AI in Agriculture: Cracking the Code of Potato Leaf Health with Deep CNNs

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Abstract-

Potato is a globally important crop, and its yield is significantly threatened by various leaf diseases such as Early Blight and Late Blight. Manual disease diagnosis is time consuming, subjective, and often inaccurate in large-scale farming. In this study, we present an automated system for the classification of potato leaf diseases using deep learning techniques. The dataset used consists of images belonging to three categories: Potato_Early_blight, Potato_Late_blight, and Potato_Healthy. To achieve high classification accuracy, we employed both a custom Convolutional Neural Network (CNN) and several transfer learning models including MobileNetV2, ResNet50, and VGG16. The data was augmented using various real-time image transformations to improve generalization and robustness. Among all models evaluated, ResNet50 and VGG16 achieved the highest accuracy of 99.61%, clearly outperforming the custom CNN and MobileNetV2. Additionally, Grad-CAM (Gradient-weighted Class Activation Mapping) was used to visualize model attention, offering explainability and trust in the model's predictions. The final system is suitable for real-time deployment using Streamlit, allowing users to upload leaf images and instantly receive diagnostic results. This work demonstrates that deep learning, when combined with effective data preprocessing and transfer learning, can provide an accurate, efficient, and scalable solution for disease detection in potato crops. The proposed method can be extended to other plant disease identification tasks, thus supporting smart agriculture initiatives and precision farming.

Keywords: Potato Leaf Disease, Deep Learning, Convolutional Neural Networks (CNN), Transfer Learning, ResNet50, VGG16, MobileNetV2, Image Classification, Grad-CAM.

I. INTRODUCTION

Agriculture contributes to alleviating poverty and fosters economic growth of individual farmers and countries' gross domestic product (GDP). It is crucial for ensuring food security and sustaining the livelihoods of the planet Earth [1]. Therefore, on a global scale, more food production is the most powerful weapon to deal with food insecurity [2]. In rural areas, agriculture is a primary livelihood, where about 80% of people are directly and indirectly involved in agricultural activities [3]. Among the different food crops cultivated globally, potatoes stand as the most favoured one. Regarding human consumption, potatoes are the third most substantial food crop after cereals (rice and wheat) worldwide [4]. Potatoes form a staple food for millions and are rich in essential vitamins, minerals, nutrients, proteins, and energy [5]. Economically, potato crops essentially contribute to the agricultural GDP of many countries. For instance, the U.S. potato industry alone generated an estimated $100.9 billion in economic activity in 2021, supporting over 714,000 employees and contributing $34 billion in wages [6]. Aligning with the Sustainable Development Goals (SDGs), potatoes contribute to several foods security targets. They are essential for promoting SDG 2: Zero Hunger [7], by providing a reliable and nutritious food source that can help reduce starvation and under nutrition. Moreover, sustainable potato cultivating practices can support SDG 12: Responsible Consumption and Production [8], by advancing efficient utilization of natural resources and reducing food waste. In general, the role of potatoes in enhancing food security and supporting economical agricultural practices underscores its worldwide importance.

A comprehensive Sankey diagram as presented in Figure 1.1 highlights the extensive range of potato diseases detected by various studies from 2007 to 2024. This diagram illustrates the intricate connections between the general category of plant diseases, the specific crop of potatoes, and the detailed list of diseases that have been the focus of research over the years. The two thick lines driving from "Plant Disease" to "Crop Potato" and after that to "Early Blight" and "Late Blight" (EB and LB, respectively) show that these two diseases are the most common among the ones considered. These thick lines imply that a considerable number of analysts universally have concentrated their endeavors on foreseeing and overseeing these diseases. The variety of thinner lines connecting ''Crop Potato'' to other diseases such as Bacterial Wilt, Common Scab, Black Scurf, and others reflect the differences of pathogens influencing potatoes and the broader scope of investigation aimed at understanding and mitigating these threats. Each line represents the linkage between the plant diseases affecting potatoes and the specific type of disease, emphasizing the comprehensive nature of the studies conducted over a long time. This chart not only underscores the significance of EB and LB within the context of potato disease research but also gives a visual outline of the broader range of diseases that have been inspected, subsequently offering a holistic view of the endeavors made to ensure the health and productivity of potato crops globally. The major potato diseases include LB, caused by water mold infestans [9], and EB, favoured by warm and wet weather conditions [10]. The agent responsible for LB is a fungal phytopathogen, known as Phytophthora Infestans and the Alternaria Solani/Alternata is responsible for EB [11]. In summary, potato LB is caused by humid, warm weather along with frequent precipitation and moderate temperature (15◦C - 20◦C) [12]. These diseases are notorious for their impact on potato crop cultivation worldwide. To get rid of diseases, pesticides are overused which further exploits human health and the environment [13] [14[15].

