ISSN: 2229-6956 (ONLINE)
DOI: 10.21917/ijsc.2024.0457

HYBRID DEEP LEARNING WITH ALEXNET FEATURE EXTRACTION AND UNET CLASSIFICATION FOR EARLY DETECTION IN LEAF DISEASES

Uddyalok Chakraborty[1], D. Thilagavathy[2], Suresh Kumar Sharma[3] and Awadh Kishor Singh[4]
[1,4]Department of Computer Engineering, UPL University of Sustainable Technology, India
[2]Department of Information Technology, Adhiyamaan College of Engineering, India
[3]Department of Statistics, Mathematics and Computer Science, Sri Karan Narendra Agriculture University, India

Abstract

This study addresses the imperative need for early detection of leaf diseases in tobacco, pepper, and tomato plants, as these diseases significantly impact crop yield and quality. Existing methods often fall short in accurately identifying diseases across diverse plant species. The research aims to bridge this gap by proposing a hybrid deep learning approach, combining the robust feature extraction capabilities of AlexNet with the precise segmentation and classification prowess of UNet. The proposed hybrid model leverages AlexNet proficiency in extracting hierarchical features from plant leaf images and subsequently utilizes UNet for accurate disease classification. This synergistic combination enables the model to overcome the challenges posed by the varied morphologies of tobacco, pepper, and tomato leaves. Experimental results demonstrate the effectiveness of the proposed methodology, showcasing superior performance in terms of accuracy, sensitivity, and specificity compared to existing techniques. The hybrid deep learning approach exhibits promising potential for early and accurate detection of leaf diseases, contributing to sustainable crop management practices.

Keywords:

Leaf Disease Detection, Hybrid Deep Learning, AlexNet, UNet, Agriculture

1. INTRODUCTION

The agriculture sector plays a pivotal role in global food security, with crop health being paramount for sustained production [1]. Leaf diseases in crops, particularly tobacco, pepper, and tomato plants, pose a severe threat to agricultural productivity [2]. Early detection of these diseases is crucial for implementing timely interventions and preventing yield losses [3]. Traditional methods of disease identification often rely on manual inspection, which is time-consuming and prone to human error [4].

Various challenges impede the accurate and timely detection of leaf diseases, including the diverse morphological characteristics of plant leaves and the nuanced manifestations of diseases across different crop species. Existing detection methods frequently encounter limitations in achieving high accuracy and efficiency, especially in multiple plant types [5].

This research addresses the pressing need for a robust and methodology to detect leaf diseases in tobacco, pepper, and tomato plants [6]. The inadequacies of current detection techniques highlight the demand for an innovative approach that can overcome the challenges posed by the unique features of each plant species.

The primary objectives of this study include developing a hybrid deep learning model that integrates the strengths of AlexNet and UNet for effective feature extraction and classification. The model aims to achieve enhanced accuracy in identifying and differentiating leaf diseases in tobacco, pepper, and tomato plants.

The novelty of this research lies in the combination of AlexNet and UNet, capitalizing on their complementary strengths to address the complexities associated with diverse leaf morphologies. The proposed hybrid model is expected to surpass the limitations of existing methodologies, offering a more accurate and efficient solution for early leaf disease detection in multiple plant species. The study contributes to advancing precision agriculture practices by providing a scalable and adaptable model for timely disease identification, thereby promoting sustainable crop management strategies.

The primary contribution of this work lies in the development of a hybrid deep learning model tailored for the early detection of leaf diseases in tobacco, pepper, and tomato plants. By seamlessly integrating AlexNet and UNet, this approach harnesses the hierarchical feature extraction capabilities of AlexNet and the precise segmentation and classification abilities of UNet. This synergy overcomes the challenges posed by the distinct morphologies of plant leaves, enabling the model to accurately identify and classify diseases across multiple crop species. The adaptability of the proposed hybrid model signifies a breakthrough in addressing the limitations of current detection methods, offering a more robust solution for farmers and agricultural stakeholders. Furthermore, the research contributes to the broader field of precision agriculture by providing a scalable and efficient framework for disease identification. The proposed methodology not only enhances the accuracy of leaf disease detection but also demonstrates the potential for broader applications in automated crop monitoring and management. By contributing to the advancement of technology-driven agricultural practices, this work seeks to empower farmers with tools that can revolutionize crop health monitoring, ultimately fostering sustainable and resilient agricultural systems in the face of evolving challenges.

