Enabling Early Treatment: A Deep Learning Approach to Multi-Class Potato Leaf Disease Identification

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Over 60% of the world's population largely depends on the agricultural sector for food, as indicated by previous studies, demonstrating the historical significance of agriculture as a means of survival. Plant infections, however, pose a serious problem that seriously reduces agricultural output. The annual loss of agricultural yield due to these diseases is roughly 25%. In this study, a novel lightweight Convolutional Neural Network (CNN) based on transfer learning is used to identify the early symptoms of potato leaf diseases. The proposed method comprises a collection of leaf images, performing image preprocessing and augmentation techniques on the data, which is then used to train a CNN model and evaluate the model's performance on new unseen images. The results of the experiment show that the CNN model accurately distinguishes the three types of potato leaf images: healthy, early blight, and late blight, with an overall accuracy of 97.33%. In order to ensure food security and reduce financial losses in agriculture, the recommended method might provide a reliable and efficient means of diagnosing potato infections. Even in the presence of serious illnesses, the model is still able to correctly identify the different disease types. This study shows how deep learning techniques can be used to classify potato diseases, adding automated and efficient disease management in potato cultivation.

Keywords: Plant disease identification, potato leaf images, image processing, deep learning, CNN, transfer learning, EfficientNetB2.

Introduction:

Agriculture has historically been a cornerstone of civilizations, providing sustenance and economic stability. However, over time, there has been a decline in agricultural production, influenced by various factors including political, social, environmental, and meteorological conditions. These complex factors have all profoundly affected the evolution of agriculture, necessitating comprehensive strategies to address its challenges and reaffirm its pivotal role in contemporary society [1]. It has consequently grown to become Pakistan's second-largest sector, which employs 45% of the labor force and adds more than 21% to the GDP. Since 63% of people reside in rural areas, a sizable percentage of the population relies on this industry for their living. Pakistan's vast agricultural territory is devoted to the production of a variety of crops, ranking fourth in production nationwide and serving as a key economic driver [2]. Recent statistics reveal that Pakistan produces approximately 4.0 million tons of potatoes, which are cultivated on 170,300 hectares of land [3].

Plant diseases and insect infestations have the potential to significantly impact agriculture and consequently, pose risks to the food quality. However, conventional preventive measures are ineffective in halting the spread of epidemic or endemic diseases in crops [4]. Timely surveillance and identification of crop diseases, coupled with robust crop protection measures, are instrumental in averting quality losses in production. Effective disease management hinges on timely surveillance and accurate identification, enabling targeted interventions to mitigate losses. By detecting and addressing potential issues early on, farmers can implement targeted strategies to mitigate the impact of diseases, thereby safeguarding the quality and yield of their harvests [4]. Evaluating the severity of a disease visually proves to be laborious, time-consuming, and lacks reliability due to the necessity of professional (subjective) intervention. However, infections and bug infestations often manifest distinctive patterns, offering a valuable opportunity to establish precise diagnoses. Developing precise diagnostic methods based on these patterns can enhance efficiency, reduce reliance on subjective judgment, and expedite the response to crop ailments, safeguarding both quality and yield in agricultural production [5].

Recent advancements in computer imaging technology have provided farmers with viable solutions to the detection challenges they encounter [5]. The significance of Convolutional Neural Networks (CNNs) plays a crucial role in plant leaf disease classification, offering unparalleled capabilities in contemporary agricultural research. Specifically designed for image analysis, the class of deep neural networks has overcome challenges associated with disease detection by autonomously extracting intricate features from raw image data [6]. In contrast to conventional approaches that require human feature engineering, CNNs distinguish between texture, color, and shape, which are necessary for precise disease classification. Their scale-invariance ability is particularly valuable, as leaf diseases can manifest in diverse shapes and sizes. One of the biggest advantages of using CNNs is transfer learning, enabling us to use pre-trained models that are trained on large datasets, like ImageNet or MS COCO, for new classification tasks with limited training images.

This approach significantly reduces the computational resources required compared to training a model from scratch, making it feasible for agriculture where labeled datasets may be scarce or costly to obtain [7]. In the past, computer vision models were perceived as black boxes; lacking transparency in making decisions about image classification, including disease identification. However, recent advancements in explanatory methods have transformed this perception. These new methods provide insights into what the computer vision model considers during classification and identification tasks. By understanding the model's reasoning, researchers can pinpoint factors contributing to reduced performance and implement strategies to enhance classification accuracy and decision-making.

