An Innovative Deep Learning Technique to Identify Potato Illness

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Abstract

Potato cultivation is important for world food security as it itself is attacked by a great number of diseases like early blight and late blight, which cause a lot of damage to the yield and quality of the crop. But deep learning offers a great opportunity to address these disease detections; however, how effective this will be in the potato-growing environment in Pakistan is still not known. This research is designed to evaluate the convolutional neural network (CNN) by building custom datasets that denote the local disease description. The ultimate intention is to develop a high-accuracy, reliable disease detection model that will suit the particular needs of Pakistan. The project, therefore, tries to address data imbalance with the use of the synthetic minority oversampling technique (SMOTE) and develop a CNN architecture that is optimized to provide high diagnostic accuracy. Acquired through real-world pictures, the assessment of the model's performance shows significant progress in detecting potato diseases. This research can give innovative and productive locally useful solutions, which might transform the management of diseases for Pakistani farmers while improving food security and economic stability. These deep learning systems also need to be context-sensitive and reliable, which in turn would help preserve long-term agricultural productivity in Pakistan and beyond.

Keywords: CNN, Potato Disease, SMOTE, Deep Learning

1. Introduction

For millions of people worldwide, growing crops is more than simply an agricultural endeavor. Crop production is intricately woven with economies and cultures, from large-scale commercial agricultural operations to rural subsistence farmers [1]. This serves as a link to the inherited cultural history and customs of many people. Crop cultivation is a dynamic and resilient alternative to other sources of income because it enables people to feed themselves while contributing to their communities [2]. Potatoes are important in agriculture. They represent the tenacity and resiliency of agriculture and are more than simply a simple meal. Both smallholder farmers and major commercial producers can grow potatoes because of their well-known capacity to adapt to a range of soil types and temperatures [3]. Rich in carbohydrates, vitamins, and minerals, these tubers are nutritional powerhouses that greatly enhance dietary variety and global food security. Moreover, the efficient cultivation of potatoes in terms of land and resource utilization demonstrates their value in feeding the world's growing population [4]. On the lowest leaves of the afflicted plants, this fungal pathogen first manifests as tiny black lesions. These lesions have a distinctive concentric ring pattern and grow similarly to a target [5]. As the disease worsens and leaves wither and die, the plant's capacity to photosynthesize and grow is diminished. In addition to causing aesthetic damage, early blight may have negative financial and food security effects. Reduced photosynthesis due to leaf loss leads to lower yields because plants invest less energy in tuber growth. Moreover, damaged potatoes are usually of inferior quality, which lowers their market worth. In many regions, early blight, which grows best under warm, humid conditions, is a persistent danger to potato harvests [6]. Owing to its preference for cold, humid environments, which are prevalent in many countries that cultivate potatoes, Late Blight is more destructive than Early Blight [7]. Late blight is characterized by clear symptoms and indicators. Large, cotton-like, water-soaked sores that are often encircled by white, fuzzy growth, are the result of infection. The plant rapidly loses its leaves as the illness worsens and the lesions become black and necrotic. Moreover, tubers may rot owing to viral infiltration, making them unsuitable for human consumption. Late Blight poses a special difficulty because of its genetic variability and pathogenicity. Resistance mechanisms in potato cultivars may be swiftly overcome by the disease, thereby negating the value of previously successful management strategies. These declines in agricultural output have a significant effect worldwide. According to estimates, diseases such as early and late light reduce agricultural production worldwide by 16% annually. This is a startling statistic with important ramifications [8]. Food prices are affected by the increasing costs of food production owing to lower agricultural yields. Customers may find it more difficult to afford necessary food goods because of rising supermarket costs [9]. We would need to boost food production by approximately 70% to guarantee a consistent supply of food. However, the enduring danger of illnesses in vital commodities, such as potatoes, threatens our capacity to meet this rising need. The consequences are more noticeable in regions where potato growth is a significant industry. Potato crops are a major source of revenue for both smallholders and subsistence farmers. These delicate ecosystems are upset when illnesses occur, leading to a shortage of food, hardship on the economic front, and even forced migration. The significance of precise disease detection in agriculture cannot be overstated, especially with regard to potato diseases, such as early light and late light. Reducing the effects of these diseases on agricultural output and overall food security requires early and precise diagnosis. To address this need, several approaches and technologies have been developed, which may greatly enhance the detection of agricultural diseases [10].

