RESEARCH ARTICLE

Evaluating CNN and Conventional Machine Learning Approaches for Early Detection of Potato Infections by Alternaria Solani and Phytophthora Infestans

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Abstract:

Potato crops are majorly affected by fungal and oomycete diseases; the most popular and harmful diseases are early blight and late blight caused by Alternaria solani and Phytophthora infestans. In most cases, their symptoms are visually similar in the early stages. It is difficult to accurately identify them and apply specific treatment or implement other disease management strategies.

Identification procedures based on Artificial Intelligence, especially the Deep Learning and Machine Learning techniques, are always working effectively compared to the manual or traditional procedures.

This study presents the differences between the performance of a deep learning model, such as a CNN, in comparison to a few popular traditional Machine Learning classifiers for identifying Alternaria solani and Phytophthora infestans infections in potato plants. We selected, trained, tested, and validated models of a Convolutional Neural Network (CNN), Support Vector Machine (SVM), and K-Nearest Neighbours (KNN) on an expertly vetted dataset of images of leaves with early blight, late blight, and healthy types. The CNN model trained on some raw image data performed better than the other two models, achieving an accuracy of 91.7%.

On the other hand, the traditional models, such as SVM and KNN, which depend on manually selected features, achieved accuracy of 68.3% and 14.3%.

The results powerfully highlight the advantage of CNN-based deep learning models in handling complex tasks such as plant disease classification, owing to their exceptional capability for learning meaningful features. The significant performance difference has been noticed in this work, which strongly confirms that the deep learning model is the best paradigm in fine-grained visual classification in agriculture.

Keywords: Plant Disease Detection, Potato Disease Detection, Classification of Crop Diseases, Support Vector Machine, K-Nearest Neighbours, Convolutional Neural Network, Phytophthora infestans, Potato Leaf Disease, Late Blight, Early Blight, Alternaria solani, Image Classification, AI Image Classifications, Deep Learning, Machine Learning

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I. INTRODUCTION

Potato is an agricultural crop that is planted worldwide and is a vital source of food. Nonetheless, some diseases pose a major threat to the production of plants, particularly oomycete and fungal diseases. Early blight and late blight, which are cause by Alternaria solani, and Phytophthora infestans, are among the most devastating of them. These are significantly causing losses in crops in many countries across the world. The two diseases have similar symptoms at an early stage, and hence, they cannot be easily differentiated by manual identification strategies. Misidentification causes a delay in implementing proper treatment, increased and often indiscriminate dependency on pesticides, and results in both economic and ecological impacts. Thus, the creation of sound and automated disease detection strategies has been essential in ensuring that the production of potatoes has a strong, sustainable foundation.

Manual observation and classical machine learning techniques, including SVM and KNN, among others, have been employed as traditional methods for detecting plant diseases, but have provided only partial solutions. However, these approaches are heavily dependent on manual characteristics and are not well able to generalise to large and mixed datasets. After involving the Convolutional Neural Networks (CNN) as a deep learning (DL) in AI, image-based classification tasks have greatly improved. CNNs are also adept at automatically extracting hierarchical features from original image data, thereby eliminating the need for manual preprocessing and enabling more accurate recognition of complex visual features.

This work presents a comparative evaluation of a CNN against traditional ML methods for detecting A. solani and P. infestans infections. A selected collection of potato leaf images was considered, consisting of the following classes: healthy, early blight, and late blight. The findings showed a significant performance difference, with CNN performing at 91.7%, while SVM and KNN performed at 68.3% and 14.3%, which can be considered low performance. In addition to other evaluation criteria, CNN also proved to be more accurate, with a higher recall and F1-score. It demonstrates its strength in addressing the issue of class imbalance and its ability to detect the nuances of visual similarities between early and late blight symptoms.

These findings go beyond the dataset used for the rest of the study. This study demonstrates the practical relevance of CNN in the automation of agriculture using image classification. The example from this study shows that CNN can learn intricate visual characteristics with no human assistance. Early and precise detection of diseases with the help of CNN can assist farmers in following specific interventions, reducing unnecessary chemical use, and preserving crop yield. Additionally, the framework of comparisons established in this research will serve as a reference point for reviewing other models in the future when classifying plant diseases.

