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Revolutionizing potato crop management: Deep learning-driven potato disease detection with convolutional neural networks

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Abstract
Potato cultivation is essential for ensuring global food security, yet it faces significant threats from diseases such as early blight and late blight, resulting in substantial yield losses. To address this challenge, integrated disease management strategies are pivotal, encompassing cultural practices, disease-resistant varieties, and timely fungicide applications. Recent advancements in artificial intelligence (AI), particularly in deep learning, hold promise for revolutionizing disease detection in agriculture. This study aims to contribute to these efforts by developing a highly accurate and efficient system for early disease detection in potato crops using deep learning techniques. Through the utilization of convolutional neural networks (CNNs), transfer learning, and data augmentation, the proposed model showcases significant potential in automating the identification and classification of potato leaf diseases. Rigorous experimentation and evaluation demonstrate that the proposed CNN model achieved an impressive accuracy of 97.82% in classifying potato early and late blight diseases. These findings underscore the efficacy of CNNs in agricultural disease management and highlight the transformative role of AI technologies in bolstering global food security efforts.

Keywords: Potato disease detection, convolutional neural networks (CNN), deep learning, early blight and late blight, machine learning

Introduction

Potato cultivation is vital for global food security, yet it confronts considerable challenges from diseases like early blight and late blight, attributed to pathogens such as *Alternaria solani* and *Phytophthora infestans*, resulting in notable yield reductions. Integrated disease management strategies are essential, encompassing cultural practices, employment of disease-resistant varieties, and timely application of fungicides (Vilvert *et al*., 2022) [16]. Managing pests and diseases in potato crops entails a blend of biological, cultural, and chemical approaches, including practices like strategic irrigation and maintaining high standards of crop hygiene. Creating a comprehensive disease management plan is essential, including proper seed and soil treatment to prevent storage growth and preserve potato quality. In storage management, post-harvest options like proper temperature control, airflow management, and the use of fungicides are crucial in managing diseases effectively. In summary, preventive measures like seed treatments, soil treatments, integrated pest management strategies, and proper storage management are essential in combating diseases threatening potato production and promoting sustainable agricultural practices (Mora *et al*., 2021) [11].

Artificial intelligence (AI) technologies, notably deep learning, present promising avenues for transforming disease detection in agriculture. Through techniques like convolutional neural networks (CNNs), researchers have made significant strides in automating the identification and classification of plant diseases using visual symptoms. These advancements offer the potential to accelerate diagnosis, facilitating early detection of diseases that could otherwise cause significant crop productivity losses. Scholars like Kuricheti *et al*. (2021) [8] have investigated deep transfer learning-based approaches, showcasing the efficacy of CNN models in accurately classifying potato leaf diseases. Their work contributes to establishing more efficient disease management strategies in agriculture.

This study endeavors to contribute to the ongoing improvement of agricultural practices by employing AI and deep learning techniques. Through the utilization of deep learning, transfer learning, and data augmentation methodologies, our aim is to develop a highly precise and effective system capable of detecting plant diseases early, thereby mitigating their detrimental impact on potato crop yields. Ramya and Kumar (2021) [12] have emphasized the importance of deep transfer learning architectures in their research, which leverage multiscale feature extraction and batch normalization to enhance the accuracy of plant disease detection and classification. These findings underscore the potential of AI-driven approaches in equipping farmers with proactive disease management tools, ultimately promoting greater food security and sustainability in potato production worldwide.

The integration of AI technologies presents significant promise in tackling the challenges posed by plant diseases in agriculture. Through the application of deep learning techniques, researchers and agricultural stakeholders can create more effective and precise systems for disease detection and management, ultimately safeguarding crop yields and bolstering food security. As evidenced by studies such as that of Ramya and Kumar (2021) [12], the implementation of advanced neural network architectures and optimization techniques can notably enhance the accuracy and dependability of disease identification processes. Continued research and innovation in this domain are essential to further refine AI-driven solutions and facilitate their widespread adoption, ultimately benefiting farmers and global food systems alike.

Related works

The application of deep learning models, particularly Convolutional Neural Networks (CNNs), has exhibited significant success in detecting and classifying plant diseases, notably those affecting potato crops. Numerous researchers have concentrated on disease prediction in potato leaves, utilizing the Plant Village dataset to train their models effectively. Khalifa *et al*. (2021) [7] introduced a CNN model for identifying early blight (EB), late blight (LB) diseases, and healthy classes, trained on the PlantVillage dataset. Sanjeev *et al*. (2021) [15] employed a Feed-Forward Neural Network (FFNN) for disease identification using the Plant Village dataset. Rozaqi and Sunyoto (2020) [14] developed a CNN model for classifying EB and LB diseases in potato leaves, also trained on the Plant Village dataset. Barman *et al*. (2018) presented a self-built CNN (SBCNN) model for detecting EB, LB, and healthy classes of potato leaf diseases using the Plant Village dataset. Tiwari *et al*. (2020) [18] utilized a pre-trained VGG19 model for feature extraction and various classifiers to classify EB and LB diseases in potato leaves, trained on the Plant Village dataset. Lee *et al*. (2020) [10] developed a CNN model to identify potato plants with EB, LB infections, and healthy leaves, utilizing region-specific data from the Plant Village dataset. Islam *et al*. (2017) [6] proposed a segment-based and multi-SVM model for detecting various potato diseases, including EB, LB, and healthy leaves, incorporating the Plant Village dataset. A recent study by Rashid *et al*. (2021) [13] introduced a novel deep learning technique called Potato Leaf Disease Detection using Convolutional Neural Network (PDDCNN) for early blight and late blight disease recognition in potatoes. This method demonstrated optimal performance with fewer parameters compared to existing models. Collectively, these studies underscore the effectiveness of deep learning models like CNNs in accurately detecting and classifying potato leaf diseases, highlighting the importance of leveraging specific datasets like Plant Village for training these models effectively.

