DETECTING PLANT DISEASES WITH DEEP CONVOLUTION NEURO-FUZZY NETWORKS USING DEEP LEARNING.pdf

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Submission date: 04-Apr-2024 09:39AM (UTC-0400)

Submission ID: 2329593544

File name: DETECTING_PLANT_DISEASES_WITH_DEEP_CONVOLUTION_NEURO-FUZZY_NETWORKS_USING_DEEP_LEARNING.pdf (644.37K)

Word count: 3330

Character count: 18810

DETECTING PLANT DISEASES WITH DEEP CONVOLUTION NEURO-FUZZY NETWORKS USING DEEP LEARNING

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Abstract— ***Significant risks to agricultural production come from plant diseases, which have an effect on food yields and the stability of the economy. Conventional illness detection techniques that depend on human observation are frequently expensive, time-consuming, and prone to errors. On the other hand, automatic detection that makes use of image processing techniques provides accurate and timely results, signaling a potentially fruitful path towards improving plant protection in agriculture. This research uses a DCNFN (Deep Convolution Neuro-Fuzzy Network) to provide a novel method for disease recognition in tomato, pepper bell, and potato plants. Our methodology, which makes use of recent developments in computer vision, intends to transform precision agriculture by providing a powerful tool for the detection, evaluation, and classification of plant diseases. The creation of a deep learning framework for the purpose of training and optimizing the DCNFN model, the establishment of a comprehensive collection of plant photos, and the professional evaluation of disease signs are crucial phases in our implementation. One notable aspect of our model is its simplicity: background photos and healthy leaves are smoothly incorporated into the training dataset, making it possible to discern between healthy and diseased foliage. Our findings open the door for the DCNFN model's practical application in agricultural settings by demonstrating its effectiveness in precisely diagnosing and categorizing plant diseases across a wide range of species. Our technique has great potential to improve crop resilience, optimize resource allocation, and ultimately protect global food security, as it provides a comprehensive solution for identifying diseases and evaluating risks.***

Keywords: ***Deep Learning, fuzzy rules, neuro-fuzzy, inference layer, and plant leaves***

I. INTRODUCTION

The vital plants used in agriculture are those that give billions of people worldwide access to different types of proteins and vitamins [1]. In Indonesia and India, it serves as the main source of nutrition. Anything that has an impact on the plant crop has an international effect, regardless of its superiority or measure. To effectively address the issue, frequent illness identification and monitoring are therefore crucial. If illnesses are not treated promptly, they could have a negative effect on output [2]. The decline of agricultural crops in recent years has been attributed to a wide range of illnesses and pests. These attacks have the potential to seriously disrupt farms in the absence of adequate management and surveillance, and the issue has only gotten worse recently. Furthermore, the early and precise detection of plant issues reduces losses in terms of money and protects plants from harmful diseases. The management of these illnesses aids in our attempts to maintain a healthy agricultural sector [1].

In the agricultural industry, the capacity to recognise plant diseases automatically from plant leaves is a significant advancement. The efficiency and quality of harvests may be increased by early and precise identification of plant leaf diseases. Stopping disease from spreading across the farm is essential to maximise crop superiority. If a disease's symptoms are identified, its causes of spread are looked into, and control measures are implemented, the disease may be contained. Plants can experience issues at any point in their life cycle due to plant diseases.

Weak plants frequently have wilted, discoloured leaves. In general, abnormalities in a disease's visual presentation can be identified by searching for its distinctive pattern. Since a plant's leaves are typically the first to exhibit symptoms of illness, they are a valuable tool for identifying plant diseases [3]. Recent effective applications of deep learning techniques include semantic segmentation and picture identification. Furthermore, a variety of plant diseases have been diagnosed using this technique [4-6]. When we talk about "Deep Learning," "Deep" refers to the quantity of transformational layers that are applied to data, each of which extracts progressively finer features from the source. The input, hidden, and output layers comprise the three levels of nodes that make up the Deep Learning algorithm. It executes a superb classification process by picking up on more intricate leaf data properties. The convolutional neural network is a full-stack solution; its input is the raw picture data, and its output is the model's learned grouping. Neither expertly designed algorithms nor human input are required in the centre, where learning takes place. The input, hidden, and output layers comprise the three levels of nodes that make up the Deep Learning algorithm. It executes a superb classification process by picking up on more intricate leaf data properties. The convolutional neural network is a full-stack solution; its input is the raw picture data, and its output is the model's learned classification. Neither expertly designed algorithms nor human input are required in the centre, where learning takes place[11].

