

Potato Leaf Disease Detection Using Deep Learning

¹Chhaya M Zala and ²Krishna K Shah

^{1,2}Department of Computer Engineering, The Charutar Vidya Mandal (CVM) University, Anand, India

E-mail: ¹chhayagohel@gcet.ac.in, ²krishnashah2093@gmail.com

ABSTRACT

Agricultural land is not only crucial for feeding people but also plays a significant role in boosting the Indian economy. Potato cultivation, in particular, plays a vital role in global food security. However, it faces various challenges from diseases, particularly those affecting the leaves. Therefore, detecting these diseases at an early stage is essential for improving productivity and crop yield. Traditional methods for disease detection are time-consuming, require extensive manpower, and may result in incorrect analysis. To address these challenges, this study explores the application of technologies like image processing and deep learning for automating plant disease detection in its early stages. A Convolutional Neural Network (CNN)-based model is proposed to classify potato leaf images as healthy or diseased. The dataset comprises 2152 images belonging to three classes; healthy, early blight, and late blight. The proposed model consists of 16 layers: an input layer, six convolutional layers each followed by a max-pooling layer, a flatten layer, and two dense layers. This CNN architecture achieved a testing accuracy of 95.83%. Furthermore, the performance of the proposed model was compared with various pre-trained CNN models like VGG16 and InceptionV3. A simpler approach based on color histograms was also evaluated for the same task. This paper demonstrates the practical utility and benefits of using technology in agriculture and provides a path to empowering farmers with a valuable tool for effective disease management.

Keywords: *Potato leaf disease, deep learning, convolutional neural networks (CNN), disease detection, automated detection, transfer learning*

1. INTRODUCTION

Agriculture is a cornerstone of the Indian economy, providing sustenance and employment to millions of people. According to the Department of Agriculture and Farmers Welfare, India; agriculture and its allied sectors engage more than 50% of the workforce and contribute to above 21% of the country's GVA (Gross Value Added) [1]. In such situations, if the crops are affected by diseases and they are not treated promptly, it can lead to significant economic losses and worsen global food insecurity.

Traditional methods of disease detection, although widely used, are labor-intensive, inconsistent, and prone to human error. These drawbacks emphasize the growing need for reliable and scalable automated detection systems. Without accurate diagnosis, farmers may misuse pesticides, leading to environmental harm and development of long-term resistance in pathogens, making it harder for crops to fight off diseases. To prevent this from happening, plant diseases must be detected and treated early to prevent serious consequences and to help farmers make informed decisions about disease control measures.

In response to these challenges, technological advancements—particularly in deep learning—have emerged as a powerful tool for automating plant disease detection with greater accuracy and efficiency. Among these, Convolutional Neural Networks (CNNs) have shown great promise in accurately analyzing plant images and identifying disease patterns. These models can learn from large datasets, recognize complex features, and make precise predictions, offering a significant improvement over traditional method.

Building on these advancements, this paper investigates the use of deep learning techniques for detecting potato leaf diseases. By leveraging CNNs and other advanced algorithms, the objective was to develop an automated system capable of accurately classifying different types of potato leaf diseases from images. Four different approaches were explored: transfer learning using VGG16 and InceptionV3 models, a proposed CNN architecture tailored for this specific task, and a method based on color histogram analysis combined with k-nearest neighbors (KNN) classification. Through multiple experimental approaches, the goal was to develop an automated classification system that supports timely and effective disease management, reduces the reliance on manual inspection, and ultimately enhances crop health and yield. Through this research, the study aimed to contribute to the development of more efficient and reliable tools for modern agricultural disease detection.

2. LITERATURE REVIEW

The literature review is essential for understanding the current knowledge, methods, and advancements in detecting potato leaf diseases using deep learning. It encapsulates the examination of various aspects such as disease detection methods, dataset construction, CNN architecture, transfer learning strategies, and performance evaluation metrics. By critically analyzing existing research, this review aims to identify gaps, challenges, and opportunities and lay the groundwork for the proposed methodology and contribute to advancements in automated disease detection in agriculture.