The study's issue statement is that although it is a vital component of Pakistan's food security, potatoes are vulnerable to diseases such as Early Blight and Late Blight, which have a significantly lower yield. Early detection is essential for sustaining production since chronic diseases account for over 16 percent of the worldwide decline in agricultural output. Plant village datasets have been the main source of research on disease diagnosis using deep learning techniques. However, the dataset may only be applicable in some places, such as Pakistan, owing to environmental changes. Furthermore, it could be challenging to precisely detect illnesses in Pakistan's potato crop using 2155 potato photos, the bulk of which are from the United States. Current methods for detecting illnesses are time-consuming, particularly in isolated rural locations. In Pakistan's agricultural environment, this problem emphasizes the urgent need for an efficient machine-learning-based solution that can identify diseases early and provide faster, more precise diagnostics.

Because it has the potential to solve significant concerns in agriculture and food security, this study on deep-learning-based potato disease diagnostics is significant. The use of deep learning models in this study may enhance the management of potato crops, and therefore, global food security. The precise and effective disease detection capabilities of these models may reduce the monetary losses caused by illnesses and increase agricultural productivity. Furthermore, the agricultural sector, especially precision agriculture, was significantly affected by this discovery. Farmers are able to make data-driven choices because of cutting-edge technologies, such as deep learning. Thus, agricultural operations are generally more profitable, resource allocation is more effective, and the environmental impact is lessened. Furthermore, the influence of this study may extend beyond potato crops to other crops with comparable disease signs. When customized for various crops, deep learning models may provide a scalable, precise, and affordable disease detection method. Farmers worldwide may benefit from this technology by using sustainable agricultural methods to protect their crops.

The primary goals of this study were as follows: 1) To enhance Convolutional Neural Network (CNN) models for accurate and effective potato disease diagnosis in data-poor locations. 2) To examine how the amount and quality of training data impact the ability of machine learning to identify early and late blight. 3) Examine how the accuracy of diagnosing potato diseases is affected by farmers' experience and low latency. 1) In areas with little data, such as Pakistan, how can CNN-based deep learning increase the precision of potato disease detection? 2) How does the accuracy of machine learning models used to identify potato illnesses, such as early and late light, depend on the amount and caliber of the training data? 3) What effects do low latency, and a lack of domain expertise have on the precision of potato disease detection, and how can these issues be resolved?

2. Material and Methods

This section contains the methodology of the study.

2.1. *Research Methodology*

We require a dataset that includes images of potato leaves for our study. After finding this dataset on Google Drive, we had to ensure that it complied with our specifications, even though it was a helpful resource. Label management is an essential step in the data-preparation process. Our dataset had three labels for each leaf: "healthy," "late blight," and "early blight." early blight. Similar to the descriptions, these labels provide details of the state of the leaf at that moment. However, to enable our computer program to identify them more quickly, we reduced the number of labels. In place of

"Healthy," we used "Yes" to denote a leaf that is healthy and "No" to indicate a damaged leaf. Consequently, our computer model processed the data considerably easier. We divided our dataset into two parts: training and testing. During the training phase, our computer model gained knowledge from the data and gradually increased its intelligence. A CNN or a deep learning model was used. CNNs are skilled at comprehending pictures, such as these leaves. We forced our model to practice it extensively by repeatedly using this approach. Compared with running the model over the data only once, this approach is much more successful. With every "epoch," our model became more adept at identifying and assessing pictures. Finally, we wanted to determine how well our model worked. Therefore, we randomly selected a leaf photograph from the test data. The model was asked to identify whether the leaves were ill or healthy. We ascertained whether our model had been properly trained using this test. Potato illnesses were correctly identified by the model. Further tests were performed to ensure that our model was correct. Fig. 1 shows a flow chart of the research methodology.

