Smart Agri Assist: Enhancing Leaf Disease Recognition Using Deep Learning Techniques

Sirisha Pagadala[1], Harshitha Reddy Peddakotla[2], Kusuma Mara[2], Greeshma Teja Gaddam[2] and Mythri Thammineni[2]

[1]*Department of CSE, Srinivasa Ramanujan Institute of Technology, Rotarypuram Village, B K Samudram Mandal, Anantapuramu - 515701, Andhra Pradesh, India*

[2]*Department of CSE (AI & ML), Srinivasa Ramanujan Institute of Technology, Rotarypuram Village, B K Samudram Mandal, Anantapuramu - 515701, Andhra Pradesh, India*

Keywords: Plant Disease Diagnosis, Deep Learning, MobileNet, Image Classification, Treatment Recommendations.

Abstract: Implementing disease prediction systems for potato leaves would improve agricultural productivity and crop yield through early identification. This project is focused on detecting blight diseases using Artificial Intelligence (AI) and Deep Learning techniques. The proposed system can analyse leaf images, as shown in Figure 1, using a MobileNet-based architecture to extract the critical features making sure enough attention is paid towards colour, texture as well as shape in order to do leaf classification. Along with a dense layer, this also requires a SoftMax layer to ensure that the model provides an output with a confidence score corresponding to each diagnosis in order to establish the reliability of the output. It further offers personalized therapeutic recommendations, including advice on organic and chemical pathologies and mechanical damage management, aiding farmers in tracking up on the specified pathology and damage. This indicates how deep learning is substantially changing agriculture and also holds the potential to help farmers make better decisions to minimize crop loss and increase sustainability in agricultural practices.

1 INTRODUCTION

Potatoes are an important staple crop grown worldwide crucial to food security, but potato production is frequently threatened by diseases such as Early Blight and Late Blight, leading to significant yield losses. Early and accurate disease detection is vital for the possible treatment of the crops and reducing economic losses. Traditional visual checks require trained scientists, are labor intensive and reliant on subjective training and experience, thus not widely adopted by farmers. Get involved in changing computational intelligence and neural network methods in the fight against the disease and the automation of disease recognition.

In this project we will build an AI model that, by looking at pictures of the leaves, we can identify potato diseases. It is based on a MobileNet architecture, an efficient one for visual analysis. Basically, the system is trained on potato leaf dataset containing images with different variety of potato leaves, and it classifies the diseases into three classes 1.

Figure 1: Potato Leaves.

Initial fungal infection (Early Blight) 2. Advance fungal infections (Late Blight) and 3. the healthy leaves (Healthy). Data augmentation was used to

Pagadala, S., Peddakotla, H. R., Mara, K., Gaddam, G. T. and Thammineni, M.
Smart Agri Assist: Enhancing Leaf Disease Recognition Using Deep Learning Techniques.
DOI: 10.5220/0013874000004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 819-826
ISBN: 978-989-758-777-1

make the model more robust to variation in image quality. The system not only provides classification but also confidence scores to help communicate prediction reliability, and precision treatment recommendations, in terms of both organic and chemical options for specific diseases. Crop management is enhanced and accidents minimized It.) The project brings AI into agriculture to improve agricultural performance, support sustainable solutions, and strengthen global food resilience.

2 RELATED WORKS

Liu, J., Cheng, Q., Gong, W., et al. (2022) A deep learning-based proposed tomato and potato disease recognition based on transfer learning which provides a good classification accuracy. The model showed robust performance across a range of lighting and weather conditions, suggesting its potential for agricultural use."

Arshaghi, A., Ashourian, M. & Ghabeli, L. (2023) Deep learning methods (e.g., ResNet, VGG) potato disease detection and classification were examined. Both ResNet and Inception v4 produced the best results compared to traditional machine learning methods on a curated dataset of potato leaf images.

Kumar, A., Patel, V.K. (2023) In potato leaves disease identification, developed a hierarchy deep learning-based CNN. The proposed model not only improved classification performance but also addressed the scalability challenge of computational complexity, making it suitable for real-world deployment.

