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Identification of Potato Plant Diseases using Deep Neural Network Model and Image Segmentation

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Abstract- This research proposes an approach for classifying diseases affecting potato leaves using DL and image segmentation techniques. Collecting data, preprocessing the data, segmenting an image, extracting features, and classifying the picture are the five main components of the suggested technique. The primary objective is to use image processing methods to identify diseased potato plants within the Plant Village Dataset (PVD) of photos. Diseased areas in images of potato leaves are separated using the K-Means clustering technique. A deep neural network (DNN) model with Adam and categorical cross-entropy hyperparameters categorises PLD. With the suggested approach, the classification accuracy attained is 98% for PLD detection. Our model successfully detected and classified leaf diseases in potato plants, as evidenced by experimental findings.

Keywords- Plant disease, Image segmentation, Potato Disease Detection, Machine Learning, K-means

1. INTRODUCTION

The advancement of imaging and machine learning technologies has significantly impacted various sectors, including agriculture, by offering efficient disease detection and diagnosis solutions. This study focuses on developing a novel approach for accurately identifying diseases affecting potato leaves, utilising deep learning (DL) and image segmentation techniques. The importance of automated disease detection in agriculture cannot be overstated, as it plays a crucial role in ensuring crop health, yield optimisation, and sustainable farming practices. Traditional disease diagnosis methods often rely on expert visual examination, which can be time-consuming and subjective. Moreover, certain disorders may require additional medical tests for confirmation, further delaying the diagnosis. However, with DL techniques, computers can be trained to recognise specific image patterns and anomalies, enabling rapid and accurate disease identification. This saves time and facilitates early intervention, leading to better crop management and reduced yield losses. Deep learning, in particular, has emerged as a powerful tool in plant disease diagnosis due to its ability to learn complex patterns and features directly from raw data. By leveraging large datasets of labelled images, DL models can automatically extract relevant features and classify images into different disease categories with high accuracy. This study capitalises on these capabilities by employing a deep neural network (DNN) model trained on a specialised dataset of potato leaf images.

Furthermore, image segmentation techniques, such as K-Means clustering, are utilised to isolate diseased areas within the images, enhancing the model's ability to focus on relevant regions. Combining deep learning models for classification with the help of image segmentation is a comprehensive approach that holds immense promise for accurate and efficient potato disease detection. In summary, this research aims to bridge the gap between traditional disease diagnosis methods and modern technological advancements in agriculture. By harnessing the power of DL and image segmentation, we seek to develop a robust framework for automated potato disease detection, empowering farmers with timely and actionable insights for crop management.

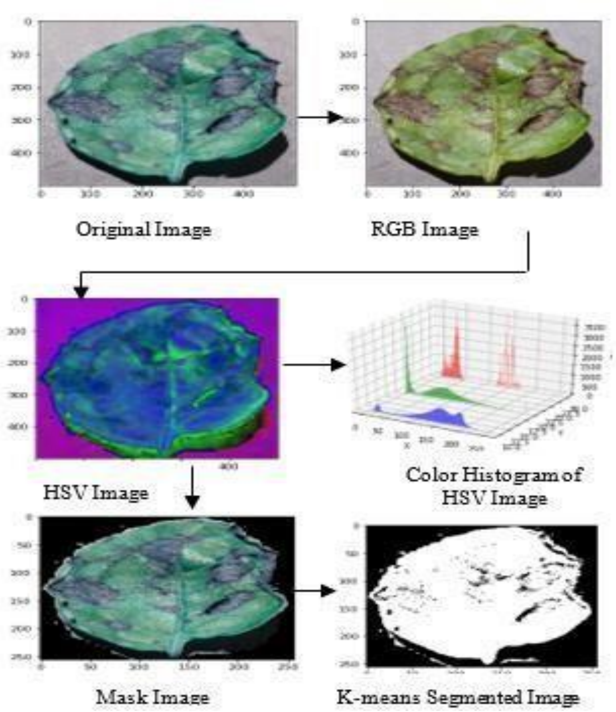

Figure 1. Colour Space Conversion Representation, (a) BGR, (b) RGB, (c) HSV, (d) Color Histogram of HSV Image, and (e) Mask Image

