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Light-Weight Deep Convolutional Neural Network Model for Classification of Potato Leaf Diseases

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***Abstract* - Potato leaf diseases pose a significant threat to global food security by reducing crop yields and economic productivity. Traditional manual inspection methods are often inefficient and error-prone, particularly in developing countries. Automated deep learning approaches provide a promising alternative for accurate and timely disease detection. This study develops a lightweight deep convolutional neural network (DCNN) for classifying potato leaf diseases, including early blight, late blight, and healthy leaves, while ensuring high accuracy, efficiency, and deployability on edge devices. A dataset of 2,152 potato leaf images, sourced from Kaggle, was preprocessed, augmented, and partitioned into 80% training, 10% validation, and 10% testing sets. A custom DCNN architecture (2.2M trainable parameters) was designed and compared against Xception, ResNet50, and InceptionV3 using precision, recall, F1-score, specificity, accuracy, and Cohen's Kappa metrics. The proposed model outperformed existing architectures, achieving 97.21% accuracy, 93.92% F1-score, 95.83% precision, 92.33% recall, 98.38% specificity, and 95.00% Kappa score, with a compact size of 25.6 MB. Deployment on a Streamlit-based web application demonstrated real-time classification capabilities, achieving near-perfect accuracy (99.99%) for early and late blight detection. The lightweight DCNN offers an efficient, accurate, and deployable solution for potato disease classification, suitable for edge devices such as smartphones. This system empowers farmers with rapid, automated diagnostics, enabling timely interventions to mitigate crop losses. Future work will focus on extending the model to additional potato species and optimizing deployment for mobile platforms.**
***Keywords:* Potato Leaf Diseases, Deep Convolutional Neural Network (DCNN), Disease Classification, Edge Devices, Precision Agriculture**

I. INTRODUCTION

The primary cause of infections in plants is food insecurity [1], [2]. Plant disease detection and classification remain major challenges for farmers. Therefore, it is essential to identify diseases in both leaves and fruits. Automatic classification of plant diseases based on their unique symptoms would greatly benefit agricultural scientists and farmers. One of the greatest problems in agricultural and horticultural science is early disease identification. Plant diseases are significant because they affect not only animals but also humans, and they have the potential to substantially reduce crop yields.

The detection and classification of diseases are critical tasks [3], [4]. Farmers have traditionally relied on visual observation to identify plant diseases. Researchers have applied image processing techniques to detect diseases more quickly and accurately, particularly in their early stages, thus enabling effective control.

The potato (Solanum tuberosum), a starchy tuber native to the Americas, belongs to the Solanaceae (nightshade) family. Potato diseases include bacterial wilt, in which all plant sections exhibit visible symptoms, and Septoria leaf spot, which begins as tiny, irregular spots on lower leaves and gradually spreads upward. The spots typically have a dark border with a gray center. In addition, insect damage, viral infections, and fungal diseases such as early and late blights contribute to low potato yields. Potatoes are widely used as a thickener in sauces and baking and are highly digestible, providing niacin, thiamin, protein, and vitamin C [5].

Potato is a significant food crop cultivated across Nigeria. As a source of vitamins, proteins, and carbohydrates, it is considered essential in both developed and developing countries. Originating from Peru and endemic to South America, potato ranks as the fourth most important food source worldwide after wheat, rice, and maize [6].

The main destinations of potato exports from Nigeria include Ghana ($547k), Niger ($213k), Kuwait ($1.31k), Sweden ($1.25k), and Benin ($920). Between 2019 and 2020, the fastest-growing export markets for Nigerian potatoes were Ghana ($547k), Niger ($27.9k), and Kuwait ($1.31k).

Machine vision and artificial intelligence (AI) [7]-[13], as noted in [14], have been applied to various domains [15]-[21], including biomedical applications [1], [20].

Convolutional Neural Networks (CNNs), one of the most widely explored deep learning approaches, have been successfully applied to many computer vision tasks [22], including plant disease recognition [23]-[25]. However, as reported in [26], [27], most CNN applications focus primarily on the classification or identification of diseases and pests. For example, Khan *et al.,* [24] used different CNN structures to classify plant diseases, achieving accuracies of 98.33% and 90.85% for mango and potato leaf infection classification with AlexNet and shallow CNNs, respectively [29]. Similarly, CNNs have been employed to classify leaf diseases in tomato, rice, and cucumber [30]-[32] and to detect weeds in soybean crops [33].

Since many diseases share similar symptoms and crops may be affected by multiple infections, accurate identification typically requires skilled experts. This makes it difficult for farmers to select appropriate nutrients or pesticides, thereby complicating disease management. To address this, researchers have applied CNNs to classify potato leaf diseases, with promising results. However, for practical impact, such models must be deployed on web applications or edge devices to enable farmers to automatically identify and classify potato leaf diseases.

This work proposes a deep learning system for the automatic, fast, and accurate classification of sweet potato leaf diseases, deployable on edge devices. The main contributions are as follows:

1. Improved classification accuracy and performance metrics for potato leaf disease detection with the proposed algorithm.
2. Enhanced classification accuracy for healthy potato leaf images.
3. A lightweight model suitable for hardware deployment.
4. A web application capable of continuous classification of input images.