The paper titled "Detection of Potato Disease Using Image Segmentation and Machine Learning", proposes an automated method to detect and classify potato leaf diseases using image

segmentation and machine learning. It analyzes over 450 images of healthy and diseased potato leaves and achieves a high accuracy of 97% with the Random Forest classifier. The process includes image processing, segmentation, feature extraction, training, and classification, leading to a robust system to identify early blight, late blight, and healthy potato leaves. The results highlight the method's effectiveness in automatic plant leaf disease detection and suggest future enhancements and extensions to other plant species. [2]

Extending the exploration of neural networks, the study "Plant Disease Detection using Convolutional Neural Network" introduces a CNN approach for detecting plant diseases, achieving a 95.8% accuracy in classifying diseases in potatoes, peppers, and tomatoes. The approach utilized image processing and deep learning techniques, offering a cost-effective and efficient alternative to manual methods. It uses Python with TensorFlow and Keras and provides real-time diagnosis through a Flask-based frontend. Future work for this paper involves expanding the dataset and commercializing the system through mobile applications. [3]

Similarly, the paper titled "Potato disease detection using machine learning," leverages CNNs to develop an automated disease detection system using leaf images. By processing over 2034 images, their model achieves an accuracy of 99.23% in disease classification. The authors suggested future developments, including an Android application for widespread farmer use, aiming to digitize and improve agricultural practices and ease farmers' burdens. [4]

Leveraging the InceptionV3 algorithm and deep learning techniques, the paper titled "Potato Leaf Disease Detection Using Inception V3" proposes a CNN-based approach for detecting diseases through leaf images. Using the Plant Village dataset and dividing it into training and testing sets, the model achieves a 90% accuracy in classifying diseases. The method offers a promising solution for early disease detection and crop management, enhancing agricultural productivity and livelihoods. [5]

Beyond CNNs, some studies explored hybrid or classical machine learning approaches. The paper "Potato plant leaves disease detection and classification using machine learning methodologies" presents a methodology for detecting and classifying diseases affecting potato plants using machine learning. By leveraging image processing and support vector machine (SVM) methodologies, the objective was to identify diseases in their early stages to enhance crop yield. Utilizing the Plant Village Dataset, the proposed framework achieves an accuracy of 95.99%. The steps involved are image segmentation, feature extraction with the Gray Level Co-occurrence Matrix, and SVM classification, to effectively distinguish between healthy leaves and those affected by early and late blight. Evaluation metrics like precision, F1-score, and recall, help demonstrate the effectiveness of the proposed model. Further enhancements suggested involve exploring advanced neural network architectures like convolutional neural networks (CNNs) to improve accuracy and robustness. [6]

Continuing the focus on CNNs, the study titled "Potato Leaf Disease Detection And Classification Using CNN" presented a method for detecting and classifying potato leaf diseases using CNNs. The study utilizes a dataset of over 2000 images and achieves a 91.41% testing accuracy. The methodology includes dataset collection, pre-processing, CNN classification, and model building, demonstrating the effectiveness of CNN in identifying early blight, late blight, and healthy leaves. The results suggest that CNN-based approaches offer a promising solution for automated disease detection and assist farmers in managing crop health. [7]

Another recent work, "Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach" proposes a deep CNN architecture for classifying potato leaf blight. Through data augmentation techniques, the dataset size is increased, leading to an improved testing accuracy of 98%. The architecture includes 14 layers, including both convolutional and fully connected. Future work suggests exploring transfer learning with pre-trained deep neural networks to enhance computational efficiency and accuracy. [8]

These studies collectively demonstrate the growing effectiveness of deep learning, particularly CNNs, in agricultural disease detection. However, most prior models either relied heavily on transfer learning without custom optimization, or were limited to single-method approaches. The present study builds upon these foundations by proposing a custom-designed CNN model and comparing it directly against VGG16, InceptionV3, and a non-deep learning method using color histograms. This comparative study provides a holistic view of model performance and aims to bridge the gap between practicality and accuracy in agricultural diagnostics.

Table I provides a detailed summary of the literature review.