Ultimately, the use of deep learning in precision agriculture holds promise for successful farming and enhanced food security worldwide.

II. RELATED WORKS

The importance of plant disease identification has led to a broad field of scientific research, as it can significantly contribute to agricultural productivity and food security. Scholars have utilised both conventional machine learning (ML) and more recent deep learning (DL), which have demonstrated some success.

Early works in this domain relied heavily on image processing and manual feature extraction. Barbedo provided a thorough review of digital image processing techniques for detecting plant disease and highlighted the limitations of manually designed features [1]. Camargo and Smith proposed an algorithm that combines colour co-occurrence matrices with Support Vector Machines (SVM) for plant disease classification, achieving moderate accuracy [2]. Besides, Phadikar and Sil applied the K-Nearest Neighbours (KNN) algorithm for rice disease prediction but faced difficulties when handling complex and large-scale datasets [3]. Although innovative, these approaches were commonly limited in their performance in real agricultural situations.

Transfer learning and data augmentation have been used to further enhance it. Lu et al. used transfer learning using pre-trained CNNs to address small training data, leading to better classification [8]. Zhang et al. proposed superior CNN structures along with the attention mechanism that enhanced accuracy and interpretability of the model in detecting maize disease [9]. These papers indicate the flexibility of CNN-based methods to various datasets and situations.

Although CNNs have consistently outperformed traditional ML methods in plant disease classification, there remains a lack of systematic comparative studies focused specifically on potato early blight and late blight. Most of the literature compares CNN models individually or as a combination of multiple crops, but they are not compared to classical algorithms like SVM and KNN under equal conditions. To fill this gap, it is necessary to measure the benefits of DL compared to ML in detection of potato diseases.

To conclude, the existing literature indicates that CNN is better at plant disease detection than conventional methods of ML. Nonetheless, little is known about direct comparative analyses of CNN, SVM and KNN in potato blight classification. This work is valuable in that it systematically compared these methods using a curated dataset of potato leaf, introducing novel knowledge on the strengths of these two methods and their potential in practice in agricultural automation.

III. DATA & MEHODOLOGY

A. Dataset

The dataset used in this research was acquired in the publicly available repository of PlantVillage on Kaggle [10]. This overall dataset includes the images of 14 species of crops, including 38 classes of different diseases and healthy leaf samples. In the context of this study, the scope was confined to potato (Solanum tuberosum) leaves.

From the dataset, three categories of potato leaf images were selected:

- Healthy potato leaves (152 images)
- Potato Early Blight (1,000 images)
- Potato Late Blight (1,000 images)

This specific selection brought about 2,152 images that were used in model development and validation.

Fig. 1 Sample images from each category of the dataset

Figure 1 presents the typical samples of every type of potato leaf that was used in this research: healthy, early blight, and late blight. These sample images display the diversity of the tracks and the visual variations in the texture of the leaves, color, and lesion patterns used in the training and testing of the models.

B. Data Preprocessing

To train the model, several preprocessing operations were performed to ensure data consistency and enhance the learning process. First, all images have been resized to a standardised resolution of 256 x 256 pixels, which made all inputs uniform in size, but without essential disease-specific attributes such as lesions and colour alterations.

The data was subsequent devided into training, validation and test sets in 80:10:10 proportions. Stratified splitting method was employed to ensure the balance of classes in the subsets, thus ensuring biasness in the evaluation process was avoided. The resulting distribution is summarized in Table 1.

TABLE I
DATASET DISTRIBUTION ACROSS SPLITS

Class	Total Images	Training Set	Validation Set	Test Set
Early Blight	1000	800	100	100
Healthy	152	121	15	16
Late Blight	1000	800	100	100

The training set was augmented using data augmentation methods to overcome the weakness of the Healthy class size. Operations that were involved in augmentation were random rotations, horizontal and vertical flipping, zoom, adjustments in brightness, and translations. Such transformations yielded more diverse samples whilst maintaining original labels of the classes hence minimal overfitting and strong performance of the trained models.

