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A CNN CLASSİFİCATİON APPROACH FOR POTATO PLANT LEAF DİSEASE DETECTİON

M. Mounika[1], L.Sahithi[2], K.Prasanna Lakshmi[3], K.Praveenya[4], N. Ashok Kumar[5]
[1,2,3,4]Students, [5]Assistant Professor
[1]Department of Information Technology
[1]Vasireddy Venkatadri Institute of Technology, Guntur, India.

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ABSTRACT
The timely detection and management of plant diseases is critical in the agricultural industry. Among these, potato leaf diseases can have a major impact on crop productivity and quality. This research addresses the important requirement for rapid and reliable disease detection in potato plants. Using Convolutional Neural Networks (CNNs), a sophisticated deep learning approach, we gain considerable progress in automating the identification process. We demonstrate the model's ability to distinguish diverse kinds of disease with an amazing accuracy rate of 98.8% through rigorous experimentation. The use of data augmentation techniques improves the model's flexibility to a variety of environmental situations. This breakthrough has significant promise for shaping agricultural methods, providing a powerful tool for early disease intervention, and ensuring global food security.
KEYWORDS - *Deep learning, Convolutional Neural Network (CNN), potato diseases, TensorFlow, Streamlit.*

I. INTRODUCTION

A nation's progress hinges on the vitality of its agricultural sector, which serves as the bedrock of sustenance for its populace. Given the importance of agriculture, the identification of plant diseases has emerged as a critical issue. Traditional methods of identifying plant diseases, while available, can be subjective, time-consuming, and resource intensive, demanding extensive knowledge and human resources. Pathogens, living microorganisms, bacterial difficulties, fungal infections, germs, and viruses are all examples of plant diseases. These include early blight, late blight , and more, all of which can severely impact potato plants, displaying symptoms on their leaves.

Early detection and action during the early phases of these outbreaks can help farmers avoid major economic losses. Plant leaf diseases can be accurately diagnosed using experimentally verified software solutions. In recent years, machine learning and deep learning have developed as formidable technologies for this aim. Given the variety of diseases seen in different climates, effective early detection is critical for minimizing losses.

Caring for plants, ensuring their robust growth, and safeguarding them from diseases are pivotal for effective country or regional management. Convolutional Neural Networks (Convnets) are used in this study to detect potato leaf diseases. We curated a Plant Village dataset on Kaggle that included images of fifteen diverse kinds of plant leaves,from which we extracted classes specific to potato leaves.

II. OBJECTIVES

- Develop a specialized CNN model for accurate potato disease identification.
- Curate a diverse dataset with images of healthy and diseased potato plants.
- Apply data augmentation techniques to enhance model performance.
- Optimize model parameters for efficient disease classification.
- Validate the model's effectiveness through comparative analysis.

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III. METHODOLOGY

3.1 Data Preparation

Data preparation is a crucial step in any deep learning project. In this context, it involves loading and formatting the potato disease dataset for further analysis and model training. The dataset, likely containing images of both healthy and diseased potatoes, is accessed and organized. This process typically involves importing relevant libraries like NumPy, Pandas, and potentially OpenCV for image handling. Images are read, and if necessary, they are pre-processed to ensure uniformity and ease of analysis. This may include tasks such as resizing images to a standardized dimension, converting them to a suitable format, and potentially normalizing pixel values to improve model performance.

3.2 Dataset Visualization

After data preparation, it's crucial to gain insights into the dataset's characteristics. Visualization plays a vital role in this process. It allows us to view sample images from the dataset, providing a visual understanding of the potato samples, their diversity, and the variations between healthy and diseased instances. This step aids in identifying potential challenges, such as class imbalance or image quality issues. It also helps in verifying if the dataset is correctly loaded and preprocessed. Common libraries like Matplotlib and Seaborn are often used for generating visualizations. These tools allow for displaying images along with their respective labels, enabling a quick overview of the dataset's contents.

