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UNET-Based Deep Learning System for Disease Detection and Classification of Plants

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Abstract

Plant disease is a persistent problem for farmers, and it is one of the most serious risks to income and food security. This initiative aims to enhance the quality and quantity of agricultural output in the nation by classifying plant leaves into sick and healthy leaf types. The smart farming system is an innovative technology that aids in the improvement of agricultural quality and quantity. Deep learning using Convolutional Neural Networks (CNN) has successfully classified various plant leaf diseases. It represents a contemporary technique that offers cost-effective disease diagnosis. CNN presents a simplified version of a much broader image. In this research, we proposed a hybrid deep learning model to detect plant diseases using mixed deep learning techniques. The UNET deep learning framework has used for disease detection and classification. In convolutional neural layer feature extraction has done and pooling layer optimized those features, finally dense layer classifies the test object. The numerous synthetic and real time plan dataset has used for evaluation. In extensive experimental analysis two machine learning and two deep learning classifiers are evaluated such as SVM, PCA, CNN and modified CNN (mCNN). The mCNN is the collaboration of VGG16 and VGG16 backbone for classification and YOLOv3 model data pre-processing. The mCNN obtains 96.80% detection and classification accuracy on heterogenous dataset which is higher than other classifiers as well as conventional classifiers.

Keywords: *Plant disease prediction; Convolutional neural network; Machine learning; Feature extraction and classification.*

Introduction

If required, nomenclature is included in the same typeface as the remainder of the document in a box here, which introduces the paper. From here on out, only headers, subheadings, graphics, and equations serve to break up the text. Section headers are numbered, bold, and 10 pt. in size. Further directions for writers are provided below. The Indian economy is based on agriculture. It supports over 70% of the population and accounts for a significant portion of the GDP. India is the greatest producer of pulses, rice, wheat, spices, and spice products globally. Any country's agriculture is dependent on the quality and quantity of agricultural goods, particularly plants. Numerous researchers used image processing, machine learning, and deep learning approaches to identify plant illness (i.e., aberrant growth or malfunction) to make this challenging work easier. Plant and tree health monitoring and disease detection are crucial for long-term agriculture. Plant diseases and pests pose a significant threat to agriculture. Plant diseases generate considerable productivity and economic losses in the agricultural business across the globe. One of the most critical objectives in overall crop disease management is to identify plant illnesses at an earlier stage to avert a more significant loss. Plant disease diagnosis entails a large amount of intricacy, which is accomplished by visual inspection of symptoms on plant leaves. Even skilled agronomists and plant pathologists often fail to detect particular illnesses due to this

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intricacy and the enormous number of farmed plants and their current issues, leading to incorrect conclusions and treatments. According to the findings, climatic change may affect pathogen growth stages and host resistance rates, resulting in physiological alterations in host-pathogen interactions. The problem is made even more difficult because illnesses are now more readily transmitted internationally. New diseases may emerge in regions where they have never been seen before and where there is, by definition, no local competence to fight them. One of the foundations of precision agriculture is the timely and precise identification of plant diseases [1]. Solving the long-term pathogen resistance development problem and avoiding the negative repercussions of climate change is vital to minimize inefficient waste of financial and other resources, resulting in healthier output. Plant diseases may be identified through several approaches. Some conditions have no evident signs, or the harm becomes apparent too late to intervene, demanding a comprehensive study. However, as most illnesses present themselves in the visible spectrum, a qualified professional's naked eye examination is the most prevalent way of diagnosing plant diseases in practice. A plant pathologist must have extraordinary observation abilities to notice specific indicators to diagnose plant diseases properly [2][3].

A disease may harm several components of a plant. But gazing at the leaves may frequently reveal illness. Automated disease detection and classification systems based on leaves are already being developed as a result. Artificial Intelligence (AI) and GPUs (Graphics Processing Units) may be able to increase plant health and production. Deep learning is accomplished by the use of neural network topologies with several processing layers. A convolutional neural network was used as the primary method of deep learning in this study. Using CNNs has shown to be a useful tool for simulating complex processes and identifying patterns in large datasets. We've summarized the most important results from this research in this section.