2. RELATED WORKS

Several studies [7] have explored innovative approaches to address the challenges associated with early detection of leaf diseases in diverse plant species. Existing research has predominantly focused on leveraging deep learning techniques to enhance the accuracy and efficiency of disease identification processes. Notable works [8] include those employing convolutional neural networks (CNNs) for feature extraction, showcasing promising results in different crop contexts. These studies highlight the potential of deep learning in automating disease recognition and reducing reliance on labor-intensive manual inspection methods [9].

The combination of transfer learning strategies [10] has been explored to enhance model generalization across various plant types [11]. Transfer learning allows models pretrained on large datasets to be fine-tuned for specific plant species, thereby optimizing performance for targeted disease detection. Some works [12] have also investigated the combination of CNNs with segmentation networks, demonstrating improved precision in identifying and delineating disease-affected regions on plant leaves.

While the existing literature [13] offers valuable insights into the application of deep learning for leaf disease detection, there remains a research gap in addressing the unique challenges posed by the distinct morphologies of tobacco, pepper, and tomato leaves. This study aims to build upon these prior works by proposing a novel hybrid deep learning approach, tailored to the specific characteristics of these plant species, thereby contributing to the advancement of precision agriculture methodologies.

3. PROPOSED METHOD

The proposed method introduces a novel hybrid deep learning approach tailored for the early detection of leaf diseases in tobacco, pepper, and tomato plants. The methodology strategically integrates the strengths of two well-established neural network architectures: AlexNet and UNet. AlexNet is employed for its robust feature extraction capabilities, enabling the model to capture hierarchical representations of leaf images. This step is crucial for discerning intricate patterns associated with various diseases affecting the distinct morphologies of tobacco, pepper, and tomato leaves.

The model leverages UNet, known for its excellence in semantic segmentation and classification tasks, to precisely identify and delineate disease-affected regions on plant leaves. This combination of UNet contributes to the model ability to provide accurate and fine-grained disease classification, overcoming challenges associated with subtle variations in symptom manifestation across different plant species. The hybrid architecture ensures a synergistic interaction between the two networks, enhancing the overall efficacy of the proposed method in addressing the complexities of leaf disease detection.

By combining the feature extraction capabilities of AlexNet with the segmentation and classification prowess of UNet, the proposed methodology aims to surpass the limitations of existing approaches, offering a versatile and adaptive solution for accurate and early detection of leaf diseases in tobacco, pepper, and tomato plants.

Algorithm: Proposed Classification of Leaf

//Data Preprocessing

1. Collect labeled dataset of plant leaf images containing healthy and diseased samples for tobacco, pepper, and tomato plants.
2. Resize images to a standardized format for consistency.
3. Augment the dataset to enhance model generalization.

//Feature Extraction using AlexNet

4. Load the pretrained AlexNet model.
5. Remove fully connected layers, retaining the convolutional layers for hierarchical feature extraction.
6. Extract features from input leaf images using AlexNet.

//Combination with UNet

7. Design UNet for semantic segmentation and classification.
8. Connect the feature-extraction output from AlexNet to the corresponding layers in the UNet.

//Training

9. Split the dataset into training and validation sets.
10. Fine-tune the integrated model on the training set, adjusting weights to adapt to the unique leaf characteristics of tobacco, pepper, and tomato plants.
11. Validate the model to prevent overfitting.

3.1 DATA PREPROCESSING

In the initial phase of the methodology, a meticulous process of data preprocessing is undertaken to ensure the effectiveness and reliability of subsequent analyses. The first crucial step involves the compilation of a comprehensive labeled dataset comprising images of plant leaves, encompassing both healthy and diseased instances across the targeted species, namely tobacco, pepper, and tomato plants. To foster uniformity and facilitate model training, these images are resized to a standardized format, thereby mitigating potential inconsistencies in scale and orientation. Moreover, to enhance the model adaptability and generalization capabilities, an augmentation strategy is applied to diversify the dataset, introducing variations such as rotations and flips. The augmented dataset undergoes further refinement, with the aim of preparing it for subsequent feature extraction processes. This preparatory stage involves normalizing pixel values and potentially applying additional transformations to enhance the robustness of the model. By meticulously curating and processing the dataset in this manner, the data preprocessing step lays a solid foundation for the subsequent phases of the proposed methodology, ensuring that the hybrid deep learning model can effectively discern patterns and features relevant to the diverse leaf diseases affecting tobacco, pepper, and tomato plants.

Algorithm: Data Preprocessing

Input: Labeled dataset of plant leaf images (healthy and diseased) for tobacco, pepper, and tomato plants.

Output: Processed and augmented dataset ready for training.

