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Integrating Local Texture Capturing Mechanisms With Convolutional Neural Networks For Enhanced Multi-Class Classification of Plant Leaf Diseases

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ABSTRACT

Plant diseases significantly affect agricultural productivity by reducing both the quality and quantity of crops. The necessity for automated image-based solutions stems from the labor-intensive and subjectively error-prone nature of traditional inspection methods performed by farmers or agricultural specialists. To maintain sustainable agriculture and prevent the spread of infections, the detection of plant leaf diseases should be performed early and accurately. Early identification of infections can also significantly reduce yield losses and minimize the excessive use of pesticides. Since leaf diseases frequently manifest as uneven texture patterns, spots, or distortions on the leaf surface, local texture capturing mechanisms have proven to be remarkably effective among many computational approaches. This study proposes a novel Deep Convolutional Neural Network (DCNN) to extract high-level hidden feature representations from leaf images. To enhance performance, the deep features are combined with traditional handcrafted texture features known as the Uniform Local Binary Pattern (uLBP). The proposed model was trained and tested using three well-known publicly available datasets: Apple Leaf, Tomato Leaf, and Grape Leaf. The model achieved test accuracies of 96%, 91%, and 96% on these datasets, respectively. The experimental results demonstrate that the proposed approach is an effective and practical method for early diagnosis of plant diseases.

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This system has potential for real-world application by farmers and agricultural experts to support disease management and contribute to the development of more resilient crops and a sustainable agricultural industry.
Keywords: Multi-Class Classification; Convolutional Neural Network (CNN); Uniform Local Binary Pattern (uLBP); Feature Fusion

1. Introduction

As a result, plant diseases pose a serious risk to agricultural output rates throughout the world, which in turn causes serious economic losses and food shortages. Traditionally, the identification and classification of such diseases have relied on the human evaluation of agricultural professionals, a method that, besides being time-consuming and expensive, happens to be unreliable and subjective [1]. Advancements in computer vision, deep learning, and artificial intelligence (AI) have revolutionized precision agriculture. Thanks to these advancements in technology, automated analysis of plant leaf pictures has made disease diagnosis more efficient and precise [2].

Machine learning techniques like K-Nearest Neighbor (K-NN), Decision Tree, and Support Vector Machine (SVM) were the only tools used in the early days of this discipline, when human-created characteristics like color, texture, and form were also used [3,4]. Although such traditional models are interpretable, they are constrained by challenges such as the imbalance in classes, prone to overfitting, and inferior performance in noisy and complicated scenarios in the field [5,6]. Convolutional neural networks (CNN) have swept the image-based disease recognition, where architectures such as VGGNet, ResNet, and MobileNet exhibited good results on learning benchmarks such as PlantVillage and PlantDoc [7,8]. The use of the CNN by researchers has been effective in diagnosing crops such as rice [3], coffee [4], tomato [9], and mulberry [10], with accuracy showing more than 97%. Additionally, cutting-edge augmentation strategies like Dual Generative Adversarial Network (DoubleGAN) and contemporary transfer learning methodologies have been utilized to improve the versatility of the model to out-of-class imbalanced datasets [11]. DoubleGAN is an architecture that uses two GANs to improve data generation quality.

In further endeavour to increase the accuracy of detection and decrease computational load, the present effort is the incorporation of deep learning in conjunction with handcrafted feature methods as a hybrid or ensemble algorithm. As an example, the results of using the combination of deep CNN-based representations and texture-based descriptors such as Local Binary Patterns (LBP) have shown benefit [12]. Hosny [12] presented a significant case that combines the features of LBP with DCNN, which, as a result, enhances the recognition of disease in tomato, apple, and grape leaves. Moreover, explainable AI (XAI) is on the rise, and this kind of method gives models a good classification accuracy as well as transparency and interpretability of the decisions made [13]. There is also a tendency to put systems of disease detection on edge devices and use real-time inference with the help of smartphones and IoT applications [6,10,14]. Trained lightweight YOLO models [1], deep learning ensembles [15], and EfficientNet with Transformer mechanisms [16] make it possible to identify the disease more effectively and efficiently in dynamic agricultural conditions.

Crop-specific and disease-specific modeling is also becoming emphasized, as exemplified in the study on wheat yellow rust [2] and the more accurate disease in wheat stratification with augmentation [17]. The formulation of real-field data like FieldPlant [18] supports this, as it negates the shortcomings of utilizing synthetic image repositories. In the future, there is also the likelihood of increasing prediction accuracy through the use of multimodal and sensor-fusion methods. Contextual sensitivity and increased forecasting are attained, as demonstrated in studies Nagasubramanian [19] and Saini [20], by incorporating image data with environmental sensor information. Further, the bibliometric analysis has revealed an increase in the academic work in the area, significantly indicating that India is in the sphere of plant disease detection research with the use of deep learning[21]. Forwarding this wave, the presented project offers an idea of a hybrid deep learning model with a combination of CNN-based learning and handcrafted features of LBP to make disease detection in diverse plant species effective, efficient, and scalable. The solution is introducing bias in real-time applications and low computational overhead to be used more extensively in practical agricultural situations.

A feature fusion framework is proposed that integrates the deep spatial feature extraction capability of Convolutional Neural Networks (CNN) with the local texture analysis strength of Uniform Local Binary Patterns (uLBP). Unlike previous approaches that rely solely on deep learning or handcrafted features, the proposed method leverages the complementary nature of both to improve classification performance across diverse crop leaf datasets. The model is designed for multi-class plant disease detection, with potential application in agriculture-based decision support systems, including mobile and edge-based real-time disease identification tools for farmers. This integration of CNN and uLBP aims to achieve higher accuracy, robustness to variations in lighting and texture, and adaptability across multiple crop species.

2. Related Work

In recent development in plant disease identification, there has been a convergence of deep learning-based systems, sensor fusion, and hybrid modelling. The developments are not only accurate, but they are also showing good generalization because of the variations in the environmental conditions and crop types. The mentioned studies have formed a solid backbone in our suggested DCNN-LBP hybrid architecture. The literature in that context can be divided into four themes: optimization-based models, attention and ensemble-based, sensor-fusion and multimodal, and explainable and efficient frameworks. With the help of this classification, one can have a clear vision of the changing research trends and their corresponding repercussions on precision agriculture.

As far as the optimization is concerned, a number of scholars have used sophisticated algorithms to optimize their feature extraction and learn better. Bharanidharan[22] employed the feature selection using a Modified Lemur Optimization Algorithm that exhibited a significant increase in the precision of the K-NN classifier regarding the recognition of paddy disease. Zhao[11] tackled data imbalance by implementing DoubleGAN, generating realistic synthetic diseased leaf images that resulted in recognition accuracy exceeding 99%. Kumar[6] designed a machine learning pipeline integrating soil-sensor data with exploratory data analysis, achieving more than 98% prediction accuracy, showcasing the power of non-visual data in disease diagnosis. Additionally, Shovon[23] introduced an ensemble framework, PlantDet, combining EfficientNetV2L, Inception, ResNetV2, and Xception. The model avoids overfitting and achieves an impressive 98.53% accuracy in rice leaf classification by using deep optimization techniques.

Increasing the dependability and robustness of models has never been easier than with the help of attention mechanisms and ensemble approaches. To show how useful preprocessing is in real-world scenarios, Alarfaj[24] used UNet for preprocessing with InceptionV3 to categorize disorders affecting pepper leaves. Luo[25] improved the YOLOv8 architecture by embedding Boundary Refinement Attention (BRA) self-attention modules, leading to a 2.8% precision gain and a 20.7% reduction in computational cost. BRA self-attention is a technique for enhancing feature boundaries in image classification. Rashid[26] presented MMF-Net, a multi-contextual CNN architecture combining visual and environmental data streams, which resulted in an impressive 99.23% accuracy for corn disease detection. Tasfi[27] provided a comprehensive review of paddy disease detection approaches, reinforcing the importance of integrating attention layers and ensemble learning techniques for improved generalization across varying disease manifestations.

