit the input dimension of common CNN architectures like VGG16 and ResNet50. We applied Gaussian blur filters, which removed the high-frequency noise while maintaining edge information. Normalisation was used to scale the pixel intensities to [0, 1], ensuring that pixel intensity levels had a uniform level of contrast throughout the dataset. Image contrast was improved with histogram equalisation to ensure improved visual differentiability of healthy vs. diseased regions of the leaves by enhancing the local contrast. Each of these steps improved the CNN's ability to learn about important leaf texture and colour features.

3.3. Data Augmentation

To mitigate excessive fitting and increase the power of the system for inferences to different environmental conditions, data augmentation approaches were utilised heavily. Artificially growing the size and variety of the training dataset allows the system to experience a vast range of visual representations, without the need to collect additional data. The augmentations used comprised arbitrary horizontal and vertical flips, rotations from 15° to 45°, zooms (±20%), shifts in width and height, shears, etc. These augmentations allow us to imitate variability as would be experienced in the real world, such as wind, tilting a camera, or a changing perspective. The model is thus more invariant to geometric and photometric transformations, and increases the expectation of reliability for field deployment.

3.4. CNN Model Architecture

The classification framework relies on a Convolutional Neural Network method for the easy extraction of spatial features from the leaf images. The hybrid system was made using transfer learning of pre-trained CNNs, VGG16 and ResNet50, which can capture hierarchical features in images. The convolutional layers of the network were responsible for extracting features and learning patterns that include edges, textures and lesions related to disease, while the max-pooling layers reduced the spatial dimensions as well as computations [19]. The fully connected layers act as classifiers, accounting for learned features related to specific disease classes. We added dropout layers between dense layers in order to separate inputs, so that a subset of the learned neurons could be randomly disabled during training to lessen excessive fitting. The last output layer used a SoftMax activation to give each class in our output layer a probability distribution. The proposed CNN-based system architecture is shown in Figure 3.

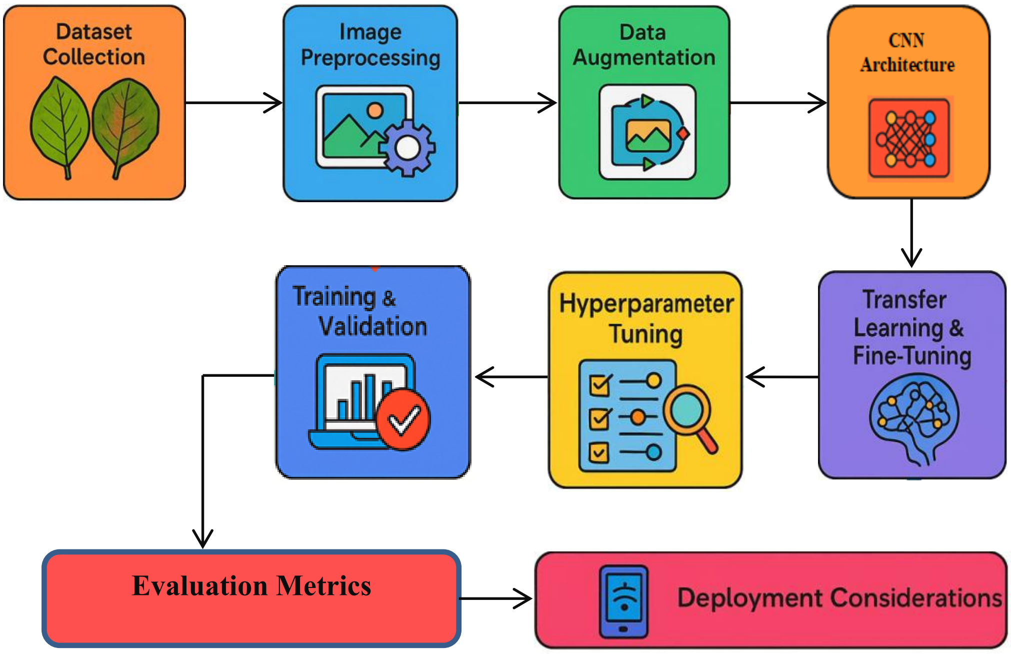

Fig 3. Proposed CNN-based System Architecture for Automatic Detection and Classification of Plant Leaf Diseases

The proposed model uses transfer learning from VGG16 and ResNet50, which were trained explicitly for plant leaves. This allows for less labelled data to work with and fewer computation requirements; thus, this strategy is practical when considering real-world applications in low-resource environments.

