

ADAPTIVE TYPE 2 FUZZY AND BPNN CLASSIFICATION BASED PLANT LEAF DISEASE DETECTION

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Abstract: Agriculture has a major role in the growth and development of every nation's economy. The productivity of the agriculture industry is impacted by the advent of multiple plant-related illnesses. Plant disease detection is important for managing this problem, educating farmers about preventing illnesses from spreading, and implementing efficient management practices. Agriculture continues to be the principal employment sector with a small percentage of the workforce despite its steadily declining contribution due to population growth. Therefore, the pace of competitive, productive, varied, and sustainable agriculture needs to be accelerated. Plant leaf damage results from incorrect pesticide selection that is frequently caused by misinterpretations of plant leaf diseases. For this reason, from the perspective of the farmer, automatic disease detection at an early stage is both significant and cost-effective. For this, proper segmentation of diseased part from the plant leaf in an accurate way is of utmost importance to diagnose the disease at earlier stage. But, its accurate detection has become a challenging task due to presence of noise in the digitally captured image, variation in background, shape and brightness in diseased images. Although numerous approaches have already been employed for this aim by researchers, other approaches connected to vision remain unexplored. Mean, Median, and Gaussian, image pre-processing methods like filtering the unwanted noise, and deep structured learning methods like neural networks are among the frequently employed techniques. We have created a new method that combines Adaptive Type 2 Fuzzy technique with Back Propagation Neural Networks to classify and detect plant leaf diseases. Our findings were derived from a dataset of village plant leaf images and leaf images from kaggle website were used as the training dataset. And also we are taking some leaf images for testing dataset. Different types of agricultural plant leaf diseases have been examined. Using photos of the leaves, the suggested system was trained to identify the leaf disease. In our suggested study, the suggested architecture improved plant leaf disease prediction to overall efficiency. Using this proposed Adaptive Type 2 Fuzzy filtering technique, we achieved the output result of MSE of 40.15, PSNR of 38.55, Correlation of

0.968, with the 26.78 milliseconds time duration of prediction which is superior to the other traditional approaches such as Mean, Media, Gaussian methods.

Keywords: Plant leaves, Leaf Disease Prediction, Pre-processing, Adaptive Type 2 Fuzzy, Deep Learning, Back Propagation Neural Network

I. INTRODUCTION

In the modern economy, agriculture plays a critical role, supporting, on average, 80% of rural households. Numerous fruits, cereals, and vegetables are grown in our nation and exported abroad. Thus, surrendering at the ideal ratio of quantity to quality is necessary. Plant diseases are unavoidable due to certain environmental variables, which mean that agriculture needs a preventative approach, as described by Horn, Lydia, et al. (2022). Any component of the plant, including the leaf, stem, and fruit, can have bacteria, fungi, or viruses that cause common diseases. Plant growth is impacted by bacteria that are located in the plant, such as Alternaria, Anthracnose, bacterial spot, canker, etc. Fungus disease in crop leaves is caused by environmental factors. Crop disease is identified by human observation of a few symptoms on plant leaves and harvested crops, and its intricacy is quickly growing. Psychopathological issues arise as a result of crop density and complexity. Even for agricultural and plant pathology specialists, the aetiology of a disease might occasionally be unforeseen, leading to conclusions and unfavourable solutions analysed by Patel, Bharati, and Aakanksha Sharaff (2023). Crop leaves' symptoms are a great way to anticipate the onset of a disease and are further enhanced by automated disease detection.

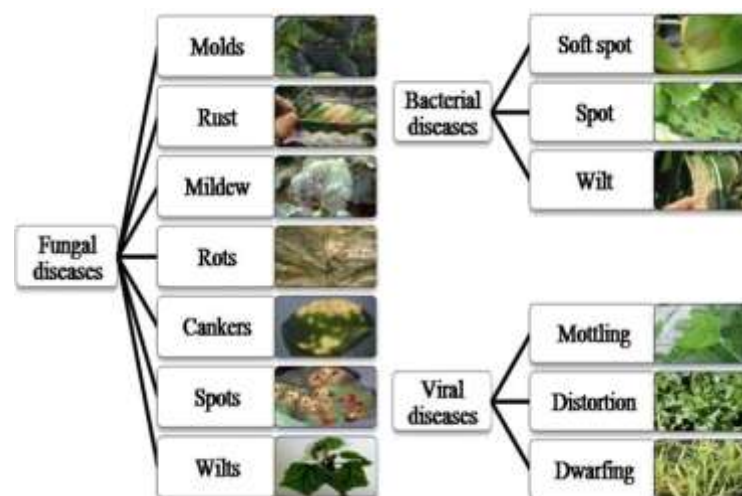


Fig.1 Different types of plants pathogens and related disease

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The above figure 1 shows the different plant diseases and its classifications. Commonly the plants are affected by Bacteria, Virus, and Fungus. So, Kaur, S., Pandey, S., & Goel, S. (2019), discussed that the plants leaves and crops leaves affected by the diseases are classified by (i) Bacterial diseases, (ii) Viral diseases, and (iii) Fungal diseases.