Applying artificial intelligence to detect and classify plant diseases enables farmers to intervene early. Expert laboratory study of plant leaves is a protracted and expensive endeavour. Farmers may swiftly and consistently make decisions through an easily accessible artificial intelligence system, facilitating early disease intervention and cost reduction [17], [18]. The application of artificial intelligence in agriculture is more significant due to advancing technologies. The adoption of artificial intelligence in agriculture has accelerated due to advancements in image processing and big data. Deep learning and machine learning research assist farmers in making educated decisions by swiftly processing agricultural data. Artificial intelligence systems identify plant diseases and detrimental elements that may adversely impact plant growth [19]. Deep learning techniques yield insights such as disease assessment and plant health evaluation by analyzing numerous plant images. Monitoring the products cultivated on agricultural grounds is essential to enhance the productivity and quality of crops in agriculture. Deep learning techniques are commonly employed to monitor and analyze agricultural products using images [20]. Deep learning techniques have been employed to address intricate issues rapidly and efficiently, facilitating their application in agriculture. The presence of fungi, microorganisms, and bacteria on plants can diminish the productivity of the cultivated crop. If these problems affecting the facility are not addressed promptly, significant economic losses will ensue. Nonetheless, the unintentional application of pharmaceuticals in research aimed at disease prevention in foliage adversely affects the environment and natural ecosystems. The excessive use of pharmaceuticals might adversely impact the natural water and soil cycles. In plant disease prevention, image processing and deep learning are often techniques for detecting plant leaf diseases. One of these studies [21] employed deep learning convolutional neural network designs for disease detection with tomato leaf images. This study involved training images of tomato leaves using the convolutional neural network architectures AlexNet, ResNet, and GoogLeNet to analyse the characteristics of diseases. The study revealed that the ResNet architecture identified tomato plant diseases with an accuracy of 97.28% during the training experiment utilizing the Stochastic Gradient Descent (SGD) optimization algorithm. A hybrid classifier method proposed for detecting diseases on plant leaves, [22] aims to classify leaf diseases of the bell pepper plant. The combined features of local binary pattern (LBP) and VGG-16structures were used for feature extraction. Random forest (RF) was used in the classification stage. A study on olive plant leaf diseases [23] established a specialized structure integrating Convolutional Neural Network architecture with Vision Transformer architecture. To do this, images were transformed into HSV, YUV, Lab, and RGB formats, and the Otsu thresholding method was applied to the channels containing specific information in each image format. This procedure allows for the acquisition of properties of the warped leaf sections to a specific extent. The study employed a two-stage technique to identify and categorize leaf degradation. Initially, a CNN based pixel classifier was used to distinguish healthy leaves from damaged ones. In the second stage, the compromised leaf pixels were classified internally. A study on disease detection in potato plants [24] examined the categorization of diseases in potato leaves utilizing the Plant Village plant disease dataset, an open resource. This work aimed to differentiate between three distinct classes, comprising images of two potato plant diseases and healthy plants. A threshold value was established on this channel to eliminate the background. The images acquired from the feature extraction process were classified into late blight, early blight, and disease-free categories using a Support Vector Machines classifier. The study suggested a computationally efficient model that attained a 95% accuracy rate. Different data sets are used in studies conducted to detect and classify leaf diseases. An important problem in these data sets may be the imbalance of the number of samples. In cases where the number of samples is imbalanced, the accuracy of the class with the majority of data tends to be high. In classes with a small number of data, performance tends to be low due to low diversity and randomness [25]. Data sets obtained in laboratory environments are more suitable for feature extraction with image preprocessing steps. Controlled lighting and a homogeneous background in the environment ease extracting leaf features. Such data sets help deep learning models achieve higher results. In addition to images taken in laboratory environments, field images are taken from the garden or field. These real-world data sets may have different lighting environments, difficult shooting conditions, and background clutter. In a study conducted in this field [26], the SaudiArabiaFlora Dataset belonging to some plant species in Saudi Arabia was created. This classifier structure, produced using the features of MobileNet, Inception, and VGG architectures, was improved to classify the created real-world dataset. In a study investigating the detection of situations such as ripening and damage in soybean plants with the deep learning method [27], techniques that will increase the performance of InceptionV3 architecture were examined. In this study, five different image classes belong to soybeans. The study investigated the effects of the layers added to the InceptionV3 architecture and the pre-trained model on performance [28]. The study also examined the impact of the transfer learning method on disease detection in the sunflower plant. The studies revealed that the EfficientNetB3 architecture outperformed other architectures regarding results. Many different methods have been preferred for classifying plant diseases in the literature. One is to improve the structure of deep learning architectures to increase classification accuracy. In many studies, an increase in accuracy rates has been observed with the proposed new deep learning architectures. Another perspective on plant disease classification has been examining the effect of transfer learning on state-of-the-art models. The effects of the transfer learning method on deep learning architectures, which are frequently preferred in detecting plant diseases, have been examined. Along with these studies, there are also studies in which the analyses are improved by performing operations on the images in plant disease datasets. These studies include systems that separate and analyse the leaf region from the 71824 background. The applicability of these methods for each dataset and environmental factor varies in many studies [29]. Considering the reviewed literature studies, the proposed method was to analyse the leaf regions desired to be classified by extracting them from the noise. Some segmentation methods in the literature have been tried in this field, and the BorB segmentation method has been proposed. Each of the diseased leaves collected for the dataset has its characteristics. Since few diseased leaves are obtained in this area, there are few images in the dataset. The data augmentation technique has been tried in this study to solve one of the problems in plant disease datasets: data scarcity. The dataset to which preprocessing steps have been applied has been made ready for training with deep learning architectures. At this stage, the transfer learning method has been used for deep learning architectures, considering that it will increase the accuracy rate in training. The effect of each method applied is presented in the results section, and detailed analyses are provided. In this way, each stage of the integrated classifier method presented in the research has become valuable. This study explores the application of deep learning techniques for accurate and efficient potato disease detection, a critical aspect of modern agriculture. In response to the growing global demand for food and the increasing prevalence of potato diseases, this research aims to enhance crop productivity and quality by enabling timely and accurate disease identification.

1.4 Objectives of the Research

Potatoes are a fundamental food crop and source of food for a wide range of populations [30] and are crucial for food security [31]. Potato disease modeling has improved with advanced technologies, but there are still important research gaps, especially in using time series forecasting. Traditional methods of disease detection in potatoes depend on manual checks, which is hard work and needs expert knowledge, causing delays in finding and responding to diseases. Most research focuses on identifying diseases using images [32], [33], [34] helpful but has its limits in early detection. The upsides of advancing disease detection in potatoes extend beyond enhancing crop yields. Healthy potato crops can thus have a direct impact on human health, providing a nutritious food source that supports overall well-being.

According to Masanobu Fukuoka [35] ‘‘the ultimate goal of farming is not the growing of crops, but the cultivation and perfection of human beings’’. Over time, various practices for disease classification have already been implemented [36]. Traditional practices can be tedious and costly. Thus, there is a decisive necessity to automate disease management more effectively and economically using ML and Artificial Intelligence (AI) which ensure timely and accurate disease detection and facilitate farmers to manage their crops efficiently. However, the application of these technologies in agriculture is still new and there are many challenges to overcome to fully recognize their abilities.

