ISSN: 2348-2079

Volume-11 Issue-2

International Journal of Intellectual Advancements and Research in Engineering Computations

Plant leaf disease prediction based on deep learning using U-net based Convolutional Neural Network

[1]G.Sivakumar, *[2]M.Udayadevi

[1]Head of the Department, Department of Computer Science and Engineering, Erode Sengunthar Engineering College (Autonomous), Perundurai, Erode-638057.
*[*2]Master of Engineering in Computer Science, Department of Computer Science and Engineering, Erode Sengunthar Engineering College (Autonomous), Perundurai, Erode-638057*

***Corresponding Author: M. Udayadevi**

ABSTRACT

Agriculture as a source of food is very important for mankind. Therefore, diagnosis of plant diseases is a major concern. Plant disease diagnosis through plant monitoring is important for sustainable agriculture. Monitoring plant diseases manually is very difficult. Managing plant diseases requires a lot of effort and expertise. Traditionally, this method of diagnosing leaf disease requires a lot of information about subjective, time -consciousness, costly. To solve this problem, we introduce the proposed U-net based Convolutional Neural Network (UNetCNN) with ReLu activation function is used to classify the plant disease. First we collect the dataset from online kaggle then preprocess the image to remove noise using median filter. Second extract the finest features of plant leaf disease from preprocessed image. Finally the proposed UNetCNN and ReLu activation is efficiently classify the plant disease. The proposed method experimental result produces better result than other methods.

Keywords: Plant Disease Prediction (PDP), deep learning, UNetCNN, median filter, finest features.

I. INTRODUCTION

Plant disease can affect plant growth and the yield of crops, and can have a social, environmental and economic impact on agriculture. Plant leaves also bring a lot of economic losses to farmers. Premature detection of these diseases is worth a special precaution. Plant disease can affect plant growth and the yield of crops, and can have a social, environmental and economic impact on agriculture. Plant leaves also bring a lot of economic losses to farmers. Premature detection of these diseases is worth a special precaution.
In this paper, accurate and timely diagnosis and classification of the disease is of utmost importance. As farmers lose control of most farming systems, weather becomes unmanageable. Any insects or vermin in the farm should be addressed immediately without undue delay. Most plant diseases can be identified by looking at the leaves. Farmer monitored the plants regularly, but failed to identify disease symptoms and used excessive amounts of fertilizers and pesticides.
Automating the diagnostic process is the solution to this problem. This can be done using a number of different image processing techniques. There are several reasons for assessing or measuring foliar disease. Knowledge of foliar disease is important for decision making about crop status and disease management decisions. In this study, an attempt was made to identify leaf diseases. 60% of people in India work in agriculture all their lives. Improvement of cultivation is considered as one of the major categories, thereby improving the economy of the country.
The objectives of this work include (i) pre-processing, (ii) texture, shape and color analysis of color images of diseased leaves. It uses image processing techniques such as Feature extraction for leaf disease identification. (iii) Classifying and distinguishing between types of diseases.

A. Aim and objective

- First we collect the dataset from online kaggle then preprocess the image to remove noise using median filter.
- Second extract the finest features of plant leaf disease from preprocessed image.
- Finally the proposed UNetCNN and Relu activation is efficiently classify the plant disease.
- The proposed method experimental result produces better result than other methods.

II. Literature survey

Agricultural systems that use the necessary infrastructure are innovative technology [1]. It improves the quality of agricultural production in countries such as tomatoes, apples, and potatoes. Common symptoms of plant damage are mycoses, bacteria, viruses, and spots where nematodes are the source of leaves, brown or black lesions, last death of lower leaves, and lower leaves and dark spots [2].

Real-time image processing is related to the typical frame rate of all processed frames required after the image is captured. This paper proposes a real-time edge detection technique for identifying images and their hardware trefoil disease (rubber leaves) [3-4].

The disease feature extraction process analyzes the appearance of features using a statistically based gray-level simultaneous occurrence matrix and texture feature equations. The disease classification process deploys an unsupervised simplified fuzzy ARTMAP neural network for disease classification types [5-6].