3.3 Data Partitioning

In machine learning, it's crucial to divide the dataset into distinct subsets for training, validation, and testing purposes. The training set is used to train the model, the validation set is used to fine-tune hyperparameters and prevent overfitting, and the test set is employed to assess the model's generalization performance. This division is essential to ensure that the model does not simply memorize the training data but can generalize its predictions to new, unseen examples. Typically, this is done by randomly shuffling the dataset and then allocating a certain percentage of the samples to each subset. Care is taken to maintain class distribution across all partitions, ensuring that the model learns from a representative sample of both healthy and diseased potatoes.

3.4 Data Augmentation and Rescaling

Data augmentation is a critical technique in computer vision tasks like image classification. It involves applying random transformations to the existing training images, such as flips or rotations. This process increases the diversity of the training set, helping the model generalize better to unseen data. In this context, horizontal and vertical flips as well as random rotations by 20% are employed. Additionally, rescaling ensures that all images are brought to a uniform size, enhancing computational efficiency and consistency during model training. The images are resized to a standardized 256x256 pixel format and rescaled for numerical stability, allowing the model to learn effectively from the data.lick.

3.5 Model Architecture

A Convolutional Neural Network (CNN), a form of deep learning model well-suited for image classification tasks, was implemented in this study. This CNN is intended to detect diseases of potato leaves.The network is composed of numerous layers, each of which serves a specific purpose in the learning process. It begins with an input layer that processes images of 256x256 pixels with RGB color channels. Preprocessing stages ensure uniformity by resizing images and rescaling pixel values to a range of 0 to 1. The network then employs a 2D convolutional layer with 32 filters, each utilizing a 3x3 kernel and ReLU activation. Subsequent convolutional layers with 64 filters extract hierarchical features. Max pooling layers follow, applying a 2x2 operation after each set of convolutional layers to reduce spatial dimensions and focus on critical features. A flatten layer transforms the multi-dimensional output into a one-dimensional array for further processing. The architecture incorporates a dense layer with 64 units and ReLU activation for feature integration, and a final dense layer with units equal to the three disease categories, employing softmax activation for probability outputs. Training leverages the Adam optimizer and Sparse Categorical Cross-Entropy loss function across ten epochs, enabling the model to discern intricate details and yield precise predictions. This meticulously designed structure demonstrates a thoughtful amalgamation of components, effectively facilitating accurate disease classification in potato leaf images.

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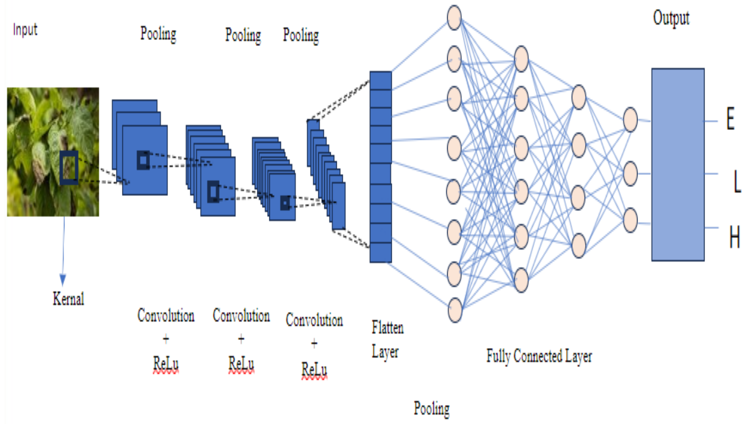

Fig 1: CNN Architecture

3.6 Model Training

Model training is a crucial phase in deeplearning where the algorithm learns patterns and relationships within the data.A Convolutional Neural Network (CNN) is trained to classify potato diseases. The model is fed batches of preprocessed images from the training set, and it adjusts its internal parameters through a process called backpropagation. This process iterates over multiple epochs, refining the model's ability to accurately classify images. The choice of optimizer (Adam) and loss function (sparse categorical cross-entropy) guide this training process, aiming to minimize the error between predicted and actual labels. The model's performance is evaluated on a separate validation set to monitor its progress.