The manuscript under discussion aims to utilize Convolutional Neural Networks (CNNs) and deep learning techniques to tackle potato early and late blight diseases in agriculture. The authors seek to provide scalable and cost-effective solutions for potato farmers, potentially benefiting the global potatoes industry. The study's key findings highlight the success of CNNs, particularly when combined with transfer learning, in identifying potato leaf diseases. Transfer learning, involving the adaptation of pre-trained models to new tasks, enhances model effectiveness. Additionally, the authors explore methods such as hyperparameter tuning to optimize the deep learning model's performance. This research not only contributes to the agricultural technology field by showcasing the efficacy of deep learning in disease identification but also lays the groundwork for scalable solutions that could potentially address other plant diseases. Overall, the findings carry implications for enhancing disease management practices, ultimately benefiting potato farmers and the broader potatoes industry.

Methodology

The methodology for developing the proposed CNN model involves outlining its architecture, training process, experimental setup, and dataset preparation. Additionally, it describes the workflow for incorporating augmented images into the training set, applying techniques such as rotation, flipping, zooming, and rescaling, each with specific parameters. The dataset is split into an 80:20 train-test split, with further details provided in Table 1. To categorize illnesses in potato leaves, automated feature extraction using deep CNNs and preprocessing of collected images are employed, with dataset images selected from public databases like Plant Village, Kaggle, and Mendeley based on intensity colour changes and differences in leaf form and size. Transfer learning with pre-trained models like NASNet Mobile, MobileNetV2, and AlexNet is utilized. A generalized overview depicted in Figure 1 illustrates the classification of potato plant leaf disease using transfer learning with a dataset from a public database. Challenges in the literature, such as incorrect identification and variation in diseases, are addressed by the proposed multi-level deep learning model, utilizing YOLOv5 image segmentation and a novel potato leaf disease detection convolutional neural network (PDDCNN) for accurate detection of early blight and late blight diseases.

Dataset Collection

In this study, the dataset utilized comprises high-resolution images of potato leaves affected by potato early and late blight (PEL) disease, as well as images of healthy potato leaves, sourced from Kaggle. With a total of 1152 images, early blight symptoms include small, dark spots on leaves and stems, which expand and turn yellow, eventually causing lower leaves to defoliate, and fruit spots rot at the stem. Late blight symptoms involve brown spots on plant stems, rapidly expanding and producing white fungal growth in wet conditions, leading to stem collapse and dark brown lesions, whereas healthy instances show no abnormalities. Each image underwent thorough examination, with only those devoid of deformities considered healthy. Selection criteria included visible blight symptoms for diseased cases and a normal appearance for healthy leaves. These images were annotated to denote the presence or absence of potato early and late blight disease, categorized as diseased or healthy, respectively. Additionally, 1152 potato leaf images from the Plant Village dataset, comprising three categories, were analyzed. The dataset was divided into training and testing sets in an 80/20 ratio for training and validation, respectively. Image dimensions were resized to 256 x 256 x 3 pixels to ensure compatibility with the Inception-v3 model and enable computationally feasible training.

Data Pre-processing

To maintain consistent input dimensions, all images were resized to 224x224 pixels. To augment the dataset and increase the number of images in each class, various data augmentation techniques were applied. These techniques aim to expand the dataset size and mitigate overfitting during the model training process by incorporating augmented images into the training set. The augmentation process significantly bolstered the model's robustness by exposing it to diverse variations in input data. Rotation, flipping, zooming, and rescaling were among the augmentation techniques applied, each with specific parameters such as width shift range, height shift range, shear range, zoom range, and horizontal flip. This augmentation strategy effectively expanded the dataset, enabling the model to learn from a broader spectrum of examples and improve its ability to generalize patterns. Following augmentation, the dataset underwent an 80:20 train-test split, allocating 80 per cent for model training and reserving 20 per cent for performance evaluation. This partitioning ensured that the model could learn from augmented data during training while facilitating a comprehensive assessment of its generalization capabilities on unseen data during testing. For further insights into the dataset's composition and characteristics, detailed information is provided in Table 1.

Image pre-processing

In addressing the presence of noise in contaminated plant leaf images, various image pre-processing methods are employed to enhance training accuracy performance. One such technique involves image clipping, where the leaf image is cropped to isolate the area of interest, thus removing extraneous elements such as leaf sand or dust. Additionally, smoothing filters are applied to achieve image smoothing, further refining the visual clarity of the leaf image. In image processing, techniques like ZCA whitening, standardized rotation, and translation are utilized for data augmentation, aiding in the augmentation of the dataset and improving the model's ability to generalize patterns effectively. These pre-processing methods collectively contribute to optimizing the quality and usability of the dataset for training deep learning models, ultimately enhancing the accuracy and reliability of disease detection algorithms applied to plant leaves.

Image Segmentation: Image segmentation is a fundamental technique for classifying each pixel in an image into specific classes, as described by Belay *et al.* (2022) [3]. Given the diverse sizes of potato plant leaves, effectively locating and segmenting the image is crucial for improving the identification of potato diseases by reducing background interference and focusing on the regions of interest for feature extraction by models such as Inception v3. This segmentation technique is achieved based on various intensity discontinuities and similarities among pixels, as explained by Ho and Wookey (2020) [5]. Image segmentation involves partitioning the image into various parts with similar features or rough resemblance, aiding in identifying feature similarities in the grey levels between pixels within an image region. In this work, segmentation is accomplished by converting RGB color mode images to the HIS model. This approach enhances the model's ability to extract relevant features and improves disease identification accuracy by isolating the regions of interest within the potato leaf images.

Classification

The considerable variability in size, shape, color, texture, background, layout, and imaging illumination of plant diseases and pests in real-time environments presents significant challenges for detection. To address these challenges, Convolutional Neural Networks (CNNs) are widely adopted due to their robust feature extraction capability. CNN architectures typically consist of cascaded convolutional and pooling layers for feature extraction, followed by fully connected layers and a softmax classification layer for identification and classification based on given inputs. This design enables CNNs to effectively learn and represent complex patterns and relationships within image data, making them well-suited for tasks such as plant disease and pest detection in diverse environmental conditions.