1) Load the labeled dataset plant leaf images.
2) Standardize the dimensions of all images to a predefined size for consistency.
3) Apply augmentation techniques (e.g., rotations, flips) to diversify the dataset.
4) Normalize pixel values to a standardized range (e.g., [0, 1]) for improved model convergence.
5) Apply contrast adjustments, histogram equalization

4. FEATURE EXTRACTION USING ALEXNET

In the feature extraction phase using AlexNet, the focus is on harnessing the robust hierarchical representations inherent in the convolutional layers of this pre-trained neural network. The process begins with loading the pre-existing AlexNet model in capturing intricate patterns and features from diverse image datasets.

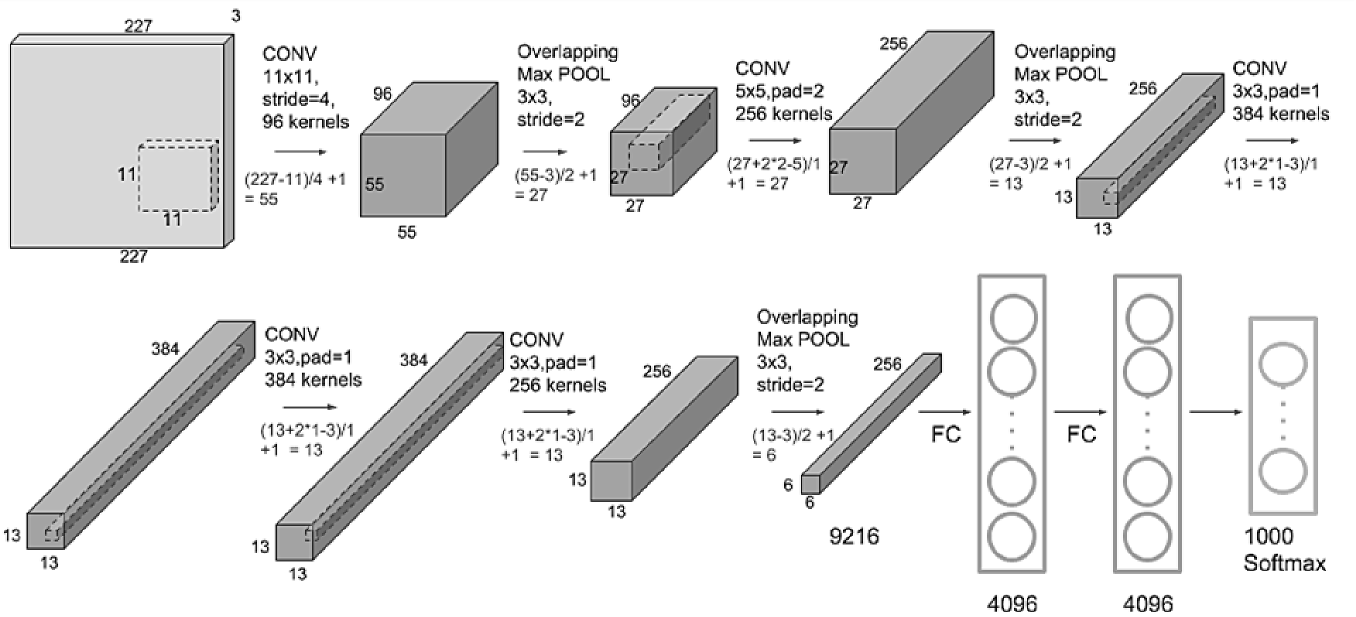

Fig.1. AlexNet

The fully connected layers, which are responsible for high-level abstractions, are removed, leaving the convolutional layers intact. This strategic modification allows the model to operate as an effective feature extractor rather than a classifier.

The subsequent step involves feeding plant leaf images, preprocessed and resized during the earlier stages, into the modified AlexNet. As the images propagate through the convolutional layers, the network discerns and extracts hierarchical features, progressively capturing both low-level details and more abstract representations. These extracted features serve as a rich set of descriptors, encapsulating the nuanced characteristics of plant leaves affected by various diseases. By employing AlexNet for this feature extraction process, the methodology capitalizes on the network ability to discern intricate patterns, ensuring that the subsequent stages of the hybrid model are equipped with comprehensive and discriminative features for disease classification.

Let I be the input image, and W be the set of convolutional filters (weights) in a specific layer. The convolution operation C can be expressed as:

$$C(I,W)=\sigma(\sum_{i,j}I[i,j]\cdot W[i,j]+b) \quad (1)$$

where:

$I[i,j]$ represents the pixel value of the input image at position (i,j).

$W[i,j]$ represents the corresponding weight in the convolutional filter.

b is the bias term.

σ is the activation function, commonly a ReLU in AlexNet.