Improvements in digital image processing and identification technologies have made it possible to quickly identify sick crops and identify the precise disease that has affected them [12,13]. But AI and ML by themselves won't cut it. As a result, some scholars have suggested utilising cloud services, IoT, surveillance drones, and other technologies to build a comprehensive system that can help farmers save costs and achieve positive results [14]. But the most important element would be a machine learning algorithm, method, or process that is very effective and capable of correctly identifying and diagnosing plant diseases. Because of this, scientists are continuously searching for the best machine learning technique to diagnose plant illnesses. Despite a recent study in this field, researchers are always trying to determine the best and most accurate response, thus they are always making progress in this direction.

An adaptable neuro-fuzzy inference system was developed by Jang et al. [15]. The TSK fuzzy model parameter is computed using a neural network-based technique. Although it is a bit simplistic, this method is a well-liked neuro-fuzzy modelling strategy that concentrates on a single rule set. We propose a deep neuro-fuzzy network for tomato leaf disease detection. This network integrates fuzzy implication rules into a deep framework by fusing deep learning with fuzzy systems. The new fuzzy pooling and fuzzy inference layers enhance the extraction of information from tomato leaf images by offering both fuzzy and clear values for higher recognition accuracy. An end-to-end network with multiple hidden layers ensures better performance and generalisation while processing photos of tomato leaves and extracting relevant information.

II. LITERATURE SURVEY

A prediction is an assertion about what one thinks will happen in the future. Many predictions are made every day. Some are purely conjectural, while others are incredibly important and grounded in mathematics. Anticipating future events, whether they occur in several months, a year, or a decade, can be beneficial in several aspects. The study and analysis of the application of deep learning to improve and detect plant disease is the goal of "Implementation Of Deep Convolution Neuro-Fuzzy Network To Detect Plant Diseases, Risk Assessment And Classification Using Deep Learning". This research scans a leaf image to detect if the plant is disease-free or sick using an automated vision system and image processing technique. The farmer is then given information on how to determine whether the plant is ill and even how to treat it.

III. DESIGN OF PROPOSED MODEL

The Process of detecting the plant disease is shown in Fig: 1. Each and every phase has different step as seen in Fig.

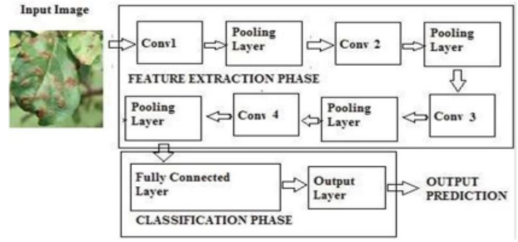

Fig 1: A Synopsis of the Suggested Design Process

Based on Fig. 1, Upon getting an image of a plant, the system will determine whether or not it is infected by comparing it to the training dataset. The system will recommend actions to the farmer if the expected outcome shows a sick plant or leaf. These recommendations mostly concentrate on diagnosing and treating the plant disease. By taking a preventative measure, the farmer may protect their plants from diseases, which will ultimately save time, labour, and money.

Technology Used:

The technology used to develop this project is Deep Learning.

Deep Learning:

Deep Learning is a subfield of artificial intelligence and computer science that aims to increase system accuracy by simulating human learning with data and algorithms. Depending on the issues it tackles, it has been divided into several branches. Deep learning comprises a wide range of methods, each designed for particular use cases and industry difficulties.