2. RESEARCH CONTRIBUTION

This research contributes significantly to potato disease detection by utilising a deep neural network (DNN) based on the Plant-Village dataset and image segmentation techniques. The key contributions of the study are outlined as follows: Firstly, a specialised dataset comprising 450 potato leaf images categorised into Early Blight (EB), Late Blight (LB), and healthy classifications was meticulously constructed. This tailored dataset serves as a valuable resource for potato disease detection research. Secondly, a comprehensive preprocessing pipeline was implemented, encompassing multiple steps such as resizing, colour space transformations, and segmentation techniques like K-means. This approach significantly enhanced the quality and relevance of the dataset for subsequent machine-learning tasks. Thirdly, a DNN architecture was developed and fine-tuned with specified parameters, including batch size, epochs, loss function, and optimiser. This tailored DNN model demonstrated high accuracy and efficiency in classifying potato leaf diseases.

Furthermore, the proposed DNN model underwent thorough evaluation using various performance metrics such as accuracy, sensitivity, F1 score, precision, and specificity. This comprehensive assessment provided valuable insights into the effectiveness of the model. Moreover, a comparative analysis was conducted, contrasting the performance of the proposed DNN model with base models like KNN, Random Forest, and Logistic Regression. This comparison highlighted deep learning techniques' superiority in classifying potato leaf disease. Additionally, the research identified key gaps related to dataset variability, disease class diversity, and model interpretability. By positioning the study within the broader context of existing research, the groundwork was laid for future research directions. Finally, graphical representations, including data distribution graphs, accuracy curves, and confusion matrices, were incorporated to visually communicate the experimental results effectively, enhancing the overall impact and clarity of this paper.

3. LITERATURE REVIEW

While commendable, the existing research on potato leaf disease detection exhibits certain gaps that merit further exploration. These gaps include a potential limitation in dataset variability, often confined to specific regions or databases, which may impede the model's generalisation to diverse environmental conditions and disease manifestations. Additionally, studies often focus on binary classifications or a subset of diseases, overlooking the broader spectrum of diseases affecting potato leaves. More extensive datasets encompassing diverse geographical locations, potato varieties, and environmental factors are needed to promote robust model performance across varied scenarios. Addressing these gaps would create more versatile and accurate PLD detection models with practical applicability in agricultural settings.

4. RESEARCH METHODOLOGY

This section outlines a sequence of image processing techniques commonly employed in machine learning and computer vision applications. Initially, the images are resized to a uniform dimension, typically 500 x 500 pixels, to establish consistency within the dataset.

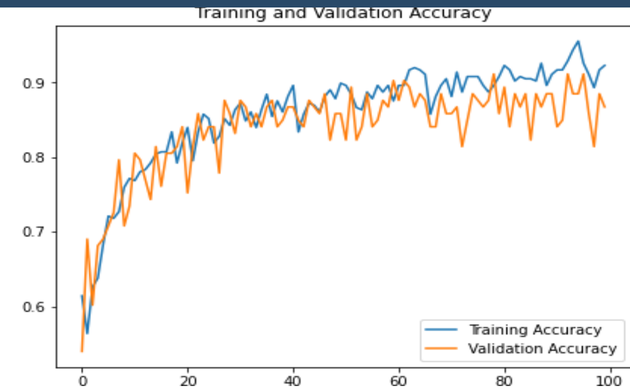

Figure 2. DNN Accuracy Curve for Training and Validation

Following this, a conversion from the BGR colour space, commonly used in OpenCV, to RGB ensures a consistent representation of colour information across all images. Subsequently, the RGB images convert to the HSV (Hue, Saturation, Value) colour space, facilitating the separation of intensity and colour details. Image masking is then applied to the HSV images, where a defined mask is utilised to isolate relevant areas while excluding extraneous background, enabling the model to concentrate on the leaf itself. Finally, K-Means segmentation is employed to partition and accentuate distinct regions within the images further, potentially aiding in detecting disease-specific patterns.