Objectives: The objectives of this study revolve around developing and evaluating a novel Convolutional Neural Network (CNN) using transfer learning to detect early symptoms of potato leaf diseases. The first objective is to curate a comprehensive dataset of potato leaf images, employing image preprocessing and augmentation techniques to enhance data quality and diversity. Subsequently, the CNN model will be trained on this dataset, with the primary goal of accurately distinguishing between healthy leaves, early blight, and late blight. The study aims to evaluate the model's overall accuracy and performance metrics, focusing on achieving high sensitivity and specificity in disease detection. In this study, a novel approach based on CNN with transfer learning was used to identify the leaf diseases of potato plants. The main contributions of the proposed study are:

- A hybrid dataset was collected from various repositories available on Kaggle.
- Data balancing was ensured with preprocessing and data augmentation techniques.
- Developed a novel lightweight CNN model based on transfer learning to accurately identify potato leaf diseases at early stages.
- Compared the proposed model with other state-of-the-art pre-trained models.

Related Work:

CNNs have become standards for image classification due to their unparalleled accuracy and ability to extract complex information from images. The extensive research on CNNs to classify plant leaf diseases demonstrates that these models are capable of identifying variations that might be indicative of disease. Leveraging CNN's ability to develop hierarchical feature maps has increased the diagnostic capacity, assisting agriculture to become more accurate and efficient. Arshad, F. et al. [2] used preprocessing techniques and data augmentation with U-Net for Region of Interest (ROI) segmentation. They used VGG-19 and Inception-V3 for feature extraction-based ensemble learning, incorporating transformers for disease classification. While achieving high accuracy, the complexity of these models may not be suitable for resource-efficient environments. In another study [4] used offline augmentation to expand the healthy class from 152 to 652, and then preprocessing techniques with online augmentation were used for model training enhancements. The training dataset used by them was from the Plant Village repository kept on Kaggle. A custom CNN model consisting of six convolutional layers and two FC layers with an Adam optimizer was trained and tested with an accuracy of 99%. Sultana, T., & Reza, M. [8] used a public dataset of potato leaves that contained 2152 images. They used three models: a custom CNN of four convolutional layers and two FC layers; ResNet-50 as transfer learning with two dense layers; another one was the same ResNet-50 with SVM as the output layer; and the final one produced high accuracy compared to the previous two models.

Haidari, A., & Kumar, A. [9] focused on identifying healthy and diseased potato leaf images using a CNN model. Through preprocessing and offline data augmentation, they expanded the training dataset significantly, achieving 97% accuracy with a custom CNN model. The authors [10] developed a custom CNN from scratch using the Plant-Village dataset of potato leaves. The proposed model consists of five convolutional layers, one dense layer, and an output layer. In dermatology, Wu et al. [11] investigated the effectiveness of CNNs, including ResNet-50, Inception V3, DenseNet121, Xception, and Inception-ResNetV2, for the classification of facial skin diseases using clinical images. Using China's largest clinical image dataset, the research established a dataset with 2656 face images representing six common skin diseases. Through extensive analysis, the models showed comparatively good results, particularly with the use of transfer learning. Comparing performances, models utilizing transfer learning achieve higher average precision and recall, showcasing their potential for the accurate classification of skin diseases. The best model, in a test dataset of 388 facial images, achieved impressive recall percentages for specific diseases, emphasizing the efficiency of the proposed approach.

Zhijia Zhu et al. [12] proposed a novel semantic segmentation algorithm, PD-Seg Net, designed for intricate agricultural scenes. It addresses the limitations of CNNs in capturing global information and handling small targets by introducing a hierarchical transformer encoder

(MiT) and innovative decoder components (Dynamic Kernel Head, Complex Points Head). PD-Seg Net showcased exceptional performance on agricultural datasets such as Minne Apple and AppleA Flower, setting new benchmarks in apple blossom and fruit segmentation. Comparative experiments with traditional and advanced algorithms validate its superiority in accuracy. The proposed method, balancing computational efficiency and precision, showcases promise for optimizing semantic segmentation in complex agricultural scenarios, contributing to the advancement of smart agriculture. The study in [13] used a modified version of the YOLOv4 model for the detection of dome galls, a Corida dichotoma leaf disease. The authors replaced the online augmentation techniques with offline data augmentation with fine-tuning for the domain task. Naeem A et al. [14] used a modified version of VGGNet to identify the presence of pests in crop fields. The model was trained from scratch, claiming comparatively good classification accuracy.

