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Research Article

Instinctive Recognition of Pathogens in Rice Using Reformed Fractional Differential Segmentation and Innovative Fuzzy Logic-Based Probabilistic Neural Network

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Rice is an essential primary food crop in the world, and it plays a significant part in the country's economy. It is the most often eaten stable food and is in great demand in the market as the world's population continues to expand. Rice output should be boosted to fulfil the growing demand. As a result, the yield of plant crops diminishes, creating an environment conducive to the spread of infectious illnesses. To boost the production of agricultural fields, it is necessary to remove plant diseases from the environment. This study presents ways for recognising three types of rice plant diseases, as well as a healthy leaf, in rice plants. This includes image capture, image preprocessing, segmentation, feature extraction, and classification of three rice plant illnesses, as well as classification of a healthy leaf, among other techniques. Following the *K*-means segmentation, the features are extracted utilising three criteria, which are colour, shape, and texture, to generate a final product. Colour, shape, and texture are the parameters used in the extraction of the features. It is proposed that a novel intensity-based technique is used to retrieve colour features from the infected section, whereas the form parameters of the infected section, such as the area and diameter, and the texture characteristics of the infected section are extracted using a grey-level co-occurrence matrix. The colour features are retrieved depending on the characteristics of the features. All three previous techniques were surpassed by the proposed fuzzy logic-based probabilistic neural network on a range of performance metrics, with the new network obtaining greater accuracy. Finally, the result is validated using the fivefold cross-validation method, with the final accuracy for the diseases such as bacterial leaf blight, brown spot, healthy leaf, and rice blast being 95.20 percent, 97.60 percent, 99.20 percent, and 98.40 percent, respectively, and 95.40 percent for the disease brown spot.

1. Detailed Analysis of Existing Study

Plant pathology is one of the most significant contributors to decreases in both the amount and quality of agricultural goods produced. For these reasons, it has a direct impact on the entire output of goods, which in turn has an impact on the revenue of farmers and the general health of the world economy. Farmers and the rest of society need food items of high quality at a reasonable price [1]. However, infection in plants can cause a significant amount of damage in the agricultural industry. Fungi, bacteria, and viruses are among the pathogens studied [2].

The majority of the time plant diseases are identified using human eyesight and a microscope in conjunction with each other. On the one hand, this method 3 requires a significant amount of time due to the fact that it requires constant monitoring of the plants [3]. On the other side, some farmers, particularly those who are new to the field and are unaware of the illness, make incorrect projections. To meet the need, researchers are attempting to transfer the influence of computer vision in agriculture [4] to other industries. Detecting and categorising plant diseases are one of the most important study concerns in the agricultural business, and it requires a lot of time and effort [5]. The agricultural economy is heavily reliant on rice, one of the world's most important food crops [2].

The most prevalent rice disease infections are bacterial leaf blight, brown spots, and rice blast, which are all bacterial diseases. The quality of the grains is greatly lowered as a result of this illness, which places a significant financial burden on farmers [6]. A rice plant's production may be increased by recognising disease signs early on and using a labour-saving procedure. It can also be reduced using less pesticides in the field by diagnosing illness early on [7]. In such cases, the advancement of image processing and the complicated algorithms that are used to anticipate crop disease in its early stages has shown to be very accurate predictions. An image processing approach is used to determine the outer look of the wounded plant [8]. On the other hand, early symptoms can be used to classify and predict the severity of a disease. This is still another option and an automated solution for the plant disease issue, which allows for the transmission of information to the farmer in order for him to use pesticides in the appropriate manner as a result [9]. Rice blast (*Pyricularia grisea*), bacterial leaf blight (*Xanthomonas oryzae*), and brown spot are the most frequent rice diseases. For a vast number of individuals, rice is the most important source of nutrition [10]. A variety of pathogenic microorganisms attack rice plants, resulting in significant crop loss in the field [11]. According to a study, the overall loss of yield in rice plants in our nation [12] is rather considerable. As a result of its widespread cultivation and abundance, rice (*Oryza sativa*) has become one of the world's most important food crops [45]. Diseases produced by bacteria, fungi, and viruses damage all parts of a plant, including the leaves and stem, as well as the fruit and seed of the plant [13]. Figure 1 gives the total yield loss in rice plants.

According to a recent analysis, a range of viruses are causing harm to even the leaves of the plants. Despite the fact that the symptoms of both viruses are similar, it is impossible for the human eye to tell the difference between them [14]. This results in people being unable to forecast the development of illnesses, which makes early detection more difficult [15]. This necessitates the use of automated detection to predict the severity of infections on rice leaves during the early stages of the disease cycle [16]. A consequence of this is that computer vision technologies are becoming more relevant in the field of sickness prediction. These image processing algorithms assist in not only forecasting sickness but also in identifying the amount of disease from early symptoms, which is very helpful information in the diagnosis of disease [17]. Farmers benefit from the use of computer vision technology, which enables them to increase agricultural productivity while minimising the use of hazardous pesticides. The most common image processing techniques include the following steps: capturing the image, preprocessing it, segmenting it, identifying the region of interest, and categorising the findings [18].

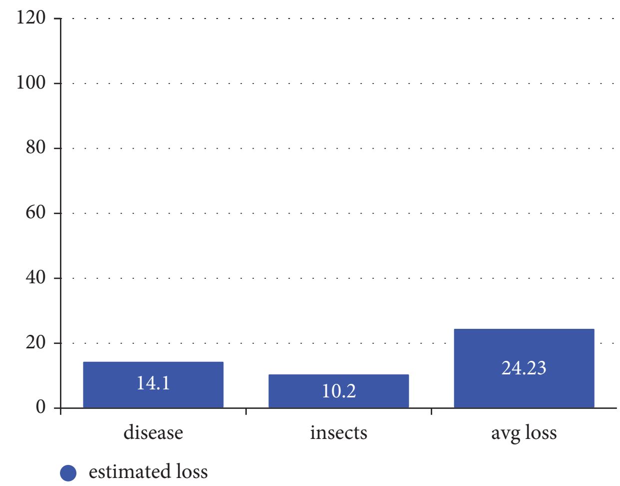

Figure 1: Annual rate of crop disease.

According to the conclusions of various surveys, there is presently no standard database that academics may access and utilise for research purposes. Using images taken in the local rice field to develop and maintain a consistent dataset for the sake of this research, this difficulty might be handled [19]. It is remarkable that this novel strategy, which is based on modified K-means segmentation, colour feature extraction, and an entirely new classification algorithm, achieves such high accuracy despite the fact that the researchers have presented six strategies in all. The automatic identification method also supports farmers in overcoming the problems involved with applying pesticides correctly in the field, which is a final benefit [20].

1.1. Problem Statement. It consists of three major steps: preprocessing and segmentation of input photographs or videos from the rice crop field, feature extraction, and recognition or prediction model implementation. Many hurdles must be overcome for such systems to achieve high illness detection and prediction accuracy. The main problem for successful illness detection and prediction is selecting models with unique feature descriptors for each disease [21].

