Potato Leaf Disease Detection Using Deep Learning

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***Abstract*—Potato cultivation faces significant challenges due to various leaf diseases that can adversely affect crop yield and quality. This study proposes a multi-model deep learning approach for potato leaf disease detection, utilizing Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Single Convolutional Neural Networks (SCNN). The CNN classifies diseases in potato leaves based on RGB images, the LSTM analyzes temporal patterns, and the SCNN focuses on spatial features. Trained on a diverse dataset, the models are evaluated using performance metrics and compared with traditional methods, showcasing the effectiveness of deep learning. The CNN model is deployed as a user-friendly application for real-time disease prediction, enhancing practical usability in agriculture. This comprehensive approach offers a versatile solution for automated potato leaf disease detection, benefiting farmers in crop health management.**

Keywords—CNN, LSTM, SCNN, Prediction, Leaf disease

I. Introduction

Potatoes, scientifically known as Solanum tuberosum, constitute a vital vegetable crop globally, particularly in India, owing to their diverse varieties and high demand. Their remarkable diversity and robust market demand make potatoes an economically significant choice for growers. Currently cultivated in over 130 developing nations, potatoes rank as the fourth most essential staple food globally. Despite the consistent upward trajectory in global potato production, diseases and pests account for a staggering 32% of annual losses [1].

In the Indian agricultural landscape, potato farmers grapple with considerable setbacks, facing an annual economic loss of at least Tk 2,500 crore due to challenges such as unsold surplus production and post-harvest losses [2]. Boasting dominance in over 125 countries, including India, potato farming stands as a prominent occupation. However, this critical crop contends with infections and diseases, notably Early blight and Late blight, negatively impacting yield and production. Potatoes, renowned for their favorable nutrient-to-price ratio, play a vital role in providing affordable nutrition on a global scale [3].

Late blight poses a significant threat to potato farmers, causing damage to leaves, stems, and tubers. Recognizable symptoms include blistered leaves turning brown or black during the drying process. Environmental conditions such as high humidity, cold temperatures, and leaf wetness contribute to the spread of late blight. Additionally, primary blight manifests as characteristic leaf spots affecting both foliage and stems, potentially girdling the plant. Tackling these challenges requires farmers to navigate through the complexities posed by warm, rainy, and wet weather [4].

Swift and accurate identification of diseases in potato plants is crucial to minimize their impact. Manual monitoring by farmers becomes challenging due to its time-consuming nature and the need for in-depth knowledge. This challenge is particularly pronounced in India, where identifying slow-progressing diseases becomes impractical. Relying on approximate assumptions and personal identifications can lead to inaccuracies, potentially exacerbating disease spread. Lack of expert advice often results in ineffective preventive measures and potential crop damage due to misinterpretation of disease intensity or improper dosage [5].

To address these challenges in the Indian context, this research proposes a Convolutional Neural Network (CNN)-based method for classifying and identifying prevalent potato illnesses. The objective is to provide Indian farmers with a fast and accurate tool for disease detection in potato crops, requiring minimal computational effort. Leveraging CNN technology, the proposed method aims to empower Indian farmers with an efficient solution for the early diagnosis and classification of diseases, ultimately contributing to the overall health and productivity of potato cultivation in the country.

II. RELATED WORKS

Various methodologies have been proposed for the detection of plant diseases, and researchers have explored diverse techniques to address the specific challenges of identifying potato leaf diseases. The following summarizes some of the notable approaches presented in the existing literature.

P. Badar et al. [1] used a segmentation strategy based on K Means Clustering on various variables (color, texture, and area) that were taken from potato leaf photos. They classified and identified diseases using the Back Propagation Neural Network algorithm, and their impressive 92% classification accuracy was attained.

U. Kumari et al. [2] extracted attributes from leaf images of tomato and cotton plants, including contrast, correlation, energy, homogeneity, mean, standard deviation, and variance, using image segmentation. After that, a neural network was used as a classifier, producing a noteworthy 92.5% classification accuracy.