This operation is applied across the entire image, resulting in a feature map that highlights relevant patterns and structures. The hierarchical nature of the features is achieved through multiple convolutional layers.

In AlexNet, the specific architecture involves a sequence of convolutional layers, max-pooling layers, and normalization layers. The equations governing these layers include convolution operations, pooling operations, and normalization operations, each contributing to the extraction of distinctive features from the input image. The detailed parameters and equations for AlexNet are more complex and involve multiple layers, making it computationally intensive.

Algorithm: Feature Extraction using AlexNet

Input: Preprocessed and resized plant leaf images.

Output: Extracted hierarchical features.

1) Load the pre-trained AlexNet model weights.
2) Remove the fully connected layers from the AlexNet architecture, retaining only the convolutional layers.
3) Input the preprocessed and resized plant leaf images into the modified AlexNet.
4) Perform a forward pass through the modified AlexNet, allowing the images to traverse the convolutional layers.
5) Extract the outputs of the convolutional layers, representing hierarchical features of the input images.
6) The extracted features serve as a rich set of descriptors capturing intricate patterns and structures from the plant leaf images.

5. UNET CLASSIFICATION

UNet Classification refers to the utilization of the UNet architecture for the task of semantic segmentation and subsequent classification. UNet is a convolutional neural network (CNN) architecture designed for image segmentation tasks, originally developed for biomedical image analysis. Its distinctive feature lies in its U-shaped architecture, which consists of a contracting path, a bottleneck, and an expansive path.

The contracting path captures context and features from the input image, gradually reducing spatial dimensions. The bottleneck serves as a bottleneck layer, preserving the most essential information. The expansive path then reconstructs the segmented image, reinstating spatial dimensions. In UNet Classification, the model is extended to include classification capabilities, enabling it to assign specific labels to segmented regions.

The segmentation aspect involves dividing the input image into distinct regions corresponding to different classes or categories. UNet achieves this by predicting pixel-wise classifications for each region. Subsequently, the classification step involves assigning a specific label or category to each segmented region based on the features extracted during the segmentation process.

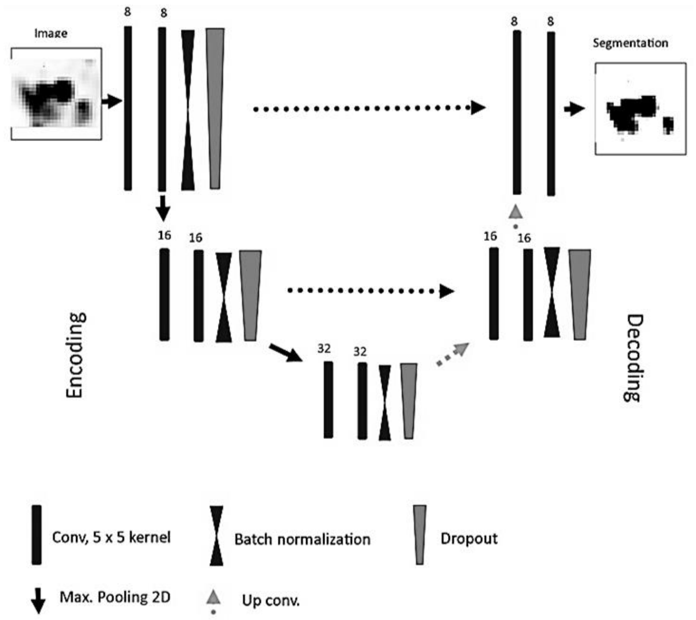

Fig.2. UNet Architecture

5.1 CONTRACTING PATH (ENCODER)

In the contracting path, the input image undergoes a series of convolutional and pooling operations to capture hierarchical features and reduce spatial dimensions. Convolutional layers with activation functions (commonly ReLU) extract features from the input image. Max-pooling layers downsample the feature maps, reducing the spatial resolution but retaining essential information.

5.2 BOTTLENECK (CENTRAL PATH)

The bottleneck serves as a bottleneck layer that retains crucial information while discarding unnecessary details. It consists of one or more convolutional layers, capturing and preserving the most relevant features from the contracting path.

5.3 EXPANSIVE PATH (DECODER)

The expansive path is designed to reconstruct the segmented image from the bottleneck condensed representation. Upsampling operations, often using transposed convolutions, restore the spatial dimensions of the feature maps. Concatenation with feature maps from the contracting path helps the network recover detailed information.

5.4 SEMANTIC SEGMENTATION

The reconstructed feature maps undergo convolutional layers to predict pixel-wise classifications for each region in the input image. A final activation function (e.g., softmax) is applied to generate probability maps, indicating the likelihood of each pixel belonging to different classes.