The remainder of this paper is structured as follows: Section 2 presents the related work, Section 3 explains the methodology, Section 4 discusses the results, and Section 5 concludes the paper.

II. REVIEW OF LITERATURE

A Mahalanobis distance classifier for classifying potatoes in terms of size, shape, and other defects was presented in [34]. The distinction between defects and diseases was made using eccentricity and central moments. Potatoes with irregular shapes were further identified using Fourier descriptors. In [35], the authors worked on potato classification using co-occurrence matrices and histograms to extract features for each RGB and HSV channel. A genetic algorithm was employed for feature selection, and classification was performed using a nearest neighbor approach. Detection rates of 83.3%, 88.5%, and 84.7% were achieved for good, rotten, and green potatoes, respectively. In [36], a real-time method was developed to identify atypical potatoes. A linear discriminant analysis was performed using Fourier descriptors and geometrical characteristics as input to find the most relevant features. Experimental results showed 98.8% accuracy for regular potatoes and 75% for deformed potatoes.

In [37], a graph-cut approach was proposed to recognize potato leaf diseases and assess their severity. The method incorporated the graph-cut algorithm, Otsu thresholding, color statistical thresholding, local binary patterns, and classifiers. Results showed that the SVM classifier, combined with LBP, attained the highest accuracy of 92.1%. In [38], an algorithm was proposed to detect and classify four potato leaf diseases, achieving 97.2% accuracy.

Similarly, the methodology in [39] outperformed other techniques, with an average detection accuracy of 97.73% across various potato disease types. In [40], a system based on AdaBoost was introduced to discriminate between blemished and non-blemished pixels.

After extracting color and texture features, the AdaBoost algorithm automatically selected optimal features for classification and performed effectively. The study in [41] proposed a methodology to classify potato leaf diseases and distinguish them from healthy leaves, achieving 97.89% accuracy.

The authors fine-tuned a VGG16 architecture and compared it with existing methods. Furthermore, [42] presented a system to categorize potato patches into five distinct classes.

III. MATERIALS AND METHODS

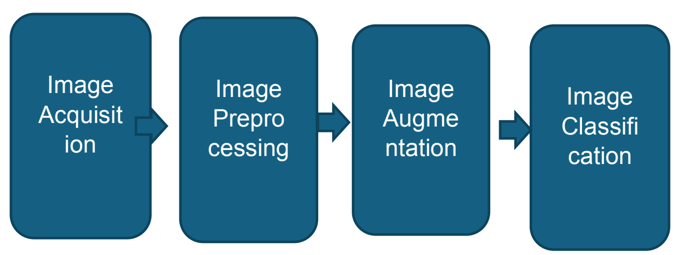

Fig. 1 Proposed Methodology

A. Image Acquisition

The dataset used for this research was obtained from the Plant Village dataset, which contains approximately fifteen (15) categories of plant diseases with a total of 20,693 images. However, this study only considered three (3) of those categories, utilizing 2,152 images. The distribution of images across the three categories is shown in Fig. 2 as follows: healthy potato leaves - 152, early blight - 1,000, and late blight - 1,000.

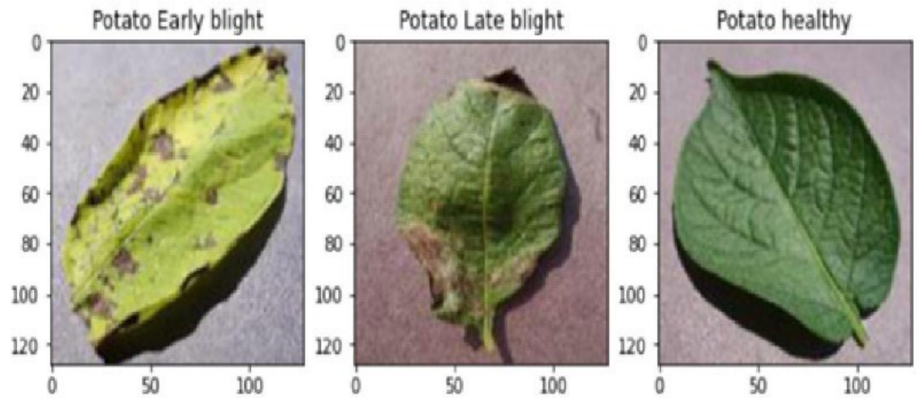

Fig. 2 Sample Images of Potato Leaf Images

B. Image Preprocessing

Image preprocessing refers to the process of modifying, combining, or removing image data to prepare it for analysis. This procedure is also commonly referred to as data cleaning.

Proficiency in data cleaning is crucial for data scientists and machine learning engineers, as the quality of preprocessing directly affects the insights that models can extract from the data. In this study, the image folders were restructured to facilitate ease of use with TensorFlow and Keras helper classes.

C. Image Augmentation

Deep learning tasks [44]-[46] require large amounts of data; therefore, it was necessary to augment the existing dataset [47]-[50]. The TensorFlow Image Data Generator class was used for augmentation. This class was configured to generate new images by randomly modifying the original images. The modifications applied included cropping, zooming, brightening, darkening, elongating, and stretching of the original images.