Table 1: Details of the proposed dataset

Dataset	Potato Early Blight	Potato Healthy	Potato Late Blight	Total
Train	400	122	400	922
Test	100	30	100	230

Feature Extraction

In Belay *et al.* (2022) [3], deep learning techniques were employed for feature extraction to automatically extract deep characteristics from acquired images. This process aids in classifying the given images into predefined classes, such as diseased (PEL) and healthy.

Feature extraction using the proposed CNN model

Feature extraction plays a pivotal role in object recognition and classification, particularly in digital image analysis. It involves extracting pertinent features from images crucial for distinguishing between different classes of objects while maintaining consistency within the same class. This process serves as a crucial dimensionality reduction step, essential for efficient pattern recognition and machine learning. In the specific domain of identifying potato leaf diseases, deep learning techniques, notably Convolutional Neural Networks (CNNs), are utilized for feature extraction from acquired images. By automatically extracting deep characteristics from these images, CNNs facilitate the classification of the images into predefined classes such as diseased (PEL) and healthy leaves. CNNs, inspired by biological models of human vision, operate through multiple layers that mimic the human visual system's processing hierarchy, capturing spatial and temporal dependencies within images by applying filters across different layers. Feature extraction with CNNs condenses the image representation, requiring fewer computations while preserving essential features for accurate prediction. The CNN architecture comprises several layers, including convolutional layers, ReLU layers, pooling layers, dropout layers, and fully connected layers. In this study, a hierarchical structure of feature maps is constructed by consecutively applying learnable filters to the input image. The initial convolutional layer captures low-level features such as edges, corners, texture, and lines, while subsequent layers extract higher-level features based on more complex characteristics, aiding in the identification of objects and structures within the image.

To optimize the CNN model for feature extraction, three convolutional layers were employed to ensure the capture of both low-level and high-level features relevant to potato leaf disease classification, ultimately leading to the highest accuracy in the experiment. Additionally, before feature extraction, pre-processing techniques such as standardization, thresholding, and binarization were applied to digital images. These techniques help enhance the quality of the images and improve the extraction of meaningful patterns. The extracted patterns are then utilized to form feature vectors, which aid in the recognition and categorization of objects during the classification process. In this study, feature extraction was specifically performed using the inception-v3 model, a widely used architecture known for its effectiveness in image classification tasks. Leveraging the inception-v3 model further enhances the efficacy of the classification process, enabling the accurate identification of potato leaf diseases based on the extracted features.

Model Training

After the CNN network architecture was utilized to extract features from the input images, the CNN model underwent training using a set of labeled training images. Subsequently, the classification process categorized the data into the desired categories using the retrieved features, as described by Belay *et al*. (2022) [3].

Softmax

In this study, CNN models served as input data for the SoftMax classifier to determine the probability of the expected label for potato diseases. The SoftMax classifier, utilized for recognition purposes, aims to ascertain the likelihood that the input belongs to a specific class. It produces values in the range of 0 to 1, where the sum of all probabilities equals one, as explained by Ho and Wookey (2020) [5]. The notable advantage of using SoftMax lies in its ability to easily define the output probabilities range, along with its efficiency in terms of training speed and prediction accuracy. Furthermore, SoftMax accepts the output from the last fully connected layer and is employed for classifying potato images into specific classes, such as PEL or healthy. The CNN model was initialized with pre-trained weights derived from the selected architecture. The training data was then fed into the model, and the model parameters were optimized using a suitable optimization algorithm, such as Adam. Throughout the training process, iterations over the training set occurred for a predetermined number of epochs, while adjusting the learning rate to minimize the classification loss and enhance the model's performance.

Hyperparameter Settings

In the study by Belay *et al*. (2022) [3], hyperparameters play a crucial role in optimizing the model's performance. These settings, determined before training begins, significantly impact the model's learning process. Table 2 summarizes the hyperparameters employed throughout the model training. Various aspects of the model, such as optimization algorithms, learning rates, batch sizes, and regularization techniques, are fine-tuned to achieve optimal performance.

Optimization algorithms

Regarding optimization algorithms, the proposed model utilizes the Adam optimization technique to minimize the error rate. Adam is widely used in deep learning research due to its effectiveness in adjusting model weights and modifying parameters to minimize the loss function. This optimization method calculates an adaptive learning rate for each parameter, scaling the learning rate with squared gradients and a moving average of the gradient. By leveraging Adam optimization, the model efficiently updates its weights via backpropagation of error, ultimately enhancing its ability to learn and generalize from the training data.

