Design and Implementation of an Efficient Rose Leaf Disease Detection using K-Nearest Neighbours

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Abstract*: Plants are prone to different diseases caused by multiple reasons like environmental conditions, light, bacteria, and fungus. These diseases always have some physical characteristics on the leaves, stems, and fruit, such as changes in natural appearance, spot, size, etc. Due to similar patterns, distinguishing and identifying category of plant disease is the most challenging task. Therefore, efficient and flawless mechanisms should be discovered earlier so that accurate identification and prevention can be performed to avoid several losses of the entire plant. Therefore, an automated identification system can be a key factor in preventing loss in the cultivation and maintaining high quality of agriculture products. This paper introduces modeling of rose plant leaf disease classification technique using feature extraction process and supervised learning mechanism. The outcome of the proposed study justifies the scope of the proposed system in terms of accuracy towards the classification of different kind of rose plant disease.

Keywords: Plant Disease, Rose, Machine Learning, KNN, Classification.

I. INTRODUCTION

Agriculture and farming have an essential role in sustaining human life. Life depends on food, and cultivation of plants-(vegetable plants, ornamental plants, medicinal plants, etc.), hence it is a direct means of livelihood, which includes economic aspect, social aspect, and environmental aspect [1]. Economy and good health depend on the quality standards of field crops and other edible products, which are mostly influenced by environmental factors [2]. Since various filed crops are cultivated and harvested products are transported to other states or even exported to other countries. Therefore, it is essential that agricultural products must be produced with high quality. According to different climatic conditions and soil fertility, multiple farming practices being adopted by the farmers [3]. However, in addition, farmers and crop cultivators suffer from water scarcity and different plant diseases [4-5]. By adopting some technical support and facilities, these issues can be controlled and shortened to a large extent, and even food productivity can be improved accordingly. Special attention needs to be paid to the planning and development of effective mechanisms that can promote sustainable growth in the agricultural sector. In the agricultural sector, classification and identification of rose plant disease are one of the important research topics [6-7]. Roses are ornamental plants and preferable choice of people with a variety of interests (such as gardening, Design and Implementation an Efficient Rose Leaf Disease Detection using KNN decoration, worship, etc.). Roses are the most planted flowers across the globe and are actually being planted for profit-making intents and to meet our emotional needs [8]. Unfortunately, rose plant is susceptible to much infection and disease caused by bacteria and fungus that progressively destroy its health, tempting value, and has cause an adverse effect on its pricing and sales. The primary cause of rose plant diseases is due to bacteria, viruses, a fungal infection like anthracnose, mildew, rust, etc. [9]. Therefore, effective and timely disease mitigation strategies act as a utility factor in this case. However, it is a very rigorous and frustrating subject for agricultural experts to fully detect and classify different diseases in plants and field crops based on leaf analysis. The traditional approach involves a manual process that requires more time for analysis, long-term observation to recognize the root cause and arrive with effective solutions [10]. Therefore, identifying plant diseases by just looking at the leaves of plants is not an easy task, because diseases may have similar symptoms and patterns. It is also noticed that there is a lack of an automated mechanism in traditional systems that can perform the classification and identification of different nature of the disease [11]. But with the advancement in image processing and statistical analysis mechanisms, this gap can be bridged by developing a cost-effective and automated classification mechanism that considers the external appearance of infected plants and leaf conditions. Plant diseases may vary or may have identical feature in colour, shape, and size, and each disease has different characteristics and attributes [12-13]. Based on such information, the automated system can classify the nature of disease on plant and at the same time provides strategic guidance to cure and preventions without consuming so much time and involvement of manual processes. In the past few years, various research studies have been made that explored potential issues in the development of an effective solution for plant disease recognitions [14-18]. However, till date no any existing solution claimed to effective, and some of them are highly associated with a computational complexity that doesn't provide higher accuracy in the classification of plant disease. However, existing research works also provide a large scope to come up with novel solutions.

