International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Enhancing Feature Extraction in Plant Image Analysis through a Multilayer Hybrid DCNN

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Submitted: 28/05/2023 **Revised**: 07/07/2023 **Accepted**: 26/07/2023

Abstract: Plant image analysis plays a pivotal role across diverse domains such as agriculture, botany, and environmental monitoring. The accurate identification and classification of plant species from images are fundamental for tasks like biodiversity assessment, disease detection, and crop management. This study introduced an innovative approach to plant image analysis through the Multilayer Hybrid Deep Convolutional Neural Network (MHDCNN), a novel architecture that synergizes the strengths of CNN and LSTM. The objective is to amplify feature extraction capabilities and elevate classification accuracy, thereby achieving exceptional precision in plant species identification Various activation functions like “Tanh”, “ReLU”, “softmax”, and “sigmoid” are integrated into the architecture to impact learning dynamics. Extensive experiments using a diverse plant image dataset validate the approach. The MHDCNN achieves an impressive 99.8% classification accuracy, highlighting its effectiveness in handling complex plant images. By blending CNN + LSTM architectures and carefully selecting activation functions for enhanced feature extraction, this research advances plant image analysis techniques. This novel approach not only contributes to deep learning (DL) in plant biology but also paves the way for future innovations in image-based plant analysis methods.

Keywords: *Multilayer Hybrid Neural Network, Plant Image Analysis, Feature Extraction, Convolutional Neural Network, Activation Functions.*

1. Introduction

The application of DL techniques in a variety of fields has resulted in remarkable advancements in recent years, particularly in the areas of image analysis and pattern recognition. The field of plant disease detection and classification is one area that has benefited significantly from these advancements [1, 2]. [S]uch a field has become much more advanced as a result. Infectious diseases of plants represent a significant risk to the world's food supply, which in turn results in significant economic losses and environmental concerns. The prompt and accurate identification of plant diseases is essential to the successful implementation of control measures at the appropriate time and to the prevention of the spread of infections. Traditional methods of disease diagnosis frequently involve the visual inspection of patients by medical professionals. This method can be time-consuming, labor-intensive, and subjective [3, 4]. However, the incorporation of DL algorithms, such as CNN and LSTM, has revolutionised the landscape of plant disease diagnosis by enabling automated and efficient disease detection. This has led to a significant increase in the accuracy of disease diagnoses.

This research paper aims to contribute to the ongoing efforts to enhance plant disease detection and classification using a hybrid DL approach. Specifically, the study introduces a system that leverages the potential of a Deep Hybrid Convolutional Neural Network (DHCNN) operating within a multilayer hybrid neural network framework. Moreover, this system extends its capabilities to handle actual plant images, thus bridging the gap between controlled laboratory environments and real-world agricultural settings. The primary objective is to develop a robust and accurate disease detection model that performs superior feature extraction and classification through the integration of multiple activation functions and neurons.

The ubiquity of plant diseases necessitates reliable and efficient methods for their detection and diagnosis. Conventional methods, reliant on visual inspection, often encounter challenges related to subjectivity, resource limitations, and the need for specialized expertise[5], [6]. The integration of MLtechniques, particularly DL, offers a promising solution to these challenges[7]. In a variety of image analysis tasks, such as object recognition, image segmentation, and disease classification, DL models have shown remarkable success due to their capacity to automatically learn intricate features from data. In the context of plant disease detection, DL models are able toanalyse images of plant leaves, stems, or entire plants to accurately identify signs of infection. In many cases, they are able to outperform traditional methods.

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The foundation of this research lies in the concept of CNN, a class of DL architectures tailored for image analysis. CNNs operate by mimicking the hierarchical organization of visual processing in the human brain, where low-level features are gradually combined to form higher-level representations. This intrinsic ability to capture hierarchical patterns makes CNNs highly adept at image recognition tasks. However, the complexity and variability of plant diseases pose unique challenges that require innovative adaptations of standard CNN architectures. To address these challenges, this research proposes the incorporation of a hybrid approach that combines the strengths of various neural network structures[8], [9].