Disruption of the plant's energy-utilising mechanism causes plant disease. This might be micro (biochemical/physiological/cytological) or macro (environmental) (symptoms). The sick plant cannot produce or live. Plant diseases are anything different than normal. In plants, the disease is any deviation from the norm that causes physiological disruptions or structural changes that are lasting enough to stunt growth, create aberrant forms, or induce the early death of a plant or person [22]. The symptoms, i.e., how the plant appears after the pathogens have established in the host, alert us to the fact that it is sick. A disease symptom or indication is a plant's reaction to a sick state. All of them combined to create a clinical diagnosis known as a disease syndrome. The discoloration is a typical sign of plant disease caused by parasitic or nonparasitic pathogens. Colour changes in the entire plant or in one or more segments. Colour change (yellowing) is a typical symptom of plant disease [23]. The severity of the condition determines the degree of discoloration. Shoots and buds show more symptoms than older portions. The stem, roots, and fruits might be discolored. Necrotic spots and holes are frequent plant disease signs. Spots vary in size, shape, and colour, as do their margins. In certain disorders, the spots and their edges have specific properties. Spot symptoms are caused by fungi, bacteria, viruses, nutritional deficiencies, and physiologic disorders [24]. In certain circumstances, streaks and stripes signify illness development. The leaf blade, leaf sheath, stem, and other plant components may develop small linear lesions. Blight and blast are deadly illnesses. The intensity of infection causes fast tissue death in infected plants, killing leaves, blossoms, and other above-ground plant components. This is called blight. A blast occurs when a leaf blade, bud, or other plant component is completely destroyed.

The goal was to help a farmer recognise a disease by its symptoms. The farmers are expected to use these technologies as a consequence of this research, which will help them manage their finances and time.

This study's goal was to identify infections in rice plant leaves using early signs. An excellent example is computer vision. This project's purpose was to build a shared collection of pictures related to rice plant diseases. This project's objective was to improve colour feature extraction and dynamic image segmentation to detect pathogenic regions and colours in paddy photographs. This project's purpose was to produce effective computer vision algorithms for identifying rice plant diseases and to test the real-time constructed algorithm.

In the agricultural area, identifying and classifying plant diseases may be very tough tasks to do. As a result, the rice plant illnesses are diagnosed and categorised based on the early signs using the algorithm that has been established. The rest of the study consists of Section 2 that consists of a literature survey, Section 3 consists of proposed work, and experimental results are concluded in Section 3.4.

2. Literature Survey

In the agricultural industry, image processing is critical to the success of the business. As a result, computer vision is intended to aid farmers in protecting their farms from many elements of damage via picture processing and analysis [25]. Researchers have embarked on one of the agriculture's most difficult plant disease eradication tasks. As a result, according to multiple sources, computer vision using MATLAB is utilised to identify the sickness from its early signs and symptoms. As an example, [26] presented a paper on computer vision to identify 12 different diseases, including those of wheat, cotton, grapevines, sugarcane (including passion fruit), cassava citrus (including coconut tree), soybean (including coffee), corn (including common bean), and soybean (including common bean). It is the author's intention in this work to fully describe the pre-first phase of picture capture and the key characteristics of utilising a digital camera. When capturing a photograph, some noise disturbance might occur, and the author clearly outlines the technique used to remove noise from an image. The preprocessing stage is the second step. Finally, the author discusses leaf segmentation, which entails extracting useful information from a leaf via the use of distinct clusters, as explained by the author [27]. It is the process of modifying a picture to get the intended outcome, for as by brightening or sharpening the image, to achieve the desired result. The leafstalk and holes may be eliminated using the grey picture of area segmentation to segment the image. Extracting feature information includes removing texture, shape, and colour information. Finally, the procedure of using images to compare the similarities between sick and healthy plants is properly classified with the help of the classification approach [28]. These reports may be used to aid in the successful resolution variety of challenging challenges. As a result, according to this research, computer technology may be used to address the issue of identifying various plant illnesses in less time and with more accuracy, which can be distinguished by a change in the colour of the leaves. Several image processing algorithms were tested in a study conducted [29] to diagnose and categorise plant diseases based on early signs. In the agricultural area, identifying and classifying plant diseases may be very tough tasks to do [30].

Among other things, Zhang and colleagues (2014)[32] examined a variety of features to detect yellow rust in wheat plants, using a variety of methodologies and processes in their investigation. The authors of [33, 34] proposed a categorisation system for the automated identification of sickness in the tulip plant to enhance efficiency. Sena et al. [35, 36] describe a tool built by Polder et al. that allows users to analyse several metrics in order to assess the correctness of image processing results.

It is possible to enhance agriculture by giving farmers and other stakeholders with appropriate water for plant growth and competitive crop pricing and high-quality pesticides for the crop; this would benefit the farmer and other stakeholders [37]. Crop cultivation has the potential to increase the production of food items and other herbal goods, as well as the production of other agricultural products. There are a number of additional benefits that occur as a result of this process, including the development of microscopic microparticles and the development of small living animals, such as earthworms, which are used in oxidising the soil by creating holes in the ground to allow for the growth of plants. Following cultivation, the crops are mixed with the surrounding land to produce manure, which helps to increase the soil's fertility by increasing its organic matter content. Agricultural practices are critical since food is required for human existence, and hence, they must be effective. Despite advances in technology, conventional agricultural practices are still widely used today, mostly due to a lack of awareness about the most current technical developments in the field. Intensive farming, shifting cultivation, shifting cultivation with a high degree of intensification, plantation cultivation, and wetland cultivation are all examples of new agricultural practices that may be applied to enhance this agricultural system.

To accommodate the increased population, it is vital to increase agricultural productivity. However, as a consequence of the presence of a disease, the production has been severely decreased. As a consequence, it is critical to pay particular attention to ways to increase productivity. It is important to note that environmental changes, disease, and pests all have an influence on a plant's capacity to reproduce. This disorder manifests itself in several ways, with changes in colour, texture, and shape being among the most obvious [13, 24]. Donatelli and colleagues [9, 22] created a formalised version of their work. It is critical to get an accurate diagnosis as soon as possible to prevent the plants from incurring a major loss of productivity [21, 38].

A length of time had elapsed before profits became a possible component in the creation of larger harvests. So, to raise total productivity, the use of herbicides has progressively grown. These insecticides, on the other hand, are toxic and have a severe influence on the whole ecosystem. Besides that, it represents a severe hazard to human health. It has been observed that different sorts of living organisms, such as viruses, bacteria, and fungus, produce different forms of infection in plants, depending on the type of infection they induce. As a consequence, technological advancements have provided agriculture with a firm basis of support for many years. In addition to having an impact on small-scale farmers, the repercussions of plant disease also have an impact on food security in general. Those who study plants, on the other hand, have recorded instances of the sickness, which is highly reliant on the characteristics of the numerous symptoms. It might be caused by a virus, a fungus, a vitamin deficiency, bad weather, or a misunderstanding of what happened. The suggested research, in light of these considerations, demonstrates the relevance of how agriculture plays a critical role in computer technology via the usage of various programmes and the method by which they are generated.

The agricultural discipline has produced a number of researchers who have documented how various diseases impact plants via a range of ailments that present themselves in a variety of ways. Pathogenic organisms, which include bacteria, viruses, and fungal agents, are responsible for the bulk of illnesses on the planet. Pathogens harm plants in a number of ways, much as they do to humans and other animals.

The combined effects of the injured plants result in a broad range of symptoms, including wilting, browning, root rot, yellowing, and other signs of disease. First and foremost, an accurate diagnosis must be obtained to safeguard the plant from infection [20, 39]. According to the author, as a consequence of this sickness, the quality of the grains has been severely lowered. There are a variety of variables contributing to the disease's spread, including water stress, inadequate input management, and direct seeding conditions. Following the completion of this investigation, it was identified which particular fungicides would have an influence on the growth of the pathogen under consideration [40]. A strategy for identifying three types of rice plant disease, namely bacterial leaf blight (BLB), rice sheath blight (RSB), and rice blast, has been developed and tested (RB). Throughout this research, it is illustrated how the technique is implemented from the beginning of colour transformation, starting with RGB image conversion and progressing through the different channels to the conclusion of colour transformation. Later, these channels are utilised to aid vector machines, which are used to distinguish between the final categorisation and various pathologies. It was discovered that phalaenopsis seedlings were suffering from Phytophthora black rot (PBR) disease. It was also discovered that there are three types of bacterial soft rot (BSR), bacterial brown spot (BBS), and bacterial brown spot (BBS). In this step, it is required to compare the final classification with two different classifiers, such as the Bayes classifier and the BPNN technique, to ensure that the final classification is accurate. The degree of accuracy might go as high as 97 percent [41].