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With the support of advanced learning mechanisms, there is a possibility of bridging the gap of existing research efforts. Therefore, this paper introduces a formulation of a novel automated system for the detection of different disease in plants, considering only the condition of plant leaf. The proposed study mainly focuses on multiple rose plant disease named as anthracnose, mildew, rust, and leaf spot. The significant contribution in the proposed study are as follows: The study considers a two different dataset downloaded from the internet source after Design and Implementation an Efficient Rose Leaf Disease Detection using KNN which manual data preparation is carried out to fed appropriate input data to the formulated system. Initially, the image is pre-processed and then subjected to the attribute's extraction process, and finally, a classification operation is executed using KNN-(k-Nearest Neighbor) supervised learning algorithm. The rest of the sections are structured in the following pattern: Section presents the related work and problem identification. Section III describes the proposed system, followed by schematic architecture and implementation strategies. Section IV exhibits outcome and performance assessment of the proposed system work. Finally, the overall contribution and significance of the proposed work are concluded in Section V.

II. RELATED WORK

Since there have been many types of research towards addressing the issues in the detection and categorization of disease in plants using leaf image, few relevant research works are discussed below: The authors in the research work of (Yang Lu et al.[19]) used a deep convolutional neural network for performing detection of disease type in rice plants. This study adopted a dataset of a huge collection of images of paddy stems and leaves. The authors have performed a classification operation considering various common rice diseases. The outcome of this study revealed that the presented solution achieved higher accuracy compared to the traditional machine learning approach. (Prakash et al. [20]), adopted the mechanism of color conversion and k-means clustering for the process of image segmentation. The study uses GLCM features for the extraction of attributes and Support Vector Machine-(SVM) for performing detection and classification of diseases. The experimental process was accrued out considering citrus plant leaves. In the study of Gittaly (Dhingra et al. [21]), the authors have used a fuzzy-based segmentation scheme, and multiple membership functions are applied for assessing the ROI component of the image. The study has considered multiple classifiers to recognize the plant leaf as diseased. The dataset considered in this study contains 400 images that are prepared with equally 200 diseased and 200 non-diseased leaf images. The outcome of the study demonstrated that the random forest-based classification method outperforms the other approaches. (Pooja et al. [22]) considered a mechanism based on HSI conversion, and image segmentation. In this study, a k-means clustering mechanism and thresholding mechanism is adopted for the segmentation. This study also uses a mechanism for GLCM features for feature selection and SVM for the classification of the various leaf diseases. (Nidhis et al. [23]) designed a framework Design and Implementation an Efficient Rose Leaf Disease Detection using KNN using an image processing technique to recognize disease on paddy leaves. Here, the authors have computed the severity of disease on plant leaves based on the determination of the affected area. The study offers an assistive mechanism that suggests applying the suitable pesticides for different common disease on the paddy crop. (Pranjali et al. [24]) considered k-means clustering-based segmentation operation, and gaussian filtering was carried over input image for the image enhancement. In classification, the study extorted 54 features, and Linear SVM is used to leave disease classification. The experimental task was carried out on grape leaf for recognition of two types of disease, i.e., downy mildew and powdery mildew. In the work of (Kulinavar and Hadimani [25]), the authors have used K-means based segmentation operation for ROI evaluation. In the attribute selection process, color and texture attributes are extracted for the classification. SVM is used in the disease identification process using multiple classes of image Rice, Soybean, Carrot, and Rose. The study outcome demonstrates the effectiveness and scope of the presented study. (Taohidul Islam et al. [26]) designed a classification model in which they adopted the image processing mechanism to perform an analysis of the portion affected by the diseased. In this, the Naïve Bayes classifier is considered for disease detection in the rice plant. The study only extracted features, and based on these features; this study effectively identified multiple rice plant diseases. The study has advantageous benefits that it performs overall computation without involving any complicated process and has a faster response time. (Ferreira et al. [27]) also presented their contribution in this area where they have created a very large dataset where thousands of images of the different plant-like Soybean, grass weeds, and the soil is considered. CNN based learning model is used for the classification of weeds in soybean plants and grass. The presented approach has achieved significant outcomes for the weed classification using the image processing mechanism.