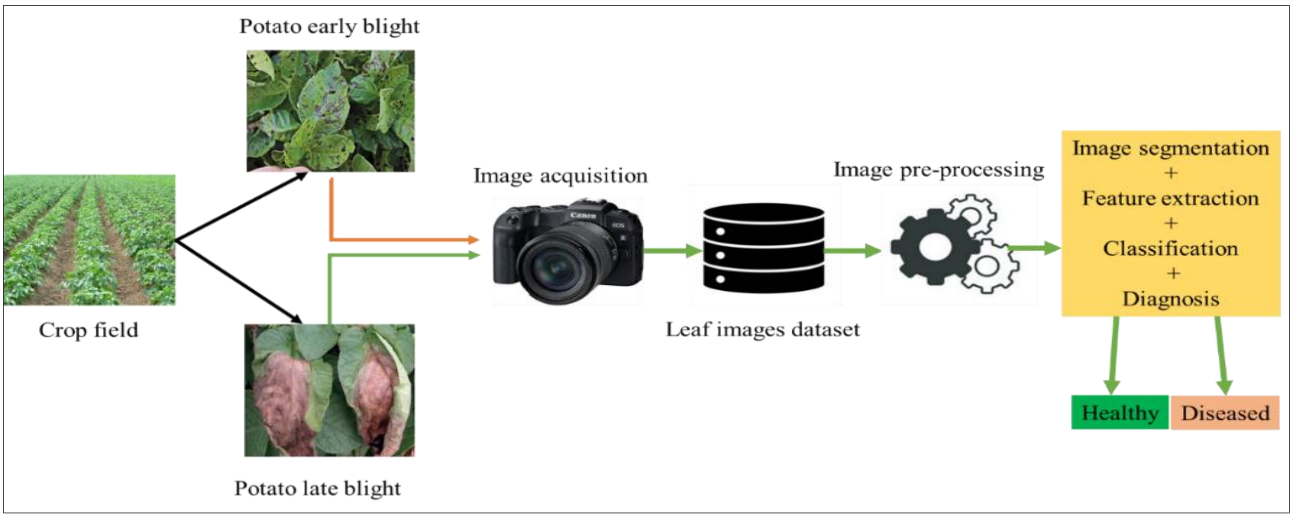

Fig 1: Architecture used in the study

Learning rate

In the study conducted by Belay *et al*. (2022) [3], the learning rate plays a crucial role in controlling the amount of weight updated during backpropagation, a fundamental aspect of training the proposed model. Determining the appropriate learning rate was identified as one of the most challenging components of the experiment. Through various simulations, it was discovered that training at a low learning rate takes longer compared to training at a higher rate. However, despite the longer training time, supplying a lower learning rate yielded better performance in the model. As a result, a learning rate of 0.001 was selected for all experiments conducted in the study. This carefully determined learning rate was crucial in optimizing the model's training process, ultimately leading to improved performance and accuracy in classifying potato leaf diseases.

Loss function

In the proposed model discussed by Belay *et al*. (2022) [3], the choice of loss function is crucial in evaluating how effectively the model achieves its specified goal. The loss function, also known as a cost function, quantifies the disparity between the predicted outputs of the model and the actual labels. This selection is influenced by factors such as the activation functions employed in the model's output layer and the nature of the problem being addressed (e.g., regression or classification). Since the proposed model is aimed at solving a classification challenge, specifically categorical classification, SoftMax is employed as the activation function in the final fully connected layer to determine the class label. Consequently, for this type of classification problem with more than two classes, Categorical Cross-Entropy (CCE) loss function is chosen. Although other loss functions like Binary Cross-Entropy (BCE) and Mean Squared Error (MSE) exist, Categorical Cross-Entropy is recommended for problems with multiple classes due to its effectiveness in handling such scenarios. This choice ensures that the model's performance is accurately evaluated and optimized throughout the training process, leading to improved classification accuracy and generalization.

Number of epochs

In the study conducted by Belay *et al*. (2022) [3], the number of epochs, representing the number of iterations the complete dataset goes through during training, plays a crucial role in optimizing the model's performance. Through experimentation, it was discovered that using too few or too many epochs could lead to a significant gap between the training and validation errors, indicating suboptimal model performance. After conducting numerous experiments, it was determined that setting the number of epochs to 100 resulted in optimal model performance. This carefully chosen value allowed the model to undergo sufficient iterations through the dataset, facilitating effective learning and convergence towards an optimal solution. By selecting an appropriate number of epochs, the model was able to strike a balance between underfitting and overfitting, ultimately leading to improved generalization and classification accuracy.

Batch size: In the experiment conducted by Belay *et al.* (2022) [3], the batch size parameter plays a crucial role in determining how many inputs can be sent to the network at once during training. Given the complexity of the dataset and the computational limitations of the computer, breaking the input data into smaller groups, or batches, is necessary to facilitate efficient model training. To optimize the training process and reduce computing time, a batch size of 32 was chosen for training the model. This batch size strikes a balance between processing efficiency and computational resources, allowing the model to efficiently learn from the dataset while minimizing training time. By feeding the network smaller batches of data sequentially, the model can update its parameters more frequently, leading to faster convergence and improved training performance. Overall, the carefully chosen batch size parameter contributes to the successful training and optimization of the deep learning model for classifying potato leaf diseases.

Model Evaluation

Evaluated the trained model on the testing set to assess its performance. Evaluation metrics such as accuracy, precision, recall, and F1-score to measure the model's effectiveness in detecting PEL disease were estimated. Confusion matrix was generated to analyse the model's performance in terms of true positives, true negatives, false positives, and false negatives. Accuracy is the ratio of correctly classified samples to the total number of samples, providing an overall measure of classification performance. It is suitable when observations for each class are balanced. Mathematically, accuracy (per cent) is calculated as:

$$\text{Accuracy (\%)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \times 100$$

Precision measures the proportion of true positives among all samples classified as positive, offering insights into the classifier's ability to correctly identify each class. Precision (per cent) is computed as:

$$\text{Precision (\%)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100$$

Recall indicates the ability to identify all relevant instances in a dataset and avoid false negatives. It evaluates the classifier's performance in capturing all positive instances. Recall (per cent) is expressed as:

$$\text{Recall (\%)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100$$

F1 Score is the harmonic mean of precision and recall, providing a single metric to assess the classifier's overall performance. It is commonly used in binary classification tasks but can be extended to multi-class scenarios. F1 Score (per cent) is calculated as:

$$\text{F1 Score (\%)} = 2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \times 100$$

Where

- **True Positive (TP):** Number of samples correctly identified as Healthy.
- **False Positive (FP):** Number of samples incorrectly identified as Healthy.

- **True Negative (TN):** Number of samples correctly identified as diseased.
- **False Negative (FN):** Number of samples incorrectly identified as diseased.

Table 2: Summary of hyper parameters used for model training

Parameter	Values
Epoch	100
Batch Size	32
Activation Function	SoftMax
Loss Function	Categorical Cross-Entropy
Optimization Algorithm	Adam
Learning Rate	0.001

Results and Discussion
All of the details of the experiment including the outcomes of each experiment and the discussions of these results are described in this section. The experimental results are presented in the form of figures and tables.