TABLE I. SUMMARY OF LITERATURE REVIEW

Paper Title	Dataset	Method	Accuracy
Detection of Potato Disease Using Image Segmentation and Machine Learning [1]	PlantVillage - Potato - 3 classes - 450 images	Random Forest Classifier	97%
Plant Disease Detection using Convolutional Neural Network [2]	PlantVillage - Potato, Bell Pepper, Tomato - 15 classes - 20,639 images	Convolutional Neural Network (CNN)	95.82%
Potato Disease Detection Using Machine Learning [3]	Collected from field - Potato - 7 classes - 2034 images	CNN	Training - 98.36% Testing - 98.81%
Potato Leaf Disease Detection Using Inception V3 [4]	PlantVillage - Potato - 3 classes - 2152 images	CNN – InceptionV3	90%

Paper Title	Dataset	Method	Accuracy
Potato Plant Leaves Disease Detection and Classification using Machine Learning Methodologies [5]	PlantVillage - Potato - 3 classes - 300 images	K-means algorithm, Gray Level Co-occurrence Matrix, SVM	95.99%
Potato Leaf Disease Detection and Classification using CNN [6]	PlantVillage - Potato - 3 classes - 1150 images	CNN	91.41%
Artificial Intelligence in Potato Leaf Disease Classification: A Deep Learning Approach [7]	PlantVillage - Potato - 3 classes - 1722 images	CNN	Non-augmented - 94.8% Augmented - 98%

3. METHODOLOGY

To develop a robust and effective potato leaf disease detection system, the methodology begins with data acquisition, which involves downloading and curating a comprehensive dataset of potato leaf images. Next, the images were pre-processed by resizing, rescaling, and augmenting, then splitting into training and validation sets, to make the model more robust. These pre-processed images were subsequently used to train the models, including advanced techniques like transfer learning with VGG16 and InceptionV3 to enhance the performance. Subsequently, the performance of various models was evaluated by comparing their training and testing accuracies. Finally, the trained models were deployed to automatically detect and classify diseases in potato leaf images. Fig 1. portrays the workflow for the proposed methodology.

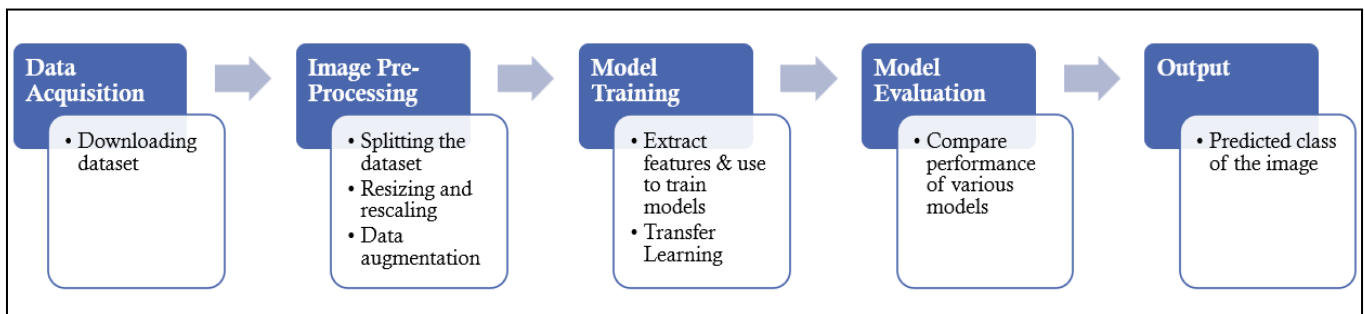


Fig 1. Workflow for Potato Leaf Disease Detection

3.1 Data Acquisition

In machine learning and deep learning applications choosing the right dataset is crucial as it plays an impact on the model's ability to learn and provide accurate results on real-world data. The dataset utilized for this model has been derived from a publicly available PlantVillage [9] database. This database contains over fifty thousand images for fourteen different crop species and diseases. Potato species-related data were selected from the database for the implementation of the CNN model. From the extensive database, a subset of 2152 images belonging to three distinct classes was selected. The three classes and their respective number of images are mentioned in Table II.

TABLE II. DATASET DETAILS

Class	Number of Images
Potato Early Blight	1000
Potato Late Blight	1000
Potato Healthy	152
Total	2152

For training the model, the dataset was split into training and testing sets in an 80:20 ratio, with 80% of images being allocated for training the model and 20% reserved for testing

purposes. After splitting, a total of 1721 images from 3 classes were present in the training set and 431 images were set aside for testing. This split ensured the model learned effectively from a majority of the data, while reserving the remainder to test how it performs on new, unseen data. Fig 2. shows sample images of each class taken from the Plant Village dataset.