- **Problem Identification:** The conventional methods for classifying the plant leaf diseases are a human vision-based mechanism that requires expert advice, which practically is a very time consuming and expensive process. The Machine learning-based method enables an effective and time-saving mechanism that can identify the different diseases, make a suitable decision for prevention and treatment. Very few existing works considered the identification and classification of disease in rose plants using machine learning mechanisms. The next section presents signification contribution Design and Implementation an Efficient Rose Leaf Disease Detection using KNN made in the proposed study towards the identification and classification of Rose plant disease.

III. PROPOSED SYSTEM

The proposed system introduces a scheme of rose plant disease identification. The main motive of proposed modelling is to provide an efficient mechanism to classify plant disease based on analysis of leaf spot and infection so that effective prevention can be taken to avoid losses in plant quality, thereby yield quantity-aware agriculture product.

Figure 1 depicts the overall processes involved in the design of proposed modelling for rose plant leaf disease identification and classification.

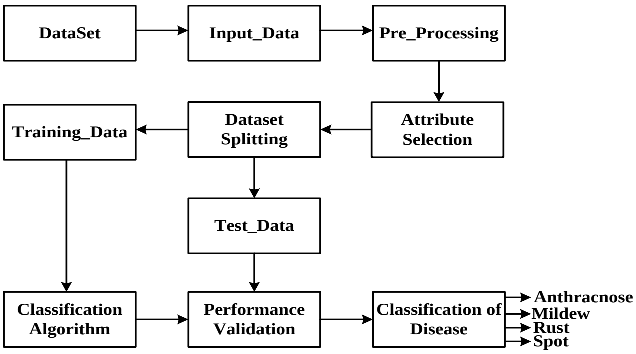


Figure 1 Schematic Representation of Proposed Plant leaf disease classification

The modelling of the introduced plant leaf disease detection approach is performed using the analytical methodology. The model design contains several functional blocks for the disease prediction and acts as an assistive tool for providing a solution to recover from the leaf disease. The first module of the proposed system is subjected to the dataset collection/preparation so that specific input data can be given to the system for further computations. In order to perform time-efficient and accurate classification operation, the system modelling executes the pre-processing operation over the input data. The execution of the pre-processing module performs noise filtering and visuality enhancement that leads to the generation of a refined version of input data with precise visual and information quality. Further, the refined version of the input Design and Implementation of an Efficient Rose Leaf Disease Detection using KNN image is then subjected to the segmentation process and future extraction process in order to attain all vital statistical attributes of input data for the disease classification. In the next operation of the proposed system, splitting of the dataset is conducted where a maximum set of datasets is considered for model training, and the remaining part is considered for testing-set for the validation of training performance. Finally, a supervised learning mechanism is adopted to perform statistical estimation for the rose plant leaf disease classification and identification.

A. Description about Dataset

In the process of the search for the dataset, we encounter two different datasets one is from Kaggle and another from the UCI, but both the dataset is for different plant leaf classification. Therefore a manual process of database creation is performed to build the reposit for training and testing data for the classification of the disease.

B. Description of Categories of Dataset

The feature description of all four diseases such that Anthracnose, Mildew, Rust, and Spot are discussed briefly as follows:

i) Anthracnose: This is a disorder to the structure of leaves, vegetables, and stems. The fungal disease causes that. On leaves, it generally causes dark spots and sunken regions on the leaves. It initially appears as small irregular yellow and darkens brown as they age and may cover whole leaves parts. If it is not prevented, then this can lead to defoliate plants. Figure 2 exhibits a sample representation of the Anthracnose disease.