3. Proposed Methodology

3.1. Flow Chart of Proposed Methodology. This approach is shown in Figure 2, which can be downloaded in its entirety here. Image processing methods such as those in this design can help predict and classify an illness in the rice plant, and they can do this. Photographic Picture Capture: to capture an image, a digital camera is utilised [40]. Any unwanted noise from the picture using image preprocessing is removed (second step).

The quality of the picture is quite crucial since it is greatly dependent on the algorithm that has been built. As a result, it creates a vast amount of data that comprise various rice plant illness photographs to detect the disease [34]. Therefore, high-resolution photographs of rice plants are taken into consideration throughout this procedure. The collection of photographs of rice plants is the first step in the process of collecting various photographs of rice plants. As a result, hardware devices are totally responsible for the acquisition process [39]. As a result, high-quality digital cameras are employed to take photographs straight from the agricultural field in this instance. In addition, certain photographs are collected from the farmer's online page and used for additional editing and manipulation. Images may be collected in three different ways: using a single sensor, strips of sensors, or sensor arrays [38]. The combination of electrical energy and the sensor is used to capture an image of the scene that is being scanned, and this picture is then stored in the memory of the computer. The following are some of the issues experienced while attempting to collect the image data.

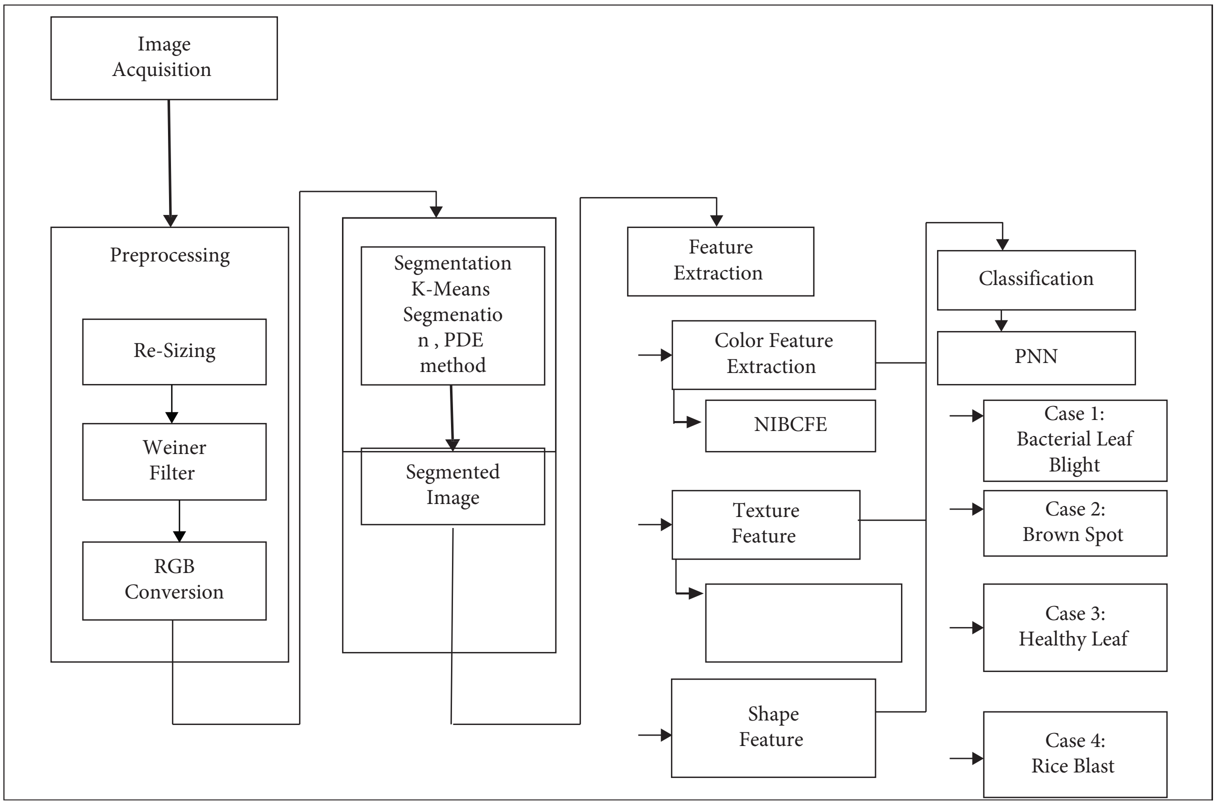

Figure 2: Architecture of proposed methodology to predict and classify disease in rice plant leaf image acquisition.

3.1.1. Data Acquisition Leaf Sample Collection. The photographs for this study effort were acquired using a digital camera straight from a paddy field in Neduvasal, Pudukkottai District, world, for which the images were used.

3.1.2. Camera Features. As illustrated in Figure 3, the capturing device Canon EOS 3000D digital camera has a calibration grey card with extra functions in addition to the standard characteristics.

The following image acquisition steps are executed to find the healthy and diseased images.

(1) Image Acquisition Structure—Figure 4 depicts the image acquisition structure from the input for assessing the symptoms of the illness in the different classes of rice plants, which is used for disease analysis.

(a) Photographic Shooting Season—in 2017, leaf samples were collected from a wide array of rice plants, each of which has its own unique illness, during the late spring shooting season, we were able to obtain healthy leaves in addition to the flowers as shown in Figure 4.

(b) Field—the samples are gathered on agricultural land that is about 2.471 acres in size.

Figure 3: Features of Canon SLR EOS 3000D 18MP digital camera.

(c) Image Collection—the dataset utilised in this study work comprises images of several rice plants and the diseases that affect them, including brown spot (Helminthosporiosis) and bacterial leaf blight. Figure 5 shows the various rice images from the datasets.

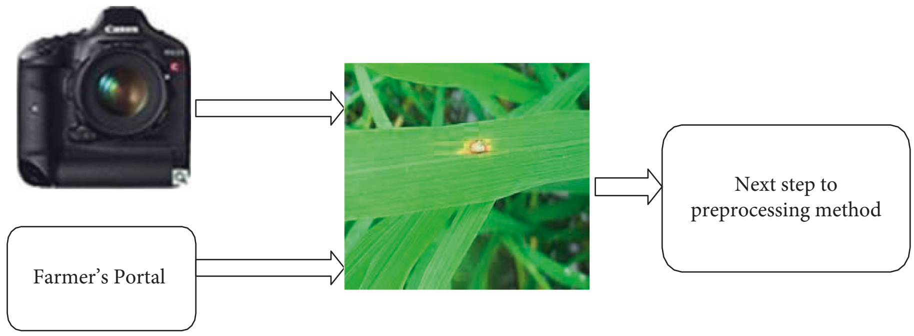

Figure 4: Structure of image acquisition.

(a) (b) (c) (d)

Figure 5: Rice plant statistics. (a) Bacterial leaf blight, (b) brown spot, (c) rice blast, and (d) healthy leaf.

Table 1: Total dataset of this research work.

Host plant	Disorder	Sample field image	IRRI
Rice	Bacterial leaf blight	40	5
	Brown spot	29	6
	Rice blast	10	5
	Healthy leaf	30	0
	Total	109	16
		125	

(d) Total Dataset—as discussed earlier, the collected total of 125 image samples are shown in Table 1 with disorders and healthy leaves in numbers.

(e) Illumination—the photographs were shot in a controlled area and under the same lighting conditions.