Due to changing climatic conditions, crops in Tensong were affected as a result of a sharp decline in agricultural production [7-8]. When conditions worsen, crops can become vulnerable to infection by drugs that cause fungi, bacteria, viruses and other diseases. The methods that can be used to prevent plant loss can be done by real-time identification of plant diseases.

Rice is the most important crop in Asian countries. Most people rely on rice for their food, as rice is considered the staple food of Asian countries. Rice is affected by many diseases that affect farmers' yield losses [9-10]. This method proposes a method for identifying blast furnace and brown spot diseases.

III. MATERIALS AND METHODOLOGY

Plants are susceptible to diseases and various disease-related attacks. Many causes are characterized by environmental conditions that affect plants, such as temperature, humidity, excess or lack of food and light, and widespread diseases like bacteria, viruses, and fungi. The proposed system uses the UNetCNN method to identify the plant leaf diseases. It can achieve maximum accuracy if the data is good. The proposed architecture diagram depicted in figure 1.

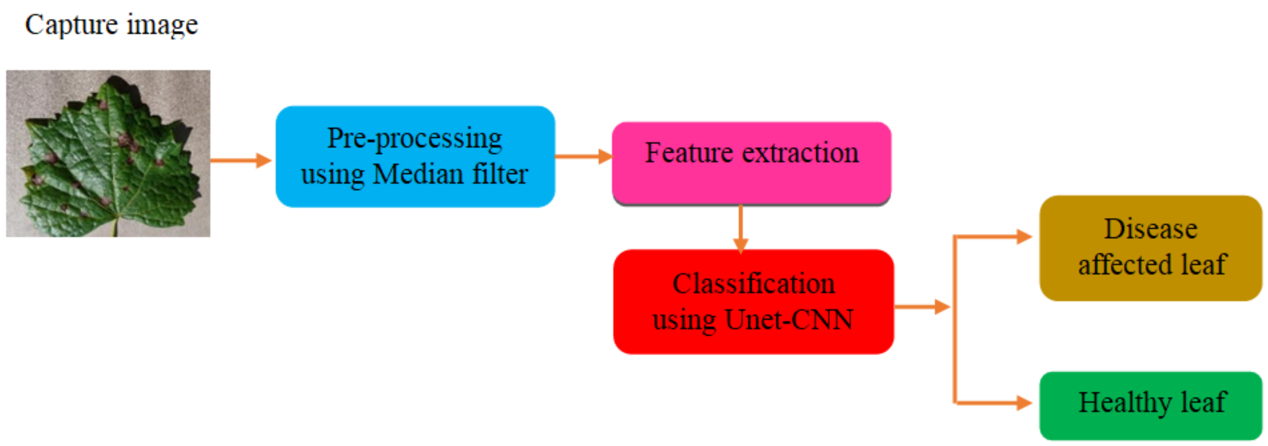

Fig 1: Proposed diagram

The proposed effective leaf disease diagnosis method is based on deep learning (DL) method and ROI extraction. A deep CNN model is built with an algorithm to extract regions of interest. Thus, a proposed leaf disease prediction model is realized.

A. Dataset collection

In this module, we use the public dataset's new plant disease database (NPDD). NPDD has 54303, including plant leaf images of normal and diseased leaves. It is divided into 38 classes according to the seeds and conditions. We analyzed 50,000 images of plant leaves with labels distributed in 38 sections and attempted to indicate the disease. Adjust the image size to 256 x 256 pixels and run the optimization and sample forecast with compressed images. The dataset is about 87KB, and the sick leaves are about 87K and are divided into 38 different types. The entire data set is divided into a ratio of 80/20 of training and validation (testing) packages to save the directory structure.