Therefore, there’s a need for better, automated methods to predict diseases, helping to reduce crop losses and ensure food security. Most research relies on images, but we need to explore time series data, including weather and plant conditions. This gap is a chance for more research. This thesis aims to close the gap between manual and advanced techniques, showing new methods for early disease detection and management. These advanced techniques could lead to better results, helping future studies, improving resource use, and enhancing food security. In recent years, potato cultivation has been drastically influenced by diseases [37]. Early and timely detection of outbreaks can prevent significant financial losses for farmers. Scientists have suggested that forecasting algorithms provide early predictions to help in preventing and controlling various diseases. The objective of this study is,

i) to understand the importance of potatoes for global food security, provide a thorough review of existing methods used by researchers globally for potato disease management by focusing on advancements in modern technology, and

ii) Suggest improvements in efficient potato cultivation to ensure its role in mitigating global food security issues.

II. LITERATURE SURVEY

According to Nishad et al. [38] in 2022, K-means clustering and data augmentation are performed. VGG16 outperforms 97% accuracy, followed by VGG19 and then ResNet with 95% and 67% accuracy, respectively. The imagery data composed of unhealthy (EB and LB), and standard (healthy) leaves were taken from a repository available on Kaggle for examination using the CNN model with 96.8% accuracy. Pasalkar et al. [39], Sai Ponnuru and Amasala [40], and N. The dataset from Kaggle called the new ‘‘plant disease dataset’’ (PDD) was taken with 600 images and resulted in 97.4% accuracy for the study [41], whereas the Plant Village dataset from Kaggle was taken for the study [42], and achieved an impressive accuracy of 99.54% and 97.82%, respectively. Catal Reis and Turk [43], For classification, 10 distinct models were used, including DenseNet201, DenseNet121, NasNetLarge, Xception, ResNet152v2, EfficientNetB5, EfficientNetB7, VGG19, MobileNetV2, and hybrid model (EfficientNetB7 and ResNet152V2). The highest accuracy of 98.67% was obtained by DenseNet201 with a loss of 0.04. Anim-Ayeko et al. 2023 [44], (2152: potato and 4500: tomato). Other performance metrics like rec, pre, and F1-Score have also been observed. Pineda Medina et al. 2024 [45], developed an offline mobile application for detecting potato diseases into three different classes (EB, LB, and healthy). Shrivastava et al. [46] for the detection of three classes of potato diseases using image classification was carried out in 2023. The VGG19 and ODCNN models were adopted for the analysis. For D1 and D2, accuracy rates of 98.26% and 99.22%, respectively were obtained. For EB disease identification at different growth stages,

For plant disease identification, Jha et al. 2024, [47] proposed DNN-based ensemble models which integrate Residual Net, MobileNet, and Inception models. The disease classification was carried out for infected (EB and LB) and healthy classes based on the Plant Village dataset having 857 images. The ensemble model resulted in 98.86% accuracy which should be higher than individual DNN models. In 2021, Kumar Shukla et al. [48] introduced a DFS (Disease Forecasting System) for the identification of diseases in potato crops. The system was developed by the integration of K-means clustering, CNN, and SVM model and achieved 97.90% accuracy. Arshaghi et al. 2023 [49] proposed a convolutional neural network model to predict five different potato diseases, including healthy plants. The researchers compared the proposed model with other established CNN models like AlexNet, GoogleNet, and VGG, highlighting the superior performance of the proposed model. Kang et al. 2023 [50] used a lightweight NN model to classify potato diseases. The imagery dataset was used consisting of 5450 images. The model achieved an accuracy of 93% for EB and LB predictions. In 2023, Samatha et al. [51] IoT with advanced image processing to distinguish healthy and unhealthy potatoes. An M-SVM model with CNN and DNN models was implemented and an accuracy of over 99% was observed. In 2023, Bonik et al. [52] used a DL approach to classify potato plants as healthy or affected by EB and LB diseases. A dataset of 3561 images was fed to the CNN model and achieved an accuracy of 94.2%.

In 2023, Sharma et al. [53] utilized a CNN model with three different activation functions (Elu, Swish, and ReLU) on a dataset of 1722 images, attaining a high accuracy of 98% with a swish activation function loss of 0.04. In 2022, Shi et al. [54] used drones equipped with hyperspectral cameras i.e., UAVs to capture images of potato fields in China. The imagery data was then applied to predict LB. Verma et al. 2023 used data augmentation on a dataset of 1500 images. In 2014, Dutta et al. [55] embraced RS indices such as NDVI and LSWI to foresee LB in potatoes. The dataset was composed of satellite images. In 2017, Patil et al. [56] used ML and DL-based image processing to predict EB and LB in potatoes. A dataset of over 892 images was employed for SVM, RF, and ANN models. The maximum accuracy of 92% was achieved using the ANN model. In 2011, Shankar Ray et al. [57], used hyperspectral data to predict LB in potatoes by analyzing vegetation indices from Nijjarpura Village, India. A maximum accuracy of 99.75% with the SVM model was observed. Rayhan Asif et al. 2020 [58] compared CNN models such as AlexNet, ResNet, VggNet, LeNet, and sequential model on a dataset of 1500 images, achieving a 97% accuracy in predicting EB and LB. In 2021, Islam Tarik et al. [59] used a CNN-based sequential model on a dataset of over 2034 images to diagnose potato diseases, achieving a 99.23% accuracy. In 2022, Bangal et al. [60] and Islam and Sikder [68] predicted EB, LB, and healthy potato classes using a CNN model with accuracies of 91.41%

and 100% respectively, on the Plant Village dataset. In the same year, Kothari et al. [61] among various models, ResNet50 performed the best, achieving an accuracy of 98%.
Fall et al. [62] explored a visual approach to detect LB in potato plants. The study indicated that the CNN model outperformed the others. Hou et al. 2022 [63] focused on using ML to analyze images of potato plant leaves to detect LB. Distinct models, including SVM, KNN, and DT were employed and reported a high accuracy of 99%. Recent advances in agricultural technology, especially ML, DL, and AI, have significantly improved how we manage crops. The developed sprayer reduced chemical use by 42-43%, lowering costs and environmental impact. Similarly, Farooque et al. 2023 [64] experimented with a smart sprayer that uses DL to find and treat weeds and diseased plants in potato fields and sprayer accurately targets plants needing treatment. ML has been applied in various fields beyond crop disease diagnosis, including crypto currency price prediction [65], where it is used to enhance predictive accuracy by integrating macroeconomic, microeconomic, and technical indicators.

