1. INTRODUCTION
For assurance of public security, various biometrics security techniques have been proposed such as face, iris, hand geometry etc. Among the all available biometrics recognition techniques, iris recognition is proved to be the most reliable and efficient technique. In iris recognition, retinal iris image is analyzed using color as well as texture features. Most of the earlier work ignores the application of microvascular network for iris recognition. The retinal blood vessels of iris has unique structure and these patterns are randomly distributed, which can be used for identification of human being.

In this paper, an iris recognition system is proposed based on blood vessel segmentation. Various texture features such as GLCM, Gabor and Local Binary Patterns are extracted from the enhanced images. The well-known KNN, SVM and Naïve Bayes classifiers are used for classification of the features. Another important objective of this paper is to study the different texture based features for classification of the features.

Basic theme of the proposed work is iris recognition by using blood vessel segmentation of retinal image. The proposed system consists of five stages. The main objective is recognition of iris samples. The first step is data collection procedure where iris image samples are taken for further processing and data measurements. Second phase of this experimental study is to pre-process the iris image samples for a standard benchmark and most importantly removal of noises to obtain the enhanced noise free images. Third and one of the most important phases is blood vessel segmentation. Then fourth one is feature extraction. Here in this phase Gabor wavelet, Local Binary Patterns and GLCM texture based features from the enhanced images are extracted by computing. The well-known KNN, SVM and Naïve Bayes classifiers are trained using these features which are then further used for iris recognition.

2. RELATED WORK
In 1936 the ophthalmologist Burch suggested the idea of utilizing the iris in human identification. Aran and Flom in 1987 adopted Burch’s idea of identifying people based on their individual iris feature. In 2004, J. Daugman applied Gabor filters to create the iris phase code, he registered excellent accuracy rate on different number of iris datasets. He used Hamming distance between two bits for phase matching [1].

In 2004, Son et al., used linear discriminant analysis (LDA), Direct Linear Discriminate Analysis (DLDA), a Discrete Wavelet Transform (DWT), and PCA and to extract iris features [2].

In 2007, R. Al-Zubi and D. Abu-Al-Nadin applied a circular Hough transform and Sobel edge detector in segmentation process to find the pupil's location. Also, Log-Gabor filter is applied to generate the feature vectors. This method achieved 99% accuracy rate [3].

In 2008, R. Abiyev and K. Altunkaya suggested a fast algorithm for localization of the inner and outer boundaries of iris region using Canny edge detector and circular Hough transform, also, a neural network (NN) was suggested for classification the iris patterns [4].

In 2011, the iris region was encoded using Gabor filters and Hamming distance by S. Nithyanandam [5].
In 2012, Ghodrati et al. proposed a novel approach for extracting the iris features using Gabor filters. The Genetic algorithm was proposed to compare two different templates [6]. Gabor approach was more distinctive and compact on feature selection approach.

In 2013, G. Kaur [7] suggested two different methods using the Support Vector Machine (SVM). SVM results were FRR=19.8%, FAR = 0%, and overall accuracy rate = 99.9%. Choudhary et al. in 2013 [8], proposed a statistical texture feature depended iris matching method using K-NN classifier. Statistical texture measures include standard deviation, mean, skewness, entropy etc., K-NN classifier matches the current input iris with the trained iris images by computing the Euclidean distance between two irises. The system is tested on 500 iris images, which gives good classification accuracy rate with reduced FRR/FAR.

Jayalakshmi and Sundaresan in 2014 [9] proposed Kmeans algorithm and Fuzzy C-means algorithm for iris image segmentation. The two algorithms were executed separately and the performances of them were 98.20% of accuracy rate with low error rate.

In 2015, Homayon [10] suggested a new method based neural network for iris recognition. The proposed method is implemented using LAMSTAR classifier that utilized CASIA-v4.0 database. The accuracy rate was 99.57%.

In 2016, A. Kumar and A. Singh suggested a novel method for extracting the feature and the recognition was implemented on 2D discrete cosine transform (DCT). They applied the DCT to extract the most discriminated features in iris [11]. The patterns have been tested on two iris datasets; IIITD and CASIA V4.0 for matching the iris phase using Hamming distance. The accuracy rate were 98.4% and 99.4% for IIITD and CASIA V4 database respectively.