The common bacterial diseases for plants and crops are, soft spot, wilt, etc,. And the viral diseases affected the plants are, mottling, distortion, and dwarfing. The fungal diseases affected the plants are, rust, mildew, rots, and cankers, etc,. These are the most diseases for common plants and crops diseases affected. These kinds of diseases are predicted and classified used in many techniques. Among this Artificial Intelligence is the most accurate image processing method to find out the plant crop diseases using its leaf images. In AI prediction and classification technique, the Machine Learning and Deep Learning techniques are most widely used approaches for image processing in disease predictions and classifications.

1.1 Image Processing

In image processing technique, Deep Learning technique is a sub-system of the AI techniques. It is similar to the machine learning method, the current work created a deep learning model to identify several agricultural diseases. The disease detection model consists of three steps: step 1 is identifying crops; step 2 is determining the occurrence of diseases; and step 3 is identifying the sorts of diseases. And the following methods are used to predict the plant crop growth and diseases given by Islam, Md Manowarul, et al (2023).

Generally the image processing consists of the following process:

- (i) Pre-processing (noise removal),
- (ii) Segmentation,
- (iii) Feature Extraction, and
- (iv) Classification.

1.2 Pre-processing

Pre-processing is the procedure for raising the calibre of an input image. It is a crucial phase in the recognition process since a noisy image directly affects the classification of diseases' outcomes. Denoising, contrast correction, and edge enhancement are the three stages

this approach takes to improve an input image of plant leaves analysed by Sivanantham Kalimuthu et al., (2022).

The mapping function is essentially carried out via deep learning classification. It uses sample input to map to the required class or label. Many techniques for image processing with sickness detection are already available. Artificial neural networks are used in Sabrol, Hiteshwari, and Satish Kumar's (2020) image processing method to recognize brinjal leaves.

1.3 Segmentation and Feature Extraction

In image segmentation, each image is split as a large number of parts or regions. In image segmentation, the image is divided starkly and accurately. A section of an image is the outcome of image segmentation, which consists of a removed group of contours of the total image, taken from Alliou, H., et al (2020).

The feature extraction process looks for several traits that best describe an image of plant leaves. A feature selection algorithm is used in the second stage to choose the most noticeable features. Five categories of features were extracted during feature extraction. They are paddy-related features, geometric features, colour features, texture features, and fractal features, given by Geetha, A. (2022).

1.4 Classification

The work of identifying the plant to which the input paddy belongs is the study's final phase, and it is crucial for the discipline of botany. The core of the algorithm is an iterative recognition process that compares characteristics taken from the input image with feature vectors corresponding to photos of plant leaves from the pre-built dataset Argüeso, David, et al. (2020).

The proposed system mainly focused to remove the noise from leaves image improves the classification efficiency. Pre-processing techniques are essential for tasks involving image processing and computer vision, with varying applications. This research adaptive type 2 fuzzy filters, particularly when handling variable and unpredictable environmental circumstances, changes in leaf appearance, and a variety of disease kinds. Proposed filter effectively handle the leaf diseases dataset and compared to the existing techniques.

This paper's summary is structured as follows. Section II, explain various techniques involved to plant leaf diseases detections and its related previous work, Section III explained to proposed system design of our newly constructed leaf disease prediction pre-processing technique, Section IV presents proposed adaptive Type 2 Fuzzy algorithm and existing Mean, Median, Gaussian algorithms comparability of filtering experimental outcomes. Section V elaborates on the proposal's conclusion and potential future application.

II. LITERATURE REVIEW

To identify different plant crop illnesses of the leaves, fruits, and vegetables, early detection of crop diseases of the plant picture is required. A variety of algorithms that can accurately and effectively segment the affected area and extract distinct information from an image of a diseased crop plant have been developed in an effort to build a variety of classification algorithms that will enable the timely identification of a variety of plant-related illnesses. In recent years, it has become evident that the application of image analysis in several domains is vitally important. The literature has employed a variety of algorithms to identify plant crop diseases. Numerous methods have been employed in the literature to classify diseases, extract characteristics from infected crops, and separate diseased parts. The present review of literature is divided into two subsections based on the identification of plant crop diseases.

An efficient method will be to identify the illnesses by an automated computer-based model by John, Sreya, and Arul Leena Rose Peter Joseph. (2023). Plant disease identification is made easier by the combination of ML algorithms and image processing techniques. The dataset for the proposed work consists of plant leaf photos from ten different crops. Following acquisition, the pictures are pre-processed using Gaussian filtering and BPDFHE, an improved form of histogram equalization. PSNR, SSIM, and MSE are among the metrics used to compute and compare the results. Compared to the current preprocessing techniques, our method performs more accurately.

A high-quality image at the system's input is becoming more and more necessary with the introduction of cutting-edge imaging-based techniques for the diagnosis of plant diseases using leaf images. The accuracy of the segmentation and feature extraction stages is largely dependent on the high contrast, noise-free image. The hybrid pre-processing methodology presented in this article serves the two primary objectives of the pre-processing step by Kaur,

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Bobbin prêt. (2021). After using a modified technique based on BPDFHE for Contrast Improvement, an adaptive median filtering approach is used to limit the noise in the input image. This generates the competing model. By calculating the characteristics of image quality, the performance is assessed and compared to current techniques.