D. Image Classification

Artificial intelligence (AI), specifically deep learning, has been widely employed for numerous applications [51]. Convolutional Neural Networks (CNNs) have been utilized in several studies for plant disease detection.

In this work, a lightweight CNN model was developed for the classification of sweet potato leaf diseases.

E. Modeling

The figure 3 shows model architecture used for the research.

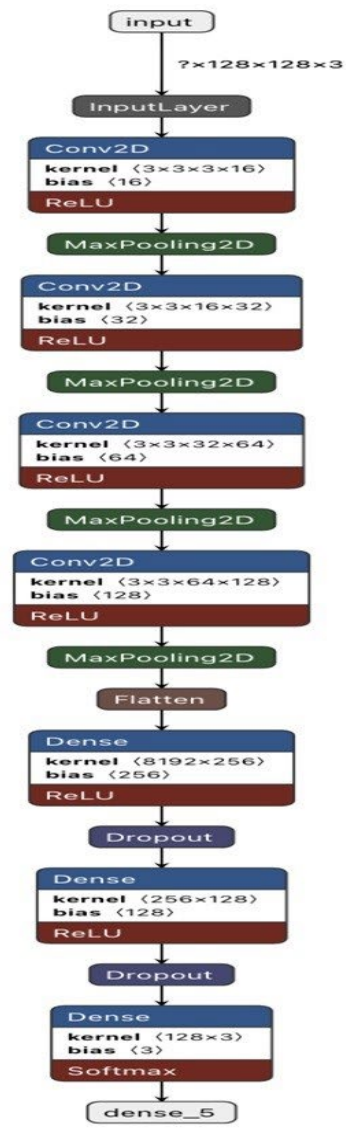

Fig. 3 Proposed Model Architecture

The architecture has a total of 2,228,131 trainable parameters from four (4) convolution layers, four (4) maxpooling layers and three (3) dense layers. The Figure 4 shows the filters used in each block.

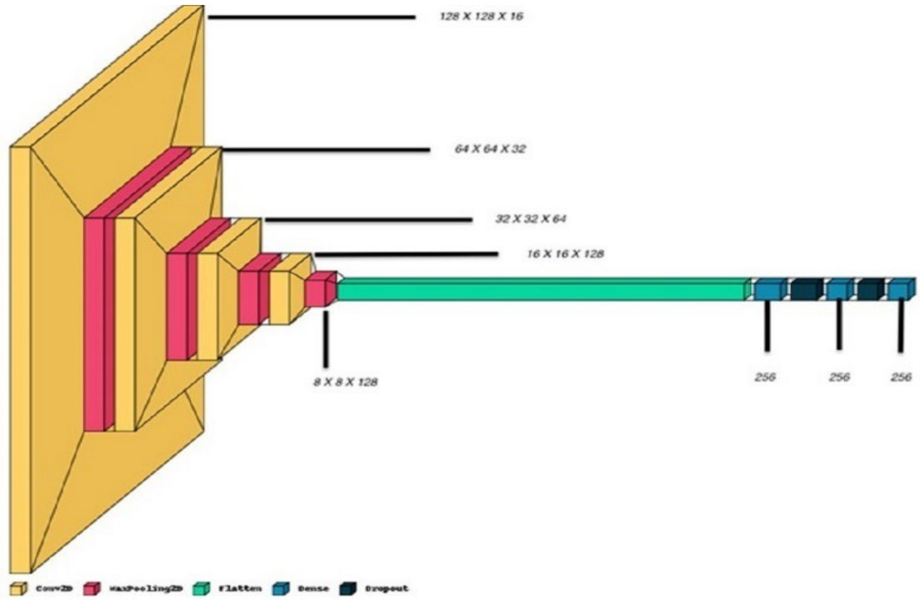

Fig. 4 Block View of Proposed Architecture

The metrics were calculated based on values obtained from confusion matrix which can be True Positives (TP) i.e. the model correctly predicts a positive class, True Negatives (TN) i.e. model correctly predicts a negative class, False Positives (FP) i.e model incorrectly predicts a positive class, and False Negatives (FN) i.e model incorrectly predicts a negative class.

Precision: This is the ratio between the number of true positive outcome and the total number of positive outcomes. This is measured with TP and FP as in eq. (1).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (1)$$

Recall: This is called sensitivity. It is probability that the model will correctly identify positive samples, given that they are indeed positive. This is measured with TP and FN as in eq. (2).

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (2)$$

F1 Score: This is the harmonic mean of sensitivity and precision, providing a single measure to assess the overall quality of binary classification. This is measured with TP, FN and FP as in eq.(3).

$$\text{F1 Score} = \frac{2*TP}{2*TP+FN+FP} \quad (3)$$

Specificity: This is the probability that the model will correctly identify negative samples (healthy leaves), given that they are indeed negative. This is measured with TN and FP as in eq. (4).

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

Accuracy: This is the percentage of correct predictions. This is measured with TP, TN, FN and FP as in eq. (5).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (5)$$

Cohen_kappa_score or K: This is the statistical measure used to assess effectiveness of the classification model. This is measured with TP, TN, FN and FP as in eq.(6).

$$\text{K} = \frac{2*(TP*TN-FN*FP)}{(TP+FP)*(FP+TN)+(TP+FN)*(FN+TN)} \quad (6)$$

IV. RESULTS AND DISCUSSION

A. Results

1. Experimental Setup

This research was implemented using Python 3.7 with TensorFlow and Keras frameworks for deep learning tasks, and Streamlit for web deployment. The model was executed on an HP system with an Intel® Core™ i5 CPU M 540 @ 2.53 GHz, 8 GB of RAM, running Windows 10 Pro.