- To better classify the input picture data by extracting multiple characteristics from the data collection and building a strong model.
- We also develop a hybrid classification algorithm that collaborates with a convolutional neural network and a recurrent neural network to detect heterogeneous plant diseases.
- We also support the acceptance of heterogeneous image data set that includes plant leaf disease and fruit disease for the entire data set.

The remainder of the article explains the literature survey that was proven in Section 2, and Section 3 outlines the recommended implementation approach with a specified research methodology. Section 4 contains the algorithm specifics that will be utilized to implement the suggested design. Section 5 discussed the experimental setup and results achieved on various datasets with hybrid classification model. Finally, in section 6, we demonstrate the proposed research's conclusion and future work.

Literature Survey

Diseases that affect the quality and yield of crops are a major issue in agriculture. When a single or a few crops are grown, the agricultural economy may be severely affected by plant diseases, which can cause moderate to severe damage to large areas of crops cultivated. Disease-diagnosis tools have been developed to prevent large losses. Biology and immunology are able to discover what causes a problem. Many farmers are unable to use these strategies because they lack the necessary expertise or funding. Food and Agriculture Organization data shows that the majority of farms are owned and maintained by families in disadvantaged nations. Many of the world's people live in these dwellings. [2] Poverty, food insecurity and restricted access to markets and services continue. Farmer-friendly techniques have been developed after extensive research.

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Precision agriculture takes use of modern technology to improve decision-making [3]. Modern digital technologies have made it feasible to make cost-effective decisions because of the vast volumes of data they gather in real time. No matter how much data is processed into meaningful ideas by decision-support systems, this challenge still needs further work. Regression, clustering, gaussian models and Nave Bayes are only few of the techniques that may be used to analyze data (SVM). There is an increase in the usage of deep learning (DL) approaches in agriculture. As computer vision and artificial intelligence improve, this might alter (AI). More exact projections are made possible because to these new technologies, which are superior to more conventional methods. Difficult challenges may be solved faster with the help of new computer hardware advancements. It's not a little discovery. A cutting-edge technology, DL can be used for more than only land cover classification. Deep neural networks (DNNs) perform well in hyperspectral analysis [4]. CNNs excel at applications such as crop categorization [5,6], fruit counting, yield prediction, disease detection, and visual identification [9,10]. In various investigations, AlexNet [11] and GoogLeNet [12] achieved the best results [7,8,13–15]. Pre-trained networks are more effective [13].

A comprehensive collection should comprise diverse images. generative adversarial networks (GANs) [16] may produce synthetic data when training material is insufficient. Existing DL solutions for plant disease detection are successful, but there's need for improvement. Traditional machine learning approaches are used to identify ailments [17]. The SVM classifiers to identify healthy and Bakanae-infected rice seedlings. The authors found the recommended procedure to be less subjective and time-consuming than standard naked-eye assessment. Another study employed SVM, KNN, and a probabilistic neural network to decrease human involvement. Features, background removal, and segmentation were highlighted by the authors. There were 19 of them who agreed with me. Color, density, and location, as well as the weather conditions at the time the images were taken, were all characteristics that affected the detection rate of aphids in wheat fields, according to [20]. SVM outperformed all other classifiers, including KNN, NB, SVM, DT, and recurrent neural networks.

Similarly, only a few studies have observed at sophisticated training strategies; for example, [21] looked at the performance of various deep learning frameworks are trained from scratch as well as transfer learning methodologies. By comparing state-of-the-art DL structures for the categorization of plant disease, comparison research was done to demonstrate the relevance of the fine-tuning approach [22]. The most current discoveries in the field of plant disease categorization are given in detail.