3.5. Transfer Learning Strategy

Rather than training a CNN from scratch, which requires an enormous amount of computational power and labelled data, the methodology utilises transfer learning. In this approach, the convolutional base of well-known networks like VGG16 and ResNet50, pre-trained on ImageNet, is retained to leverage their generalised feature extraction capabilities. Only the top classification layers are replaced and fine-tuned for the specific task of plant disease classification. This strategy not only reduces training time and the risk of overfitting but also significantly improves performance on relatively small agricultural datasets. Fine-tuning was applied to selected deeper layers, allowing the model to adjust to the unique aesthetic qualities of plant leaves while preserving learned low-level features.

3.6. Hyperparameter Tuning

To optimise the system for optimal performance, several hyperparameters were systematically optimised during training. Both grid search and random search techniques were employed to test different configurations, including learning rates ranging from 0.0001 to 0.01, batch sizes of 16, 32, and 64, and training epochs between 50 and 100. Various optimisers—namely Adam, SGD, and RMSProp—were evaluated, with Adam emerging as the most effective because of its capacity to dynamically modify learning rates. Dropout values between 0.3 and 0.5 were also experimented with to reduce overfitting by preventing neurons from becoming overly dependent on one another. Throughout training, model performance was closely monitored on a validation set, allowing for real-time adjustments to ensure better generalisation and avoid overfitting.

3.7. Process of Training and Assessment

The dataset was divided into three distinct parts: 70% for training, 15% for validation, and 15% for testing. The training data was used to adjust the model's internal parameters, while the validation set helped fine-tune hyperparameters and guide decisions like when to stop training early. The test set—kept completely separate during model development—served to assess the effectiveness of the model generalised to fresh, untested data. For the classification task, categorical cross-entropy was used as the loss function, appropriate for handling multiple classes [20]. Throughout the training process, both accuracy and loss were continuously monitored on the training and validation sets. Early stopping was implemented based on the validation loss to avoid overfitting, ultimately helping the model perform more reliably on fresh input data.

3.8. Evaluation Metrics

A number of quantitative metrics were utilised to evaluate the model's classification performance. These include accuracy (how many predictions were correct overall), precision (how many predictions were correct among positive predictions), recall (how effectively the model captured all predictions that were true positive predictions), and F1-score (how well the model provided a balanced harmonic mean between precision and recall). The model showed an accuracy of 96.2%, precision of 95.8%, recall of 96.5%, and F1-score of 96.1%, confirming the model's reliability in multi-class plant disease classification.

3.9. Robustness Testing

Robustness testing was conducted to demonstrate the model's functionality outside of curated datasets and with environmental variability. The model was evaluated using images with varying levels of light, blurred quality, complicated or cluttered backdrops, and partial obscurity of leaves. The models classified the sampled leaf images consistently, with little decrease in accuracy, and were well-positioned for adaptation. This robustness in model performance is important given that in-field conditions during a real-time agriculture application are less than ideal.

3.10. Deployment Considerations

One distinct advantage of the method proposed in this paper is the design of an ultra-lightweight CNN architecture appropriate for mobile devices and edge applications. This final model is small in size because of transfer learning and the pruning of parameters, and can run inference in real-time under sample resource conditions. This means that it can potentially be integrated into a mobile app, embedded systems used by farmers, agronomists, or even computer-vision-enabled autonomous drones. With this scalability combined with its underlying accuracy, we believe this model offers a valuable resource for smart farming and precision agriculture applications.