3.2. Preprocessing. In most cases, this step is concerned with image preprocessing methods that are used to eliminate undesired noise from the picture. On the other hand, image preprocessing is the essential stage in the analysis of an image by computer vision, and it is accomplished via the use of several image preprocessing methods. Various elements, such as weather conditions, illness, lighting circumstances, the type of radiation employed, and the sensitivity of the detector used, might contribute to the appearance of noise in a photograph. As a result, not only does this strategy eliminate undesired noise but it also increases efficiency, and it also enhances certain picture properties that may be used for further processing as a result.

3.2.1. Noise Removal in Rice Plant Images. During the process of photographing a picture, the noise will be generated. In the presence of noise, it is possible that the real visual features are lost. The imaging sensors may be impacted by a variety of elements, including the quality of the sensing element and the ambient circumstances itself, at any given moment. The resultant picture may be modified by the temperature of the sensor, the charge-coupled device (CCD), and the amount of light shining on it. As a consequence, the outcome of noise in the picture is the mistake that must be corrected before further processing can begin. Another point to consider is that the picture has been corrupted as a result of the environment or lighting flaws. Figure 6 demonstrates the advancement of noise reduction technology throughout time.

A filtered image is created by artificially inflating the original image with noise and then applying filtering algorithms to eliminate undesired information from the image. There are a number of techniques that has been used to find the quality of the image such as follows:

(i) Gaussian noise
(ii) Salt and pepper noise
(iii) Median noise
(iv) Wiener noise

Among these filters, the Wiener filter shows the best result for further processing. Hence, the final comparison results are described as follows.

3.2.2. Gaussian Noise. The Gaussian filter is specially used for blurred image and to eliminate the noise in the image as detail. It is the standardised approach to separate the wavy and rough components. This filter works as taking the average value of the pixel and its surrounding pixel for calculation. Thus, based on the pixel value the image is smoothened.

The Gaussian function is as follows:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-x^2}{2\sigma^2}}, \tag{1}$$

where x denotes the standard deviation.

In this work, the standard deviation plays an important role to filter the unwanted noise and is compared with various performance metrics. Here, the pixel value is calculated through arithmetic mean value. Through the value kernel matrix, values are identified from the noisy region. Next, with the help of addition kernel matrix values the final noisy pixel is replaced by the resultant value to remove unwanted noise. Hence, there are various preprocessing techniques for noise removal. This Gaussian filter is applied to analyse the image and the quality of the results that are presented as follows: Figure 7(a) shows the original image of paddy diseased image, Figure 7(b) shows resized image, Figure 7(c) shows noised image, and Figure 7(d) shows the result of Gaussian filter image.

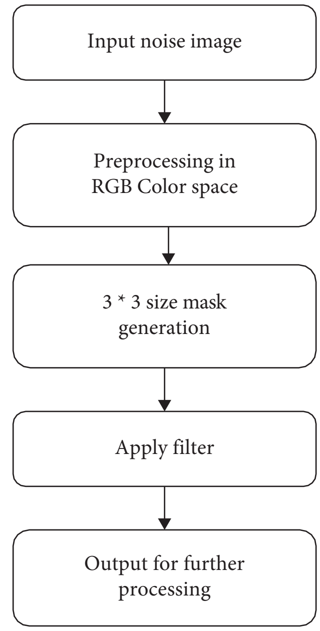

Figure 6: Structure of preprocessing techniques.

3.2.3. Salt and Pepper Noise. It is caused by an abrupt loss of clarity in the picture, which results in the salt and pepper noise being produced. In most cases, this is referred to as data dropout. As a result, the noise appears as white or black pixels at random locations across the picture. The brightest pixel in the darkest zone and the darkest pixel in the brightest region are found in dead pixels. This dead pixel is created by the picture being converted from analogue to digital format. As a result, the goal of the salt and pepper method is to delete pixels that are not altered by utilising filtering processes.

$$\begin{aligned}\text{Salt and Pepper} &= \int_B^A \text{for } g = a(\text{“Pepper for } g) \\ &= b(\text{“salt”}).\end{aligned} \tag{2}$$

Here,

(i) A and B are probability value.
(ii) Pepper noise is taken to 0.
(iii) Salt noise is taken to 255.

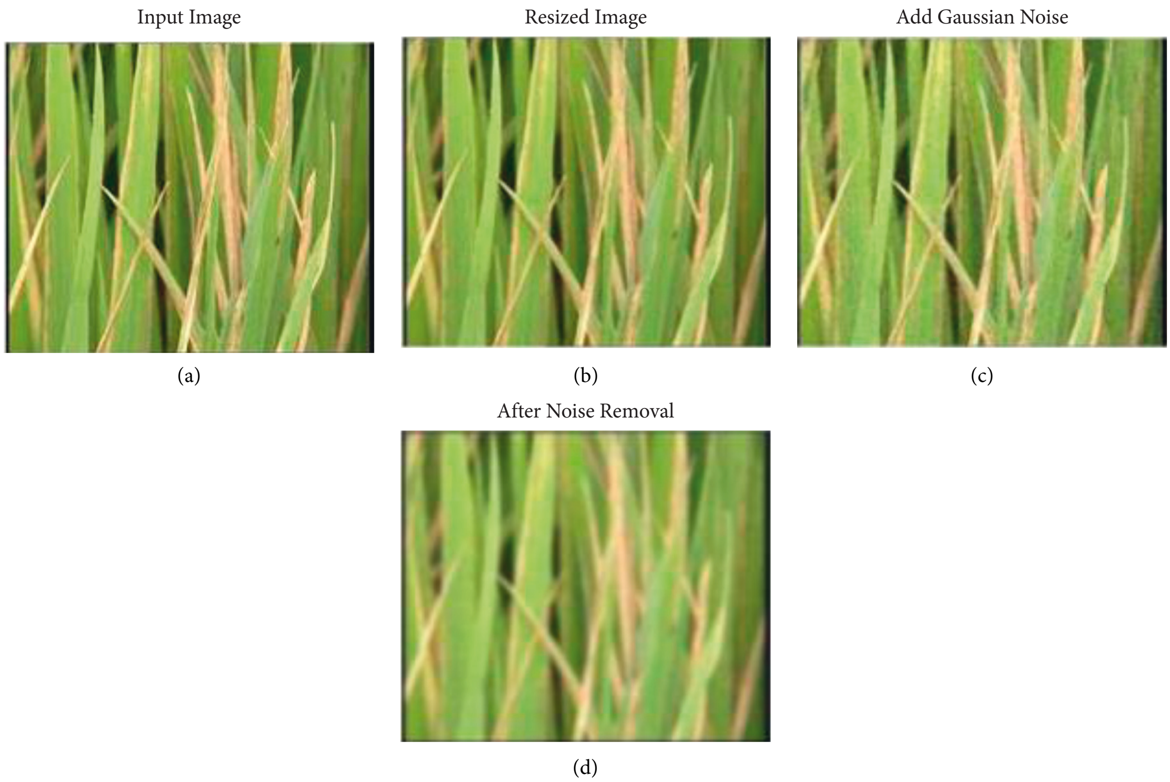

Figure 7: Results of Gaussian noise. (a) Original image of bacterial leaf blight. (b) Resized image. (c) Denoised image. (d) Image obtained after denoised using the Gaussian filter.