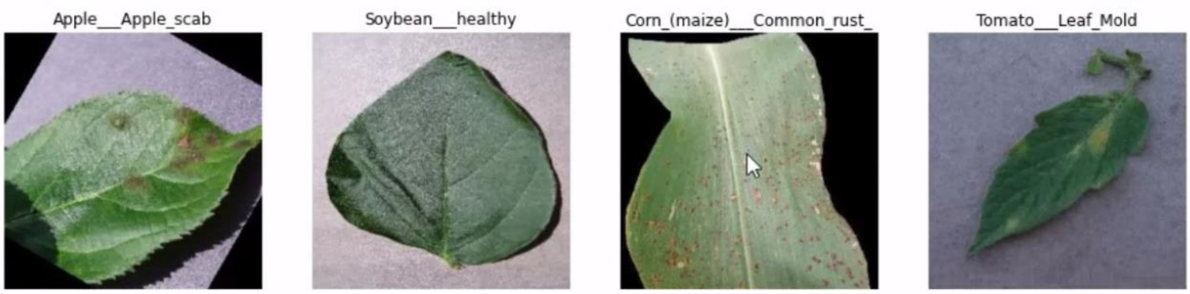

Fig 2: Plant disease sample images

B. Median filter

The median filter method aims to enhance the image's quality. The median filter extracts noise from an image. It is a non-linear technique for gray or salt and pepper noise removal. Applying this filter is used to reduce noise in the image. This filter is famous and keeps the edge.

$$Mean\ (\mu) = \sum_{x,y}^{M} N(x,y)$$

The above equation is used to extract useful information μ from input leaf image$N(x,y)$. Let us assuming x, y is the pixel and M is the total number of pixel in the image.

$$Standard\ deviation\ \sigma = \left(\frac{1}{M-1}\sum_{x,y}^{M}(N(x,y)-\mu)^2\right)^{\frac{1}{2}}$$

The above equation is used to find gray level in the imageσ.

$$Contrast\ (C_T) = \left\{\sum_{x,y}^{M} \sigma(x,y)\right\}, |x-y| = M$$

The above equation is used to estimate the plant leaf image contrast level based onσ.

C. Feature extraction

An image feature is a piece of information associated with content/object that helps to identify the content/object uniquely. Assign appropriate class labels to categorize things by their properties. In this particular hierarchy, leaf color, texture, morphology, and texture are diagnostic methods for plant leaf diseases.

$$E_{gy} = \sum_{x,y=0}^{M} {C_T}_{x,y}^{2}$$

The above equation is used to calculate the leaf energy $E_{gy}$of the processed dataset. The energy of the texture segments is defined as the order quantity in the image.

$$\text{Correlation } C_n = \sum_{x,y}^{M}(x,A)(y,B)\,E_{gy}(x,y)$$

The above equation is used to estimate correlation C_n based on energy. C_n is the linear correlation between a grayscale pixel and its neighbors. Correlation values are +1 and -1 for images with positive and negative correlations. Assuming that, A and B is the pixel direction.

$$En_{py} = \sum_{x,y=0}^{M} C_n(x,y) * \log\big(P(x,y)\big)$$

From equation is used to estimate the entropy (En_{py}). Entropy is a metric that calculates the randomness of an image. Irregular images have low first-order entropy, and uniform images have high entropy. Let us assume P is the probability of pixel x and y.

$$S_S = \frac{E(En_{py}-\mu)^3}{\sigma}$$

From equation is evaluate the skewness S_S in disease affect leaf. The S_S measures the asymmetry. A distribution or data set is symmetric if it looks the same to the left and to the right of a central point.

$$H_{ty} = \sum_{x,y}^{M} \frac{S_S(x,y)}{1+|x-y|}$$

From equation is estimate the homogeneity H_{ty}in the disease leaf. H_{ty} is the value of the element of the diagonal secret of the GLCM element. In the case of a diagonal component, the value is one, and the limit is 0 to 1.

$$D_m = \sqrt{\frac{4 * area}{\pi}}$$

The above equation is evaluate the diameter for disease affected area diameter D_m. This part proficiently picks the disease features from the pre-processed image.

D. U-net based Convolutional Neural Network

UnetCNN has proposed to decrease the number of parameters used and accurately adjust the network structures into visual tasks. CNN usually comprises a series of layers that that function can compile. CNN comprises four types of layers: convolutional layers (CL), Relu and S -sigmoid functions, Max-pooling, and fully connected neurons. The CL is a series of mathematical operations to extract input image features. Overview layers are usually used after CL. In this layer, the size of the output line obtained from the folding layer decreases. After receiving the final matrix, the pool and activating functions are sent to the input layer, as presented in figure 3.