Experimental Setting
For the classification of potato early and late blight (PEL), the experimental setup involved utilizing Python as the programming language and Anaconda Jupyter notebook as the primary tool for code development. The model was trained with specific hyperparameters: the loss function was defined as categorical cross-entropy, and the Adam optimizer was employed with a learning rate set to 0.001. The training process consisted of 100 epochs, with a batch size of 32. The experimentation was conducted on a system equipped with HLBS Technologies for Tomorrow, running Windows 11 Pro on a 64-bit operating system with an x64-based processor. The system utilized a 12th Gen Intel(R) Core (TM) i7-12700 processor operating at 2.10 GHz, with 16 GB RAM.

Experimental Results
In this study, our objective was to evaluate the accuracy of a Convolutional Neural Network (CNN) classifier in distinguishing potato early and late blight (PEL) disease from images. The dataset consisted of sample images illustrating distinct symptoms of PEL. Early blight symptoms included small, dark spots on leaves and stems, which gradually expanded and turned yellow, leading to lower leaf defoliation and fruit spot rot at the stem. On the other hand, late blight symptoms comprised brown spots on plant stems, rapidly spreading with white fungal growth in humid conditions, ultimately resulting in stem collapse and dark brown lesions. Healthy instances displayed no visible abnormalities. To bolster the model's robustness, various data augmentation techniques such as flipping, rotation, and zooming were applied to the sample images from the dataset.

During the training of the CNN model, several hyperparameters were fine-tuned, including 100 epochs, a batch size of 32, SoftMax activation function, Categorical Cross-Entropy loss function, Adam optimization algorithm, and a learning rate set at 0.001 (refer to Table 2). Fig. 4A illustrates the iterative reduction in both training and validation set losses as the model undergoes training. This reduction indicates the effective learning process of the model, gradually converging towards the global minima. By the 40th epoch, both training and validation losses had reached their minimum values, subsequently stabilizing around 0.2 by the 100th epoch.

In Fig. 4B, we observe an upward trend in accuracy for both the training and validation sets over successive iterations. The peak accuracy was attained around the 40th epoch. However, beyond this point, a noticeable discrepancy in accuracy between the training and validation curves emerged. While the training curve reached a peak accuracy of 90.00 percent by the 100th epoch, the validation curve peaked at the 50th epoch, consistently maintaining an accuracy exceeding 90.00 percent in subsequent iterations. Notably, our model demonstrated an accuracy of at least 90 percent in the majority of iterations, resulting in an overall classification accuracy of 97.82 percent. Furthermore, when tested on a separate test set, the trained model exhibited an accuracy of 97.82 percent, correctly predicting PEL disease and identifying healthy potato plants. This high level of accuracy underscores the efficacy of the CNN classifier in accurately diagnosing PEL disease from images, highlighting its potential as a valuable tool in agricultural disease management.

The confusion matrix is a specific table that simplifies the assessment of whether the model mislabels one class as another, providing a visual representation of the model's performance. Fig. 6 illustrates the confusion matrix comparing the true class against the predicted class in the split test set of images for Potato Early and Late Blight (PEL) disease. The calculated values describe the classification rate for individual classes, with higher color density signifying higher accuracy for the individual classes.

The proposed dataset comprises a total of 922 potato plant images, categorized into three classes: Potato Early Blight, Potato Healthy, and Potato Late Blight. In the training set, there are 400 images each for Potato Early Blight and Potato Late Blight, while Potato Healthy comprises 122 images. The test set consists of 100 images each for Potato Early Blight and Potato Late Blight, with 30 images for Potato Healthy. This dataset ensures a balanced distribution of samples across the different classes, facilitating effective training and evaluation of machine learning models for the potato disease classification task.

Evaluation metrics such as accuracy, precision, recall, and F1 score of the developed model on the recognition of PEL disease were determined using the confusion matrix. Table 3 presents the evaluation metrics for the developed PEL disease detection using CNN. It is evident from Table 3 that the developed model shows an Accuracy of 97.82 percent, Precision of 97.83 percent, Recall of 97.82 percent, and F1 Score of 97.82 percent. These metrics demonstrate the effectiveness and reliability of the developed CNN model in accurately detecting and classifying Potato Early and Late Blight disease.

Table 3: Model evaluation metrics

Evaluation metrics	Per cent
Accuracy	97.82
Precision	97.83
Recall	97.82
F1 Score	97.82