The dataset was split into training, validation, and testing sets in an 80:10:10 ratio, comprising 1,722 images for training, 215 images for validation, and 215 images for testing. Training and validation were performed simultaneously, while the test set was reserved for later evaluation. The model was trained for 25 epochs. The proposed model was built using TensorFlow's Sequential class and other relevant classes provided by the TensorFlow library. For comparison, the model's performance was evaluated against ResNet50 [52], InceptionV3 [53], [54], and Xception [55].

2. Model Performance

The accuracy and loss of the proposed model are presented in Fig. 5. The training and validation accuracies were both 97%, while the training and validation losses were 0.09 and 0.07, respectively.

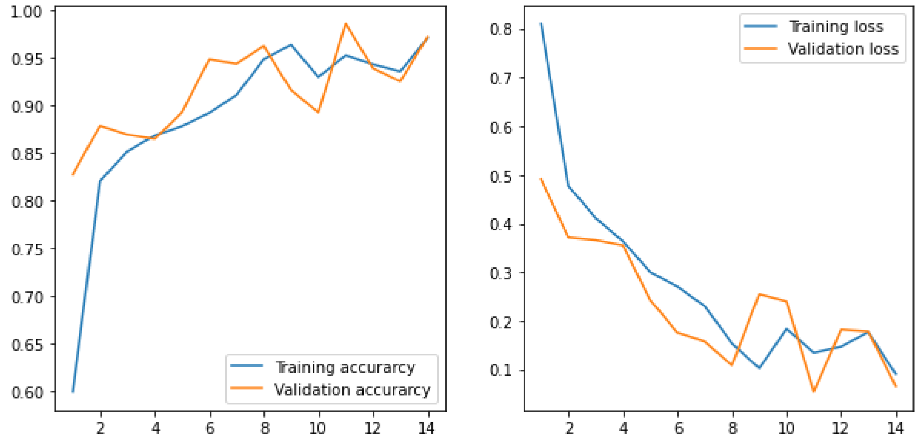

Fig. 5 Graph of Accuracy and Losses (Proposed)

An accuracy of approximately 98% was achieved on the testing dataset. The changes across the three classes are presented in the confusion matrix shown in Figure 6. The diagonal cells represent correctly classified results, while the off-diagonal cells indicate misclassifications.

The accuracy and losses of InceptionV3 is presented in Figure 7 while the changes for the three (3) classes is presented in confusion matrix (Figure 8).

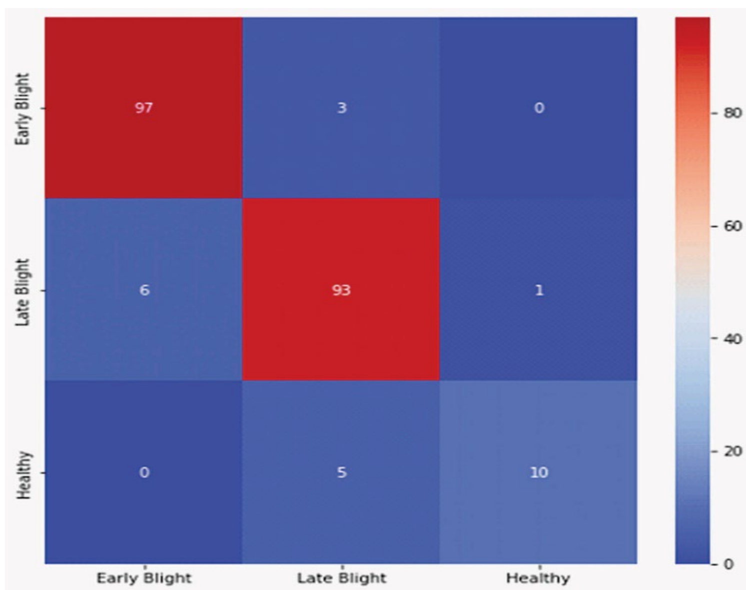

Fig. 6 Confusion Matrix for Classification of Potato Leaf Image Test Data (Proposed)

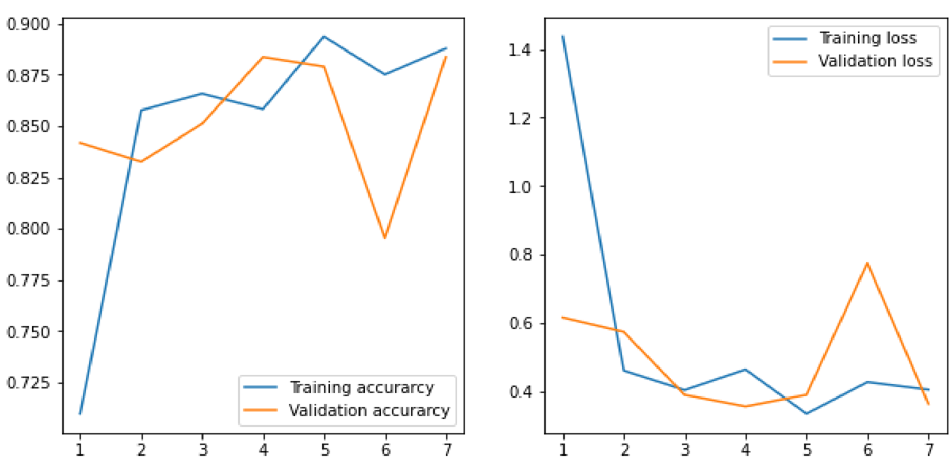

Fig. 7 Graph of Accuracy and Losses (Inceptionv3)

