A COMPARATIVE ANALYSIS ON PLANT LEAF DISEASE DETECTION USING ANN, CNN, AND RNN WITH GLCM FEATURES

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Abstract
Detecting plant leaf disease at an early stage is crucial for effective disease management and preventing significant crop loss. Early detection involves identifying symptoms like discoloration, spots, or lesions on the leaves before they spread extensively. Traditional methods include regular visual inspection by trained personnel, but these can be time-consuming and subjective. With advancements in technology, modern approaches utilize image processing, machine learning, and deep learning techniques to automate and enhance the detection process. High-resolution images of plant leaves are analysed to detect subtle changes in colour, texture, and shape. These methods can identify specific diseases by comparing features with a database of known symptoms, enabling precise and early diagnosis. Early intervention can then be applied, such as targeted pesticide application or other control measures, minimizing the impact on the crop and reducing the spread of the disease. The agricultural sector faces significant challenges due to plant diseases, which can lead to substantial crop losses. The advent of machine learning techniques, specifically Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), has provided new avenues for accurate and efficient plant disease detection. This paper aims to compare the accuracy of these three machine learning architectures in diagnosing plant leaf diseases.

Keywords –Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Convolutional Neural Network ((CNN), Gray Level Co-occurrence Matrix (GLCM), Feature Extraction.

I. INTRODUCTION

Plants are omnipresent and it is the support of all life on Globe and an important resource for human well-being. The first and foremost step during design phase is leaf recognition which further continued to get the final identification of plant leaf disease. Plant leaf disease plays vital role in different areas like medicine and agriculture etc., Due to several serious problems like global warming and absence of consciousness of plant knowledge, the leaf groups are becoming rare and many of them are about too extinct. Development of a rapid and efficient classification and detection methodhas become an area of active investigation. Traditional methods of plant leaf disease detection often rely on expert knowledge and visual inspection, which can be time-consuming and subjective. Machine learning, particularly deep learning, has emerged as a powerful tool for automating the detection process.

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Fig. 1.1 Infected Plant Leaf

II. METHODOLOGY

The proposed framework consists of following main steps which are

1) Give acquired leaf image of plant as input.
2) Convert it to gray scale image.
3) Apply median filter to enhance the quality of image.
4) Extracting features by using GLCM
5) Prepare Model design and implementation
6) Training the dataset
7) Testing the dataset
8) Compare the results

The architecture workflow depicts the steps involved and the corresponding input and output. The methodology used to compare the disease infected leaf (Unhealthy) images is as shown in Fig. 2.1.

2.1 Generalized View

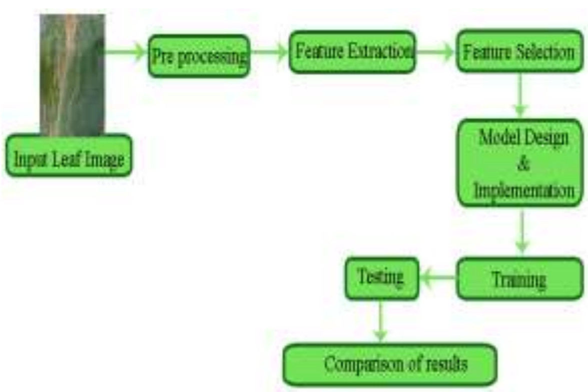

Fig. 2.1 Block diagram of the system

2.2 Data Collection:

This study utilizes publicly available datasets comprising images of healthy and diseased plant leaves. The Plant Village dataset is used, which includes images of various crops and their corresponding diseases, serve as the primary source.

2.3. Image Pre-processing

After obtaining digital images, image pre-processing techniques can be further used for analysis of region of interest. The pre-processing is used to read the input image into the Jupyter Notebook and also to remove the noise present in the image. Image pre-processing consists mainly of following steps.