3. DEVELOPMENT OF THE PROPOSED SYSTEM
Proposed approach for Iris category recognition is divided in following steps

Prepare a database of known Iris image samples

Pre-processing (Noise removal using median filtering)

Feature extraction (Combine the features of GLCM, Local Binary Pattern and Gabor wavelet for better performance)

Classification/Recognition (SVM,KNN and Naïve Bayes classification Algorithm)

Iris classification using blood vessel segmentation can be categorized in various steps as follows.

Pre-process the iris images to remove noise using median filtering.

Blood vessel segmentation from the iris images.

Building an offline database of GLCM, LBP and wavelets features of all training images.

Train the SVM,KNN and Naïve Bayes classifier using the computed features of the training data.

Pre-process the candidate iris image using median filtering to remove noise and obtain GLCM, LBP and Gabor wavelet features of the candidate Iris image.

Recognize the candidate iris image using SVM,KNN and Naïve Bayes classification.

The flow of the proposed system is depicted in figure 1.

3.1 Image Preprocessing
Digital images are greatly affected by various noise. While acquiring the image, noise is the unwanted signal introduced. The various types of noise are detected. When the noise is introduced in the image, the pixel values of the image do not reflect...
their original intensity. Noise can be introduced in image in various ways. It depends in the way in which image is created. The median filter is used for reducing the noise from the image. It is mostly similar to mean filter.

Blood Vessel Segmentation
The noise free iris images are used for segmentation of blood vessels. The algorithm for blood vessel segmentation is as bellow-

Algorithm:
1. Read Image.
2. Resize image for easier computation.
3. Convert RGB to Gray.
5. Background Exclusion by using Average Filter.
6. Take the difference between the gray image and Average Filter Image.
7. Threshold the image using the IsoData Method.
8. Convert to Binary
9. Remove small pixels by using morphological open operation
10. Overlay the images

3.2 Feature Extraction
The global feature extraction of the segmented blood vessel images is performed. The various features of the segmented iris image such as Gabor wavelet features, GLCM texture features as well as Local Binary Patterns (LBP) are extracted, which are further used for iris recognition using SVM.

Gabor Features Extraction
We employed Gabor filters to extract textures of different sizes and orientations (i.e. Gabor-based texture feature). A Gabor filter is defined by a two-dimensional Gabor function, \( g(x, y) \):

\[
g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp \left[ -\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right) \right] + 2\pi W x
\]

where \( \sigma_x \) and \( \sigma_y \) denote the scaling parameters of the filter in the horizontal (x) and vertical (y) directions, and W denotes central frequency of the filter.

3.3 GLCM Texture Features Extraction
The gray-level-co-occurrence matrix (GLCM) is a well-known statistical method for examining the textures which takes into account the spatial relationship of pixels. For representing the texture of the image, GLCM functions calculate the frequency of pairs of pixels having specified values and having specific spatial relationship. Then GLCM is created and statistical measures are extracted from matrix.

We have extracted four features – GLCM contrast, GLCM homogeneity, GLCM correlation and GLCM energy. GLCM contrast deals with measuring the variance in grayscale levels in the image. GLCM homogeneity deals with the similarity of grayscale levels across the image. Thus, if the changes in grayscale are larger, the GLCM contrast is more. Similarly GLCM homogeneity will be less. Finally, the overall probability of having distinctive grayscale patterns in the image is represented by GLCM energy measures.

3.4 LBP Feature Extraction
The steps involved in creating the LBP features are as follows:
Divide the examined window in to cells (e.g. 8x8 pixels per cell).
Considering each pixel in a cell, perform the comparison of each pixel to its 8 neighbors (on its left-top, left-middle, left-bottom, right-top, etc.) The pixels are followed along a circle, i.e. clockwise or counter-clockwise.
“0” is written when the value of center pixel is more than the value of the neighbor pixel. “1” is written in the other case. Thus 8 digit binary numbers is produced.
The histogram is computed, by calculating the frequency of occurrence of each number over the cell. (i.e., each combination of which pixels are smaller and which are greater than the center). Thus the feature vector of 256 dimensions is created in the form of histogram.
The histogram is normalized optionally.
The normalized histograms of all cells are normalized. Thus the feature vector for the entire window is created.