Sharma, A., Zhang, L., & Tanwar, S. (2021) A new deep learning framework used for the early detection of late blight in potato crops. The system, which relied on hyperspectral imaging and CNN architectures, predicted the onset of plant disease before the manifestation of visible symptoms, supporting preventive farming practices.

Yuan, D., Wu, C., & Li, J. (2020) A hybrid CNN model was suggested in that combined traditional image processing techniques with deep learning methods for detecting potato leaf disease. In that case, the work increased the efficiency of the feature extraction, especially for late blight and early blight diseases.

Kong, G., Wang, H., Wang, L., et al. (2022) incorporated deep learning and edge computing for accurate real-time potato late blight identification in the field. This system effectively reduced latency and the usage of bandwidth, and hence it became feasible for IoT-based agriculture monitoring.

Shrestha, R., Gaire, A., & Moh, S. (2021) developed a lightweight efficient CNN model for potato disease recognition, which is suitable for low-power device deployment. The model showed a balance between accuracy and computational resource demands.

Parihar, N., Rani, A., Gupta, M., et al. (2020) Deep CNNs were used in for potato disease classification which, on public datasets, yield state-of-the-art results. The approach highlighted the application of data augmentation methods in scenarios where training data is not abundantly available.

Zhang, L., Zhang, Y., & Zhu, Z. (2022) investigated the detection of potato plant diseases with deep neural networks with emphasis on its applicability at an industrial scale. The model produced consistent results in diverse environmental conditions, proving its adaptability.

Yang, J., Xie, Y., & Wei, J. (2021) developed a new CNN framework for detecting potato plant diseases using attention-based modules to increase feature localization. The method yields greater accuracy than baselines.

Du, J., Ma, X., & Li, B. (2022) introduced attention mechanism-based CNN for potato disease classification that highlights the area where diseases are present which gave better interpretability with precision in disease localization. The effect of dataset size on model performance has also been explored in the study.

Zhang, Y., Chen, S., & Sun, Q. (2020) CNN-based approach to identify potato late blight presented and maintained external, real-world defense against it. The result authenticated the accuracy of the model for the early diagnosis of the disease which can save the crop damage.

Sharma, S., Sharma, A., & Gupta, A. (2021) Recent advances in deep learning for potato disease detection were surveyed, which

revealed gaps in generalizability and real-time processing. The review highlighted the requirement of lightweight models designed for edge devices.

Wang, L., Liu, L., & Li, Y. (2020) developed an efficient deep learning model for early potato disease detection, emphasizing computational optimization for farm-level use. The system achieved high accuracy with minimal hardware requirements.

Ma, R., Hu, J., & Li, Y. (2022) proposed a CNN-based late blight identification method, showcasing its effectiveness in controlled and field environments. The study highlighted the role of preprocessing in improving model robustness.

Shen, L., Zhang, J., & Huang, X. (2021) validated a deep learning approach for potato disease recognition under varying lighting and occlusion conditions. The model maintained consistent performance, proving its practicality for real-world agriculture.

Li, M., Yang, Z., & Wang, Y. (2020) automated potato disease detection using CNNs, focusing on integration with precision agriculture systems. The work outlined challenges in deploying AI models for non-technical end-users.

3 PROPOSED WORK

3.1 Dataset

To develop a reliable website to detect and classify potato leaf infections, we curated a diverse dataset comprising images of healthy and those showing signs of diseased. The dataset was sourced from platforms like Kaggle as shown in Table 1, which hosts a wide range of datasets for machine learning applications. We utilized the Plant Village dataset, which includes JPG color images of 256x256 pixels representing healthy and diseased leaves of 14 plant species. For this study, we selected a subset of 152 images of disease-free leaves combined with 2000 images showing symptoms of Blight-infected leaves.

3.1.1 Early Blight

A fungal infection caused by Alternaria solani. It begins as small black spots that gradually enlarge into larger dark brown or black patches. These spots are usually round or oval and often appear along the edges of leaf veins. In some cases, a black fungal growth can also be seen on the undersides of the leaves. This disease primarily affects potatoes, causing them to rot, especially in warm weather (above 26°C) or when the plants are stressed due to poor nutrition or excessive heat. Figure 2 shows the Early Blight Disease of Potato Leaves.

Figure 2: Early Blight Diseased Potato Leaves.