The algorithms those are capable of precisely identifying the most common wheat leaf diseases. Data processing and leaf imaging techniques have recently been widely used in expensive systems to assist farmers in monitoring a vast area of wheat plantations. In this study, the images are enhanced and unwanted distortions are eliminated by the use of a hybrid pre-processing method. The damaged regions of the pre-processed photos were segmented using fuzzy C-Means. Rajesh Kanna, R., and V. Ulagamuthalvi used a CNN is used to integrate the data into a disease classification model. To evaluate how effective the recommended strategy was, Kaggle data and a number of measures were used. Based on the input images, this study shows that the hybrid pre-processing model achieved 95% accuracy, whereas the classic LSTM technique achieved 92% accuracy.

Many mistake kinds brought on by a variety of circumstances, such as the environment and the tools utilized, result in noise in a leaf image. It is also an addition to faults that occur during image processing, encoding, and storage. The primary way that the Gaussian-Noise (GN) effect reduces the quality of leaf images is by introducing either higher or lower contrast in the input image's edge region. The methods and techniques for eliminating noise from leaf picture studies are covered in this article. The main goal here would be to enhance the leaf picture quality by pre-processing in order to boost the automated Leaf Disease Detection (LDD) model's performance. The techniques and methods for eliminating noise from leaf picture studies are covered by Dhivya, R., and N. Shanmugapriya. (2022). Here, the main goal is to improve the automated Leaf Disease Detection (LDD) model's performance by pre-processing the leaf picture to a higher quality. DCT, DWT, and K-means Singular-Value-Decomposition and DWT (K-SVD-DWT)" are the filtering techniques we suggest using in this study to pre-process the leaf image. The metric known as "Peak-Signal-to-Noise-Ratio (PSNR)" was utilized to ascertain which filtering strategy was preferable. The highest PSNR denoised image's output can be sent to the segmentation job for a further LDD operation.

Productivity may be impacted if leaf infections are not discovered early on. The initial stage of every image processing application is picture pre-processing. The illnesses in plant leaves are identified using a number of algorithms. Unfortunately, these algorithms often fail

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to produce the desired results when applied to noisy photos or images captured in low light. Noise, variations in lighting, and camera position make pre-processing of these photos essential. The initial stages of picture processing help the subsequent ones. The suggested technique involves first sharpening the image and then denoising it with the median filter. Next, k-means clustering is used to segment the picture. A higher-quality image was produced by combining these techniques explained by Deepa. (2018).

The traditional method of identifying plants takes a long time and is difficult. Conversely, plant knowledge and the capacity to recognize different plant species are vanishing with time. The fundamental reasons behind the development of this study were the shortcomings of manual identification and a lack of knowledge. Therefore, the primary goal is to evaluate the effectiveness of various machine learning algorithms and determine which one is optimal for implementing in the future construction of a mobile application that will identify Sri Lankan plants herbs, fruits, and vegetables by utilizing their leaves. This study concentrates on the efficient classification and pre-processing of manually collected leaf collections. Noise reduction, image improvement, and transformation were carried out during the pre-processing phase. After that, characteristics were taken out in terms of color, texture, and shape. After normalizing the data, the dataset was subjected to five machine learning algorithms for categorization. In the end, the Multilayer Perceptron algorithm's accuracy and loss curves were used to determine the algorithms' classification accuracy. The methods for K-Nearest Neighbors, Random Forest, Multilayer Perceptron, Support Vector Machine, and Decision Tree have classification accuracies of 84.82%, 82.88%, 80.85%, 75.45%, and 64.39%, in that order. The Support Vector Machine and Multilayer Perceptron algorithms performed satisfactorily, based on the findings from Dissanayake, D. M. C., and W. G. C. W. Kumara. (2021).

The automatic diagnosis of plant diseases with minimal processing time is the main challenge facing these systems constructed by Deepa, N. R., and N. Nagarajan. (2021). The Kuan filtered Hough transformation based reweighted linear program boost classification technique is introduced to increase the disease detection accuracy (DDA) with least time. Three steps are involved in the KFHT-RLPBC technique: pre-processing, feature extraction, and classification. A variety of leaf photos are taken from the plant dataset. During the pre-processing stage, the Kuan filter is used to eliminate noise from the input leaf images, enhancing the image quality and increasing the accuracy of disease diagnosis. To extract features related to shape, texture, and color, applies the Hough transform. By using feature

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extraction, the KFHT-RLPBC technique lowers the temporal complexity (TC) associated with disease detection. In order to diagnose the sickness at an earlier stage by constructing the number of weak learners, the classification is completed by applying the RLPBC. By combining the weak learner findings, the boosting classifier creates a strong one that achieves maximum illness detection accuracy while minimizing error. The experimental evaluation of the plant village dataset is carried out with respect to three parameters: time complexity, accuracy of illness diagnosis, and peak signal to noise ratio. According to experimental data, this technique decreases time complexity compared to previous works while improving peak signal to noise ratio and disease detection accuracy.

Sharma, P., Hans, P., & Gupta, S. C, (2020, January), discussed that the different types of diseases attack crops as a result of seasonal variations in agricultural sector. The quality and quantity of crop produced are impacted by these diseases, which initially harm the plant's leaves before spreading to the entire plant. The abundance of plants on the farm makes it exceedingly challenging for the human eye to identify and categorize each plant's condition. Furthermore, because these illnesses could spread, it is critical to diagnose every plant. Thus, for quick and simple disease detection, classification, and necessary treatment execution, we are introducing in this study an artificial intelligence based automatic plant leaf disease detection and classification system. The objective of our method is to raise crop productivity in agriculture. This method involves a number of phases, including the gathering of images, image pre-processing, segmentation, and classification.