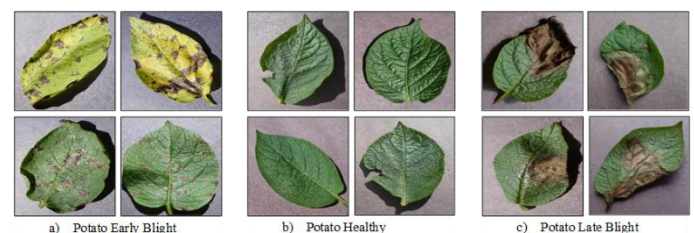


Fig 2. Sample Images of Plant Village Dataset

3.2 Pre-Processing

Once the dataset was finalized, image preprocessing was carried out to ensure consistency and improve model performance. Here, all images were resized to a uniform dimension of 256 x 256 pixels to standardize their sizes and ensure consistency across the dataset. Then, pixel values were rescaled by dividing each pixel value by 255, to obtain a range between 0 and 1, to facilitate efficient model training. Data augmentation techniques were applied to add randomness and

diversity to the dataset. This includes flipping the images horizontally and vertically and randomly rotating them by up to 0.2 radians to simulate different viewing angles. These steps enhanced the model's robustness and generalization capability by exposing it to varied input conditions.

3.3 Proposed Model

Following preprocessing, a Convolutional Neural Network was designed for the classification task, as CNNs are well-suited for image classification due to their ability to automatically learn hierarchical features from raw pixel data. The model comprises multiple layers, including convolutional layers for feature extraction, pooling layers for reducing the size of the data, and dense layers for the final classification. Fig 3. presents the model summary.

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(32, 30, 30, 64)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 64)	36928
max_pooling2d_4 (MaxPooling2D)	(32, 6, 6, 64)	0
conv2d_5 (Conv2D)	(32, 4, 4, 64)	36928
max_pooling2d_5 (MaxPooling2D)	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16448
dense_1 (Dense)	(32, 3)	195
Total params: 183747 (717.76 KB)		
Trainable params: 183747 (717.76 KB)		
Non-trainable params: 0 (0.00 Byte)		

Fig 3. Model Summary of the Proposed Model

The proposed CNN architecture includes 16 layers in total: 6 convolutional layers, 6 max-pooling layers, 1 flatten layer, and 2 dense layers (including the output layer). The input images define the shape of the input layer. Key hyperparameters of the model include a batch size of 32, an image size of 256x256, 3 channels, and a learning rate for the Adam optimizer. The model uses 2x2 filters in pooling layers to reduce the size of feature maps and 3x3 filters in convolutional layers to detect patterns in the images. These

parameters facilitate the training process and optimize the performance of the model. The model is trained over 50 epochs, indicating that the entire dataset is passed through the neural network 50 times during the training process, allowing it to learn over multiple iterations and improve its accuracy.

The convolutional layers use the Rectified Linear Unit (ReLU) activation function, which adds non-linearity to help the model capture complex patterns. Max-pooling layers reduce the spatial dimension of the data, making the model faster, reducing complexity, and preventing overfitting by keeping only the most important features. The output layer uses the softmax activation function to handle multi-class classification, converting the model's outputs into probabilities, where the highest probability indicates the predicted class label.

3.4 Other Approaches Implemented

In addition to the proposed CNN model, three other approaches were evaluated to compare performance and validate robustness.

a) Approach 1: Color Histogram with KNN

The first alternative approach leverages color-based features and a traditional classifier. This method combines the simplicity of color histograms with the K-Nearest Neighbors (KNN) algorithm for image classification. Color histograms serve as a feature representation by capturing the distribution of colors within an image. Histograms were calculated for the hue channel in the HSV color space for each image, focusing on capturing color-related features that are often indicative of different diseases. The histograms were then used as input features for training a KNN classifier, with k set to 5. The classifier was trained on these histograms to distinguish between classes such as "Healthy," "Early Blight," and "Late Blight." When classifying new images, the KNN model computes the histogram of the input image provided and identifies the nearest neighbors of the training set. The most common class among these neighbors determines the predicted label. This approach offers a straightforward yet effective way to utilize color information for disease detection.

b) Approach 2: InceptionV3

The second method utilizes transfer learning by fine-tuning a pre-trained InceptionV3 model. InceptionV3, developed by Google Research [10], is a deep learning model known for its efficient design, which balances model depth and computational efficiency. The architecture includes inception modules, which incorporate multiple convolutional filters of different sizes within the same layer that allow the network to process information at multiple scales, capturing both local and global features effectively. In this implementation, a pre-trained InceptionV3 model was used as a feature extractor. The top layers of the model were removed to accommodate a custom classification head tailored for potato leaf disease detection. The custom head included a global average pooling layer, which reduces the spatial dimensions of the feature maps, followed by a dense layer with softmax activation for classification. The base model's weights were kept frozen during training, while the new classification layers were trained on the specific dataset to learn specific features. This approach

leverages the model's strong feature extraction capabilities to enhance the classification of potato leaf diseases.