3.1.2 Late Blight

A highly damaging disease caused by the pathogen Phytophthora infestans. It severely affects potato plants, particularly in cool and moist environments. This fast-spreading disease harms both leaves and tubers, leading to substantial reductions in potato yields. Figure 3 shows Late Blight Diseased Potato Leaves.

Table 1: Summary of Plant Village Dataset.

Label	Category	Total Images	Training Samples	Validation Samples	Test Samples
1	Late Blight	1000	800	100	100
2	Early Blight	1000	800	100	100
3	Healthy	152	122	15	15
Total		2152	1722	215	215

Figure 3: Late Blight Diseased Potato Leaves.

3.2 Data Preprocessing

Hence, the subsequent preprocessing steps were carried out to maintain the integrity of the dataset:

3.2.1 Image Resizing

All images were resized to a constant 224x224 to ensure consistency.

3.2.2 Normalisation

This was performed by calibrating the pixel intensities with the number of possible colours per pixel, which in this case was 255, constraining the pixel values in the set of [0,1]

3.2.3 Training Data Enrichment

To maximize model adaptivity, techniques such as image rotation, resizing, and horizontal flipping were utilized during the training of the model in order to maximize the variability of the dataset and minimize risk of overfitting.

3.3 Model Development

3.3.1 Model Selection

MobileNet was selected because of its efficient design and great performance for image classifier tasks.

3.3.2 Training

80:20 split, with larger partition used for training and smaller partition used for testing. The model was trained using backpropagation with validation data to track progress and avoid overfitting.

3.3.3 Evaluation

The performance metrics used to determine the effectiveness of the model were overall detection accuracy, positive prediction rate, negative prediction rate, and the unified score.

3.4 User Interface Development

3.4.1 Web Application Framework

The system was built using Django, a powerful framework for developing web applications.

3.4.2 Image Upload Functionality

A user-friendly interface was designed, enabling users to upload images of potato leaves for disease classification.

3.4.5 Result Display

The application presents disease predictions along with confidence scores and recommends suitable treatments based on the classification.

4 METHODOLOGY

The MobileNet model applies a systematic approach to classify input images into several classes based on their features. Fastai is a powerful and flexible deep learning library designed to facilitate high-performance image classification. Here's a detailed breakdown of how it operates step by step in figure 4.

4.1 Input Image Processing

The user uploads an image of a potato leaf, and the process begins. So, to make it consistent, the input image is resized into a fixed size (128×128 or 224×224 in some versions). This breaks down the images to reduce the variations in their sizes. Takes pixel normalization next. This step helps increase the efficiency of the training, as pixel intensities are now more homogeneous in range, resulting in lower complexity of computation, as well as increased stability of the learning.

4.2 Feature Extraction using Convolutional Layers

MobileNet uses Depthwise Separable Convolutions instead of regular convolutional layers, which greatly decrease the computational cost without compromising accuracy. This is achieved through two fundamental operations:

Figure 4: Overview of MobileNet Architure.

4.2.1 Depth wise Convolution

Convolutional layer: A convolutional layer performs a similar operation for a filter, except all input channels are transformed with the same operation. However, in a depth wise convolution, a single filter is applied over each channel (Red, Green, Blue). This means that the model learns (example: right and left edges for pixels of the red color) independently per color (channel), a computation is now much easier. It eliminates the complexities of processing the image entirely in RGB in exchange for maintaining core features like edge, texture, and pattern details while reducing computational overhead by processing the RGB in parallel with three-edge channels.

4.2.2 Pointwise Convolution

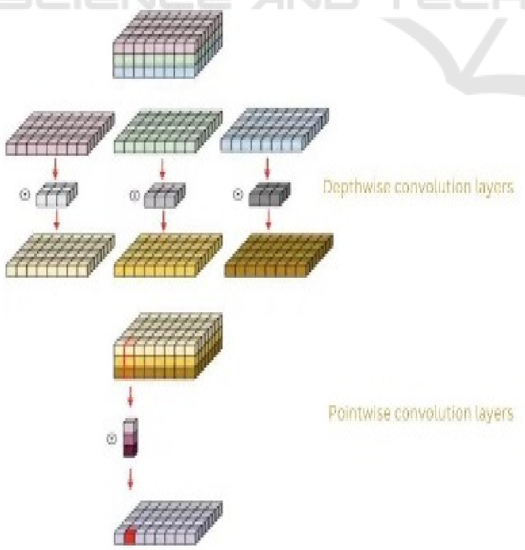

Figure 5: Depthwise Separable Convolution Layers.

