

Early Disease Detection in Potato Plant using Deep Learning for Precise Agriculture

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Abstract—Abstract—Potatoes are a key staple food worldwide, ranking fourth in global consumption. The COVID-19 pandemic has further increased potato consumption, but the crop's cultivation faces significant challenges due to diseases like Common Scab, Black Scurf, Black Leg, and Pink Rot, particularly in India. These diseases can severely reduce potato yields, leading to major financial losses for farmers. Given the crop's economic significance, improving disease detection and management is crucial. Initial detection with accurate detection of these diseases is crucial for better crop management, which ultimately supports a sustainable food supply chain.

Traditional methods for detecting potato diseases often fall short, especially for early intervention. As a result, advanced technologies like Deep Learning (DL) offer promising alternatives. This proposed system uses Convolutional Neural Networks (CNNs) to classify potato leaves as diseased or healthy, focusing on five categories: Early Blight, Healthy, Late Blight, Non-potato, and object. A simple CNN model is trained and tested for image classification tasks. By developing a web interface that allows farmers to upload leaf images, the proposed system aims to provide an easy-to-use tool for early disease identification.

Index terms- Potato disease, CNN, DL, Plant disease classification, Smart farming technologies.

I. INTRODUCTION

In India, extensive potato cultivation has reached approximately 53 million metric tons as per 2023 records. Unfortunately, 15.75% of this yield is lost annually due to various diseases affecting the crops. Potatoes are particularly affected by diseases like early blight, late blight, black scurf, pink rot, and common scab. Among these, early blight and late blight are the most predominant and damaging type of diseases in potato plants. The decision to focus on potato plants, rather than other crops, is driven by their global importance as a staple food and their economic significance. Potatoes are the fourth most consumed food crop worldwide, [1]. In India, potatoes are a crucial component of the diet and a significant agricultural product, making the effective management of potato diseases vital for food security and farmer livelihoods.

Potato plants are particularly susceptible to various types diseases due to their unique biological and environmental interactions. The most significant threats are early blight, which is caused by the alternaria solani fungus, and late blight is caused by the oomycete Phytophthora infestans. These pathogens thrive in the cool, moist conditions that are often ideal for potato cultivation, with early blight commonly developing in warm, humid environments.

The fungus *Alternaria solani* infects the foliage, causing dark, concentric lesions on the leaves, which can lead to defoliation and reduced tuber yield. Late blight, is tarnished for its rapid spread under cool, wet conditions [2,3,4]. The pathogen *Phytophthora infestans* can destroy entire fields within few days, leading to rotting of leaves, stems, and tubers.

Among the diseases affecting potato plants, early blight and late blight are prioritized due to their widespread occurrence and severe impact on crop yields. These blights cause the majority of losses in potato production, making them critical targets for disease management strategies [5]. Prioritizing these blights allows for more effective and specialized interventions to protect potato crops.

II. RELATED WORKS

In this study, multiple approaches were employed to develop and evaluate models for potato leaf disease detection under varying environmental conditions and dataset sizes. A multi-level deep learning model [7] utilizing YOLOv5 for image segmentation. However, Potato Leaf Disease Detection Convolutional Neural Network (PDDCNN) was trained on the PlantVillage dataset and tested on both PLD and PlantVillage datasets, achieving accuracies of 48.8% and 86.38%, respectively. However, the model struggled with recognizing early and late blight due to limited parameters and environmental variability. Another approach integrated machine learning and IoT devices [2] to predict and monitor diseases by analyzing environmental conditions, achieving 93.89% accuracy, though the focus was limited to a single disease, excluding abiotic and biotic stress factors. Additionally, deep learning models using VGG16 and Inception ResNetV2 [1] were trained on healthy and diseased potato images, achieving accuracies of 96% and 94%, respectively. While these models demonstrated potential in improving crop management, their performance across other crops remains unexplored. To address accuracy and computational time challenges, a customized convolutional neural network [8] was developed, minimizing pooling layers to retain salient features and validated using the PlantVillage dataset, achieving 96% accuracy. However, the reliance on pre-processed images raises concerns about its real-time applicability. An integrated image processing and machine learning approach [5] combining the PlantVillage database and Support Vector Machine (SVM) achieved 95% accuracy across 300 images, though its reliance on a small, pre-processed dataset may limit generalizability. Another methodology focused on determining the severity of Late Blight using image processing and neural networks [13], achieving 93% accuracy with a small dataset of 27 images, indicating potential limitations in broader applications.