III. PROPOSED WORK

Most of the image data in existing research has been acquired from web scrapping tools, Kaggle, open source repositories, plant village dataset, plant leaf disease, the internet, and manually captured photographs in fields using drones, and hyperspectral cameras.

Technological advancements in plant disease detection include capturing good quality images, image processing using computer software, categorizing leaf infection symptoms with ML algorithms for automating disease detection from the symptoms on new leaves, and benefiting from AI for smart farming. Advanced computing in agriculture, using ML, AI, and DL, enhances precision agriculture (PA) by analyzing data from weather stations, sensors, and satellite imagery.

These technologies optimize crop yields, predict diseases, optimal resource management, disease early warning, PA, enhanced food quality, crop monitoring, more research endeavors in agriculture, and automate irrigation, leading to increased efficiency, reduced costs, and sustainable farming practices.

The process of potato crop disease classification begins with the collection of diverse input data, including images of potato crop leaves, which may be taken from fields, existing databases, hyperspectral cameras, UAV, online sources, remote sensing, and plant village database or time series data such as temperature, humidity, and other environmental factors obtained from weather stations. These inputs undergo pre-processing to enhance quality and remove noise, with image pre-processing including resizing, normalization, augmentation and filtering, whereas time series data may be smoothed and normalized.

Following pre-processing, feature extraction is performed on both data types: image features such as color, texture, and shape are analyzed, whereas time series highlights might incorporate statistical measures, trends, and patterns over time. The extracted features are then organized into a structured format, such as feature matrices for images and time series data and stored in a database for proficient management. This organized data is used to train the DL algorithms.

The detailed design process will be described in the subsequent sections.

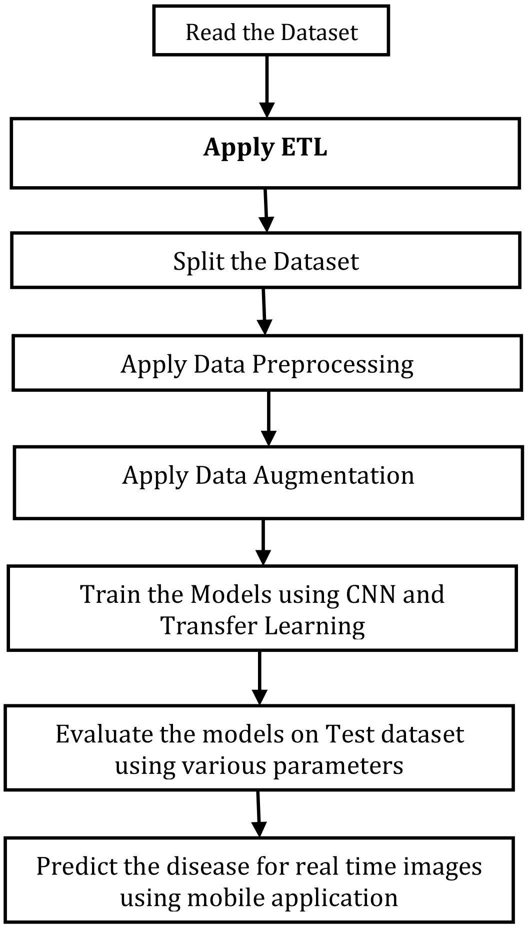

Figure 3.1: Proposed model steps.

3.1 Potato Disease Detection using ResNet50

Step 1: Data Preparation:

1.1. Import the necessary libraries (tensorflow, Matplotlib, os, etc.).
1.2. Copy relevant image folders (Potato___Early_blight, Potato___Late_blight, and Potato___Healthy) into a working directory.
1.3. Load the image dataset using tf.keras.utils.image_dataset_from_directory () with proper image_size and batch_size.

Step 2: Dataset Splitting
2.1. Define a function get_dataset_partition_tf() to split the dataset into **train**, **validation**, and **test** sets.
2.2. Shuffle the dataset and apply caching and prefetching using AUTOTUNE.

Step 3: Data Preprocessing
3.1. Define a Sequential layer for image resizing and rescaling (1./255).
3.2. Define a data augmentation pipeline using RandomFlip, RandomRotation, etc.

Step 4: Load the Pretrained ResNet50 Model.
4.1. Load the base model from tf.keras.applications.ResNet50 with include_top=False, weights='imagenet', and freeze the weights (trainable=False).

Step 5: Build the Classification Model.
5.1. Define a Sequential model with the following layers:
- Input Layer
- Preprocessing Layers (Resizing, Rescaling, Augmentation)
- Pretrained ResNet50 base model
- Global Average Pooling
- Dense Layer with 128 units and ReLU activation
- Dropout Layer (0.3)
- Output Dense Layer with 3 units (softmax for 3-class classification)

Step 6: Compile the Model
6.1. Use Adam optimizer.
6.2. Use SparseCategoricalCrossentropy as the loss function.
6.3. Add accuracy as the evaluation metric.

Step 7: Compile the Model
7.1. Use Adam optimizer.
7.2. Use SparseCategoricalCrossentropy as the loss function.
7.3. Add accuracy as the evaluation metric.

Step 8: Evaluate the Model
8.1. Use model.evaluate() on the test dataset to get final accuracy.
8.2. Generate a classification report and confusion matrix.
8.3. Plot training/validation accuracy and loss curves.

Step 9: Interpretability (Optional)
9.1. Apply **Grad-CAM** to visualize attention on disease-infected regions of leaves.
9.2. Select last convolutional layer for ResNet50 (e.g., 'conv5_block3_out') and compute gradients.

3.2 Proposed Algorithm

Input: Image dataset of potato leaves with three classes
Output: Trained model with accuracy score.

```
1. BEGIN
2.  Import all required libraries (TensorFlow, Keras, etc.)
3.  Load image dataset from directory
4.  Resize all images to 224x224 pixels
5.  Split dataset into:
      - 80% Training Set
      - 10% Validation Set
      - 10% Test Set
6.  Preprocess images:
      - Normalize pixel values to [0, 1]
      - Apply caching and prefetching for efficiency
7.  Load ResNet50 base model with:
      - Weights = 'imagenet'
      - include_top = False
      - Freeze all layers (trainable = False)
8.  Define custom classification model:
      - Add Global Average Pooling layer
      - Add Dense layer with 128 units and ReLU activation
      - Add Dropout layer (rate = 0.3)
      - Add Output Dense layer with 3 units and SoftMax activation
9. Compile the model with:
      - Optimizer = Adam
      - Loss = Sparse Categorical Crossentropy
      - Metric = Accuracy
10.  Train the model on training data
      - Use validation data for performance monitoring
      - Train for 50 epochs
11.  Evaluate the model on the test dataset
12.  Display final accuracy score
13. END
```

IV. RESULTS

Table 4.1 is the comparative analysis for the models implemented for potato disease detection based on the three classes.