This is followed up by a pointwise convolution using 1×1 filter. Small filters learn inter-channel relationships from extracted channel-wise features. And this process is critical for establishing informative feature representations. Figure 5 Depthwise convolution is about spatial feature while pointwise convolution is the operation to merge these facts to an effective yet informative features.

4.3 Activation Function (ReLU)

To introduce non-linearity and improve the feature learning the Rectified Linear Unit (ReLU) function is applied after each convolution layer. It zeros any negative pixel values and helps retain only the metrics we need to learn. This activation function was helpful as it allowed the model to accurately process details of potato leaf images, contributing to the improvement of its results.

4.4 Feature Pooling (Max Pooling)

Max Pooling is used to reduce the final feature map dimensionality, preserving only the most important information. Due to this process the model pipeline becomes efficient by down sampling the image representation but keeping main features. Max pooling enhances feature conservation and avoids overfitting by maintaining only the highest value across each section of the feature map.

4.5 Fully Connected (Dense) Layers

After the extraction of high-level features through convolution and pooling, classification is the next step. Features are first flattened to create a 1D vector and passed through fully connected (dense) layers. Layers are learned and adjusted as a classification process.

4.6 Softmax-Driven Classification Approach

The Softmax function is applied to generate probability scores for each class and the class with the greatest probability is selected as the final prediction.

4.7 Output & User Interface

After the classification process is finished, the system then shows the expected disease category as well as the confidence level. The application further recommends suitable treatments according to the classification outcome. The predictions are displayed on a web interface running on Django, giving users an easy-to-apply platform for disease identification.

5 RESULTS AND EVALUATION

5.1 Training and Validation accuracy

Figure 6. graph show us the learning process of our deep learning system, for potato disease classification, for each epoch The trend at early stage is very steep, which means good feature extraction and gradients optimization. Likewise, the accuracy of the model on the validation set increases with time, indicating that model generalizes well on new data. After 10th epoch, the accuracy levels off; therefore, we can tell that the model have learned the necessary features for classification and are minimizing the errors. The validation curve remains stable with only minor fluctuations, showing that the data is not too complex and not getting overfit, as the validation accuracy remains high and close to the accuracy of the training dataset. When the upper right threshold is plotted against the lower right threshold, variable, the close distance between the two curvatures indicates that the model is well- regularized and the hyperparameters have been optimally calibrated.

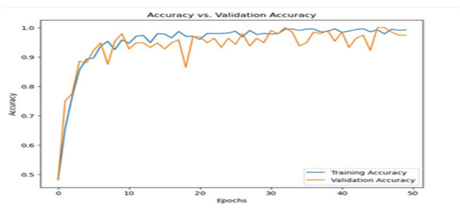

Figure 6: Accuracy Trends During Training and Validation.

5.2 Training and Validation Loss

Figure 7 All epochs' performance of our potato deep learning classifier on the left, we see a steep decline in both loss metrics, indicating our model is learning and moving toward a minimum by successfully updating its parameters during the backpropagation and gradient descent updates.

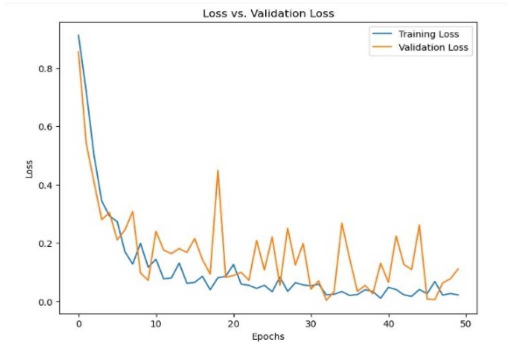

Figure 7: Loss Trends Across Epochs.