A cloud-based Farm as a Service (FaaS) system [3] was also developed, integrating IoT devices for comprehensive agricultural analysis and prediction. Despite its validation in a strawberry infection prediction system, its scalability and effectiveness in diverse environments remain untested. The study further explored the implementation of IoT in agriculture [9], including wireless sensors for soil preparation, crop status, irrigation, and pest detection, as well as the use of UAVs for crop surveillance. While offering a broad overview, this approach may lack depth in addressing specific agricultural challenges. Lastly, a novel biosensor [14] developed by Hebrew University of Jerusalem and Israel Agricultural Research Organization detects hidden potato diseases using luminescent, genetically engineered bacteria. While promising, its high costs and limited availability challenge widespread adoption, making affordable IoT and DHT11 sensors a practical alternative for disease detection.

III. METHODOLOGY

A. General disease detection system

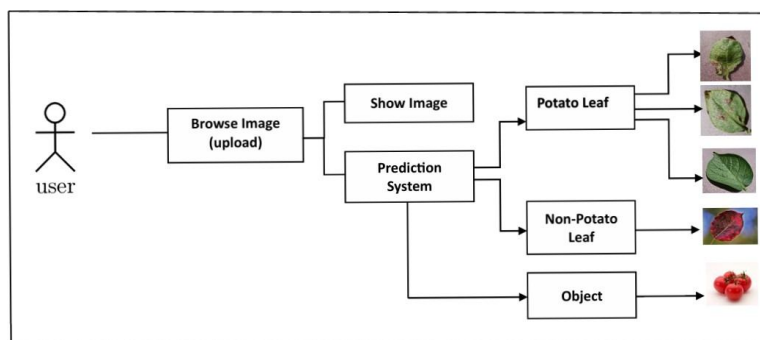


Fig. 1. General Potato Disease Detection System

The Figure 1 shows the General Potato Disease Detection System created with Streamlit for image classification. The interface features a “Browse Image” button for uploading images, which are then displayed for user verification. This verification step is crucial for accuracy, allowing users to confirm or re-upload images if necessary. This flexibility enhances user experience and system reliability.

B. Prediction Model

The uploaded image is processed by the prediction model, shown in Figure 2, which uses a trained Convolutional Neural Network (CNN) to classify the image into Early blight, Healthy, Late blight, Non-Potato Leaf and Object

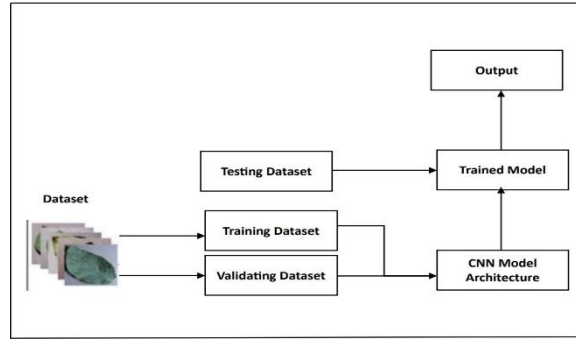


Fig. 2. Prediction model for potato disease detection

The results are displayed immediately, enabling quick decision-making for early disease detection. The system also records these results in a database, facilitating trend tracking and supporting ongoing agricultural management and research.

Dataset

The dataset is taken from the Kaggle Website [15] consisting of 3135 images that were divided into three classes: early blight, healthy, late blight. As per requirements two more classes were added namely Non potato leaf and Objects. Overall, 6035 images from all the classes and is dumped on the link: [16] This dataset is divided into 90% training data and 10% testing data, with the training set further divided into 80% training dataset and 10% validating dataset.

Training Dataset

The training dataset consists of 4,828 images, which is 80% of the total 6,035 image dataset. This subset is used to train and validate the performance of CNN model, allowing to learn patterns and features while minimizing overfitting. This ensures the model performs on new and unseen data.