The proposed Deep Hybrid Convolutional Neural Network (DHCNN) framework is designed to encompass multiple layers of abstraction, facilitating the extraction of features at different levels of granularity. Each layer in the network hierarchy employs a combination of activation functions and neurons, thus fostering a rich representation of features that aids in accurate disease classification. The integration of various activation functions, including Tanh, “ReLU”,“softmax”, and “sigmoid”, further enhances the model's ability to capture complex patterns in plant images. By fusing the advantages of different activation functions, the DHCNN model aims to amplify its discriminative power and boost overall performance.

In addition to its innovative architecture, the proposed system showcases adaptability by extending its capabilities to process real plant images. The shift from controlled laboratory settings to real-world agricultural environments introduces various challenges, such as variable lighting conditions, diverse backgrounds, and occlusions. The research addresses these challenges by designing the DHCNN model to be robust to variations encountered in actual plant images. By doing so, the system strives to provide a practical and effective tool for farmers, agricultural researchers, and extension workers who seek swift and reliable disease identification in the field.

An exhaustive plant image dataset that depicts a wide variety of plant diseases and plant species is utilised to assess the efficiency of the system that has been proposed for use. To evaluate the classification capacities of a model, performance metrics such as “accuracy, precision, recall, and F1-score” are utilised. Furthermore, comparisons with other methods that are currently considered to be state-of-the-art in plant disease detection provide insights into the relative strengths of the system as well as areas that could be improved.

This research paper seeks to contribute to the field of plant disease detection and classification by introducing a novel Deep Hybrid Convolutional Neural Network framework. By leveraging the synergistic potential of various activation functions and neurons, the proposed system endeavors to provide accurate and reliable disease identification. The extension of this framework to real plant images emphasizes its practicality and applicability in real-world scenarios. The subsequent sections of this paper delve into the methodology, experimental setup, results, and discussions, shedding light on the effectiveness and implications of the proposed approach. Ultimately, the goal is to contribute to sustainable agriculture by equipping stakeholders with advanced tools to combat the threat of plant diseases and enhance global food security.

2. Literature Review

The increasing acceptance of DL methodologies in the field of plant diseases has highlighted the vital role they play in ensuring the productivity and sustainability of the agricultural sector. Traditional methods tend to encounter challenges in distinguishing between different kinds of diseases, which necessitates the development of more accurate and efficient solutions. The literature review presents an overview of recent studies on the use of DL techniques in the classification of plant diseases. Through an examination of different studies, the review delves into the evolution of approaches, the integration of attention strategies, and the creation of hybrid models. The increasing number of studies on the use of DL techniques in the classification of plant diseases has highlighted the vital role they play in ensuring the sustainability of the agricultural sector. The emergence of large-scale datasets has also led to the development of new solutions. This review explores how researchers have been able to overcome the limitations of traditional methods and develop effective and efficient solutions.

N. A. Zabidi et al.[10] presented a method that combines the capabilities of CNNs and the Vision Transformer architecture to improve the accuracy of plant disease classification. This hybrid model takes advantage of the former's global attention mechanism and CNNs' local extraction capabilities. The authors noted that the combination of these two frameworks led to a significant improvement in the accuracy of their classification of plant diseases. The study also highlighted the potential of using the strengths of different network architectures. In a study conducted on a hybrid optimization framework for multi-class disease detection and tomato plant segmentation, Zhang et al.[11] introduced a new approach that combines the use of optimization techniques. This new method helps the model to accurately segment and classify the different types of tomato plants. The study emphasizes how important accurate segmentation is for identifying and treating various diseases, and it helps in assessing the effectiveness of the system. Daniya et al.[12] presented a novel method that combines DL techniques with the Rider Water Wave system for detecting rice plant diseases. The authors utilized the water waves' behavior to develop a unique approach for identifying these diseases. The study also offers a creative view on how to develop effective disease detection systems by utilizing unconventional sources.