M. Islam et al. [3] centered on the Plant Village dataset's image segmentation for photos of potatoes [1]. Using a multiclass Support Vector Machine on the segmented images, they were able to classify the images with an astounding 95% accuracy..

C. G. Li et al. [4] categorized and identified fungal infections on grape leaves using image segmentation. Color, texture, and form data were extracted using K Means clustering, and Support Vector Machine (SVM) was employed to classify diseases.

J. Chen et al. [5] categorized and identified fungal infections on grape leaves using image segmentation. Color, texture, and form data were extracted using K Means clustering, and Support Vector Machine (SVM) was employed to classify diseases.

Using the Faster R-CNN method for image identification and classification is a recent development.
A. Ramcharan et al. [6] implemented transfer learning for cassava disease images, which benefited the field.

III. DATASET DESCRIPTION

The dataset utilized for this research is sourced from Kaggle, a renowned open-source database, specifically the Plant Village Dataset [1]. This is a large dataset with about 55,000 carefully labeled photos of different fruits and vegetables, including apple, blueberry, cherry, grapes, peach, pepper, orange, tomato, and potato. Both colored and grayscale images are included in each category, which corresponds to a different crop. One noteworthy aspect of the dataset is the inclusion of thoroughly documented images of both disease-free leaves and leaves in good health.

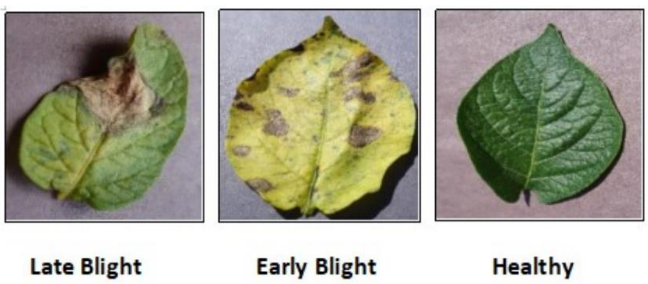

Figure 1: A sample picture for every class

There are various leaf disease types associated with each crop category; for classificational purposes, each disease type is regarded as a distinct class. The dataset is further divided into two categories: one type comprises images of leaves with backgrounds, and the other type includes images without any backgrounds.

There is a non-uniform distribution of images in the various classes, with between 152 and 1000 images per class. The dataset is reduced to three classes—healthy leaf images, late-blight images, and exclusively potato images—for this study. The train-test-split of the data is shown in Table 1, which also includes information on the number of samples in each class for the training and testing sets.

Table 1: Train-Test-Split for Potato Leaf Disease Classification

Label	Category	Number	Training sample	Test sample
1	Early Blight	1000	787	213
2	Late Blight	1000	791	209
3	Healthy	152	122	30
Total		2152	1700	452

This dataset forms the foundation for training and evaluating the proposed Convolutional Neural Network (CNN) model, specifically tailored for the classification of potato leaf diseases.

IV. PROPOSED APPROACH

A. Pre-processing technique

Pre-processing constitutes a crucial phase in the development of any machine learning project. Specifically, in the context of a plant leaf classification project, several techniques are employed to enhance speed and accuracy, including data splitting, caching, and shuffling. Data splitting is imperative for partitioning the dataset into distinct sets allocated for training, testing, and validation purposes. This strategic division prevents the model from overfitting to the training data, thereby ensuring robust performance on unseen data. Data splitting is imperative for partitioning the dataset into distinct sets allocated for training, testing, and validation purposes. This strategic division prevents the model from overfitting to the training data, thereby ensuring robust performance on unseen data.
Caching is a valuable strategy wherein pre-processed data is stored in either memory or disk. This storage optimization facilitates faster data retrieval during the training phase, consequently reducing the overall time required for data loading and pre-processing. The result is an enhanced efficiency of the model. Shuffling represents another vital pre-processing technique, involving the randomization of the order of training examples. This randomness serves to prevent the model from learning any inherent order within the data, fostering a more generalized and adaptable learning process. Collectively, these pre-processing techniques play a pivotal role in optimizing data inputs. The objective is to cultivate a high-quality and unbiased training environment for the model, ensuring its proficiency in performing well on novel, unseen data. Through the refinement of data inputs, pre-processing substantially contributes to improving the overall accuracy and efficiency of the machine learning model.