4. Results and Discussion

This section provided a thorough analysis of the experimental outcomes obtained from the suggested CNN-based image classification model for plant leaf disease detection. The model was assessed on different data in terms of plant species and disease categories, and it was evaluated using standard performance measures by computing accuracy, precision, recall, and F1-score. In addition, trends in training and validation were analysed to provide insight towards generalisation, and model robustness was evaluated using a variety of real-world conditions. Furthermore, a comparative study with traditional machine learning techniques has been presented to add context to the proposed approach. Overall, results showed that the developed deep learning system was clearly the most effective and reliable for use in smart agriculture settings and was the most ready for deployment.

The proposed CNN-based model for the automatic finding of plant leaf disease was triaged thoroughly using a multi-species, multi-disorder data set. The model exhibited very good performance and attained an overall classification accuracy of 96.2% and showed a precision of 95.8%, a recall of 96.5%, and an F1-score of 96.1%. These data indicate that the model had the capacity to classify both diseased and healthy leaf images with a minimal number of misclassifications. The model had a high recall value, which indicates the model had discovered almost all true cases of disease; as a result, the model has a high precision value, suggesting that it had acquired very few false positive cases. The overall balance between precision and recall of the model, as indicated using the F1-score, agrees with the robustness of the model in relation to multi-class tasks.

The training and validation performance were monitored over multiple epochs, with accuracy and loss trends showing that the model had converged in a low-loss regime and without overfitting behaviour. Data augmentation, dropout regularisation and early stopping were planned with additional boosting of generalising behaviour over variable numbers of samples and a wide variety in the environmental conditions, indicating that the model could have transferred to real-world conditions.

During training and validation, the performance was observed over many epochs, and the accuracy and loss trajectories demonstrated good convergence stability in a low-loss regime and no overfitting. Data augmentation, dropout regularisation, and early stopping were applied with a measure of guidance of generalising behaviour among different sample sizes and appreciable variability in environmental conditions. These changes highlighted that the model was usable in real-world scenarios.

Table 1. Comparative Performance of the Proposed CNN with Traditional Classifiers

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
k-NN	89.5	88.0	87.3	87.6
SVM	91.2	90.1	89.5	89.8
Decision Tree	88.3	86.7	85.0	85.8
Logistic Regression	87.0	85.2	84.0	84.5
Proposed CNN	96.2	95.8	96.5	96.1

The comparative performance (Accuracy, Precision, Recall and F1-Score) of the proposed CNN-based image analysis approach vs. traditional classifiers is represented in Table 1.