IV. RESULTS

The suggested model was trained for a total of 50 epochs with a small batch size of 8. Following that, the model's competency on the test set was evaluated and benchmarked against a baseline for performance comparison. The results of the experiment demonstrate an excellent level of accuracy in classifying potato illnesses. The model had an overall accuracy of around 98.8%. This high level of precision indicates the effectiveness of the Convolutional Neural Network (CNN) architecture in distinguishing between healthy and unhealthy potato plants. The use of data augmentation techniques such as random flips and rotations, which increased the diversity and variability of the training data, is credited with the strong performance. As a result, the model's capacity to generalize effectively to previously encountered samples was enhanced. The experimental results validate the utility of deep learning approaches in automated plant disease categorization, emphasizing their importance in modern agriculture for crop disease detection and mitigation.

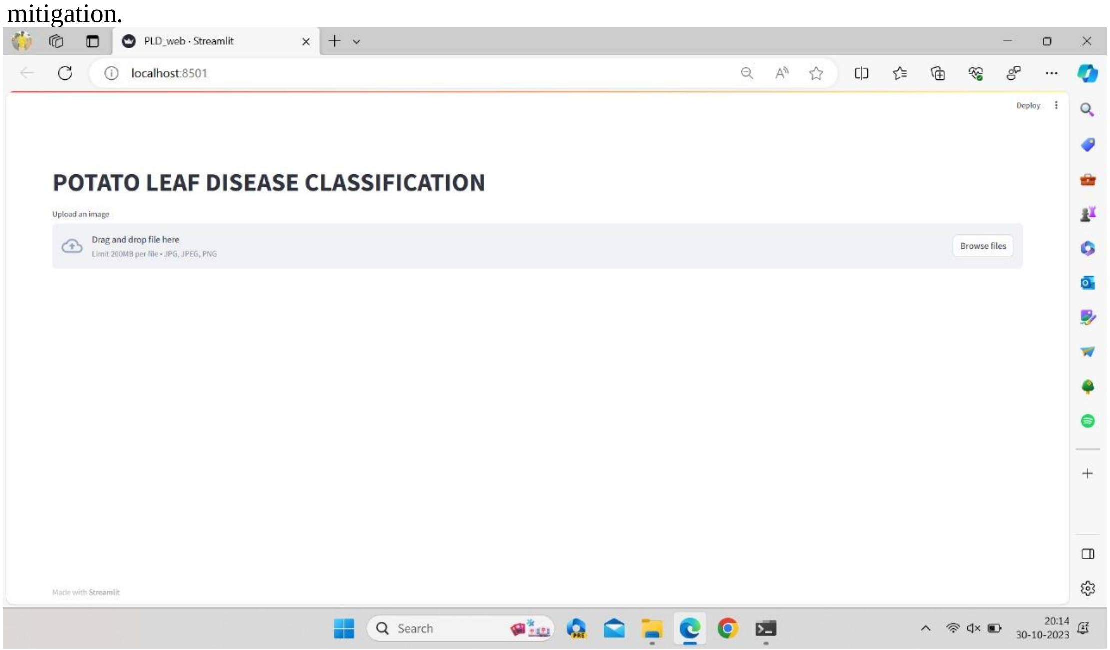

Fig.2: Interface to upload a leaf

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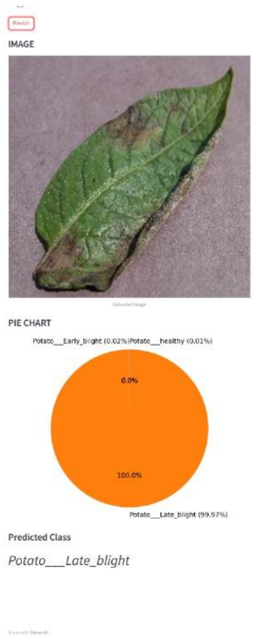

Fig 4: Potato Late Blight

Figure 4 This image displays a potato leaf afflicted by blight, evident in its distinct dark lesions, signaling a potential fungal infection.