Sensor-fusion and IoT-driven strategies are increasingly contributing to the development of intelligent, real-time plant disease monitoring systems. Saini[20] introduced Attention-based Multi-Input Multi-Output Neural Network (A-MIMONN), an attention-based model that ingests multi-sensor environmental inputs and achieved a 97% F1 score, underlining the synergy between deep learning and environmental sensing. A-MIMONN, a network handling multiple input-output relationships. Liu[28] predicted blister blight in tea crops using an IoT framework coupled with Multiple Linear Regression, reaching 91% accuracy and demonstrating the utility of statistical methods when integrated with smart farming tools. Patil and Kumar[29] proposed Rice-Fusion, a multimodal model that combines CNN-extracted image features with meteorological sensor inputs, outperforming conventional CNN and MLP baselines. These works are supported by Chaki and Ghosh[21], whose bibliometric analysis underscores the exponential growth of IoT and multimodal research in agricultural technology.

Another notable trend is the emphasis on explainable and efficient architectures for practical deployment. Oad[30] employed an ensemble of deep-learning models enhanced with Local Interpretable Model-agnostic Explanations (LIME) based visual explanations, enabling end-users and agronomists to interpret the specific features used for disease classification. LIME, a method for interpreting model predictions. While keeping computational economy in mind, Vishnoi[14] achieved 98% accuracy in diagnosing apple leaf diseases using a lightweight CNN architecture that was enhanced with data augmentation methods, including flipping, shearing, and scaling. These contributions are pivotal in translating AI research into user-friendly, interpretable solutions for real-world applications, especially in resource-constrained environments.

Diagnostics for plant diseases are evolving in response to the need for portable and scalable treatments. With a 96.4% success rate, Salam[10] built an Android-specific real-time detection system using MobileNetV3Small to diagnose mulberry illnesses, providing farmers with a useful tool. Amin[31] integrated DenseNet121 and EfficientNetB0 for corn leaf classification, optimizing both accuracy (98.56%) and computational cost, making them ideal for mobile or edge deployment. Furthermore, Khattak[32] designed a CNN-based model for citrus leaf and fruit disease detection using datasets from PlantVillage and citrus-specific sources. The model achieved 94.55% accuracy and demonstrated promising generalization capabilities across related crop types, reinforcing its adaptability. A deep learning method for automatically estimating the severity of plant diseases using leaf photos was presented by Wang[33]. Convolutional neural networks are used in the technique to extract information and accurately categorize infection levels. Their findings show that deep learning offers a scalable, effective, and impartial method for determining the severity of plant diseases.

In summary, the convergence of optimization techniques, attention-driven modeling, sensor-integrated systems, and explainable lightweight frameworks is revolutionizing plant disease detection. These advancements not only elevate classification accuracy but also pave the way for real-time, scalable, and user-friendly applications. Taken as a whole, they provide the groundwork for our proposed DCNN-LBP hybrid model, which aims to improve multi-class plant disease classification by combining the advantages of neural architectures with local texture analysis.

3. Materials and Proposed Methodology

3.1. Dataset

Using three datasets obtained from the famous PlantVillage repository—which can be accessed via platforms like Kaggle—the suggested approach for plant leaf disease classification is based. Developed by researchers at Pennsylvania State University, the PlantVillage project aims to support precision agriculture and provide accessible solutions for identifying crop diseases, especially in resource-constrained regions. With over 54,000 high-quality photos of plant leaves, the collection includes healthy samples, photographs of 14 crop species, and images of over 26 distinct illnesses. There are a lot of different crops that are covered, such as strawberries, grapes, potatoes, maize, cherries, peaches, peppers, and more. Supervised learning tasks in computer vision and deep learning are well-suited to these images since they include the plant species, illness kind (if present), and health state.

There are 3,171 raw photos in the Apple Leaf

Dataset, the first dataset. A total of 630 pictures are labeled as Scab, 621 as Black Rot, 275 as Cedar Rust, and 1,645 as Healthy in this dataset. One example from each class is shown in **Figure 1**. Geometric data augmentation methods, including translation, flipping, scaling, and rotation, were used due to the dataset's apparent class imbalance. These operations increased the dataset to 4,645 images while preserving the biological integrity.

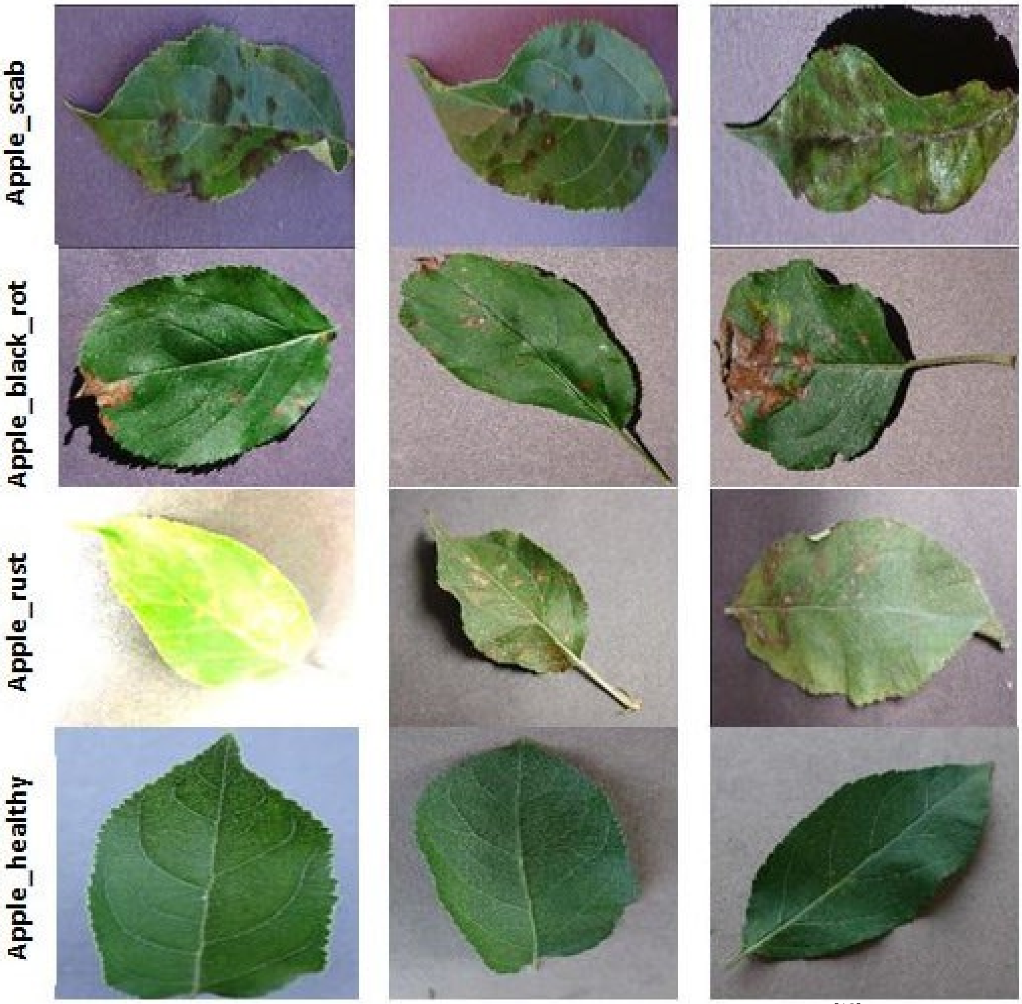


Figure 1. Sample images from the apple leaf dataset for each class [12].