Classification Using SVM
Once the features have been extracted, these extracted features are then used for iris classification using SVM. Support Vector Machines also known as Kernel Machines are a well-known and most accurate set of algorithms. The SVM is similar to bayes classifier in many ways. The SVM is comparatively difficult to train and slow to evaluate. But it is more accurate. If we increase the dimensionality of the data, it is very easy to separate the data. The N dimensional space is used by SVM.
where N is the number of samples in the training set. Due to this, SVM is able to classify data with arbitrary complexity. But the major drawback of this method is outliers. They are responsible for sabotaging the classifier easily.

**Classification Using KNN**

KNN pattern recognition, the k-nearest neighbors algorithm (k-NN) is a non-parametric method used for classification and regression.[12] In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:

In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms. Both for classification and regression, a useful technique can be to assign weight to the contributions of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones. For example, a common weighting scheme consists in giving each neighbor a weight of 1/d, where d is the distance to the neighbor.[2]

The neighbors are taken from a set of objects for which the class (for k-NN classification) or the object property value (for k-NN regression) is known. This can be thought of as the training set for the algorithm, though no explicit training step is required.

### 3.5 Classification Using Naïve Bayes

In machine learning, naïve Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features.

Naïve Bayes has been studied extensively since the 1950s. It was introduced under a different name into the text retrieval community in the early 1960s,[13]:488 and remains a popular (baseline) method for text categorization, the problem of judging documents as belonging to one category or the other (such as spam or legitimate, sports or politics, etc.) with word frequencies as the features. With appropriate pre-processing, it is competitive in this domain with more advanced methods including support vector machines.[14] It also finds application in automatic medical diagnosis.[15]

Naïve Bayes classifiers are highly scalable, requiring a number of parameters linear in the number of variables (features/predictors) in a learning problem. Maximum-likelihood training can be done by evaluating a closed-form expression,718 which takes linear time, rather than by expensive iterative approximation as used for many other types of classifiers.

### 4. DATASETS USED

**Digital Retinal Images For Vessel Extraction: DRIVE Database**

The DRIVE database[16] has been established to enable comparative studies on segmentation of blood vessels in retinal images. The photographs for the DRIVE database were obtained from a diabetic retinopathy screening program in The Netherlands. The screening population consisted of 400 diabetic subjects between 25-90 years of age. Forty photographs have been randomly selected. 33 do not show any sign of diabetic retinopathy and 7 show signs of mild early diabetic retinopathy. Each image has been JPEG compressed.

**High Resolution Fundus (HRF) Image Database**

This database [17] has been established by a collaborative research group to support comparative studies on automatic segmentation algorithms on retinal fundus images. The public database contains at the moment 15 images of healthy patients, 15 images of patients with diabetic retinopathy and 15 images of glaucomatous patients.

**DRIONS Database**

The DRIONS database [18] consists of 110 colour digital retinal images. Initially, it were obtained 124 eye fundus images selected randomly from an eye fundus image base belonging to the Ophthalmology Service at Miguel Servet Hospital, Saragossa (Spain). From this initial image base, all those eye images (14 in total) that had some type of cataract (severe and moderate) were eliminated and, finally, was obtained the image base with 110 images.

**Real Time Images From hospital Dataset**

We have obtained real time retinal images of 65 patients from the hospital.

**MMU Dataset**

We chose to work with the Multimedia University (MMU) iris database [19], contributing a total of 450 images, 5 images per iris, 2 irises per subject. All images were taken using the LG Iris Access 2200 at a range of 7-25 centimeters. We chose this particular dataset over the others we found online for the following reasons:

1. It was free.
2. Due to some privacy issues, most iris datasets require lengthy registration processes, official paperwork, and administrative contacts. How- ever, we had no trouble acquiring this dataset within a few days.
3. Most datasets offer 3 or fewer images per iris. This particular dataset provides 5 images per iris, giving our machine learning algorithms some functional ease.

