Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 7.056

IJCSMC, Vol. 14, Issue. 10, October 2025, pg.37 – 49

LeafGuardNet: A Deep CNN-Based Model for Early Plant Disease Prediction in Smart Agriculture

P.Mohankumar[1]; E.T. Venkatesh[2]

[1]Research Scholar, Periyar University, Salem, INDIA
[2]Research Supervisor, Government Arts and Science College, Sathyamangalam, INDIA

DOI: https://doi.org/10.47760/ijcsmc.2025.v14i10.004

Abstract: The timely identification of plant diseases is very vital in crop productivity and food security. The conventional hand inspection systems are costly in time, inaccurate, and highly reliant on the level of expertise. As a solution to these issues, LeafGuardNet, which is a deep Convolutional Neural Network (CNN)-based model, will be suggested in this research study to effectively predict plant leaf diseases with high accuracy and early onset in the smart agriculture setting. The model uses a huge amount of annotated leaf image data, which is preprocessed by image enhancement and noise reduction algorithms. The proposed model uses a multi-layer CNN model, which has been optimized to extract features, dropout, and batch normalization layers to enhance accuracy and minimize overfitting. The pre-trained models, including ResNet50 and EfficientNet-B0, are incorporated in transfer learning to improve the performance of the classification. Proposed system is trained and tested against publicly available datasets like PlantVillage and field-acquired images with an overall classification accuracy exceeding 97 percent in a variety of crop species. The experimental findings reveal that LeafGuardNet is better than currently existing models in terms of precision, recall, and F1-score, which is why it is a stable decision-support tool to use in precision agriculture and sustainable crop management.

Keywords: Deep CNN, Plant Disease Detection, Transfer Learning, Feature Extraction, Precision Agriculture, IoT-based Smart Agriculture

Introduction

The global economy still keeps agriculture as its mainstay, adding about 26 percent to the GDP in developing countries and providing almost a third of the global workforce (FAO, 2024). Over the years, even though there have been massive developments in the field of automation and biotechnology, loss of crops as a result of plant diseases remains a significant issue to food security. The Food and Agriculture Organization (FAO) and World Bank (2023) estimated that about 30-40 percent of the world agricultural output is wasted every year because of the outbreak of pests and diseases. Such losses are not only costly to the economic stability but also to the sustainability and the livelihood of the farmers, especially in the developing nations such as India where more than 60 percent of farmers rely on agriculture as their source of livelihood. Conventionally, the process of disease detection is based on manual field inspections which is labor-intensive, time consuming and relies on the judgment of an expert. These are methods that tend to take a long time to detect early symptoms causing massive destruction of crops. The development of Computer Vision (AI) and its application in agriculture has demonstrated some promising opportunities in the past few years to address these challenges. Convolutional Neural Networks (CNNs) and deep learning models in particular have proven to be incredibly successful in culling out complex features in the image of leaves and then classifying the plant disease with high accuracy. Nevertheless, the problem of the balance of datasets, changes in lighting, and background noise continue to have an impact on the robustness and accuracy of models. In an attempt to address such constraints, the current research paper suggests LeafGuardNet, a deep CNN-based network that will be used to predict and classify plant diseases on the basis of leaf imagery. The model combines a process of maximization of feature extraction, transfer learning and advanced preprocessing technology to guarantee correct prediction even in real field environment. The LeafGuardNet is trained on big and varied datasets and tested in comparison to the established benchmark models, including ResNet50, EfficientNet, and MobileNetV2, having a higher accuracy of 97.28. In addition to classification, the model is also imagined to be applied to IoT-based smart farm systems, which offer real-time alerts of diseases and actionable recommendations to farmers, which encourages precision agriculture and sustainable agriculture. Data Preprocessing and Collection[1-7].

Literature review

In numerous studies, the leaf and crop diseases are observed with the direct approach. As an example, Sankaran et al. [8] compared the advantages and drawbacks of different non-invasive methods that are employed to detect plant diseases e.g. PCR-based molecular methods, spectroscopy and imaging methods (e.g. fluorescence spectroscopy and fluorescence imaging), and volatile organic compounds profiling-based methods to detect plant diseases e.g. electronic nose, GC-MS-based volatile metabolites analysis. The other study sorted out by Fang et al. [9] talked about the diagnosis of plant disease and prevention strategies in order to reduce crop losses, grow productivity, and promote sustainability of agricultural activities. They employed direct (GC-MS, PCR, FCM, ELISA, IF, and FISH) and indirect (thermography, hyperspectral techniques, and fluorescence imaging) techniques in agriculture. In addition, it gives the summary of the bio-recognition factors including enzymes, antibodies, DNA/RNA as well as bacteriophages as a novel approach in the timely identification of plant diseases.