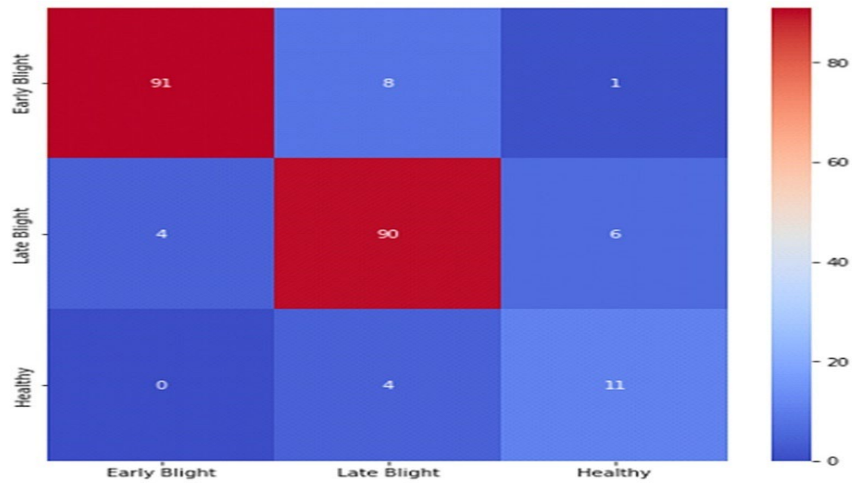

Fig. 8 Confusion Matrix for Classification of Potato Leaf Image Test Data (Inceptionv3)

An accuracy of 91% and 93% was obtained for the training and validation of the Xception model, with corresponding training and validation losses of 0.31 and 0.23. This model achieved lower accuracy and higher losses compared to the proposed model. The accuracy, losses, and confusion matrix of the Xception model are presented in Figs. 9 and 10.

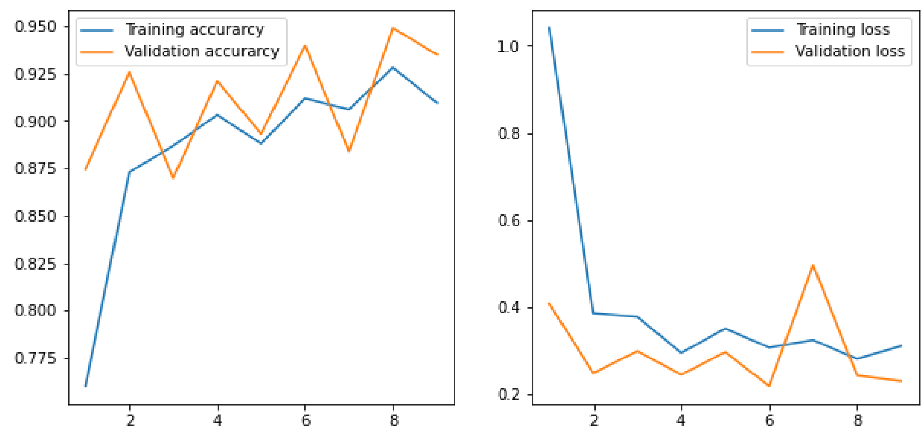

Fig. 9 Graph of Accuracy and Losses (Xception)

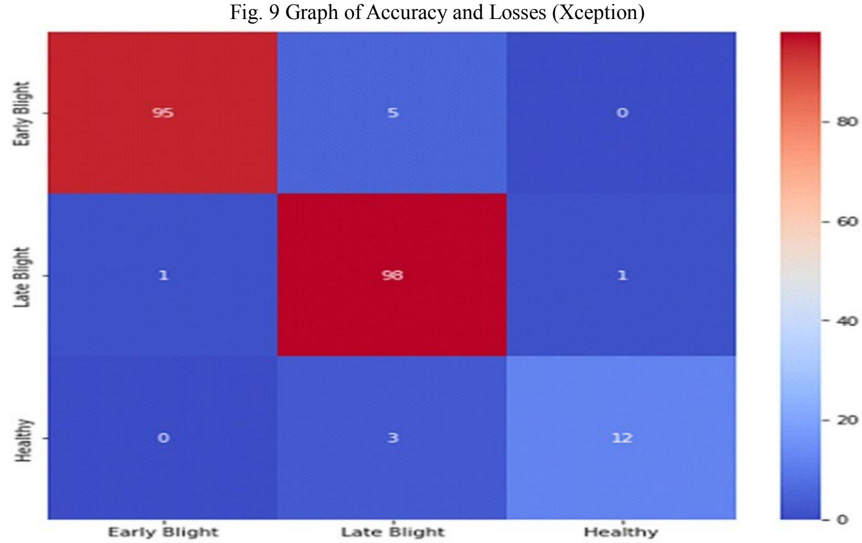

Fig. 10 Confusion Matrix for Classification of Potato Leaf Image Test Data (Xception)

An accuracy of 92% was obtained for both training and validation, with corresponding training and validation losses of 0.32 and 0.33. This model achieved lower accuracy and higher losses compared to the proposed model. The accuracy and loss graphs of ResNet50 are presented in Fig. 11, and the classification results for the three classes are shown in the confusion matrix in Fig. 12.