With the use of resizing, normalisation, balanced splitting, and augmentation, effective preprocessing of the dataset was achieved as an effective basis to the comparative analysis of CNN, SVM and KNN models in potato disease classification.

C. Model Selection

To ensure a comprehensive comparison between a deep learning and traditional machine learning paradigm, three different classifiers were chosen: Convolutional Neural Network (CNN), Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) algorithm. This selection was motivated by the interest to compare automated feature extraction and manual feature engineering as conceptualized in Figure 2.

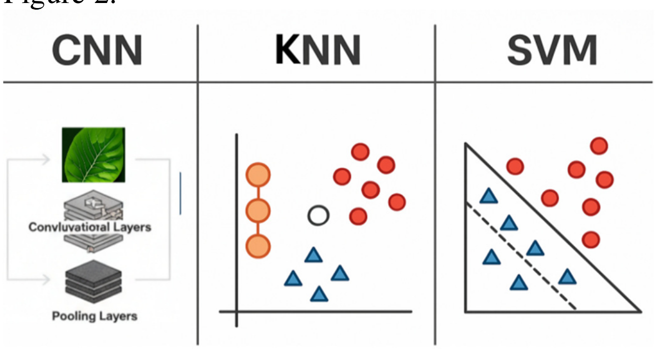

Fig. 2 Selected DL and ML Models

1) Convolutional Neural Network: The CNN was selected for its superior ability to automate feature extraction, which is essential when complex image data is needed. Its structure, which is based on convolutional and pooling layers, enables it to learn spatial hierarchies of features by utilizing the original pixel values. This allows it to be used as the state-of-the-art option in manual feature engineering removal, and it is thus employed for tasks such as image classification, including the detection of plant diseases.

2) Support Vector Machine: The SVM was chosen as a strong traditional classifier to be used as a comparative strength. It works on the principle of searching for the best hyperplane that maximizes the margin among the various classes. It is performance-intensive on the quality of the input features, and thus a useful benchmark to compare the usefulness of hand-crafted HOG features to the trained representations of the CNN.

3) K-Nearest Neighbours: The KNN algorithm was included as a simple and instance-based baseline model. It also categorizes an image as one that is mainly like most of its most similar training examples in the feature space. The fact that it was as complex and non-linear as it illustrates the constraints of a simple distance-based method with engineered features to this task.

D. Model Architechture

In this part, I describe the framework and architecture of the three classification models that I use in the current work: a Convolutional Neural Network (CNN), a Support Vector Machine (SVM), and a K-Nearest Neighbours (KNN) model. All the models were used and optimized to evaluate their performance in the potato leaf disease classification problem.

1) Convolutional Neural Network: The CNN model was developed using TensorFlow Keras, featuring a sequential structure consisting of 4 convolutional blocks to extract features and completely connected layers to learn these features. This model takes in 224x224x3 input images. Every convolutional block consists of:

- A convolutional layer with ReLU activation
- A dimensionality reduction layer of MaxPooling2D
- Dropout layer (rate = 0.25) is used to prevent overfitting.

The filters in the convolutional layers are increased in number (32, 64, 128, 256) to find hierarchical features of low-level edges to high-level patterns. The output of the final Covn block is flattened and passes through two dense (512 and 256 units, ReLU activation and Dropout=0.5) layers.

The last layer is based on a softmax activation function and has three units, corresponding to the three target classes. The model was assembled using the Adam optimizer with a learning rate of 0.001 and was trained on categorical cross-entropy loss.

