Artificial Intelligence for Disease Detection in Potato Crops under Smart Farming

Hussana Johar R B
Assistant Professor, CSE(AI&ML) ATME College of Engineering
Mysore,VTU, Belagavi, Karnataka
husnavais@gmail.com

ABSTRACT

The global population has surged since 2022, heightening the urgency of ensuring food security amidst escalating demands. Agriculture remains pivotal in addressing this challenge, yet it grapples with the persistent threat of plant diseases, which contribute significantly to worldwide crop losses. However, accurately identifying these diseases, particularly in their early stages, remains a significant hurdle. Automated plant disease identification and diagnosis systems are thus indispensable. To confront this challenge, this study focuses on creating specialized databases for potatoes global food security. These crops face threats from various bacterial and fungal diseases, accentuating the urgency for effective disease management. Additionally, the study delves into developing a dataset specific to potato cultivation, a staple crop vulnerable to diverse diseases. Leveraging deep learning models for image classification, the study demonstrates the effectiveness of a single model, achieving approximately 83% accuracy in identifying potato crop diseases. Trained exclusively on the potato dataset, shows promising performance, paving the way for enhanced disease management strategies in potato farming.

Keywords— *Image Processing, Plant Disease Classification, AI in Agriculture, Convolutional Neural Network*

I. INTRODUCTION

In many nations, one of the main reasons for crop loss is plant diseases. Experts visually evaluate cases using traditional illness analysis methods, resulting in a longer diagnosis process compared to automation techniques. Additionally, there may be a scarcity of experts in some regions. To address this issue, automatic image analysis-based plant disease detection is crucial. Such automation not only expedites the diagnosis process but also serves a crucial function in assessing the seriousness of the condition, forecasting yield, and suggesting suitable treatments. Potatoes are essential food grains with numerous health benefits. They serve as vital sources of food and energy globally and are cultivated in large quantities to sustain expanding populations in many nations. However, like other food grains, potatoes are susceptible to various diseases and pests. Illnesses affecting potatoes can significantly hinder crop growth and reduce production. Common diseases include late blight virus Y, among others.

Convolutional Neural Network (CNN) has emerged as a popular method for plant disease detection, leveraging image analysis techniques. The effectiveness of convolutional neural networks is strongly influenced by the richness and size of the dataset. dataset used for training. Properly labeled, high- quality datasets are essential for optimal performance. Deep learning based CNN models require extensive data for training, as insufficient data can lead to diminished performance. Therefore, ensuring a sufficient volume of high-quality data is critical for training effective CNN models in potato disease detection. The objective of the proposed system are: i) To Develop a CNN architecture capable of accurately classifying images of plants into healthy or diseased categories, with further classification of specific diseases where possible. ii) Curate a comprehensive dataset of plant images covering various crops and diseases. iii) Analyze the effectiveness of the CNN model in recognizing and classifying plant diseases compared to existing methods and benchmarks. This paper has been organized as follows: The research subject, problem, and objectives are explained in detail in the first section. Section 2 provides an overview of current methodologies. System architecture and strategies are described in Section 3. In section 4, implementation details are provided, and the paper concludes with a conclusion.

II. LITERATURE REVIEW

To understand what has already been implemented and updated techniques used various papers are studied and explained in brief in this section.

Abdulridha et al.[1] focus on identifying target spot and bacterial spot illnesses in tomatoes using hyperspectral imaging techniques conducted via UAV (Unmanned Aerial Vehicle) and benchtop methods. It investigates the effectiveness of UAV- based hyperspectral imaging for early disease detection. Convolutional neural networks (CNNs) are used by Afonso et al. researchers in their publication [2] to identify blackleg illness in potato plants. It offers a CNN-based method for reliably and automatically identifying the signs of blackleg disease in potato plants. Afzaal et al. discuss the detection of early blight, a potato disease, using artificial intelligence methods, specifically focusing on remote sensing techniques in paper [3]. It draws attention to the timely identification and management of early blight in potatoes crops through the application of AI algorithms and remote sensing data. Agarwal et al. investigate computer vision-based methods for fruit disease categorization and detection in paper [4], hoping to take advantage of clever advancements in computational sciences and communication. It proposes novel computer vision algorithms for accurate and rapid detection of fruit diseases, contributing to advancements in agricultural technology.

Ahmad Loti et al. [5] offer a comprehensive analysis of both deep learning and machine learning. techniques for detecting diseases and pests in chili plants. It demonstrates the efficacy of machine learning and deep learning techniques in pest and disease identification, offering insights into precision agriculture practices. In paper [6] Al-Amin et al. Forecasting potato diseases based on leaf images utilizing deep convolutional neural networks, with the goal of enhancing digital agricultural systems. This paper presents a deep learning methodology designed for identifying potato diseases from leaf pictures, enabling prompt detection and management of health issues.