The Tomato Leaf Dataset, which contains 18,160 raw pictures, is the second dataset that is used. **Figure 2** shows a single example from each category. Bacterial spot, early blight, late blight, and yellow leaf curl virus are among the illnesses and healthy leaf samples included in its 10 categories. It is appropriate for multi-class classification jobs since each class has a large and evenly distributed number of pictures.

Furthermore, 4,062 pre-augmentation photos from the Grape Leaf Dataset were also used. Deadly Measles, Esca (Black Rot), Leaf Blight, and Healthy are the four categories into which the data is categorized. **Figure 3** illustrates one representative sample from each class. Similar to the Apple dataset, data augmentation was applied to expand it to 4,639 images, ensuring improved generalization and addressing class imbalance. All datasets were divided into training, validation, and testing subsets following an 80–20 training-validation split, ensuring a fair evaluation of the model's performance.

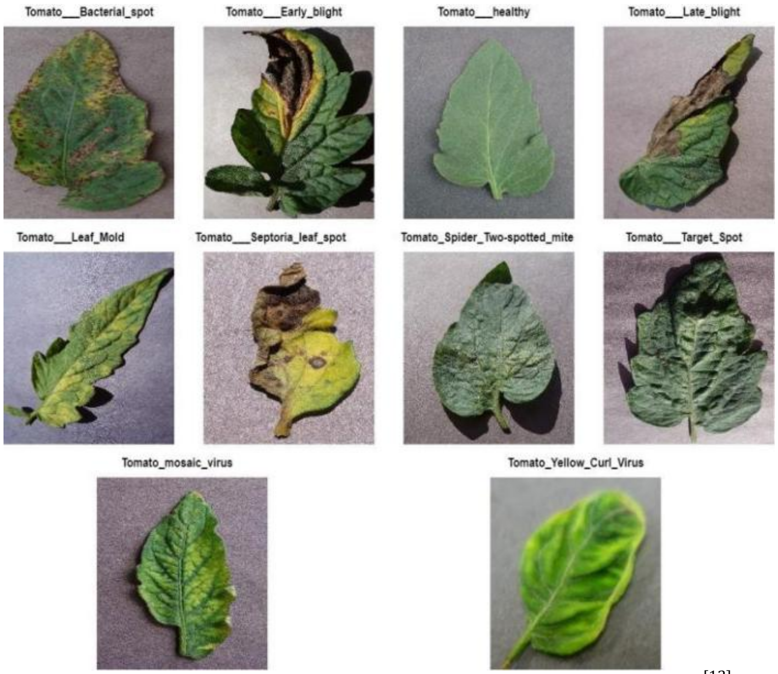


Figure 2. Image samples for each class in the tomato leaf dataset [12].

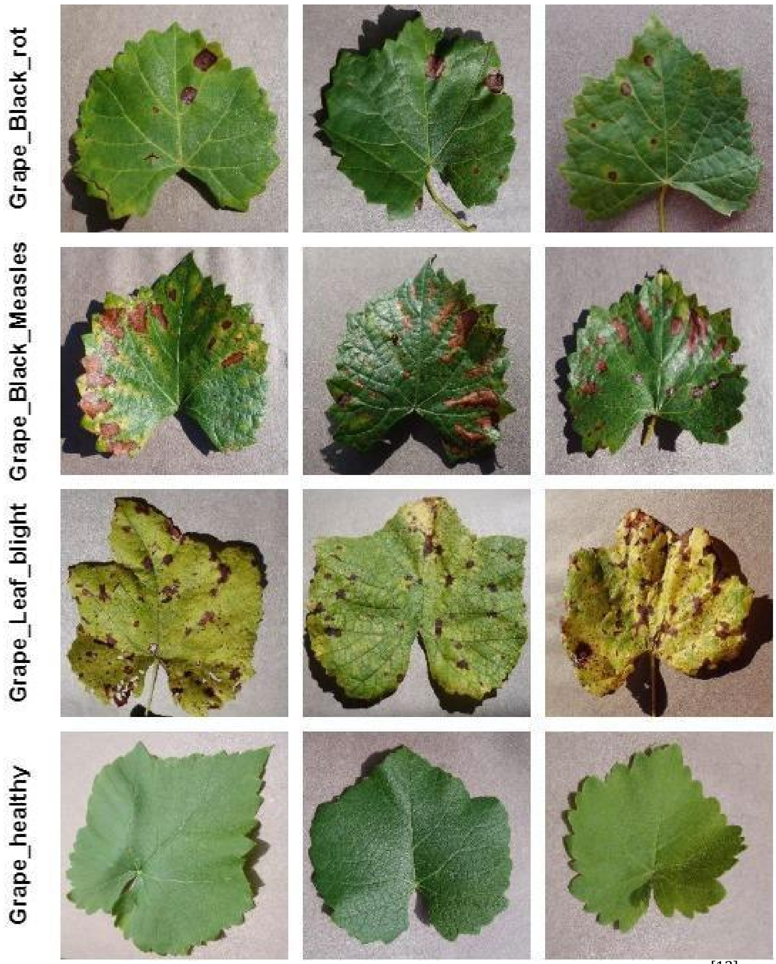


Figure 3. Sample images from the grape leaf dataset for each class [12].

Table 1 depicts the total images present in the dataset, number of classes for each species (Apple, Tomato, Grape) and whether augumentation is needed for the proposed architecture or not.

Table 1. Dataset Overview for Plant Leaf Disease Classification.

Dataset	Total Images	Classes	Augmentation Used?
Apple Leaf	3,171	4	Yes
Tomato Leaf	18,160	10	No
Grape Leaf	4,062	4	Yes

3.2. The Proposed Architecture

A new architecture for plant disease classification has been developed, which combines deep characteristics with uLBP traits. Extraction of features, fusion of those features, and classification are the three primary steps it employs. **Figure 4** displays the process of using a deep convolutional neural network (CNN) to extract deep features from images of plant leaves. Subsequently, uLBP is used to get accurate data on the local texture. The CNN's flatten layer is responsible for immediately concatenating the feature sets, creating a single, unique representation of the features. Once this fused feature vector has been passed through a fully connected layer, classification is performed using the softmax activation function. By using both deep and handcrafted uLBP characteristics, the model enhances its discriminative ability in detecting plant diseases. This hybrid approach improves classification performance while ensuring computational efficiency and practical feasibility. The fusion of CNN and uLBP features allows the model to capture both global spatial information and local texture patterns, making it well-suited for real-time diagnosis in resource-limited agricultural environments.

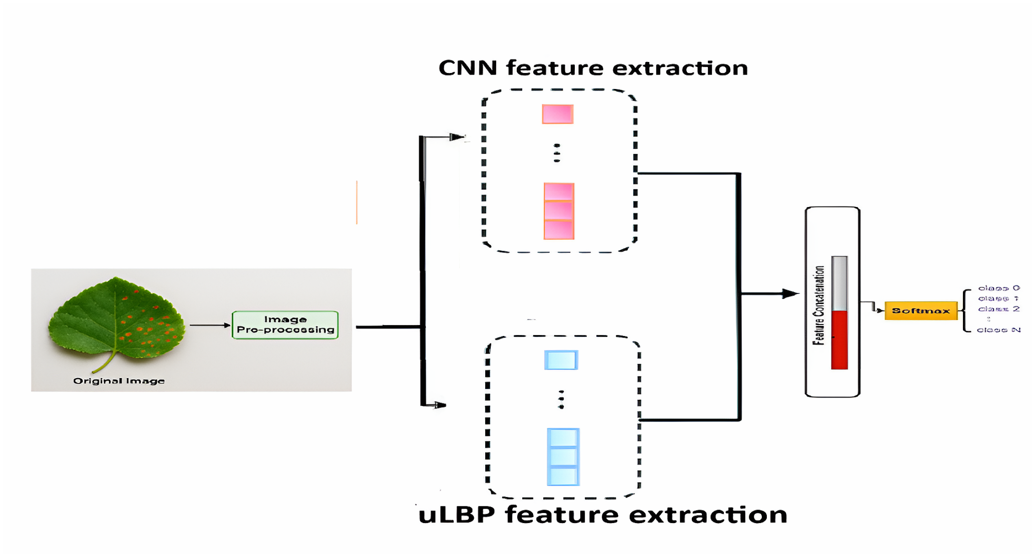


Figure 4. The proposed architecture for plant leaf disease classification (CNN + uLBP).