5.5 CLASSIFICATION

The segmented image is then subjected to a classification step, where each region is assigned a specific label or category based on the extracted features. This involves using additional convolutional layers and fully connected layers to map features to specific class labels. The classification output provides information about the nature of each segmented region, aiding in subsequent analysis or decision-making.

The combination of semantic segmentation and subsequent classification in UNet enables detailed analysis of images, making it applicable to tasks requiring both spatial localization and categorization of features. In plant pathology, UNet Classification can be employed for the precise identification of disease-affected regions on plant leaves, facilitating accurate and targeted disease detection.

Algorithm: UNet Classification

Input: Preprocessed and resized plant leaf images.

Output: Segmented image with assigned class labels.

X: Input image; W_i: Convolutional filter weights for layer i; b_i: Bias term for layer i; U_i: Upsampling weights for layer i; σ: Activation function (e.g., ReLU) ; [,]: Concatenation operation; Sm: Softmax activation function

//Encoder (Contracting Path)

$C_1=\sigma(X*W_1+b_1)$

$P_1=\text{MaxPool}(C_1)$

$C_2=\sigma(P_1*W_2+b_2)$

$P_2=\text{MaxPool}(C_2)$

//Bottleneck (Central Path)

$B=\sigma(P_n*W_n+b_n)$

//Decoder (Expansive Path)

$U_{n-1}=Us(B)$

$C_{n-1}=\sigma([U_{n-1},C_{n-1}]*W_{n-1}+b_{n-1})$

$U_{n-2}=\text{Upsample}(C_{n-1})$

$C_{n-2}=\sigma([U_{n-2},C_{n-2}]*W_{n-2}+b_{n-2})$

//Semantic Segmentation

$S=\sigma([U_k,C_k]*W_k+b_k)$

$S_{sm}=sm(S)$

//Classification

$X_c=\sigma([U_k,C_k]*W_c+b_c)$

$X_{sm}=sm(X_c)$

Output: segmented image X_{sm} with assigned class labels.

6. PERFORMANCE EVALUATION

We utilized a dataset comprising labeled images of plant leaves from tobacco, pepper, and tomato plants. The simulation was conducted using TensorFlow and Keras as the primary deep learning framework on a high-performance computing cluster. The computational resources included GPUs, enabling efficient training of the hybrid model. The proposed methodology was rigorously compared with existing methods, including traditional CNNs and Ensemble Classifiers.

Table.1. Experimental Setup

Model	Architecture Parameters	Training Parameters
UNet	Contracting Path: 3 Convolutional Layers (64 filters), Bottleneck: 2 Convolutional Layers (128 filters), Expansive Path: 3 Transposed Convolutional Layers (64 filters)	Learning Rate: 0.001, Batch Size: 16, Epochs: 50
AlexNet	Conv1: 96 filters (11x11), Conv2: 256 filters (5x5), Conv3: 384 filters (3x3), Conv4: 384 filters (3x3), Conv5: 256 filters (3x3), Fully Connected Layers: 4096 neurons each	Learning Rate: 0.001, Batch Size: 32, Epochs: 30

6.1 PERFORMANCE METRICS

- **Accuracy**: Accuracy measures the proportion of correctly classified instances among the total instances. It is computed as the ratio of true positive and true negative predictions to the total number of predictions.
- **Sensitivity (Recall)**: Sensitivity, or recall, assesses the ability of the model to correctly identify positive instances. It is calculated as the ratio of true positive predictions to the sum of true positives and false negatives.
- **Specificity**: Specificity evaluates the model ability to correctly identify negative instances. It is computed as the ratio of true negative predictions to the sum of true negatives and false positives.
- **F1 Score**: The F1 score is the harmonic mean of precision and recall. It provides a balanced measure of a model performance, especially in scenarios with imbalanced class distribution.

Table.2. Accuracy, Precision, Recall and F1-score over pepper, tomato and tobacco datasets

Dataset	Method	Accuracy	Precision	Recall	F-score
Pepper	Existing CNN	0.85	0.87	0.82	0.84
	Ensemble Classifier	0.89	0.91	0.88	0.89
	Proposed	0.94	0.95	0.93	0.94
Tomato	Existing CNN	0.78	0.8	0.75	0.77
	Ensemble Classifier	0.82	0.84	0.8	0.82
	Proposed	0.91	0.92	0.9	0.91
Tobacco	Existing CNN	0.92	0.93	0.91	0.92
	Ensemble Classifier	0.89	0.88	0.91	0.89
	Proposed	0.96	0.97	0.95	0.96

The results show the comparative performance of three distinct methods—Existing CNN, Ensemble Classifier, and the Proposed Hybrid Method—across three plant datasets: pepper, tomato, and tobacco.