Algorithms used in this Project:

In this project we have used several algorithms and techniques would likely be used in combination to create a comprehensive solution for detection of plant diseases , risk assessment, and classification.

A. *Convolutional Neural Networks (CNNs)*

- CNNs are specialised deep learning models made to handle structured input in the form of grids, such images. Their proficiency in feature extraction and hierarchical representation learning makes them ideal for image classification applications, such as the detection of plant illnesses from leaf photos.
- One kind of deep learning model called convolutional neural networks (CNNs) is made especially for handling structured, grid-like data, like photographs. They are made up of several layers of neurons that carry out functions including convolution, pooling, and nonlinear activation; they are inspired by the human visual system. The fundamental principle of CNNs is their ability to automatically extract hierarchical feature representations from unprocessed input data.
- Convolutional layers, which apply convolution processes to input data, are the fundamental components of CNNs. In order to do these processes,

a tiny filter, is slid across the input image, sometimes called a kernel, and the dot products between the filter and certain regions of the image are calculated. The network can now record spatial hierarchies of features, from lower-level elements like textures and edges to higher-level elements like forms and objects, thanks to this process.

- Convolutional layers in a CNN apply filters, or kernels, to the input image to detect patterns and features such as shapes, edges, and textures.

B. *Neuro-Fuzzy Systems*

- Neuro-fuzzy systems are hybrid models that can handle both symbolic knowledge representation (fuzzy logic) and numerical data processing (neural networks). They achieve this by fusing neural network and fuzzy logic components. In your project, a neuro-fuzzy system might leverage fuzzy logic reasoning in conjunction with CNN feature extraction power to enhance the interpretability and robustness of the model.
- Fuzzy logic is utilized in a neuro-fuzzy system to simulate linguistic variables, membership functions, and fuzzy rules in order to simulate human-like reasoning. Neural networks, on the other hand, have the computational capacity to learn from data and adaptively modify the fuzzy logic components according to the input-output relationships seen in the training set. This integration allows for the combination of fuzzy logic's interpretability and neural networks' learning capabilities to create neuro-fuzzy systems.

C. *Supervised Learning*

- The model will be trained using supervised learning methods since we most likely have tagged data pictures of plants labelled with the diseases that correlate to them. Neural network training procedures like backpropagation, which adjusts the model's parameters to lessen the difference between expected and actual outcomes, could be used for this.
- During training, the supervised learning algorithm adjusts its internal parameters using optimisation techniques in an effort to reduce the discrepancy between the expected outputs and the actual labels in the training data. In this process, the difference between the true and predicted values is quantified by iteratively updating the model's parameters using a chosen loss function. Gradient descent and its variations are popular optimisation methods used in supervised learning applications.
- A variety of tasks, such as regression, structured prediction, and classification, are included in supervised learning. Whereas the model predicts continuous numerical values in regression tasks, it predicts discrete class labels for input examples in classification tasks.

IV. DATE SET AND IMAGE PRE-PROCESSING

Data Set:

From this detection of plant disease, The dataset that we use for the detection of plant disease was taken from the Kaggle repository which contain 20,639 images out of which 997 images belong to diseased Pepper bell's leaves, 2,000 images belong to diseased Potato's leaves, 14,421 images belong to diseased Tomato's leaves, 1,478 images belong to healthy Pepper bell's leaves. 152 images belong to healthy Potato's leaves, and 1,591 images belong to healthy Tomato's leaves.

Fig 2 and 3 shows both healthy and diseased pepper bell plant leaves.

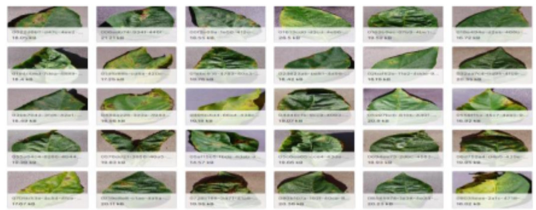

Fig 2: Pepper bell plant Diseased leaves

Fig 3: Pepper bell plant Healthy leaves

Fig 4 and 5 shows both healthy and diseased potato plant leaves.