The drawbacks of existing systems are discussed in the above reviews. Pre-processing of plant leaf image is done by using various techniques. It involves the noise removal by using different types of filters. Choosing the filter for image pre-processing technique is the important factor in disease identification. The above mentioned pre-processing filters having various demerits of CPU processing time consumption, accurate level of disease identification, Clarity of noise removal, intensity of images filtering, etc. Depends upon these parameters, the proposed Adaptive Type 2 Fuzzy method is constructed to overcome the aforementioned limitations.

III. SYSTEM DESIGN

The proposed study describes an experiment utilising filtering method with deep learning technique for the agricultural sector. Adaptive Type 2 Fuzzy method proposed to handle the pre-processing filter and back propagation neural network (BPNN) in order to detect and classify the disease in plant's leaves. Figure 2 explains about the proposed Adaptive Type 2 Fuzzy filtering technique.

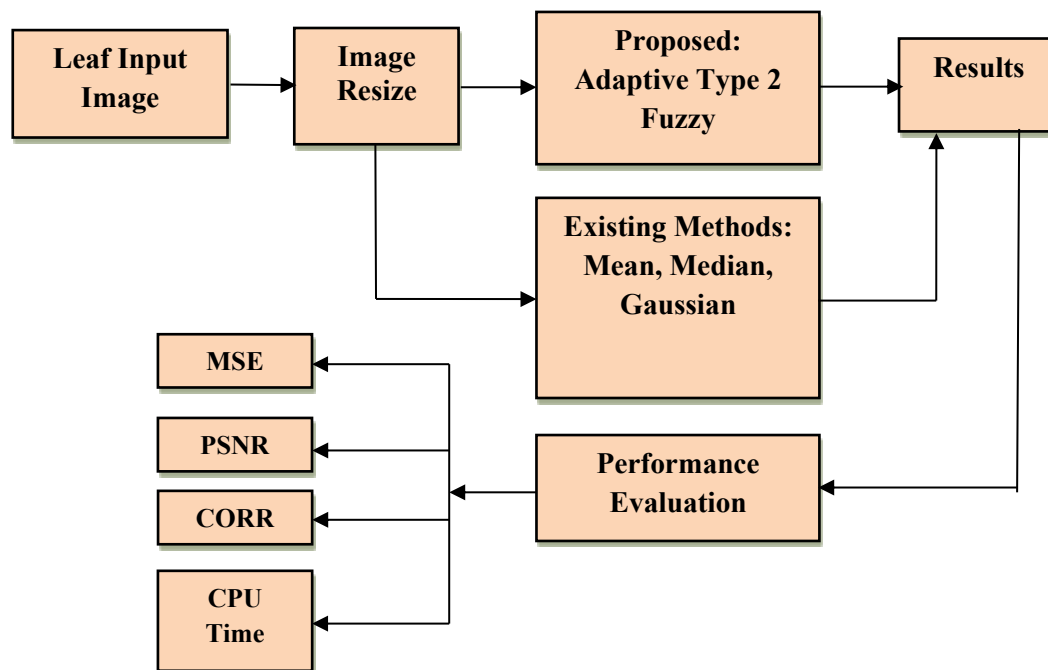


Fig.2 General block diagram for Leaf disease pre-processing

Here, a plant leaf images are taken as the input of the system. The raw leaf images are converted into the resized images. After that, these resized images are fed into the existing pre-processing algorithms such as Mean, Median and Gaussian filters as well as the suggested Adaptive Type 2 Fuzzy filtering method. Here, the unwanted noises in the leaf images are removed. The existing and proposed results such as MSE, PSNR, Correlation, and CPU time duration were compared.

3.1 Filtering Methods

The main goal of applying filters to improve an image is to suppress either the low frequencies, which improve the image or identify edges, or the high frequencies, which smooth the image. One way to manipulate an image is to apply a filter to highlight specific elements or exclude others. Numerous methods exist, and the optimal choices may vary according on the image and its intended application. Many tasks, such as edge identification, noise reduction,

sharpening, and smoothing, can be accomplished with image filtering. The various filters used for pre-processing in our research work are explained in following.

3.2 Mean Filter

A typical filter type in image processing for smoothing or blurring a picture is a mean filter, sometimes referred to as an average filter or box filter. The average intensity value of each pixel's nearby pixels within a given neighbourhood or kernel size is substituted for the intensity value of each individual pixel. To reduce noise, enhance images, and get ready for additional analysis or feature extraction, mean filters are frequently employed in image pre-processing activities. As a basic technique in the realm of image processing, they offer an easy-to-use yet efficient method of reducing noise and producing smoother images.

$$\text{Mean} = (\text{Sum of all the observations} / \text{Total no. of observations}) \text{ ----- Eqn (1)}$$

One can compute the mean, which is the average of the given numbers, by dividing the sum of the numbers by the entire number of numbers. Frequently employed to decrease noise in photos, it blurs and smoothes the image. The neighbourhood sub image window, centered at point (x,y) , with dimension $M \times N$, is represented by R_{xy} . The surrounding pixel account detail is substituted for the gray level $J(x, y)$ for the gray level of pixel (x, y) in K by the filter.