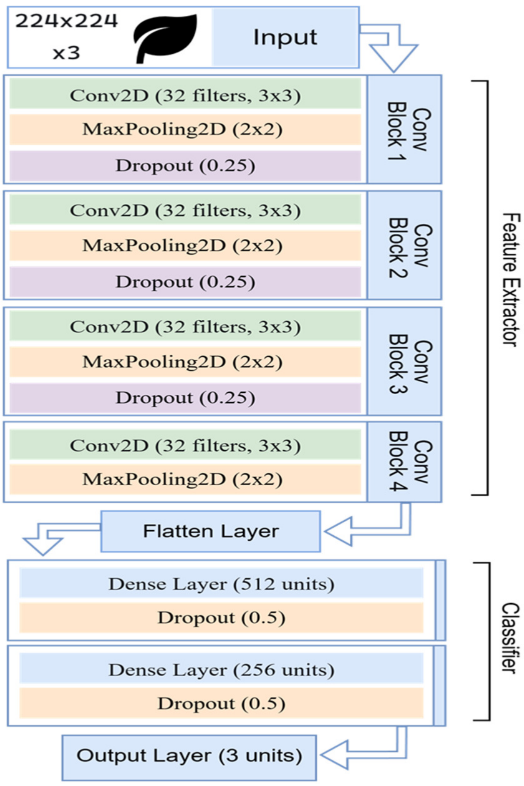

Fig. 3 Architecture of the proposed CNN model showing convolutional blocks, filter sizes, and dense layers.

2) Support Vector Machine: Scikit-learn was used to implement the SVM with linear kernel together with a regularization parameter C=1.0. The Histogram of Oriented Gradients (HOG) was applied to extract input features, and it represents the local grayscale image gradient structures. The model aims at identifying the best hyperplane that maximizes the distance between the various classes in the feature space.

3) K-Nearest Neighbours: The KNN classifier was based on the Euclidean distance to determine similarity between HOG feature vectors. k was parameterized to 3, implying that the classification of each test sample was done by the majority of its three closest neighbours in the training set.

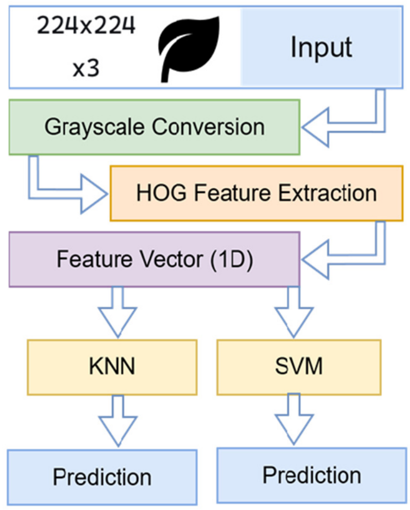

Fig. 4 Architecture of two traditional ML Classifier (KNN and SVM)

This concludes the detailed discussion of the three model architectures adopted for this comparative study. The CNN was built as a hierarchical and deep feature learner with the capacity to handle raw pixel values, whereas the SVM and KNN were set to a strong baseline based on HOG features. It is based on this difference in architecture that the argument of whether the representational power of deep learning offers a significant advantage over more traditional machine learning paradigms is formed in the implementation of the specified task of potato disease classification. The second section describes the experimentation and training procedure performed on these models.

E. Model Evaluation

A rigorous evaluation framework was employed to quantify model performance on the held-out test set $D_{test.}$ Let y_i denote the true label and $\hat{y}_i$ the predicted label for the i-th sample.

The main measure was the Weighted Accuracy that considers the imbalance of classes:

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{N} 1(yi \ = \ \hat{y}i\ )$$

where N is the total number of samples and 1 is the indicator function.

For a deeper analysis, performance was evaluated per-class c using the standard definitions of precision (P_c) and recall (R_c), based on true positives (TP_c), false positives (FP_c), and false negatives (FN_c):

$$P_c = \frac{TP_c}{TP_c+FP_c}\ ,\ R_c = \frac{TP_c}{TP_c+FN_c}$$

The per-class F1-score, the harmonic mean of precision and recall, served as the key metric for assessing the discrimination between the visually similar Early Blight and Late Blight classes:

$$F1_c = \frac{P_c \times R_c}{P_c+R_c}$$

The macro-averaged scores were calculated to provide equal significance of all classes. Confusion matrices C were used to visualize and analyze the error patterns of the models C where C_{ij} is the number of samples in class i that are predicted to be in class j. This multi-dimensional method gave a detailed evaluation of the efficacy and strength of classification.