B. Segmentation

Following the pre-processing of the dataset, the subsequent imperative is the segmentation into distinct training, testing, and validation sets. This segmentation holds significant importance, facilitating the evaluation of the model's performance on unseen data—a pivotal measure to counteract overfitting. Typically, the dataset undergoes division into a training set (utilized for model training), a validation set (employed for hyperparameter tuning and overfitting prevention), and a testing set (utilized for the final assessment of model performance). While the split ratio can vary based on dataset size, a common practice is a 80% allocation for training, 20% for validation, and testing. Ensuring a random distribution during the split is crucial, warranting that each segment comprises a representative sample encompassing the entire dataset. Techniques such as stratified sampling prove instrumental in achieving this randomness, guaranteeing proportional representation of each class in every split. In essence, segmentation emerges as a pivotal stride in the machine learning model development process. It not only enables the assessment of model performance but also provides the opportunity to make necessary adjustments to enhance accuracy through informed iterations.

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Found 2152 files belonging to 3 classes.
Using 1722 files for training.
Found 2152 files belonging to 3 classes.
Using 430 files for validation.
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Figure 2. Segmentation of data for training and validation

C. Feature extraction

Following the dataset segmentation, the subsequent pivotal phase is feature extraction. This step involves extracting pertinent information or features from the images, enabling the machine learning model to discern between healthy and diseased potato leaves effectively. The extraction process primarily focuses on color and texture features derived from the leaf images. Color-based features can be acquired through methods like color histograms or color moments, while texture-based features can be extracted using techniques such as Local Binary Patterns (LBP) or Gray-Level Co-occurrence Matrix (GLCM). The amalgamation of these features provides a comprehensive representation of the potato leaf images, furnishing the machine learning model with the necessary information for accurate predictions. The selection of a specific feature extraction technique is contingent upon the dataset's characteristics and the nature of the problem at hand. Feature extraction assumes critical importance in the machine learning pipeline, wielding influence over the quality of features employed by the model for predictions. An effective feature extraction method should adeptly capture the essential characteristics of potato leaves while filtering out extraneous and irrelevant information. This meticulous curation ensures that the model is equipped with high-quality input features, thereby contributing to the precision of its predictions.

D. Feature selection

Following the extraction of features from the images, the subsequent crucial step is feature selection, aimed at identifying the most pertinent and influential features that significantly contribute to the classification of images as either healthy or diseased. This pivotal phase is known as feature selection, and among the variety of methods available, this project employs filter methods. Filter methods operate by evaluating and ranking features based on their relevance to the target variable. The features undergo scoring using statistical tests such as chi-square, ANOVA, and correlation. Subsequently, features with the highest scores are chosen for further analysis. Filter methods offer computational efficiency and adeptly handle datasets with a large number of features. In this specific project, filter methods are harnessed to discern the most crucial features from the extracted colour and texture features. The features are systematically ranked based on their correlation with the target variable, distinguishing between healthy and diseased classifications. The top-ranked features are then cherry-picked for the training of the deep learning model. This strategic feature selection not only aids in reducing the dimensionality of the dataset but also contributes to the overall accuracy enhancement of the model, thereby optimizing its performance.