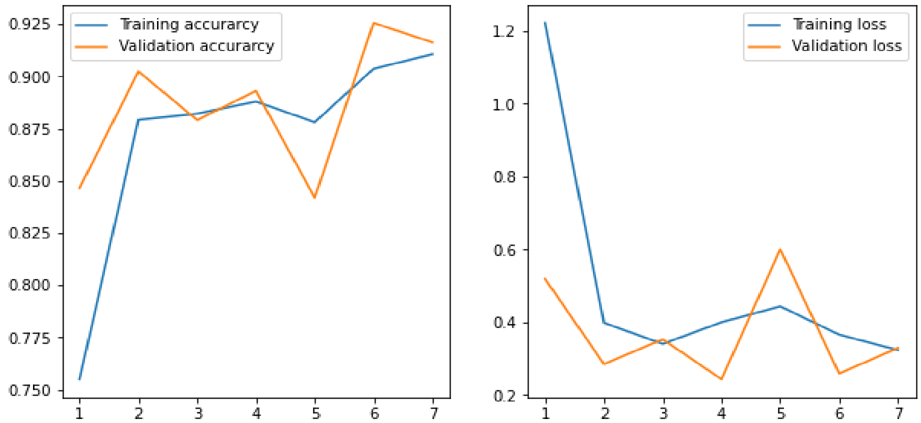

Fig. 11 Graph of Accuracy and Losses (Resnet50)

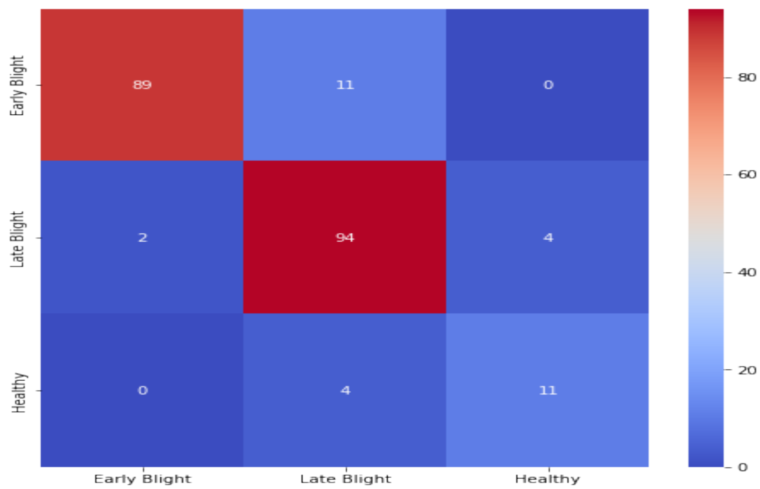

Fig. 12 Confusion Matrix for Classification of Potato Leaf Image Test Data (Resnet50)

3. Comparison with Existing Models

A summary of comparison of proposed model with existing models (Table I).

TABLE I COMPARISON WITH STATE-OF-ART MODELS

Metrics	**Proposed**	**Xception**	**ResNet50**	**InceptionV3**
Accuracy (%)	97.21	95.35	90.23	0.23
F1 Score (%)	93.92	92.60	85.49	4.25
Precision (%)	95.83	94.57	85.79	83.30
Recall (%)	92.33	91.00	85.44	85.44
Kappa score (%)	95.00	91.68	82.63	82.75
Specificity (%)	98.38	97.22	94.41	4.65
Size (MB)	25.6	81.1	81.1	84.3

From Table I, the performance of four models-Proposed, Xception, ResNet50, and InceptionV3-was evaluated using multiple metrics. The highest accuracy of 97.21% was obtained for the Proposed model, while Xception achieved 95.35% accuracy. Both ResNet50 and InceptionV3 recorded accuracy scores of 90.23%. The Proposed model also demonstrated superiority in F1 score with the highest value of 93.92%, followed by Xception at 92.60%, and InceptionV3 at 85.49%.

In terms of precision, the Proposed model outperformed the others with 95.83%, followed by Xception at 94.57%, InceptionV3 at 85.79%, and ResNet50 with the lowest precision of 83.30%. The recall metric similarly highlighted the Proposed model's strength, achieving 92.33%, with Xception at 91.00%, and both InceptionV3 and ResNet50 at 85.44%. For Cohen’s Kappa, the Proposed model attained the highest score of 95.00%, followed by Xception at 91.68%, ResNet50 at 82.75%, and InceptionV3 at 82.63%. The Proposed model also achieved the highest specificity at

98.38%, while Xception scored 97.22%, and both InceptionV3 and ResNet50 recorded around 94%.

