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# Grape leaf image classification based on machine learning technique for accurate leaf disease detection

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## Abstract
Grape leaf diseases have a major impact on the growth of grape industry and grape crop yield. Thus, there is a need of a grape disease detection in early stages of disease so that disease spread and their impact could be controlled and development and production of grape industry remain continuous and active. However, the detection of grape leaf disease in initial stages is highly critical and challenging. Therefore, in this article, machine learning technique is adopted for the early detection of grape leaf disease and accurately distinguish between various classes of disease. Furthermore, Convolutional Neural Network based Classification (CNNC) model and improvised K- Nearest Neighbor (IKNN) model are introduced for classification of leaf diseases. High quality histogram and extended histogram features are obtained to provide structural, pattern, boundary and discriminative information. Then, classification process is performed on the obtained high quality gradient based features. Classification accuracy is improved to a great extent using proposed CNNC and IKNN model. The accuracy of the proposed CNNC and IKKN model is tested with the help of public dataset named as Plant-Village Dataset. The performance of proposed CNNC and IKKN model is compared with various traditional classification models considering classification accuracy.

**Keywords** Grape leaf disease · Classification · IKKN model · Histogram gradient features · Convolutional neural network (CNN)

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## 1 Introduction

Grapes are one of the most popular fruit not just in India, but also across all over the globe. It is also one of the oldest fruit crop in terms of cultural significance. Generally, grapes are utilized as a fresh, sweet and healthier fruit. Furthermore, grapes have numerous health benefits and carries several nutrients which is the reason that grapes are prescribed by several doctors for faster recovery from various health issues. However, grapes are also utilized for producing wines and raisins across all over the world, especially in the European countries and in USA. However, currently India occupies 7th position in producing grapes among all the countries across the world based on the report of Indian Council of Agricultural Research (ICAR), 2017. It is stated that INDIA exports around 53, 910 tons of grapes to other countries every year which is around 1.54% share of total grape exports across all over the globe [13]. Therefore, grapes are one of the most essential fruit cop in INDIA which provide boost to the country's economy to a significant extent as well as enhances annual crop yield.

Furthermore, production of grapes is highly profitable due to their wide utilization as a fresh fruit and in making wines and raisins and their ease of growing in various environmental conditions [17]. The production of wine has evolved significantly in the recent years. The one of the most famous and common wine is termed as *Vitis Vinifera*. However, several surveys has claimed that currently there are more than ten thousand varieties of wine is available across all over the world [15]. Moreover, viticulture industry is evolved significantly in the countries like Spain, Italy, France, United States of America (USA), Chile and Australia. Among these countries, Italy is the largest producer of wine and Spain is the first country which have their dedicated land for wine production and then followed by others [9]. This proves the significance of grape production across all over the world.

However, crop and leaf diseases are one of the biggest reason for famine and food insecurity on earth. It is predicted by various phytology experts that around 16% loss occurs annually in global crop yield due to these plant diseases [2]. These diseases in the leaves of grapes can affect the quality and grape production yield to a significant level. Furthermore, grapes are highly susceptible to plant diseases which is a challenging and concerning area and they required utmost care and protection from plant diseases to remain fresh and useful. The availability of disease just not decrease the crop yield but also affects the economy of the country. The famous diseases which can occur in grapes and affect their production rate and quality are Powdery mildew, anthracnose and Downy mildew etc [1]. These diseases can cause enormous loss to their crop yield and can occur in the leaves, fruits and stem of the grape crop.