c) Approach 3: VGG16

The third method also uses transfer learning, this time with the VGG16 architecture, known for its uniform structure. VGG16 is a deep convolutional neural network developed by the Visual Geometry Group at the University of Oxford [11]. It consists a total of 16 layers, that use small 3x3 filters. These layers include 13 convolutional and 3 fully connected layers. This architecture is known for its uniform structure and simplicity. The transfer learning approach was implemented using a pre-trained VGG16 model, which was fine-tuned for the purpose of potato leaf disease detection. The top classification layer was removed and the weights of the pre-trained layers were frozen, to retain the learned features. A custom classification head was then added, consisting of a flatten layer, followed by dense and dropout layers, ending with a softmax activation layer for multi-class classification. Further, Adam optimizer was used in compiling the model. It was trained on a pre-processed dataset of potato leaf images, and the training process was monitored for 50 epochs to optimize the model's performance.

After training each model, performance evaluations were conducted to compare the accuracy and robustness across all approaches.

4. RESULTS

This section presents the outcomes of the experiments and highlights the effectiveness of the proposed CNN model in accurately identifying potato leaf diseases from images. The performance of the proposed CNN model was evaluated using standard accuracy metrics on both training and testing datasets. The model achieved a high training accuracy of about 99.18% and a testing accuracy of 95.83%. This indicates that the model learned to generalize from the training data and performs reliably on new, unseen data.

The training and validation curves for loss and accuracy over 50 epochs, are illustrated in Figure 4. As shown, the model's training accuracy steadily increased, while the validation accuracy followed a similar trend, with slight fluctuations. Both training and validation losses decreased, indicating the model is learning effectively, though occasional fluctuations in validation loss may indicate minor overfitting tendencies. Overall, these graphs reflect the model's learning progress and demonstrate its generalization capability on unseen data.

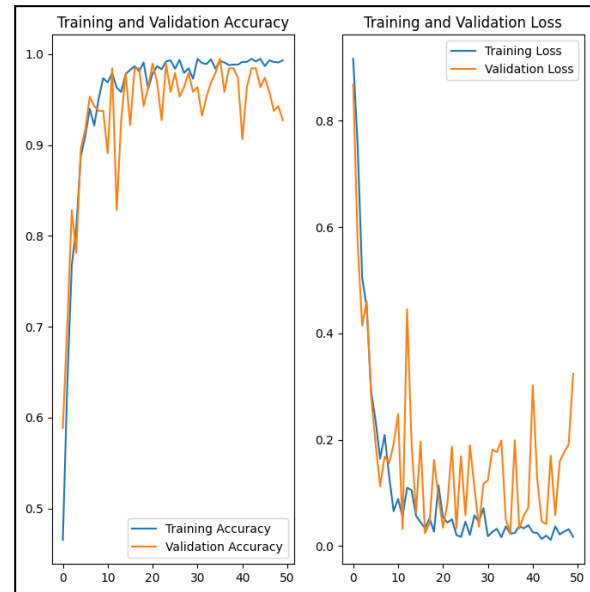


Fig 4. Training and Validation Accuracy and Loss Graphs for the Proposed Model

Further, to validate the robustness of the model, its performance was compared with three alternative approaches. Table III presents a comparative summary of the training and testing accuracies across all evaluated methods. Additionally, a visual inspection of the model's classified outputs confirmed consistent and accurate identification of plant disease categories. These results suggest that the proposed CNN model could serve as a valuable and reliable tool for automating plant disease detection, which could greatly benefit agriculture by enabling timely and accurate disease identification.

TABLE III. COMPARISON OF ACCURACIES OF VARIOUS APPROACHES

Method	Epochs	Training Accuracy	Testing Accuracy
VGG16	50	93.72%	95.36%
InceptionV3	50	96.86%	97.22%
Colour Histogram using KNN	-	97.26%	96.28%
Proposed CNN Model	50	99.18%	95.83%

In addition to quantitative metrics, a visual inspection of the outputs was conducted. Figures 5 to 8 illustrate the classification results produced by each evaluated approach.

