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Comparative Analysis of Deep Learning Models for Potato Leaf Disease Detection

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Abstract—**In India, agriculture plays a crucial role in ensuring food security and employment for its large population. The agricultural sector contributes significantly to the country's economy. Potato cultivation is prominent in India, with potato being a staple food, rich in essential nutrients, and having various indigenous and improved varieties. However, potato crops face challenges from fungal diseases like Early Blight and Late Blight, which can cause substantial economic losses. Currently, manual observation is the prevalent method for disease detection, but it has limitations. It is often impractical due to time constraints and limited expertise, leading to potential errors and inadequate treatment. This approach can result in crop failure due to delayed or incorrect interventions. Automatic plant leaf disease detection system utilizing technologies like Machine Learning, Deep Learning, and Computer Vision are being developed to promote timely and accurate detection. Among the varieties of techniques available, Deep Learning algorithms, and specifically Convolutional Neural Networks (CNNs), have emerged as formidable tools for disease classification. By autonomously learning complex features and patterns from images, CNNs demonstrate remarkable proficiency in distinguishing between healthy and diseased plant leaves, making them a pivotal component of modern agricultural innovation. This study focuses on using various self-built and pre-trained DL models for disease detection in potato leaves using two different verified datasets, and undertaking a comparative assessment of the different models. The research showed that out of the eight models used, ResNet50 gives the best accuracy for this experiment, followed by VGG16, CNN-KNN Hybrid, VGG19, SBCNN, InceptionV3, AlexNet, and CNN-SVM Hybrid.**

Keywords— Deep Learning, Convolutional Neural Networks, Potato Leaf Disease Detection, ResNet50, VGG16, CNN-KNN Hybrid, VGG19, InceptionV3, SBCNN, AlexNet, CNN-SVM Hybrid

I. INTRODUCTION

India is an agriculture-based country. Agriculture plays a major role in ensuring food security as well as employment for its large population [2]. Potato is one of the main crops cultivated in India. Potatoes are a staple food for a large part of the Indian population. However, these potato crops are affected by two major fungal diseases: Early Blight and Late Blight. Early blight, caused by the fungus Alternaria solani, appears during the early stages of growth and affects the lower leaves first. On the other hand, late blight, caused by the pathogen Phytophthora infestans, appears only after the blossoming period and affects both foliage and tubers [3]. These diseases, if left untreated, can cause substantial loss to the economy of the country. Therefore, their timely detection and treatment is necessary to avoid such condition.

In the current scenario, most of the farmers are dependent on manual observation skills to detect the presence of any of these diseases in the crops [7]. In India, the most commonly employed method for detecting and identifying plant leaf diseases remains unaided visual examination by local specialists or the farmers themselves. But this method is not very feasible due to the extent of observation time required and non-availability of experts in certain regions. It might also lead to inefficient results arising from human errors in evaluating the crop condition. This can result in crop failure from inability to provide timely treatment in the form of required quantity of necessary pesticides or in few cases, providing incorrect treatment due to misjudgment of the disease.

An automatic system for detecting plant leaf diseases is necessary in order to address this situation, delivering precise outcomes within a short timeframe. Presently, many technologies such as Machine Learning and Deep Learning, Computer Vision, Remote Sensing and Drones, IoT and Sensor Networks, are being used to make such a system easily accessible and available to the farmers. Deep Learning (DL) is one of the important fields that have achieved a significant progress in this domain [4]. DL algorithms, such as Convolutional Neural Networks (CNNs), are widely used in automatic disease detection. These algorithms can learn and recognize patterns in plant leaf images, enabling rapid and accurate disease classification and diagnosis.

This study is also based on ML and DL frameworks. The study involves the utilization of custom-built and pre-trained CNNs for the purpose of categorizing images of Potato Leaves into three distinct groups: Early Blight, Late Blight, and Healthy. Eight models have been employed which include Self-Build CNN (SBCNN, referred to as CNN in the rest of the paper), ResNet50, VGG16, VGG19, InceptionV3, AlexNet, CNN-SVM Hybrid, and CNN-KNN Hybrid, and it has been found that ResNet50 gives the best results for this case. The paper is structured into V sections: Section II outlines previous research on the detection of potato leaf diseases by other researchers, Section III elaborates on the proposed methodology, Section IV encompasses the results and associated discussions, and Section V draws the paper to a close by summarizing the work and discussing future plans.

II. RELATED WORK

Numerous works have been undertaken over time in the field of disease detection in plant leaves. Here, a variety of approaches for the detection of leaf diseases in Potato plant used by various researchers have been reviewed.

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Ananthi et al. in [1] developed a CNN-based system with user-interface in which initially, the captured leaf images undergo preprocessing including conversion to grayscale, resizing and feature extraction, and then the processed images are used for training the neural network to differentiate and categorize diseases affecting potato leaves, achieving an impressive accuracy rate of 98.54%.