Figure 2 Sample of Anthracnose disease in plant leaf

ii) Mildew: This is one of the frequently known leaf diseases in rose plants and is caused by the “Podosphaerapannosa” fungus. Common signs of this disease are the growth of white powdery, which can later affect all parts of plant leaves. This disease is common in warm and humid weather. Figure 3 shows a sample representation of Mildew.

Figure 3 Sample of Mildew disease in plant leaf

iii) Rust: Rust in rose plant leaves caused by the parasitic disease caused by a fungus called “Phragmipedium.” Ruts disease in rose plants mostly appearing in the spring season and continues until all the leaves fall. Figure 4 shows a sample representation of rust.

Figure 4 Sample of Rust disease in plant leaf

iv) Spot: This is a disease that appears in the form of black spots and is caused by a fungal disease known as "Diplocarponrosae," which ultimately causes the rose plant leaves to become light-yellow colored with black spots and fall off. This disease becomes worst after long, wet weather in spring. Figure 5 shows a demonstrated sample representation of black dots.

Figure 5 Sample of black Spot disease in plant leaf

ii) Implementation Strategy

The design and implementation of the introduced plant leaf disease detection system are modelled with five operational phases, which consist of data preparation, input data pre-processing, segmentation, attribute design, and Implementation of an Efficient Rose Leaf Disease Detection using KNN selection, and classification.

The analytical strategies adopted in the system implementation are discussed as follows:

a) Dataset Preparation

Appropriate datasets are essential in the overall design implementation of the proposed system, that is, from an initial training stage to validation of classification performance. In the proposed system, the datasets were taken from the Internet source. The rose leaf images from the datasets are manually classified and labelled in the training-set, and randomly selected unlabelled images are provided in the testing-set. Therefore, the images in training-set are dissimilar from the images contained in the testing-set, and (70%) sample data were used for training, and (30%) sample data were used in the testing phase. The categories of the source data files are labelled as, L={L1, L2, L3, L4}, where L1= Anthracnose, L2= Mildew, L3= Rust, and L4= Spot.

b) Pre-processing

Pre-processing serves as a vital function towards a reduction in the requirement of large storage space and computational complexity in algorithms. In the pre-processing task, the input image will undergo different processing mechanisms to obtain a refined image, thereby providing meaningful image interpretation and revealing hidden information contained in the image. In this process, the study initially considers an image-(Im) form the dataset as input data that can be represented as follows:

$I_m | I_u(x,y) =$

$$\begin{bmatrix} I_u(0,0) & I_u(0,1) & \cdots & I_u(0,n-1) \\ I_u(1,0) & I_u(1,1) & \cdots & I_u(1,n-1) \\ \vdots & \vdots & \vdots & \vdots \\ I_u(m-1,0) & I_u(m-1,1) & \cdots & I_u(m-1,n-1) \end{bmatrix}_{m \times n \times 3}$$

Where, I_u (x, y) refers to a function that describes intensity value at each point and is a product of reflectance $r(x,y)$ *and intensity* $i(x,y)$. Numerically, it can be stated as:

$$I_m(x,y) = [r(x,y) \times i(x,y)]$$

The first operation of pre-processing is to perform an image enhancement operation followed by resizing, and mapping intensity value in the input image. This process has a favorable impact on computational performance after the image is resized. In the next step of pre-processing, the RGB image is transformed into HSV. In this S component is first processed as it increases the whiteness. The processing of the S component is carried out based on the multiplication saturation channel by scale factor 2. After the successful execution of pre-processing steps, segmentation operation is applied over the pre-processed image to carry out further signification operation towards disease classification.

c) Segmentation

Image segmentation is an important operation that refers to the sequential procedure of identifying the area of interest by dividing an input image into different segments. The basic requirement is to transform the image details into more expressive and easier representation to perform an effective analysis of the infected portion of the image. In this regard, the K-means clustering mechanism is considered in the proposed work to classify the affected and unaffected parts of the disease effectively. Here, clustering is the procedure that describes a function of grouping the pre-processed input images into the cluster. In this, the infected parts of leaves are extracted from the plant leaf, i.e., set of features into K classes.