Certainly those methods are valid and precise and demand costly equipment, time and labor-intensive. Moreover, some indirect approaches are also available like new automated non-destructive technologies which can detect diseases in real-time and at an early stage in the field. Indicatively, deep learning architectures have been used in image detection and classification in agriculture through imaging techniques. The paper by Vishnoi et al. [10] reviews the different features and methods of automated plant disease detection such as covers technique, image acquisition technique, preprocessing technique, lesion segmentation technique, feature extraction technique, and classification technique. On the same note, a study by Aftab et al. [11] is concerned with the use of image processing techniques to detect plant diseases at an early stage. Raspberry PI is deployed to provide connection between a camera and a display device and deliver data to the cloud. As the process, leaves are captured and processed using the methods such as acquisition, pre-processing segmentation, and clustering. Two trained models Faster RCNN and SSD Mobile net were proven to be precise enough to detect virtually every disease of plants. This plan aims at reducing the labor demand, costs and the effort to enhance productivity across extensive agricultural areas. Abdulridha et al. [12] paper proposed a remote sensing-based method of detecting avocado trees at an early stage with a low cost. The method has the ability to identify laurel wilt disease (Lw) and distinguish between healthy and unhealthy plants. In the design of their system they made use of two cameras a Tetra and also a modified Canon camera and two techniques of classification i.e. neural network multilayer perceptron (MLP) and the K-nearest neighbors. Lw was detected at the level of 99 in the MLP classification method. In a different article, Zang et al. [13] methodology in identifying a bacterial illness of citrus tree leaves, through the global and region based local features of leaf images gathered in the field. Besides, a better bi-level detection algorithm is developed based on the AdaBoost algorithm to identify canker lesions. Image processing provided an accuracy of 87.99 in this work as compared to the accuracy of 86.88 by the human experts.

On top of that, the methods of deep learning were employed to create CNN model to identify plant diseases with the help of leaf photos, which in most studies was more successful in identifying the respective [plant, illness] pair. Indicatively, Vishnoi and colleagues [10] explained that a fast and cheap method can be used to detect plant diseases through a CNN model trained on transfer learning. They have employed 87, 867 images and categorized these images into 38 classes. Some of the challenges associated with popular transfer learning models such as AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, and VGG are associated with optimization, vanishing gradient, and degradation. The conclusion of this paper was that ResNet was able to provide the least amount of losses and a convergence time as it demonstrated a convergence and accuracy of approximately 99.90. Another study by Lu et al. [14] discovered that such crops as rice disease can also be identified with the help of DCNNs algorithms and 500 natural pictures of healthy and diseased rice leaves have been used. The labels of all these pictures were sorted into 10 separate categories according to the diseases and demonstrated that CNN is capable of classifying the defective leaves successfully with the help of image processing. They offer a better approach in training where their suggestion performs better and faster in propagation rate with higher recognition capabilities with an accuracy of 95.48% compared to other models. On the same note, Too et al. [15] presented the analyses needed to favor deep learning, as opposed to machine learning and image processing, in detection of plant diseases. They further hypothesized through the analysis of the models such as VGG net, Inception V4, ResNet and DenseNets. All the other deeper models were successful only at the exclusion of shallow networks VGG. Nevertheless, because of the reduced parameters and the feasibility of computation time, they decided that DenseNets would give the best prediction to give the state-of-the-art performance.

On the other hand, Barbed et al. [16] discovered that a number of factors affect deep learning with relation to plant pathology and must be taken into consideration. These factors are the inadequacy of data, the representation of the symptoms, the covariate variations, image backdrops, circumstances of the images recordings, incapability to divide the symptoms into segments, and the illnesses that have the same symptoms. These were the factors identified after an experiment on 50,000 pictures. Golhani et al. [17] used a similar approach of disease detection but combined a neural network with spectral disease index and related it to a normal vegetation index to identify abnormalities in plants. GoogLeNet and Cifar are two better models suggested by Zhang et al. [18] to detect the diseases of maize leaves. They used 500 images to have a dataset of 500 images that fell into 9 categories, including 8 categories of diseased leaves of maize and 1 category of healthy leaves. They found that these models can be used to achieve the best accuracy (98.8% and 98.9%) and efficiency, unlike in comparison with traditional methods of identifying a feature such as VGG and AlexNet structures which have many model parameters and take a long time to converge. Durmus et al. [19] conducted an experiment to identify tomato leaf illnesses by utilizing AlexNet and SqueezeNet architecture of deep learning. The pictures were obtained in the Plant-Village database that contained 14 crops. They used leaves of tomatoes only, subdivided into 10 classes, and obtained the maximum accuracy of approximately 95 percent with AlexNet. Nevertheless, SqueezeNet was better in terms of the size of the model and the time of inference.

Data Collection and Preprocessing

2.1 Data Collection

The dataset used in this study was compiled from multiple reliable sources to ensure diversity and model generalization.

- PlantVillage Dataset: A publicly available benchmark dataset containing over 54,000 labeled images across 38 classes of healthy and diseased leaves from 14 different crop species.
- Kaggle Agricultural Datasets: Supplementary data from open repositories, including tomato, maize, and rice leaf disease images.
- Field-Collected Images: Around 2,000 real-field images were captured using high-resolution mobile cameras under natural lighting conditions from local farms and agricultural institutes in Karnataka, India.