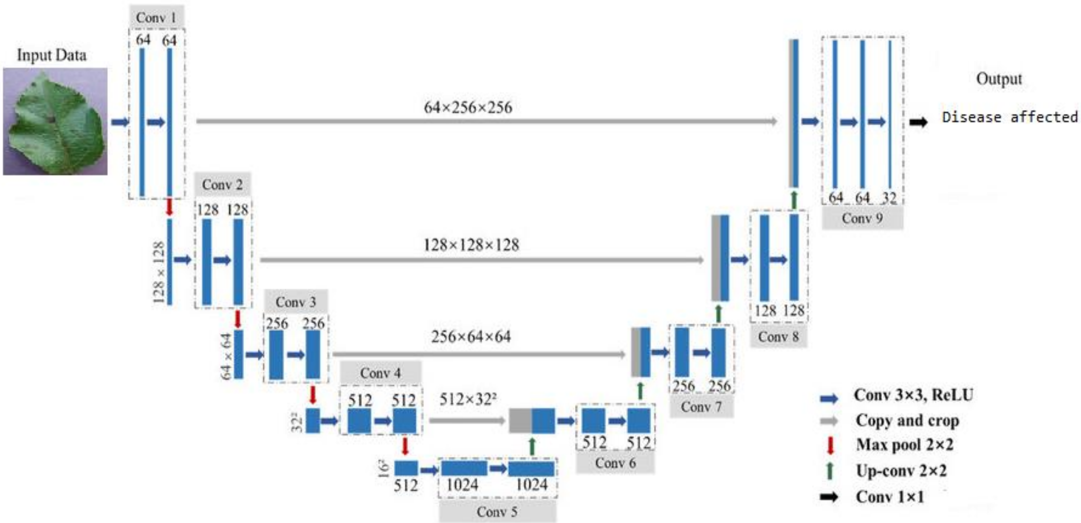

Fig 3: General architecture diagram for UnetCNN

Algorithm steps:

Require: Feature extracted leaf image D_m
Ensure: classification result as healthy or not
Step 1: Initialize the random weight values for each layer
Step 2: Now estimate the Convolutional layer (CL) input image

$\mathrm{CL} = \omega + \sum D_m$

Apply ReLu activation function

$CL' = ReLu(CL)$

Now these values are fed into Max-pooling layer

Step 3: Each Max-pooling layer nodes sums with initial weight

$MP = Bias + \sum CL'$

Apply ReLu activation function

$MP' = ReLu(MP)$

Now these values are trained into fully connected layer

Step 4: Each fully connected neuron

Update the initial weight and bias

$\omega_{up} = \omega_{Init} + \Delta\gamma$

$bias_{up} = bias_{init} + \Delta\gamma$

Now we estimate the output of leaf disease

$Fc = \sum MP' * \omega_{up} + bias_{up}$

Apply ReLu activation function

$Fc' = ReLu(Fc)$

Return optimized result

The above algorithm steps produced efficient categorization results for plant leaf disease. Figure 3 explains the flowchart for plant disease prediction using Unet-CNN algorithm.