E. Evaluation

Evaluation constitutes a fundamental component of any machine learning project, providing a means to gauge the model's performance. In this project, the evaluation of our Convolutional Neural Network (CNN) model involved the utilization of the ROC curve and accuracy metric. The ROC curve serves as a visualization tool, illustrating the classification model's performance at different thresholds. It delineates the trade-off between the true positive rate (sensitivity) and false positive rate (1-specificity) across various threshold values. This graphical representation proves invaluable for selecting the optimal threshold tailored to a specific classification problem. Accuracy, a widely adopted metric for classification model assessment, represents the percentage of correctly classified samples in the test dataset. In this project, accuracy served as a primary metric to assess the overall performance of our CNN model. However, it's acknowledged that accuracy alone may not suffice, particularly in cases of imbalanced datasets. In such instances, precision, recall, and F1 score are alternative metrics employed to measure model performance. The evaluation protocol involved the segmentation of the dataset into training, validation, and testing sets. The model underwent training on the training set, hyperparameter tuning on the validation set, and eventual performance evaluation on the testing set. The ROC curve was plotted, and the accuracy of the model on the test set was calculated. This comprehensive analysis, incorporating both the ROC curve and accuracy, facilitated the determination of potential overfitting or underfitting. Adjustments were made as necessary to enhance the model's performance, ensuring its robustness and efficacy in handling unseen data.

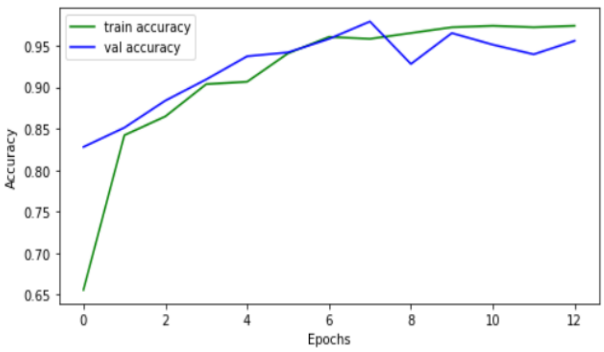

Figure 3. ROC curve for accuracy

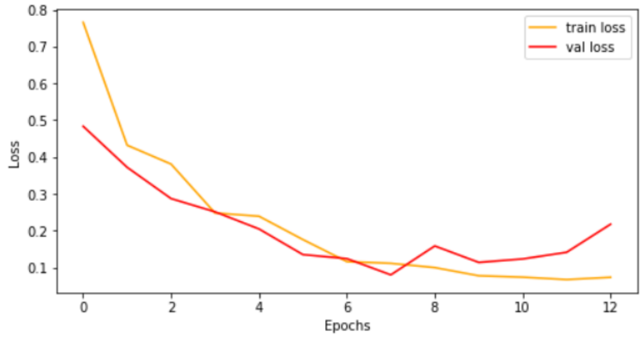

Figure 4. ROC curve for loss

F. Final Prediction

The culminating step in the project involves predicting whether an input image of a potato leaf is healthy or diseased based on the trained model. This prediction is realized by passing the preprocessed and segmented image through the trained Convolutional Neural Network (CNN) model. The model, in turn, generates a probability score indicative of the likelihood that the input image is either healthy or diseased. To solidify the prediction, a threshold probability score is established. If the output probability score exceeds this threshold, the input image is classified as diseased; conversely, if it falls below the threshold, it is classified as healthy. The selection of the threshold value is contingent upon the desired trade-off between false positives and false negatives. Upon making the final prediction, the outcome can be presented to the user along with a confidence score, representing the level of assurance the model has in the prediction. This provision assists users in making informed decisions regarding the health of their plants and empowers them to undertake appropriate actions to prevent or treat any identified diseases. This integration of a confidence score provides a nuanced understanding of the model's certainty in its prediction, enhancing the utility and reliability of the system for end-users.