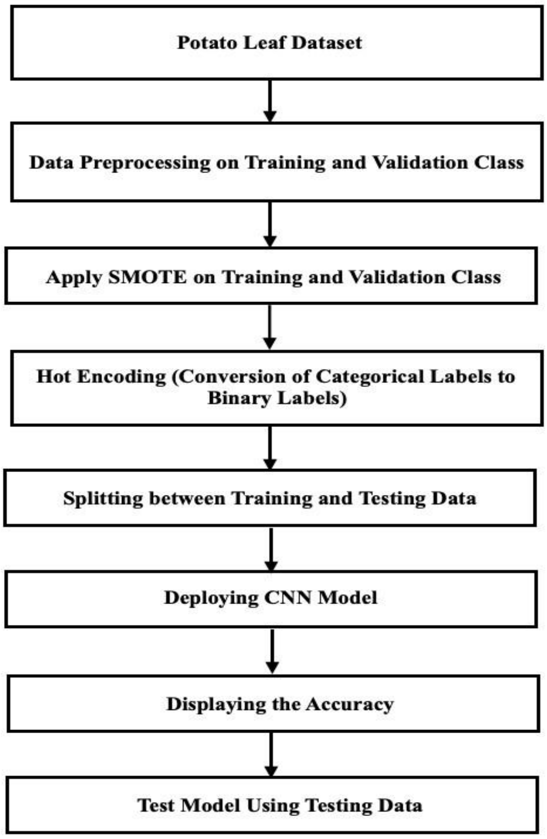

Fig. 1. Flow Chart of Research Methodology.

2.2. *Data Collection*

This study specifically focused on three distinct potato varieties: Coroda, Mozika, and Sante. These varieties are commonly cultivated in the Okara district of Central Punjab, a region known for substantial potato production. To ensure data diversity, potatoes were grown in rows and images and videos were captured under varying environmental conditions, replicating real-world scenarios. To create a valuable resource for detecting potato diseases in Pakistan's Central Punjab region, researchers developed the Potato Leaf Dataset (PLD). They collected real-time videos and images using different devices including mobile phones, digital cameras, and drones. These devices were carefully selected to capture data from various angles and distances. When capturing images with mobile phones and digital cameras, they were positioned quite close, 1-2 feet away from the potato plants. Drones, on the other hand, were flown at a higher altitude, approximately 5-10 feet, to avoid any distortion caused by the movement of the plant leaves. This ensured that the dataset contained high-quality images. To make the dataset even more useful, images and videos were taken under different environmental conditions, similar to what farmers experience in the real world. This diversity in conditions helps train models to effectively recognize diseases under various circumstances. Fig. 2 shows a sample image of the training class.

Fig. 2. Sample Images from the Training Class.

2.3. *Population of Sampling*

Table 1 shows a summary of the Potato Leaf Dataset, where the expert team of plant Pathologist finalized 4,062 potato leaf images in the potato leaf dataset (PLD). These images represent both healthy and diseased leaves, respectively. Owing to the large volume of data for various potato plant diseases, the healthy and infected leaves were annotated by the researchers using the LabelMe tool. To facilitate the development of a robust machine learning model for disease detection, plant pathologists categorized the images into three distinct classes: early blight, late blight, and normal (healthy) leaves. The resulting distribution within the PLD dataset comprised 1,628 images for early blight, 1,414 images for late blight, and 1,020 images for healthy leaves.

Table 1 Summary of Potato Leaves Dataset.

Class Labels	Samples
Blight Early	1628
Healthy	1020
Late Blight	1414
Total Samples	4062

Table 2 and Table 3 show the test class potato leaves dataset before and after smote, the SMOTE technique has been widely used to handle a class imbalance in various machine learning applications, including image classification, text classification, and disease detection.

After applying the SMOTE technique, our balanced dataset improved the performance of our model and increased its accuracy in detecting potato disease. These annotated and labeled images were used to train a deep learning model for potato disease detection.

Table 2 Testing Class Potato Leaves Dataset. (Before SMOTE)

Class Labels	Quantity
Blight Early	1132
Healthy	1303
Late Blight	816
Total Quantity	3251

Table 3 Validation Class Potato Leaves Dataset. (Befoe SMOTE)

Class Name	Quantity
Early Blight	163
Late Blight	151
Healthy	102
Total Quantity	416

Table 4 shows the training and validation class potato leaf dataset after smoothing, which ensured the availability of high-quality annotated images for training the model, resulting in improved accuracy and reliability of the detection system.