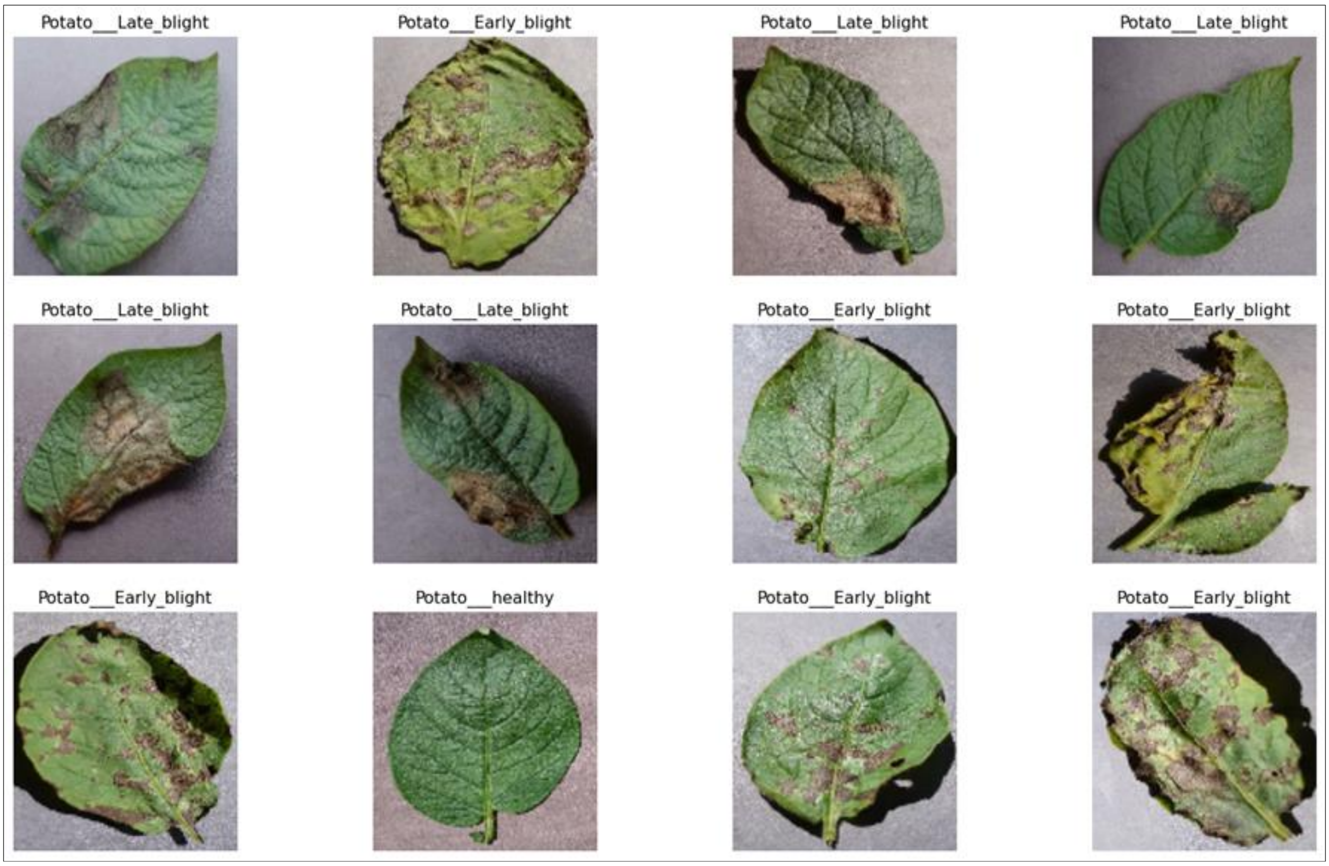

Fig. 2: Sample images of potatoe healthy and rust affected leaves from the dataset

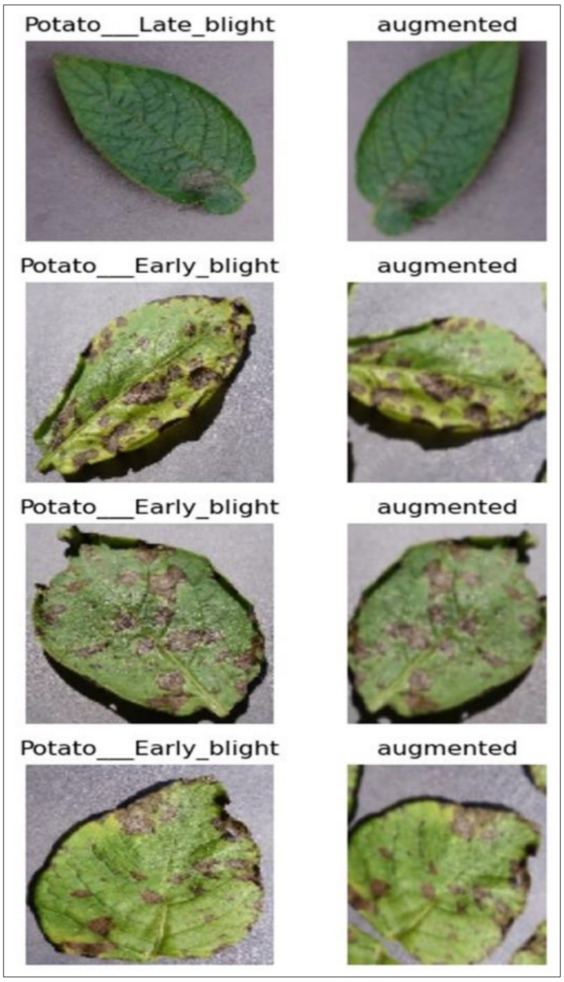

Fig 3: Sample images from the data set after image augmentation

Table 4: Performance Comparison of Different Models for Prediction of Potato Early and Late Blight Diseases

Sl. No.	Model name	Accuracy	precision	recall	F1 score
1	Proposed CNN	97.82	97.82	97.82	97.82
2	Alex Net	43.47	18.9	43.47	26.35
3	DenseNet121	83	87.8	83	81.81
4	InceptionV3	95.2	96.53	95.53	96
5	LeNet-5	93.47	94.17	93.47	93.48
6	Mobile Net	96.56	99.56	99.56	99.56
7	ResNet50	96.95	97.53	96.95	97
8	VGG16	97.69	97.81	97.69	97.71
9	Efficient Net	13	1.7	13	3
10	VGG19	43.47	18.9	43.47	26.35

