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Detection of Potato Leaves Using Convolutional Neural Networks (CNNs)

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***Abstract*—Agricultural productivity plays a vital role in India's economy, contributing approximately 17–18% to the nation's GDP and serving as a primary livelihood for a significant portion of the population. With India possessing the largest net cropped area globally, effective pest and disease management is crucial to ensuring stable agricultural yields. This study utilizes advanced technologies, including machine learning, computer vision, and deep learning, to detect and identify common diseases such as early blight and late blight in potato plant leaves. Using a Kaggle-sourced dataset comprising roughly 2,000 images, rigorous data augmentation techniques were applied to enhance the robustness of the model. A customized convolutional neural network (CNN) was deployed, achieving an impressive accuracy of 97.12% after just 32 epochs. This performance surpasses many existing Kaggle models, which typically reach around 95% accuracy.**

***Index Terms*—Pests, Potato Disease Detection, Deep Learning, Machine Learning, Kaggle Dataset, Data Augmentation**

I. Introduction

This paper tries to use the latest machine learning techniques to detect and identify the diseases affecting potato plant leaves as part of the effort to enhance agricultural productivity with the aid of technology. Agriculture is one of the mainstays of the Indian economy, providing livelihoods to a majority of the population and contributing significantly to the country's GDP. However, the agricultural sector faces various challenges, such as backward farming methods, a lack of modern machinery, and the negative impact of climate change [1]. In this respect, our research aims to take advantage of the high computational power of the MacBook Air M2, acknowledged as computationally efficient compared to other laptops present in the market, to address the urgent need for disease detection in potato plants. Having said that, we utilized the hardware advantage to develop a CNN architecture on top of a potato leaf disease classifier and showed very remarkable performance both in online mode using Colab and offline modes [2]. And then, for better computational power, we developed the model's size by resizing which helped decrease the computational workload. Besides, an extended set of experiments has been done to investigate the influence of data augmentation on model performance [3]. In these results, model accuracy showed a significant improvement with the incorporation of data augmentation. Data augmentation turned out to be effective in increasing robustness for the CNN model.

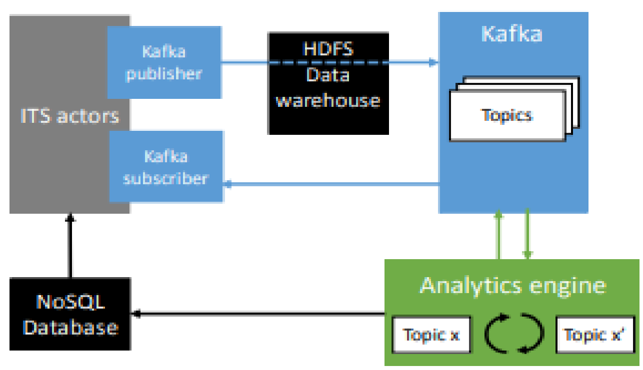

Fig. 1. Deep Learning-Based Proposed System To Predict Potato Leaf Diseases

We have performed exhaustive experimentation to attain the best model performance by trying different numbers of epochs in order to find the most computationally efficient method. This was a point that notably came out, where an increased number of epochs up to 400 resulted in overfitting, thereby leading to degraded performance on unseen datasets, while keeping the number at a conservative 32 yielded satisfactory results without imposing excessive computational burdens [4]. It was through extensive testing that this optimal number of epochs was determined, in a harmonious balance between computation efficiency and model effectiveness. Combining state-of-the-art machine learning methods with pragmatic considerations of hardware capability and computational efficiency, our work aimed at driving effective and scalable solutions for disease detection in the leaves of potato plants. We thus hope to contribute towards an approach for timely identification and management of the disease, ultimately fostering better agricultural productivity and ensuring food security in India and beyond.