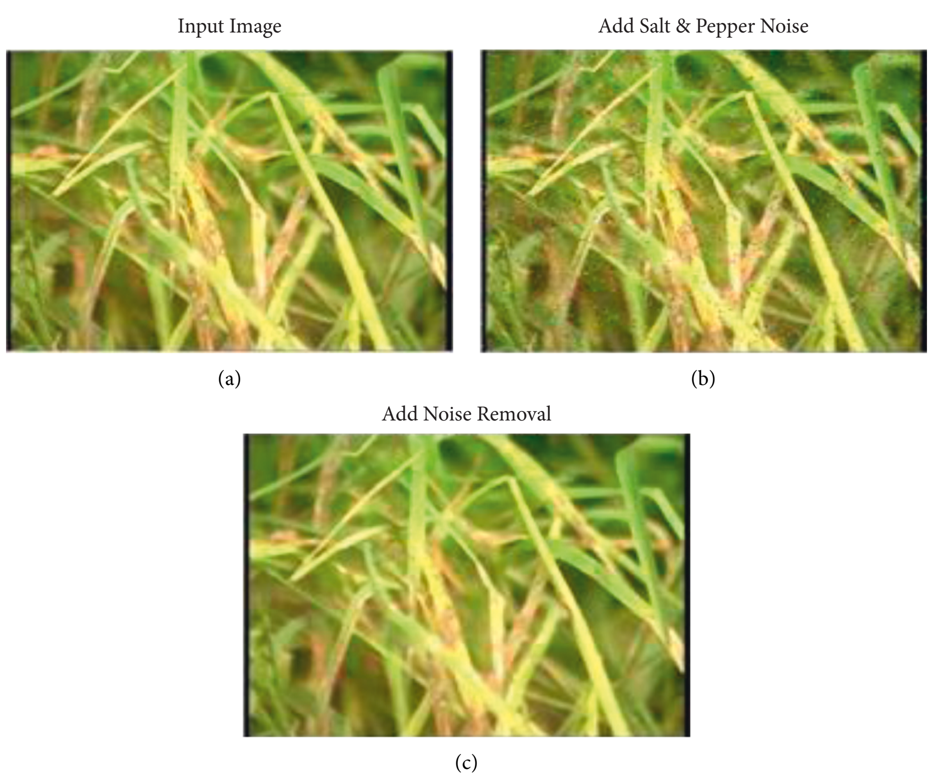

Figure 8: Results of salt and pepper noise. (a) Input image of rice blast. (b) Denoised image. (c) Image obtained after denoised by salt and pepper.

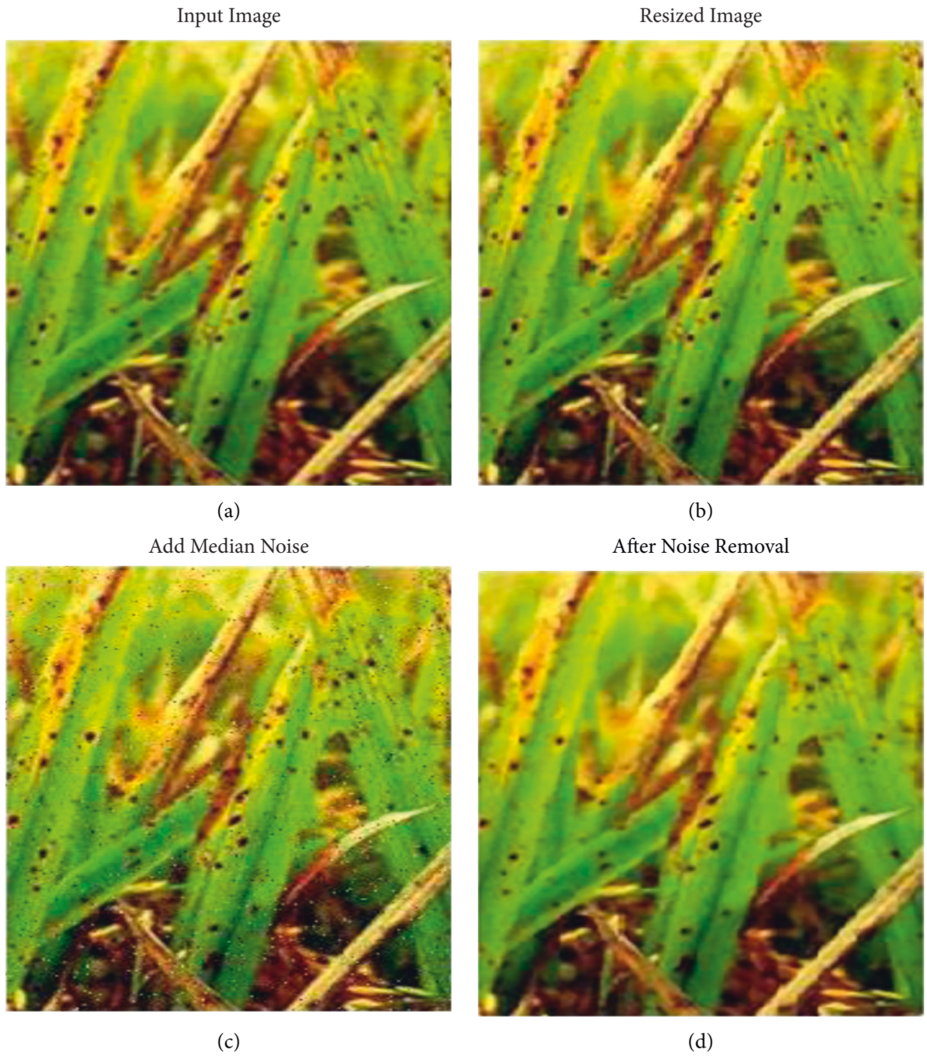

Figure 9: Results of median noise. (a) Input image of rice blast. (b) Resized image. (c) Denoised image. (d) Image obtained after denoised by median noise.

Finally, this salt and pepper noise is used to enhance the quality of the image for better performance. Figure 8(a) shows the original image of diseased rice image, 8(b) shows noised image, and 8(c) shows the result of salt and pepper noise.

3.2.4. Median Noise. Nonlinear filters such as the median filter are used to reduce random noise from images. To be more specific, the median filter looks for the nearest neighbour pixel that may be used to replace the complete pixel. Instead of replacing the mean values, it substitutes the median of those values depending on the numerical order of the data using the nearest neighbour pixel. As a result, this filer captures the information needed for smoothing filters in great detail. It is easy to use and is utilised in the suppression of excessive noise. However, when compared to the suggested technique, the accuracy of this filter is much lower than that of the proposed method, while at the same time, this median filter was used to improve the overall quality of the picture as shown in Figure 9. Images of rice infected images are shown as follows: in Figure 9(a), their original sizes, Figure 9(b), their shrunk sizes, Figure 9(c), their noised sizes, and Figure 9(d), their results of the median filter images.

3.2.5. Wiener Noise. In this process, the filtering is done to eliminate the unwanted pixels in the images. Here, the filtering process is carried out using a Wiener filter. In this process, image resizing, enhancing, and image filtering are applied to visualise the quality of the image. The Wiener filter is used to filter away the undesirable noise in this section, and the filtering process is completed here. As a result, the Wiener technique is utilised to filter away the noise from the specific dishonoured signal. This filter is based on a statistical approach and desired frequency response. Therefore, this filter deals with the image filtering from various aspects. The chief goal of the Wiener filter is to reduce the error rate as much as possible. This filter has the

Figure 10: Wiener filter results from different rice plant diseases. (a) Input image of bacterial leaf blight. (b) Result obtained from the Wiener filter. (c) Input image of brown spot. (d) Result obtained from the Wiener filter. (e) Input image of healthy leaf. (f) Result obtained from the Wiener filter. (g) Input image of rice blast. (h) Result obtained from the Wiener filter.

capability to reduce the noise and to remove the blurred quality. Also, the process of image resizing is done for further processing. The image can be resized for the transformation of image, display, and storage purposes.

The following are the main characterisation of Wiener filters.