d) Attribute Selection

After executing the pre-processing operation over the input leaf, multiple attributes are extracted to describe the diseased region. The system considers the extraction of both types of attributes (i.e., texture attributes and color attributes). The color features include extraction of the mean- (m) or average value and standard deviation(sd) value, where the texture feature includes the GLCM features.

a) Extraction of color feature attributes

Initially, RGB components are determined for the disease portion in a plant leaf, and various statistical features are further computed. Here, HSV components from the input image are taken out and computation of statistical features like mean-(m) and standard deviation as follows:

For mean value-(m) computations:

$$m = \frac{i}{n}\sum_{x=1}^{n} Ip_{xy} \quad \text{.... (eq.1)}$$

For standard deviation-(sd) computation:

$$sd = \sqrt{\frac{i}{n}\sum_{x=1}^{n}(Ip_{xy} - m)^2} \quad \text{.... Equation (2)}$$

Here, n indicates the overall number of pixels and $Ip_{(xy)}$ is the pixel value.

b) Extraction of texture feature attributes

Texture based attributes are estimated based on the spatial association among the sets of intensity pixels. For a quantified displacement, various attributes are computed from GLCMs as follows:

- **Computation of Homogeneity-(H) feature attribute:** (Estimates the variations in image intensity)
  $$H = \sum_{y=0}^{n} \frac{Ip_{xy}}{1+(x-y)^2}$$
- **Computation of contrast-(c) feature attributes:** (Estimates spatial frequency of an image)
  $$c = \sum_{y=0}^{n} Ip_{xy}(x-y)^2$$
- **Computation of correlation-(C_{rl}):** (Estimates linear dependence property of gray-levels of adjacent pixels)
  $$C_{rl} = \sum_{y=1}^{n} Ip_{xy}\frac{(x-m)(y-m)}{sd}$$
- **Computation of Dissimilarity-(D_A):** (It is a difference mean that refers to the average value of the gray level disparity distribution among adjacent voxels)
  $$D_A = \sum_{k=0}^{n-1} k\left(Ip_{x-y}\right)^2$$

- **Computation of Energy-(E): (**Estimates texture uniformity)

$$E = \sum_{y=0}^{n} (Ip_{xy})^2$$

- **Computation of Angular second moment-(ASM):**

$$ASM = \sum_{x}^{n} \sum_{y}^{n} (Ip_{xy})^2$$

a) Classification of rose plant leaf disease using KNN Classifier

KNN algorithm is a class of supervised Machine Learning mechanism which is most commonly adopted for performing classification operation and also subjected to the other predictive problems. For executing classification operation, KNN uses statistical attributes or feature similarity to forecast new data-points, which means that these points assigned a value based on condition, i.e., how well the new data point matches in the training feature. The computation is carried out based on estimating the minimum space of length between the given point and other points. In the case of rose disease classification, the Euclidean-distance between the test datasets and training datasets is computed. Based on the distance values, a sorting function is called to arrange then in an ascending sequence, after which it will select the most efficient k rows from the sorted sequences. In this way, it estimates the similarity metrics and, thus, the category/class of the test dataset. The algorithm for implementation of the proposed system for rose leaves disease classification is discussed where the algorithm initially takes input data in form image, i.e., Im from the dataset, and after successful execution, it generates output as disease classification and identification, i.e., D_L. The significant steps involved in the overall implementation of the adopted methodology are as follows:

Algorithm-1 Rose Leaves Disease Classification

Input: I_m
Output: (classified disease)
Start

1- Import $\leftarrow I_m$
2- $I_{re} \leftarrow f_1(I_m)$
3- $I_p \rightarrow f_2(I_{re})$
4. $I_{seg} \leftarrow f_3(I_E)$
5- $A_{select}\ [A_T, A_C] \leftarrow f_4(I_{seg})$
6- $F_V \rightarrow f_5(A_{select})$
7- Apply $\rightarrow$ *KNN*
8. $T_{rdt}\_T_{sdt}(n\%, m\%) \rightarrow D_n, D_m$
9- Classify $\rightarrow f_6([Dn, Dm]) \rightarrow P$
10- R $\rightarrow$ L3 (Classified disease)
11- $f_7(x) \rightarrow$ *(performance metric)*
12- return $\rightarrow$ *Outcome*

End

The computing steps discussed above is designed for classifying plant leaf disease using optimal statistical feature-attributes and supervised learning mechanism. At the initial step of the algorithm, the input image-(I_m) is imported from the specified path (line 1). The image-(I_m) taken for input may be associated with redundant data, higher dimension, and uneven scaling of the data points. Therefore, in this regard, the system executes pre-processing operation where Im is transformed into a more specific and meaningful form. This process results in a reduction of irrelevant information and offers ease of computational efforts during the algorithm runs. This operation is accomplished by implementation of data transformation, normalization function, where the input image Im is subjected to function f1(x) (line 2), which performs the transformation operation of mapping intensity value in the input image to achieve a resized version of the input image-(IE). The processed RGB image is then transformed to HSV, where S component of the image is then processed based on multiplication saturation channel by scale factor 2 (line 3). The pre-processed image-(Ip) is then carried for segmentation using function f3(x) over Ip. This function calls a k-clustering mechanism for performing the clustering mechanism where an infected portion of leave disease is separated from the original image (line 4). In the next process, the statistical attributes are selected using a function (f4) over segmented image Iseg. The extraction of attributes carried based on the GLCM mechanism where only relevant attributes-(AT, AC) are considered based on the texture information and color information, respectively (line 5). After the selection of statistical attributes, the system then executes its operation, which is subjected to a feature vectorization in which extracted statistical attributes are converted into the vector-(F_V)by calling another function f5(x), which refers to label encoding mechanism (line 6). This most significant step in the proposed algorithm as it offers final attributes in the form of a feature vector that leads to the possibility of getting accurate results in the disease classification process. In the next step of the algorithm, the proposed system applies KNN classifiers towards the initialization of classification operation (line 7). In this phase, the training and testing operations are executed considering feature vectors where both datasets are subjected to the specific number of contents, i.e., n% of data are selected for training operation (Trdt), and m% of data are chosen for the testing-(Tsdt). Therefore, in this context, trained data-(Dn) and testing data-(Dm) will be the new input for the system to further execute a classification for disease identification (line8). In the next step, the algorithm mainly calls ML function (i.e., KNN classifier)overtrained data-(Dtr), and Dn, which after execution generates outcome in terms of classified disease type, i.e. (L3), where L refers L1, L2, L3, L4, i.e., different categories of rose leaves disease (line9 and line10). Finally, the outcomes of the proposed methodology are achieved using statistical function f7(x) in terms of multiple performance metrics.

IV. OUTCOME ANALYSIS

The proposed system presented a supervised learning-based plant disease classification mechanism. In this section, the performance analysis of the proposed rose plant disease classification model is discussed. The modelling of the entire framework design is conducted using a numerical computing platform. Also, the performance assessment is carried out in terms of accuracy rate, precision rate, and recall rate.

The visual and quantified outcome is provided below:

4.1 Visual Outcome

An analysis of the proposed system performance is demonstrated for multi-pre-processing and segmentation operation.