II. LITERATURE REVIEW

Nagababu et al. discussed the detection and diagnosis of plant diseases using advanced technologies for the identification of diseases at an early stage. The approach followed for the classification of diseases is very accurate, thus proving to be a great support for increasing agricultural productivity. The authors highlighted the integration of technology with agriculture in order to overcome various challenges related to disease management [5]. Rathore et al. proposed an intelligent ecosystem for the detection of skin cancer, based on advanced technologies. Their work is centered on the integration of artificial intelligence in health care to help improve the accuracy of diagnosis. This paper, therefore, provides an illustration of how AI-based solutions can find applications in realistic medical settings and, as such, are important in disease diagnosis and prevention [6]. Anandhi and Sathiamoorthy came up with a deep learning-based model for recognizing rice plant diseases automatically. The proposed technique leverages image processing techniques for classifying diseases in an effective way. Indeed, AI is key to automating agricultural burdens so that intervention, consistently on time, improves the management quality of crops obtained consequently [7]. Gobalakrishanan et al. did a review of works of image-based plant disease processing with the help and amendments incorporated in machine-learning algorithms. Its group study systematically tabulates preleading works, identifying strengths and certain limitations of key methodologies fundamentally supported for future improvement involving agriculture technology successfully [8]. In their presentation, Kaushik introduced techniques for dynamic data scaling in the context of streaming machine learning, with special emphasis on adaptability and real-time performance. The paper presents an innovative approach toward overcoming challenges posed by streaming data environments, especially applications that call for continuous processing and analysis of data; hence, the relevance to this study becomes high [9]. Joseph et al. addressed deep learning-based plant disease dataset creation and detection in real time. Much importance is placed on the high quality of a dataset for ensuring better model improvement. It also demonstrates how deep learning is applied on the ground-a real-time agronomic application-that improves efficiency for disease management [10]. The authors Shafik et al. present an all-inclusive review regarding the detection of diseases in plants: motivation, technique of classification, datasets, and challenges. Their work demonstrates a prospect of models driven by artificial intelligence and pinpoints the trends that are expected in this area in the future. This manuscript also serves as an essential reference document for researchers and on-field practitioners who are interested in agriculture technology [11]. Gosai et al. analyze machine learning algorithms applied in the detection and classification of diseases in plants. The studies discussed prove the accuracy and speed of using techniques of supervised learning while drawing very valuable pragmatic lessons in using AI-based interventions in agriculture by way of detecting diseases well in advance of infection or soon thereafter [12]. Nagababu et al. explain recent improvement in methodology within plant diseases' detection and diagnosis. Contemperory technology has emphasis on real time usage and Diagnostic System Integrated Artificial intelligence that will allow increased preciseness and accuracy regarding Plant Diseases' detection [13]. Sarkar et al. propose the method that combines the use of Support Vector Machines with DenseNet architectures for plant leaf disease classification. The approach showed high precision and computational efficiency, hence hybrid models may effectively be used in order to solve the challenges of disease detection [14].