Therefore, the prevention of crop yield losses and quality maintenance of product is highly depends on the accurate detection of these diseases and accordingly accurate pesticides can be utilized. However, in many crop disease prevention methods, several protection products are utilized which are harmful for environment as well as human health. In several methods, disease diagnostic tools like Microscope and DNA sequence recognition tools are utilized which are very expensive and out of reach for most of the farmers [2]. Besides, in several cases automated Wireless Sensor Network (WSN) [3, 14] and remote sensing techniques [5, 6] are utilized for prevention of grapes from aforementioned diseases. However, these techniques are utilized only for disease prevention. Therefore, a suitable technique to accurately identify the disease and examine disease characteristics is required so that accordingly actions can be taken to cure the affected plant. The proper identification of grapes disease involves the precise segmentation of affected region of leaves in grapes, segmentation quality evaluation, and extraction of various features which gives information about their patterns and their boundaries, detection of disease type using classification techniques. The proper detection of plant disease can provide significant enhancement in crop yield percentage and quality of product. However, the detection of plant diseases are very critical and challenging, especially in case of leaf disease identification due to the same type of symptoms for varied diseases, availability of different type of symptoms for a single disease at varied stages of plant emergence and availability of different leaf diseases at the same time. One of the most emerging technique for disease identification in plants is digital image processing techniques.

Thus, several research community experts have shown immense interest in the detection of grape disease and provided various solutions which are presented in the following paragraph. In [19], a back propagation enabled neural network and image analysis method is adopted to detect disease in grape leaves. This technique utilizes wavelet transform to reduce noise present in the digital images and then extract segmented regions of leaves and then features of grape diseases are examined. In [12], a data augmentation approach is adopted the disease detection of grape leaves based on the generative adversarial networks. Here, high quality features are extracted to find out characteristics of grape leaf lesions. Training is performed using deep gradient penalty method. In [16], leaf disease identification method is presented enhance quality of production. Here, leaf disease classification techniques are also adopted to examine and study the disease behaviour and disease type and fusion methods are used to perform effective classification. In [10], a comprehensive review is presented for plant disease detection based on image processing techniques. Several image processing and machine learning techniques are examined which provide details of plant disease behaviour. It is evident from various researches that CNN architecture can automatic analyse and train images to extract efficient features like color, texture etc. Furthermore, the detection and classification of objects is mainly based on efficient training of model. Therefore, CNN is extensively used for image classification process as a highly efficient machine learning technique.

Besides, this study focuses on highlighting the critical gap present in the available existing techniques and provide details of the methods which can enhance disease identification accuracy in early stages. However, potential available disease identification algorithms are not mature enough to utilize in practice and many challenges need to be discussed like accurate detection of leaf diseases, finding out the factors which can affect quality of crop production in the affected region and precise feature extraction etc.

The contribution of work can be classified as follows:

Therefore, in this article, Convolutional Neural Network based Classification (CNNC) model and Improvised K- Nearest Neighbor (IKNN) classifiers are adopted for the accurate identification of grape leaf disease and to compare the performance of both the classifiers. Here, the proposed CNNC and IKNN models segregates the detection of leaf disease into four stages. Here, first stage discusses about the noise reduction process in pre-processing and then segmentation of leaf lesions which is obtained in author's previous paper. Then, feature extraction process in performed on segmented images to understand the nature of diseases and lastly, classification on leaf disease images is performed for the leaf disease identification is performed using CNNC and improvised KNN model. Accurate classification of leaf diseases images is very critical and challenging process. Here, a customized pattern recognition method is utilized to identify boundary, pattern and lesion features. Here, histogram representation of obtained features are presented based on the pixel encoding methods. Furthermore, high quality training of grape leaf images is performed to obtain simulation results and experimental results outperforms all the available existing algorithms in terms of classification accuracy, sensitivity and specificity.

This article is arranged in following manner. Section 2, discusses about the mathematical representation of proposed CNNC and Improvised KNN classifier for the analysis of leaf disease detection. Section 3, discusses about the simulated results and their comparison with traditional classification algorithms and section 4 concludes the article.

Teachers and participants flourish in their knowledge of their efforts as they desired, and they are nourished by the expertise and commitment of teachers and directors to their teaching and growth. Leaders can be agents of school reform when they can genuinely create trust within the school community involving parents, students, and teachers [15]. The bright side of the school partnership, especially between directors and teachers, is all mentioned above. However, if the reverse occurs and the partnership is misplaced, the causes and consequences for this divergence and their impact on others should be understood.