CNN Model

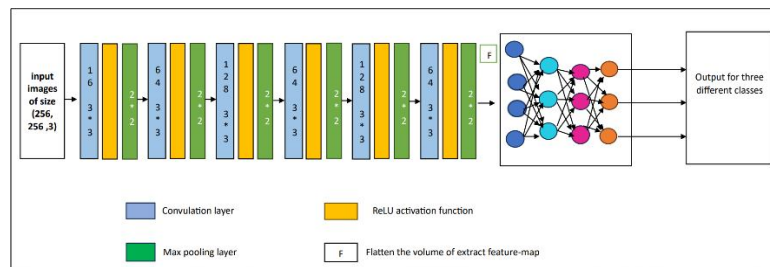


Fig. 3. The CNN model for potato disease detection.

The Figure 3 represents a typical Convolutional Neural Network used for image classification [8]. The detailed explanation of each component is as followed:

Input Layer: It accepts the input images from the user for classification. Here, the input images of random size are converted into input image of size 256×256 pixels with RGB color channels by the neural network.

First Convolutional Layer (C): The first layer of the network is a convolutional layer that applies 16 filters of size 3×3 to the input image. The convolution operation is defined as show in (1):

$$(I * K)(i, j) = \sum_m \sum_n I(i + m, j + n) \cdot K(m, n) \quad (1)$$

Where, I is the input image, K is the kernel matrix (filter) i, j are the coordinates of the output feature map, and m, n are the coordinates of the kernel.

Activation Function (AF): After the convolution operation, a ReLU (Rectified Linear Unit) activation function is applied element-wise as shown in (2):

$$ReLU(x) = \max(0, x) \quad (2)$$

Where, x is the input vector.

AF introduces non-linearity into the proposed model, thus allowing it to learn more complex features.

First Max Pooling Layers (P): Next, a max pooling layer reduces the spatial dimensions of the feature maps while retaining the most important information. The max pooling operation is defined as shown in (3):

$$P(i, j) = \max_{m, n} (F(s \cdot i + m, s \cdot j + n)) \quad (3)$$

Where, F is the input feature map, P is the pooled feature map, s is the stride (step size), typically 2, i, j are the coordinates of the pooled feature map, m and n are within the pooling window (usually 2×2).

Subsequent Convolution and Pooling layers: The network uses convolutional and max pooling layers to extract higher-level features and reduce dimensions.

It starts with a 64-filter 3×3 convolutional layer with ReLU, followed by 2×2 max pooling with stride 2. This is repeated with a 128-filter convolutional layer and max pooling. Additional 64 and 128 filter convolutional layers, each followed by max pooling, are used. This structure helps learn complex features and manage complexity.

Flatten Layer: After the final max pooling layer, a flatten layer converts the 2D feature into a 1D vector.

However, this transformation is crucial as it prepares data for the fully connected (dense) layers using (4).

$$x = Flatten(X) \quad (4)$$

Where, x represents the 2D feature maps and X mapping function.

Fully Connected (Dense) Layers: The first dense layer takes the flattened vector as input and uses a ReLU activation function as shown in (5) to introduce non-linearity.

$$y = ReLU(W \cdot x + b) \quad (5)$$

Where, y is the output vector, W is the weight matrix, x is the input vector, and b is the bias vector.

Output Layer: The final layer is the output layer, producing the output for three different classes. The softmax activation function as shown in (6) is used for multi-class classification.

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{j=1}^n e^{z_j}} \quad (6)$$

Where, z_i is the i^{th} element of the output vector and n is the total number of classes.

Loss Function and Backpropagation: During training, the loss function (e.g., cross-entropy loss) as shown in (7) identifies the difference between the predicted output and the actual label.

$$Loss = - \sum_i y_i \log(p_i) \quad (7)$$

Where, y_i is the true label, and p_i is the predicted probability.

Backpropagation is used to update the weights to minimize the loss. The gradient of the loss function with respect to each weight is calculated and used to adjust the weights as shown in (8).

$$\omega_{new} = \omega_{old} - \eta \cdot \frac{\delta Loss}{\delta \omega} \quad (8)$$

Where, ω_{new} is the updated weight, ω_{old} is the current weight, η is the learning rate, $\delta Loss$ is the gradient of the loss with respect to weight.

➤ Trained Model: A trained model is optimized using the training dataset to make accurate predictions on new data.

After training and validation, the CNN model is evaluated with a testing dataset of 1,584 images. The trained model is then saved in the .keras format for integration with the Streamlit interface, enabling it to classify new user-uploaded images effectively.

➤ Output: The final output is the classification result, which categorizes the uploaded image into one of the predefined classes (potato leaf - healthy or diseased, non-potato leaf or object).