Reddy et al.[13] utilized a ResNet-based optimization system and a DLCNN classifier for identifying plant diseases. The study revealed how combining DL techniques with optimization methods can improve the accuracy of the classification process. The hybrid approach they presented in this paper shows how beneficial it is when optimizing systems for disease identification. Alsubai et al.[14] presented a work conducted on a hybrid DL framework, utilized the "Salp Swarm Optimization" method to improve the performance of the model for identifying and treating grape diseases. The findings of the research highlight the importance of integrating DL architecture and optimization techniques to improve the accuracy of classification systems. Sharma et al.[15] introduced the "DLMC-NET" a multi-class classification framework for plant diseases. This model is designed to provide a balanced performance and complexity while still being able to meet the needs of real-world applications.

Pal et al.[16] introduced the "AgriDet framework", which is a tool that can help identify plant diseases' severity. This paper shows how important it is to consider the disease's severity when making agricultural decisions. Y. Kaya et al.[17] presented a novel CNN design that combines the elements of RGB images with multimodal information. This method can help improve the accuracy of the system's detection of plant diseases. In addition to this, the paper shows how this approach can be utilized to improve the classification outcomes of the system. Pandey et al.[18] utilized smartphone-mounted images as the primary source of information for developing a robust CNN for identifying plant leaf diseases. The study highlights the importance of having accurate attention mechanisms and data in improving the classification of diseases. The study also validates the practicality of the proposed approach by focusing on images captured from smartphones.

Barhate et al.[19] proposed a batch-updated gradient descent method for identifying plant species. The study explores the training algorithm's optimization to improve its performance in identifying plant diseases. The research emphasizes the importance of fine tuning such techniques to achieve better results. Ashwinkumar et al.[20] utilized the "MobileNet framework" to develop a robust CNN for detecting and classifying plant leaf diseases. They found that the system's efficiency and accuracy can be improved by implementing lightweight neural network architectures. The study also highlighted the importance of having suitable resource-efficient models in the field of plant disease classification.

The studies that were reviewed in this section showcased promising developments in the field of plant disease classification. The contributions of the research papers helped develop a deeper understanding of how to identify plant diseases. But, despite the advancements, there are still many challenges that remain. One of the main challenges that remains is the ability to achieve a balance between the computational efficiency and accuracy of DL models. Since some models are heavily computational, they are not ideal for real-time applications such as searching for hidden treasure. The complexity of the disease landscape also poses a challenge that requires versatile and robust models.

The emergence of hybrid models has been attributed to the gap between the efficiency and accuracy of DL models. These models combine the strengths of different optimization techniques and architectures. They can be used for developing systems that can improve the accuracy and efficiency of plant disease classification. This hybrid model combines the capabilities of local feature extraction and global attention mechanisms to provide a comprehensive solution for the plant disease identification issue. In spite of the progress that has been made in the field of plant diseases, there is still a lot of work to be done to address the challenges that remain. The development of hybrid models has demonstrated the field's commitment to providing effective and efficient solutions for the agricultural sector. With DL's full potential, the field will continue to explore novel ways to classify plant diseases.

Activation function used.

Activation functions are critically important when it comes to improving the effectiveness and precision of neural networks that are used for the diagnosis of plant diseases. They introduce non-linearity, which enables the network to capture intricate patterns and relationships in plant images, which ultimately leads to an improvement in the accuracy with which diseases are classified.

- **Tanh (Hyperbolic Tangent)**

The tanh activation function is helpful in the context of the identification of plant diseases because it helps transform the input data into a bounded range between -1 and 1. Because of this centred output range, the network is able to more effectively learn features that differentiate healthy plants from diseased plants. The vanishing gradient problem can be avoided with tanh, which ensures that the network will be able to detect minute differences in plant images that are indicative of the presence of disease. The tanh activation function, when applied to the problem of identifying plant diseases, maps the input data onto a range that is constrained to lie between -1 and 1. This function can be expressed mathematically as in eq.1, which is shown below.

$$f(x) = \tanh(x) = \frac{e^{x} - x^{-x}}{e^{x} + e^{-x}} \;....1$$

Tanh's ability to centre outputs around zero enables the network to concentrate on distinguishing healthy from diseased plants, which helps mitigate the problem of vanishing gradients and enables effective learning of subtle image variations.