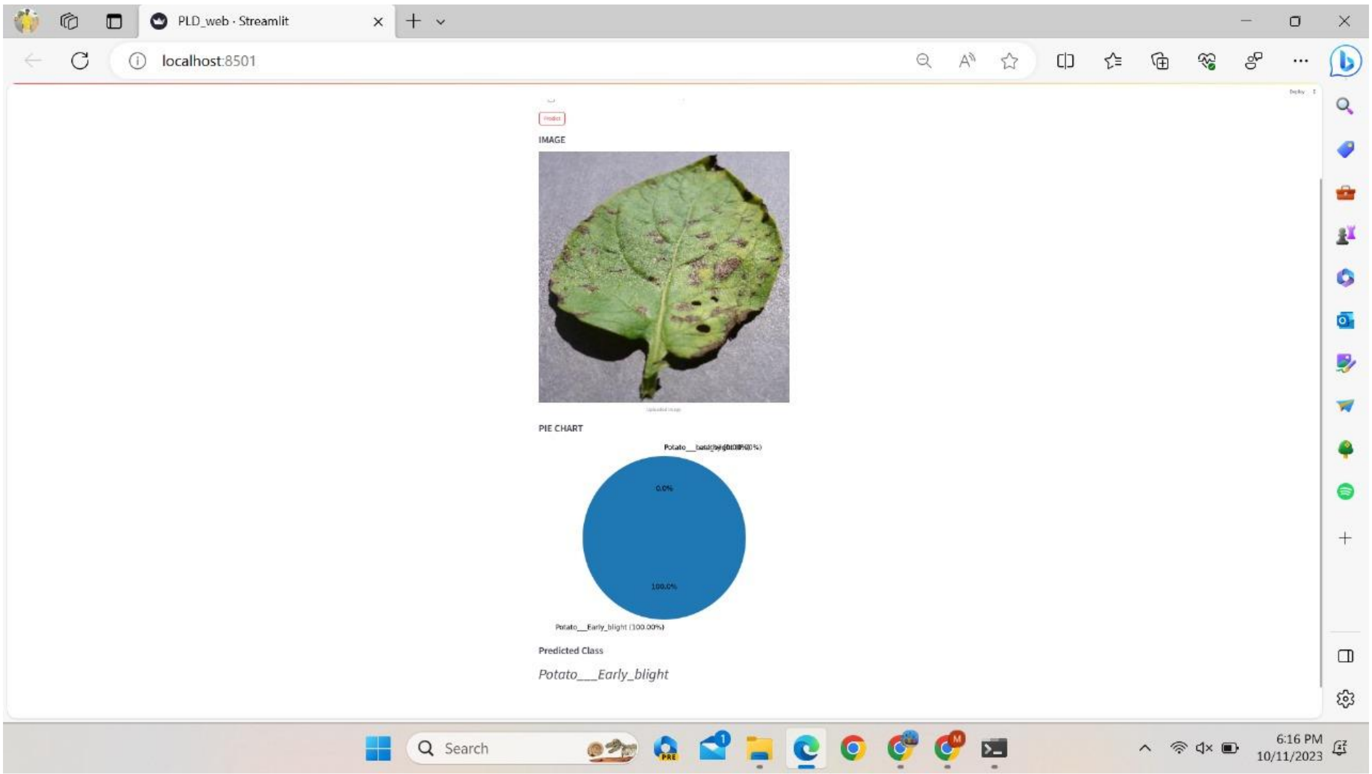

Fig.5: Potato Early Blight

Figure 5 A potato leaf is shown suffering from late blight, characterized by water-soaked lesions and sporulation on the undersides.