Regarding model size, the Proposed model was the most compact at 25.6 MB, whereas Xception and ResNet50 were both 81.1 MB, and InceptionV3 was the largest at 84.3 MB. Overall, the Proposed model demonstrated superior performance across accuracy, precision, F1 score, recall, Kappa score, specificity, and size metrics. Xception performed well in most metrics, while ResNet50 and InceptionV3 showed comparatively lower performance in several areas. Table II presents a comparison of existing approaches with the developed system.

TABLE II COMPARISON OF DEVELOPED SYSTEM WITH EXISTING SYSTEM

Author	**Dataset**	**Technique**	**Accuracy (%)**	**Size (MB)**
Sholihati *et al.,* (2020)	Potatoes	VGG 16, VGG19 CNN	91	-
Hou *et al.,* (2021)	Potato Leaves	KNN, SVM , ANN, Random Forest Classifier	97.4	-
Islam and Sikder (2022)	Potato Leaves	CNN	100	-
Nishad *et al.,* (2022)	Potato Leaves	VGG 16, VGG19 and ResNet50	97	-
Samatha *et al.,* (2023)	Potatoes	Modified SVM and CNN	97-99	-
Oishi *et al.,* (2021)	Abnormal & Healthy Potato Leaves	Deep Learning Models	96.7	-
Authors (2023)	Potato Leaves & Healthy	Proposed System	~100	5.6

The comparison is based on technique, dataset, and accuracy on test samples to validate system performance. This paper used both similar and dissimilar techniques, as well as a similar dataset, for comparison.

It was observed that [56] used VGG16 and VGG19 CNN models on a potato dataset, achieving 91% accuracy; the model size was not specified. Reference [37] employed KNN, SVM, ANN, and Random Forest Classifier techniques on a potato leaf dataset, achieving 97.4% accuracy, with no model size reported. Reference [57] focused on potato leaves and achieved 100% accuracy using CNN; the model size was unspecified. Reference [58] utilized VGG16, VGG19, and ResNet50 on a potato leaf dataset, achieving 97% accuracy; the model size was not mentioned. Reference [59] applied modified SVM and CNN techniques on a potato dataset, obtaining accuracy in the range of 97-99%, with no model size reported. Reference [60] employed deep learning models on a dataset containing abnormal and healthy potato leaves, achieving 96.7% accuracy; the model size was unspecified. In contrast, the proposed system achieved approximately 100% accuracy for potato leaves and healthy samples, with a model size of 25.6 MB.

4. Deployment

The deployment to a web application was performed using Streamlit-a popular Python framework for deploying deep learning models on the web without requiring interaction with frontend code. The interface displaying the outputs of test samples is shown in Fig.13.

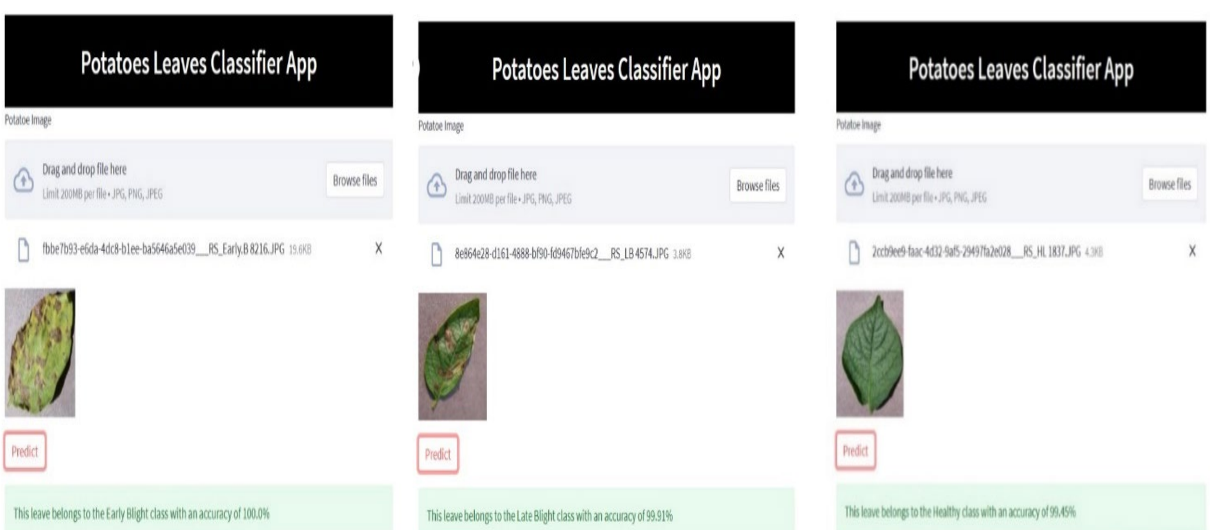

Fig. 13 System Outputs for Test Samples

The developed web application was also tested with test data and the accuracy obtained is presented in figure 14.