Assumption 1. The process in which the spectral characteristics are known to autocorrelation requirement: physical realisation must be identified based on the result.

$$W(f1, f2) = \frac{H * (f1, f2) s_{rr}(f1, f2)}{|H(f1, f2)|^2 s_{rr}(f1, f2) + s_{rn}(f1, f2)}. \quad (3)$$

Here, $s_{rr}(f1, f2) + s_{rn}(f1, f2)$ shows the power spectra of the input image and $H(f1, f2)$ shows the blurred filter image in the Fourier domain. It performs the deconvolution of inverse filtering to estimate the unwanted noise.

Such noise fall is a typical preprocessing step to get better results of later processing (e.g., image segmentation). After the noise removal process, the separation of RGB channel is processed for the filtered image. Figure 10(a) shows the original image of various rice diseased image and shows the result of the Wiener filter image.

Figure 10 gives the filter image. Finally, a proposed automated image preprocessing method has been implemented and applied to remove the noise in image through computer vision. So far, the best algorithm is compared with the other three existing methods using different parameter metrics.

3.3. Different Performance Measures of Preprocessing Method of Peak Signal-to-Noise Ratio (PSNR). The term peak signal-to-noise ratio investigates the image quality between two different images such as the original input image and the sensed image. This calculates the ratio of the images between the highest power of the signal and the corrupted image. Perhaps, the maximum and minimum values of ratio change the quality of the image.

The mathematical representation of PSNR is computed via MSE.

$$\text{PSNR} = 10\log_{10}\left(\frac{2^2}{uss}\right). \quad (4)$$

Here, Q is the maximum variation in the input image.

3.3.1. Mean Square Error (MSE). This MSE is a type of error metric calculation used to estimate the average square value. This estimator measures the difference between two images between the estimated value and the more accurate estimated value. Hence, the quality of the estimator is also measured between the two images.

The mathematical representation of MSE is computed as follows:

$$\mathrm{MSE} = \frac{\sum_{P,Q}\left|I_1(P,Q)\cdot I_2(P,Q)\right|^2}{P^{*}Q}. \tag{5}$$

Here, P represents the number of rows in the input images and Q represents the number of columns in the input images.

3.3.2. Signal-to-Noise Ratio (SNR). This method measures the sensitivity based on the ratio between single power and noise power. In the meantime, this SNR calculates the signal of the image from the background noise image.

The mathematical representation of SNR is computed as follows. Here, I_1 and I_2 represent the sensitivity of two images.

$$\mathrm{SNR} = 20 * \log 10 \frac{(I_1 - I_2)}{\mathrm{MSE}}, \tag{6}$$

Based on the similarity measures, PSNR, MSE, and SNR are found to be the best to satisfy.

3.4. RGB Colour Model. The following equations were used to transfer the image from RGB to the HSI colour model.

$$\begin{aligned}
\mathrm{Hue}(H) &= 2 - \mathrm{ACOS}\left\{\frac{[(R-G)+(R+G)]}{\sqrt[2]{(R-C)2+(R-G)(C-B)}}\right\}, \quad B > G,\\
\mathrm{Intensity}(I) &= \frac{R+G+B}{3},\\
\mathrm{Saturation}(S) &= 1 - \frac{3\min(R+G+B)}{R+G+B},
\end{aligned} \tag{7}$$

where H means hue, which describes the pure colour of the image. S means saturation, which describes how much white colour is diluted with pure colour. V means value, which describes the brightness of the colour.

R, G, and B represent the colour model of red, green, and blue channels, respectively, and ε is an arbitrarily minute value, which helps to eliminate division by zero.

Figure 11 represents the RGB components of bacterial leaf blight in rice plant diseased leaf. Here, the greenest colour pixels represent a healthier portion. So, the different RGB components are analysed using the HSV colour space model. Using this colour space model, the RGB colour is analysed to extract the specific infected portion of the leaf.

3.5. Image Segmentation. In computer vision, segmentation is the process of dividing a picture using an unsupervised learning technique, as opposed to supervised learning. Region-based segmentation, edge-based segmentation, clustering-based segmentation, and other types of image segmentation are included in this classification. The clustering approach, as seen in Figure 11, is the most often used kind of picture segmentation. To isolate the area of interest from the rest of the picture, this clustering approach made use of a variety of segmentation algorithms.

To do this, the sick component must be separated from the area of interest. As a result, it is necessary to find an appropriate approach for identifying the information. The three separate approaches involved are K-means segmentation, fuzzy-means clustering algorithm (FCM), and the suggested novelty based K-means method, all of which are compared to the segmented area before being used for further processing. For the final choice, multiple performance measures such as mean structural similarity (MSSIM), dice similarity, and Jaccard coefficient are calculated based on the different performance metrics.

$$q^{\underline{x}} = \left(\text{Intensity of}\frac{\text{image}}{\text{total}}\text{number of pixels}\right). \tag{8}$$

The histogram equalised image can be defined as follows:

$$Z_{x,y} = \mathrm{base}\left((Z-1)\sum_{y=0}^{c_4} xq^{z})\right), \tag{9}$$

$$\frac{\partial O}{\partial y}\left(\int_0^O yqO(y)\mathrm{d}a\right) = \partial O(O)\left(y^{-1}\right)(O))\frac{\mathrm{d}}{\mathrm{d}O}. \tag{10}$$

Equations (9) and (10) represent the preprocessing of the input image. While the results show that the equalisation procedure utilised produces flat histograms, it may also soften and enhance the appearance of histograms.

3.6. Leaf Segmentation Using Partial Differential Technique. Over the last several years, it has been an increasingly important and time-consuming endeavour to separate both the leaf and the spot area, which has become more difficult

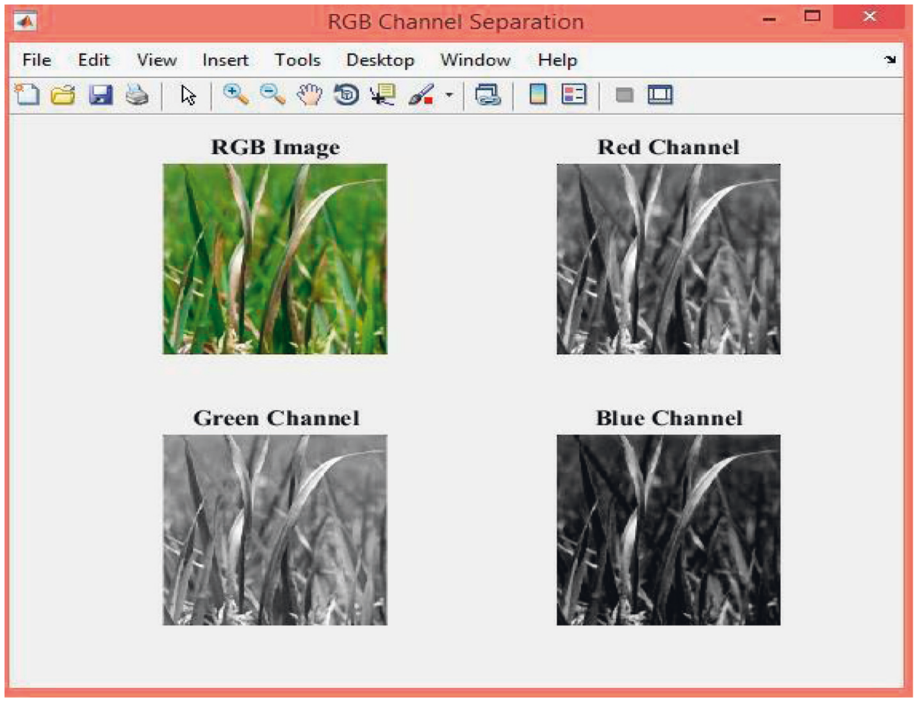

Figure 11: RGB components of bacterial leaf blight in rice plant diseased leaf.