IV. ALGORITHMS AND OPTIMIZERS

The proposed system includes two key algorithms: one for data balancing and another for using the Adam optimizer to minimize the loss function. These algorithms are essential for improving data balance and optimization, thereby enhancing the system's performance and accuracy.

A. Data balancing

Data balancing ensures equal class representation, preventing bias in CNNs for potato disease detection. Techniques like oversampling and under sampling improve model accuracy and fairness by creating a more representative dataset [8]. This allows CNNs to fully utilize available data. The designed algorithm is as follows:

Input: Directory of healthy potato leaf images from the PlantVillage dataset.

Output: Directory containing an increased number of healthy potato leaf images.

Initialize i to 0 // i is loop counter

While $i \leq 4$: // Loop runs 5 times

Select 12 random images

Create a 10×10 grid for each selected image Increment i by 1

Stop when $i > 4$

The dataset was normalized to expedite computation speed, and data augmentation techniques were employed to robustly train the model so as to avoid overfitting [1], [4]. Augmentation included horizontal and vertical flips, rotations within -20 to $+20$ degrees, shearing within -40 to $+40$ degrees, and random shifts up to 50% of the image's width and height. The Figure 4 shows some random images from each class based on the data balancing algorithm.

B. Adam Optimizer-Sparse Categorical Cross entropy

Optimizers are algorithms utilized to minimize loss through weight adjustments [1], [4]. The Adam optimizer accelerates gradient descent, making it ideal for large datasets. It combines momentum with exponential weighted averages and adaptive learning rates. By integrating elements of gradient descent, momentum, and RMSprop, Adam improves optimization performance across diverse data scenarios.

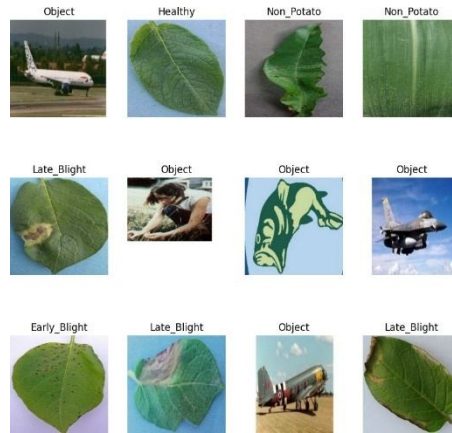


Fig. 4. Random sample images from each class in the dataset

Momentum is an optimization algorithm that enhances gradient descent by adding a portion of the previous update to the current weight update. These approach reduces fluctuations, helping the model converge faster to the optimal solution, particularly when gradients fluctuate or have high variance. It maintains a steady direction, accelerating convergence towards minimizing the loss function. The update rule for Momentum concept [20] is given in (9) through (10).

$$\omega_{t+1} = \omega_t - \alpha m_t \quad (9)$$

$$m_t = \beta m_{t-1} + (1 - \beta) \left[\frac{\delta L}{\delta w_t} \right] \quad (10)$$

Where, m_t : Aggregate gradients at time t (initially $m_t = 0$), w_t : Weights at time t , α : Learning rate at time t , δL : Derivative of the loss function, δw_t : Derivative of weights at time t , and β : Moving average parameter (typically 0.9).

RMSprop (Root Mean Square Propagation) is an adaptive learning rate optimization algorithm that adjusts learning rates for each parameter by dividing the current rate by the exponentially decaying average of squared

gradients. This method [20] stabilizes the learning process by independently adapting rates for different parameters, making it effective in scenarios where gradients vary widely across different dimensions of the data. The evaluation of weights at time t is done using (11).

$$w_{t+1} = w_t - \frac{\alpha_t}{\sqrt{v_t + \epsilon}} \left[\frac{\delta L}{\delta w_t} \right] \quad (11)$$

$$v_t = \beta v_{t-1} + (1 - \beta) \left[\frac{\delta L}{\delta w_t} \right]^2 \quad (12)$$

Where, w_t : Weights at time t , α_t : Learning rate at time t , δL : Derivative of the loss function L with respect to w_t , v_t : Exponentially weighted moving average of squared gradients, β : Moving average parameter (typically 0.9), ϵ : Small positive constant (e.g., 10^{-8}).