Table 4.1: Accuracy Score.

Algorithm Implemented	Accuracy Score
Custom CNN	98.44%
MobileNetV2	98.05%
ResNet50	99.61%
Vgg16	99.61

This table summarizes the classification performance of different deep learning models implemented to detect and classify potato leaf diseases (Early Blight, Late Blight, and Healthy) using image data.

Figure 4.1: Final Accuracy comparison of all the implemented models.

☐ Custom CNN
A self-built Convolutional Neural Network (CNN) was designed and trained from scratch. Despite being a relatively simple architecture compared to transfer learning models, it achieved a high accuracy of **98.44%**, demonstrating the effectiveness of deep learning in plant disease detection even without pre-trained knowledge.

☐ MobileNetV2
MobileNetV2, known for its lightweight and efficient architecture, was used with transfer learning. It achieved an accuracy of **98.05%**. Although slightly lower than others, its smaller size makes it ideal for deployment on mobile and edge devices in real-world agricultural settings.

☐ ResNet50
ResNet50, a deep residual network known for solving vanishing gradient problems using identity shortcut connections, achieved a top accuracy of **99.61%.** This reflects its strength in learning deep representations from complex features in leaf images.

☐ VGG16
The VGG16 model, despite being an older and heavier architecture, also performed excellently with an accuracy of **99.61%.** Its deep stack of convolutional layers helped in capturing fine-grained visual cues from diseased and healthy leaves.

☐ Conclusion
Both **ResNet50 and VGG16** yielded the best performance among all models tested, making them strong candidates for deployment in real-world automated disease diagnosis systems. The Custom CNN also performed impressively given its simplicity, while MobileNetV2 offers a trade-off between speed and accuracy suitable for on-device inference.

Table 4.2: Loss Score Comparison.

Algorithm Implemented	Loss Score
Custom CNN	0.0375
MobileNetV2	0.0659
ResNet50	0.0364
Vgg16	0.0225

The loss score quantifies the difference between predicted class probabilities and the actual labels during model training. A **lower loss** generally indicates better model performance, especially in terms of confidence and convergence stability.

☐ VGG16
VGG16 achieved the **lowest loss score of 0.0225**, confirming its excellent ability to generalize and minimize classification errors. Its deep and consistent convolutional structure allowed it to learn meaningful patterns in the potato leaf dataset effectively.

☐ ResNet50
ResNet50 recorded a **loss score of 0.0364**, which is very close to that of VGG16. This result showcases its strength in deep feature extraction and highlights its robustness against overfitting due to the residual connections in its architecture.

 Custom CNN

The custom-built CNN also performed well, with a **loss of 0.0375**, only slightly higher than ResNet50. This demonstrates that even a model trained from scratch, when well-structured and optimized, can perform competitively with transfer learning models on domain-specific data.

 MobileNetV2

MobileNetV2 showed a **loss score of 0.0659**, the highest among the models tested. While still reasonably low, it suggests that the model might struggle slightly more with confidently classifying certain disease categories, likely due to its lighter architecture designed for mobile applications.

The **loss score analysis** complements the accuracy results, further reinforcing **VGG16** and **ResNet50** as the top-performing models. VGG16 stands out as the most confident model in its predictions, while the custom CNN also proved its effectiveness. MobileNetV2, despite its slightly higher loss, remains valuable for low-resource deployment scenarios.

V. CONCLUSION

The comparative analysis of the implemented models, based on both accuracy and loss metrics, reveals that **VGG16 and ResNet50** consistently outperformed other architectures. Both achieved the highest classification accuracy of **99.61%**, demonstrating exceptional ability to distinguish between Early Blight, Late Blight, and Healthy potato leaves. Additionally, **VGG16 recorded the lowest loss score of 0.0225**, indicating its superior confidence and stability in predictions. **ResNet50**, with a very close loss of **0.0364**, also confirmed its robustness and effective learning capacity. The **custom CNN** model achieved a strong accuracy of **98.44%** and maintained a competitive loss score (**0.0375**), validating the strength of a carefully designed architecture even without pretraining. **MobileNetV2**, while delivering slightly lower accuracy (**98.05%**) and higher loss (**0.0659**), remains a practical choice for mobile and edge deployment due to its lightweight nature. Overall, VGG16 emerges as the most balanced model in terms of both accuracy and loss, followed closely by ResNet50, making them ideal candidates for real-world agricultural disease detection systems.

VI. REFERENCES

[1] P. Mishra, A. A. Alhussan, D. S. Khafaga, P. Lal, S. Ray, M. Abotaleb, K. Alakkari, M. M. Eid, and E.-S.-M. El-kenawy, ‘‘Forecasting produc tion of potato for a sustainable future: Global market analysis,’’ Potato Res., vol. 67, no. 4, pp. 1671–1690, Mar. 2024, doi: 10.1007/s11540-024 09717-0.

[2] P. Smith et al., ‘‘which practices co-deliver food security, climate change mitigation and adaptation, and combat land degradation and desertifica tion?’’ Global Change Biol., vol. 26, no. 3, pp. 1532–1575, Mar. 2020, doi: 10.1111/gcb.14878.

[3] World Bank. (2024). Agriculture and Food. [Online]. Available: https://www.worldbank.org/en/topic/agriculture/overview.

[4] H. Campos and O. Ortiz, The Potato Crop: Its Agricultural, Nutritional and Social Contribution To Humankind. Cham, Switzerland: Springer, 2019, doi: 10.1007/978-3-030-28683-5.

[5] Potato Production Worldwide From 2002 To 2022, Statista, Hamburg, Germany, 2022.