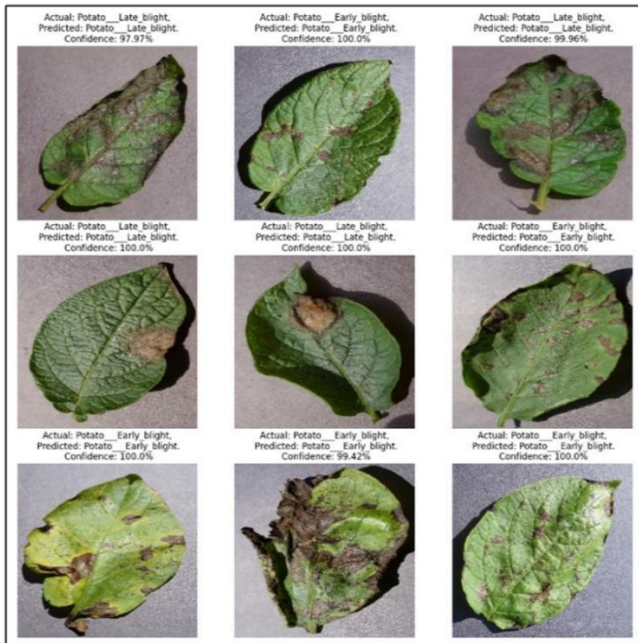


Fig 5. Outputs of the Proposed Model

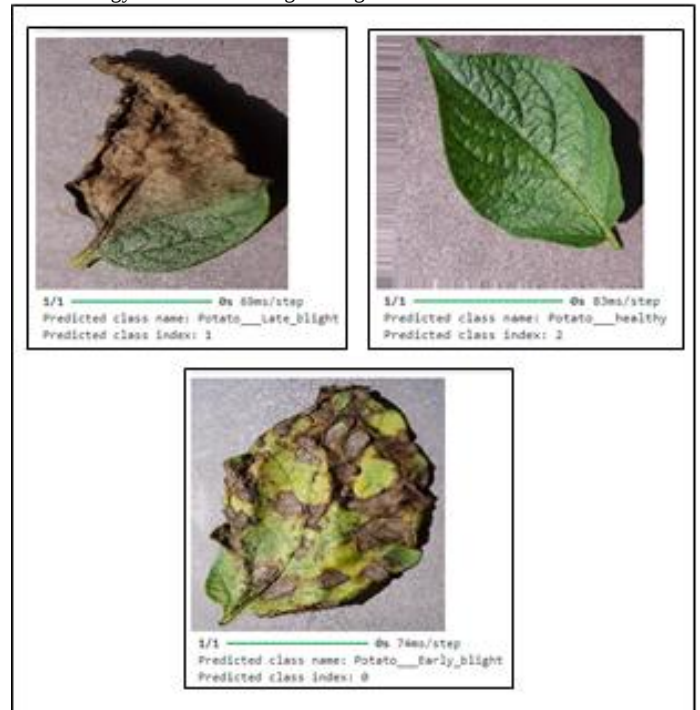


Fig 7. Outputs of Approach 2 – InceptionV3

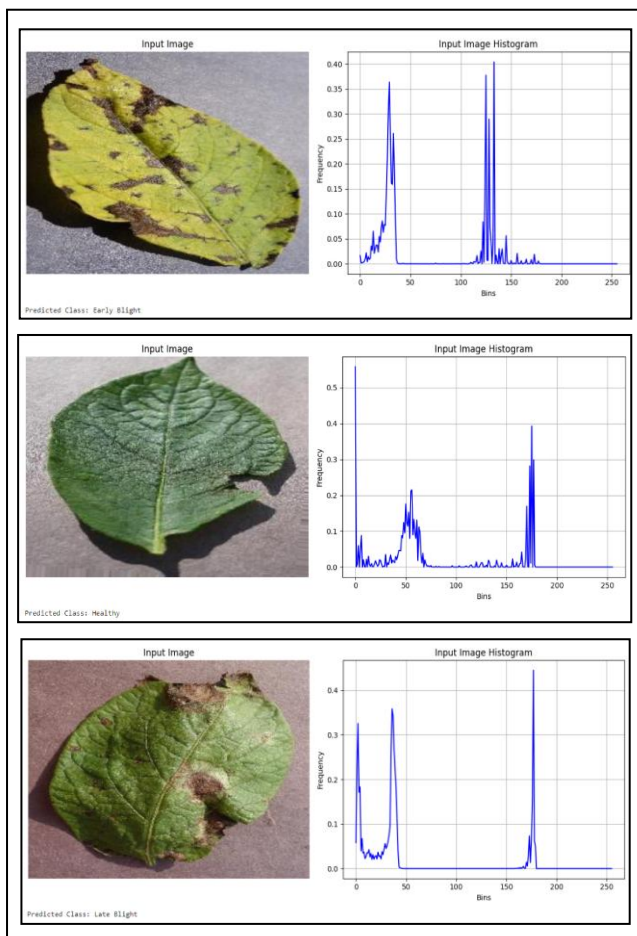


Fig 6. Outputs of Approach 1 – Color Histogram using KNN

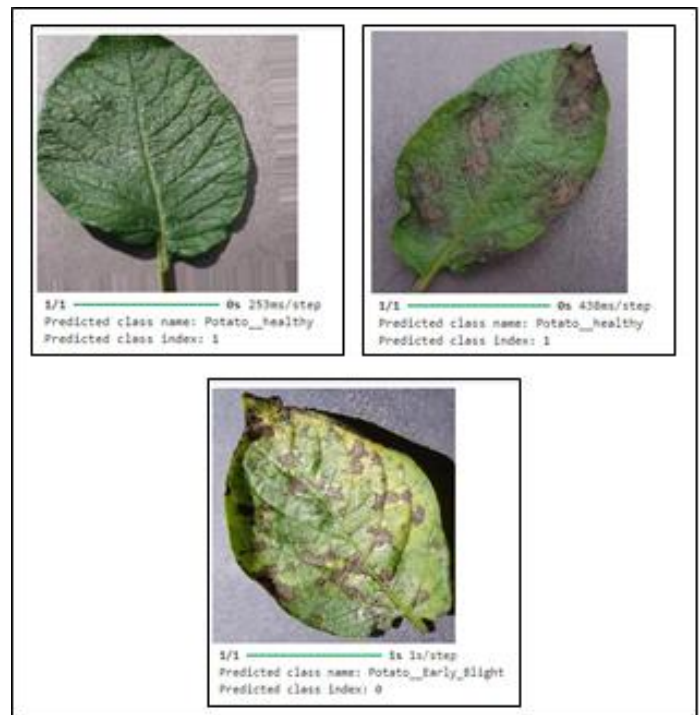


Fig 8. Outputs of Approach 3 – VGG1

Overall, the results confirm that the proposed CNN model offers a reliable and practical solution for potato leaf disease detection, demonstrating competitive performance across multiple evaluation benchmarks.

5. CONCLUSION

In conclusion, this study successfully developed and evaluated a Convolutional Neural Network (CNN) model for potato leaf disease classification, using TensorFlow and Keras. The proposed CNN model has exhibited promising performance in accurately identifying potato leaf diseases based on input images. Through systematic experimentation with architectural configurations, filter sizes, and hyperparameters, the model achieved high training and testing accuracies. Data augmentation and preprocessing techniques further enhanced the model's robustness and generalization capabilities. Overall, the findings demonstrate the potential of CNN-based methods for automated plant disease diagnosis, offering a valuable tool for farmers and agricultural professionals to monitor and manage crop health more effectively. The proposed approach contributes to precision agriculture by enabling early disease diagnosis, supporting healthier crops and more efficient farming practices.

6. FUTURE SCOPE

Looking ahead, there are several directions in which this work can be further extended and refined. Future research could involve exploring advanced CNN architectures and fine-tuning hyperparameters to further improve model accuracy and generalization. Incorporating a more diverse dataset across various crops and disease types could also enhance the model's generalizability and applicability in broader agricultural contexts. Moreover, the application of disease detection could be extended to additional crop types beyond the current scope to increase the system's overall impact. Additionally, developing a user-friendly web application for deploying and utilizing the model would also enhance its accessibility. This would make it easier for farmers and agricultural professionals to use the system and bridge the gap between technology and practical agricultural solutions. Overall, this study lays a strong foundation for future innovations in automated plant disease detection and serves as a step toward integrating AI-driven solutions in real-world agricultural systems.