V. RESULTS

A. Experimental Setup

Utilized the potato leaf datasets sourced from Kaggle [15] to train and evaluate this model, implemented using TensorFlow version 2.16.1. The dataset comprises 6035 potato leaf images, evenly distributed across five classes. During training, augmented the dataset with 4828 additional images over 50 epochs. The model's evaluation was conducted on 151 real images, demonstrating satisfactory performance with 338,565 trainable parameters and a training duration of 186 milliseconds. To optimize neural network weights, Adam optimizer has been employed. Detailed model architecture and training parameters are depicted in Figure 5.

Layer (type)	Output Shape	Param #
sequential (Sequential)	(None, 256, 256, 3)	0
sequential_1 (Sequential)	(None, 256, 256, 3)	0
conv2d (Conv2D)	(None, 254, 254, 16)	448
max_pooling2d (MaxPooling2D)	(None, 127, 127, 16)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	9,280
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_3 (Conv2D)	(None, 28, 28, 64)	73,792
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_4 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_4 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_5 (Conv2D)	(None, 4, 4, 64)	73,792
max_pooling2d_5 (MaxPooling2D)	(None, 2, 2, 64)	0
flatten (Flatten)	(None, 256)	0
dense (Dense)	(None, 128)	32,896
dense_1 (Dense)	(None, 5)	645

Fig. 5 Features of CNN model considered for the proposed system

B. Evaluation Metrics

To evaluate the model's performance, a confusion matrix is used, as shown in Figure 6. This matrix compares actual and predicted classes, with the vertical axis indicating true labels and the horizontal axis showing predicted labels. Each cell represents the number of instances where the actual class (row) was predicted as a certain class (column).

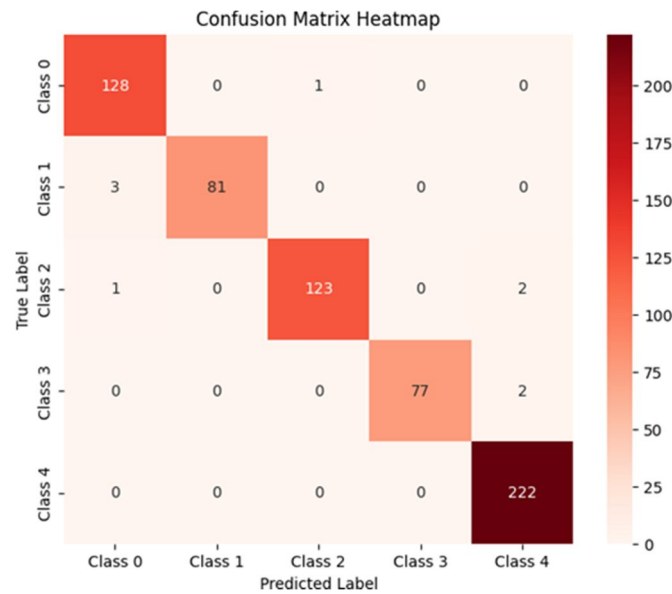


Fig. 6. Confusion matrix of proposed model

Overall, the model shows high accuracy in identifying Healthy plants, Early Blight, Late Blight, and Objects. The confusion is minimal, particularly between Early Blight and Late Blight, and between Non-Potato Leaf and Object, indicating areas where the model could be improved.

C. Performance Analysis

Training and Validation Accuracy

Training and Validation of the proposed system is done for accuracy and loss metrics. During training, the training accuracy measures the model's correctness on the training data, indicating how well it learns from the provided examples. Validation accuracy, on the other hand, evaluates the model's performance on unseen validation data as shown in Figure 7.

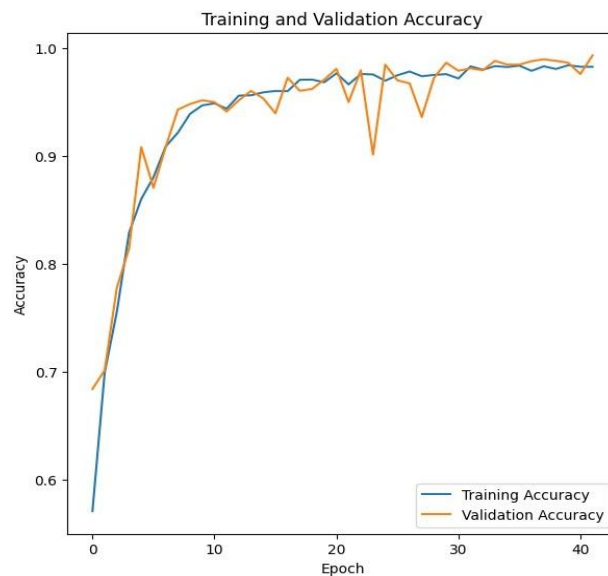


Fig. 7. Training and Validation Accuracy Plot

Training and Validation Loss

Training loss quantifies the error between predicted and actual values during training, reflecting how well the model fits the training data. Validation loss measures the model's performance on unseen validation data. The Figure 8 shows the plot of Training and Validation Loss of the proposed system.