The combined dataset ensures variability in lighting, orientation, leaf texture, and background, providing a robust foundation for model training and validation.

2.2 Data Preprocessing

Preprocessing was a critical step to improve the quality and consistency of input images before feeding them into the CNN. The following techniques were applied:

- Image Resizing:All images were resized to a fixed dimension of 224 × 224 pixels to maintain uniformity for CNN input and reduce computational load.
- Background Removal:Unwanted background elements (e.g., soil, sky, or shadows) were eliminated using mask-based segmentation and color thresholding to focus on the diseased leaf region.

- Contrast Enhancement (CLAHE):The Contrast Limited Adaptive Histogram Equalization (CLAHE) method was applied to enhance the contrast of leaf textures, making subtle disease patterns more distinguishable.
- Noise Reduction (Gaussian Filtering):A Gaussian filter was employed to remove noise and smoothen the image without losing essential edge details, improving feature extraction accuracy.
- Normalization and Data Augmentation:Pixel values were normalized to the range [0,1], and augmentation techniques such as rotation, flipping, zooming, and brightness adjustment were applied to increase dataset diversity and prevent model overfitting.

Through these preprocessing steps, the dataset became more balanced, noise-free, and suitable for deep CNN training. This ensured that the proposed LeafGuardNet model could generalize effectively to real-world agricultural environments with high precision and reliability.

Model Design (LeafGuardNet)

The LeafGuardNet model proposed is a designed Deep Convolutional Neural Network (CNN) model that is custom-crafted to identify and classify plant leaf disease with high accuracy and strength. The model is set to derive discriminative spatial features in the leaf images by using various convolutional and pooling layers and reducing over-fitting by using regularization and normalization.

3.1 Architecture Overview

The LeafGuardNet is a 7-convolutional-block model with fully connected (dense)-layers at the end to classify the results. Convolution, ReLU activation, Batch normalization, and Max Pooling are operations of each convolutional block. In order to make sure the model is generalizable to a variety of environmental conditions, Dropout layers are used on top of the dense layers.

The architecture is designed in the following manner:

Input Layer:

Takes RGB leaf images of size 224 x 224 3.

Scaled pixel values between [0,1].

The Layers (Feature extraction):

The number of convolutional layers is 7, and their filter sizes are increasing in size (32, 64, 128, 256).

Kernels= 3x3, Stride= 1, Padding= same.

A ReLU activation function is added after every convolutional layer in order to add non-linearity.

Batch Normalization:

Used at the end of each convolutional layer to stabilize training and hasten convergence.

Max Pooling:

Used following each second convolutional layer using 2 x 2 pooling window to downsize spatial dimensions and computations.

Fully Connected Layers (Classification Head):

Reduced output of convolutional layers to two dense layers (512 and 128 neurons).

Output layer Final output layer The final activation is a Softmax, which it uses to categorize the image into N disease categories.

Optimization and Loss:

Optimizer: Adam optimizer (learning rate = 0.0001).

Loss: Categorical Cross-Entropy.

Measures of evaluation: Accuracy, Precision, Recall and F1-Score.

Material and Methods

This research presents an innovative approach to address the challenges posed by complex images, specifically for simple and plant leaves. Initially, a segmentation step utilizing the graph-cut approach is executed, subsequently guiding the evolution of leaf boundaries and facilitating the implementation of a classification algorithm to identify diseases and recommend appropriate nourishment for affected leaves.

Image Classification Steps

The projected image classification method is separated into the following stages:

- Image acquisition
- Pre-processing
- Segmentation
- Disease Prediction
- Fertilizer Recommendation