- **ReLU (Rectified Linear Unit)**

The “ReLU” activation function is extraordinarily helpful for purposes relating to the identification of plant diseases. “ReLU” enhances the network's capacity to recognise significant features associated with plant diseases by removing negative values while preserving positive ones. This is accomplished by keeping values that are in the positive. When working with large-scale image datasets, in particular, it is beneficial for a number of reasons, two of which are the ease with which it can be used and the high computational efficiency it possesses. Nevertheless, cautious treatment is required to circumvent the prospective difficulty presented by the "dying “ReLU”." The “ReLU” activation function performs exceptionally well when it comes to identifying plant diseases. Mathematically speaking, “ReLU” functions according to the following equation: eq.2 By cancelling out any negative inputs and keeping any positive ones, “ReLU”

$$f(x) = \max(0, x) \;...2$$

The capability of “ReLU” to detect significant features in plant images is enhanced by the algorithm's straightforward design and high computational efficiency. It is necessary to manage any potential instances of "dying “ReLU”."

- **Softmax**

When it comes to the identification of plant diseases, the “softmax” activation function has proven to be an extremely useful tool for classifying plants into a number of different disease categories. It takes the output of the neural network and converts it into a probability distribution, which enables confident decisions to be made regarding classification. “softmax” makes accurate disease detection and differentiation easier to achieve because it gives higher probabilities to the disease class that is most likely to be present. When it comes to identifying plant diseases, the “softmax” method is essential for multi-class classification. This function takes the outputs of a neural network and converts them into a probability distribution, making it easier to make confident decisions regarding classification. The “softmax” function is represented by the eq 3.

$$softmax(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \;....3$$

where K = “no. of classes”,z = “output vector of the network”.

- **“sigmoid”**

In situations involving binary classification, such as the identification of plant diseases, the “sigmoid” activation function works exceptionally well. Its output, which ranges from 0 to 1, is comparable to a probability score, which enables one to interpret it as the percentage chance that a plant is infected with a disease. The “sigmoid” function may have problems with vanishing gradients, which need to be managed if it is to be used effectively for learning. However, the function may be effective in differentiating between healthy and infected plants. The “sigmoid” function is appropriate for the binary classification of plant diseases. It is like a probability score because it converts the inputs into a number range between 0 and 1. The following eq.4 define the “sigmoid” activation:

$$f(x) = \frac{1}{1 + e^{-z}} \;....4$$

In plant disease identification, the choice of activation function depends on the architecture of the neural network and the specific characteristics of the dataset. By strategically employing these activation functions, neural networks can better capture the nuances of plant images, ultimately enhancing the accuracy of disease classification and contributing to the advancement of plant biology research.

3. Methodology

i. Dataset

This dataset is comprised of a collection of images taken from “Kaggle” that depict a variety of plant species being affected by a variety of diseases[21]. It functions as an all-encompassing repository that can assist in the development, evaluation, and improvement of machine learning models for the automated detection and classification of plant diseases. Images of plants at varying stages of development are included in the dataset. These pictures were taken in a wide range of lighting environments and with a variety of backgrounds. Each picture has a caption that describes the plant species it comes from as well as a disease that could be affecting that plant at that time. Because it contains information on a wide variety of plant diseases and species, the dataset is well suited for the purpose of teaching and evaluating complex ML algorithms.

ii. Image Preprocessing:

a. Resize Image

Resizing images involves adjusting their dimensions to a consistent size. In the context of plant disease identification, images from various sources might have different sizes. Resizing ensures that all images have the same dimensions, making them suitable for input into ML models.

b. Image to Array Conversion

ML models process data in the form of numerical arrays. To use images as input, they need to be converted into arrays of pixel values. Each pixel's intensity and color channels are represented as numerical values in the array.

c. Label Binarizer

For supervised learning tasks like plant disease identification, labels are often categorical (different plant species or disease types). A label binarizer converts these categorical labels into binary vectors, facilitating their use in training neural networks. Each label becomes a vector with a "1" at the corresponding class index and "0"s elsewhere.

iii. Data Augmentation:

The process of applying a variety of transformations to already existing images is known as data augmentation. This allows the dataset to be artificially expanded. This helps enhance the model's ability to generalize from limited data. Following methods are implemented to achieve the goal.