IV. RESULT AND DISCUSSION

This section presents an in-depth discussion of the experimental findings from the assessment of the Convolutional Neural Network (CNN), Support Vector Machine (SVM), and K-Nearest Neighbours (KNN) in the classification of potato leaf disease. The evaluation is conducted based on quantitative measurements, confusion measurements, and dynamics of training to offer a multidimensional perspective of the capabilities and limitations of each model.

A. Model Training and Convergence:

The CNN model is trained using the following training progression, as shown in Fig. 5, where the accuracy and loss curves are plotted against the 14 training epochs and the 14 validation epochs, respectively. The accuracy curves increase steadily and are parallel to the validation accuracy, following the training accuracy closely, and reach a high accuracy of around 92%. On the same note, both sets of loss curves monotonically reduce and converge to a minimum value. A considerable disparity between the training and validation measures of this synchronised behaviour indicates that the model was able to learn without overfitting. Effective convergence is an indication of the effectiveness of architectural decisions, such as batch normalisation and dropout, in guaranteeing generalised and stable learning.

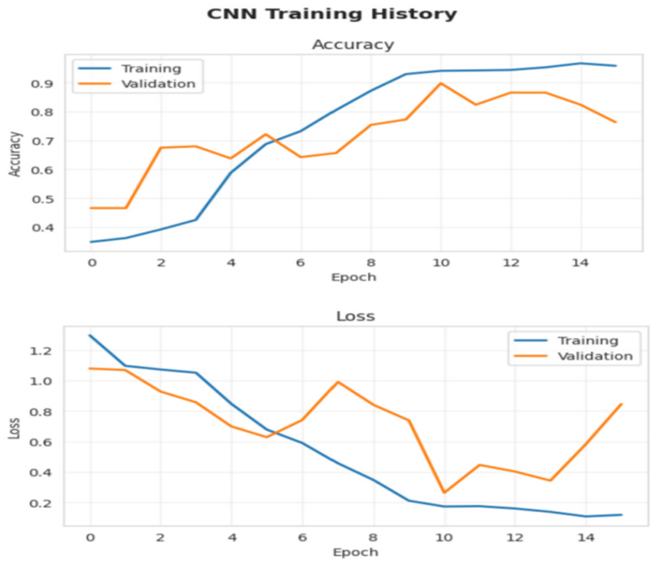

Fig. 5 CNN training history showing (a) accuracy and (b) loss curves for training and validation sets.

B. Comparative Perfomance Evaluation:

The quantitative performance of all three models on the held-out test set is summarised in Table II below. The CNN model was found to perform exceptionally well, with a test accuracy of 91.7%. It also scored highly on precision (0.922), recall (0.917), and F1-score (0.916), demonstrating a balanced and strong classification ability across all three classes. Traditional ML models, on the other hand, perform much worse. The test accuracy of the SVM was 68.3% with moderate precision (0.640) and recall (0.683). The KNN model was also a very poor predictor, giving only an accuracy of 14.3%. Its precision (0.573) was standard, but its recall (0.143) and F1-score (0.166) were of a critical order, as it showed its underlying deficiency in correctly identifying positive instances in the data set.

TABLE IIIII
COMPARATIVE PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1-Score
CNN	0.9167	0.9218	0.9167	0.9162
SVM	0.6833	0.6402	0.6833	0.6592
KNN	0.1433	0.5727	0.1433	0.1663

The difference in performance is visually illustrated in Fig. 6, a bar chart that compares the models in all the metrics. There is a definite advantage of the CNN compared to other models, as it performs significantly better and proves its superiority in this image classification problem.

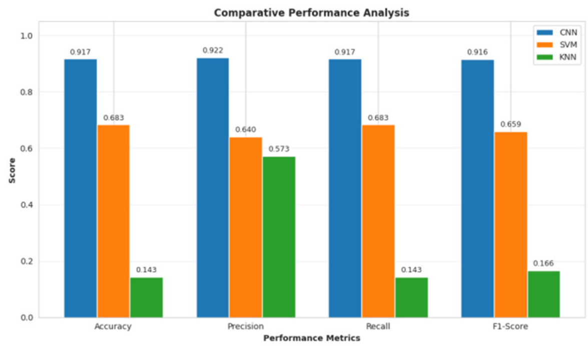

Fig. 6 Comparative performance analysis of CNN, SVM, and KNN models across accuracy, precision, recall, and F1-score metrics.