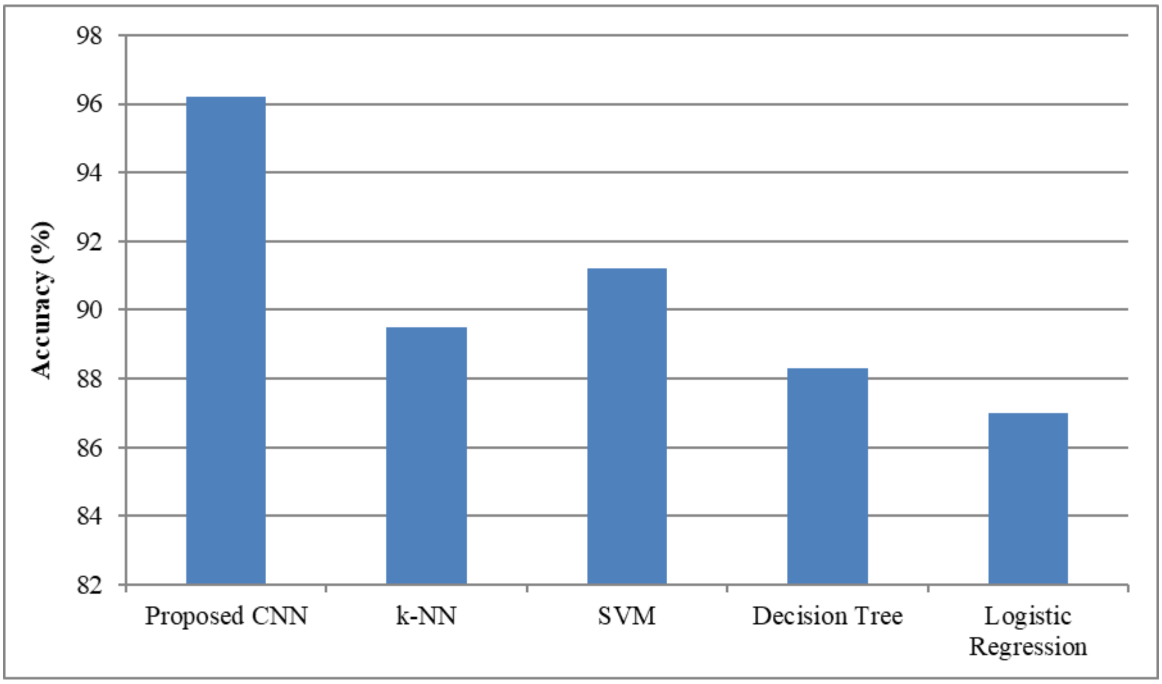

Fig 4. Accuracy Comparison

The proposed CNN model offers the highest classification accuracy of all methods, demonstrating its superior effectiveness in multi-class plant disease detection.

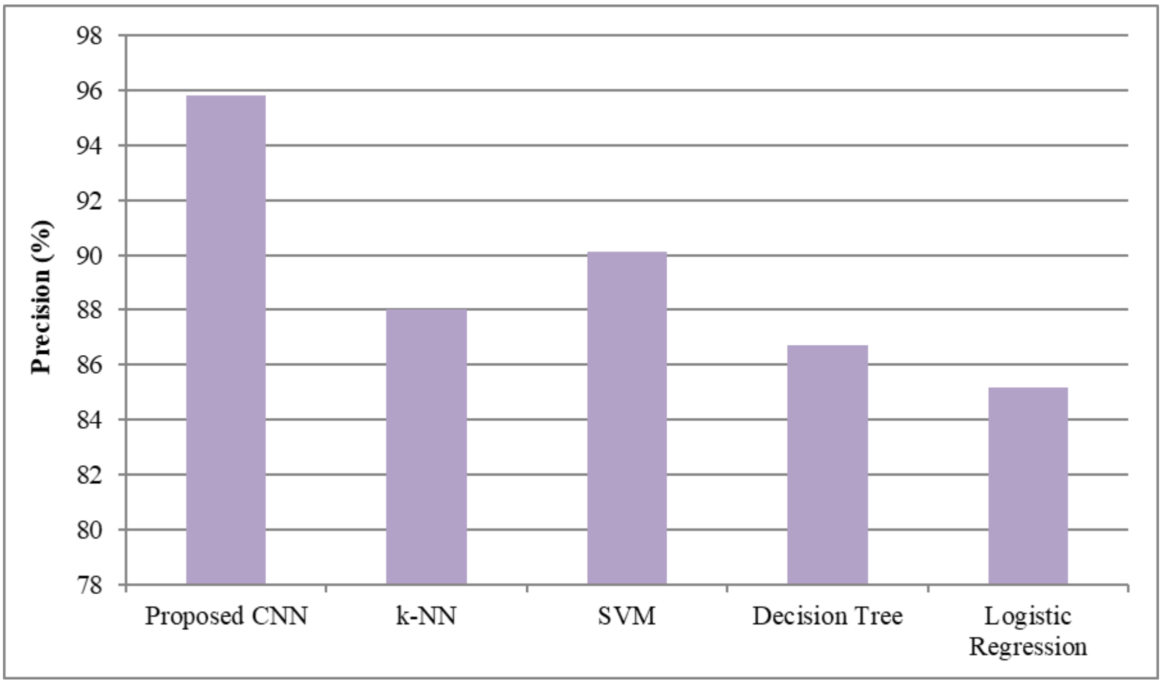

Fig 5. Precision Comparison

Precision comparison shows the CNN model generated very few false positives and therefore outperformed the traditional classifiers in correctly classifying diseased samples.