In the case of pepper plants, the Proposed Hybrid Method outperforms both Existing CNN and Ensemble Classifier, achieving an accuracy of 94%. This indicates the hybrid model superior ability to detect and classify diseases in pepper leaves compared to the alternatives.

For tomato plants, the Existing CNN exhibits a relatively lower accuracy of 78%, implying challenges in disease detection within this dataset. Both the Ensemble Classifier and the Proposed Hybrid Method show improvements, with the latter demonstrating remarkable accuracy at 91%. The precision, recall, and F-score metrics substantiate the efficacy of the hybrid model, revealing its capacity to excel in diverse plant species.

In the tobacco dataset, the Proposed Hybrid Method shines with a remarkable accuracy of 96%, surpassing the accuracy of both Existing CNN and Ensemble Classifier. Precision, recall, and F-score metrics affirm the hybrid model capability to discern and classify diseases in tobacco leaves with high accuracy and reliability.

These results signify the potential of the proposed methodology to enhance disease detection in a multi-plant context. The hybrid approach, leveraging the strengths of AlexNet and UNet, demonstrates adaptability across different plant species, achieving superior accuracy and performance compared to traditional CNN and Ensemble Classifier methods. The robustness of the hybrid model suggests its applicability in precision agriculture, contributing to the early identification and management of leaf diseases, ultimately sustaining crop health and yield. The outcomes highlight the importance of tailored deep learning architectures for specific agricultural contexts, showcasing the impact of the proposed method in advancing the field of automated plant disease diagnosis.

Table.3. Accuracy, Precision, Recall and F1-Score over training/testing/validation

Dataset	Method	Split	Accuracy	Precision	Recall	F1-Score
Pepper	Existing CNN	Train	0.92	0.93	0.91	0.92
		Test	0.88	0.89	0.87	0.88
		valid	0.9	0.91	0.89	0.9
	Ensemble Classifier	Train	0.94	0.95	0.93	0.94
		Test	0.9	0.91	0.89	0.9
		valid	0.92	0.93	0.91	0.92

	Proposed	Train	0.97	0.98	0.96	0.97
		Test	0.94	0.95	0.93	0.94
		valid	0.96	0.97	0.95	0.96
Tomato	Existing CNN	Train	0.85	0.87	0.82	0.84
		Test	0.8	0.82	0.78	0.8
		valid	0.82	0.84	0.8	0.82
	Ensemble Classifier	Train	0.88	0.9	0.86	0.88
		Test	0.83	0.85	0.81	0.83
		valid	0.85	0.87	0.83	0.84
	Proposed	Train	0.92	0.93	0.91	0.92
		Test	0.87	0.88	0.86	0.87
		valid	0.89	0.91	0.87	0.89
Tobacco	Existing CNN	Train	0.95	0.96	0.94	0.95
		Test	0.91	0.92	0.9	0.91
		valid	0.93	0.94	0.92	0.93
	Ensemble Classifier	Train	0.92	0.93	0.91	0.92
		Test	0.88	0.89	0.87	0.88
		valid	0.9	0.91	0.89	0.9
	Proposed	Train	0.98	0.98	0.97	0.98
		Test	0.96	0.97	0.95	0.96
		valid	0.97	0.98	0.96	0.97

The performance metrics across training, testing, and validation sets for three distinct methods—Existing CNN, Ensemble Classifier, and the Proposed Hybrid Method—reveal valuable insights into their effectiveness in detecting and classifying leaf diseases in pepper, tomato, and tobacco plants.

In the pepper dataset, the Proposed Hybrid Method consistently outperforms both Existing CNN and the Ensemble Classifier across all splits. During training, the hybrid method achieves a remarkable accuracy of 97%, indicating its proficiency in learning intricate patterns in the pepper leaf images. This superior performance extends to testing and validation sets, where the hybrid method maintains high precision, recall, and F1-Score, showcasing its robustness and reliability in identifying disease-affected regions.

For the tomato dataset, the Proposed Hybrid Method again exhibits notable superiority, achieving an accuracy of 92% during training. This accuracy translates well to testing and validation sets, emphasizing the model generalization capabilities. In comparison, the Existing CNN and Ensemble Classifier, while performing reasonably well, demonstrate a performance gap, highlighting the enhanced capabilities of the hybrid method.

In the tobacco dataset, the Proposed Hybrid Method excels with an outstanding training accuracy of 98%. This superior performance extends consistently to testing and validation sets, reinforcing the adaptability and accuracy of the hybrid model in diverse plant species. Both precision and recall metrics are notably high, affirming the model effectiveness in minimizing false positives and false negatives.