- Image Resizing (128*128)
- Gray conversion
- Median filter
- Contrast Enhancement
- Data Augmentation (Rotation, flipping, scaling, cropping and zooming)

The acquired MRI scanned image, stored in database is converted to gray scale image of size 256*256. It includes median filter for noise removal.

2.3.1 Median filter

In this work an efficient filter referred to as the median filter, is applied to the image. The median filter is a nonlinear digital filtering technique, is often used to remove noise. Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise. It works by moving pixel by pixel through the image, replacing each value with the median value of neighboring pixels.

The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value. Image processing researchers commonly assert that median filtering is better than linear filtering for removing noise in the presence of edges.

2.4 Feature Extraction

The third step of the proposed work is featuring extraction. Transforming the input data into the set of features is called feature extraction. Features are used as inputs to classifiers that assign them to the class that they represent. In this work Gray Level Co-occurrence Matrix (GLCM) features are extracted.

2.4.1 GLCM Features

The Gray Level Co-occurrence Matrix (GLCM) is a popular technique for texture analysis, which can be used as part of a plant leaf disease detection system. The GLCM computes how often pairs of pixels with specific values and in a specified spatial relationship occur in an image. From this matrix, various statistical measures can be extracted, such as contrast, correlation, energy, and homogeneity, which help in detecting disease patterns.

greycomatrix () computes the GLCM for specified distances and angles. The matrix gives a statistical distribution of pixel intensity pairs, describing how often one pixel with intensity `i` is found adjacent to another pixel with intensity `j`.

The Following GLCM features are extracted in this study:

- Contrast
- Correlation
- Homogeneity
- Entropy
- Energy

Contrast: The contrast is one of the many features that can be derived from the GLCM, which provides a measure of the intensity contrast between a pixel and its neighbor over the whole image.

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The formula for calculating the contrast from a GLCM is:

$$\text{Contrast} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 \cdot P(i,j)$$

Correlation: The correlation is another feature derived from the Gray Level Co-occurrence Matrix (GLCM) and measures the linear dependency of grey levels on those of neighboring pixels.

$$\text{Correlation} = \frac{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-\mu_i)(j-\mu_j) P(i,j)}{\sigma_i \sigma_j}$$

Homogeneity The homogeneity is a feature derived from the Gray Level Co-occurrence Matrix (GLCM) that measures how similar the elements of the GLCM are to its diagonal. It provides insight into how uniform the texture is within an image.

$$\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)}{1+|i-j|}$$

Energy: The **energy** (also known as **angular second moment** or **uniformity**) is a feature derived from the Gray Level Co-occurrence Matrix (GLCM) that measures the uniformity of the texture. It quantifies the sum of squared elements in the GLCM, indicating how texturally uniform an image is.

$$\text{Energy} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (P(i,j))^2$$

B. References

Plants are among the earth's most useful and beautiful products of nature. Plants have been crucial to mankind's survival. The urgent need is that many plants are at the risk of extinction. About 50% of ayurvedic medicines are prepared using plant leaves and many of these plant species belong to the endanger group. So it is indispensable to set up a database for plant protection. We believe that the first step is to teach a computer how to classify plants. Leaf /plant identification has been a challenge for many researchers. Several researchers have proposed various techniques. In this paper we have proposed a novel framework for recognizing and identifying plants using shape, vein, color, texture features which are combined with Zernike movements. Radial basis probabilistic neural network (RBPNN) has been used as a classifier. To train RBPNN we use a dual stage training algorithm which significantly enhances the performance of the classifier. Simulation results on the Flavia leaf dataset indicates that the proposed method for leaf recognition yields an accuracy rate of 93.82% [1].