## 2 Modelling of proposed machine learning techniques

This section discusses about the comprehensive mathematical modelling of identifying features of grape leaves and perform classification on obtained features using Convolutional Neural Network based Classification (CNNC) model and proposed improvised KNN classifier for the detection of grape leaf disease and study their nature and structure related information. Digital Image processing and machine learning techniques are widely adopted for the identification of leaf disease. Furthermore, structure is one of the most essential and fundamental feature of an object which plays a significant role in pattern recognition techniques. Besides, CNN classification model have several advantages over state-of-art-techniques for image analysis. However, CNN requires large training which can enhance computational complexity and limited training data can heavily affect the performance of classification process. Therefore, training data limitation and due to time complexity, IKNN model is adopted for efficient classification. The main advantage of using IKNN model is high-quality custom feature extraction and enhancement of classification accuracy.

Thus, structure related features are segregated into two categories for the accurate detection of leaf disease. Structure related features gives information about the object pattern, their shape and boundaries which is the most crucial part of feature extraction process. First category provide information about Histogram Gradient based Features (HGF) whereas second category gives details of Extended Histogram Gradient based Features (EHGF). The Histogram Gradient features provide information of discriminative and invariant nature of obtained features for the grape leaves and then obtain histogram representation of uniform gradients to identify the disease and their structure. On the other side, the Extended Histogram Gradient feature gives details of magnitude, sign of filter responses and salient pixels which focuses on central area. Further, this magnitude, sign and salient pixels information is utilized for the pattern related histogram representation. Furthermore, the detailed mathematical representation of obtained features and classification process is shown in the below paragraph.

Consider for a central area of pixels in an image $M$, the Histogram Gradient based Feature (HGF) are evaluated as,

$$HGF_{s,T} = \sum_{t=0}^{T-1} i\left(r_{s,t} - r_n\right).2^t \tag{1}$$

$$i(r) = \begin{cases} 1, & r \geq 0 \\ 0, & r < 0 \end{cases} \quad (2)$$

Where, $r_n$ represents the gray scale value of the central area of pixels in an image whereas $r_{s,\,t}$ is defined as the gray scale value of the $t^{th}$adjacent pixels on a circle whose radius is defined as $s$. The total number of adjacent pixels is defined by $T$. Then, rotational constant HGF is defined by following equation,

$$HGF^{U}_{s,T} = \begin{cases} \sum_{t=0}^{T-1} i(r_t - r_n), & D\left(HGF_{s,T}\right) \leq 2 \\ T+1, & otherwise \end{cases} \quad (3)$$

Where, $U$ represents rotational constant form of HGF and obtained HGF are uniform with $D \leq 2$. Here, $D$ is uniformity evaluator which is defined by following equation,

$$D\left(HGF_{s,T}\right) = |i(r_{T-1} - r_n) - i(r_0 - r_n)| + \sum_{t=0}^{T-1} |i(\mathrm{r}_t - r_n) - i(r_{T-1} - r_n)| \quad (4)$$

After the computation of gradients for every pixel, histogram of gradients is built for the input image.

Furthermore, histogram representation of multi-scale domain can be obtained with the help of Extended Histogram Gradient based Features (EHGF).

To determine the multi-scale histogram representation, magnitude and sign components of filter responses is evaluated by following equation,

$$i_{s,t} = i\left(r_{s,t} - r_n\right), \quad b_t = \left|r_{s,t} - r_n\right| \quad (5)$$

Then, these components are encoded to obtain multi-scale histogram representation by following equation,

$$EHGF_{s,T} = \sum_{t=0}^{T=1} i(b_t - n).2^t \quad (6)$$

Where, the average value of $b_t$ for the input image is denoted by $n$. The central area of pixels in the obtained image in Eq. (6) are encoded by following equation,

$$EHGF_{s,T} = i(r_n - n_J) \quad (7)$$

Where, the average gray scale value of central pixels in an image is denoted by $n_J$. Ultimately, the magnitude, sign of filter responses and salient pixels are joined together to form a multi-scale histogram and that histogram is transformed into vector form to obtain the image with clear structure and fine boundaries.