Deep learning meta-architectures are utilized to handle the challenge of object identification on a single platform. Deep learning algorithms in this sector are rare. [23] Early image detection algorithms that used a CNN included RCNN. Regional proposal approaches proved to be a big step forward in object identification. In agriculture, very little research has been done on the use of DL methods to diagnose plant diseases. Plant disease detection and localisation were performed using deep learning models in [24]. Using the authors' own annotated tomato leaf images improved the mean average accuracy. Two distinct techniques to automate pest identification were developed and evaluated using ML/DL learning algorithms [25]. This investigation's goal was to identify the pest in greenhouse tomato and pepper plants. According to the researchers' results, deep learning approaches beat machine learning algorithms. One of the reasons is that deep learning algorithms are capable of completing detection and classification tasks in a single step. Cassava leaves were recently studied using the Single Shot Detector (SSD), with promising findings [26]. CNN's plant disease diagnostic job was employed in another recent study to gauge the degree of abnormalities in plant leaves [27].

There are a number of datasets that may be used for a variety of real-world applications. As an example, recent advances in object classification and detection studies were made possible by the ImageNet collection [28]. MS COCO [29] has 91 common object classes, each of which has more than 5k labeled examples. Over 2500k data instances have been discovered and cataloged

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along with the 328k photos. Object instances in the MS COCO dataset outnumber those in ImageNet (3.0) and PASCAL (2.3). Training weights using the MS COCO dataset helped make it simpler for students to transfer their knowledge. Since the research area is shown in photographs, the Plant Village [30] dataset was used.

1.1. Proposed System Design

This system evaluates plant disease detection and classification using a modified convolutional neural network-based deep learning algorithm. According to figure 1, initially, we collect the data from numerous sources, such as some synthetic data sets or a few real-time data sets. The preprocessing has been done using noise removal, and misclassified instances have been removed in the normalisation phase. In an actual convolutional neural network, the conventional layer works to extract features, while optimisation is done in the feeling layer. The deep convolutional Framework has been used with n number of epoch sizes. Finally, according to the trained model, the dense layer classifies the entire test in instances. In the below section, we determine each phase of the proposed system concerning the module.

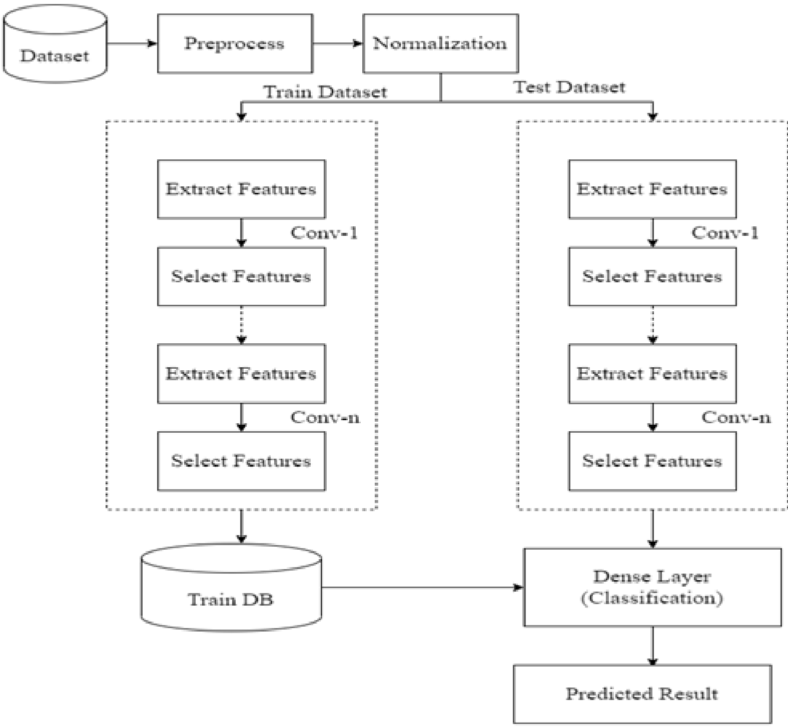

Fig. 1. Propose model for plant disease detection and classification using mCNN

2.1.1 Image acquisition

This module collects plant image datasets from various sources, such as real-time validated image datasets and some synthetic datasets. The dataset may be imbalanced sometime, and it contains noisy images. In the second section, we pre-process and normalized the entire dataset to achieve the best results for training and testing.