3.2.1. The Deep CNN Architecture

The suggested architecture of a Deep Convolutional Neural Network (CNN) is designed to efficiently identify plant leaf diseases without requiring human intervention for feature extraction. That it can learn and recognize patterns in raw photographs automatically is a major plus. The leaf photos are first subjected to several pre-processing procedures, including sharpening, image filtering, and scaling to a consistent 64 × 64 pixel size, before they are input into the model. The design has three max-pooling layers for feature reduction, convolutional layers for feature extraction, and dense layers for feature interpretation and performance.

The model uses convolutional layers, which are auto-feature detectors. There are 32 filters in the first layer and subsequent layers with an increasing number of filters in the intermediate layers until the last convolutional layer, in which there are 128 filters.

There exist max-pooling layers between every two layers of the convolutional variety, and their purpose is to reduce the feature maps' spatial dimension, which will lower the quantity of operations that have to be performed by the model and focus it on the most significant parts of its images.

Following feature extraction, the feature maps are transferred to the dense layers after being compressed to a one-dimensional vector. With the aid of ReLU, these thick layers are activated, allowing the model to learn more complex patterns by introducing nonlinearity. Dropout layers are employed to enhance generalization capabilities of the model as well as avoid overfitting. These layers temporarily turn off a small portion of the neurons when training is set, and this causes the model to memorize features that are stronger and they function well on unseen data.

Finally, a softmax layer is used to perform the classification, and this layer returns a probability score for each category and assigns the image to the one with the highest score. The model is framed in such a way that it detects images of plant leaves, taking them to have various categories, and contains four data sets of apple, grape, and tomato, each containing one class per set and ten classes per set, respectively. The proposed CNN network is quite accurate and efficient with an appropriate arrangement of convolutional filters, pooling, dropout, and dense layers. It is a very capable plant disease detection system in agriculture.

3.2.2. Uniform Local Binary Pattern

Uniform Local Binary Pattern (uLBP) is an improvement of the well-known Local Binary Pattern (LBP) method and is considered by most to be a more effective texture descriptor, particularly in image classification and recognition applications. The disadvantage of the simple LBP technique led to ULBP, which considers patterns of more significance regarding texture representation. Using this method, a pattern will be deemed to be uniform in case it has not more than two transitions (either between one and zero, or the opposite transition) in the binary sequence, and the pattern is taken to be circular. As an example, the pattern of 00000000 or 11100000 is uniform; the pattern of 10101010 is non-uniform.

The rationale of employing ULBP is to choose uniform patterns as the texture features in natural photos make up an immense majority. Encoding only these patterns, one will be able to considerably decrease the dimensionality of the feature vectors, but preserve the most discriminative patterns.

Given the problem of plant leaf disease classification, by deploying ULBP, the model is further able to highlight key changes in the texture of disease leaves, e.g., spots, wrinkles, or lesions, etc., and thus enhance the performance of the classification.

In the analysis of the ULBP feature, a fixed-sized window (normally, 3 × 3), the pixel in the grayscale picture is compared with those of its neighbors. When the pattern surrounding a pixel satisfies the uniformity criterion, then it is given a distinctive label that corresponds to that particular pattern. Irregular patterns classification is merged into one to simplify the calculation. The end product of this is a ULBP image with the most applicable large texture characteristics of the original textured leaf image, which facilitates the learning of the disease-related pattern in the convolutional neural network with ease.

4. Results and Discussion

In order to implement the proposed method, the TensorFlow and Keras frameworks were used. Every experiment was carried out in a Jupyter Notebook environment, which offered a dynamic and adaptable platform for building, training, and evaluating models.

During training, the hyperparameters were standardized to guarantee uniformity in all experiments. Learning, validation, and testing were the three segments of the dataset. The experimental configurations were established with the following parameters: batch size = 32, learning rate = 0.001, and number of epochs = 15. In addition, a mechanism was put in place during training to halt training early if there was no further increase in validation performance, which helped avoid overfitting.

A number of conventional performance measures were calculated to assess the accuracy and efficacy of the suggested approach, including Accuracy, Precision, Recall, F1-score, Area Under the Receiver Operating Characteristic (AUC-ROC) curve, and the Confusion Matrix [34]. Here are the definitions of these metrics:

$$Accuracy = \frac{tp + tn}{tp + fp + fn + tn} \tag{1}$$

$$precision = \frac{tp}{tp + fp} \tag{2}$$

$$recall = \frac{tp}{tp + fn} \tag{3}$$

$$F1score = \frac{2tp}{2tp + fp + fn} \tag{4}$$

Where *tp*, *tn*, *fp*, and *fn*, represent true positive, true negative, false positive, and false negative, respectively.

The proposed CNN model is compared to popular transfer learning techniques for illness categorization in apple leaves in **Table 2**. The proposed model achieved the best results compared to the others, with a robust accuracy of 96.0% and precise, recall, and F1-score of 97.0%. Using the same accuracy and an F1-score of 96.4%, VGG16 came in second. With an F1-score of 91.0%, AlexNet underperformed relative to other models, whereas GoogleNet achieved an F1-score of 95.0%. All measures showed that the suggested CNN model was more consistent.

Table 2. Comparison of the proposed deep CNN model and the transfer learning-based models for apple leaf disease classification.

Model	Precision	Recall	F1-Score	Accuracy
Proposed CNN Model	97.0%	97.0%	97.0%	96.0%
VGG16 [12]	96.7%	96.5%	96.4%	96.0%
GoogleNet [12]	95.0%	95.0%	95.0%	94.0%
AlexNet [12]	91.0%	91.0%	91.0%	92.0%

In **Table 3**, we can see how the suggested CNN model stacks up against VGG16, GoogleNet, and AlexNet in terms of illness categorization in tomato leaves. Although the suggested model had respectable results (90.0% F1-score and 91.0% accuracy), the transfer learning models fared better. Both VGG16 and GoogleNet performed better than the others, with 95.0% and 94.0% F1-scores, respectively. Notably, with a score of 94.8%, GoogleNet achieved the best accuracy. It seems that transfer learning models performed better in this instance when it came to detecting diseases in tomato leaves.

Table 3. Comparison of the proposed deep CNN model and the transfer learning-based models for tomato leaf disease classification.

Model	Precision	Recall	F1-Score	Accuracy
Proposed CNN Model	90.0%	91.0%	90.0%	91.0%
VGG16 [12]	95.0%	95.0%	95.0%	94.0%
GoogleNet [12]	94.0%	94.0%	94.0%	94.8%
AlexNet [12]	91.0%	91.0%	91.0%	91.0%

Various models' results for disease categorization in grape leaves are shown in **Table 4**. With a 96.0% accuracy rate and an F1-score of 97.0%, the suggested CNN model somewhat beat the competition. With recall and accuracy both reaching 96.0%, all models were able to consistently recognize the target. While AlexNet's accuracy was 95.5 %, VGG16's was 95.0 %, and GoogleNet's was 95.6 %. This exemplifies the suggested model's marginal advantage in terms of overall efficacy for grape leaf disease categorization.

After proving that the suggested CNN model successfully recovered pertinent features from images of plant leaf diseases, we further validated the feature fusion framework's performance. Three separate datasets—Apple Leaf, Tomato Leaf, and Grape Leaf—were used for the assessment. **Figures 5–7** show the comparable findings for the Apple, Tomato, and Grape leaf datasets, respectively.

Table 4. Comparison of the proposed deep CNN model and the transfer learning-based models for grape leaf disease classification.