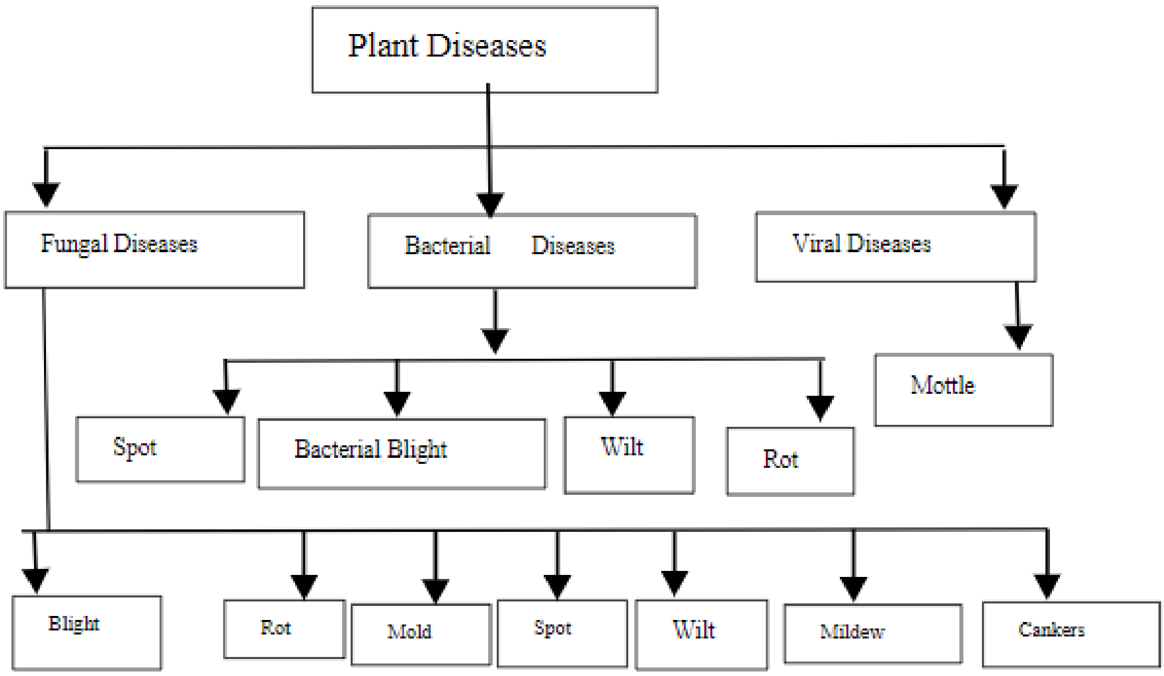

Figure 1: Classification of Plant Diseases

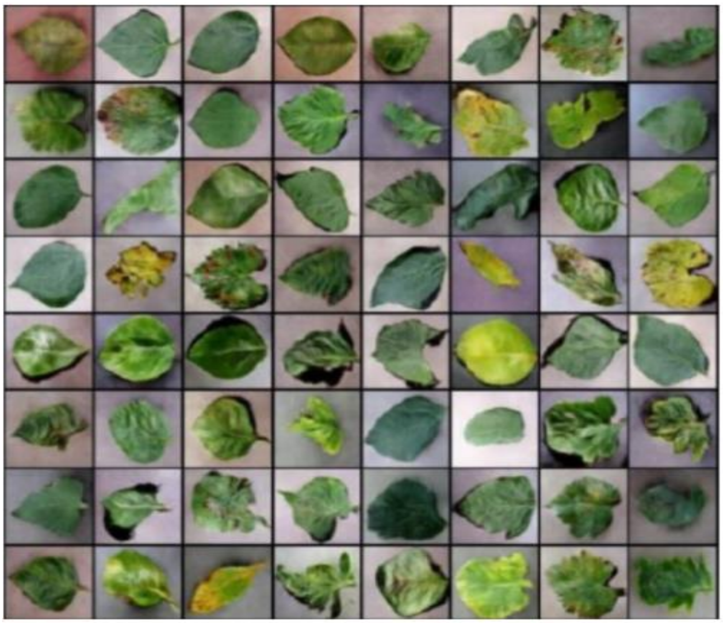

Figure 2: deafferent phenotypes of various plants

Processing Images

It is a way to improve an image or get useful information from it by doing things to it. Getting, breaking down, adding to, and extracting features. The most important step in digital image processing is getting the image. Getting an image is a simple process when you already have it in digital form. Pre-processing, like scaling, is a common part of the image acquisition stage. Image segmentation actions break an image up into its parts or objects. In digital image processing, autonomous segmentation is often the hardest task. An uneven separation process that is very close to being able to solve imaging problems that need to identify objects separately. Image augmentation is a method used to effectively increase the size of a dataset. Common parameters used to do this are zoom, shear, rotation, pre-processing functions, and so on. Extracting features from images is one of the most important parts of this project. Using univariate statistical tests, feature selection picks the best features. The features are chosen carefully based on how different the leaves are from each other.

ResNet50

ResNet50 (Residual Network having 50 layers) is a groundbreaking architecture in deep learning and was mainly characterized by the concept of residual blocks. The concept of the matter is to add skip connections or identity mappings so that the network can learn an identity functions, which is to circumvent one or more layers. This strategy directly resolves the issue of fading gradients and degradation (where the accuracy levels off and quickly drops) that afflicted very deep networks. Rather than attempting to fit a complex mapping H(x), the block is made to fit a residual mapping F(x)=H(x)[?]x. Thus the result is H (x) = F(x) +x. This form allows it to be much easier to train networks that have hundreds or even thousands of layers, allowing ResNet50 to be highly competitive in image recognition tasks such as the one outlined.