REFERENCES

- [1] MoA & FW | Government of India, India." Ministry of Agriculture & Farmers Welfare, https://agriwelfare.gov.in/en/Agricultural_Statistics_at_a_Glance. Accessed 18 March 2024.
- [2] Iqbal, M. A., & Talukder, K. H. (2020, August). Detection of potato disease using image segmentation and machine learning. In 2020 international conference on wireless communications signal processing and networking (WiSPNET) (pp. 43-47). IEEE.
- [3] Sanmati RM, Utkarsh Srivastava, Vaishnavi S Korlahalli, Varshitha K, 'Plant Disease Detection using Convolutional Neural Network'. IRJET, Volume: 08 Issue: 07 July 2021.
- [4] Tarik, M. I., Akter, S., Al Mamun, A., & Sattar, A. (2021, February). Potato disease detection using machine learning. In 2021 Third International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV) (pp. 800-803). IEEE.
- [5] Chugh, G., Sharma, A., Choudhary, P., & Khanna, R. (2020). Potato leaf disease detection using inception V3. *Int. Res. J. Eng. Technol*, 7(11), 1363-1366.
- [6] Singh, A., & Kaur, H. (2021). Potato plant leaves disease detection and classification using machine learning methodologies. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1022, No. 1, p. 012121). IOP Publishing.
- [7] Bangal, Pagar, Patil, Pande. "Potato Leaf Disease Detection And Classification Using CNN." *International Journal of Research Publication and Reviews*, vol. 3, no. 5, May 2022, pp 1510-1515.
- [8] Khalifa, N. E. M., Taha, M. H. N., Abou El-Maged, L. M., & Hassanien, A. E. (2021). Artificial intelligence in potato leaf disease classification: a deep learning approach. *Machine Learning and Big Data Analytics Paradigms: Analysis, Applications and Challenges*, 63-79.
- [9] "Plant Village." Kaggle, <https://www.kaggle.com/datasets/arjuntejaswi/plant-village>.
- [10] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826).
- [11] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.
- [12] Sofuoğlu, C. İ., & Brant, D. (2024). Potato Plant Leaf Disease Detection Using Deep Learning Method. *Journal of Agricultural Sciences*, 30(1), 153-165.
- [13] Acharjee, T., Das, S., & Majumder, S. (2023). Potato leaf diseases detection using deep learning. *International Journal of Digital Technologies*, 2(1).
- [14] Rashid, J., Khan, I., Ali, G., Almotiri, S. H., AlGhamdi, M. A., & Masood, K. (2021). Multi-level deep learning model for potato leaf disease recognition. *Electronics*, 10(17), 2064.
- [15] Arshad, F., Mateen, M., Hayat, S., Wardah, M., Al-Huda, Z., Gu, Y. H., & Al-antari, M. A. (2023). PLDPNet: End-to-end hybrid deep learning framework for potato leaf disease prediction. *Alexandria Engineering Journal*, 78, 406-418.
- [16] Ashikuzzaman, M., Roy, K., Lamon, A., & Abedin, S. (2024, May). Potato Leaf Disease Detection By Deep Learning: A Comparative Study. In 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT) (pp. 278-283). IEEE.
- [17] Kothari, D., Mishra, H., Gharat, M., Pandey, V., Gharat, M., & Thakur, R. (2022). Potato leaf disease detection using deep learning. *Int. J. Eng. Res. Technol*, 11(11).
- [18] Tiwari, D., Ashish, M., Gangwar, N., Sharma, A., Patel, S., & Bhardwaj, S. (2020, May). Potato leaf diseases detection using deep learning. In 2020 4th international conference on intelligent computing and control systems (ICICCS) (pp. 461-466). IEEE.

AUTHOR PROFILES

1. Chhaya M Zala received the B.E. degree in Computer Engineering from Government Engineering College, Bhavnagar, under Gujarat Technological University, India. She completed her M.Tech. in Information Technology from Dharmsinh Desai University, Nadiad, where she was awarded the Gold Medal. She is currently pursuing her Ph.D. from Charutar Vidya Mandal University, India. Her research interests include Pattern Recognition, Machine Learning, and Image Processing.

2. Krishna K Shah is currently pursuing her final year of B.Tech. in Computer Science and Design Engineering from G. H. Patel College of Engineering & Technology (GCET), affiliated with Charutar Vidya Mandal (CVM) University. Her research interests include Deep Learning and Artificial Intelligence.