Sudi et al. in [2] built an end-to-end neural network system that employs a CNN encoder-decoder model to accurately classify potato leaf images as healthy or infected, with a remarkable accuracy of 99.07%. The research has demonstrated that CNN outperforms alternative deep neural networks such as ANN and SVM in the context of recognizing and classifying diseases observed in potato leaves.

In the work of Iqbal et al. [3], a system was introduced to automatically identify and classify potato leaf diseases. This was achieved through a combination of image processing and machine learning methods. By performing image segmentation and applying seven different classifier algorithms to a dataset of over 450 images, the researchers determined that the Random Forest classifier exhibited the highest accuracy at 97%.

In the study by Barman et al. [4], an evaluative analysis was carried out using deep learning techniques to identify potato leaf diseases, focusing on data augmentation. Various Convolutional Neural Network (CNN) architectures were contrasted, resulting in the recognition of Self-Build CNN (SBCNN) and MobileNet as the top-performing models.

In their research detailed in [5], Deep Kothari et al. introduced a deep learning-focused approach for classifying two separate diseases affecting potato plants by assessing the condition of their leaves. The team employed models such as GoogleNet, ResNet50, and VGG16, attaining a 97% accuracy rate within the initial 40 epochs of training in the convolutional neural network (CNN) process.

In their work cited as [6], Harisha et al. introduced a model that leverages pre-trained models such as VGG-19 to enhance the extraction of pertinent components from the dataset. By employing various classifiers, the study achieved a high accuracy of 97.8% on the test dataset.

Sholihati et al. classified four types of diseases in potato plant using the VGG16 and VGG19 models in [7], achieving an accuracy of 91%. Tiwari et al. in [8] employed transfer learning to create an automated system aimed at diagnosing and categorizing diseases present in potato leaves.

In [9], Eser Sert presented an improved technique for object detection by integrating Faster R-CNN with the GoogLeNet classifier. This novel approach utilized image stitching, the Faster R-CNN model, and the GoogLeNet architecture to efficiently detect both potato and pepper leaves, as well as to identify various diseases affecting these leaves. The empirical study highlighted that the newly suggested technique outperformed existing methods in the domain, particularly in the accurate detection of leaf diseases.

Kumar et al. in [11] present a method for automatic potato leaf disease detection involving preprocessing, fuzzy segmentation, feature extraction, and classification, achieving notable accuracy: k-NN (83.39%), LR (89.72%), ANN (92.54%), and SVM (99.75%), with SVM standing out.

In a recent study in [12], Vadivel et al. focused on addressing the significant impact of plant diseases on agriculture by leveraging artificial intelligence, specifically deep learning models like ResNet50, Inception V3, VGG16, and VGG19, for early and accurate detection of potato leaf diseases. The research demonstrated that the VGG19 model exhibits superior performance with an impressive accuracy of 99%, showcasing its potential for optimizing disease detection in the agriculture sector.

There exists a notable research gap in the exploration of deep learning models specifically tailored for potato leaf disease detection. While various models have been assessed, limited research has delved into the optimization of model parameters for enhanced performance in potato leaf disease detection. Bridging these gaps can significantly contribute to the development of more accurate, efficient, and application-ready deep learning models in the realm of agricultural disease diagnosis. In this research, the model parameters such as *No. of Epochs*, *Batch Size*, and *Dataset Split Ratio*, are optimized and the best model versions have been used for comparisons.

III. PROPOSED METHODOLOGY

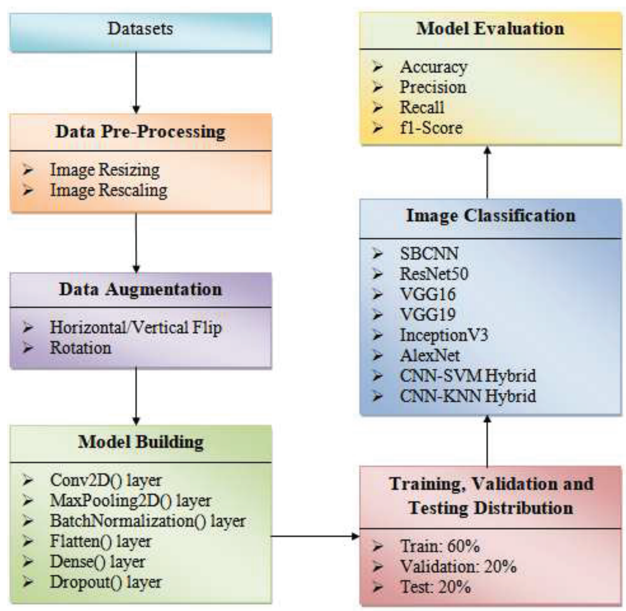

Fig. 1. Overall architecture of the proposed methodology

As described in Fig. 1, the proposed methodology in this paper includes seven main steps: acquiring Datasets, Data Pre-Processing, Data Augmentation, Model Building, Training, Validation and Testing Distribution, Image Classification, and Model Evaluation.