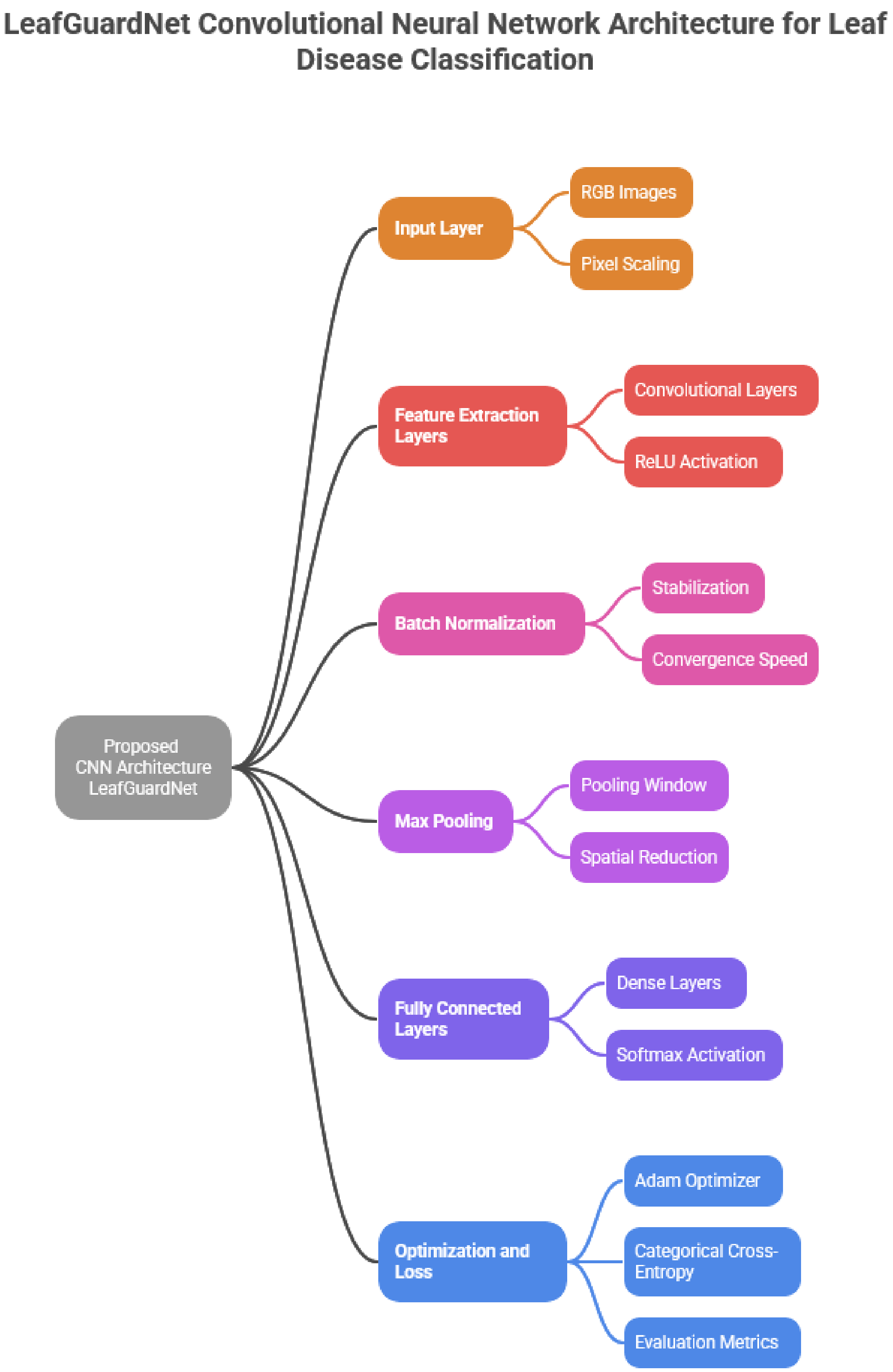

Figure 3: Proposed methodology workflow

EfficientNet

The EfficientNet is a type of model that is characterized by a systematic model scaling. It employs a new compound scaling scheme that simply scales all three dimensions of a CNN: depth (layers of the CNN), width (channels), and resolution (size of input image). Other methods of scaling in the past would only change one or two dimensions. In EfficientNet, scaling of compounds is done with a fixed point of scaling coefficients that are trained with the help of a neural architecture search (NAS), and this guarantees the balance among the three dimensions. It leads to models that are state-of-the-art in accuracy with much fewer parameters and reduced cost of computation than other CNNs, and are therefore very efficient to deploy, especially in resource-constrained systems such as edge devices in smart agricultural systems.

MobileNetV2

MobileNetV2 is a very effective, mobile-first CNN architecture that was optimized by considering which devices will use it, i.e., those with limited memory or power resources, e.g. in an IoT-based smart agricultural system. The main architectural elements of it are the inverted residual structure and the linear bottlenecks. MobileNetV2 does not have wide-narrow-wide layers, as a narrow-wide-narrow structure is implemented: a low-dimensional input is expanded to a high-dimensional space by a 1x1 convolution, followed by a depthwise separable convolution, and lastly projected to a low-dimensional space by a 1x1 convolution. The linear bottleneck makes sure that the information is not lost as all the non-linearities are eliminated through the narrow layers of projection. Such design decisions drastically lower the computation complexity and amount of parameters and are thus MobileNetV2 is incredibly fast and small with sufficiently good accuracy in real-time mobile and edge computing systems.