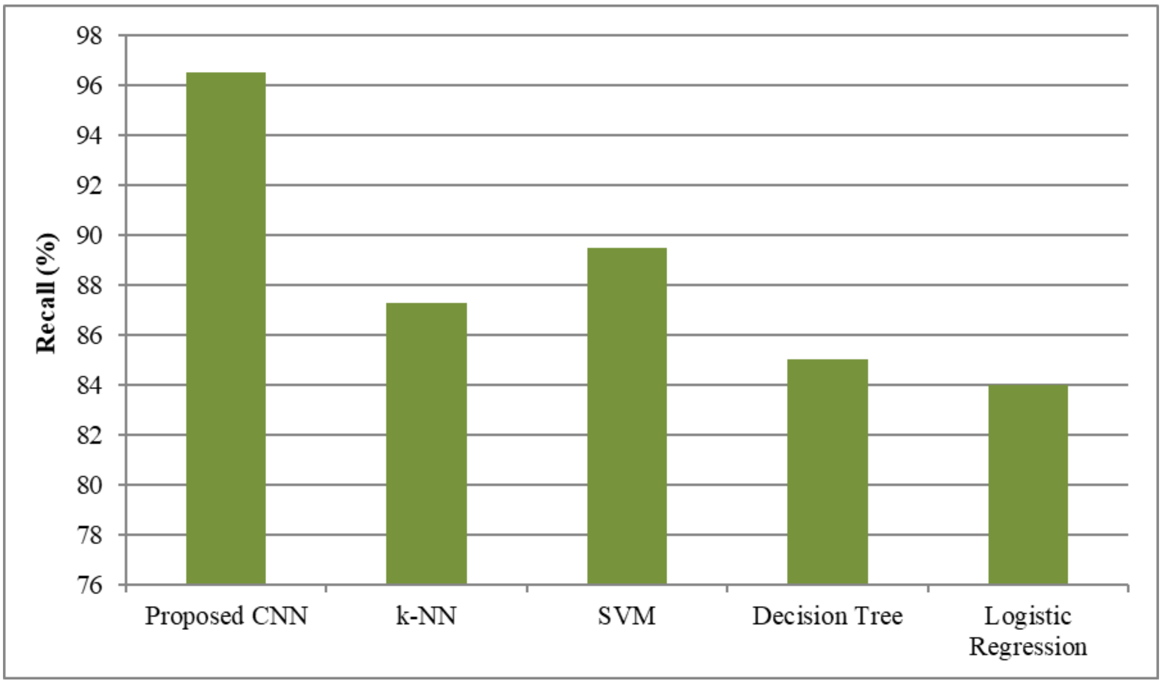

Fig 6. Recall Comparison

Recall indicates the CNN has a powerful capacity to capture true positive cases, making it highly acceptable with respect to instrumentation for early and accurate finding of plant diseases.