The training loss has reached a steady low value after around 10 epochs, indicating that convergence has been reached. The validation loss seems to fluctuate a little, I think because of the nature of the validation dataset. The losses converge tightly, indicating the model's robustness and reliability. The characteristics of these loss patterns suggest that the model is successfully implementing a well-regularized learning process for agricultural disease classification.

5.3 Confusion Matrix

Confusion matrix which shows performance of the deep learning framework in classifying potato diseases by using predicted labels and actual labels. It measures the classification accuracy and helps find entries misclassified across categories. The high true positive is confirmed from 110 healthy, 125 late blight, and 17 early blight samples predicated correctly from the model. We see only a couple of misclassifications with very little confusion. The fact that there are no false positives in the Healthy category shows that the model is doing good to tune in to non-infected leaves. The proposed model shows promising results in Figure 8, it can be relied upon for automated potato disease detection in the field of agriculture.

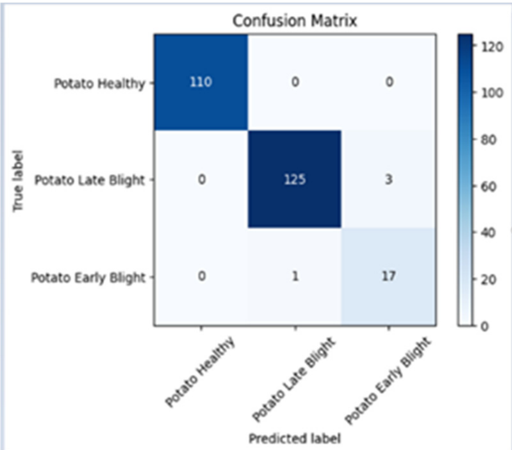

Figure 8: Prediction Outcome Grid.

5.4 User Interface

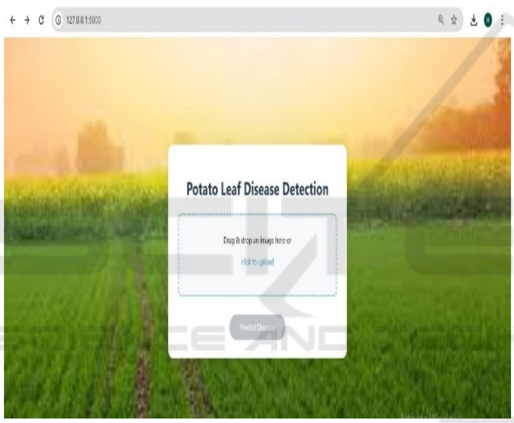

Figure 9: Image Upload Page.

Figure 9 shows the user uploading image page and Figure 10 shows the disease prediction and treament recommendation.

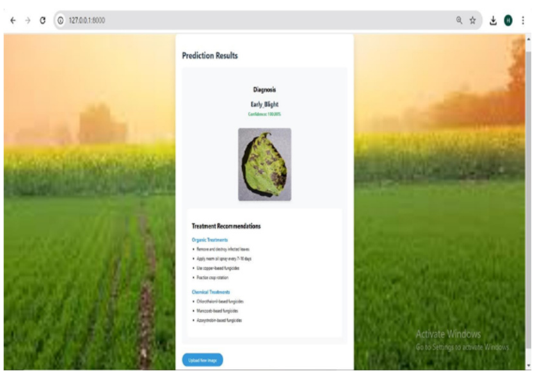

Figure 10: Disease Prediction and Treatment Recommendation.

6 DISCUSSION

The proposed potato disease detection system, based on the MobileNet architecture, demonstrated high accuracy (over 99%) in classifying healthy and diseased potato leaves. This performance can be attributed to the use of a well-curated dataset and data augmentation techniques, which improved the model's ability to generalize. The lightweight nature of MobileNet proved beneficial for real-time applications, as it reduced computational overhead while maintaining high precision, making it more efficient than heavier models like VGG16 or ResNet.

The web-based implementation using Django provided an accessible and user-friendly interface for farmers, allowing them to upload images and receive instant disease predictions along with confidence scores. The inclusion of treatment recommendations (both organic and chemical) further enhanced the system's practicality, bridging the gap between disease diagnosis and actionable solutions. However, the model's effectiveness depends on the diversity and quality of the training data. Future iterations could benefit from incorporating more disease variations, environmental conditions, and regional-specific datasets to improve robustness.