Table 1 Visual outcome of Image Pre-processing

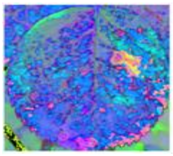
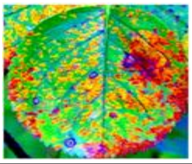
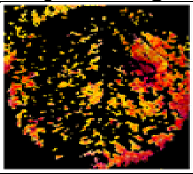
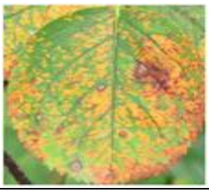
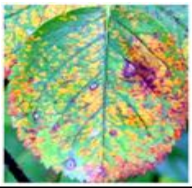
		
RGB to HSV	Scaled Saturation Part	Leaf disease Portion

Table 2 Visual outcome of HSV Colour Conversion and Image Segmentation

		
Input Image-(Rust disease)	Resized Image-(dimension reduction)	Enhanced Image

From table-2, it is evident that the proposed system offers a multi-level of pre-processing operation, which provides a more enhanced and descriptive image for the effective classification. In the segmented image, it is clear that the green portion is ignored from the image. As the system only meant to consider leaf disease portion, and an unwanted green portion can lead to cause an adverse impact in the attributes selection process.

4.2 Quantified Outcome

This section exhibits the performance of the proposed system based on numerical analysis considering multiple performance parameters such as precision (P_R) and recall rate (R_R).

$$P_R = \frac{Total\ number\ of\ accuratly\ identified\ desease\ leaves}{Total\ number\ of\ detected\ leaves}$$

$$R_R = \frac{Total\ number\ of\ accuratly\ identified\ desease\ leaves}{Total\ number\ of\ expected\ desease\ leaves}$$

Table 3 Performance score of the proposed system

Performance Metric	Input image disease leaves-(Rust)
Precision	250/291
Recall	250/250

Table 3 exhibits a quantified outcome in terms of precision and recall rate. The precision score shows 250 out of 291 for the infected image, whereas the recall rate shows 250 accurately identified disease as there are existing 250 disease leaves image. The system performance is also demonstrated based on the comparative analysis, where the proposed system performance in disease classification is compared with the existing system [28]. In the work of [28], the study has focuses on the classification of plant disease using an image processing mechanism where the Gaussian filter was applied and SVM classifier-based classification approach. Figure 6 and Figure 7 depicts comparative analysis in terms of accuracy(%) and error(%).

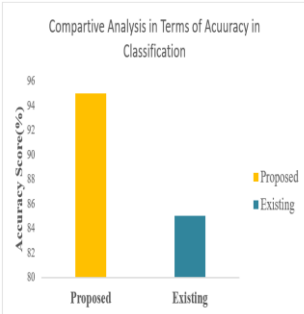
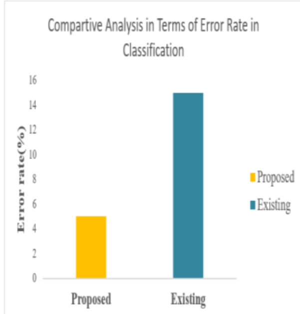
	

Figure 6 Analysis of Accuracy	**Figure 7 Analysis of error**

From figure 6 and figure 7, it can be evaluated performance achieved by the proposed system for the classifying rose plant leaf disease is quite better compared to the existing system. The reason behind this is that the proposed system offers multi-level pre-processing steps, whereas in the existing system deals with only Noise filtering. The multi-level pre-processing operation in this work provides a detailed interpretation of input image that can assist in further operations carried in the proposed system to extract significant feature-attributes. Another reason is that the proposed system is not associated with any complex form of implementation strategy as KNN is adopted, which is quite easy to implement can perform multi-class data classification.

V. CONCLUSION

The proposed work presented a rose-leaf disease detection scheme where input data is taken from the large, manually prepared dataset that consists of four common types of disease. In pre-processing, a multi-level step operation is performed, followed by HSV color conversion to achieve a refined version of the image for segmentation and significant attribute selection. A clustering mechanism is applied in the segmentation operation, and both color and texture features are extracted. A supervised learning KNN classifier is adopted for the classification/identification of the rose plant disease. The experimental outcomes are assessed and compared in terms of accuracy and error scores. The study outcome suggests better performance achieved by the introduced methodology for disease identification and classification.

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