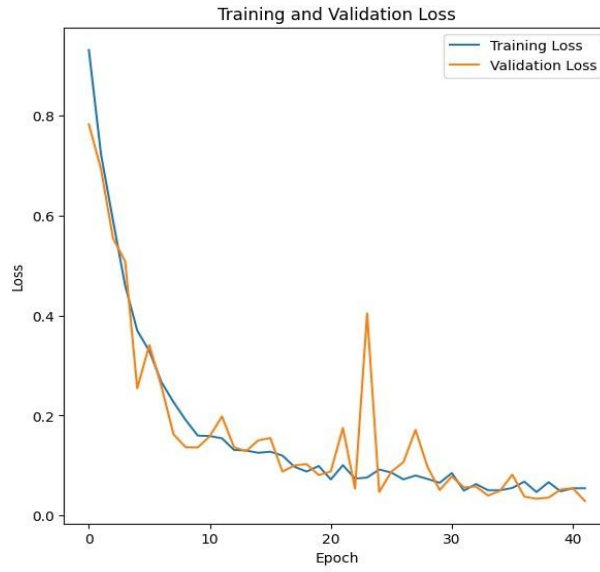


Fig. 8. Training and Validation Loss Plot

Precision, Recall and F1 Score: The Figure 9 shows the plot of Precision, Recall and F1 score of the proposed system. Precision is the ratio of true positives to total positive predictions, with high precision indicating low false positives. Recall is the ratio of true positives to total actual positives, with high recall indicating low false negatives. F1 Score is the harmonic mean of precision and recall, providing a balanced metric. A high F1 score suggests good overall performance.

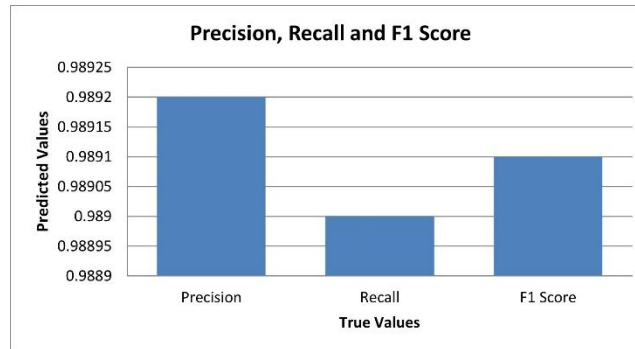


Fig. 9. Precision, Recall, and F1 Score plot

TABLE I: PERFORMANCE ANALYSIS OF PROPOSED MODEL

Classes	TP	FP	TN	FN	Precision	Recall	F1-Score
Early Blight	128	4	507	1	0.9697	0.9922	0.9808
Healthy Blight	81	0	555	3	1.0000	0.9643	0.9818
Late Blight	123	1	511	2	0.9762	0.9840	0.9880
Non-potato leaf	77	0	558	2	0.9747	0.9747	0.9747
Object	222	4	413	0	0.9823	1.0000	1.0000

The class wise values for all evaluation parameters for proposed model are summarized in Table 1. From this it is very clear that proposed system achieved best of it result in identification of diseases in potato leaf.

VI. CONCLUSION

The deep learning system detected and classified the potato leaf diseases using the convolutional neural network (CNN) network as healthy, early blight, late blight, non-potato leaf and object, by demonstrating high accuracy of 98.59%. The web application provides real-time disease detection and management, preventing financial

losses from delayed treatment. The system created a dataset, developed an effective CNN model and implemented an accessible web interface. It shows that deep learning can effectively address agricultural problems, improving crop yield and quality with timely disease management.