-Identification of leaf and plants is an area of research which has gained a lot of attention in these years and is also an important tool in the field of agriculture, crop rotation, cultivation, forestry and much more. The process generally begins with the acquisition of images i.e., enhancement of leaf images, segmentation of leaf, its feature extraction and the classification. Today, Classification of plants using its various categories has been a broad application. In this paper we presentdifferent techniques which can be used for plant leaves classification. The classification method includes some segmentation algorithms and pattern classification techniques. This technique helps in plant-leaf classification. This process and analysis is effective and the performance of the leaf classification system is analyzed using Radial Basis Function Neural Network (RBFNN). RBFNN enables non linear transformation followed by linear transformation to achieve a higher dimension in hidden space. RBFNN is trained and tested for various categories of leaf images using different Grey Level CoOccurrence Matrix(GLCM) Features. The results show satisfactory performance and the highest accuracy of 93.04% is achieved using Gaussian Kernels. [10] .

2.5 Classification

Classification is the process where a given test sample is assigned a class on the basis of knowledge gained by the classifier during training. Classification technique is applied to the plant leaf image database.

2.5.1 Artificial Neural Network:

Artificial Neural Networks contain artificial neurons which are called units . These units are arranged in a series of layers that together constitute the whole Artificial Neural Network in a system. A layer can have only a dozen units or millions of units as this depends on how the complex neural networks will be required to learn the hidden patterns in the dataset. Commonly, Artificial Neural Network has an input layer, an output layer as well as hidden layers. The input layer receives data from the outside world which the neural network needs to analyze or learn about. Then this data passes through one or multiple hidden layers that transform the input into data that is valuable for the output layer. Finally, the output layer provides an output in the form of a response of the Artificial Neural Networks to input data provided.

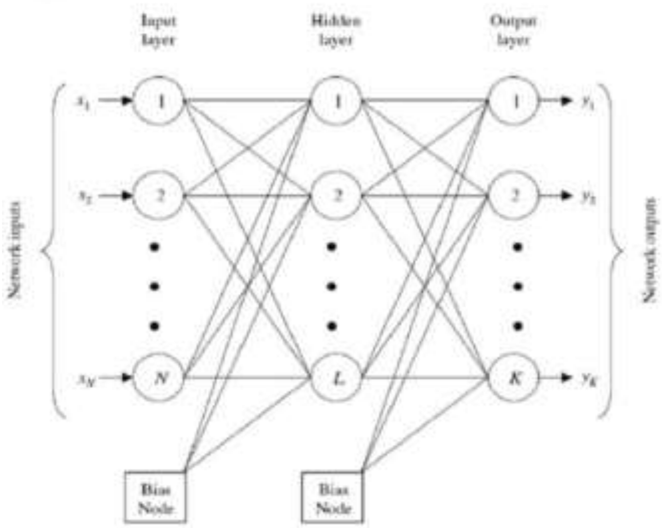

Fig. 2.2 Architecture of ANN

2.5.2 Recurrent Neural Network:

Recurrent Neural Network (RNN) is a type of Neural Network where the output from the previous step is fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other. Still, in cases when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the existence, which solved this issue with the help of a Hidden Layer. The main and most important feature of RNN is its Hidden state, which remembers some information about a sequence. The state is also referred to as Memory State since it remembers the previous input to the network. It uses the same parameters for each input as it performs the same task on all the inputs or hidden layers to produce the output. This reduces the complexity of parameters, unlike other neural networks.

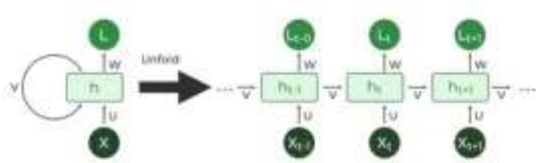

Fig. 2.3 Architecture of RNN

2.5.3 Convolution Neural Network:

A Convolutional Neural Network (CNN) is a class of deep neural networks that is particularly effective for processing structured grid data like images. Here's a simplified overview of how CNNs work:

2.5.3.1. Convolutional Layers: The core idea is to use convolutional layers, which apply a set of filters (kernels) to the input data. Each filter detects specific features like edges, textures, or patterns. As the filter slides (or convolves) across the input, it produces feature maps that highlight where these features are present.