[6] National Potato Council Releases Groundbreaking Report on U.S. Potato Industry's Contribution To America's Economy, Nat. Potato Council, Washington, DC, USA, May 2024.

[7] P. Atukunda, W. B. Eide, K. R. Kardel, P. O. Iversen, and A. C. Westerberg, ‘‘Unlocking the potential for achievement of the UN sustainable development goal 2-‘zero hunger'-in africa: Targets, strategies, synergies and challenges,’’ Food Nutrition Res., vol. 65, pp. 1–19, May 2021, doi: 10.29219/fnr.v65.7686.

[8] S. Khanal, K. Karimi, S. Majumdar, V. Kumar, R. Verma, S. K. Bhatia, K. Kuca, J. Esteban, and D. Kumar, ‘‘Sustainable utilization and val orization of potato waste: State of the art, challenges, and perspec tives,’’ Biomass Convers. Biorefinery, vol. 14, no. 19, pp. 23335–23360, Oct. 2024, doi: 10.1007/s13399-023-04521-1.

[9] R. Verma, R. Mishra, P. Gupta, Pooja, and S. Trivedi, ‘‘CNN based leaves disease detection in potato plant,’’ in Proc. 6th Int. Conf. Inf. Syst. Comput. Netw. (ISCON), Mar. 2023, pp. 1–5, doi: 10.1109/ISCON57294.2023.10112080.

[10] H. Afzaal, A. A. Farooque, A. W. Schumann, N. Hussain, A. McKenzie-Gopsill, T. Esau, F. Abbas, and B. Acharya, ‘‘Detection of a potato disease (early blight) using artificial intelligence,’’ Remote Sens., vol. 13, no. 3, p. 411, Jan. 2021, doi: 10.3390/rs13030411.

[11] J. Pasalkar, G. Gorde, C. More, S. Memane, and V. Gaikwad, ‘‘Potato leaf disease detection using machine learning,’’ Current Agricult. Res. J., vol. 11, no. 3, pp. 949–954, Jan. 2024, doi: 10.12944/carj.11.3.23.

[12] P. Sharma, B. K. Singh, and R. P. Singh, ‘‘Prediction of potato late blight disease based upon weather parameters using artificial neural network approach,’’ in Proc. 9th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT), Bengaluru, India, Jul. 2018, pp. 1–13.

[13] I. R. Lake, L. Hooper, A. Abdelhamid, G. Bentham, A. B. A. Boxall, A. Draper, S. Fairweather-Tait, M. Hulme, P. R. Hunter, G. Nichols, and K. W. Waldron, ‘‘Climate change and food security: Health impacts in developed countries,’’ Environ. Health Perspect., vol. 120, no. 11, pp. 1520–1526, Nov. 2012, doi: 10.1289/ehp.1104424.

[14] A. Al-Sadi, "Impact of plant diseases on human health," Int. J. Nutri tion, Pharmacol., Neurological Diseases, vol. 7, no. 2, p. 21, 2017, doi: 10.4103/ijnpnd.ijnpnd_24_17.

[15] R. A. C. Jones, "Global plant virus disease pandemics and epidemics," Plants, vol. 10, no. 2, p. 233, Jan. 2021, doi: 10.3390/plants10020233.

[16] A. Kaur et al., "Artificial Intelligence Driven Smart Farming for Accurate Detection of Potato Diseases: A Systematic Review," in IEEE Access, vol. 12, pp. 193902-193922, 2024, doi: 10.1109/ACCESS.2024.3510456.

[17] D. S. Joseph, P. M. Pawar, and K. Chakradeo, "Real-time plant disease dataset development and detection of plant disease using deep learning," IEEE Access, vol. 12, pp. 16310–16333, 2024.

[18] V. E. González-Rodríguez, I. Izquierdo-Bueno, J. M. Cantoral, M. Carbú, and C. Garrido, "Artificial intelligence: A promising tool for application in phytopathology," Horticulturae, vol. 10, no. 3, p. 197, Feb. 2024.

[19] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: A review," Plant Methods, vol. 17, no. 1, pp. 1–18, Dec. 2021.

[20] K. Dokic, L. Blaskovic, and D.Mandusic,"From machine learning to deep learning in agriculture—The quantitative review of trends," IOPConf.Ser., Earth Environ. Sci., vol. 614, no. 1, Dec. 2020, Art. no. 012138.

[21] K.Zhang,Q.Wu,A.Liu, and X.Meng,"Can deep learning identify tomato leaf disease?" Adv. Multimedia, vol. 2018, pp. 1–10, Sep. 2018.

[22] M. Bhagat, D. Kumar, and S. Kumar, "Bell pepper leaf disease classification with LBP and VGG-16 based fused features and RF classifier," Int. J. Inf. Technol., vol. 15, no. 1, pp. 465–475, Jan. 2023.

[23] H. Alshammari, K. Gasmi, I. Ben Ltaifa, M. Krichen, L. Ben Ammar, and M. A. Mahmood, "Olive disease classification based on vision transformer and CNN models," Comput. Intell. Neurosci., vol. 2022, pp. 1–10, Jul. 2022.

[24] M. Islam, A. Dinh, K. Wahid, and P. Bhowmik, "Detection of potato dis eases using image segmentation and multiclass support vector machine," in Proc. IEEE 30th Can. Conf. Electr. Comput. Eng. (CCECE), Apr. 2017, pp. 1–4.

[25] S. V. Moravvej, R. Alizadehsani, S. Khanam, Z. Sobhaninia, A. Shoeibi, F. Khozeimeh, Z. A. Sani, R.-S. Tan, A. Khosravi, S. Nahavandi, N. A. Kadri, M. M. Azizan, N. Arunkumar, and U. R. Acharya, "RLMD PA: Areinforcement learning-based myocarditis diagnosis combined with a population-based algorithm for pretraining weights," Contrast Media Mol. Imag., vol. 2022, no. 1, Jan. 2022, Art. no. 8733632.

[26] E. Amri, Y. Gulzar, A. Yeafi, S. Jendoubi, F. Dhawi, and M. S. Mir, "Advancing automatic plant classification system in Saudi Arabia: Introducing a novel dataset and ensemble deep learning approach," Model. Earth Syst. Environ., vol. 10, no. 2, pp. 2693–2709, Apr. 2024.