The mobile app can be developed for user-friendly interface which will simplify navigation and a real-time disease detection which will enable the farmers to capture and analyze images in the field, providing immediate disease diagnoses and recommendations. An IoT-based system can enhance potato disease detection by identifying specific diseases and enabling early detection with pathogen-specific biosensors. Monitoring soil and plant health can measure key parameters like nutrient levels, moisture, and pH, helping to detect environmental stress factors that may lead to diseases.

REFERENCES

- [1] S. Sadiq, K. Razzaq Malik, W. Ali and M. Munwar Iqbal, "Deep Learning-Based Disease Identification and Classification in Potato Leaves", *Journal of Computing & Biomedical Informatics*, vol 5, no. 01, pp. 13–25, 2023.
- [2] Patrick Kiplimo Toroitich, "A Model for early detection of potato late blight disease: A case study in Nakuru County", Thesis, Strathmore University, 2017.
- [3] Kim S, Lee M and Shin C, "IoT-Based Strawberry Disease Prediction System for Smart Farming", vol 18, no 4051, *Sensors*, 2018.
- [4] S. Vijai and A.K. Misra, "Detection of plant leaf diseases using image segmentation and soft computing techniques.", *Information Processing in Agriculture*, vol 1, pp. 41-49, 2017.
- [5] M. Islam, Anh Dinh, K. Wahid and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine.", *IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)*, Windsor, ON, Canada, 2017.
- [6] L. S. Pinto, A. Ray, M. U. Reddy, P Perumal and P. Aishwarya, "Crop Disease Classification using Texture Analysis", *IEEE International Conference on Recent Trends in Electronics Information Communication Technology (RTEICT)*, Bangalore, India, 2016.
- [7] J. Rashid, I. Khan, G. Ali, S. H. Almotiri, M. A. AlGhamdi and K Masood, "Multi-Level Deep Learning Model for Potato Leaf Disease Recognition", vol 10, no 2064, *Electronics*, MDPI, 2021.
- [8] M. H. Al-Adhaileh, A. Verma, T. H. H. Aldhyani and D. Koundal, "Potato Blight Detection Using Fine-Tuned CNN Architecture", vol 11, no 1516, *Mathematics*, MDPI, 2023.
- [9] Malik, Arvind, and Ramarcha Kumar, "An Overview on Agriculture in India.", *International Journal of Modern Agriculture*, vol 10, no. 2, 2021.
- [10] Kumar S. and Raghavendra B. K., "Diseases Detection of Various Plant Leaf Using Image Processing Techniques: A Review.", *5th International Conference on Advanced Computing & Communication Systems (ICACCS)*, Coimbatore, India, 2019.
- [11] U. Y. Tambe, A. Shobanadevi, A. Shanthini and H. Hsu, "Potato Leaf Disease Classification using Deep Learning: A Convolutional Neural Network Approach.", *Recent Trends in Data Science and its Applications*, River Publishers, 2023.
- [12] Tiwari, M. Ashish, N. Gangwar, A. Sharma, S. Patel and S. Bhardwaj, "Potato Leaf Diseases Detection Using Deep Learning", *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, India, 2020.
- [13] S. Biswas, B. Jagyasi, B. P. Singh and M. Lal, "Severity identification of Potato Late Blight disease from crop images captured under uncontrolled environment", *2014 IEEE Canada International Humanitarian Technology Conference (IHTC)*, Montreal, QC, 2014.
- [14] Veltman, D. Harpaz, S. Melamed, Z. Tietel, L. Tsrur, E. Eltzov, "Whole-cell bacterial biosensor for volatile detection from *Pectobacterium*-infected potatoes enables early identification of potato tuber soft rot disease", vol. 247, *Talanta*, 2022.
- [15] <https://www.kaggle.com/datasets/arjuntejaswi/plant-village>
- [16] <https://drive.google.com/file/d/1DJxQ2XUkHRNp5vv8VuE8Yv0ouEqDuRrB/view>
- [17] K. Gupta, K. Gupta, J. Jadhav, R. V. Deolekar, A. Nerurkar and S. Deshpande, "Plant Disease Prediction using Deep Learning and IoT.", *6th International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, 2019.
- [18] <https://jupyter.org/>
- [19] <https://medium.com/analytics-vidhya/web-application-in-10-minutes-with-streamlit-99685e3350e0>
- [20] Diederik P. Kingma and Jimmy Lei Ba, "Adam: A Method for Stochastic Optimization.", *3rd International Conference for Learning Representations*, San Diego, 2015.