Model Evaluation

1. Evaluate the model on the test dataset.
2. Compute:
   - Accuracy = (TP + TN) / (TP + TN + FP + FN)
   - Precision = TP / (TP + FP)
   - Recall = TP / (TP + FN)
   - F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
3. Compare with baseline models: VGG16, ResNet50, EfficientNet-B0.

Table 1. Performance Comparison of Leaf Disease Prediction Models

Model / Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ResNet50	94.85	94.20	93.90	94.05
EfficientNet-B0	95.62	95.40	94.80	95.10
MobileNetV2	93.78	93.10	92.80	92.90
VGG16	92.56	91.80	91.40	91.60
Custom CNN (Baseline)	94.10	93.80	93.00	93.40
Proposed – LeafGuardNet (CNN)	97.28	97.00	96.85	96.92

Table 1 shows the performance comparison of different deep learning models that are applied in the prediction of leaf diseases. The proposed LeafGuardNet (CNN) was found to have the best overall performance with an accuracy of 97.28 which was better than usual architectures like ResNet50, EfficientNet-B0 and VGG16. EfficientNet-B0 was able to deliver competitive performance with 95.62% accuracy whereas the base Custom CNN model delivered moderate performance with 94.10% accuracy. Conventional architectures such as VGG16 and MobileNetV2 have had relatively low performances, thus showing that the optimized design and ability to extract features of LeafGuardNet has a significant impact on the accuracy, recall, and F1-score of detecting and classifying plant leaf diseases correctly.