Table 4 Training and Validation Class Potato Leaves Dataset. (After SMOTE)

Class Name	Labels	Quantity
Training	Blight Early Blight, Healthy Late	1303,1303,1303
Validation	Blight Early Blight, Healthy Late	1303,1303,1303
	Total Quantity	7818

A CNN is a deep learning model that uses interconnected neurons to detect and learn hierarchical features from images, making it effective in tasks such as image classification, object detection, and facial recognition. SMOTE addresses class imbalance in datasets by generating synthetic examples for minority classes, thereby preventing biases in models such as disease detection and fraud detection. One-hot encoding is a data preprocessing technique that converts categorical data into a numerical format for machine-learning algorithms, particularly in tasks such as natural language processing and image classification.

3. Results and Discussion

We aimed to evaluate the performance of our deep learning model for potato disease detection under various conditions. We conducted a series of experiments to assess the accuracy and reliability of our model. Fig. 3 shows model accuracy. These experiments included evaluating the model with and without the synthetic minority oversampling technique (SMOTE) and varying the dropout rates. The results of these tests shed light on the behavior of the model in different scenarios. Before SMOTE and setting the dropout value to 0.25 accuracy the training fluctuated between 0.94 and 0.99. This means that during training, the model performed well, with accuracies ranging from 94% to 99%. However, during validation, the accuracy of the model was slightly lower, fluctuating between 0.80 and 0.85. This indicates that when the model was evaluated on new unseen data (validation), its performance was slightly lower than that of the training data.

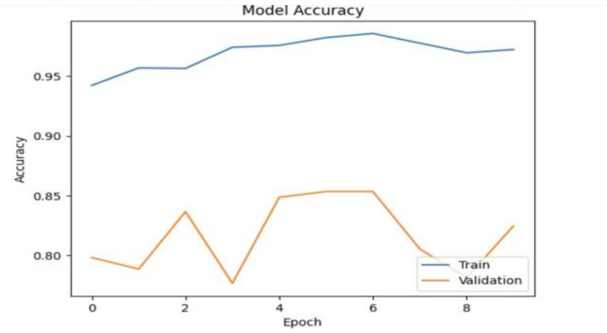

Fig. 3. Model Accuracy Graph.

Fig. 4 shows the model loss graph. During training, it varied between 0.1 and 0.2. A lower loss value indicated that the model fits the training data well. However, during validation, the model loss was higher, ranging from 0.6 0.9. This suggests that the performance of the model is not as good when evaluated on new data.

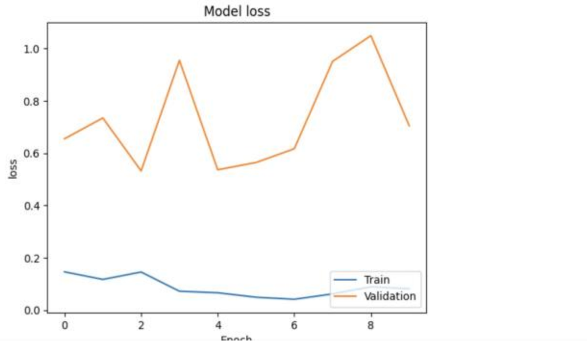

Fig. 4. Model Loss Graph

Fig. 5 shows the model accuracy after SMOTE, and with a dropout value of 0.25, it is evident that there was a notable difference between the training loss and accuracy in the deep learning model. In terms of the model accuracy, during training, it fluctuated between 0.94 and 0.99. This means that during training, the model performed well, with accuracies ranging from 94% to 99%.