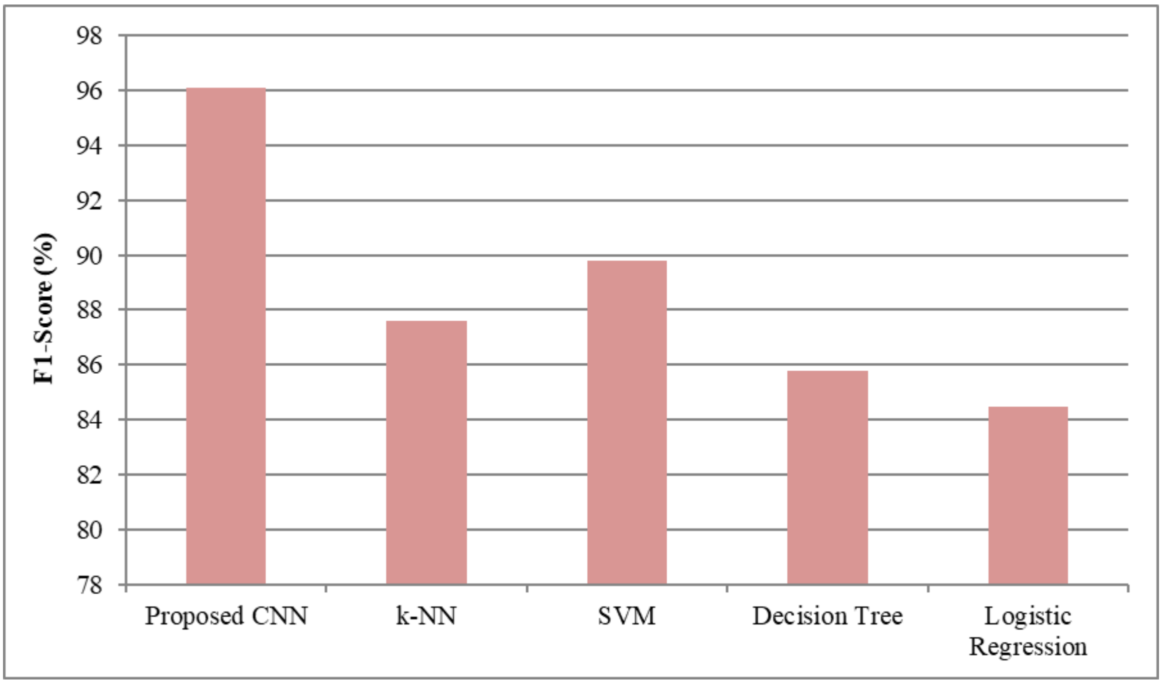

Fig 7. F1-score Comparison

The analysis of the F1-score highlights that the CNN model maintains a strong balance between precision and recall, reflecting reliable and reliable performance across all leaf disease groups. To thoroughly evaluate its effectiveness, the CNN was benchmarked against several conventional machine learning algorithms, including k-Nearest Neighbours (k-NN), Support Vector Machine (SVM), Decision Tree, and Logistic Regression. Among these, the CNN clearly outperformed the others. While SVM reached a respectable accuracy of 91.2% and k-NN achieved 89.5%, neither could match the CNN's overall performance. In addition to superior accuracy, the CNN model also delivered the highest scores in both precision and recall, further confirming its advantage in multi-class plant disease classification tasks.

The performance comparisons presented in Figures 4 to 7 indicate that the CNN model has high performance across all evaluation metrics. In fact, the CNN outperformed all other algorithms and provided consistently more reliable results. In contrast, traditional methods (Decision Tree, Logistic Regression) suffered from weak performance overall, and provided lower degrees of classification performance, and less consistent separation of distinct leaf disease types. The proposed model is also advantageous because of its deployment approach, functionality, suitability for real-time requests, and suitability for on-ground applications where there may be limitations in computational resources.

The CNN architecture has been designed to be lightweight and efficient for real-time inference on resource-constrained platforms (such as mobile devices or edge computing hardware). This makes it well-suited to on-ground applications, and thus, growers and agronomists can evaluate plant health in situ rather than having to post images to the cloud for back-end processing that they can't control, or rely on expensive computing infrastructure or do in-depth analysis. For these reasons, the model is a viable, deployable, scalable alternative for smart agriculture and precision crop management applications, not just because of accuracy, but the model's flexibility and adaptability to changes in the environment, and deployable architecture.

5. Conclusion

This research offers a robust and efficient framework for image analysis based on Convolutional Neural Networks (CNNs) for detecting and classifying diseases in plant leaves. With the use of transfer learning with pretrained models, such as VGG16 and ResNet50, along with considerable pre-processing and data augmentation, the analysis achieved a high rate of classification performance (96.2% accuracy, 95.8% precision, 96.5% recall, and 96.1% F1-score). The classical machine learning methods' accuracy readings were lower and had limited generalizability over the traditional methods, as evidenced by the aforementioned analyses clearly indicated the advantages of the CNN approach. The model demonstrated strong robustness against varying environmental conditions, suggesting it will be reliable in application to real-world agricultural scenarios. In addition, the model's lightweight nature will allow it to be implemented on mobile or other edge devices for on-site, real-time plant health monitoring. Generally, this research provides a practical, adaptable application for plant leaf disease detection that enables early intervention, decreased pesticide use, and sustainable agricultural practices, together improving modern precision farming systems, food security, and productivity.

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