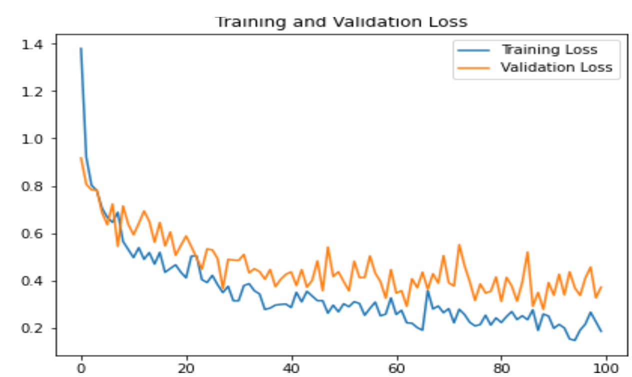

Figure 3. DNN Plotting loss curve of train and validation

5. CLASSIFICATION MODEL

The classification model employed in the deep neural network (DNN) encompasses fully connected layers, where each neuron establishes a comprehensive link to all learning-optimised feature maps from the preceding DNN layer. Through these interconnected layers and the activation function, class scores are computed. This classifier receives an input vector of optimised features derived from the fitness function optimisation approach. It generates a probability indicating the most likely disease class for a given image of a plant leaf. The DNN's multi-neuron structure comprises layers of neurons, facilitating the transmission of information between successive layers. These neurons acquire the capability to translate sensory input into meaningful behaviour.

Additionally, this work outlines the parameters for building and training the deep neural network, focusing on designing a suitable DNN architecture for Potato Leaf Disease (PLD) classification. Key hyperparameters such as batch size, set to 64 to update the model based on 64 images per training iteration, and epochs, trained over 100 iterations to feed the full training dataset into the network, are defined. The categorical cross-entropy loss function minimises the discrepancy between distributions in multi-class classification tasks. Furthermore, the Adam Optimiser is employed due to its flexible learning rate, which optimises the training process by adjusting learning rates for each variable. These hyperparameters are critical for optimising the model's performance during training and inference.

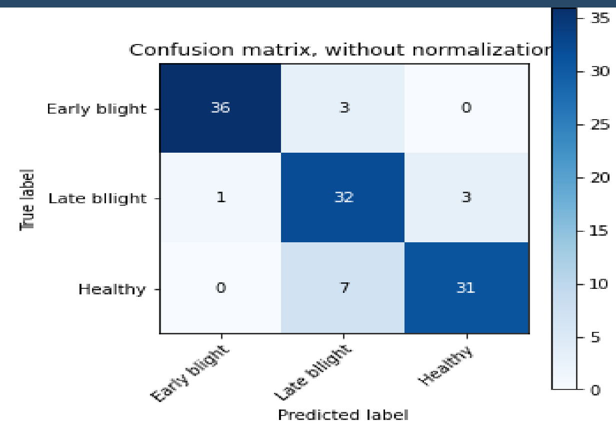

Figure 4. DNN Confusion matrix without normalisation

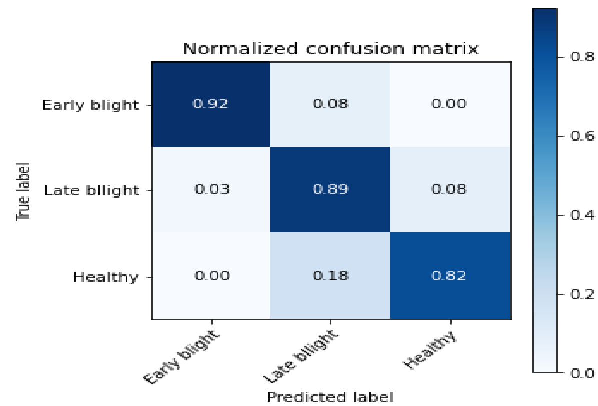

Figure 5. DNN Confusion matrix with normalisation

Table 1. Classification report of Proposed DNN model

	precision	recall	f1-score	support
Early blight	0.97	0.92	0.95	39
Late bllight	0.76	0.89	0.82	36
Healthy	0.91	0.82	0.86	38
accuracy			0.88	113
macro avg	0.88	0.88	0.88	113
weighted avg	0.89	0.88	0.88	113

Table 2. DNN Model Parameters Performance

Performance	DNN
Accuracy (Training)	98.52
Accuracy (Testing)	87.61
F1 score	88
Precision	89
Sensitivity	92.3
Specificity	96.96

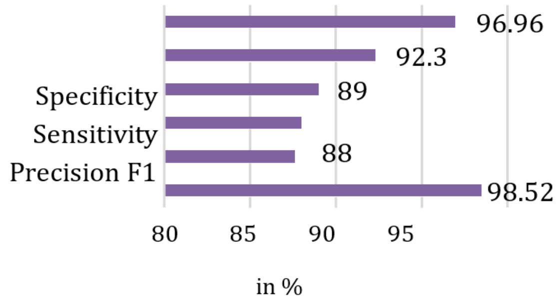

Figure 6. represents the performance of the DNN Model.