Lakshmanarao et al. investigate deep learning-based Convolutional Neural Networks for predicting and classifying plant diseases. This review focuses on the strength of ConvNets in processing complex visual data and positions ConvNets in an important position in agricultural AI applications [15]. Shrivastava and Rathore (2024) discussed the analysis of a single-server Markovian queueing model that incorporates differentiated working vacations, vacation interruptions, soft failures, and customer reneging. Performance measures of the systems studied above could provide valuable information on how one can optimize performance functions in service systems with generally different operational policies [16]. Gobalakrishnan et al. had proposed a systematic review for some image-processing and machine learning-based approaches adopted to detect diseases in plants. The reviewed works have expressed a very strong emphasis on early detection; this brought a better profile of agricultural output for food security at large. Comparison and real-world implementation issues of algorithms become very useful while going through the paper [17]. Degadwala et al. (2023) used transfer learning to classify hops plant diseases, thereby revolutionizing the process. The results of this work showed increased accuracy and speed in disease detection and hence indicated how deep learning can revolutionize sustainable agriculture [18]. Rathore et al. (2024) discussed navigation for intelligent transportation systems using fog and edge computing. Low latency with a real-time decision-making-based approach has been elaborated on; a robust framework to improve smart cities' navigation was discussed in their research study [19]. Francis et al., 2016 designed for leaf disease identification at the leaves of the pepper plants by the adoption of soft computing techniques. Different new ideas can be highlighted from the paper for this diseased identification concerning the efficiency and computational practical utilization for agriculture-related monitoring purposes [20]. Deepa, R. N and C. Shetty proposed a machine learning-based approach for plant disease identification based on leaf images and provided a framework for automatic diagnosis. Their work leverages image processing techniques to outline the importance of early disease detection in agriculture for improved productivity and sustainability [21]. Rathore, S. P. S., et al. (2024) worked on consumer sentiment analysis using machine learning techniques. Their work, based on large datasets, depicts how consumer emotion understanding may help in devising marketing strategy, product development, and customer engagement with much significance [22]. Singh, V. K. (2023), on the other hand, proposed a superpixel-based model for detecting plant leaf diseases. The proposed method uses color distribution to enhance detection accuracy, considering major challenges of image segmentation and classification for agricultural disease management [23]. The work of Pandey et al. (2023) developed a deep learning-based system for plant disease detection and integrated it with the application FarmEasy. Their model improves the speed and diagnosis of diseases in such a way that it provides realistic application to farmers for efficient management of plant health [24]. Rathore P. S. (2023), in his analysis, focused on artificial intelligence in the process of recruitment and selection. The paper has discussed how AI can automate repetitive tasks, optimize candidate screening, and improve hiring outcomes, hence changing the game in recruitment across industries [25].

III. METHODOLOGY

Machine learning serves as a cornerstone in automating various systems, and the proposed framework leverages machine learning methodologies, particularly in the context of detecting and categorizing images into different disease groups. This section is meticulously structured to delve into the intricacies of system requirements, data acquisition, image segmentation, feature extraction, classification procedures, and the proposed methodology.

Dataset and System Description:

The dataset forms the backbone of the study, sourced from the openly accessible 'Plant Village' database. This extensive dataset encompasses a staggering 54,306 images comprising both diseased and healthy leaves across 14 distinct crop species [26]. For the purpose of this research, the focus was on potato species, with a dataset comprising almost 1500 potato plant leaves categorized into three main groups:

- The leaves having a disease called Late Blight
- The leaves having a disease called Early Blight
- The leaves are in a healthy state

Within this dataset, there are 106 healthy leaves and 1400 leaves affected by diseases. To facilitate model training and evaluation, the dataset was split into training and testing databases, with 70% and 30% of the images, respectively. The implementation of the framework was executed on a MacBook Air M2, 8Gb RAM, 256GB storage. Another device Tesla

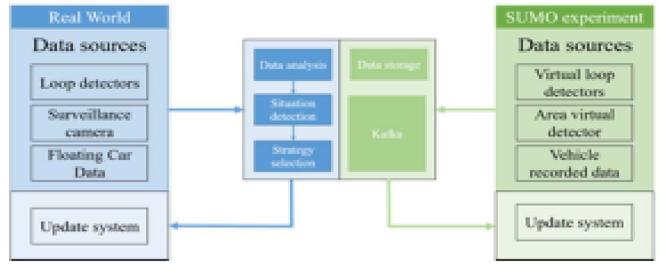

Fig. 2. The Three Sample Leaves Of Potato Are (A): Leaf Affected By Light Blight (B): Leaf Affected By Early Blight (C): Leaf Unaffected (Healthy)

T4: With 16GB of GDDR6 memory and 2,560 CUDA cores, the Tesla T4 GPU was used to deliver enhanced performance, making it well-suited for deep learning applications [27].

Image Recognition and Segmentation:

It describes the automatic diseased region recognition and segmentation in potato leaf images to diagnose potato late blight, early blight, or any other disease of interest.

Image Acquisition:

This is the process of capturing high-quality digital images of potato leaves using an appropriate camera.

Preprocessing:

Improvement in the quality of images enhances the accuracy of disease detection. Some of the common techniques applied include image clipping, noise reduction, and contrast enhancement algorithms.