Methodology:

The proposed study aimed to develop a novel light-weight CNN model for the classification of potato leaf disease. The general flow of the proposed study is depicted in Figure 1. All the steps are defined in detail in this section.

Image Preprocessing:

Image pre-processing techniques are essential for improving the accuracy and generalization of deep learning models. It is a critical step in training CNN models, and the use of appropriate pre-processing techniques can significantly improve the accuracy and generalization of the CNN models. One of the crucial steps in image pre-processing is to scan the entire training dataset and remove any images that are unsuitable for the training process. This step ensures that the model is trained on high-quality images that are relevant to the task at hand. Another important pre-processing step is resizing the images to a specific size during training. This is particularly important when training CNN models, as they require fixed input sizes. In the proposed study, all images were resized to 256 x 256. Image normalization is another widely used technique in deep learning, also known as rescaling. This technique involves rescaling the input image intensities to a specific range, typically between 0 and 1. Rescaling is useful for fast training, improving loss optimization, and gradient-based optimization. By rescaling the input image intensities, the model can learn more efficiently and effectively, leading to better performance.

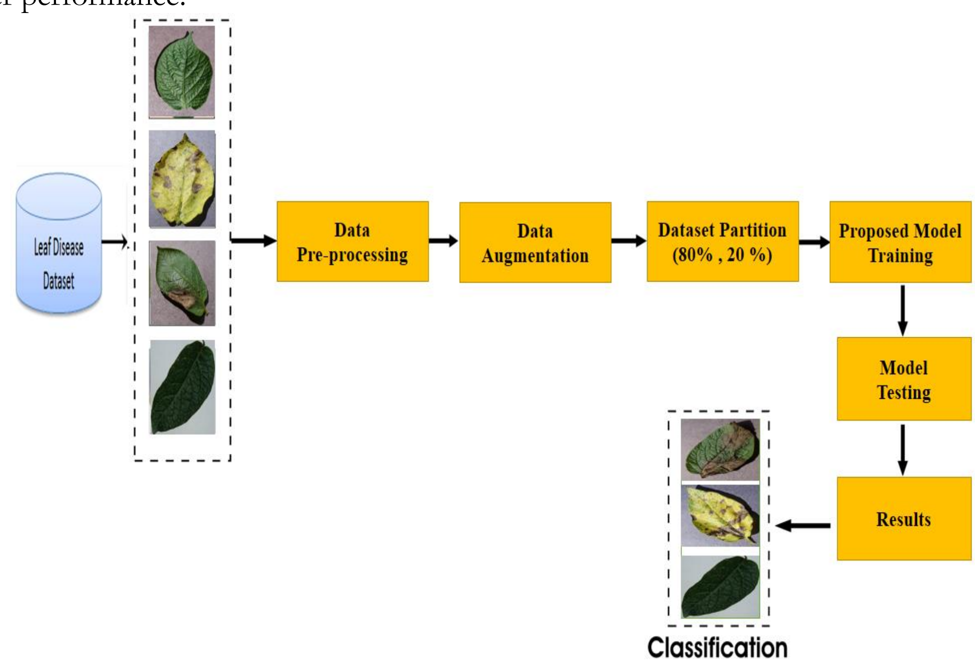

Figure 1: General Flow of the proposed study

Data Augmentation:

Data augmentation is a technique used in machine learning and computer vision to artificially increase the size of training datasets by generating new samples from existing ones [15]. This process helps combat overfitting, improve generalization capabilities, and enhance model robustness against various transformations or perturbations that may occur during real-world scenarios. There are several methods for performing data augmentation, including rotating, scaling, flipping, shearing, or cropping images to create diverse representations of original data points. Color manipulations like changing brightness, contrast, saturation, hue, or adding noise can introduce variations without altering the underlying content. Data augmentation has been widely adopted across numerous domains, such as image recognition, natural language processing, and time series analysis. It allows researchers to train more accurate and reliable models with limited resources while maintaining high-performance levels when deployed in production environments. However, it's essential to ensure that augmented data remains representative of the original distribution and does not lead to negative consequences. Figure 2 shows the augmentation techniques used in this study.