3.3 Median Filter

The median filter operates within a rectangle of plant's leaf images. Depending on the following parameters, it alters the size of the photos during the filtering process. The median value of each output pixel is found in the 3-by-3 neighbourhood surrounding the corresponding pixel in the input images. Nevertheless, zeros take the place of the image borders. The filter's output is a single value that, at the time S is centered at (x,y) , replaces the current pixel value at that location. The basic operation of median filter in digital image processing is place the neighbourhood around each pixel in an image. After by using some algorithm Analyse the values of every pixel in the vicinity, and then change each pixel's original value to one based on performance achieved through analyse that neighbourhood pixels.

Alqadi, Ziad A., and Mohamad Tariq Barakat (2021) explained the ability of six alternative image filtering algorithms to rebuild noise-affected images is contrasted. These techniques are designed to reduce signal noise that could be introduced during image transmission. The Spatial Median Filter, a novel algorithm, is presented and contrasted with

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existing image smoothing methods. The algorithm is comparable to these methods, according to experimental data. This algorithm is modified to produce more accurate reconstructions than other well-liked methods.

The median filter defined as, two images $X(x)$ and $Y(x)$,

$$\text{Median}[X(X) + Y(X)] = \text{median}[X(X)] + \text{median}[Y(X)] \quad \text{----- Eqn (2)}$$

The data is smoothed by these filters yet the fine features are preserved. But the median filter is suitable for removing salt and pepper noise effectively.

3.4 Gaussian Filter

The Gaussian Filter (GF) is one of the most popular filtering algorithms. The GF uses a Gaussian distribution, whose mean is an affine function of the measurement, to express the belief in the current condition. The GF is viewed as a specific case of a much larger class of filters that were produced by loosening the restriction on the approximation posterior's form. Based on this, we list a few requirements that prospective generalisations must meet in order to maintain the GF's computational efficiency, Kumar, Arvind, and Sartaj Singh Sodhi. (2020).

The main usage of Gaussian filter is blurring images and removes the noise and details. The Gaussian function is defined as one dimension is as,

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \quad \text{----- Eqn (3)}$$

Where the distribution's standard deviation are denoted by the symbol. The mean of the distribution is thought to be zero. One of the important behaviour of Gaussian function is the standard deviation which is located between +/- the σ account for 68% of the set. The σ account for 95 % from the mean while using two standard deviation (blue and brown). Likewise 98 % while using three standard deviations (blue, brown and green). These are very important when designing a fixed length of Gaussian kernel.

3.5 Proposed Adaptive Type 2 Fuzzy Method

A complex technique that uses fuzzy logic and adaptation to improve image processing jobs is the Adaptive Type-2 Fuzzy method in image pre-processing. Adaptive Type-2 Fuzzy technique and its pre-processing applications are summarized as follows: The specifics of the

suggested Adaptive Type 2 Fuzzy filter design for picture pre-processing are presented in this section. A fuzzy membership function is what distinguishes type 2 fuzzy sets, which we have developed for image pixel enhancement. Based on the lowering of the classification problem, the adaptive type 2 fuzzy system offers a primary benefit. To turn the hazy pattern classification problem into a precise one, the suggested Adaptive type 2 fuzzy set is utilized. As opposed to regular fuzzy sets, regulated degrees of uncertainty are maintained by using adaptive type 2 fuzzy sets. Moreover, the suggested technique, which needs fewer parameters to obtain the best answer, eliminates the noisy pixels from the input photos, given by Olivas, Frumen, et al. (2019).

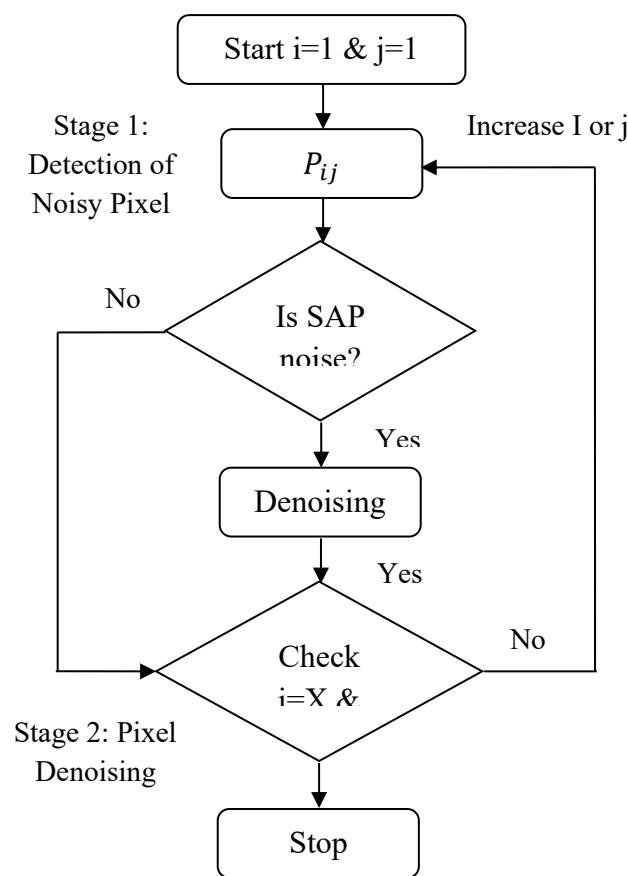


Fig. 3 Flow Chart for Adaptive Type 2 Fuzzy Filter

The above figure 3 shows and explain about the working flow chart of adaptive type 2 fuzzy filter. The process of noisy detection and pixel denoising are done by using this flow of working. Here, X and Y are the size of the input image. And Pij is the pixel intensity at (i,j).