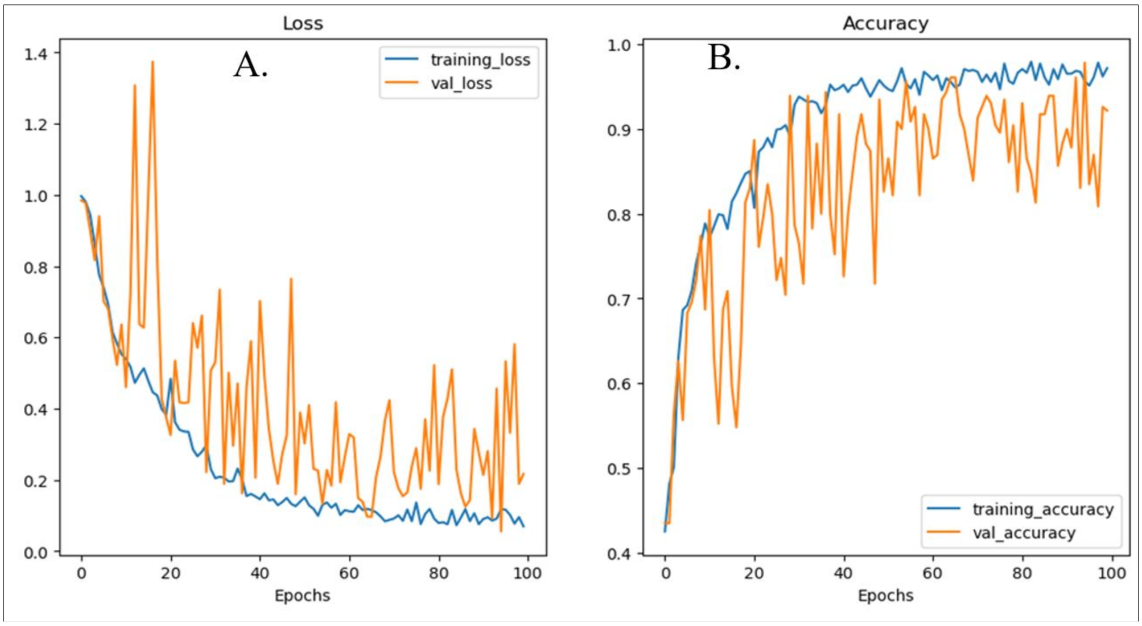

Fig 4: Model accuracy and loss curves

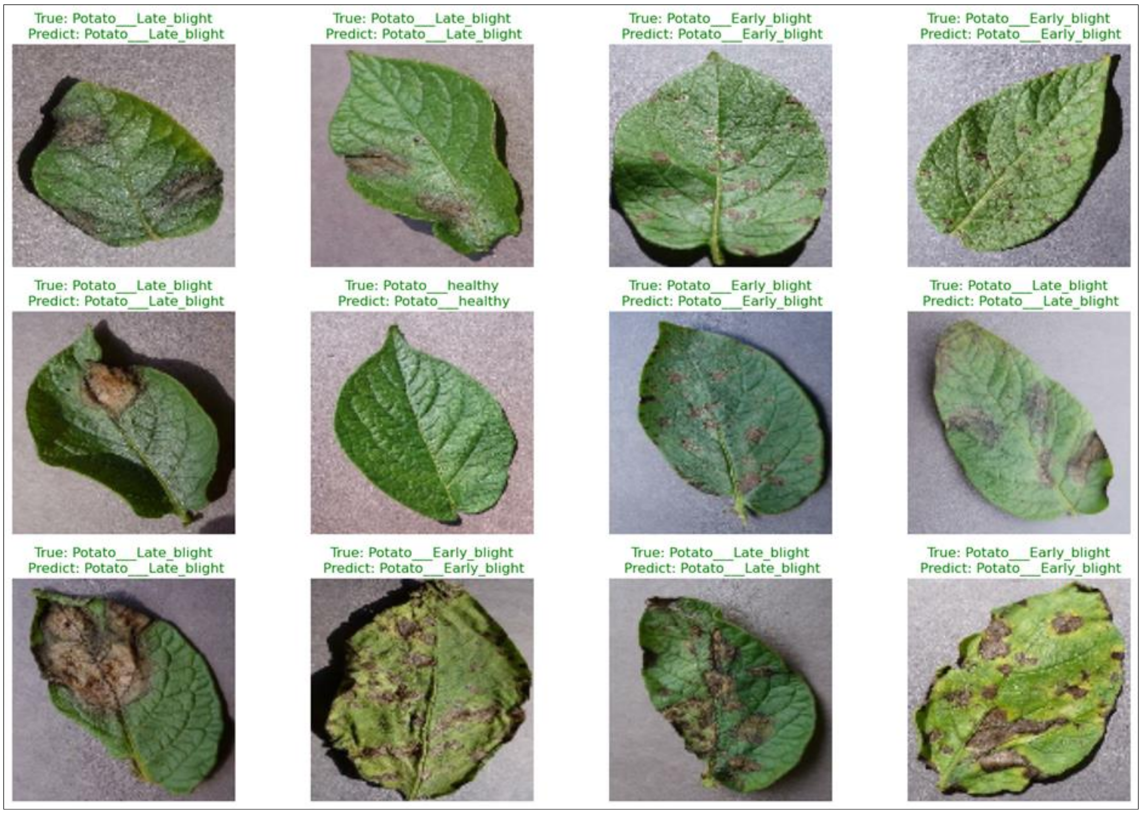

Fig 5: Prediction accuracy of the model

Table 4 summarizes the performance metrics of various models utilized for predicting potato early and late blight diseases. Among these models, the proposed CNN model achieved the highest accuracy, precision, recall, and F1 score, with values of 97.82 percent across all metrics. In comparison, other models such as AlexNet and VGG19 demonstrated lower performance, with accuracy scores of 43.47 percent. DenseNet121, InceptionV3, LeNet-5, MobileNet, ResNet50, and VGG16 exhibited comparatively better results, achieving accuracy scores ranging from 83 percent to 97.69 percent. Notably, EfficientNet displayed the lowest performance, with an accuracy of 13 percent.

These metrics offer insights into the effectiveness of different models in accurately classifying potato diseases, highlighting the superiority of the proposed CNN model in terms of overall classification performance. In a recent study conducted in 2024, a Convolutional Neural Network (CNN) demonstrated an impressive accuracy of 97.82% in classifying Potato Early and Late Blight (PEL). This achievement highlights the CNN's effectiveness in distinguishing between healthy potato leaves and those affected by these diseases. Previous research has also emphasized the utility of CNNs in potato disease classification. For instance, Afzaal *et al*. (2021) [1] utilized AlexNet for Potato Early Blight Detection, achieving an accuracy of 93.50%. Similarly, Hassan *et al*. (2019) employed ResNet50 for Potato Late Blight Detection, achieving an accuracy of 95.60%. These findings suggest that various CNN models can be successfully applied to different types of potato diseases, resulting in notable accuracy rates.