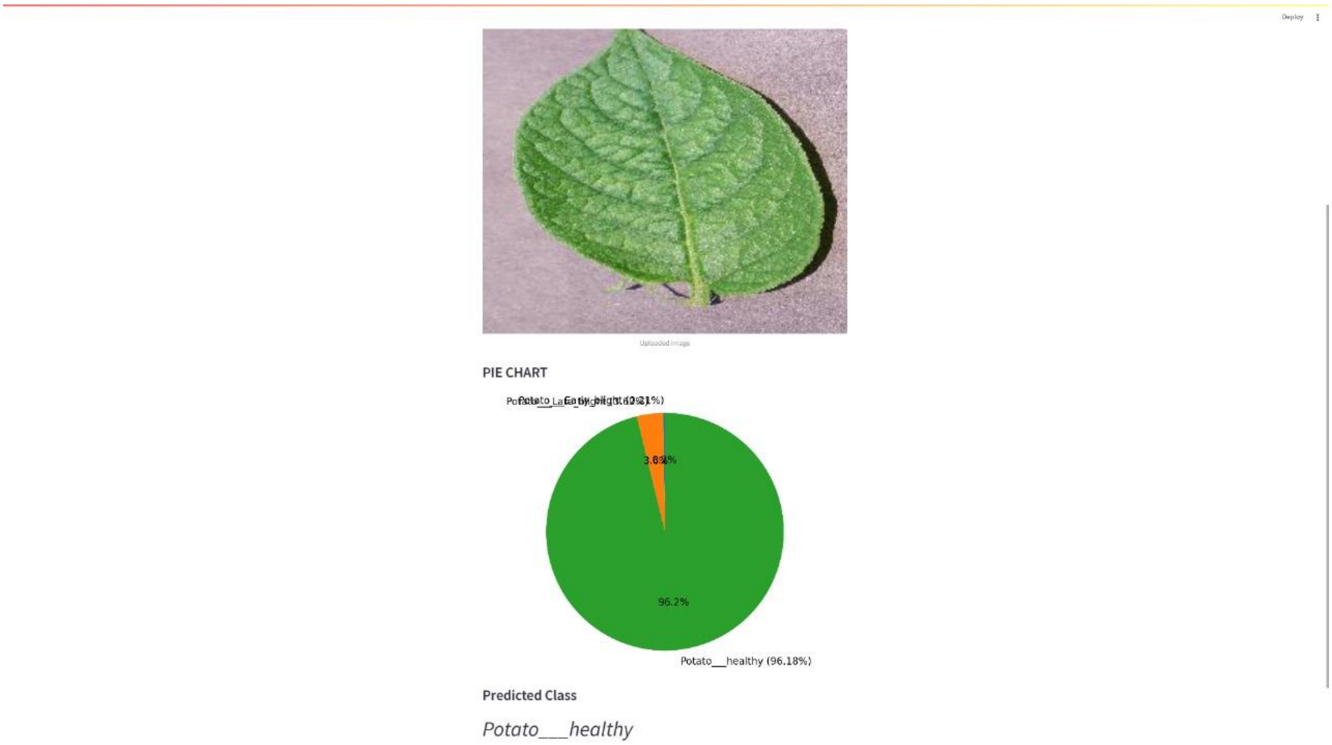

Fig.6: Potato healthy

Figure 6 This picture shows disease-free potato leaf exemplifies an ideal condition for a thriving plant, crucial for optimal crop yield.

V. CONCLUSION

The creation of the online application using the Streamlit module marks a major changing point in the identification of potato leaf disease. The integration of a Convolutional Neural Network (CNN) with three output classes, constructed using TensorFlow in a sequential architecture, has yielded promising results. Convolutional layers, max-pooling layers, and dense layers are some of the essential elements that the model includes and are responsible for its efficiency.Advanced deep learning methods combined with a user-friendly online interface have significant potential to improve agricultural practices and ultimately support sustainable crop management.

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