Such a significant difference in performance, expressed through a 23.3 percentage point margin in favour of CNN over SVM, creates an unquestioned pecking order among the models. Its findings clearly state that the deep learning model is the most powerful one, and the low success of KNN highlights the inefficiency of simple distance-based algorithms in this complex visual recognition problem.

C. Analysis of Classification Pattern:

The confusion matrices in Fig. 7 gives a deeper understanding of the model's behaviour. The CNN (Fig. 7a) matrix shows high diagonal dominance, with 98 out of 100 Early Blight leaves and 87 out of 100 Late Blight leaves being correctly identified. The significant confusion lies in the classification of these two types of blights, where 2 Early Blight leaves are incorrectly classified as Late Blight, and 13 Late Blight leaves are incorrectly classified as Early Blight. This means that although the CNN is very functional, the most difficult issue in the task is the ability to differentiate the minor visual differences between the two diseases. The Healthy category is recognised with a high level of accuracy (13 of 16 correct).

SVM (Fig. 7b) reveals another error profile. It shows that there is a high propensity to mix up the two types of blights, with 32 Early Blight cases being classified as Late Blight, and 47 Late Blight cases being classified as Early Blight. Worryingly, the model did not correctly recognise any Healthy leaves, classifying all 16 as either Early or Late Blight. This implies that the HOG characteristics were insufficient to distinguish the visual peculiarities of a healthy leaf from those of a diseased leaf.

KNN (Fig. 7c) exhibits a nearly failed mode, resulting in extreme misclassification across all categories. The most predicted class was the “Healthy” one, which it attributed to 143 of the total 184 images in the test, containing the overwhelming majority of Early and Late Blight samples. This is an indicator of the curse of dimensionality and the failure of Euclidean distance in the high-dimensional HOG feature space to address the given issue.

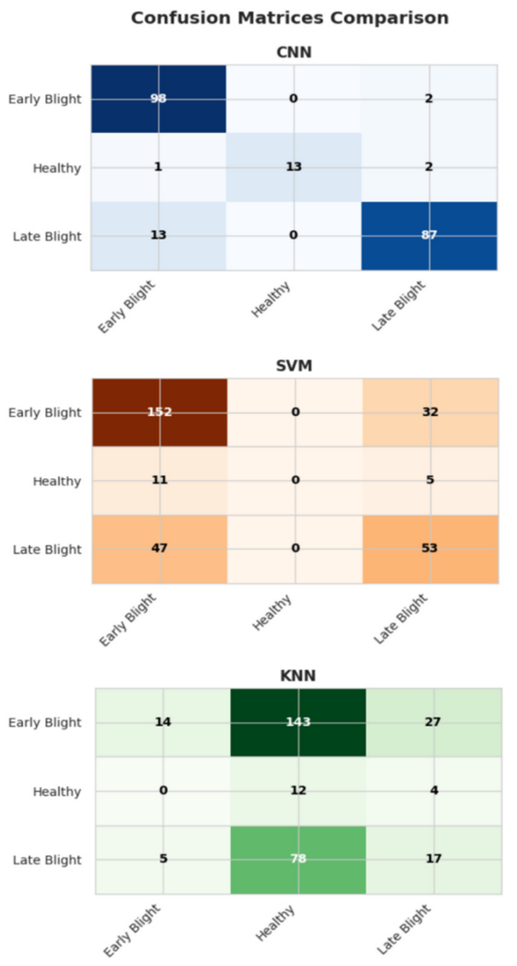

Fig. 7 Confusion matrices for (a) CNN, (b) SVM, and (c) KNN models. The matrices reveal the specific misclassification patterns between Early Blight, Healthy, and Late Blight classes.