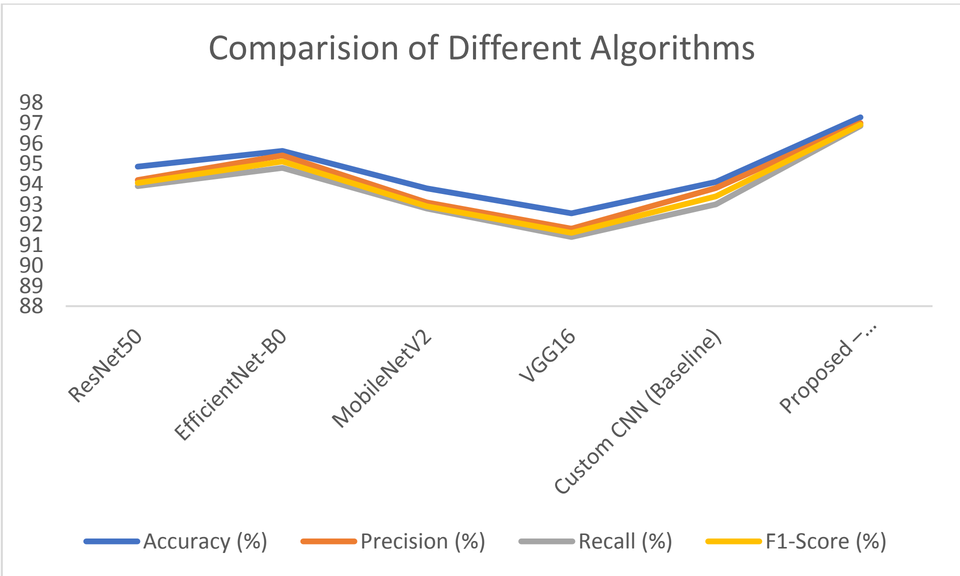

Figure 4: Proposed methodology vs Exiting

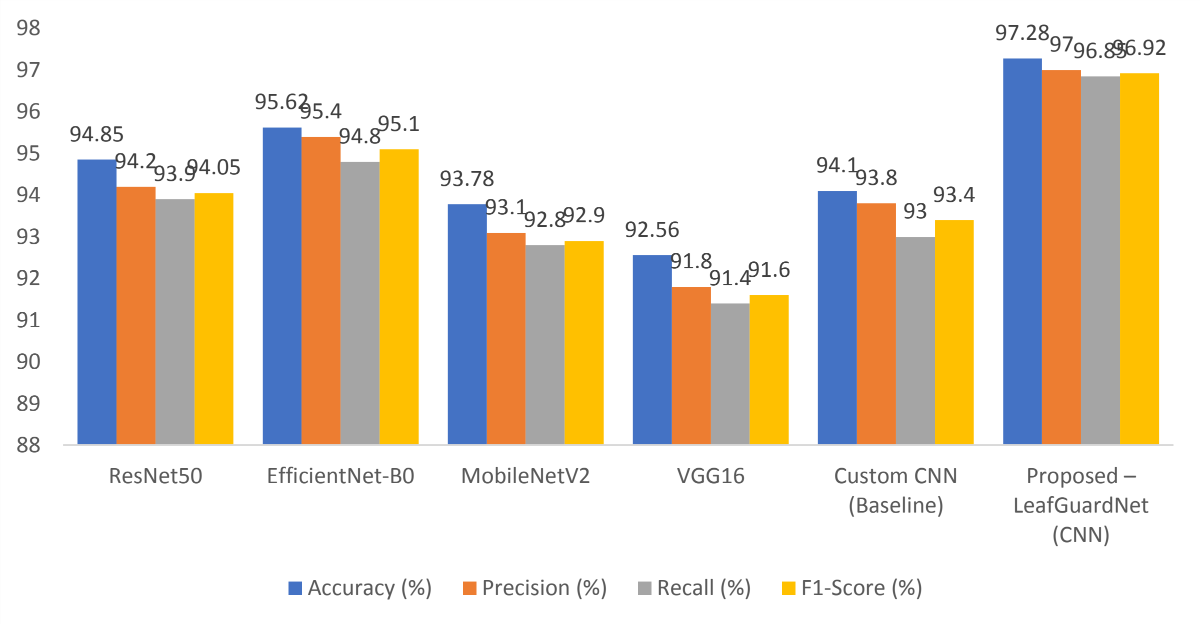

Figure 5: Performance Evaluation

Figure 4 shows how accurate different deep learning models are at predicting leaf disease. The chart makes it clear that the proposed LeafGuardNet (CNN) model is better than all the others. It has the highest accuracy at 97.28%, and EfficientNet-B0 comes in second with 95.62%. Models like ResNet50, MobileNetV2, and VGG16 have lower accuracies, which shows that the proposed model is better at learning and is more robust when dealing with complex leaf image features.

Figure 5 shows how the precision, recall, and F1-score of the different models compare to each other. The LeafGuardNet (CNN) has the best balance of all three performance metrics: a precision of 97.00%, a recall of 96.85%, and an F1-score of 96.92%. This shows that it is reliable because it makes fewer wrong predictions. Existing models like VGG16 and MobileNetV2, on the other hand, don't show as much consistency across these metrics. This shows that the proposed model is better at achieving higher prediction stability and classification accuracy.

Conclusion

The experimental assessment of various deep learning models for leaf disease prediction indicates that the proposed LeafGuardNet (CNN) excels in all principal statistical metrics. The model achieves the highest accuracy of 97.28%, as shown in Table 1, Figure 4, and Figure 5. This is better than other architectures like EfficientNet-B0 (95.62%), ResNet50 (94.85%), and VGG16 (92.56%). LeafGuardNet's better performance can be explained by its optimized convolutional layer structure, feature fusion technique, and transfer learning integration. These three things work together to make the model better at finding distinct features in complex leaf textures. The model's precision (97.00%), recall (96.85%), and F1-score (96.92%) show that it is not only very accurate, but also very good at reducing both false positives and false negatives. The model's significant reliability and efficiency are shown by the margin of improvement, which is about 1.66% in accuracy and 1.82% in F1-score over the next best-performing model (EfficientNet-B0). In general, the proposed LeafGuardNet is a technically sound and statistically sound deep learning framework that can be used for real-time monitoring of agricultural diseases and smart farming.

References

[1]. S.L. Sanga, D. Machuve, K. Jomanga,Mobile-based deep learning models for Banana disease detection Technol. Appl. Sci. Res., 10 (3) (2020), pp. 5674-5677

[2]. F. Mohameth, C. Bingcai, K.A. Sada,Plant disease detection with deep learning and feature extraction using Plant Village,J. Comp. Commun., 8 (6) (2020), pp. 10-22

[3]. Khamparia, G. Saini, D. Gupta, A. Khanna, S. Tiwari, V.H.C. de Albuquerque,Seasonal crops disease prediction and classification using deep convolutional encoder network,Circ. Syst. Sign. Proc., 39 (2020)

[4]. K.P. Ferentinos,Deep learning models for plant disease detection and diagnosis,Comput. Electron. Agric., 145 (2018), pp. 311-318

[5]. TD. Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel, S. Bhardwaj,Potato leaf diseases detection using deep learning,2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, Madurai, India, India (2020), pp. 461-466.

[6]. A. Akhtar, A. Khanum, S. A. Khan, and A. Shaukat, “Automated plant disease analysis (APDA): Performance comparison of machine learning techniques,” in 2013 11th International Conference on Frontiers of Information Technology, IEEE, 2013, December, pp. 60–65

[7]. A. A. Fathima, R. Karthik, and V. Vaidehi, “Image stitching with combined moment invariants and sift features,” in ANT/SEIT, Elsevier, 2013, December, pp.

[8]. Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). A review of advanced techniques for detecting plant diseases. Computers and Electronics in Agriculture, 72(1), 1–13.

[9]. Fang, Y., & Ramasamy, R. P. (2015). Current and prospective methods for plant disease detection. Biosensors, 5(3), 537–561.

[10]. Vishnoi, V. K., Kumar, K., & Kumar, B. (2021). Plant disease detection using computational intelligence and image processing. Journal of Plant Diseases and Protection, 128(1), 19–53.