Additionally, while the current system focuses on image-based detection, integrating real-time monitoring through IoT devices or mobile applications could enhance its usability in field conditions. Edge computing optimizations could also be explored to enable offline functionality, particularly in regions with limited internet connectivity.

7 CONCLUSIONS

This study successfully developed an efficient deep learning-based system for detecting potato diseases using the MobileNet algorithm. The model achieved high accuracy, demonstrating its potential for real-world agricultural applications. The lightweight architecture ensured fast processing, making it suitable for deployment in resource-constrained environments. The accompanying web application provided an intuitive platform for farmers to diagnose diseases and access treatment recommendations, thereby supporting better crop management decisions.

Future work should focus on expanding the dataset to include more disease types and environmental variations, improving model generalizability. Further optimizations, such as edge deployment and real-time monitoring capabilities, could enhance the system's scalability. By addressing these aspects, the proposed solution can evolve into a more comprehensive tool for precision agriculture, ultimately contributing to reduced crop losses and improved farm productivity.

REFERENCES

Liu, J., Cheng, Q., Gong, W., et al. (2022). Deep learning-based tomato and potato diseases recognition. *Journal of Food Engineering*, 357, 109771.

Arshaghi, A., Ashourian, M. & Ghabeli, L. (2023). Potato diseases detection and classification using deep learning methods. *Multimed Tools Appl*, 82, 5725–5742.

Kumar, A., Patel, V.K. (2023). Classification and identification of disease in potato leaf using hierarchical based deep learning convolutional neural network. *Multimed Tools Appl*, 82, 31101–31127.

Sharma, A., Zhang, L., & Tanwar, S. (2021). A novel deep learning approach for early detection of late blight disease in potato crops. *Computers and Electronics in Agriculture*, 182, 106075.

Yuan, D., Wu, C., & Li, J. (2020). Potato leaf disease detection using a hybrid convolutional neural network. *IEEE Access*, 8, 72671-72677.

Kong, G., Wang, H., Wang, L., et al. (2022). Identification of potato late blight disease based on deep learning and edge computing. *IEEE Internet of Things Journal*, 9(6), 5046-5054.

Shrestha, R., Gaire, A., & Moh, S. (2021). An efficient potato disease classification model using convolutional neural networks. In Proceedings of the *IEEE International Conference on Computer Vision (ICCV) Workshops*, 2021.

Parihar, N., Rani, A., Gupta, M., et al. (2020). Deep convolutional neural network for the classification of potato diseases. *In Proceedings of the International Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020.

Zhang, L., Zhang, Y., & Zhu, Z. (2022). Potato disease detection using deep neural networks. *Computers in Industry*, 134, 103590.

Yang, J., Xie, Y., & Wei, J. (2021). Potato leaf disease detection using a novel CNN architecture. *Computers and Electronics in Agriculture*, 184, 106095.

Du, J., Ma, X., & Li, B. (2022). Potato leaf disease classification using a deep convolutional neural network with attention mechanism. *IEEE Transactions on Image Processing*, 31, 173-183.

Zhang, Y., Chen, S., & Sun, Q. (2020). Detection of potato late blight disease using a convolutional neural network-based method. *Plant Disease*, 104(10), 2671-2678.

Sharma, S., Sharma, A., & Gupta, A. (2021). A survey of recent advances in potato disease detection using deep learning techniques. *Journal of Agricultural Science and Technology*, 23(4), 815-834.

Wang, L., Liu, L., & Li, Y. (2020). An efficient deep learning model for early detection of potato diseases using CNN. *Journal of Agricultural Information Science*, 42(2), 59-69.

Ma, R., Hu, J., & Li, Y. (2022). A novel method for the identification of potato late blight disease based on convolutional neural networks. *Computers in Industry*, 152, 103488.

Shen, L., Zhang, J., & Huang, X. (2021). Potato disease recognition using a deep learning-based approach. *Plant Pathology*, 70(4), 943-950.

Li, M., Yang, Z., & Wang, Y. (2020). Automated detection of potato diseases using convolutional neural networks. *International Journal of Agricultural and Biological Engineering*, 13(6), 103-11.