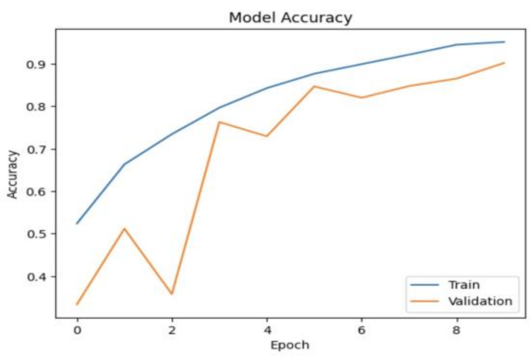

Fig. 5. Model Accuracy Graph after SMOTE.

Fig. 6 shows the model loss graph after SMOTE. However, during validation, the model's accuracy was slightly lower, fluctuating between 0.80 and 0.85. This indicates that when the model was evaluated on new unseen data (validation), its performance was slightly lower than that of the training data.

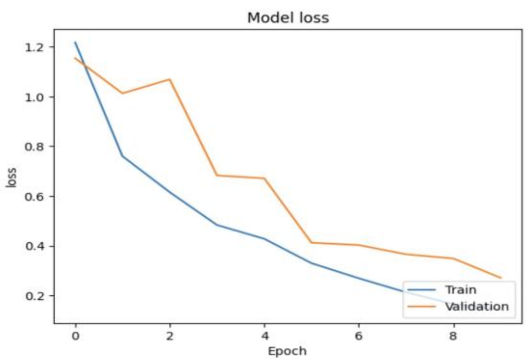

Fig. 6. Model Loss Graph after SMOTE.

Overall, applying SMOTE in combination with a dropout rate of 0.25 played a crucial role in enhancing the model's accuracy and reducing its loss, making it a promising approach for improving disease detection in potato leaves. The increased capacity of the model to classify healthy and diseased leaves can have a positive impact on potato crop management and yield. Although the above parameters demonstrated great results, fine-tuning of the parameters may result in an optimal model. Fig. 7 shows the model accuracy with SMOTE applied to balance the dataset, and a dropout rate of 0.35, which exhibited substantial improvements in accuracy and loss. The accuracy for validation increased from 0.55 to 0.95, indicating that the model became more proficient at correctly identifying healthy and diseased potato leaves. Training accuracy improved from 0.1 to 0.99, highlighting the model's effectiveness in learning from the data.

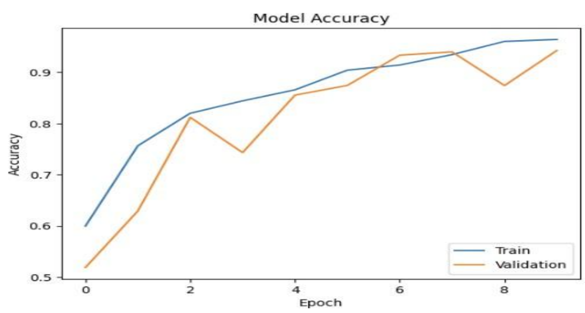

Fig. 7. Model Accuracy Graph.

Fig. 8 shows the model loss graph with SMOTE. In terms of loss, which measures the extent of errors, the validation loss decreased significantly from 1 to 0.1. The training loss also experienced a remarkable reduction, dropping from 0.99 0.05. These lower loss values indicate that the model is highly efficient in making precise predictions and minimizing errors.

The combination of SMOTE and a dropout rate of 0.35 resulted in a model with optimal performance. This not only increased the accuracy but also significantly reduced the loss, making it a highly effective tool for potato disease detection and classification. This optimized model makes a substantial contribution to potato crop management and disease control. Table 5 shows the results for each "epoch," which is a complete cycle through the training data. Loss" represents how well the model performs. When training started, the loss was relatively high (1.04 in the first epoch).

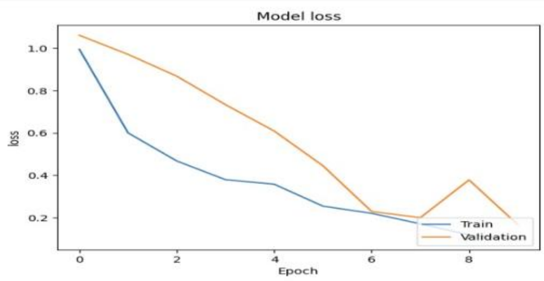

Fig. 8. Model Loss Graph.