This is the general formula for the Type-2 Adaptive Fuzzy System:

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- The input space is represented by A, while the output space is represented by B.
- Consider that the input variables are represented by X as a vector in A and the output variables are represented by Y as a vector in B.

It is possible to see the AT2FS as a mapping $F: A \rightarrow B$, where F is a combination of many functions:

$$F(X) = D \text{ Fuzz} (R \text{ infer} (W \text{ train} (X))) \text{ ----- Eqn (4)}$$

Where,

X: This is probably the systems or model's input. An array of features, a vector, or another type of data could be used.

W: A set of weights for inference or training could be represented by this. Typically, W stands for weight parameters in machine learning contexts.

R: Based on the trained input $W \text{ train} (X)$, this probably represents an inference function or process.

D: Applied to the inference step's output, this section might constitute a defuzzification procedure.

A rule-based system, a neural network layer, or another inference mechanism could be indicated by the letter R in fuzzy logic or machine learning.

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1: for every pixels  $p_r \in I$  do
2: if  $p_r \in \{0, 1\}$  then
3: retain  $p_r$ ;
4: continue
5: while  $p_r \in \{0, 1\}$  do
6: Initialize  $H = 1$ 
7: Compute  $P_{ij}^H$  using (3) and  $\Delta\mu P_{ij}^H$  using (12)
8: if  $\Delta\mu P_{ij}^H(p_r) \geq T_h$  then
9: retain  $p_r$ 
10: break
11: if  $\sigma^H \leq \epsilon$  then
12:  $p_r = m$ ;
13: break
14: Compute  $G_{ij}^H$  using (13)

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Fig.4 Pseudo-code for Adaptive Type 2 Fuzzy method

The above figure 4 depicts the pseudo-code for our suggested method of Adaptive Type 2 Fuzzy. Impulse noise primarily affects the images' salient elements with ease. We suggested an adaptive Type 2 Fuzzy filter that filters a picture in three phases in order to restore the noisy image. Known as noisy pixel identification, the first step of the proposed filter design involves providing the corrupted image as an input image I of size $M \times N$. Next, the input image's pixel position is represented by $I(i, j)$. Owing to the impulse noise, only a portion of the image's pixels are distorted; the remaining pixels are regarded as noise-free.

IV. RESULT AND DISCUSSION

The experiment was successfully evaluated, producing a number of leaf disease results for various parameters using the Mean, Median, and Gaussian approaches that are now available filters. The proposed Adaptive Type 2 Fuzzy method underwent successful experimental study, yielding best result for various parameters. MATLAB 2013A is used to find the performance evaluation with the Adaptive Type 2 Fuzzy system for the detection of disease prediction of plant leaves.

The effectiveness of the current system was covered in this section, which has Mean Square Error (MSE), Peak Signal Noise Ratio (PSNR), Correlation (CORR), and CPU Execution time ratings. When compared to the current systems, the suggested system with the novel way of leaf disease prediction will be more effective.

4.1 Dataset

Gathering input photographs of various plant leaf kinds is the first step in the project. Real-time cameras or mobile devices can be used to capture these unprocessed photos. Validation and introduction of the recently built Adaptive Type 2 Fuzzy filtering method are carried out using unstructured image data analysis of individual images; datasets are obtained from the Kaggle and UCI website. In the training raw images of dataset, there are many characteristics for plant leaf images. During the proposed system's testing and training phases, the suggested pre-processed model for our deployment was trained using a publically available dataset, detailed by Vasavi, P., Punitha, A., & Rao, T. V. N. (2022).

4.2 Mean Square Error (MSE)

When evaluating the quality of picture compression, the Mean-Square Error (MSE) is used. The MSE calculates the squared cumulative error between the original and compressed images; the smaller the MSE value, the less the error.

From the below formula, MSE is calculated:

$$\text{MSE} = \frac{\sum_1^n (x-y)^2}{M*N} \text{----- Eqn (5)}$$

Table 1 Mean Square Error

Algorithm	MSE
Mean Filter	75.60
Median Filter	67.36
Gaussian Filter	60.48
Adaptive Type 2 Fuzzy	40.15

MSE output of the existing and proposed filter is shown in the above table 1. The existing system's MSE outputs for Mean filter 75.60, Median filter 67.36, Gaussian filter 60.48, and proposed system of Adaptive Type 2 Fuzzy is 40.15. This suggested approach achieves better MSE result comparing than above existing systems. And its graph is clearly plotted in below figure 5.