[27] Y. Gulzar, "Enhancing soybean classification with modified inception model: A transfer learning approach," Emirates J. Food Agricult., vol. 36, pp. 1–9, Apr. 2024.

[28] Y. Gulzar, Z. Ünal, H. Aktaş, and M. S. Mir, "Harnessing the power of transfer learning in sunflower disease detection: A comparative study," Agriculture, vol. 13, no. 8, p. 1479, Jul. 2023.

[29] L. Lei, Q. Yang, L. Yang, T. Shen, R. Wang, and C. Fu, "Deep learning implementation of image segmentation in agricultural applications: A comprehensive review," Artif. Intell. Rev., vol. 57, no. 6, p. 149, May 2024.

[30] S. Savary and L. Willocquet, "Modelling the impact of crop diseases on global food security," Annu. Rev. Phytopathol., vol. 58, no. 1, pp. 313–341, Jun. 2020, doi: 10.1146/annurev-phyto-010820-012856.

[31] D. M. Rizzo, M. Lichtveld, J. A. K. Mazet, E. Togami, and S. A. Miller, "Plant health and its effects on food safety and security in a one health framework: Four case studies, 'OneHealthOutlook, vol.3, no.1, pp. 1–9, Dec. 2021, doi: 10.1186/s42522-021-00038-7.

[32] J. Pasalkar, G. Gorde, C. More, S. Memane, and V. Gaikwad, "Potato leaf disease detection using machine learning," Current Agricult. Res. J., vol. 11, no. 3, pp. 949–954, Jan. 2024, doi: 10.12944/carj.11.3.23.

[33] M. D. Sai Ponnuru and L. Amasala, "Revolutionizing potato farming: A CNN-powered approach for early blight and late blight detection to ensure global food security," in Proc. IEEE Int. Students Conf. Electr., Electron. Comput. Sci. (SCEECS), Feb. 2024, pp. 1–5, doi: 10.1109/sceecs61402.2024.10482138.

[34] N. Sagar, K. Suresh, R. Ramanji, M. Bharath, Y. Naveesh, Ravichandra, and C. Archana, "Revolutionizing potato crop management: Deep learning-driven potato disease detection with convolutional neural net works," Int. J. Adv. Biochem. Res., vol. 8, no. 3, pp. 644–653, Jan. 2024, doi: 10.33545/26174693.2024.v8.i3h.811.

[35] M. Ng, "Farming for the cultivation of human beings," The Anglican, May 30, 2024.

[36] J. S. I. Ingram, P. J. Gregory, and A.-M. Izac, "The role of agro nomic research in climate change and food security policy," Agricult., Ecosyst. Environ., vol. 126, nos. 1–2, pp. 4–12, Jun. 2008, doi: 10.1016/j.agee.2008.01.009.

[37] Z. Gao, L. R. Khot, R. A. Naidu, and Q. Zhang, "Early detection of grapevine leafroll disease in a red-berried wine grape cultivar using hyper spectral imaging," Compute. Electron. Agricult., vol.179,Dec.2020, Art. no. 105807.

[38] M. A. R. Nishad, M. A. Mitu, and N. Jahan, "Predicting and classifying potato leaf disease using K-means segmentation techniques and deep learning networks," Proc.

Comput. Sci., vol. 212, pp. 220–229, Jul. 2022, doi: 10.1016/j.procs.2022.11.006.

[39] J. Pasalkar, G. Gorde, C. More, S. Memane, and V. Gaikwad, "Potato leaf disease detection using machine learning," Current Agricult. Res. J., vol. 11, no. 3, pp. 949–954, Jan. 2024, doi: 10.12944/carj.11.3.23.

[40] M. D. Sai Ponnuru and L. Amasala, "Revolutionizing potato farming: A CNN-powered approach for early blight and late blight detection to ensure global food security," in Proc. IEEE Int. Students Conf. Electr., Electron. Comput. Sci. (SCEECS), Feb. 2024, pp. 1–5, doi: 10.1109/sceecs61402.2024.10482138.

[41] N. Sagar, K. Suresh, R. Ramanji, M. Bharath, Y. Naveesh, Ravichandra, and C. Archana, "Revolutionizing potato crop management: Deep learning-driven potato disease detection with convolutional neural net works," Int. J. Adv. Biochem. Res., vol. 8, no. 3, pp. 644–653, Jan. 2024, doi: 10.33545/26174693.2024.v8.i3h.811.

[42] H. Catal Reis and V. Turk, "Potato leaf disease detection with a novel deep learning model based on depthwise separable convolution and transformer networks," Eng. Appl. Artif. Intell. vol. 133, Jul. 2024, Art. no. 108307, doi: 10.1016/j.engappai.2024.108307.

[43] A.O.Anim-Ayeko, C.Schillaci, and A.Lipani,"Automatic blight disease detection in potato (solanum tuberosum l.) and tomato (solanum lycop ersicum, l. 1753) plants using deep learning," Smart Agricult. Technol., vol. 4, Aug. 2023, Art. no. 100178, doi: 10.1016/j.atech.2023.100178.

[44] D.P.Medina, I. M.Cabrera, R. A. de la Cruz, L. G. Arzuaga, S. C. Portal, and M. Bianchini, "A mobile app for detecting potato crop diseases," J. Imag., vol. 10, no. 2, p. 47, Feb. 2024, doi: 10.3390/jimaging10020047.

[45] V. K. Shrivastava, C. J. Shelke, A. Shrivastava, S. N. Mohanty, and N. Sharma, "Optimized deep learning model for disease prediction in potato leaves," EAI Endorsed Trans. Pervasive Health Technol., vol. 9, pp. 1–7, Sep. 2023, doi: 10.4108/eetpht.9.4001.

[46] P. Jha, D. Dembla, and W. Dubey, "Deep learning models for enhancing potato leaf disease prediction: Implementation of transfer learning based stacking ensemble model," Multimedia Tools Appl., vol. 83, no. 13, pp. 37839–37858, Oct. 2023, doi: 10.1007/s11042-023-16993-4.