2.5.3.2 Activation Function: After applying the filters, the result is passed through an activation function, typically a ReLU (Rectified Linear Unit), which introduces non-linearity into the model. This helps the network learn more complex patterns.

2.5.3.3 Pooling Layers: To reduce the spatial dimensions of the feature maps and to make the network computationally efficient, pooling layers (such as max pooling) are used. Pooling reduces the size of the feature maps while retaining the most important information.

2.5.3.4. Fully Connected Layers: After several convolutional and pooling layers, the high-level features are flattened into a vector and passed through fully connected layers. These layers combine the features to make final classifications or predictions.

5. Output Layer: The output layer uses an activation function like softmax for classification tasks, providing probabilities for different classes.

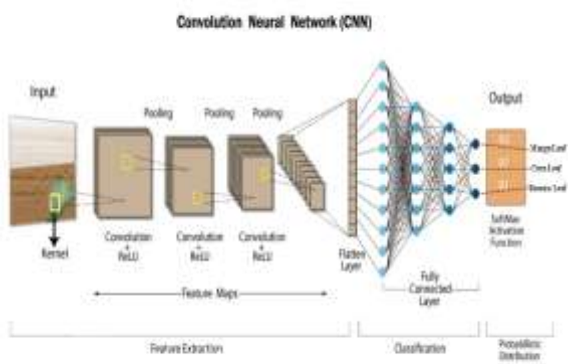

Fig. 2.4 Architecture of CNN

Extracted texture features using GLCM of leaf diseased images are considered as values, and each image feature representation is a record**.** In this study ANN, RNN and CNN classifier is used to detect plant leaf as healthy or unhealthy leaf (Infected).

2.5.4 Data Description

The Leaf image data description of the proposed method is shown in table.

S.No.	Type of Image	Number of Images
1	Healthy Leaf Images	100
2	Unhealthy Leaf Images	100

Table 2.1: Dataset Description

For each region, we calculated the following four set of features. The attributes descriptions are shown in Table 2.2 below.

S.No.	**Attribute**	**Category**
1	Contrast	Numeric
2	Correlation	Numeric
3	Homogeneity	Numeric
4	Energy	Numeric
5	Leaf Image	Class

Table 2.2: Attribute Description

III. RESULTS AND DISCUSSION

An experiment has been conducted on a plant leaf image data set with python libraries like keras, tensorflow, scikit learn, etc., based on the proposed flow diagram as shown in Fig 2.1.

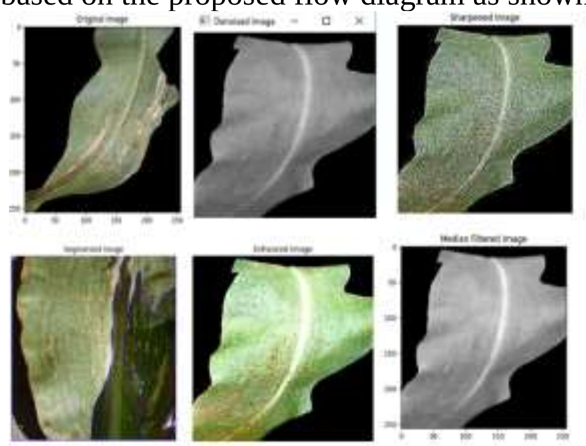

Fig. 3.1 Preprocessing Image

Features extracted using ANN with GLCM such as contrast, correlation, homogeneity, energy, entropy. Then texture feature set listed in "Table 3.1" is extracted using GLCM statistical method.

S.No.	GLCM Features (ANN)	Healthy	Unhealthy
1	Contrast	0.2000	1.5000
2	Correlation	0.9000	0.4000
3	Homogeneity	0.9000	0.5000
4	Energy	0.8000	0.3000

Table 3.1. Extracted GLCM Features using ANN

Features extracted using RNN with GLCM such as contrast, correlation, homogeneity, energy, entropy. While RNNs are traditionally used for sequential data like time series or text, they also be applied to sequences of features extracted from images.