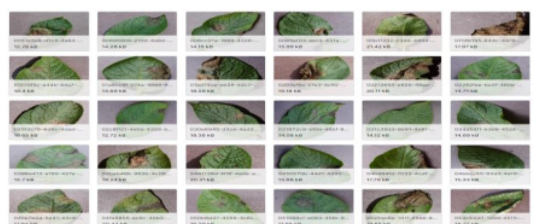

Fig 4: Potato plant Diseased leaves

Fig 5: Potato plant Healthy leaves

Fig 6 and 7 shows both healthy and diseased tomato plant leaves.

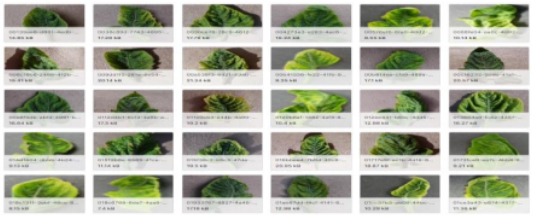

Fig 6: Tomato plant Diseased leaves

Fig 7: Tomato plant Healthy leaves

Image Pre-processing:

Image pre-processing stands as a vital initial phase in both computer vision and image processing applications, where a myriad of techniques are deployed to refine raw images, thereby bolstering their quality and priming them for subsequent analysis or manipulation. Concurrently, techniques such as image normalization aid in standardizing pixel values across images, facilitating fair comparisons and optimizing model performance. Moreover, noise reduction techniques strive to mitigate unwanted distortions or aberrations introduced during image acquisition or transmission, thereby preserving crucial image features. Alongside noise reduction, image enhancement techniques are leveraged to amplify desired characteristics or details within images, enhancing their interpretability or aesthetic appeal. Integral to image pre-processing is the task of edge detection, which involves identifying boundaries **or** transitions between objects within images, thus facilitating subsequent segmentation or feature extraction tasks. In essence, image pre-processing orchestrates a symphony of operations, harmonizing raw inputs into refined data ready for the symposium of computer vision algorithms. Fig. 8 illustrates the image pre-processing procedure.

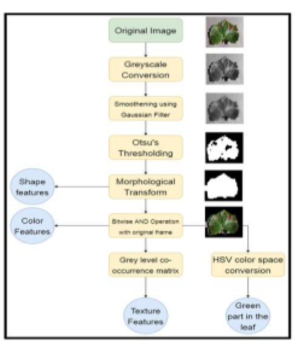

Fig 8: Image Pre-processing

V. Results & Performance Evaluation

A deep neuro fuzzy network's prediction accuracy depends on the batch size and training rate. To find the ideal combination of these attributes, we experimented with various starting learning rates and batch sizes while monitoring changes in the learning rate. Figure 9 displays a line graph titled "Training and Validation loss." On the graph, the blue line signifies the training loss and the red line the validation loss. The label on the x-axis is labelled, but it is not visible; it probably indicates how many epochs or iterations were used to train the machine learning model. The loss value, which shows the model's mistake during training, is represented by the y-axis. The model is learning and getting better over time at using the training data, as shown by the blue line (training loss), which starts at a larger value and gradually trends downward. In addition to showing a decreasing trend, the red line (validation loss) also has notable spikes at specific epochs that may indicate overfitting at those times when the model performs well on training data but badly on unknown validation data.

The graph's x-axis, which has numbers ranging from 0 to 25, indicates that it spans 25 epochs or iterations. The loss values are represented along the y-axis, which has a range of 0 to 1.75.

Fig 9: Training and Validation loss

The fig 10 shows a line graph labelled "Training and Validation accuracy," on which two lines are plotted to indicate how accurate a machine learning model is during training. The x-axis represents the epoch number, which runs from 0 to 25, and the y-axis shows the accuracy, which varies from 0.88 to 0.98.