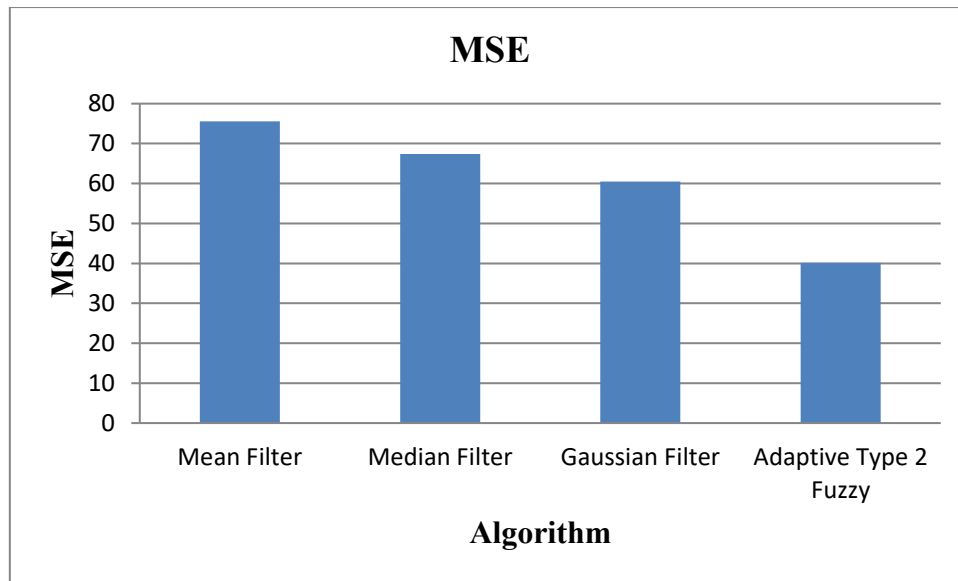


Fig.5 MSE Graph

4.3 Peak Signal-To-Noise Ratio (PSNR)

The Peak Signal-to-Noise Ratio (PSNR), which is expressed in decibels, is computed between two pictures. This ratio is employed to compare the original and compressed image quality. Increasing PSNR value result in better quality compression or reconstruction of the image.

PSNR is calculated using the formula,

$$PSNR = 10 * \log_{10}\left(\frac{R^2}{MSE}\right) \text{----- Eqn (6)}$$

Table 2. Peak Signal Noise Ratio

Algorithm	PSNR
Mean Filter	25.32
Median Filter	28.76
Gaussian Filter	30.84
Adaptive Type 2 Fuzzy	38.55

The existing algorithms of Mean, Median, and Gaussian filter’s PSNR output are mentioned in the above table 2. It gives the outputs values of 25.32, 28.76 and 30.84 respectively. The proposed Adaptive Type 2 Fuzzy delivers the PSNR output of 38.55 which is

better than other existing systems. And based on this output values, the PSNR graph is explained in figure 6.

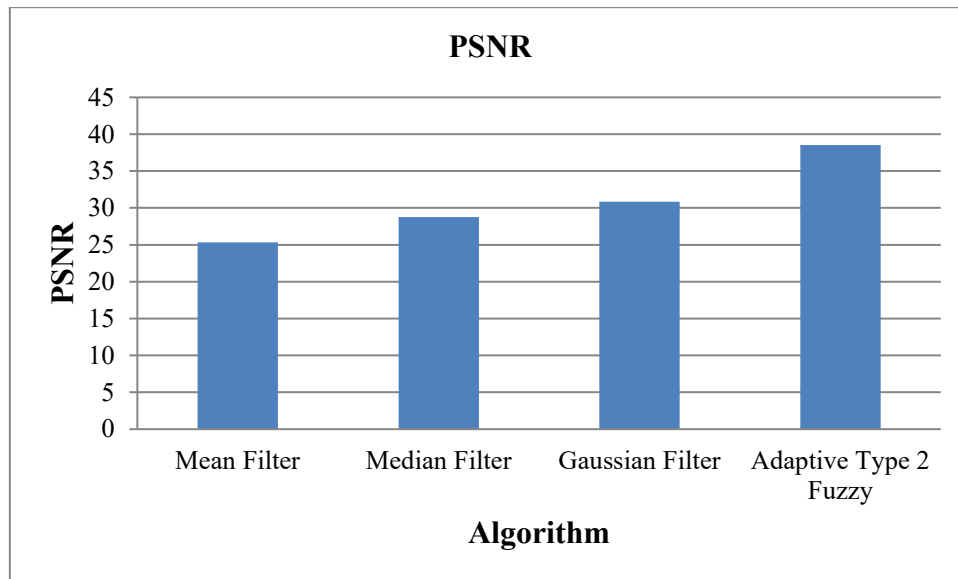


Fig.6 PSNR Graph

4.4 Correlation (CORR)

Correlation is the process of transferring a filter mask, also called a kernel, over an image and calculating the total of the products at each point. Correlation is determined by the filter's displacement.

Correlation is calculated using the formula,

$$\text{Correlation} = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \text{----- Eqn (7)}$$

Table 3. Correlation

Algorithm	Correlation
Mean Filter	0.925
Median Filter	0.948
Gaussian Filter	0.956
Adaptive Type 2 Fuzzy	0.968

The above table 3.3 mentioned about the correlation output values of existing filters and proposed filter. Existing algorithm's correlation values are 0.925, 0.948, and 0.956 for Mean,

Median, and Gaussian filters respectively. And our newly designed Adaptive Type 2 Fuzzy algorithm gives the correlation output is 0.968. This is comparatively greater than the existing systems. Based on the table 3, the correlation graph of existing and proposed systems is shown in below figure 7.