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Fig. 2. Sample images of potato leaf – (a) Early blight, (b) Late blight, (c) Healthy

A. Datasets

Two datasets have been used for this study. The first dataset is collected from the publicly available PlantVillage database [3]-[9] and the second dataset is the Potato Leaf Disease Dataset [11]. 3652 images of potato leaves, 2152 belonging to the first dataset and 1500 belonging to the second dataset, have been analyzed. Images from both the datasets belong to one of the following three class labels: Potato Early Blight, Potato Late Blight, or Potato Healthy. Fig. 2 displays sample images representing the three distinct classes.

B. Data Pre-Processing

This includes two steps: Image Resizing and Image Rescaling. The input images are resized to a standardized dimension: 256 x 256 pixels for CNN and 224 x 224 pixels for the other seven models, i.e. ResNet50, VGG16, VGG19, InceptionV3, AlexNet, CNN-SVM Hybrid and CNN-KNN Hybrid. These images are then rescaled to bring the input pixel values, originally in range [0, 255], to be in the range [0, 1], by applying the scale transformation with parameter value (1.0/255).

C. Data Augmentation

In this study, different augmentation techniques are applied to the training set using pre-processing layers from Keras library in Python. These include simple geometric transformations, like horizontal and vertical flip, rotation etc.

D. Data Pre-Processing

Out of the eight models used in the study, two base models and two hybrid models have been exclusively built: CNN, AlexNet, CNN-SVM Hybrid, and CNN-KNN Hybrid. For the remaining four models, pre-trained versions have been used, by importing these from the Keras library. A short description of the eight models is as follows:

i. *CNN: CNN* is built using a *resize_and_rescale* layer, a *data_augmentation* layer, six *Conv2D()* layers, six *MaxPooling2D()* layers, one *Flatten()* layer and two *Dense()* layers.
ii. *ResNet50:* ResNet stands for Residual Network and *ResNet50* comprises a 50-layer CNN architecture, encompassing 48 convolutional layers, a MaxPool layer, and an average pool layer.
iii. *VGG16: VGG16* is a 16-layer deep CNN, with three fully connected layers and 13 convolutional layers.
iv. *VGG19: VGG19* is a CNN consisting of 19 layers, consisting of 16 convolutional layers and 3 fully connected layers.
v. *InceptionV3: InceptionV3* is a CNN that is 48 layers deep, and is the third edition of Google's Inception Convolutional Neural Network.
vi. *AlexNet: AlexNet* contains five *Convolution2D()* layers, three *MaxPooling2D()* layers, eight *BatchNormalization()* layers, one *Flatten()* layer, three *Dropout()* layers and four *Dense()* layers.
vii. *CNN-SVM Hybrid:* A *CNN-SVM Hybrid* model combines a Convolutional Neural Network (CNN) with a Support Vector Machine (SVM) as the classifier for image classification.
viii. *CNN-KNN Hybrid: A CNN-KNN Hybrid* model combines Convolutional Neural Networks (CNN) and K-Nearest Neighbors (KNN) for image classification.

E. Training, Validation and Testing Distribution

The datasets utilized in this research were partitioned into three distinct segments: training, validation, and testing. The training dataset served the purpose of training the models, whereas the validation and test datasets were employed to assess the performance and effectiveness of the trained models. To achieve this division, each dataset was allocated in a 60:20:20 ratio, signifying 60% for training, 20% for validation, and 20% for testing purposes.

F. Image Classification

This study incorporates eight distinct architectural models for categorizing potato leaf images into three classes: Early blight affected, Late blight affected, and Healthy. These include CNN, ResNet50, VGG16, VGG19, InceptionV3, AlexNet, CNN-SVM Hybrid, and CNN-KNN Hybrid.

G. Model Evaluation

Following the training of the model using the *Train* and *Validation* datasets, the model's performance is assessed on the Test dataset based on *accuracy* and *loss* scores. Two graphs depicting the *Training and Validation Accuracy & Loss* of the model, along with the *confusion matrix* and few *sample predictions* with their *confidences* are obtained. The *Average Time per Epoch* has been calculated for each model. The *classification report*, containing statistics like *precision*, *recall*, *f1-score* and *support* for each class, together with their *macro average*, *weighted average* and the overall *accuracy*,

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is also generated for each model. Fig. 3 demonstrates the seven recorded attributes for one of the trained models.

Finally, the result of the study was compared with results of other similar studies.