Then, Confined Intensity Directional Order Relation (CIDOR) method is used to define the intensity relationship between adjacent pixels by keeping gradient features as rotational constant. The CIDOR method exploit confined ordinal data to determine intensity relationships between adjacent pixels for every central area of pixels of an image. Then, a directional set encoding strategy is designed to segregate the adjacent pixels into multiple sets by pointing to a particular dominant direction by maintaining rotational invariance. Then, encoding is performed on set wise intensity relationships. It is very essential to determine the dominant direction for suitable encoding. The dominant direction can be determined by replacing gray scale value for every pixel to the average gray scale value of arbitrary shaped regions of an image. Then, the average gray scale value of arbitrary shaped regions around central area of pixels $y$ in an image $M$is determined by following equation,

$$\overline{r}_n = \theta\left(R_{n,v}\right) \tag{8}$$

$$\overline{r}_{s,t} = \theta\left(R_{s,t,v}\right) \tag{9}$$

Where, arbitrary shaped regions of size $v \times v$ around central area of pixels $y$ is represented by $R_{n,\,v}$ whereas $R_{s,\,t,\,v}$ is denoted as arbitrary shaped regions around the $t^{th}$adjacent pixel. Here, $\theta(\cdot)$ provide the average gray scale value of arbitrary shaped regions. This model enhances robustness towards Noise and also provide extended details of structure related information for grape disease. Then, adjacent pixels are rotated by pointing to a particular dominant direction to develop a rotational constant sequence. The dominant direction is expressed as the index of adjacent pixels whose gray scale difference from central area of pixels is maximum shown in following equation,

$$A = \arg \max_{t \in \{0,1,\ldots\ldots,T-1\}} \left|\overline{r}_{s,t} - \overline{r}_n\right| \tag{10}$$

The utilization of maximum filter response can provide discriminative information of obtained features. After the evaluation of dominant direction, rotate the sequence till $A$ comes at the first place,

$$\begin{aligned} & r'_{s,0}, \ldots\ldots\ldots r'_{s,T-1} \\ := & \left(\overline{r}_{s,A}, \ldots\ldots, \overline{r}_{s,T-1}, \overline{r}_{s,0}, \ldots\ldots, \overline{r}_{s,A-1}\right) \end{aligned} \tag{11}$$

Where, the symbol $:=$is used for element-wise operation. Further, multiple sets are formed by evenly separating the pixels in the rotated sequence. This pixels are uniformly spaced in the set. The number of pixels in every set are limited to 4, to guarantee low dimensionality of encoded features. Therefore, total number of sets are $w = T/4$ for every sequence,

$$\overline{r}'_j = \begin{cases} \left(\overline{r}'_{s,0}, \overline{r}'_{s,w}, \overline{r}'_{s,2w}, \overline{r}'_{s,3w}\right), & j = 1 \\ \left(\overline{r}'_{s,1}, \overline{r}'_{s,w+1}, \overline{r}'_{s,2w+1}, \overline{r}'_{s,3w+1}\right), j = 2 \\ \quad \vdots \\ \left(\overline{r}'_{s,w-1}, \overline{r}'_{s,2w-1}, \overline{r}'_{s,3w-1}, \overline{r}'_{s,T-1}\right), j = w \end{cases} \tag{12}$$

Where, $\overline{r}_j^{\prime} \in j = 1, 2, .....w$ is defined as the vector whose elements have gray scale values of $w^{th}$ set of adjacent pixels. Lastly, intensity relationships are encoded between the adjacent pixels for every set,

$$L_{s,T,j} = f\left(\varphi\left(\overline{r}_j^{\prime}\right)\right) \tag{13}$$

Where, $\varphi(\cdot)$ is a sorting function to make order of vector elements in the non-descending form and provide an index vector of sorted vector elements. Furthermore, $f(\cdot)$ is a function which transform the obtained index vector into an unique integer.