Table 5 Validation Class Potato Leaves Dataset.

Epoch	Loss	Improvement
1	1.04	Improved
2	0.72	Improved
3	0.60	Improved
4	0.44	Improved
5	0.35	Improved
6	0.30	Improved
7	0.24	Improved
8	0.19	Improved
9	0.14	Improved
10	0.10	Improved

This means that the model was not very good at identifying diseases at the beginning. As the training continued (from epochs 1 to 10), it was observed that the validation loss consistently decreased. This is beneficial because the model is better at its job. By the time we reached the 10th epoch, the loss was only 0.10, which is much lower than the initial value. This suggests that the model is highly accurate in identifying potato leaf diseases. It is crucial to select the correct number of epochs during training to obtain the best performance from the model without making it overly complex.

The decision to limit the training of the deep learning model to only 10 epochs was made with careful consideration. Although training for more epochs can lead to further improvements in the model's performance, it is important to strike a balance. The use of a higher number of epochs can have drawbacks, particularly the risk of overfitting. In our case, this would mean that the model could become too specific to the examples it was trained on, potentially making it less effective in identifying new instances of potato leaf diseases. By observing the validation loss as the training progressed, it became clear that after 10 epochs, the loss reached a plateau and did not improve further. This suggests that the model learned as much as possible from available data. Pushing the model to train for more epochs might not have yielded significant benefits but could have increased the risk of overfitting. These insights collectively demonstrate the nuanced relationship among the number of epochs, model progression, and overfitting mitigation. By carefully selecting an appropriate number of epochs and incorporating techniques, such as dropout, we were able to utilize the power of deep learning to achieve accurate potato leaf disease classification while avoiding common pitfalls. This study aimed to identify better ways to identify diseases in potato plants, such as early and late blight. You see that potatoes are important for both food and life. Many people rely on them, but sometimes diseases can harm these potato plants, which means there is less food to eat, and farmers can lose money. The problem with these diseases is that they can damage not only the leaves but also the stems, roots, and potatoes themselves. When that happens, it is not good because we need potatoes to feed people worldwide. In addition, when diseases hurt potato crops, it can be expensive to grow. Looking into the future, it is important to know that an increasing number of people will live on Earth. To ensure that there is enough food for everyone, we need to produce a lot more food. Therefore, finding better ways to protect potato plants from disease is important. Current methods for identifying these diseases in potato plants are slow.

4. Conclusion and Future Work

We embarked on a journey to utilize the power of emerging deep-learning approaches to revolutionize the detection of potato plant diseases, particularly in early and late light. Our research journey can be divided into several key phases, starting with dataset collection, preprocessing, and ensuring balanced data using the SMOTE technique. We then delved into model development, where we defined a Convolutional Neural Network (CNN) architecture tailored to our task. We achieved impressive accuracy by training our model, thereby demonstrating the potential of deep learning in agriculture. Our study culminated in the successful implementation of our model for practical disease detection, which is evident in the high accuracy achieved on a sample image. This marks a significant step towards early disease identification and, subsequently, better crop management and higher yields for potato farmers. Although our study has made significant strides in the field of potato disease detection using deep learning, some areas warrant further exploration. The limitations of available datasets, especially in the context of specific regions such as Pakistan, point to the need for region-specific data-collection efforts. Additionally, research can focus on optimizing the model architectures and training processes to achieve even higher accuracy levels. Future research in the field of potato disease detection using deep learning should prioritize the collection of diverse region-specific datasets. This involves capturing images and data from various potato-growing regions in Pakistan that encompass different potato varieties and environmental conditions. The creation of a more extensive dataset will enable deep learning models to generalize and improve their accuracy in real-world settings. Combining these data with deep learning models can lead to a holistic approach disease management, allowing for proactive measures to prevent outbreaks. As deep learning models evolve, efforts should be made to make these solutions more accessible to farmers, especially in the remote areas of Pakistan. User-friendly interfaces and mobile applications can be developed to enable farmers to capture images, diagnose diseases, and receive recommendations directly from their smartphones. This approach can democratize advanced technology and empower farmers to make informed decisions regarding their potato crops.

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Authors Introduction

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