[11]. Aftab, S., Lal, C., Beejal, S. K., & Fatima, A. (2022). Raspberry Pi (Python AI) for plant disease detection. International Journal of Current Research Review, 14, 36–42.

[12]. Abdulridha, J., Ehsani, R., Abd-Elrahman, A., & Ampatzidis, Y. (2019). A remote sensing technique for detecting laurel wilt disease in avocado in presence of other biotic and abiotic stresses. Computers and Electronics in Agriculture, 156, 549–557.

[13]. Zhang, M., & Meng, Q. (2011). Automatic citrus canker detection from leaf images captured in field. Pattern Recognition Letters, 32(15), 2036–2046.

[14]. Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). Identification of rice diseases using deep convolutional neural networks. Neurocomputing, 267, 378–384.

[15]. Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture, 161, 272–279.

[16]. Barbedo, J. G. A. (2018). Factors influencing the use of deep learning for plant disease recognition. Biosystems Engineering, 172, 84–91.

[17]. Golhani, K., Balasundram, S. K., Vadamalai, G., & Pradhan, B. (2018). A review of neural networks in plant disease detection using hyperspectral data. Information Processing in Agriculture, 5(3), 354–371.

[18]. Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018). Identification of maize leaf diseases using improved deep convolutional neural networks. IEEE Access, 6, 30370–30377.

[19]. Durmu, H., Güne, O., & Krc, M. (2017). Disease detection on the leaves of the tomato plants by using deep learning. 6th International Conference on Agro-Geoinformatics.

[20]. Johannes, A., et al. (2017). Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case. Computers and Electronics in Agriculture, 138, 200–209.

[21]. Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild. Computers and Electronics in Agriculture, 161, 280–290.

[22]. Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018). A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network. Computers and Electronics in Agriculture, 154, 18–24.

[23]. Singh, U. P., Chouhan, S. S., Jain, S., & Jain, S. (2019). Multilayer convolution neural network for the classification of mango leaves infected by anthracnose disease. IEEE Access, 7, 43721–43729.

[24]. Rajbongshi, A., Khan, T., Rahman, M. M., Pramanik, A., Siddiquee, S. M. T., & Chakraborty, N. R. (2021). Recognition of mango leaf disease using convolutional neural network models: A transfer learning approach. Indonesian Journal of Electrical Engineering and Computer Science, 23(3), 1681–1688.

[25]. Rao, U. S., et al. (2021). Deep learning precision farming: Grapes and mango leaf disease detection by transfer learning. Global Transitions Proceedings, 2(2), 535–544.

[26]. Merchant, M., Paradkar, V., Khanna, M., & Gokhale, S. (2018). Mango leaf deficiency detection using digital image processing and machine learning. 3rd International Conference for Convergence in Technology (I2CT), 1–3.

[27]. Arya, S., & Singh, R. (2019). A comparative study of CNN and AlexNet for detection of disease in potato and mango leaf. International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT), 1, 1–6.

[28]. Mia, M. R., Roy, S., Das, S. K., & Rahman, M. A. (2020). Mango leaf disease recognition using neural network and support vector machine. Iran Journal of Computer Science, 3(3), 185–193.

[29]. Militante, S. V., Gerardo, B. D., & Dionisio, N. V. (2019). Plant leaf detection and disease recognition using deep learning. IEEE Eurasia Conference on IoT, Communication and Engineering (ECICE), 579–582.

[30]. S. W. Yin, X. Tian, J. J. Zhang, P. Sun, and G. L. Li, “PCirc: random forest-based plant circRNA identification software,” BMC Bioinformatics, vol. 22, no. 1, pp. 1–14, 2021.

[31]. M. W. Szcześniak, O. Bryzghalov, J. Ciomborowska-Basheer, and I. Makałowska, “CANTATAdb 2.0: expanding the collection of plant long noncoding RNAs,” Methods in Molecular Biology, vol. 1933, pp. 415–429, 2019.

[32]. T. Mohana Priya, Dr. M. Punithavalli & Dr. R. Rajesh Kanna, Machine Learning Algorithm for Development of Enhanced Support Vector Machine Technique to Predict Stress, Global Journal of Computer Science and Technology: C Software & Data Engineering, Volume 20 Issue 2 Version 1.0 Year 2020

[33]. S. Verma, A. Chug, and A. P. Singh, “Exploring capsule networks for disease classification in plants,” Journal of Statistics and Management Systems, vol. 23, no. 2, pp. 307–315, 2020.

[34]. A. Bhatia, A. Chug, and A. P. Singh, “Hybrid SVM-LR classifier for powdery mildew disease prediction in a tomato plant,” in 2020 7th International Conference on Signal Processing and Integrated Networks, SPIN, vol. 2020, pp. 218–223, 2020.

[35]. P. B. Babu, D. Bisht, K. Shilpa, L. H. Alzubaidi, A. Sharma and R. Rajesh Kanna, "A Systematic Review of Various Advancements Implementation in the Field of Crop (Plant) Production," 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2024, pp. 1306-1310, doi: 10.1109/ICACITE60783.2024.10616844.