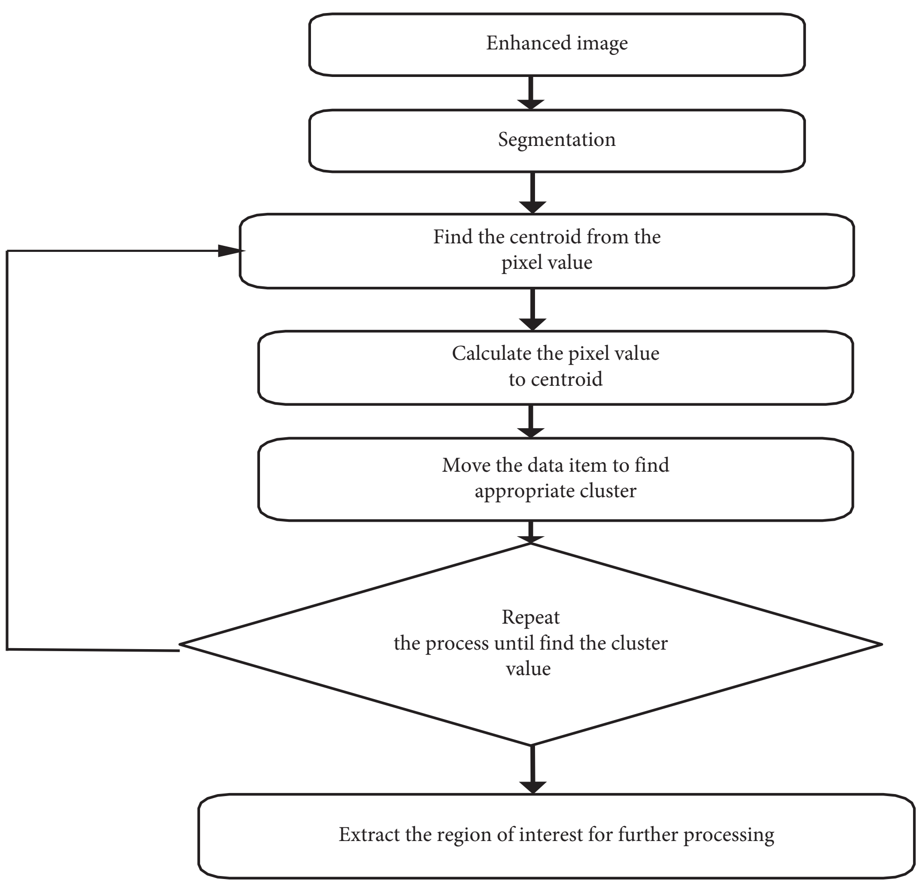

Figure 12: Flow diagram for the image segmentation process.

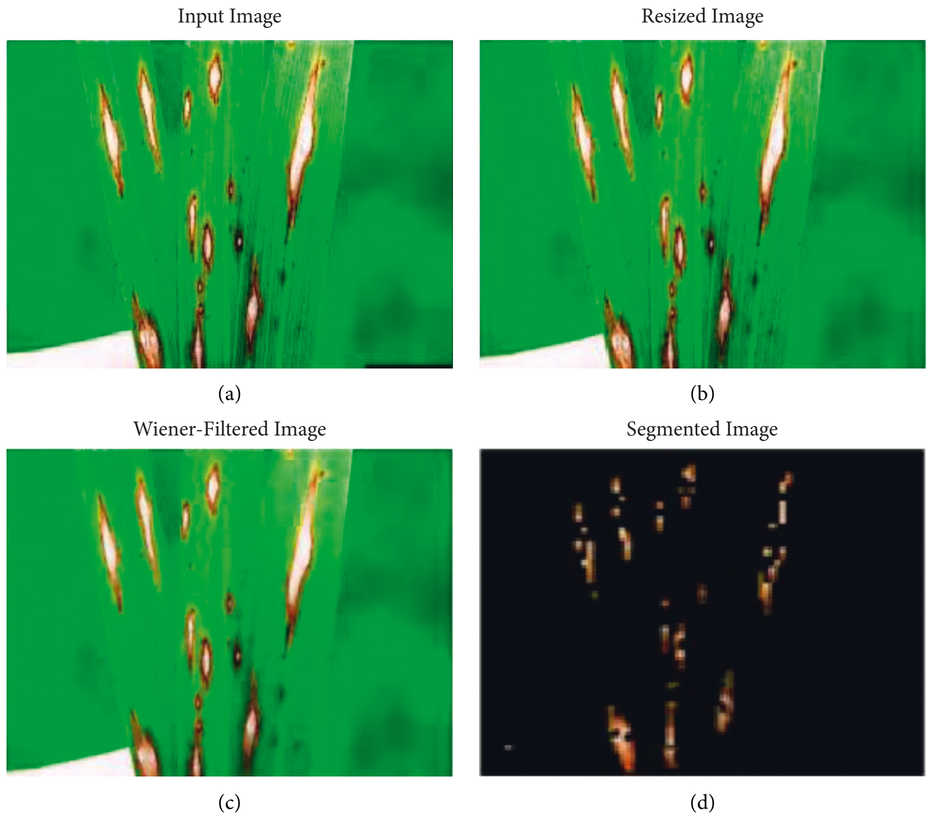

FIGURE 13: Region of interest separated from segmentation using K-means segmentation. (a) Input image of rice blast. (b) Size adjustment of the input image. (c) Removing the noised image. (d) Diseased part segmented using K-means segmentation.

and time-consuming to do. A large number of segmentation algorithms must be created to do this. Each method segments the picture using a different mode of operation. To separate data, three kinds of segmentation procedures may be used: manual segmentation, semi-automatic segmentation, and completely automated segmentation (see figure 12). Among the three ways, manual segmentation is the fastest and most easiest to do. During manual segmentation, leaf margins are identified by two distinct radiologists or by the same radiologists at various times in the same picture when two radiologists are working together on the same image. It is feasible to explain the structure and observation of medical pictures with the use of a segmentation strategy of this kind. It is crucial to highlight that there are various issues to be concerned about in this area, with the most significant being the degradation of picture quality and the emergence of artefacts. Equation (4) in the input segmentation represents a segmentation from another organ in the image, which is represented by a segmentation from another organ in the picture by the pixel that was used to create the picture, and O is the overall intensity of the image.

$$L[y] = O[y] + S[o] + \phi, \quad y \in S, \tag{11}$$

subject to the initial conditions

$$v(y,0) = h_0(y)_{+}\, v_t(y,0) = h_1(y), \ldots, v_t^{(x-1)}(y,0) = h_{-1}(y), \tag{12}$$

and spatial conditions are represented in equation (12).

$$u(\theta,t) = h_0(t),\, u_z(0,t) = \hbar_1(t). \tag{13}$$

Using this approach, we first apply the Laplace transformation to equation (14) in relation to the variable t, and we get the following result:

$$v(y) = L[O[v(y)] + S[v(y)]] + L[\phi(y,x)], \tag{14}$$

Using I.C. equation (17), we get

$$t^{o}\tilde{v}(y,t) = i^{-}(y,t) + L[O|v(y,x)] + G[v(y,x)]] + \tilde{\phi}(y,t), \tag{15}$$