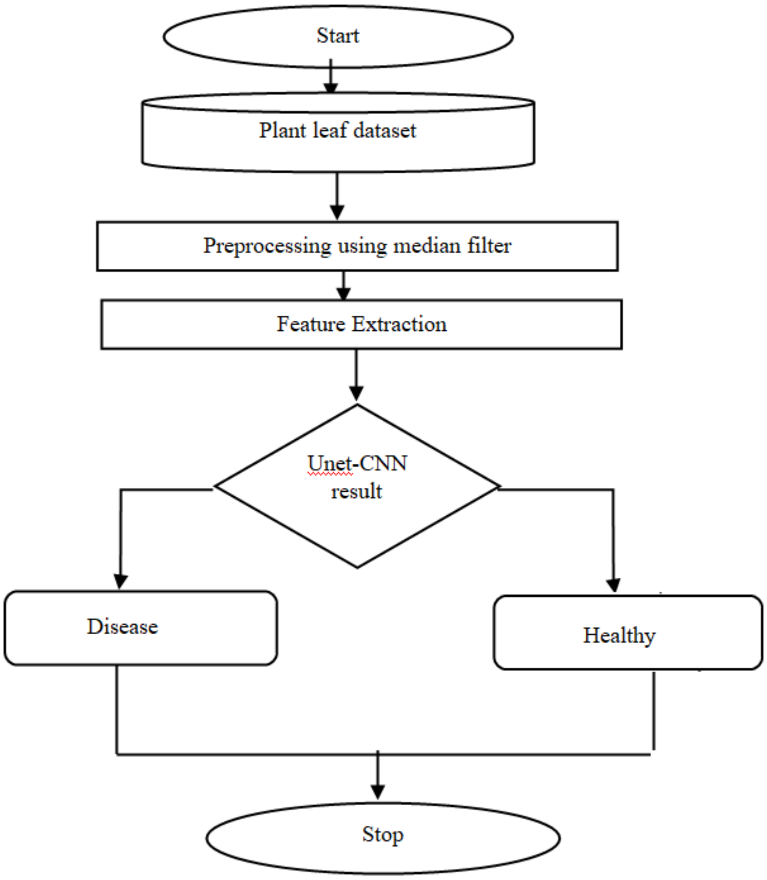

Fig 3: Flowchart for plant leaf disease prediction

Fig 4: Optimized result for disease classification

Figure 4 explores a Unet-CNN algorithm get optimized results for plant leaf classification.

IV. Experiment result analysis

This section efficiently identifies the plant disease using Unet-CNN algorithm compared to previous methods. Table 1 describes the model parameters for prediction environment.

Table 1: Simulation parameter for plant leaf disease prediction

Parameters	Ratings
Environment	Anaconda/Jupyter notebook
Language	Python 3.11.1
Dataset name	NPDD
Total images	54303
Training	80%
Validation	20%

Previous algorithms are Support Vector Machine (SVM) and K-Nearest Neighbor (KNN).

	Filename	Predicted classes
0	AppleCedarRust1.JPG	Apple___Cedar_apple_rust
1	AppleCedarRust2.JPG	Apple___Cedar_apple_rust
2	AppleCedarRust3.JPG	Apple___Cedar_apple_rust
3	AppleCedarRust4.JPG	Apple___Cedar_apple_rust
4	AppleScab1.JPG	Squash___Powdery_mildew
5	AppleScab2.JPG	Apple___Apple_scab
6	AppleScab3.JPG	Potato___Early_blight
7	CornCommonRust1.JPG	Corn_(maize)___Common_rust_
8	CornCommonRust2.JPG	Corn_(maize)___Common_rust_
9	CornCommonRust3.JPG	Corn_(maize)___Common_rust_
10	PotatoEarlyBlight1.JPG	Potato___Early_blight

Fig 4: Disease predicted class

Figure 4 explores an efficiently plant leaf disease prediction class using Unet-CNN algorithm.

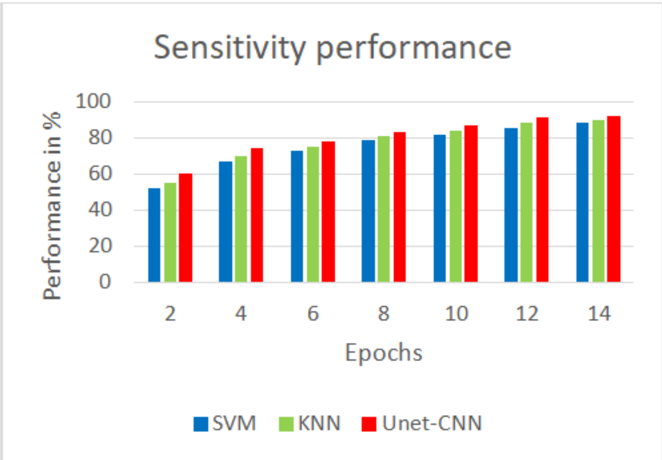

Fig 4: Analysis of sensitivity performance

In figure 4 describes the analysis of sensitivity performance for plant disease prediction. The above graph x-axis is number of epochs and y axis is gradually increased performance in % according to epochs. The proposed obtained 92% of sensitivity performance than other methods.