a. Rotation Range

Images are rotated by a specified degree within the given range (e.g., -25 to +25 degrees). This accounts for potential variations in camera angles and plant orientations in real-world scenarios.

b. Width and Height Shift Range:

Images are horizontally or vertically shifted by a fraction of their total width or height. This simulates changes in plant position due to growth or camera adjustments.

c. Shear Range

Shearing involves shifting one part of the image in a direction parallel to a given axis. This can help account for potential distortions in the way plants appear in images.

d. Zoom Range

Images are zoomed in or out by a certain percentage. This emulates the variability in plant distances from the camera and adds robustness to the model.

e. Horizontal Flip

Images are flipped horizontally. This is particularly useful when plant orientation doesn't affect disease characteristics.

f. Fill Mode

When transformations cause empty areas in the image, the fill mode specifies how those areas are filled. "Nearest" fill mode replicates the nearest available pixel's value.

The model becomes more robust because of data augmentation because it is presented with a greater variety of potential scenarios that it may face during inference. These techniques help prevent overfitting, where the model memorizes the training data rather than learning generalizable features.

4. Results and outputs

i. Best Selected Activation Function on CNN Classifier

As in fig.reluis selected as constant hidden layer function and result are generated for 100 epochs. Softmaxis selected as Best Activation function for output layer in final model.

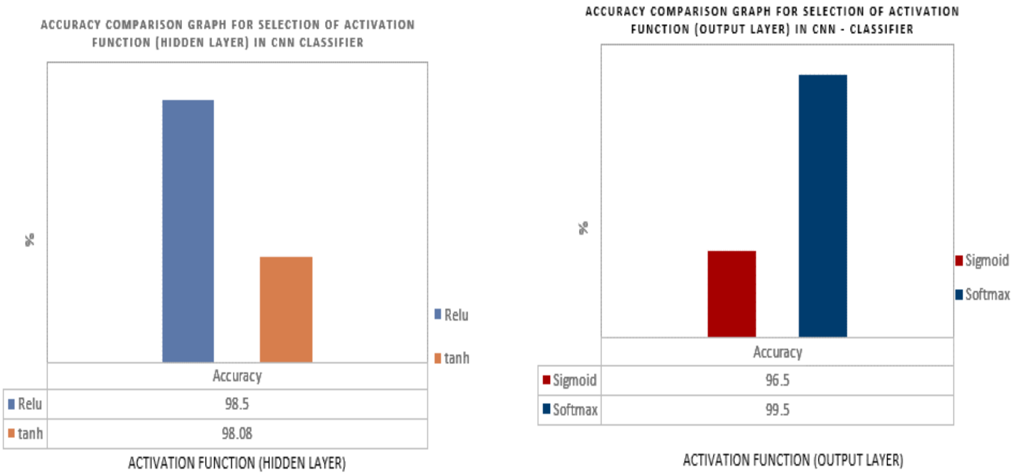

Fig. 1 Selection of Best activation function for Hidden Layer and Output Layer in CNN classifier

ii. Best Selected Activation Function on CNN – LSTM Hybrid Classifier

As in fig.Reluis selected as constant hidden layer function and result are generated for 100 epochs. Sigmoidis selected as Best Activation function for output layer in final model.