S.No.	GLCM Features (RNN)	Healthy	Unhealthy
1	Contrast	0.1000	1.2000
2	Correlation	0.9500	0.5000
3	Homogeneity	0.9300	0.6000

4	Energy	0.8500	0.4000

Table 3.2 Extracted GLCM Features using RNN

Features extracted using CNN with GLCM such as contrast, correlation, homogeneity, energy, entropy. While CNN can learn spatial patterns from an image itself.

S.No.	GLCM Features (CNN)	Healthy	Unhealthy
1	Contrast	0.2500	1.7000
2	Correlation	0.9300	0.5500
3	Homogeneity	0.8800	0.6500
4	Energy	0.8300	0.4500

Table 3.3 Extracted GLCM Features using CNN

3.1 Performance Evaluation The performance of ANN using metrics such as accuracy, precision, recall, F1-Score and ROC-AUC.

Confusion Matrix: The confusion matrix is used to measure the performance of two class problem for the given data set. The right diagonal elements TP (true positive) and TN (true negative) correctly classify Instances as well as FP (false positive) and FN (false negative) incorrectly classify Instances. Confusion Matrix Correctly Classifiy Instance and TP+TN Incorrectly Classifiy Instance FP+FN.

ANN	Predicted: Diseased	Predicted: Healthy
Actual: Diseased	90	10
Actual: Healthy	5	95

Table 3.4: **Confusion Matrix of ANN**

The performance of RNN using metrics such as accuracy, precision, recall, F1-Score and ROC-AUC.

RNN	Predicted: Diseased	Predicted: Healthy
Actual: Diseased	70	30
Actual: Healthy	20	80

Table 3.5: Confusion Matrix of RNN

The performance of CNN using metrics such as accuracy, precision, recall, F1-Score and confusion matrix.

CNN	Predicted: Diseased	Predicted: Healthy
Actual: Diseased	95	5
Actual: Healthy	3	97

Table 3.6: **Confusion Matrix of CNN**

Accuracy: It is defined as the ratio of correctly classified instances to total number of instances. The effectiveness of the proposed method has been estimated using accuracy measure.

Accuracy = (TP + TN) / (TP+TN+FP+FN) where,
True Positive (TP): Number of Unhealthy leaf images correctly classified

False Positive (FP): Number of Healthy images classified as Unhealthy

True Negative (TN): Number of Healthy images correctly classified

False Negative *(FN)*: Number of Unhealthy images classified as Normal.

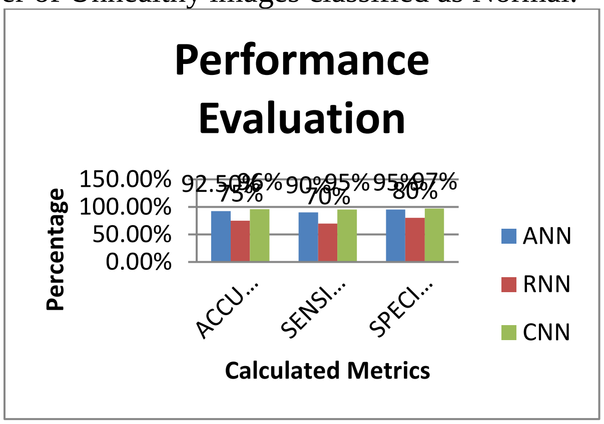

Fig. 3.2. Comparison of performance evaluation

IV. CONCLUSION

In this paper, a comparison for classifying plant leaf disease infected images from healthy images was proposed. In the pre-processing step, the developed approach used median filter to remove unwanted distortions, artifacts and acquire a good quality of an image. Feature extraction performed using GLCM then ANN, RNN and CNN used to classify the healthy leaf and Unhealthy leaf. The accuracy of 92.5%, 75% and 96% is found in detection of plant leaf disease of ANN, RNN and CNN respectively.

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