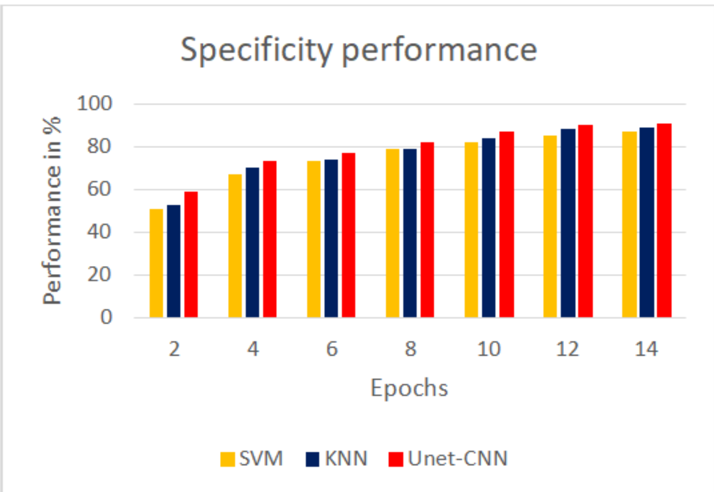

Fig 5: Analysis of specificity performance

In figure 5 describes the analysis of specificity performance for plant disease prediction. The above graph x-axis is number of epochs and y axis is gradually increased performance in % according to epochs. The proposed obtained 91% of sensitivity performance than other methods.

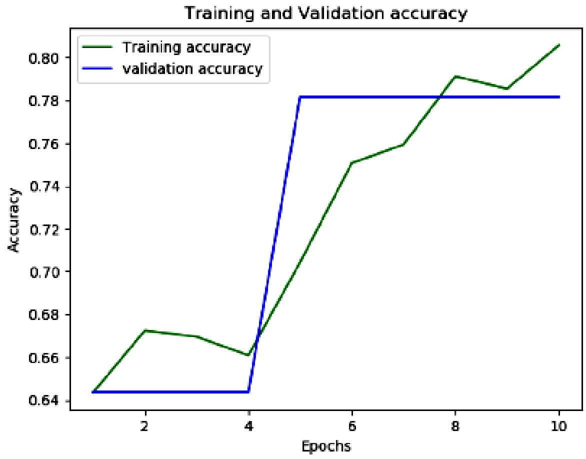

Fig 6: Training vs. validation result for accuracy

Figure 6 describes the training vs validation result for accuracy of plant disease prediction using Unet-CNN technique. The proposed has obtained 90% of training accuracy and 85% of validation accuracy for disease identification.

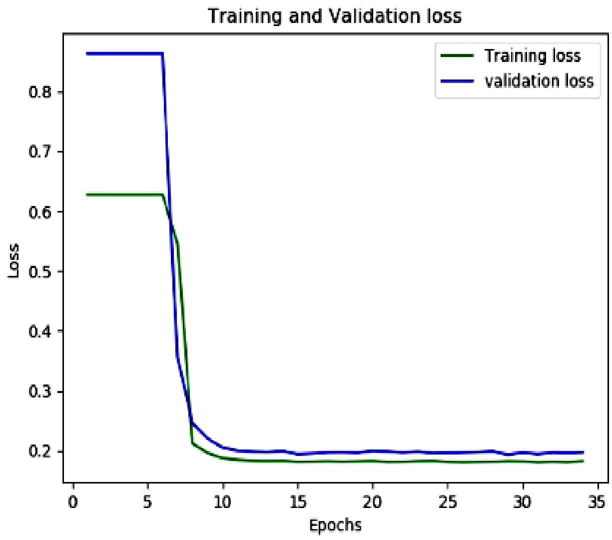

Fig 7: Training vs. validation result for loss

Figure 7 explores a training and validation for loss for predict leaf disease prediction. The proposed training loss result is 0.15 and validation loss is 0.24 for plant disease classification.

V. CONCLUSION

In this novel present U-net based Convolutional Neural Network (UNetCNN) with ReLu activation function is used to classify the plant disease. First we collect the dataset from online kaggle then preprocess the image to remove noise using median filter. Second extract the finest features of plant leaf disease from preprocessed image. Finally the proposed UNetCNN and ReLu activation is efficiently classify the plant disease. The proposed method experimental result produces better result than other methods. In future, to improve plant disease identification based on segmentation and feature selection using deep learning techniques. The segmentation is used to identify the interest of region for plant disease such as spot's diameters, perimeter, size etc.

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