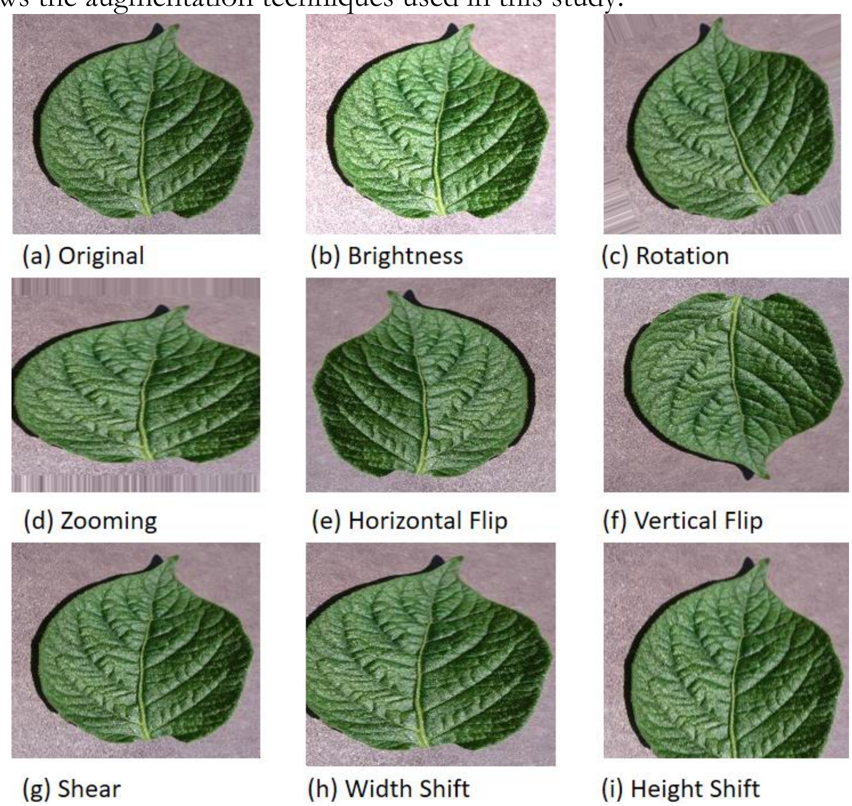

Figure 2: Shows data augmentation

Proposed Model:

In this study, a novel CNN model based on transfer learning was trained to efficiently identify the potato leaf images as healthy or diseased. Using pre-trained neural network models typically built on massive datasets like ImageNet and tuning them on a smaller dataset customized for the job at hand is known as transfer learning in deep learning for image processing. The pre-trained models comprise pre-learned general features suitable for image identification tasks; this strategy enables faster training and improved performance. Through fine-tuning, the model used less training data and computing resources to achieve improved accuracy by adjusting its parameters to the unique characteristics of the new dataset.

In the proposed model, EfficientNet-V2 was used to extract the features from leaf images. EfficientNet-V2 is a pre-trained model used as transfer learning, introduced by Google AI researchers in 2019 [16], and represents a paradigm shift in CNN architecture design. With its unique approach to scaling network depth, width, and resolution, Efficient Net aims to achieve optimal performance while maintaining computational efficiency. An evolution of the Efficient Net architecture builds upon the principles of compound scaling, wherein all dimensions of the network were uniformly scaled to strike a balance between model complexity and computational cost. Unlike traditional methods that focus solely on increasing depth or width, Efficient Net adopts a holistic approach, leading to superior performance across various computer vision tasks. One of the notable enhancements in EfficientNetB2 is the integration of Mobile Inverted Bottleneck Convolutional (MB Conv) layers and the novel Fused-MB Conv in the early stages of the network. This strategic inclusion enhances feature extraction and representation efficiency, thereby contributing to improved overall performance. This approach also adopts smaller 3x3 kernel sizes over its predecessor's 5x5 kernels, reducing computational overhead while maintaining or even enhancing the network's ability to capture intricate features from input images. Additionally, the elimination of the last stride-1 stage streamlines the architecture, furthermore enhancing its efficiency without compromising effectiveness.

Moreover, EfficientNetB2 introduced a pioneering approach to progressive learning, inspired by progressive resizing. Adapting regularization strength based on image size ensures consistent and optimized training, mitigating the drop in accuracy traditionally associated with progressive resizing. EfficientNetB2's architectural components, including modules and sub-blocks, are meticulously designed to optimize performance and efficiency. Modules such as Module 1, Module 2, Module 3, Module 4, and Module 5, along with various sub-blocks, contribute to the cohesive structure of the network, facilitating efficient feature extraction and representation. Comparative analysis demonstrates the superiority of EfficientNetB2 over other CNN architectures in terms of efficiency, model size, speed, and performance. Through compound scaling, EfficientNetB2 achieves a remarkable balance between accuracy and efficiency, outperforming models like ResNet-50 while maintaining similar computational costs. EfficientNetB2's innovative architecture, leveraging MBConv layers and Squeeze-and-Excitation optimization, underscores its ability to revolutionize deep learning. EfficientNetB2's ability to strike a delicate balance between accuracy, efficiency, and speed positions it as a groundbreaking advancement in computer vision, opening doors for significant progress in a wide range of real-world applications.