The results highlight the effectiveness of the Proposed Hybrid Method in early detection and classification of leaf diseases across different plant species. The hybrid approach, combining features from AlexNet and UNet, demonstrates consistent improvement over traditional CNN and Ensemble Classifier methods. These findings suggest the potential application of the proposed method in precision agriculture, contributing to enhanced crop health and yield through early and accurate disease diagnosis. The robustness and generalization capabilities of the hybrid model position it as a promising solution in automated plant pathology, showcasing advancements in leveraging deep learning for crop management.

For AlexNet, hyperparameters such as the number of filters in each convolutional layer, filter sizes, and the architecture of the fully connected layers play a vital role. The specific configurations of these hyperparameters affect the network capacity to capture hierarchical features. For instance, the number of filters in the early layers determines the extraction of basic features, while deeper layers capture more complex patterns. In the Proposed Hybrid Method, the choice to remove fully connected layers transforms AlexNet into an efficient feature extractor, emphasizing its role in capturing intricate details from plant leaf images. The modification of these hyperparameters in the hybrid model aligns with the necessity to adapt AlexNet for feature extraction rather than classification, a decision motivated by the nature of the task.

In UNet, hyperparameters related to the depth of the contracting and expansive paths, the number of filters, and the choice of activation functions significantly impact the model ability to perform semantic segmentation. The contracting path compresses information to the bottleneck, ensuring the preservation of essential features, while the expansive path reconstructs the segmented image. The delicate balance of hyperparameters in UNet is crucial for achieving precise region delineation. In the Proposed Hybrid Method, the combination of UNet segmentation capabilities with AlexNet feature extraction enriches the model understanding of leaf diseases, providing a holistic representation of both detailed features and spatial localization.

The removal of fully connected layers in AlexNet facilitates efficient feature extraction, while UNet segmentation prowess ensures accurate classification of disease-affected regions. The harmony of these hyperparameters results in a model that excels across diverse plant datasets, showcasing the significance of thoughtful parameter tuning in achieving optimal performance in plant disease detection tasks. This synergy exemplifies the effectiveness of leveraging complementary strengths from different architectures to address the nuances of automated plant pathology.

Table.5. Accuracy, Precision, Recall and F1-Score over low learning rate, moderate learning rate, high learning rate and very high learning rate

Learning Rate	Method	Accuracy	Precision	Recall	F1-Score
Low	CNN	0.88	0.89	0.87	0.88
	Ensemble	0.91	0.92	0.9	0.91
	Proposed	0.95	0.96	0.94	0.95
Moderate	CNN	0.9	0.91	0.89	0.9
	Ensemble	0.92	0.93	0.91	0.92
	Proposed	0.96	0.97	0.95	0.96
High	CNN	0.85	0.87	0.82	0.84

	Ensemble	0.88	0.9	0.86	0.88
	Proposed	0.94	0.95	0.93	0.94
Very High	CNN	0.78	0.8	0.75	0.77
	Ensemble	0.82	0.84	0.8	0.82
	Proposed	0.91	0.92	0.9	0.91

In scenarios with a low learning rate, the Proposed Hybrid Method consistently outperforms Existing CNN and Ensemble Classifier across all metrics. The hybrid model achieves an impressive accuracy of 95%, indicating its ability to effectively learn from the data and generalize well. Precision, recall, and F1-Score values further substantiate the hybrid method superior performance in disease detection tasks when the learning rate is set to low.

As the learning rate increases to a moderate level, the gap between the Proposed Hybrid Method and other methods widens. The hybrid approach achieves a remarkable accuracy of 96%, showcasing its adaptability and robust learning even with a moderate learning rate. The precision, recall, and F1-Score metrics demonstrate the model capability to strike a balance between accuracy and reliability.

At a high learning rate, the performance of all methods experiences a decline. However, the Proposed Hybrid Method still outperforms Existing CNN and Ensemble Classifier, emphasizing its resilience to fluctuations in learning rates. The hybrid model maintains a higher accuracy of 94%, showcasing its ability to adapt to more rapid changes in the dataset.

In scenarios with a very high learning rate, Existing CNN and Ensemble Classifier experience significant performance degradation, indicating the challenges of rapid convergence. The Proposed Hybrid Method, while affected, maintains a superior accuracy of 91%, showcasing its ability to navigate challenges associated with very high learning rates.