Aminuddin et al. [7] introduces an improved deep learning model for recognizing chili diseases, particularly focusing on handling small datasets effectively. It presents an advanced deep learning architecture tailored enabling the precise and effective identification of chili illnesses, tackling issues with the scarcity of data. In their study [8], Arshaghi et al. provide insights into multimedia tools and applications while discussing the application of deep learning methods for identifying and classifying potato diseases. Focusing on multimedia-enabled disease detection systems, it examines the use of deep learning strategies for the automatic recognition and categorization of potato illnesses. Arya Rajeev [9], makes a comparison between CNN and AlexNet for detecting diseases in potato and mango leaves. This research enhances the understanding of deep learning models within agricultural contexts by examining the comparative performance of CNN and AlexNet architectures for disease identification in potato and mango leaves.

In their research, Attri et al. provide an in-depth examination of the role of machine learning in agriculture, focusing specifically on crop management [10]. The study delivers a detailed overview of the machine learning techniques employed in agriculture, highlighting their contributions to various aspects of crop management, including yield forecasting and disease identification. In the research conducted by Ayoub Shaikh et al. [11], the potential applications and advancements of artificial intelligence and machine learning in precision agriculture and smart farming are explored. The paper discusses how AI and machine learning are being integrated into precision agriculture and the potential for these technologies to revolutionize farming practices and increase productivity. Basavaiah Anthony [12] focuses on classifying tomato leaf diseases by utilizing various feature extraction methods, contributing to wireless personal communication technologies are discussed. It introduces an innovative method for categorizing diseases in tomato leaves through various feature extraction techniques, which has potential applications for wireless communication technologies in agricultural settings.

BR et al. discusses a deep learning model for detecting and classifying plant diseases, as presented at the IEEE Third International Conference on Inventive Research in Computing Applications in 2021. This work introduces a deep learning model tailored for the recognition and classification of plant diseases. demonstrating its use at a prominent computer conference. In a paper [14], G. Arun presents a nine-layer deep convolutional neural network for detecting plant leaf illnesses, including information on electrical and computational and electrical engineering for agricultural applications.

Research from the 2019 IEEE Global Conference on Technological Advancement is presented by Govardhan Veena in paper [15], which addresses the use of random forest algorithms for tomato plant disease diagnostics. It investigates the application of random forest algorithms for diagnosing tomato plant diseases, with findings presented at a prominent global technology conference. These papers explore themes including the integration of technology for real-time illness diagnosis in potatoes, transfer learning, and the fusion of various imaging modalities.

III.PROPOSED SYETEM

The proposed systems aim is to develop a robust, accurate, and user friendly plant disease detection system that addresses the unique challenges and requirements of agricultural stakeholders. The system has various phases as shown in Figure 1 and explained further in this section.

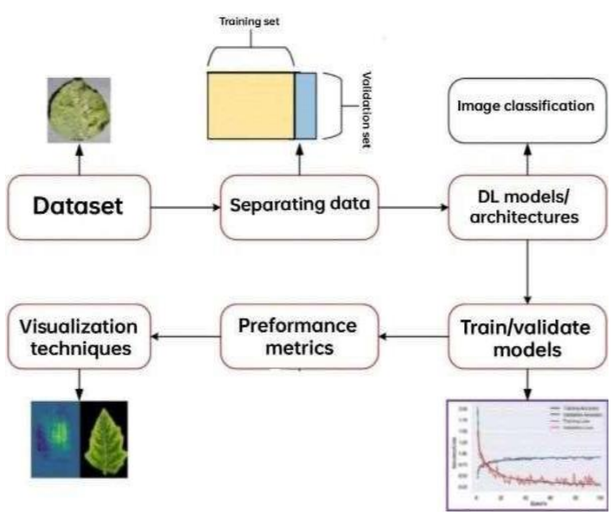

Figure 1: Proposed System

Data Acquisition and Preprocessing: A diverse and extensive dataset comprising plant images exhibiting various diseases has collected. Through rigorous preprocessing, including consistent labeling, standardized image resolution, and noise reduction is carried out to guarantee the dataset's dependability and quality.

CNN Model and Training: CNN architecture is used which is equipped with sophisticated methods like transfer learning and data augmentation. By setting up the model using weights that have already been trained from ImageNet, helps to expedite the training process and enhance generalization. Further refinement of the model is achieved through gradient descent optimization, minimizing classification errors specifically on the plant disease dataset.

Integration and Real-time Deployment: The proposed system has integrated the trained CNN model into mobile or online applications to facilitate the identification of diseases in real time. The system has an intuitive user interface designed for farmers and agronomists. Facilitating the seamless upload of plant photos and immediate access to disease identification results. Additionally, practical advice for disease management is provided to empower users in making informed decisions.

Data Separation: The dataset includes both training and validation sets. The model is trained using the training set, and the validation set is used to evaluate the model's performance and fine-tune its parameters.