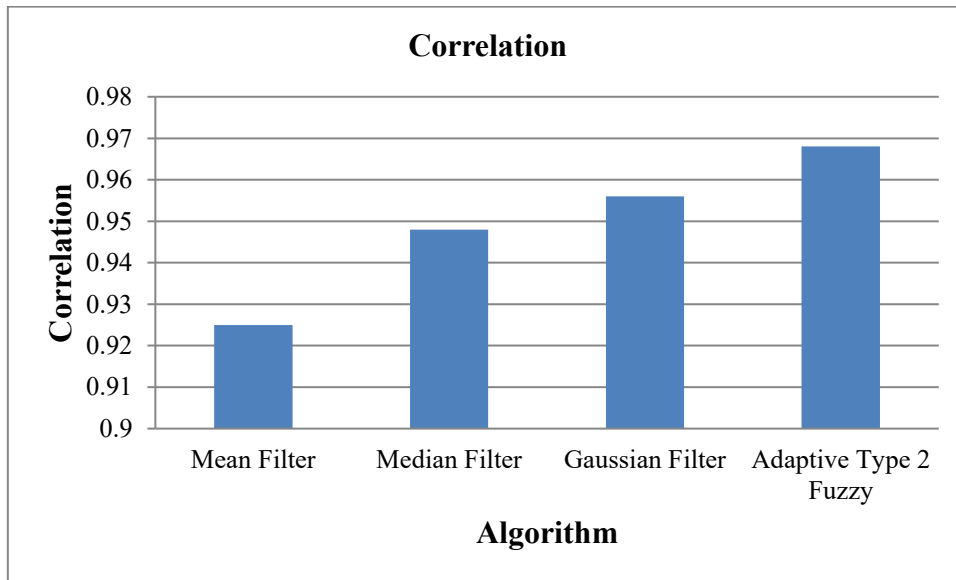


Fig.7 Correlation Graph

4.5 Time Consumption

The total amount of time that the process spends executing, also known as the execution time or CPU time, can be determined using the formula below.

$$\text{Time Duration} = IC * CPI * T \text{----- Eqn (8)}$$

Table 4. Time Consumption

Algorithm	Time Consumption (ms)
Mean Filter	52.35
Median Filter	48.80
Gaussian Filter	40.56
Adaptive Type 2 Fuzzy	26.78

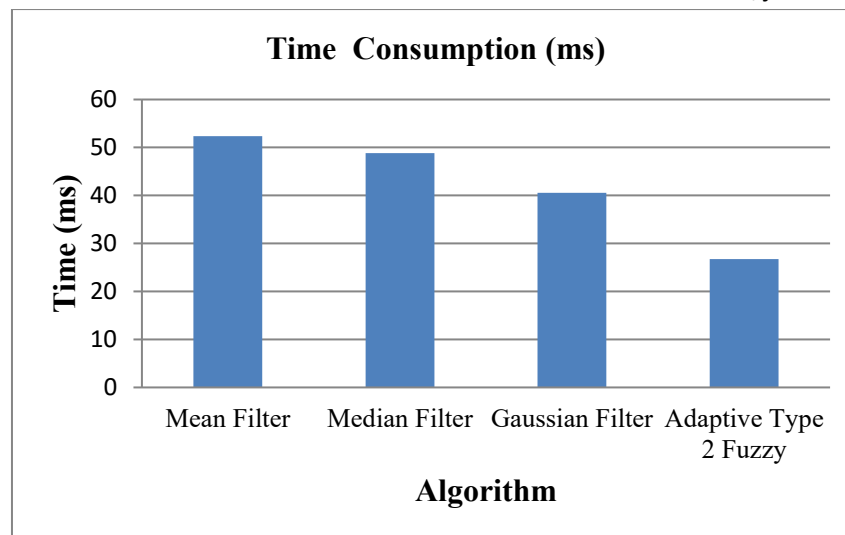


Fig.8 Time Consumption Graph

The time taken of the existing and proposed algorithm is described in the above tabulation 4. The existing algorithms take the time duration of 52.35 ms for mean, 48.80 ms for Median, and 40.56 ms for Gaussian filters. Our newly designed Adaptive Type 2 Fuzzy filter takes the time consumption of 26.78 milliseconds and its takes less duration of time comparing than the above existing systems. Depending upon the above tabulation, the time duration graph is plotted in below figure 8.

V. CONCLUSION

An innovative filtering method was created to use an image processing algorithm to determine the physicochemical characteristics and disease prediction of different leaves of plants in different situations. In order to guide and search for various new leaf disease detection solutions for further enhancing exploitation; the Adaptive Type 2 Fuzzy algorithm has a tendency to consider the merits of diverse information in the best available global context. Their findings demonstrated that this Adaptive Type 2 Fuzzy gives greater and better output than the current techniques of Mean, Median, and Gaussian filtering methods, with respect to MSE of 40.15, PSNR of 38.55, correlation of 0.968, and CPU consumption time takes the less duration of 26.78 milliseconds. This work can be expanded to address a wide range of common plant leaf diseases for various crops and plants, which would be more advantageous in agriculture to increase productivity as well as good agricultural environment. Additional options exist for optimizing the suggested model with hyper-parameters including regularization and dropout in future.

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