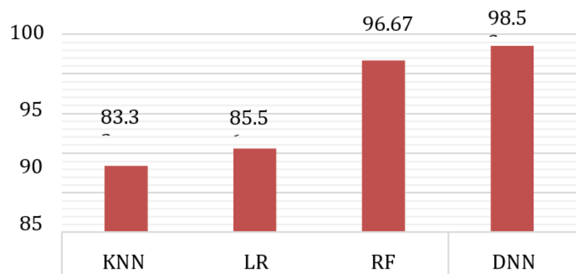

Figure 7. Accuracy Comparison Between Baseline Model and Proposed DNN Model

6. RESULTS AND ANALYSIS

The performance evaluation of the deep neural network (DNN) model for potato leaf disease (PLD) classification is presented herein, utilising various performance metrics and visualisations to assess its efficacy. The DNN model achieves remarkable accuracy, with 98.52% on the training dataset and 87.61% on the testing dataset, indicating its proficiency in correctly classifying potato leaf diseases. Additionally, with a precision of 89%, the model demonstrates the ability to accurately classify positive instances (i.e., diseased potato leaves) without misclassifying healthy leaves. High sensitivity, also known as recall, is exhibited by the model at 92.3%, signifying its capability to correctly identify most diseased instances in the dataset. The F1 score, a harmonic mean of precision and recall, is reported at 88%, reflecting the overall balance between precision and recall, which is crucial for robust disease classification. Moreover, the model's specificity is notably high at 96.96%, indicating its proficiency in correctly identifying negative instances (i.e., healthy leaves) without misclassifying diseased leaves. Figure 2 depicts the accuracy curve for training and validation datasets, showcasing the model's learning progress over epochs. A steady increase in accuracy on both datasets signifies effective learning without overfitting. Figure 3 illustrates the loss curve for training and validation datasets, demonstrating the model's convergence during training. A decreasing trend in loss indicates successful optimisation of the model parameters. Figures 4 and 5 present the confusion matrices with and without normalisation. These matrices visually represent the model's classification performance across different disease classes, where diagonal elements represent correctly classified instances and off-diagonal elements indicate misclassifications. Figure 7 compares the accuracy between the baseline models and the proposed DNN model, highlighting the latter's superiority in PLD classification compared to traditional machine learning approaches. The high accuracy, precision, recall, and specificity achieved by the DNN model validate its efficacy in accurately classifying potato leaf diseases. The F1 score reflects a balanced trade-off between precision and recall, which is essential for robust disease detection. Visualisations such as accuracy curves and confusion matrices provide insights into the model's performance across different disease classes, aiding in result interpretation and validation. The comprehensive evaluation of the DNN model demonstrates its effectiveness in potato leaf disease classification, paving the way for practical applications in agriculture. The reported performance metrics and visualisations offer valuable insights into the model's strengths and limitations, guiding future research and development in this domain.

7. CONCLUSION AND FUTURE WORK

The deep neural network (DNN) model, employing the Adam optimiser, a batch size of 64, 100 epochs, and categorical cross-entropy loss, achieves impressive performance metrics, with training and testing accuracies of 98.52% and 87.61%, respectively. These results underscore its effectiveness in accurately classifying potato leaf diseases, demonstrating high precision (89%), recall (92.3%), F1 score (88%), and specificity (96.96%). The model's superior performance notably surpasses traditional machine learning approaches, as evidenced by comparison plots. Future research avenues include enhancing dataset diversity to improve model generalisation across varied environmental conditions and disease manifestations. Additionally, efforts to enhance model interpretability and real-world deployment are crucial for practical applicability in agriculture. Addressing these aspects will contribute to developing more versatile and accurate disease-detection models for potato leaf. The comprehensive evaluation of the proposed DNN model provides valuable insights into its strengths and limitations, guiding further advancements in this domain.

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