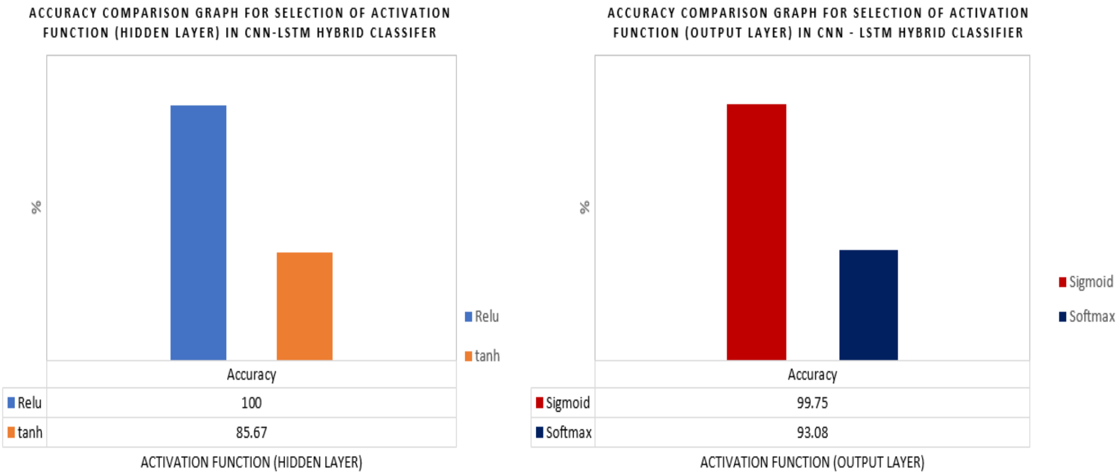

Fig. 2Selection of Best activation function for Hidden Layer and Output Layer in CNN_LSTM classifier