Model	Precision	Recall	F1-Score	Accuracy
Proposed CNN model	97.0%	97.0%	97.0%	96.0%
VGG16 [12]	96.7%	96.5%	96.4%	96.0%
GoogleNet [12]	95.0%	95.0%	95.0%	94.0%
AlexNet [12]	91.0%	91.0%	91.0%	92.0%

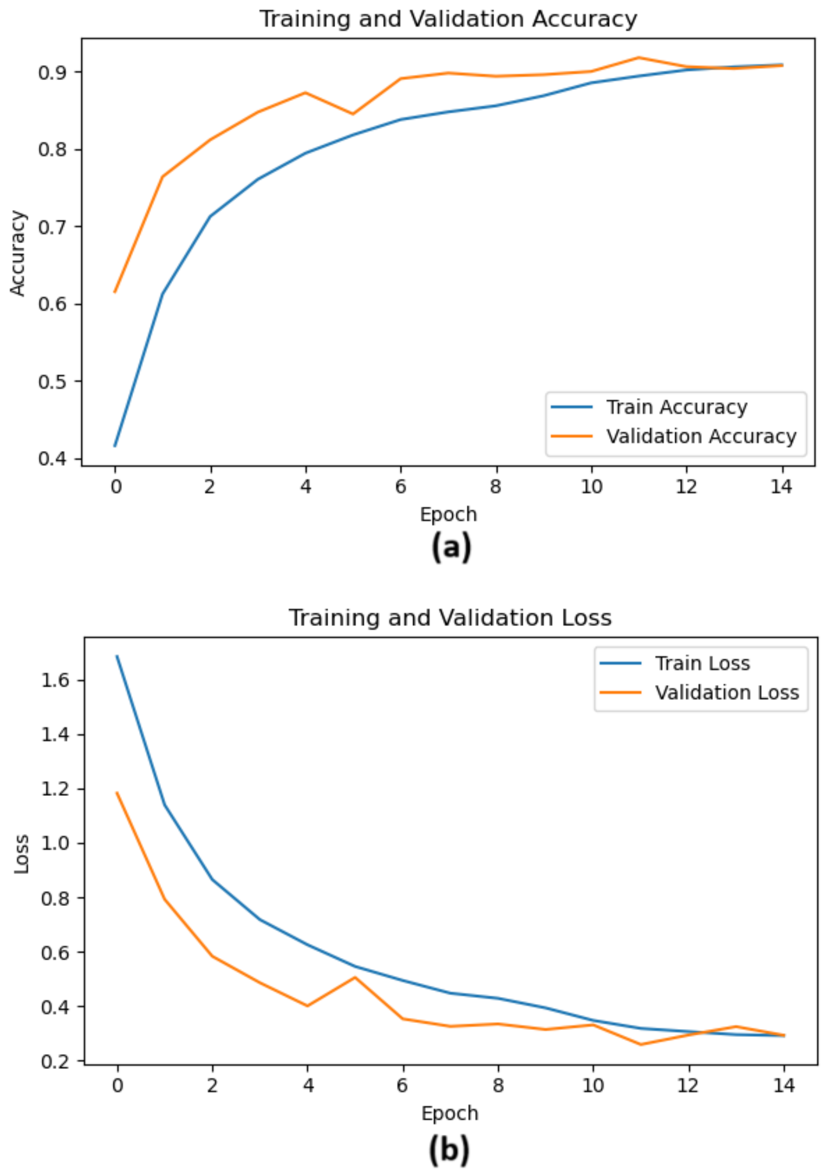


Figure 5. Training and validation results of the CNN + uLBP model on the Apple dataset: (**a**) Accuracy, (**b**) Loss.

When trained and evaluated on the Apple Leaf dataset, the model demonstrated consistent improvements in accuracy and loss across fifteen epochs. The training accuracy increased significantly, from 52% to more than 94%, as shown in **Figure 5a** and in validation accuracy, going from about 52% to over 94%, and finally reaching about 95%, all of which point to strong generalization performance. Effective learning with little overfitting was shown by the steady reduction of the training losses from 1.1 to below 0.8, and the validation losses decreased from 0.8 to below 0.2, respectively **Figure 5b**. Based on these findings, the model demonstrates that it is successfully learning from the Apple leaf dataset without experiencing overfitting.

The model's classification performance increased gradually throughout the course of its 15 training epochs on the Tomato Leaf dataset. Training and validation accuracies increased to above 90%, demonstrating strong model generalization. As expected, there was a considerable improvement in the loss curves; specifically, the validation loss fell from 1.1 to around 0.35, and the training loss fell from 1.6 to about 0.3.

Figure 6 demonstrates that the model was able to acquire critical features without experiencing overfitting, as shown by the learning curves. When tested on the Grape Leaf dataset, the model's accuracy in training and validation rose steadily, eventually surpassing 95% in the last epoch. Effective learning and low overfitting were shown by the steady reduction of training and validation losses, which went from 1.2 and 0.8 to around 0.1, respectively.

Figure 7 displays the findings, which validate the model's stability and high performance throughout training and validation. The findings show that compared to models using individual features, the proposed feature fusion method—which combines deep CNN and uLBP features—performs much better. Different plant leaf diseases may be easily distinguished using it.

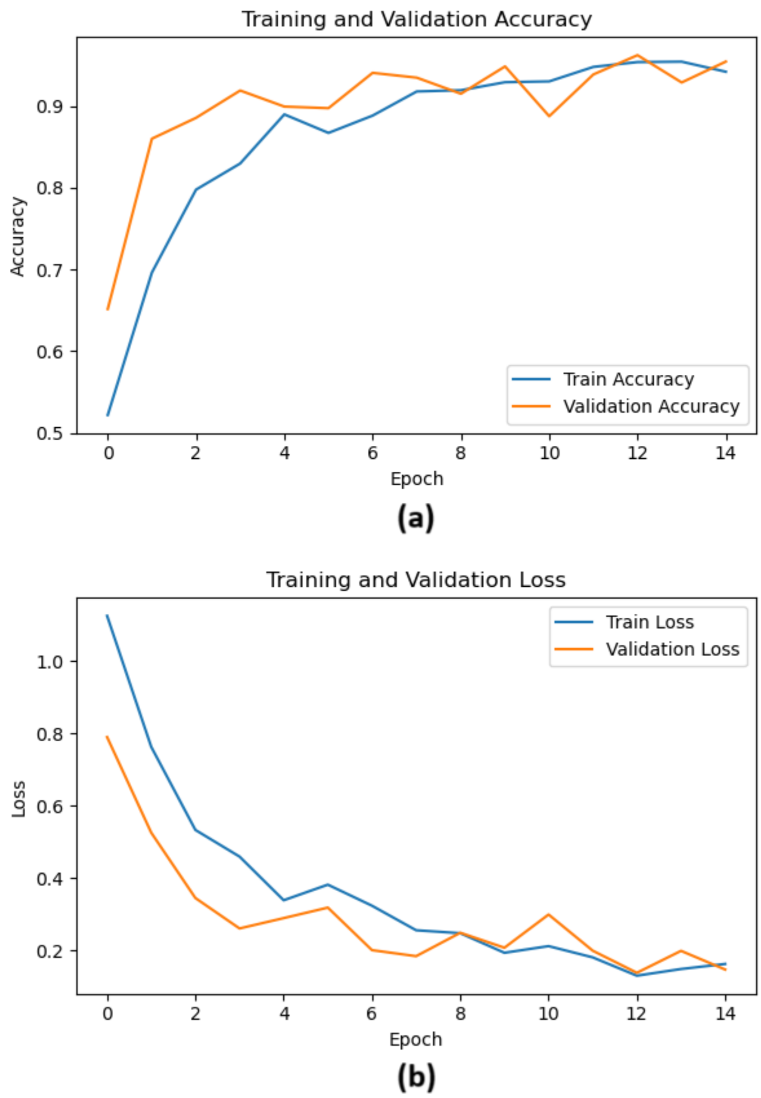
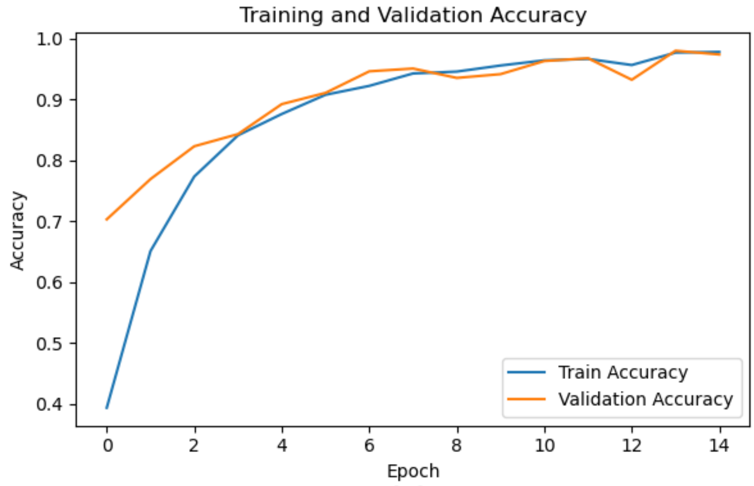
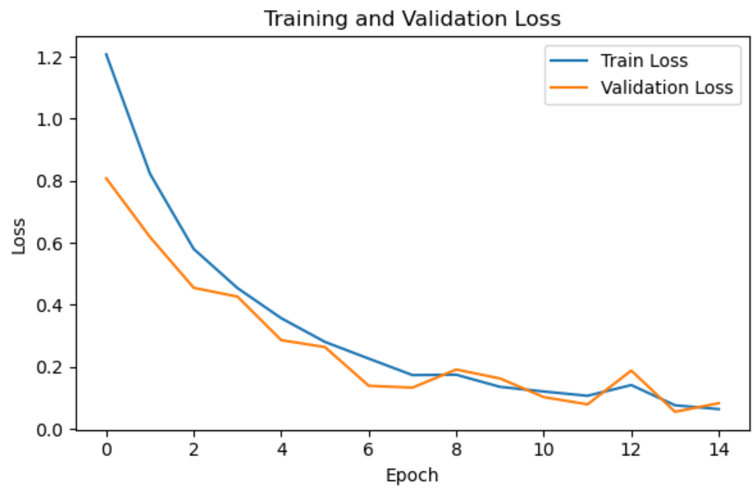