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2.1.2 Data Pre-processing

Pre-processing reduces distortion, making post-processing simpler. Pre-processing includes colour space transformation, cropping, smoothness, and enhancement. This module's use varies with image quality. Color space converting is accompanied by filtering and augmentation. If photographs are obtained in an uncontrolled setting with complicated backdrops, cropping is also necessary. It can be done manually or automatically with the help of functions.

2.1.3 Segmentation

Along with the items of interest, segmentation separates the image into sections with strong association. The number of histogram peaks, for example, is one feature of a correctly segmented picture that aids in the simple identification of healthy or contaminated samples. Plant disease detection systems have been demonstrated to function effectively using edge, threshold, location, and colour-based segmentation approaches. As a result of the considerable colour disparities between the infected leaf region and its native colour, spot colour-based segmentation emerges. In segmentation, determining a threshold value is critical.

2.1.4 Feature Extraction

The Color, texture, and form features are often used to understand images. Moments and histograms are widely used to determine colour. There are a variety of characteristics that may be found in texture. Features such as concavity and concaveness are also found for shape. Similarly Texture has been recognized as the greatest feature for plant disease identification in heterogeneous datasets. Heterogeneous datasets require a diversity of properties. Several methods are used to extract feature information.

2.1.5 Classification or Recognition

In plant disease detection systems, classification is a critical component. The method employs a picture to identify plant illnesses, therefore classification here refers to the process of categorizing plant leaf images based on diseases that have been recognized. Using photos from a training set, the classifier is trained to correctly identify or classify images from the test set. The hybrid deep learning classification algorithm we used for detection of disease with the collaboration of CNN and mCNN.

2.1.6 Algorithm Design (mCNN)

To implement this work, we design a new modified deep learning-based convolutional neural network classifier called mCNN. This algorithm is divided into two phases such as training and resting. The training module generates the rules for the entire module, while the testing phase validates disease detection and classification tests.

You then choose a training sample at random from all of the training data, where it 1,... is the goal of the chosen training sample on the tth repetition. W1 should be set to zero, and a random training sample should be chosen from the whole training set. The primary function of the objective is

$$\min(w) = \frac{\lambda}{2} ||W||^2 + f(x_{i,}, y_{i,})$$

(1)

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Secondly, calculate the gradient according to Formula (1), and then the gradient can be expressed by

$$\nabla_t = \lambda W_t - \alpha_t y_{i_\cdot} x_{i_\cdot}$$
(2)

Where $\alpha_t = \{$ [illegible] $y_{i_t}(W_t, x_{i_t})$

The updated formula of matrix W is as follows.

where ηt = 1 (λt) . Then an updated weight matrix W based on Formulas (2) can be obtained by

$$W_{t+1} = \left(1 - \frac{1}{\cdot}\right) W_t + y_{i_\cdot} x_{i_\cdot}$$
(3)

In practice, Formula (3) is used to find minima or maxima by iteration.

The implementation of proposed model for training and testing phase are described in detail in below section

2.1.7 Execution of Training

Input: Train_DB[] as training dataset, set of activation function AF[].
Output: Trained module in .PKL file for entire splited dataset
Step 1: Initialize the both algorithms Train_DB[], AF[], epoch_size
Step 2 : Extracted_Features ← ExtractFeatures(Train_DB[])
Step 3 : Selecetd_Features[] ← optimized(Extracted_Features)
Step 4 : Train.pkl ← Build_Classifier(Selecetd_Features[])
Step 5: Return Train.pkl

The above algorithm executes during the module training, in step 1 initialization has done with no. of epochs, convolutional layers etc. The step 2 describes an extract feature from training data and features are optimized in step 3. The classifier has trained in step 4 and it return trained module with .pkl file return in step 5.

2.1.8 Execution of Testing

Input: Test_DB [] as testing instance set or individual patient record, Training Background Knowledge Train.pkl, User defines threshold Th

Output: Output_Map <Predicted_class_label, Similarity_weight> optimized instance recommend by classifier.

Step 1: Read all testing records by using below equation

$$test_{Feature(m)} = \sum (.feature\_Set[A[i] \ldots\ldots\ldots\ldots A[n] \leftarrow Test\_DB)$$

Step 2: Extract selected attribute features from entire test record testFeature(m) using below equation.