Confined Intensity Directional Order Relation (CIDOR) method has following characteristics. Firstly, CIDOR method provides low-dimensional multi-scale histogram representation. Secondly, directional set encoding is used to segregate the adjacent pixels into multiple sets by pointing to a particular dominant direction and robust to irradiation differences by utilizing CIDOR method. Lastly, CIDOR method perform encoding on extracted HGF and EHGF features with magnitude of filter responses, dominant direction and intensity order information of adjacent pixels of an image.

The histogram gradient features obtained with the help of leaf input images are denoted as $HGF_{s,\ T}$ and $EHGF_{s,\ T}$.

Further, proposed IKNN model is utilized for the classification of obtained features.

For every training image utilized for the classification process in IKKN model, the obtained set of histogram gradient feature $Q = HGF_{s,\ T}, EHGF_{s,\ T}$is expressed as,

$$Q = Z\Psi \tag{14}$$

Where, $\Psi$ is defined as evaluation coefficient vector and expressed as $\Psi = \{\Psi_1,\ \Psi_2,\ \Psi_3, \ldots\ldots\ldots.\ \Psi_c\}^X$ to determine evaluation coefficients of all the training images to examine $Q$. The evaluation coefficients $\Psi_e$ of training sample $g_e$ is determined to define histogram gradient feature set $Q$. If homogeneity between obtained histogram features set $Q$ and training samples $g_e$ are larger then evaluation coefficients $\Psi_e$ value remains high. Then, classification process is performed by applying $L1$-norm regularization on the obtained histogram gradient feature set as,

$$\overline{\Psi} = \arg\min_{\Psi}\left[\|Q - Z\Psi\|_2^2 + \gamma\|\Psi\|_1\right] \tag{15}$$

Where, $\overline{\Psi}$ is defined by$\overline{\Psi} = \left\{\overline{\Psi}_1, \overline{\Psi}_2, \overline{\Psi}_3, \ldots\ldots..\overline{\Psi}_c\right\}^X$. These evaluation coefficients are utilized to choose K-adjacent neighboring pixels for histogram gradient feature set $Q$ of each image. The highest K value coefficient from $\overline{\Psi}$ is selected and expressed as$\widetilde{\Psi} = \left\{\widetilde{\Psi}_1, \widetilde{\Psi}_2, \widetilde{\Psi}_3, \ldots\ldots\ldots..\widetilde{\Psi}_K\right\}$. Then, K-adjacent neighboring pixels for histogram gradient feature set $Q$considering their corresponding training sample are expressed as,

$$X_K = \left\{\left(g_e^{iknn}, h_e^{iknn}\right)\right\}_{e=1}^{K} \tag{16}$$

The value of chosen $\widetilde{\Psi}_e$ is always stay positive i.e. $\widetilde{\Psi}_e \geq 0$ and further, evaluation coefficient set $\widetilde{\Psi}_e$ of $e - th$ adjacent neighboring pixels$g_e^{iknn}$ to characterize histogram gradient feature set $Q$ is clearly processed as the weights of $e - th$ adjacent neighboring pixels$g_e^{iknn}$ to histogram gradient feature set $Q$. Lastly, the classification estimation with the help of proposed IKNN model is,

$$h_Q = \arg\max_p \sum_{g_e^{iknn}, h_e^{iknn}} \widetilde{\Psi}_e \times \Upsilon\left(p = h_e^{iknn}\right) \tag{17}$$

Where, the class label of histogram gradient feature set is denoted as $h_Q$. Further, the proposed IKNN model identify a class between all the classes which have largest summation of weights in which selected class belongs to $K - th$ adjacent neighboring pixels. As mentioned above, the proposed IKNN model employs evaluation coefficients to find out adjacent neighbouring pixels and classify histogram gradient feature set of every image using class labels. In this way, a high classification accuracy is achieved to detect leaf disease in grape leaves.