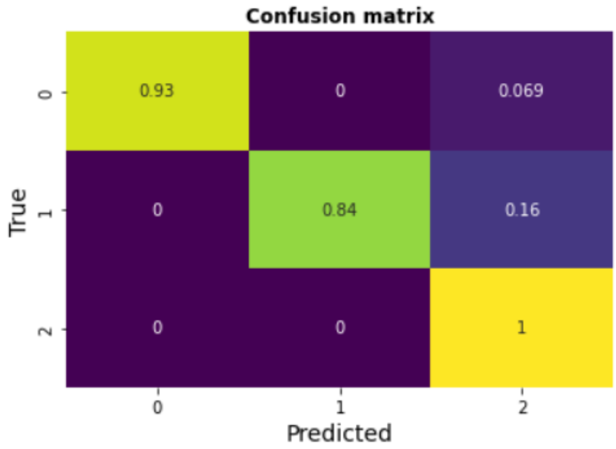

Figure 5. Confusion matrix for Prediction

V. METHODOLOGIES

A. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a special kind of deep learning tool widely used for recognizing and categorizing images. They have various layers, like convolutional, pooling, and fully connected layers, each with a specific role in figuring out what's in an image. Imagine the first layer of a CNN as a way to look at the picture, treating it like a grid of colors. The convolutional layer uses a bunch of filters to focus on different parts of the image, helping identify important features. Think of these filters as special glasses that highlight certain details. After this, there's a pooling layer, which kind of shrinks the highlighted features to simplify things. It's like zooming out a bit to get a general sense of what's going on. Max pooling, a common method, picks the most important information from each area. This process repeats with more convolutional and pooling layers, helping the computer understand increasingly complex features. Finally, all this information gets flattened and put through a fully connected layer, which makes the ultimate decision about what the image represents. In simple terms, CNNs are great at looking at pictures and figuring out what's in them by breaking down the image into smaller, understandable parts. They're like smart detectives that focus on specific details, zoom out to see the bigger picture, and finally, make a confident decision about what's in the image.

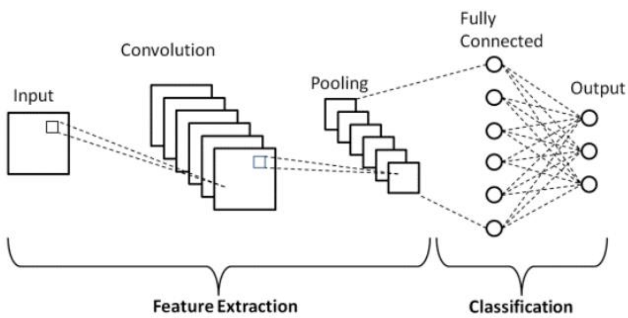

Figure 6. Architecture of CNN

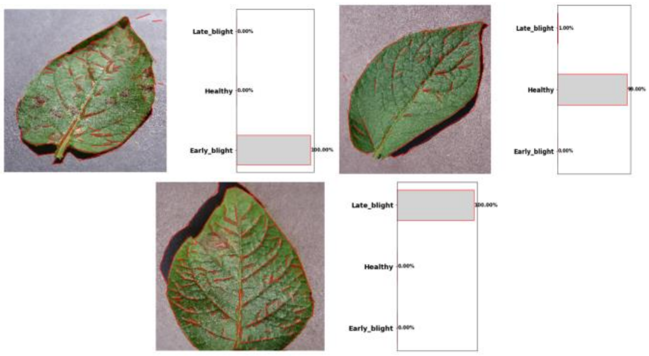

Figure 7. prediction Using CNN

B. Long Short - Term Memory (LSTM)

Long Short-Term Memory (LSTM) models prove valuable in potato leaf disease detection by effectively capturing temporal patterns and dependencies within sequences of plant leaf images. Their capability to handle variable-length sequences accommodates diverse disease progression timelines, while the sequential learning nature of LSTMs aids in recognizing evolving patterns indicative of specific diseases. These models automatically extract relevant features from images, complementing spatial feature extraction from Convolutional Neural Networks (CNNs). The integration of LSTM and CNN enables a comprehensive approach to monitoring plant health, combining spatial and temporal insights. During training, sequences of images are presented to the LSTM, allowing it to learn disease-associated patterns. Evaluation metrics, including accuracy and precision, assess the model's performance in classifying diseases or identifying healthy leaves, offering a robust solution for real-world disease monitoring in potato plants.