Extracted_Feature_Set_x[t……n] = $\sum_{x=1}^{n}(t)$ ← test_Feature (m)

Extracted_Feature_Set_x[t] contains the feature vector of respective domain

Step 3: Extract all training instance from trained modules using below function

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$\text{train\_Feature}(m) = \sum (.\ \text{feature\_Set}[A[i] \ldots\ldots A[n] \leftarrow \text{Train.pkl})$

Step 4: extract each feature as a hot vector or input neuron from $\text{testFeature}(m)$ using below equation.

Extracted_Feature_Set_y[t……n] = $\sum_{x=1}^{n}(t) \leftarrow \text{test\_Feature}$ (m)

Extracted_Feature_Set_x[t] contains feature vector for entire class labels.

Step 5: Now evaluate each testing instance with all train features

$\text{calc\_weight} = \text{calcSim}\ (\text{Feature\_Set\_x} \,||\, \sum \text{Feature\_Set\_y}[y])$

Step 6: Return calc_wSeight

The above algorithm describes the testing phase process of proposed model called mCNN. In step 1 test dataset has read with total attributes and features are extracted from test data in step 2. The similar process has done for training data in step 3 and 4 respectively. The similarity calculation has done as like dense layer in step 5. The generated weight return by similarity function return by step 6.

Results and Discussions

Extensive testing was carried out on the widow's platform using Python 3.7 and the RESNET-100 deep-learning framework. The accuracy of mCNN classification was shown using a real-time plant disease dataset (Sigmoid).

Figure 2 depicts several cross-validation strategies used in this study. 15-fold cross validation has the greatest average classification accuracy of 95.00 percent based on the data With mCNN and sigmoid function, the 5-fold cross validation likewise obtains 93.60%. Figure 2 shows the results of a 10-fold data cross validation. During module testing, both functions obtain a comparable level of accuracy.

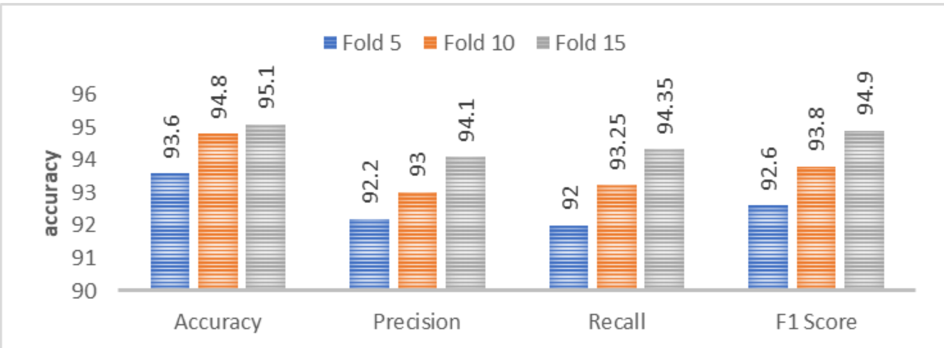

Fig. 2. system validation with various cross validation using mCNN (sigmoid)

Figure 3 shows mCNN classification accuracy using the plant picture dataset; identical experiments with various cross validation are given. Tanh-enabled mCNN achieves average classification accuracy of 93.55 percent when tested with 15-fold cross validation, according to this study.

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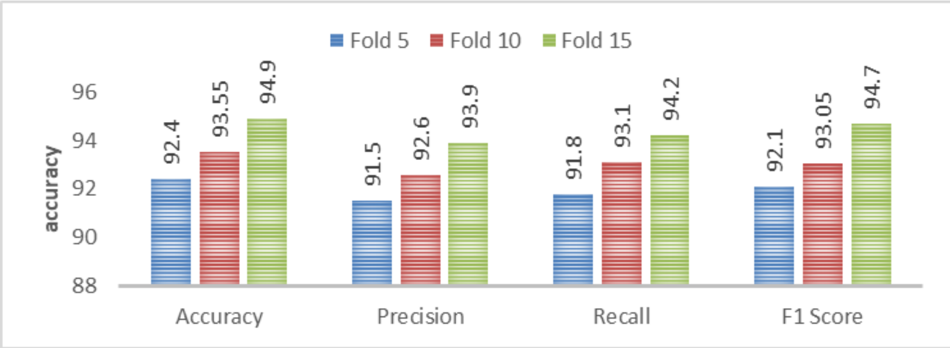