## 3 Result and discussion

This section discusses about the measure of performance using proposed CNNC and IKNN models in comparison with various state-of-art leaf classification techniques considering performance matrices like classification accuracy, Area under Curve (AUC) and sensitivity, precision etc. The identification of grape leaf disease is divided into four steps. Firstly, pre-processing methods are adopted to reduce noise and to make processing quicker. Secondly, efficient segmentation process is performed on grape leaf disease images to identify accurate boundaries and prominent leaf lesions which is accurately performed in our previous paper. Thirdly, high quality histogram and extended histogram gradient based features are extracted to get structural, discriminative and pattern related rich information which can enhance classification accuracy. Finally, classification process is performed using proposed CNNC and IKNN model to detect the grape leaf disease, their type and accordingly decisions can be taken to cure the grape leaves. Additionally, Confined Intensity Directional Order Relation (CIDOR) method is introduced for low-dimensional multi-scale histogram representation and to define the intensity relationship between adjacent pixels by keeping gradient features as rotational constant. And directional set encoding is used for maintaining rotational constant and to segregate the adjacent pixels into multiple sets by pointing to a particular dominant direction.

Here, large set of images are trained using proposed CNNC and IKNN model to evaluate leaf disease detection performance. The dataset utilized is named as Plant-Village Dataset. All the grape leaf disease images are taken from this Plant-Village Dataset. The aforementioned dataset is segregated into four classes namely, black rot, Eska measles, leaf spot and healthy. Each class has separate number of leaf disease images which are shown in Table 1. All the images have a pixel resolution of 256 × 256. All the experiments are simulated in MATLAB.

High quality features are obtained using proposed CNNC and IKNN model and efficient classification process is performed on extracted features with the help of proposed CNNC and IKNN model. Furthermore, the proposed CNNC and IKNN model accurately identify the

**Table 1** Grape leaf disease dataset

| Class | Total images |
|---|---|
| Black Rot | 1180 |
| Eska Measles | 1383 |
| Leaf Spot | 1076 |
| Healthy | 423 |
| Total Images | 4062 |

presence of disease in grape leaves and precisely determine the class that disease belongs to. Therefore, the performance of proposed CNNC and IKNN model is measured against state-of-art-classification techniques like AlexNet [11], VGG-11 [18], ResNet-34 [7], DenseNet-121 [8], Xception [4] in terms of classification accuracy. The proposed CNNC and IKNN model outperforms all the traditional classification model in terms of classification accuracy. However, the classification accuracy is higher in proposed IKNN model in comparison with proposed CNNC model. The comparison of proposed CNNC and IKNN model with traditional classification models are shown in Table 2. The results of performance matrices such as sensitivity, specificity, AUC and classification accuracy is shown in Table 3 using proposed CNNC and IKNN model. The classification accuracy is 98.07 for proposed IKNN model which is highest among all the traditional classification algorithms. Similarly, the classification accuracy is 96.60 for proposed CNNC model Table 2 results concludes that the proposed IKNN model outperforms all the state-of-art classification models. Figure 1 shows the Receiver Operating Characteristics (ROC) curve carried out with the help of proposed IKNN model for multi-class classification. Here, ROC curve is carried out for the classes black rot, Eska measles, leaf spot and healthy. Here, ROC curve is carried out between true positive rate and true negative rate. The proposed IKNN model evaluate ROC curve of multi-class classification to distinguish between different classes of leaf diseases.