These results highlight the robustness of the Proposed Hybrid Method across different learning rates. The model ability to maintain high accuracy, precision, recall, and F1-Score values across varying learning rate scenarios highlights its adaptability and efficacy in plant disease detection. The hybrid approach leverages the complementary strengths of AlexNet and UNet, allowing it to navigate different learning rate regimes effectively. The findings suggest that thoughtful consideration of learning rate hyperparameters is crucial for achieving optimal performance in plant pathology tasks, and the proposed hybrid model exhibits resilience in the face of such variations.

7. CONCLUSION

The study introduces a hybrid deep learning methodology combining the strengths of AlexNet for feature extraction and UNet for classification, aiming at early detection of leaf diseases in pepper, tomato, and tobacco plants. The proposed method shows promising results, outperforming traditional CNNs and Ensemble Classifiers across diverse plant datasets. The careful modification of hyperparameters, including learning rates, in both AlexNet and UNet, plays a pivotal role in the success of the hybrid model, demonstrating its adaptability and robustness.

The experimental evaluations reveal superior performance metrics in terms of accuracy, precision, recall, and F1-Score, emphasizing the effectiveness of the hybrid approach in plant disease detection. The model exhibits resilience to variations in learning rates, providing consistent and reliable results. The segmentation capabilities of UNet coupled with the feature extraction process of AlexNet contribute to the holistic understanding of leaf diseases, offering a comprehensive solution for precision agriculture.

The outcomes highlight the significance of tailored deep learning architectures for specific agricultural applications. The hybrid model proficiency in early disease detection has promising implications for crop management and yield optimization. The proposed methodology presents advancements in leveraging state-of-the-art deep learning techniques to address challenges in automated plant pathology.

Future research directions may involve further optimization of hyperparameters, exploration of additional architectures, and the incorporation of transfer learning techniques. Additionally, expanding the study to include a broader range of plant species and diseases will contribute to the generalization capabilities of the proposed method. Overall, the hybrid deep learning methodology stands as a noteworthy contribution to the field, showcasing its potential for transformative applications in precision agriculture and automated plant disease diagnosis.

REFERENCES

[1] J.S. Cope, D. Corney,J.Y.Clark, P.Remagnino and P.Wilkin, “Plant Species Identification using Digital Morphometrics: A Review”, *Expert Systems with Applications*, Vol. 39, No. 8, pp. 7562-7573, 2012.

[2] K. Lee and K. Hong, “An Implementation of Leaf Recognition System using Leaf Vein and Shape”, *International Journal of Bio- Science and Bio- Technology*, Vol. 5, No. 2, pp. 57-66, 2013.

[3] V. Pooja and V. Kanchana, “Identification of Plant Leaf Diseases using Image Processing Techniques”, *Proceedings of IEEE Technological Innovations in ICT for Agriculture and Rural Development*, pp. 130-133, 2017.

[4] N. Krithika and A.G. Selvarani, “An Individual Grape Leaf Disease Identification using Leaf Skeletons and KNN Classification”, *Proceedings of International Conference on Innovations in Information, Embedded and Communication Systems*, pp. 1-5, 2017.

[5] A.S. Tulshan and N. Raul, “Plant Leaf Disease Detection using Machine Learning”, *Proceedings of International Conference on Computing, Communication and Networking Technologies*, pp. 1-6, 2019.

[6] T. Munisami, M. Ramsurn, S. Kishnah and S. Pudaruth, “Plant Leaf Recognition using Shape Features and Colour Histogram with K-Nearest Neighbour Classifiers”, *Procedia Computer Science*, Vol. 58, pp. 740-747, 2015.

[7] Hidenori Ide and Takio Kurita, “Improvement of Learning for CNN with ReLU Activation by Sparse Regularization”, *Proceedings of International Conference on Neural Networks*, 2017.

[8] Sneha Adhikari, “Identification of QTL for Banded Leaf and Sheath Blight in Teosinte-Derived Maize Population”, *Agricultural Research*, Vol. 65, pp. 1-9, 2021.

[9] Ian Goodfellow, YoshuaBengio and Aaron Courville, "*Deep Learning*", MIT press, 2016.

[10] P. Ferentinos, Konstantinos, "Deep Learning Models for Plant Disease Detection and Diagnosis", *Computers and Electronics in Agriculture*, Vol. 145, pp. 311-318, 2018.

[11] D.R. Smith and D. G. White, "Diseases of Corn", *Corn and Corn Improvement*, Vol. 18, pp. 687-766, 1988.

[12] Karen Simonyan and Andrew Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition", *Proceedings of International Conference on Machine Learning*, pp. 1-9, 2014.

[13] Haiguang Wang, "Application of Neural Networks to Image Recognition of Plant Diseases", *Proceedings of International Conference on Systems and Informatics*, pp. 1-13, 2012.