Fig. 3. system validation with various cross validation using RNN-LSTM (Tanh)

Using a collection of plant photos, we investigated the accuracy rate of ReLU. Comparable tests were run with various cross validation, and the results are displayed in Table 3. In this study, the mCNN classification accuracy is 95.30 percent and 97.10 percent when tested in 10-fold cross validation, respectively.

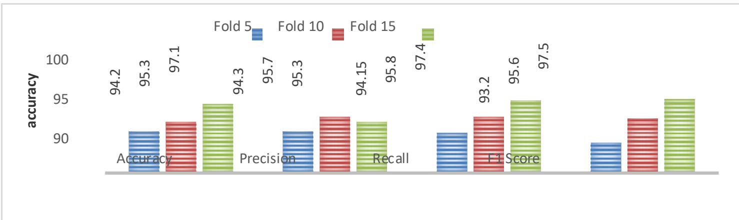

Fig. 4. system validation with various cross validation using mCNN (ReLU)

A comparison of results with and without cross-validation is shown in the following figure 4. A minimum of three hidden layers have been used to identify illness. A more accurate identification rate was obtained using this experiment than any other method, including random forest machine learning and the other two activation functions.

Comparative analysis of existing Deep Learning algorithms

In another investigation, the probability of disease detection using supervised deep learning classification. System describes four evaluations between this research results and some existing systems results has calculated on the similar as well as multiple datasets.

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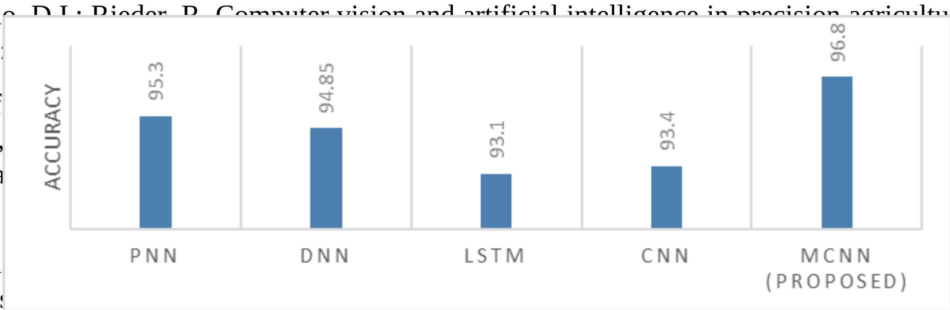

Fig. 5. Comparative analysis of proposed module with other deep learning module

PNN, DNN, LSTM, CNN or a mCNN-based hybrid model has never been used on the Plant Village dataset. As a Deep Learning model, this one is very accurate, with a precision rate of 96%. The suggested algorithms' classification accuracy is shown in Figure 5, along with the classification accuracy of a number of other well-known machine learning techniques. Training and testing sets are used to categorize or arrange the most recent predicted sample. Input function modules and class labels are included in this training set. It's possible to build classification models using this data. Models are evaluated using a subset of the test dataset's class labels as a test set for the model after this step.

Conclusion

The mCNN deep learning architecture has improved plant disease detection and categorization. Deep learning and classical machine learning methodologies were used to build a model for diagnosing plant illnesses in images of healthy and diseased leaves. As a long-term benefit, this might help the farmer grow higher-quality crops more rapidly. Deep Learning CNN has shown to be an outstanding option based on its amazing outcomes. Image processing and pattern recognition research have lately included Deep Learning techniques (DL). The attributes of a convolutional module are extracted and used to build a powerful train module. For example, the mCNN has a detection accuracy of 96% in plant picture datasets, which is a lot higher than the conventional classifiers. Many diseases may be detected using a hybrid deep learning analysis of a large plant database, according to current study.

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