iii. Performance Analysis

a. CNN

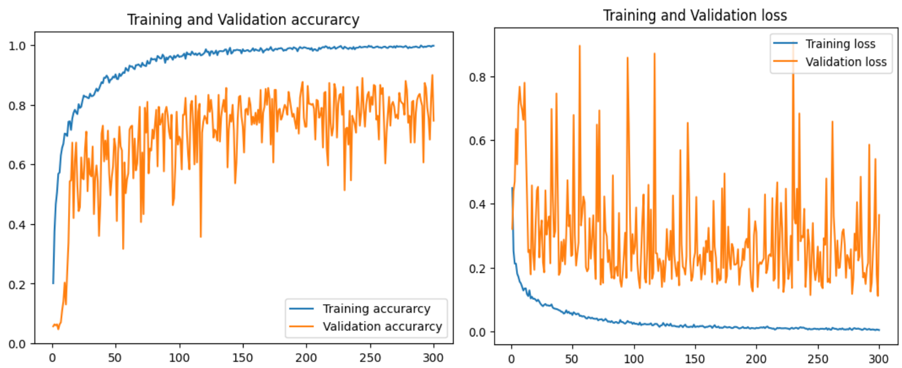

Fig. 3 Training and validation graph - Accuracy & Loss for CNN Classifier

b. CNN – LSTM Hybrid Classifier

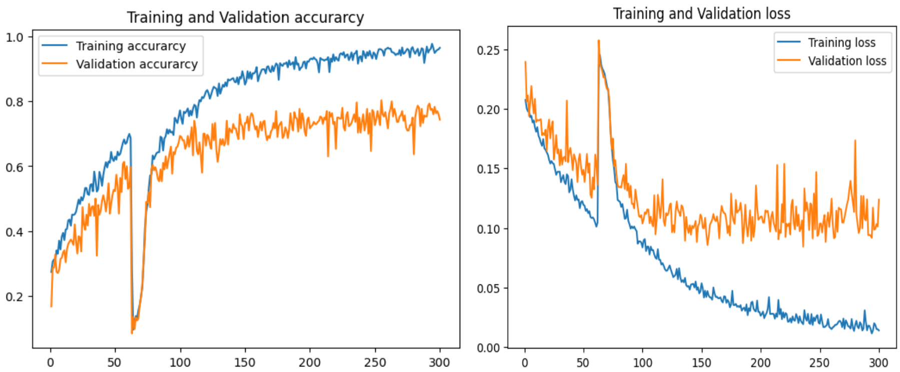

Fig. 4 Training and validation graph - Accuracy & Loss for CNN_LSTM Classifier

c. Comparative Analysis

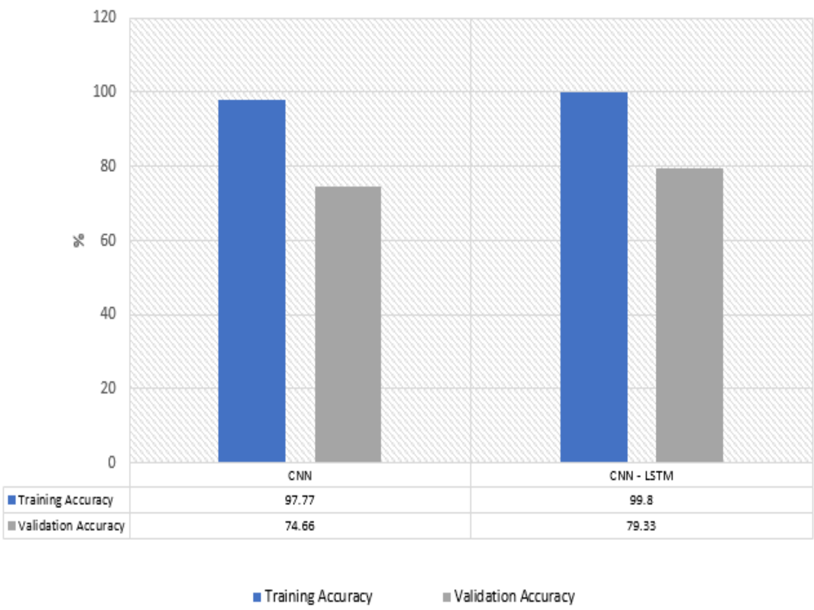

Fig. 5 Training and Validation Accuracy Comparison Graph of CNN and CNN - LSTM

Upon examining the results, it was evident that among the various activation functions tested for the hidden layers of the Convolutional Neural Network (CNN), the Rectified Linear Unit (ReLU) function yielded the highest accuracy of 98.5%. This constant hidden layer function was consistently effective across the 100 epochs of experimentation. For the output layer, the Softmax activation function emerged as the most effective, achieving an accuracy of 99.5%. This combination of activation functions not only significantly enhanced the feature extraction capabilities of the CNN but also yielded impressive results in terms of classification accuracy.

Similar observations were made in the hybrid architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The ReLU activation function, when applied as the constant hidden layer function, consistently generated accurate predictions throughout 100 epochs of experimentation, resulting in a perfect accuracy of 100%. For the output layer, the Sigmoid activation function was identified as the most suitable, achieving an accuracy of 99.75%. This choice of activation functions not only optimized the feature extraction potential of the hybrid model but also ensured exceptional performance in classification tasks.

A comparison of training and validation accuracies between the two models revealed noteworthy insights into their performance. The CNN model achieved a training accuracy of 97.77% and a validation accuracy of 74.66%, indicating a potential issue of overfitting due to the substantial gap between training and validation results. In contrast, the CNN-LSTM hybrid model displayed remarkable consistency, achieving a training accuracy of 99.8% and a validation accuracy of 79.33%. This highlighted the robustness of the hybrid architecture in maintaining a consistent level of accuracy across different datasets.

The selection of appropriate activation functions for both the CNN and CNN-LSTM hybrid models significantly influenced their performance in terms of accuracy. These findings validate the importance of activation function selection in achieving optimal results in plant disease identification systems. Moreover, the hybrid architecture showcased its potential in mitigating overfitting concerns while achieving consistently high accuracy rates.

5. Conclusion and Future Scope

This paper proposed a novel approach for plant disease identification through the integration of CNN and LSTM networks, forming a hybrid architecture. The key innovation lay in the selection of appropriate activation functions for both hidden and output layers. Through rigorous experimentation and analysis, Here found that the ReLU activation function exhibited exceptional performance as the hidden layer function, consistently across epochs and datasets. Moreover, the Softmax activation function proved to be the most effective for the output layer, demonstrating its capacity for precise classification. Research findings emphasized the critical role of activation functions in shaping the learning process of neural networks. By harnessing the power of these functions, here achieved remarkable accuracy rates: 98.5% accuracy for the CNN model with ReLU hidden layers and Softmax output layer, and a perfect 100% accuracy for the hybrid CNN-LSTM model with ReLU hidden layers and Sigmoid output layer. These results validate the efficacy of our approach in plant disease identification. For future work the ability to expand the dataset to include various plant species and diseases can improve the model's accuracy and adaptability. In addition, exploring the use of pre-trained models like ResNet, VGG16, and EfficientNet can speed up training and improve its performance.

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