[47] A. K. Shukla, R. Singh, and C. K. Dixit, "A study based on plant disease prediction system using machine leaning," Turkish Online J. Qualitative Inquiry, vol. 12, no. 10, pp. 3147–3155, 2021.

[48] A. Arshaghi, M. Ashourian, and L. Ghabeli, "Potato diseases detection and classification using deep learning methods," Multimedia Tools Appl., vol. 82, no. 4, pp. 5725–5742, Feb. 2023, doi: 10.1007/s11042-022 13390-1.

[49] F. Kang, J. Li, C. Wang, and F. Wang, "A lightweight neural network-based method for identifying early-blight and late-blight leaves of potato," Appl. Sci., vol. 13, no. 3, p. 1487, Jan. 2023, doi: 10.3390/app13031487.

[50] B. Samatha, G. R. Kumar, P. A. Rao, D. K. Rao, T. Syamsundararao, and N. Karyemsetty, "IoT-enabled potato diseases prediction using deep learning," in Proc. Int. Conf. Innov. Data Commun. Technol. Appl. (ICIDCA), Mar. 2023, pp.878–883, doi: 10.1109/ICIDCA56705.2023.10099611.

[51] C. C. Bonik, F. Akter, M. H. Rashid, and A. Sattar, "A convolutional neural network based potato leaf diseases detection using sequential model," in Proc. Int. Conf. Advancement Technol. (ICONAT), Jan. 2023, pp. 1–6, doi: 10.1109/ICONAT57137.2023.10080063.

[52] O. Sharma, Rajgaurang, S. Mohapatra, J. Mohanty, P. Dhiman, and A. Nonkra, "Predicting agriculture leaf diseases (Potato): An automated approach using hyper-parameter tuning and deep learning," in Proc. 3rd Int. Conf. Secure Cyber Comput. Commun. (ICSCCC), May 2023, pp. 490–493, doi: 10.1109/ICSCCC58608.2023.10176819.

[53] Y. Shi, L. Han, A. Kleerekoper, S. Chang, and T. Hu, "Novel cropdocnet model for automated potato late blight disease detection from unmanned aerial vehicle-based hyperspectral imagery," Remote Sens., vol. 14, no. 2, p. 396, Jan. 2022, doi: 10.3390/rs14020396.

[54] S. Dutta, S. K. Singh, and S. Panigrahy, "Assessment of late blight induced diseased potato crops: A case study for west Bengal district using temporal AWiFS and MODISdata," J. Indian Soc. Remote Sens., vol. 42, no. 2, pp. 353–361, Jun. 2014, doi: 10.1007/s12524-013-0325-9.

[55] P. Patil, N. Yaligar, and S. M. Meena, "Comparision of performance of classifiers–SVM, RF and ANN in potato blight disease detection using leaf images," in Proc. IEEE Int. Conf. Comput. Intell. Comput. Res. (ICCIC), Coimbatore, India, Dec. 2017, pp. 1–5.

[56] S. S. Ray, N. Jain, R. K. Arora, S. Chavan, and S. Panigrahy, "Util ity of hyperspectral data for potato late blight disease detection," J. Indian Soc. Remote Sens., vol. 39, no. 2, pp. 161–169, Jun. 2011, doi: 10.1007/s12524-011-0094-2.

[57] M. K. R. Asif, M. A. Rahman, and M. H. Hena, "CNN based disease detection approach on potato leaves," in Proc. 3rd Int. Conf. Intell. Sustain. Syst. (ICISS), Dec. 2020, pp. 428–432, doi: 10.1109/ICISS49785.2020.9316021.

[58] M. I. Tarik, S. Akter, A. A. Mamun, and A. Sattar, "Potato disease detection usingmachinelearning,"inProc.3rdInt.Conf.Intell.Commun. Technol. Virtual Mobile Netw. (ICICV), Feb. 2021, pp. 800–803, doi: 10.1109/ICICV50876.2021.9388606.

[59] A.Bangal,D.Pagar,H.Patil,andN.Pande,"Potatoleafdiseasedetection and classification using CNN," Int. J. Res. Publication Rev. J., vol. 3, no. 5, pp. 1510–1515, 2022. [Online]. Available: https://www.ijrpr.com.

[60] M. A. Islam and M. H. Sikder, "A deep learning approach to classify the potato leaf disease," J. Adv. Math. Comput. Sci.,

vol. 37, no. 12, pp. 143–155, Dec. 2022, doi: 10.9734/jamcs/2022/v37i121735.

[61] D.Kothari, H. Mishra, M. Gharat, V. Pandey, and R. Thakur, ‘‘Potato leaf disease detection using deep learning,’’ Int. J. Eng. Res. Technol., vol. 11, no. 11, pp. 1–5, Nov. 2022.

[62] M. L. Fall, D. M. Tremblay, M. Gobeil-Richard, J. Couillard, H. Rocheleau, H. Van der Heyden, C. A. Lévesque, C. Beaulieu, and O. Carisse, ‘‘Infection efficiency of four phytophthora infestans clonal lineages and DNA-based quantification of sporangia,’’ PLoS ONE, vol. 10, no. 8, Aug. 2015, Art. no. e0136312, doi: 10.1371/journal.pone.0136312.

[63] B. Hou, Y. Hu, P. Zhang, and L. Hou, ‘‘Potato late blight severity and epidemic period prediction based on Vis/NIR spectroscopy,’’ Agriculture, vol. 12, no. 7, p. 897, Jun. 2022, doi: 10.3390/agriculture12070897.

[64] A. A. Farooque, N. Hussain, A. W. Schumann, F. Abbas, H. Afzaal, A. McKenzie-Gopsill, T. Esau, Q. Zaman, and X. Wang, ‘‘Field eval uation of a deep learning-based smart variable-rate sprayer for tar geted application of agrochemicals,’’ Smart Agricult. Technol., vol. 3, Feb. 2023, Art. no. 100073, doi: 10.1016/j.atech.2022.100073.

[65] S. Erfanian, Y. Zhou, A. Razzaq, A. Abbas, A. A. Safeer, and T. Li, ‘‘Predicting bitcoin (BTC) price in the context of economic theories: A machine learning approach,’’ Entropy, vol. 24, no. 10, p. 1487, Oct. 2022, doi: 10.3390/e24101487.