D. Discussion of Results:

The significant performance gap, whereby the CNN outperforms the SVM by more than 23 percentage points, highlights the transformative benefit of the deep learning approach to image recognition with complex tasks. This excellence is owed to the fact that CNN can learn features hierarchically by default. The convolutional layers in the network automatically learn relevant features, including edges and textures at the low level, and disease-lesion-specific patterns at the high level, all of which can be directly produced by raw pixels. This end-to-end learning paradigm does not rely on manual feature engineering, which was the bottleneck in traditional models. The fact that the predictions made by CNN are very high as seen in Fig. 8 is another testament to its strength. In such sample predictions, the model is accurate for an Early Blight leaf with confidence of 100 per cent and a Late Blight leaf with a confidence of 99.75 per cent. This shows that the model not only provides accurate predictions but also does so with high levels of certainty, a key aspect of developing confidence in actual-life agricultural decision support systems.

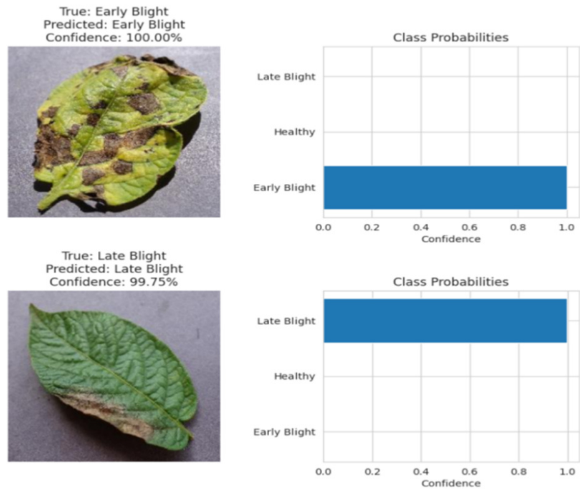

Fig. 8 Sample predictions from the CNN model

On the other hand, the ineffectiveness of the SVM and KNN models can also be directly attributed to the constraints of the HOG feature descriptor. HOG is also quite helpful in capturing the overall shape and edge, but not in capturing the delicacy required to distinguish colour, texture, and lesion patterns that would distinguish plant diseases, especially the difference between Early and Late Blight. The findings are consistent with the overall opinion in computer vision: in the case of fine-grained image classification, learned features vastly outperform hand-designed features. Finally, the experiment's findings provide testable evidence that the CNN-based method is not only more incrementally effective but also more suitable as a tool for automated detection of potato leaf diseases. The discriminative characteristics, which are directly learnt using data, provide an accuracy and reliability that is impossible to obtain in the traditional methods of ML, thus cementing their future use in precision agriculture applications.

V. CONCLUSION

A comparative study was conducted in this research between a deep learning model and traditional machine learning algorithms to investigate the basic activities of Alternaria solani and Phytophthora infestans in potent plants. Through the experiment, the Convolutional Neural Network (CNN) architecture proved to be highly effective in comparison with the SVM and KNN models, achieving a high-test accuracy of 91.7% compared to 68.3% and 14.3%, respectively. Such a significant performance disparity, greater than 23 percentage points, highlights the transformative nature of automated feature learning compared to manual feature engineering in accurately determining these pathogenic organismic agents, with this disastrous economic impact.

This is what makes CNN successful because it has the capacity to learn discriminative features hierarchically, using raw pixel data, and thus captures the pleasing visual appearance that differentiates between the early blight created by Alternaria solani and the late blight created by Phytophthora infestans. Conversely, the dependency of SVM and KNN on manually disengaged HOG features proved to be a crucial drawback of these approaches, as they could not adequately reflect the delicate pathological characteristics of individual ailments. The confidence scores of the CNN are also very high, which further proves its strength and capacity for practical use.

The results of the conducted research contribute to the ultimate claim that CNN-based deep learning can serve as a far more precise and efficient way of the automated detection of Alternaria solani and Phytophthora infestans. The article will help advance the precision agriculture domain by offering empirical support for the superiority of deep learning in addressing this high-impact issue. The model will be expanded to address a wider variety of potato diseases and will be incorporated with a real-time, mobile-based decision support system in the future to provide farmers with convenient and timely crop health management tools.

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