Figure 6. Training and validation results of the CNN + uLBP model on the Tomato dataset: (**a**) Accuracy, (**b**) Loss.



(a)



(b)

Figure 7. Training and validation results of the CNN + uLBP model on the Grape dataset: (**a**) Accuracy, (**b**) Loss.

The findings show that compared to models using individual features, the proposed feature fusion method—which combines deep CNN and uLBP features—performs much better. Different plant leaf diseases may be easily distinguished using it.

Figures 8–10 show the confusion matrices for each of the three datasets.

The model's accuracy in classifying the Apple Leaf dataset is shown by the confusion matrix, which demonstrates high performance across all four categories. A small number of samples were misclassified as Apple scab, Black rot, Cedar apple rust, or healthy leaves, but the vast majority were accurately classified. **Figure 8** shows that out of 301 samples, the "Apple_healthy" class had the greatest number of true predictions at 282, proving the model's ability to differentiate between healthy and sick leaves.

The model's ability to classify tomato leaves into 10 distinct illness groups, as well as healthy leaves, is shown by the confusion matrix. Nearly all classes exhibit near-perfect categorization; for example, Tomato_Healthy had 308 right predictions while Tomato_Yellow_Leaf_Curl_Virus had 1017. Some classes, such as Target_Spot and Early_blight, exhibit some degree of ambiguity. Despite various illnesses, overall performance is still good.

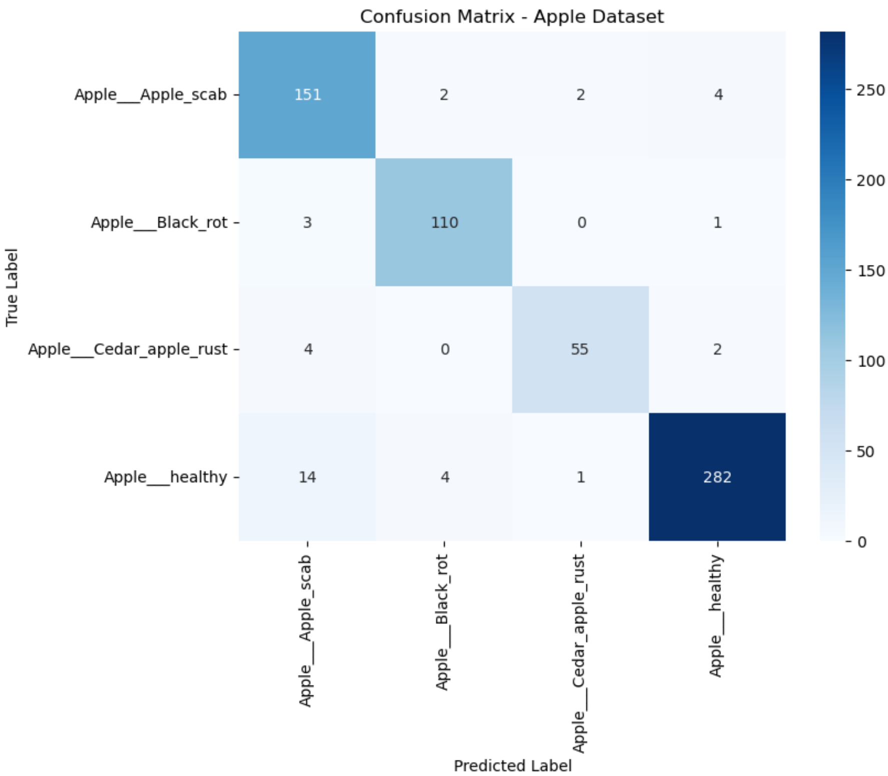


Figure 8. Confusion matrix on apple leaf dataset by the proposed architecture (CNN + uLBP).

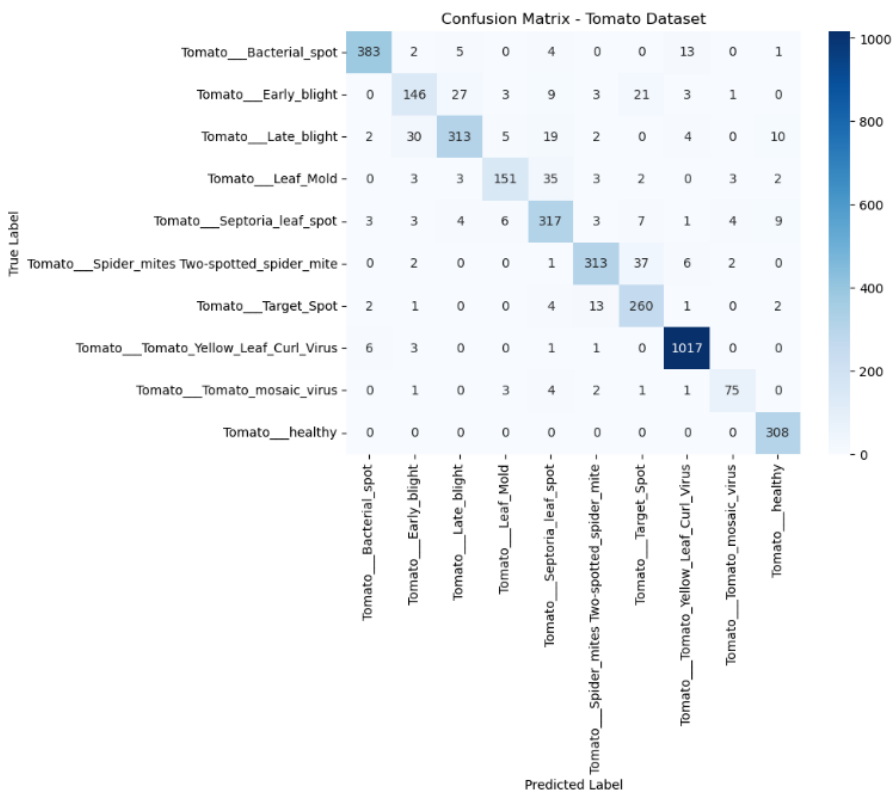


Figure 9. Confusion matrix on tomato leaf dataset by the proposed architecture (CNN + uLBP).