The proposed model underwent fine-tuning by adding, a global average pooling layer after the pre-trained backbone with a dropout of 0.5. Feature classification utilized two FC layers with 256 and 128 neurons, followed by a Softmax activation function in the output layer for disease prediction. Table 1 shows the architecture of the proposed model while Table 2 shows the list of important parameters. Each FC layer was followed by a dropout layer with a 0.3 ratio. To measure the performance of the proposed model, the following metrics were used:

$$\text{Accuracy} = \frac{\text{Number of Correct Prediction}}{\text{Total Number of Predictions}} \tag{5}$$

$$\text{Precision}_{(\text{class}_i)} = \frac{TP_i}{TP_i + FP_i} \tag{6}$$

$$\text{Recall}_{(\text{class}_i)} = \frac{TP_i}{TP_i + FN_i} \tag{7}$$

$$\text{F1\_score}_{(\text{class}_i)} = 2 \cdot \frac{\text{Precision}_{(\text{class}_i)} \times \text{Recall}_{(\text{class}_i)}}{\text{Precision}_{(\text{class}_i)} + \text{Recall}_{(\text{class}_i)}} \tag{9}$$

Accuracy measures how correctly the model is doing overall. It shows the proportion of the correct predictions to the total predictions. Precision shows how relevant the model's positive predictions are. It is the ratio of the correct/true positive cases to all the positive cases it predicted. Recall shows the model's ability to, generally, find all the positive cases. It is the ratio of the correct positive cases to all the actual positive ones. F_1-score represents the harmonic mean of precision and recall. It balances the two metrics by accounting for both false positives and false negatives. It is an excellent statistic for models that require both precision and recall, as it seeks to balance the two. These metrics collectively provide insights into different aspects of a model's performance, guiding the optimization process to enhance its effectiveness and reliability.

Table 1: Architecture of the proposed model

S No.	Layer	Filters/Neurons
1	Input (224x224x3)	
2	Backbone (EfficientNet-B2) for Transfer Learning	
15	Global Average pool (Dropout (0.5))	
16	Flatten layer	
17	Dense (Dropout (0.3)	256
18	Dense (Dropout (0.3)	128
19	Dense (Soft max)	3

Table 2: List of common parameters used in training the proposed model

Serial No	Parameter	Value
1	Optimizer	SGDM
2	Loss Function	Categorical Cross Entropy
3	Batch Size	32
4	Train Set	0.8
5	Validation Set	0.2
6	Learning rate	0.001
7	Max Epochs	120
8	E-Stopping	98
9	Shuffle	Every Epoch

The introduction of deep learning has dramatically increased the accuracy of automated systems, but it has also necessitated high-speed hardware requirements for training and testing these models [17]. Image processing-based deep learning models, in particular, frequently require high-power hardware to reduce the training time; otherwise, the training process will continue for up to a whole day or several days. In the proposed study, we used Google Colab, a cloud-based platform known for its robust architecture specifically designed for model training and testing. Using Google Colab provided access to high-value processing resources, including substantial memory and GPU capabilities, allowing us to execute our experiments more efficiently and quickly.

Training Dataset:

Training a deep learning model based on supervised learning requires a large set of images for learning domain knowledge. The size and quality of the dataset highly affect the performance and generalization of the model. There are various repositories on the internet containing potato leaf images, but they do not have a sufficient number of images as a single dataset to struggle with the most critical problem in deep learning called overfitting, which causes low accuracy and generalization in real-life scenarios. To overcome this scenario, training dataset images were collected from various repositories, and a hybrid training dataset was created with a reasonable number of images. In the proposed study, a plant-village dataset containing 2152 (1000 images per disease class and 152 healthy images) images of potato leaves and another repository (Muhammad Ardi Putra) is available on Kaggle, containing 1500 images with 500 images per class. To balance the dataset, 848 images of healthy classes were taken from another repository called the PLD dataset, available on Kaggle. The final hybrid dataset contained 4500 images from three classes, with 1500 images per class. The dataset was portioned into 300 images for testing and 4200 images for training and validation, with a ratio of 80:20.