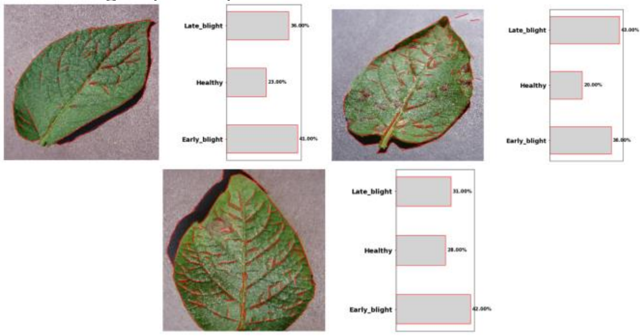

Figure 8. prediction Using LSTM

C. Spatial Convolutional Neural Network (SCNN)

The Spatial Convolutional Neural Network (SCNN) plays a crucial role in potato leaf disease detection by enhancing the understanding of spatial context information within plant leaf images. SCNN incorporates specialized layers that focus on highlighting and integrating contextual details, providing a comprehensive view of the leaf's spatial features. This model is particularly effective in discerning intricate patterns related to various diseases, contributing to improved accuracy in classification. By leveraging SCNN alongside Convolutional Neural Networks (CNNs) in the overall architecture, the combination enhances both spatial and contextual learning, ensuring a more robust and nuanced approach to detecting diseases in potato plants. The integration of SCNN serves as a valuable asset in optimizing the overall performance of the detection system, addressing the intricacies of spatial relationships within the potato leaf images.

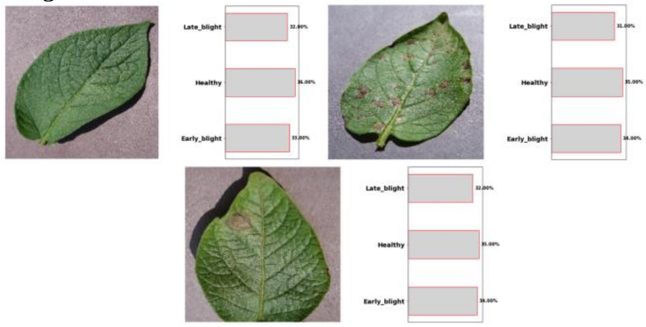

Figure 9. prediction Using SCNN

VI. CONCLUSION

Our research demonstrates the remarkable efficacy of deep convolutional neural networks in accurately identifying and categorizing potato leaf diseases. The developed model achieved an impressive F1-score of 96.71%, showcasing its exceptional accuracy in detecting two prevalent plant diseases. This advanced technique holds significant promise for substantially improving the precision of plant disease detection, leading to faster and more efficient treatment strategies. With further study and development, this technology has the potential to revolutionize the agricultural sector, mitigating the adverse impacts of plant diseases on crop yields and enhancing overall agricultural productivity.

VII. FUTURE SCOPE

Future improvements for our potato leaf disease detection model involve enlarging the dataset to include a broader spectrum of plant diseases for increased precision. Exploring transfer learning by fine-tuning a pre-trained CNN on a more focused dataset is another avenue for more efficient model operation. Additionally, we envision developing a real-time disease detection system using cameras or sensors in the field to provide farmers with timely alerts for targeted treatments. To enhance versatility, our future plans include extending the model for multi-class classification, requiring a larger and more diverse dataset and adjustments to the CNN architecture. These enhancements aim to elevate the model's effectiveness and applicability in agricultural disease management.

REFERENCES

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[4] Kumari et al.'s work [2019] on leaf disease detection, which uses artificial neural networks for classification and K-means clustering for feature extraction, advances our knowledge of efficient methods for identifying diseases in plant leaves [4].

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[8] Evgeniou and Pontil's exploration of support vector machines [2001] provides a foundational understanding of SVMs, a technique applied in various contexts, including disease classification in plant leaves [8].

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