Figure 9 shows that the model can reliably and robustly identify tomato diseases by differentiating across visually identical leaf states. The results in **Figure 9** indicate that the model performed well at classifying Black rot, Esca (Black Measles), Leaf blight, and healthy leaves in the confusion matrix. The dataset was Grape Leaf. The model's accuracy was strong across the board; it correctly predicted 270 cases of Esca and 205 cases of Leaf blight.

The general accuracy is still good, albeit there were a few misclassifications, like 12 Esca cases being mistakenly labeled as Black rot. **Figure 10** shows that the algorithm correctly differentiates between healthy samples of grape leaves and those with illnesses, suggesting that it is useful in identifying diseases in the real world.

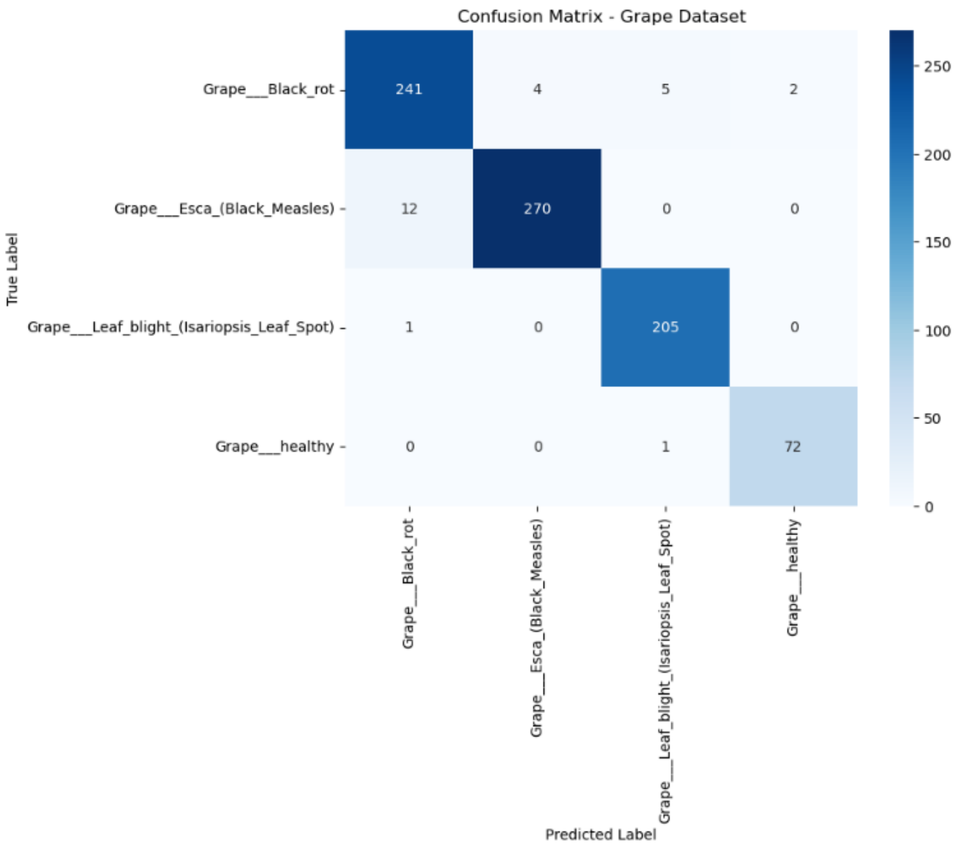


Figure 10. Confusion matrix on grape leaf dataset by the proposed architecture (CNN + uLBP).

Using the apple leaf dataset, the model was able to distinguish between various illnesses, as shown by the AUC-ROC curve. The four classes' curves are close to the top-left corner, indicating good classification performance, with AUC values of 0.98, 1.00, 1.00, and 0.99, respectively. This suggests a high overall very low number of false positives and a high percentage of true outcomes. AUC-ROC curve. The four classes' curves are close to the top-left corner, indicating good classification performance, with AUC values of 0.98, 1.00, 1.00, and 0.99, respectively. This suggests a high overall very low number of false positives and a high percentage of true outcomes.

Figure 11 shows that the model can classify diseases in apple leaves with almost perfect accuracy. The model performed very well across 10 disease classes, as shown by the AUC-ROC curve for the tomato leaf dataset. The model's great discriminative capacity is shown by the AUC values, which are close to 1.00 for most classes and yet impressively low at 0.98 for the lowest. The curves remain near the upper-left corner throughout, indicating a high true positive rate and a low false positive rate. The results show that the disease categorization of tomato leaves is strong and dependable.

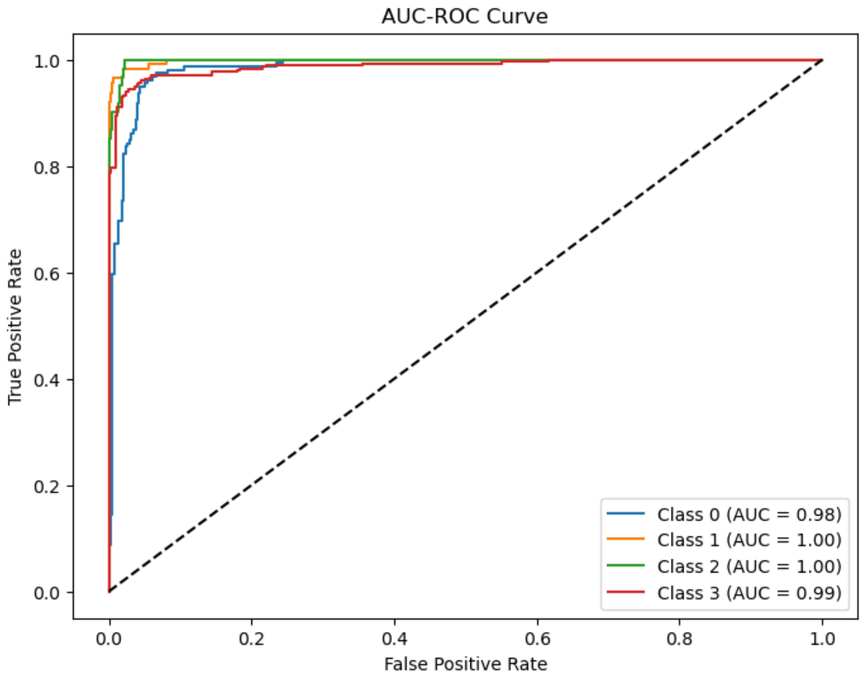


Figure 11. AUC-ROC curve on the apple leaf dataset by the proposed architecture (CNN + uLBP).

Figure 12 shows that the model achieves very high diagnostic accuracy in a variety of tomato leaf situations. Classification accuracy for all four diseases is 100% according to the AUC-ROC curve for the grape leaf dataset. The AUC score of 1.00 for each class shows how well the model can distinguish between infected and healthy grape leaves. If the ROC curves in the top left corner of the graph are very close to each other, it means that there are few false positives and many true positives. The results show that the model is reliable and accurate in identifying illnesses.