Results and Discussions:

This section provides a thorough assessment of the results obtained using the recommended methodology. In this study, a novel lightweight model was trained on a hybrid dataset for early detection of symptoms of potato leaf disease. Training CNN models from scratch normally requires a huge number of photos, which were unavailable in this circumstance. To overcome this constraint, transfer learning was used as an alternate strategy to train a multi-class classification model that could distinguish between early blight, late blight, and healthy leaves. The model was trained for 53 epochs, using an early stopping mechanism to prevent overfitting. Table 3 shows the performance of the proposed model on the test dataset. The test dataset contained 300 samples, 100 samples for each class, taken from the Plant Village dataset available on Kaggle.

Table 3: Performance of the proposed model on a test dataset

Class	Accuracy (%)	Precision (%)	Recall (%)	F_1-score (%)
Healthy	99.00	98.00	99.00	98.50
Early Blight	96.00	96.00	96.00	96.00
Late Blight	97.00	97.97	97.00	97.48
Average	97.33	97.32	97.33	97.32

These findings support the model's ability to classify potato leaf diseases. The prospective integration of this model into real-world contexts holds great promise for improving smart agriculture. This concept advances plant leaf diagnostics by providing farmers with early and rapid diagnoses, hence assuring crucial assistance for timely disease identification. Various models were trained and fine-tuned iteratively during the experimental process. We carefully modified the layered structure, and regulated parameters, and iteratively altered the model architecture by adding and removing layers like batch normalization, dropout, and pre-trained models. Following extensive testing, a model with EfficientNetB2 as its backbone, paired with two fully connected layers and the SGD optimizer, displayed higher performance and was chosen as the recommended model. Table 4 provides an in-depth analysis of our proposed model compared to other well-known pre-trained models, illustrating our model's comparatively good performance across a variety of measures. This careful model refinement procedure ensures the selection of the best architecture for effective plant disease classification, distinguishing our proposed model in terms of performance and potential real-world applications. The proposed model demonstrated strong performance, exhibiting reduced overfitting and achieving an impressive testing accuracy of 97.33 %.

Table 4: Performance comparison of the proposed model with other SOTA pre-trained models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
$EfficientNetB_0$	96.35	96.90	95.85	96.37
$MobileNet\text{-}V_2$	95.00	96.00	94.60	95.29
Proposed Model	97.33	97.32	97.33	97.32

Discussion:

The purpose of this study was to develop a lightweight, deep learning-based model to identify the early symptoms of potato leaf disease. A hybrid training dataset was collected from online sources with class balancing for the development of the model. The dataset is a key factor in any deep-learning model based on supervised learning [18]. Various experiments were done with various CNN structures, iteratively increasing and decreasing the depth of the model, and also using transfer learning with fine tuning. Due to the size of the dataset, transfer learning performed well as compared to training from scratch.

Transfer learning is an effective method for classifying images. It makes use of CNNs that have already been trained using substantial datasets, including ImageNet. These models have learned valuable features from a wide range of images, allowing them to recognize various objects and patterns. By fine-tuning these pre-trained models on a specific dataset, we can use their learned knowledge to perform accurate image classification for the new task at hand. This can save time and resources compared to training an algorithm from the very start. Transfer learning also needs strategic steps to fine-tune the model with FC layers and the width of neurons. It is also tricky to choose a pre-trained model well suited for the task at hand with good accuracy and generalization. Transfer learning initiates several steps, including the selection of a pre-trained model, removing the FC layers, freezing the base layers, adding new FC layers appropriate for the task at hand, and training the model on the new dataset of images. In the proposed study, a CNN model with EfficientNetB2 and two FC layers was trained. An early stopping mechanism was used to reduce the chance of overfitting and was tested on new unseen images with 97% accuracy.

Conclusion and Future Work:

The primary aim of this research was to utilize deep learning techniques to develop an automated diagnostic system for detecting early symptoms of potato leaf diseases. To achieve this, a hybrid dataset sourced from diverse online repositories was employed for training the model, focusing on three distinct classes of potato leaves with one normal and two healthy classes. The proposed architecture involved fine-tuning EfficientNetB2, utilizing its robust capabilities in extracting meaningful features from leaf images. Additionally, the model incorporated two FC layers, interspersed with strategically positioned dropout layers to reduce overfitting risks. The model showed impressive performance on the test dataset in comparison to other approaches.

In the future, we aim to add additional images from each class to the dataset. To increase the detection efficiency and accuracy of illnesses, we intend to explore advanced methods outside of sequential CNN structures, expand the systems to more plants, and improve the rate of disease identification with disease growth measures.

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