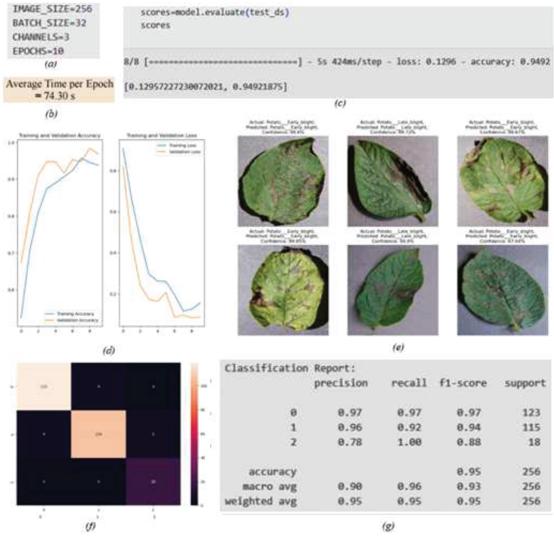

Fig. 3. Recorded Attributes of the CNN Model for Dataset 1 – (a) Model Summary, (b) Average Time per Epoch, (c) Accuracy & Loss Scores, (d) Training and Validation Accuracy & Loss Graphs, (e) Sample Prediction with their Confidences, (f) Confusion Matrix, (g) Classification Report

IV. Result and Discussion

In the comprehensive comparison of six base models and two hybrid models, it was observed that the *InceptionV3* emerged as the top-performing model in terms of *Average Time per Epoch* for both datasets. The order of efficiency, from fastest to slowest, was found to be *InceptionV3*, *AlexNet*, *CNN*, *ResNet50*, *CNN-SVM Hybrid*, *VGG16*, *VGG19*, and *CNN-KNN Hybrid*. Notably, *ResNet50* exhibited outstanding classification results, achieving highest *Accuracy* along with *Precision*, *Recall*, and *f1-score*. These findings, as summarized in Table I, highlight the trade-off between computational efficiency and classification performance, with *ResNet50* standing out as the model that excels in both aspects. The study underscores the importance of considering both computational efficiency and classification metrics when selecting a model for specific applications in machine learning and computer vision.

Table II showcases the comparison of this result with the results of other similar research studies.

V. Conclusion and Future Scope

This study employed eight models to classify potato plant diseases based on leaf images, revealing that the *ResNet50* model exhibited the most optimal performance across various metrics. It outperformed others in *Average Time per Epoch*, *Accuracy*, *Loss Scores*, *Precision*, *Recall*, and *f1-Score*. Following *ResNet50*, the models ranked in descending order of performance were *VGG16*, *CNN-KNN Hybrid*, *VGG19*, *CNN*, *InceptionV3*, *AlexNet*, and *CNN-SVM Hybrid*.

This evaluation helps identify an optimal model for developing technology, like apps and sensors, to aid farmers in early crop disease detection, potentially minimizing losses and enhancing yields. Future research can enhance the study by exploring dependencies among model parameters (e.g., No. of Epochs, Batch Size, Dataset Split Ratio) to identify the best model versions with optimal values for all parameters simultaneously.

TABLE I. ACCURACY, PRECISION, RECALL AND F1-SCORE PERCENTAGES FOR EIGHT MODELS IMPLEMENTED ON DATASET 1 AND DATASET 2

Model	Accuracy		Precision		Recall		f1-Score	
	Dataset 1	Dataset 2	Dataset 1	Dataset 2	Dataset 1	Dataset 2	Dataset 1	Dataset 2
CNN	94.92%	93.75%	95%	95%	95%	94%	95%	94%
ResNet50	98.71%	98.54%	99%	99%	99%	99%	99%	99%
VGG16	97.98%	98.12%	98%	98%	98%	98%	98%	98%
VGG19	95.63%	98.44%	96%	98%	96%	98%	96%	98%
InceptionV3	93.96%	91.99%	94%	92%	94%	92%	94%	92%
AlexNet	90.21%	94.38%	92%	94%	90%	94%	89%	94%
CNN-SVM Hybrid	87.98%	89.76%	88%	90%	88%	89%	88%	90%
CNN-KNN Hybrid	96.48%	97.36%	96%	97%	96%	97%	96%	97%

TABLE II. COMPARISON OF MOST ACCURATE MODEL IDENTIFIED IN THE PRESENT RESEARCH AND OTHER SIMILAR RESEARCH STUDIES

Reference	Name of Research Paper	Most Accurate Model Identified
[2]	A CNN Model for Disease Detection in Potato Leaves	CNN
[5]	Potato Leaf Disease Detection using Deep Learning	ResNet50
[6]	Potato Diseases Detection Using Machine Learning Techniques	VGG19
[9]	A deep learning based approach for the detection of diseases in pepper and potato leaves	Faster R-CNN-GC
Present Research	Comparative Analysis of Deep Learning Models for Potato Leaf Disease Detection	ResNet50

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