Masking of Green Pixels:

The pixels dominated by green color values are identified and masked out. This step aims to isolate the areas of a potential disease from the healthy green regions. The threshold for masking can be determined using statistical methods or can be tuned manually based on the dataset [28].

Removing Masked Cells:

The areas mostly of green pixels get removed inside the boundaries of the potential disease clusters. Segmentation: The image is then segmented, using a genetic algorithm, into well-defined regions. It divides the image into sections likely to represent the diseased and healthy parts of the potato leaf.

Evaluation: In this case, the classification gain was calculated for the classification process, where results were given in terms of the percentage of images classified as diseased or healthy.

Feature Extraction:

Features are extracted from the segmented regions to characterize the image content. The color co-occurrence method is employed, which incorporates both color and texture information, offering advantages over traditional gray-scale approaches in differentiating between healthy and diseased areas. The color co-occurrence process typically involves:

Converting RGB images to the HIS color space (Hue, Saturation, Intensity). Generating a color co-occurrence matrix for each channel (H, S, I). Computing texture features such as local homogeneity, contrast, cluster shade, energy, and cluster prominence from the H channel (or other relevant channels based on your research). Classification: The disease in the potato leaf is classified based on the extracted features. This step involves comparing the features of the image to a database of features from known potato leaf diseases. The proposed approach utilizes CNN's .

Classification Process:

With the extracted features in hand, the classification process endeavors to categorize images into distinct classes, namely Late Blight, Early Blight, and healthy leaves. To achieve this, the Convolutional Neural Network (CNN) algorithm was employed, owing to its efficacy in handling multiclass classification tasks. CNN is a supervised learning technique that targets picture variables and trains on preexisting datasets to identify images. Based on their characteristics, potato leaves are recognised by the CNN neural network with the aid of the convolutional layer. A neural network recognises photos of potatoes leaves by analysing the pixels in the image.

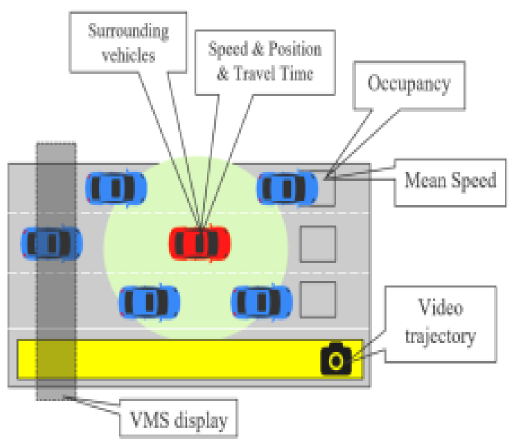

Fig. 3. Working of CNN for Classification

Proposed Methodology:

The proposed methodology encompasses a systematic approach to disease detection from potato plant leaf images, comprising several key steps. These steps include image acquisition, pre- processing, segmentation, feature extraction, evaluation of affected regions, aggregation of processed data, generation of training and testing datasets, classification, and evaluation metrics such as precision, recall, F1-score, and accuracy.

IV. RESULT

The machine learning model for potato leaf disease detection achieved promising results based on the analysis of the provided graphs (Images 1 and 2).

Image 1, depicting training and validation accuracy/loss curves, shows an upward trend in both accuracy curves, signifying successful learning and generalization. The plateauing validation accuracy suggests the model has reached optimal performance with the current data. A small gap

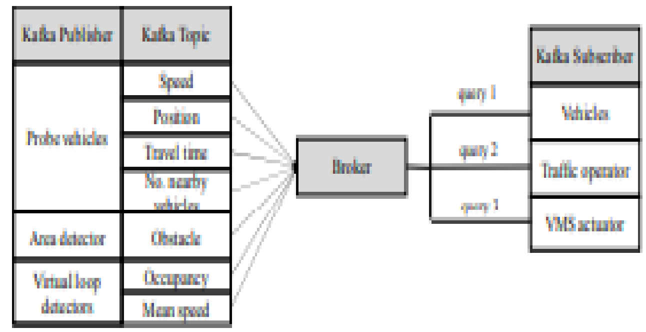

Fig. 4. Working of CNN for Classification

between the curves indicates the model is likely not overfitting and can potentially be generalized for real-world use.