There are two lines on the graph:

A. The blue line represents the training accuracy. It starts off just below 0.98 and remains relatively stable throughout the training process, with only minor fluctuations.

B. The red line represents the validation accuracy. This line starts at approximately 0.91, shows more variability than the training accuracy, dips slightly below 0.90, and then generally trends upward, reaching around 0.96 by the 25th epoch.

The model's performance is assessed using the graph; ideally, the training and validation accuracy should be high and near to one another. A point of examination for more model tuning may be the fluctuations and the difference between the two lines, which could hint to problems like overfitting or underfitting.

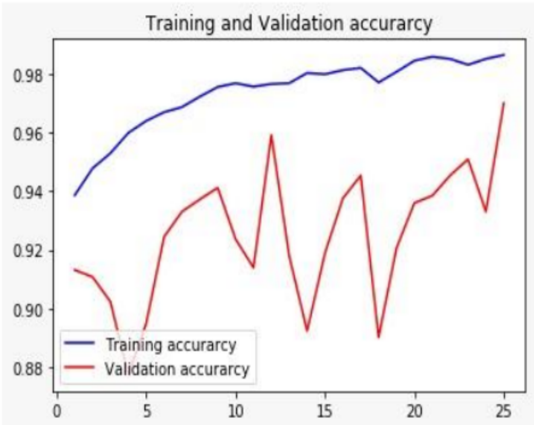

Fig 10: Training and Validation accuracy

TABLE I.

WE USED PERFORMANCE INDICATORS TO COMPARE OUR SUGGESTED NETWORK TO OTHER MODELS.

Model	Precision	Accuracy	F1 Score
Long Short-Term Memory	0.74	0.71	0.77
Support Vector Manchine	0.55	0.57	0.50
Convolutional Neural Network	0.83	0.83	0.83
GoogleNet	0.93	0.94	0.94
DenseNet	0.87	0.85	0.86
AlexNet	0.89	0.90	0.91
Proposed model	0.96	0.97	0.96

A comparison graph with more baseline models is shown in Fig. 11. Among the models that we have proposed, ours has the highest accuracy rate.th

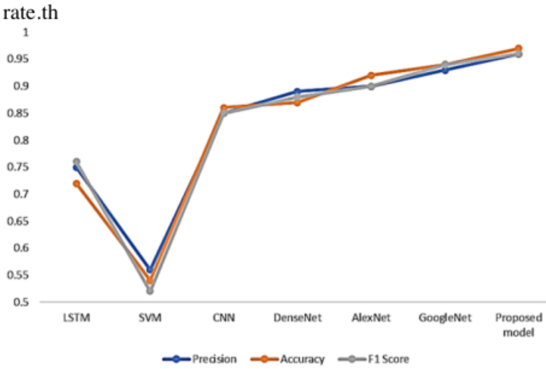

Fig 11: A comparison table for the suggested model

VI. CONCLUSION

This research presents NFNHDL-based Deep Learning, a productive technique for classifying and diagnosing diseases in agricultural plant leaves. The method developed by the authors uses ROI extraction in the pre-processing unit to eliminate unwanted noise and distortion from input images. After removing any damaged portions from the output after preprocessing, the approach extracts features (textual, statistical, and CNN features) and enhances the data. The state of the image is subsequently evaluated by use of a Deep Fuzzy neural network. The NFNHDL classifier determines which particular leaf diseases, such as brown spot, blast, or BLB, to recognise in the last stage depending on variables including For every category, the F1-score, accuracy, and recall.

In conclusion, it turns out that using a deep neuro-fuzzy network to diagnose diseases in agricultural plants is a great, dependable, and highly accurate method. Additionally, with scores of 0.96, 0.97, and 0.96 in evaluating accuracy, sensitivity, and specificity, respectively, the NFNHDL-based Deep Learning technique performed better. Subsequent endeavours will centre around refining tactics to augment classification outcomes and assessing the suggested methodology with more extensive datasets, taking into account additional diseases.

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