where

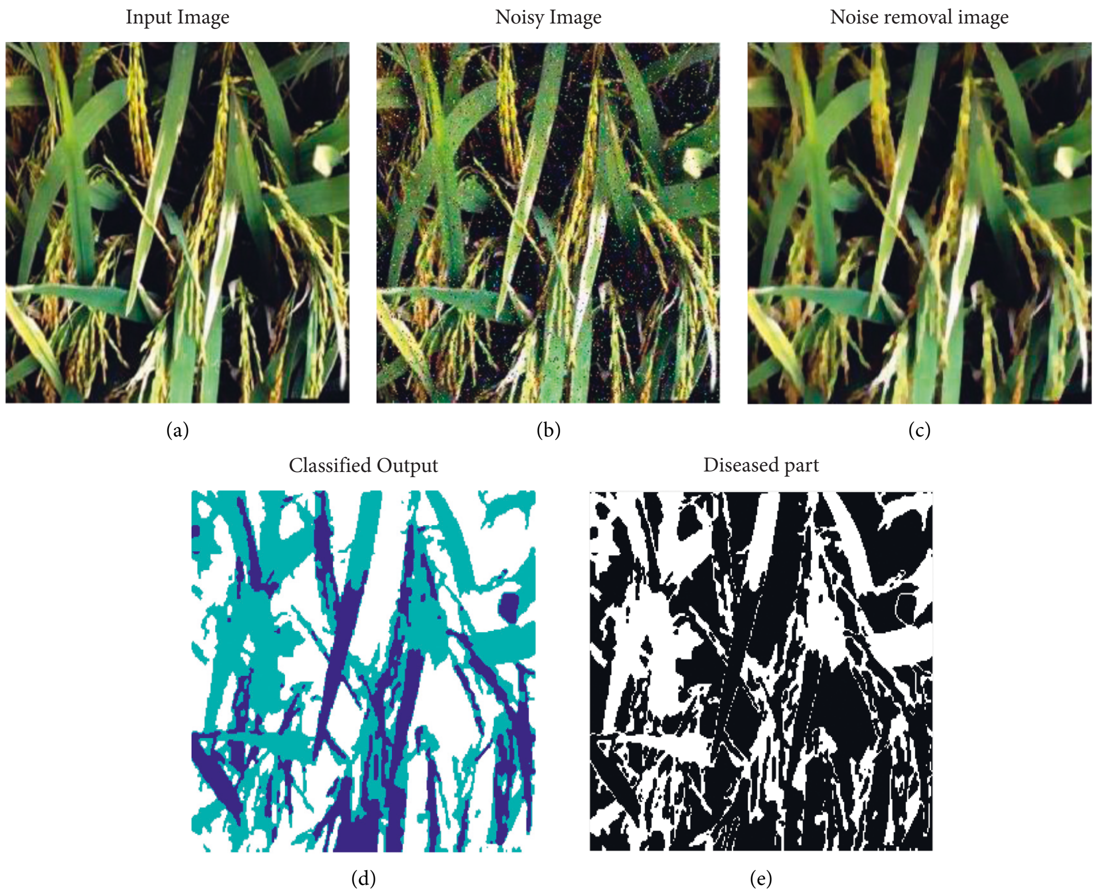

FIGURE 14: Region of interest separated from segmentation using FCM. (a) Input image of bacterial leaf blight. (b) Noised image. (c) After noise removal. (d) Colour-based using FCM. (e) Segmented greyscale image.

Choose the random values of K value from the initial centroid.
Place the K points from the group of data to represent the initial centroid.
Next, assign the object value to recalculate the K centroids. At last, compute the new K-centroid value in each.

ALGORITHM 1: Algorithm of existing K-means algorithm.

TABLE 2: Performance metrics.

Gaussian noise			
Techniques	PSNR	SNR	MSE
Bacterial leaf blight	26.497	21.026	42.654
Brown spot	35.441	19.138	32.435
Healthy leaf	23.641	18.386	76.43
Rice blast	31.974	24.74	60.712

$$
\begin{aligned}
\overrightarrow{i}(y,t) &= \sum_{s=0}^{1} xt^{(s+1)}\mu_m^2,\\
u^{-}(x,s) &= \left[\left[\frac{h^{-}(x,s)}{s^n} + \frac{1}{s^n}L[N[u(x,t)] + R[tu(x,t)]]\right] + \frac{\widetilde{\phi}(y,x)}{t^o},\right.\\
\widetilde{f}(y,t) &= \frac{i^{-}(y,t)}{t^o} + \frac{o^{-}(x,s)}{s^n},\\
Vx &= C^{-1}[\widetilde{f}(x,y)] + C^{-1}\left[\frac{1}{y^o}[O[v(y,u)] + S[v(y,t)]],\right.\\
V_0(u) &= h_0(u)\\
U_1(u) &= i_1(u),
\end{aligned}
\tag{16}
$$

where $V_u(u)$ and $G_l(v)$ are the differential transform of $v(x,y)$ and $z(x,y)$, respectively. By the above recurrence equation (17) and the initial conditions (17), the closed-form of the solution can be written as follows:

$$
X^{\text{segment}} = \sum_{s}^{o} xV_2\left(V_x, V_y\right)\cdot Vo\cdot\ \log_{c_i} + \gamma\int c_i \mathrm{d}y, \tag{17}
$$

where $W^{\text{Segmentation}}$ is the watershed segmentation.

Figure 12 gives the flow chart of the proposed work.

3.6.1. K-Means Segmentation. K-means segmentation is an effective method in unsupervised learning data to divide the infected portion from the background image. The following is how this technique begins: using the enhanced image, the data point features are collected to estimate the K-centroid value based on the Euclidean distance between the data points. Following that, the new K-centroid values are generated or selected in a random manner based on the data group. As a result of the loop generation, finally, this minimises the objective function based on the squared error function (Algorithm 1).

As a result, Figure 13 illustrates the algorithm segment of the diseased part of the rice plant image.

3.6.2. Fuzzy C-Means Method (FCM). The most popular method of the image segmentation process is the fuzzy c-means algorithm. This FCM can keep hold of more information from the original image. It is a pattern recognition method that is used to group data from other data based on metrics of intensity, distance, and connectedness between the data clusters, but the main drawbacks of FCM are it does not take any spatial dependence of the image among the pixel, but it deals with separate points as shown in the figure. To find these issues, the FCM algorithm is compared with the proposed method and the result is illustrated in Figure 14.

4. Experimental Analysis

The performance measure of the denoised picture is examined and compared with the other four techniques using photographs of rice that has been infected with a disease. The results of this analysis are utilised in two key ways. The input images are captured during the first step of the process. When the image is denoised, the noise is put directly into it using the noise fall method, which is also utilised for image enhancement. This picture was taken with a digital camera as input for the denoising operations that were performed during the second step. Consequently, in both stages, the denoised photographs are used to eliminate any undesired information from the photographs. Table 2 represents performance metrics.

5. Conclusion and Future Work

A variety of standard procedures are used in the process of diagnosing diseases in rice plant images.

Despite the fact that it has certain benefits, its principal drawback is the inaccuracy of its categorisation findings and the inaccuracy of its illness classification.

This research endeavour has resulted in the development of a novel integrated-based classifier as a consequence. It is important to categorise the photographs based on the recovered feature values, and the suggested novel fuzzy logic-based probabilistic neural network approach may be used to accomplish this task. When a range of analytical parameters, such as accuracy, specificity, sensitivity, recall, and precision, are used to evaluate and compare the performance of this proposed technique with three other existing processes, the results are overwhelmingly positive (Figure 1). As a result, it has been established that the suggested technique achieves superior results in data classification than the other present strategies. It was found that bacterial leaf blight, brown spot, healthy leaf, and rice blast were the rice diseases with the highest accuracy in classification; they were classified with 95.20% accuracy in classification, 97.60 percent accuracy in classification, and 98.40 percent accuracy in classification, respectively.

The researchers used a basic smartphone to take a picture of the injured rice plant to document the situation. While smartphones are very convenient, their functionality is severely constrained. As a consequence, farmers get enough training on how to make use of the mobile application. The increased processing speed, limited memory, and higher accuracy of continuous monitoring may make it easier to identify the plant disease without the need for specialised knowledge. To make smartphones effective in the identification of diseases, precision algorithms must be developed, but currently available algorithms are insufficient [42, 43].

Data Availability

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding this study.

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