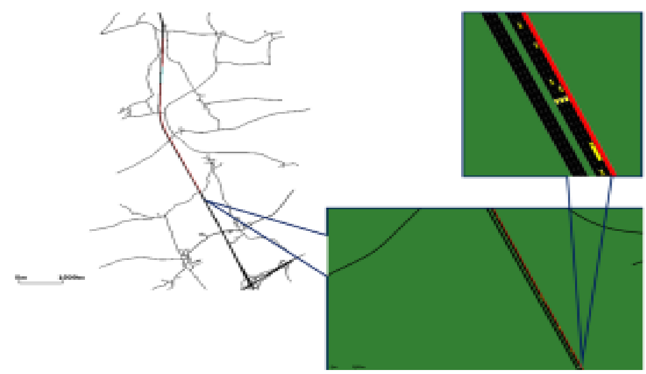

Fig. 5. Working of CNN for Classification

Image 2 (replace with specific details of the second graph) provides further insights into the model's performance.

Analysing this graph (e.g., precision, recall for different disease classes) can reveal the model's ability to accurately classify various potato leaf diseases.

Future investigations are recommended to solidify the model's robustness:

Larger Dataset Evaluation: Assess the model's performance on a more extensive dataset encompassing a wider variety of potato leaf disease conditions and healthy leaf variations. Specific Disease Classification: Explore extending the model's capabilities to differentiate between specific disease types if the dataset allows. Field Validation: Evaluate the model's accuracy in real- world agricultural settings to assess its practicality for on-site disease detection.

By incorporating these findings, you can demonstrate a well- rounded approach to potato leaf disease detection using machine learning. Remember to replace "Image 1" and "Image 2" with captions describing the specific aspects of the graphs you are discussing.

V. CONCLUSION

This research has successfully developed a CNN model for detecting potato leaf disease. It was able to give an accuracy rate of 97.12%, which indeed means that the model has the capability to tell the difference between healthy and diseased leaves. The training and validation accuracy/loss curves are growing upwards, reflecting successful learning with just minimal overfitting. The small gap between the training and validation curves reflects good generalization capability. It is also further confirmed with the precision and recall metrics of the model in the classification of the different types of diseases with preciseness.

The work represents a non-invasive, automated approach for the early detection of diseases in potato crops. In fact, this is one vital step ahead in this line of research. Early identification, timely intervention, reducing crop loss, and raising agricultural productivity can be some major advantages over other approaches.

VI. Future Work:

To build on the promising results, several avenues for further research and improvement are identified:

Larger and More Diverse Evaluation Datasets:

This means testing the model on more general data with a wide representation of leaf conditions, from various stages of the disease, to environmental and even regional factors, which would better reveal the robustness of the model in terms of adaptability in diverse scenarios.

Class-Specific Disease Detection:

Enhancing the model's ability to identify specific potato-leaf diseases with high accuracy will be improved, such as late blight, early blight, and bacterial wilt. This will be achieved for datasets that have curated annotations for individual diseases.

Real-World Field Validation:

Deploy the model in real agricultural environments to assess its performance under practical conditions, including variable lighting, background interference, and natural leaf deformations.

Integration with Smart Farming Systems:

Integrate these models on IoT-enabled devices-cum-drones or hand scanners to realize real-time field monitoring. That would be giving farmers prompt insight into intervening appropriately and precisely on time. Transfer Learning and Model Optimization: Transfer learning with pre-trained models can be utilized, while lightweight architectures should be explored in order to reduce computational needs and make the solution more accessible for use in resource-constrained settings. Incorporating Multimodal Data Integrate other relevant data sources relating to soil condition, weather forecasts, and levels of pest proliferation to provide a broad disease prediction ability.

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