Additionally, Zhang *et al*. (2021) [17] conducted a study on potato foliage disease detection using deep learning methods, achieving high accuracy rates in classifying healthy leaves, early blight, and late blight. Similarly, in a recent publication by Lee *et al*. (2023) [9], a novel approach for potato disease severity classification was proposed, demonstrating an exceptional accuracy rate of 97.86%. These findings underscore the versatility of Convolutional Neural Networks (CNNs) in accurately classifying different types of potato diseases and highlight the continuous advancements in disease detection methodologies. Overall, the results from these studies collectively demonstrate the efficacy of CNNs in accurately classifying potato diseases like Early and Late Blight. Such advancements in machine learning techniques hold significant promise for improving the efficiency and accuracy of disease diagnosis in agriculture, leading to more effective disease management strategies.

Proposed CNN

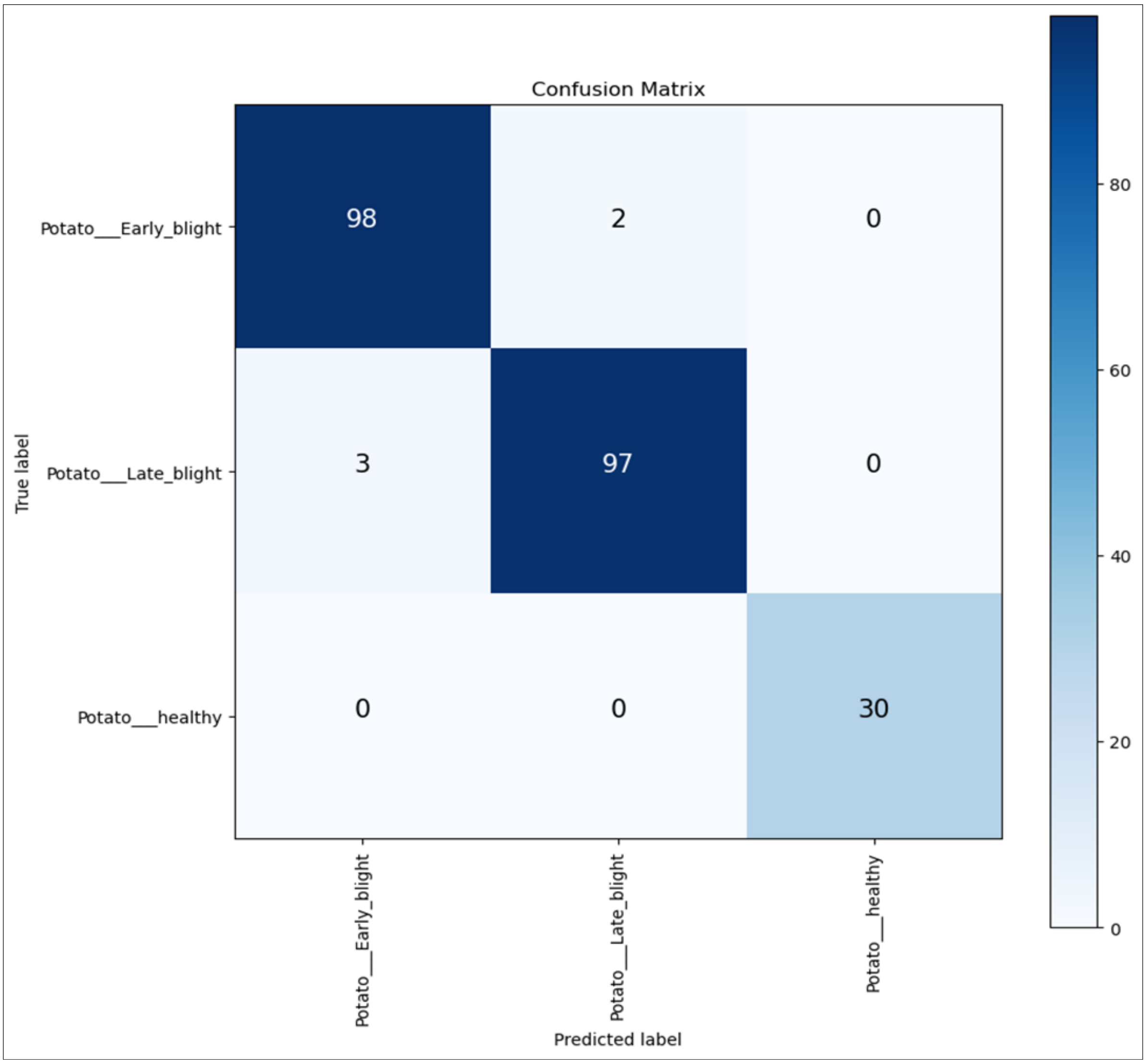

Fig 6: Confusion matrix for the developed model

Conclusion

This study demonstrates the transformative potential of Convolutional Neural Networks (CNNs) in the classification of potato leaf diseases. Through the integration of deep learning techniques, transfer learning, and data augmentation, our developed system showcases high accuracy and efficiency in early disease detection within potato crops. With rigorous experimentation, our proposed CNN model achieved an impressive 97.82% accuracy in distinguishing between early and late blight diseases, with remarkable precision in identifying healthy leaves versus those affected. These findings not only highlight CNN effectiveness in agricultural disease management but also underscore their broader applicability in addressing food security challenges. Future research should focus on refining CNN models through transfer learning and the integration of additional data sources to enhance adaptability and precision in disease classification tasks. Ultimately, the ongoing innovation in artificial intelligence holds substantial promise for revolutionizing agricultural diagnostics and advancing global food security efforts.

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Competing interests

Authors have declared that no competing interests exist.

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