**Table 2** Classification accuracy % comparison with traditional classifications models

| Algorithms | Classification Accuracy |
|---|---|
| AlexNet [11] | 91.31 |
| VGG-11 [18] | 92.45 |
| ResNet-34 [7] | 94.24 |
| DenseNet-121 [8] | 96.15 |
| Xception [4] | 96.53 |
| CNNC | 96.60 |
| IKNN | 98.07 |

**Table 3** Performance matrices result using IKNN model

| Performance Matrices | CNNC | IKNN |
|---|---|---|
| Classification Accuracy | 96.60 | 98.07 |
| Sensitivity | 92.32 | 96.77 |
| Specificity | 97.60 | 98.58 |
| Area Under Curve | 95.86 | 97.43 |

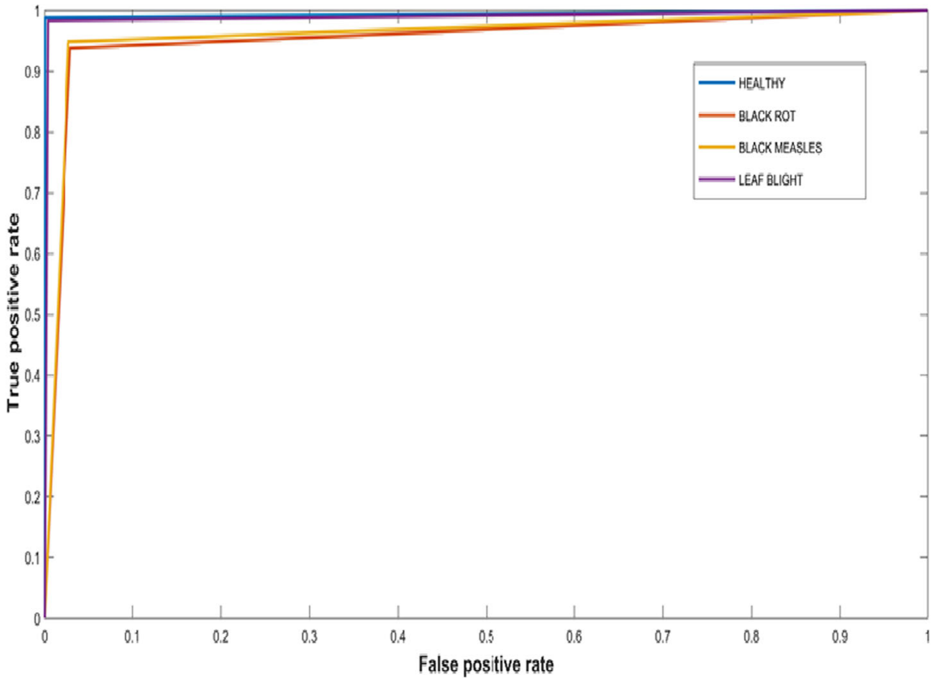


**Fig. 1** ROC Curve using proposed IKNN model for Multi-class classification

## 4 Conclusion

The significance of early detection in grape leaf disease is very important due to the extensive utilization of grape crop. Therefore, machine learning techniques are presented in this article to accurately identify grape leaf disease and distinguish between different classes of grape leaf disease. Two classification models, namely, Convolution Neural Network based Classification (CNNC) model and improvised K- Nearest Neighbor (IKNN) model. A detailed mathematical modelling is presented to obtain high-quality features. Here, histogram and extended histogram gradient based features are obtained using proposed IKNN model to improve the classification accuracy. Additionally, CIDOR method provides low-dimensional multi-scale histogram representation by optimizing the intensity relationship between adjacent pixels. And directional set encoding strategy is designed to segregate the adjacent pixels into multiple sets by pointing to a particular dominant direction. The performance of proposed CNNC and IKNN model is measured against several traditional classification models considering classification accuracy. The obtained classification accuracy is 98.07 and AUC is 97.43 using proposed IKNN model which is highest among all the state-of-art-techniques. Moreover, the obtained classification accuracy is 96.60 using CNNC model. The proposed CNNC and IKNN model outperforms all the existing techniques in terms of AUC, classification accuracy, specificity, sensitivity. Along with that, ROC curve for multi-class classification is also obtained.

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