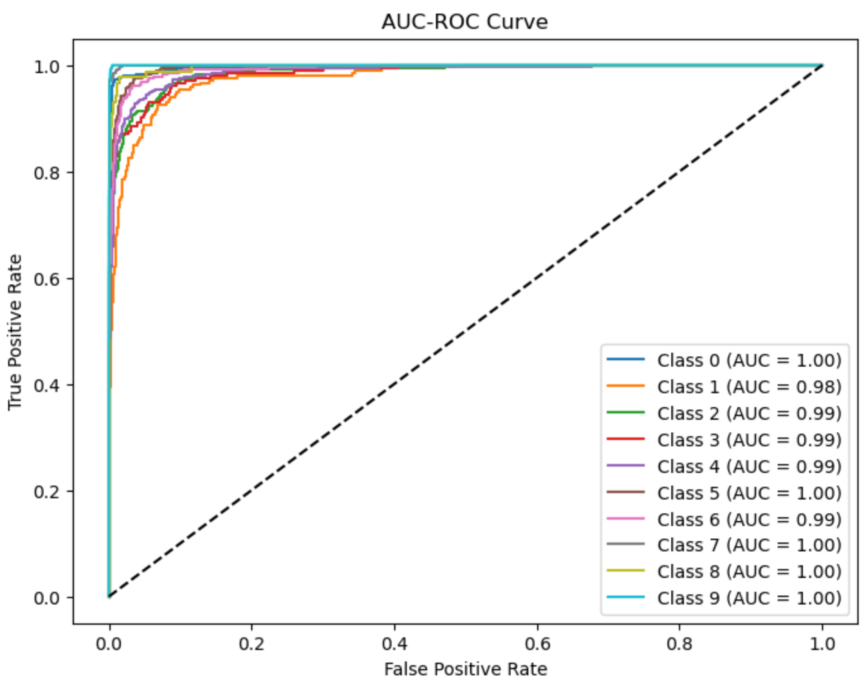


Figure 12. AUC-ROC curve on the tomato leaf dataset by the proposed architecture (CNN + uLBP).

Figure 13 shows that all types of grape leaf diseases are perfectly separable by using the classifier.

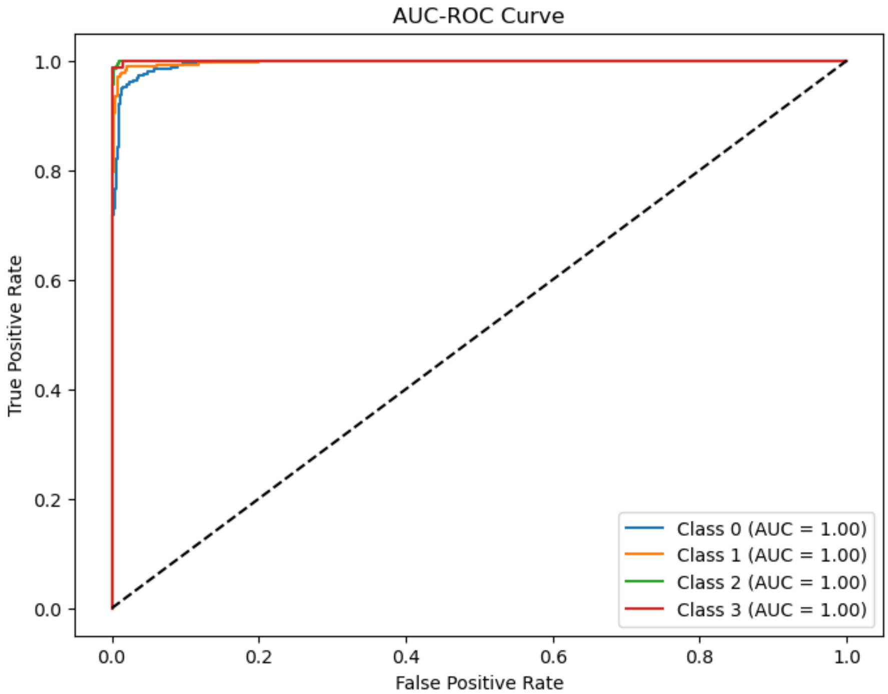


Figure 13. AUC-ROC curve on grape leaf dataset by the proposed architecture (CNN + uLBP).

In **Table 5**, we can see how the suggested approach stacks up against several cutting-edge methods for disease categorization in plant leaves. We beat the state-of-the-art on all three datasets: apple, tomato, and grape leaf. On the Apple dataset in particular, it outperforms the highest previously reported accuracy for a four-class issue by 1.6%. With accuracy increases ranging from 0.85% to 6.20%, the model outperforms all existing deep learning algorithms in the Tomato dataset. An improvement of up to 2.64% in performance is shown for the Grape leaf dataset. The method's usefulness and resilience are shown by these improvements in accuracy. The suggested model is also well-suited for immediate implementation in edge computing settings due to its small size and high computational efficiency. The model offers a scalable and realistic option for plant disease detection in precision agriculture due to its low computing cost and excellent accuracy.

Table 5. Comparison table of various approaches that are already in existence for multi-class classification for apple, tomato and grape leaf datasets.

Dataset	Authors	Method	No. of Classes	Accuracy
Apple leaf	Wang et al. [33]	VGG16	4	90.40%
	Khan et al. [35]	LBP, M-SVM	4	97.20%
	Bracino et al. [36]	GPR, quadratic SVM	3	83.30%
	Hasan et al. [37]	DWT, color histogram	3	98.63%
	Hosny et al. [12]	DCNN + LBP	4	98.80%
	Proposed	**DCNN + uLBP**	**4**	**96.80%**
Tomato leaf	Agarwal et al. [38]	CNN Model	10	91.20%
	Durmus et al. [34]	AlexNet and SqueezeNet	10	95.65%
	Elhassouny et al. [39]	MobileNet	10	90.30%
	Hosny et al. [12]	DCNN + LBP	10	96.50%
	Proposed	**DCNN + uLBP**	**10**	**91.10%**

Table 5. *Cont.*

Dataset	Authors	Method	No. of Classes	Accuracy
Grape leaf	Ahil et al. [40]	CNN Model	4	95.66%
	Tang et al. [41]	ShuffleNet V1	4	97.79%
	Akshai et al. [42]	DenseNet	4	98.27%
	Hosny et al. [12]	DCNN + LBP	4	98.30%
	Proposed	**Deep feature + LBP**	**4**	**96.30%**

5. Conclusions

This article proposed an accurate, effective, and lightweight CNN-based model for the multi-class categorization of plant leaf diseases. A novel feature-fusion approach was introduced to enhance the model's performance by combining manually generated texture features from the Uniform Local Binary Pattern (uLBP) technique with deep features derived from Convolutional Neural Networks. Three publicly accessible PlantVillage datasets—Apple Leaf, Tomato Leaf, and Grape Leaf—were used to train and assess the proposed model, which yielded test accuracies of 96%, 91%, and 96%, respectively.

Future Scope

There are other directions that might be investigated in the future, even if the proposed method for classifying diseases in plant leaves has shown encouraging results. Using advanced deep learning architectures such as Vision Transformers (ViTs), attention-based networks, or hybrid CNN-RNN models can increase the accuracy of feature extraction and categorization. The practical usefulness of the system in field situations will be significantly improved by using lightweight models for real-time disease detection on mobile or embedded devices. The suggested approach also has to be assessed in real-time applications and tested on different crop leaf diseases. Additional research in this area would improve the suggested strategy and increase its usefulness in real-world situations involving the identification of agricultural diseases. Furthermore, the model could be converted to a transfer learning model, which could be enhanced by adapting to other crops that were not included in the dataset and assessing its robustness under varying conditions.

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Data Availability Statement

Data will be uploaded to the public domain soon and will be provided to readers upon request.

Conflicts of Interest

The author declare no conflict of interest.

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