Model Architecture: The model architecture refers to the composition and setup of the deep learning model used to classify images. Neural network Combinations of convolutional, pooling, and fully connected layers are often incorporated.

Image Classification: The technique of classifying photographs into predetermined groups or labels according to their content is known as image classification. During training, the deep learning model learns to identify features and patterns in the photos and classifies them accordingly.

Train/Validate: The model receives input photos from the training set during the training phase. It learns to associate input images with their respective labels by using optimization techniques like gradient descent. The effectiveness of the model is assessed with the validation set, and it modifies its parameters to improve both accuracy and generalization.

Feature Extraction: In the proposed system dataset have three types of potato leaves: a healthy leaf, one leaf affected by early blight and another impacted by late blight. Potato plants are vulnerable to two types of diseases: early blight and late blight. The leaves of the potato plant and stems get brown blotches from early blight. Blight that appears late causes large, water-soaked lesions on the leaves and stems, and can also cause the potatoes themselves to rot.

The proposed system automatically classifies potato plants as healthy, having early blight, or having late blight. This system could be used by farmers to identify and treat potato plants with blight early, which could help to improve crop yields.

IV. RESULTS AND DISCUSSION

The proposed system is evaluated by considering various images of potato crop. This dataset is used to train the model so that accuracy of the system can be improved. “Potato Late blight,” and” Potato Early blight” are possibly depicting potato plants affected by blight as shown in Figure 2. While the early and late blight images show leaf yellowing. Potato blight, a fungal disease, can devastate potato crops, causing brown spots in early blight and browning and withering of leaves in late blight, potentially affecting.

Figure 2: Sample of Dataset

Figure 3 displays the Graphical User Interface (GUI) of the system. It includes elements for user input, image display, classification results, navigation controls, and feedback mechanisms. The GUI is designed to be visually appealing, intuitive, and functional, facilitating user interaction with the software or application, such as a potato disease detection system.

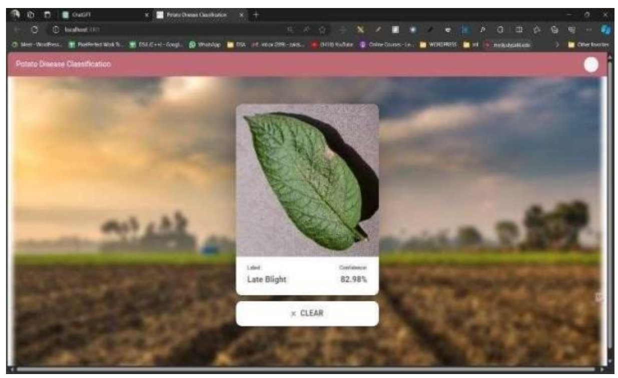

Fig. 3: GUI of Designed System

The trained model's effectiveness is evaluated through several performance metrics. These metrics include the confusion matrix, F1-score, recall, accuracy, and precision. These features help to highlight the model's predictive capabilities and identify potential areas for improvement. The accuracy chart generated for the specific dataset is shown in Figure 4.

Fig. 4: Training and Validation Accuracy

Figure 5 illustrates the loss achieved with the suggested system to meet the intended goal.

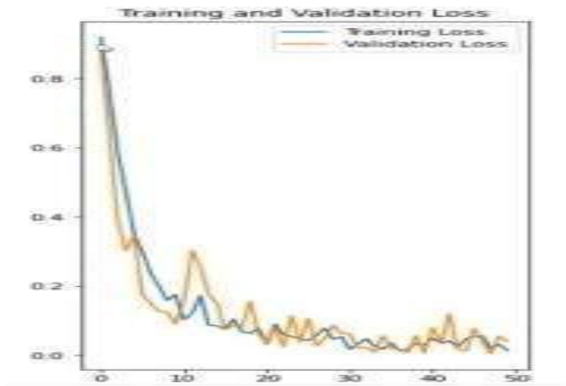

Fig. 5: Training and Validation Loss

V. CONCLUSION

The advancement of plant disease detection systems marks a notable stride in agricultural technology, providing farmers with real-time detection capabilities and enabling swift responses to diseases. Through overcoming accuracy and usability challenges, this solution boosts agricultural productivity and promotes sustainability, thereby aiding global food security efforts. The proposed system showcases technology's transformative potential in fostering resilient and sustainable farming methods, laying the groundwork for a more fruitful agricultural landscape.

The proposed system has successfully reached a significant milestone by achieving an accuracy of 84% in its diagnostics, surpassing initial performance expectations. This level of precision not only demonstrates the system's reliability in identifying specific conditions but also enhances confidence in its practical applications. The 84% accuracy rate is a testament to the effectiveness of the technological approach, validating the model's capabilities and laying the groundwork for additional improvements and practical implementation. This achievement underscores the potential of the project to contribute meaningfully to the field, ensuring more accurate and timely diagnostics in practical settings.

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