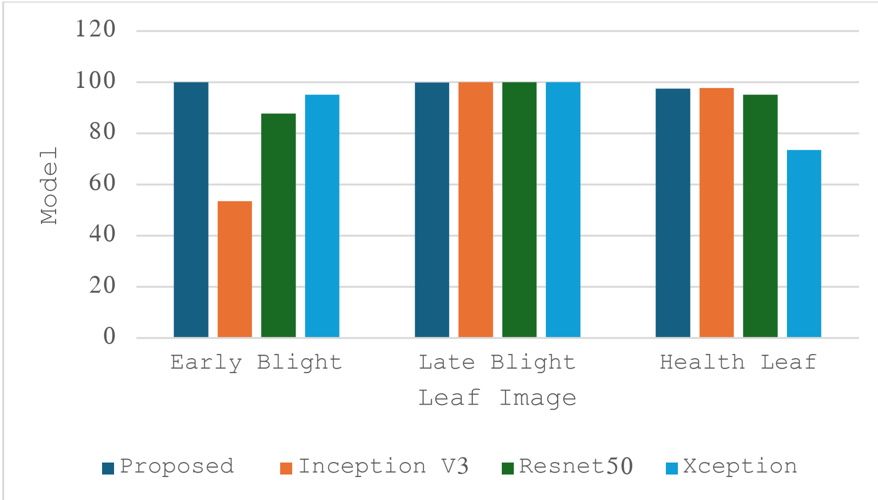

Fig. 14 Accuracy of Models for Classes

Two different leaves from the three categories were selected to compare the proposed model with ResNet50, InceptionV3, and Xception models. The leaves were tested using the models on a web application interface. The application displayed both the category of the leaf and the accuracy of the selected model.

While testing a leaf image of early blight, the proposed model recorded an accuracy of 99.99%, compared to 53.58% for InceptionV3, 87.75% for ResNet50, and 95.18% for Xception. Similarly, while testing a leaf image of late blight, the proposed model recorded an accuracy of 99.85%, compared to 99.996% for InceptionV3, 99.99% for ResNet50, and 99.99% for Xception.

However, when a healthy leaf image was tested, the proposed model recorded an accuracy of 97.48%, compared to 97.73% for InceptionV3, 95.13% for ResNet50, and 73.50% for Xception.

V. DISCUSSION

This section evaluates the performance of the proposed lightweight convolutional neural network (CNN) for potato leaf disease classification by comparing it with three widely used deep learning models: Xception, ResNet50, and InceptionV3. The comparative performance analysis, based on the following standard evaluation metrics, is presented as follows:

A. Classification Accuracy

The proposed CNN model achieved the highest classification accuracy of 97.21%, outperforming Xception (95.35%) and ResNet50 (90.23%). The result recorded for InceptionV3 (0.23%) appears to be an outlier and may indicate issues such as poor model convergence or misconfiguration during training. The superior accuracy of the proposed model highlights its strong capability in correctly identifying disease classes in potato leaves.

B. F1 Score, Precision, and Recall

The F1 score, which reflects the harmonic mean of precision and recall, further supports the model's robustness. The proposed model attained the highest F1 score of 93.92%, with precision and recall values of 95.83% and 92.33%, respectively. In contrast, Xception followed closely but slightly underperformed across all three metrics. ResNet50 showed a marked decline in effectiveness, and InceptionV3's extremely low F1 score (4.25%) reiterates the earlier indication of ineffective learning or improper data processing.

C. Cohen's Kappa Score

Cohen's Kappa Score, a measure of inter-rater agreement, also favored the proposed architecture, which achieved a score of 95.00%, indicating strong consistency between predicted and actual labels. Xception and ResNet50 recorded 91.68% and 82.63%, respectively, while InceptionV3 yielded a comparable result to ResNet50 at 82.75%.

D. Specificity

In terms of specificity, the proposed model again led with 98.38%, reflecting a high ability to accurately identify non-diseased (healthy) samples. This performance surpassed that of Xception (97.22%) and ResNet50 (94.41%). InceptionV3's specificity was notably low (4.65%), reinforcing concerns regarding its suitability for this task without additional optimization.

E. Model Size and Efficiency

One of the significant advantages of the proposed CNN model lies in its compact size. At 25.6 MB, it is substantially smaller than the other models: Xception and ResNet50 (both 81.1 MB) and InceptionV3 (84.3 MB). This size efficiency enhances the model's applicability for deployment on low-resource platforms, such as mobile devices and embedded systems commonly used in agricultural environments.

VI. CONCLUSION

In this research, a deep learning-based system was developed for the identification and classification of sweet potato leaf diseases. The proposed model was implemented on a web application. The study was conducted using a Kaggle dataset, and the results showed that the developed system achieved high recognition accuracy on the publicly available dataset. The system demonstrated a validation accuracy of 97% at 14 epochs. The experiments also indicated that the proposed model outperformed several existing models in predicting the three classes of sweet potato leaf diseases, including in terms of model size. For future research, the development of recognition systems for other potato species will be considered. Furthermore, implementation of the recognition system for sweet potato leaf diseases on edge devices, especially mobile phones, will be explored to enable easy access and convenience. Consequently, the system can be effectively used for disease detection and classification of sweet potato leaves, assisting agriculturists in quickly and accurately identifying affected plants for timely treatment.

Declaration of Conflicting Interests

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Use of Artificial Intelligence (AI) - Assisted Technology for Manuscript Preparation

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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