5. PERFORMANCE ANALYSIS
5.1 Dataset
Datasets used for evaluating the image enhancement techniques are
DRIVE Dataset (40 Instances)
DRIONS Dataset (110 Instances)
High Resolution Fundus Dataset (45 Instances)
Real Time Hospital Images Dataset (65 Instances)

5.2. Evaluations and Results
Performance of the following feature extraction techniques is evaluated using well known SVM classifier
GLCM Features
Gabor Features
LBP Features
Combined (GLCM+Gabor+LBP) Features
The effect of radon transform is evaluated on the performance.
Figure 2 shows the system developed for performance evaluation of various feature extraction techniques.

![Performance Evaluation of Various Features Extraction Techniques](image)

The performance of various feature extraction techniques using well known SVM classifier is depicted in table 1. The effect of radon transform on performance is also evaluated.

<table>
<thead>
<tr>
<th>Feature Extraction</th>
<th>DRIVE Dataset</th>
<th>DRIONS Dataset</th>
<th>High Resolution Fundus Dataset</th>
<th>Real Time Images From hospital</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>40 Instances</td>
<td>110 Instances</td>
<td>45 Instances</td>
<td>65 Instances</td>
</tr>
<tr>
<td>Gabor</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without Using Radon Transform</td>
<td>62.5</td>
<td>83.8384</td>
<td>66.6667</td>
<td>97.7778</td>
</tr>
<tr>
<td>Using Radon Transform</td>
<td>62.5</td>
<td>83.6735</td>
<td>66.6667</td>
<td>97.7778</td>
</tr>
<tr>
<td>GLCM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without Using Radon Transform</td>
<td>90</td>
<td>74.7475</td>
<td>73.3333</td>
<td>100</td>
</tr>
<tr>
<td>Using Radon Transform</td>
<td>100</td>
<td>98.9796</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>GLCM+ Gabor +LBP</td>
<td>87.5</td>
<td>93.9394</td>
<td>88.8889</td>
<td>88.8889</td>
</tr>
<tr>
<td>LBP</td>
<td>100</td>
<td>90.9091</td>
<td>97.7778</td>
<td>100</td>
</tr>
</tbody>
</table>

The performance of various feature extraction techniques using well known SVM classifier is depicted in table 1. The effect of radon transform on performance is also evaluated.
Table 1: Performance Evaluation of Various Feature Extraction Techniques

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Without Using Radon Transform</th>
<th>Using Radon Transform</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gabor</td>
<td>76.9231</td>
<td>76.9231</td>
</tr>
<tr>
<td>GLCM</td>
<td>81.5385</td>
<td>100</td>
</tr>
<tr>
<td>GLCM+ Gabor +LBP</td>
<td>92.3077</td>
<td>92.3077</td>
</tr>
<tr>
<td>LBP</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

As depicted in table 4, the radon transform can result in better recognition accuracy for GLCM and LBP. But the accuracy remains same for the gabor features as well as combined features. As analyzed from the results, the LBP gives higher classification accuracy, but GLBM when combined with gabor and LBP also gives better accuracy.

To evaluate the classification performance on various features, we have used the MMU dataset.

Table 2 shows the classification performance of SVM, Naïve Bayes and KNN classification.

<table>
<thead>
<tr>
<th>MMU Dataset</th>
<th>SVM</th>
<th>KNN</th>
<th>Naïve Bayes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gabor</td>
<td>73.7778</td>
<td>73.3333</td>
<td>83.3333</td>
</tr>
<tr>
<td>GLCM</td>
<td>68.8889</td>
<td>73.7778</td>
<td>63.1111</td>
</tr>
<tr>
<td>GLCM+ Gabor</td>
<td>74</td>
<td>78.8889</td>
<td>76</td>
</tr>
<tr>
<td>+LBP</td>
<td>66.6667</td>
<td>92.4444</td>
<td>71.7778</td>
</tr>
</tbody>
</table>

The KNN classifier gives better performance for almost all features.

6. CONCLUSION

For iris recognition, we have performed the blood vessel segmentation. After segmentation of blood vessels, instead of considering the structure of the vascular pattern of the iris, we have considered the global texture features of the segmented blood vessels of the iris. In this proposed system, the person is authenticated using his own unique retina pattern. Though, the number of images used to evaluate the performance of the proposed system is not more, the performance of the system and the results are interesting. The GLCM, Gabor and LBP texture features are considered separately. For classification, we have used SVM, KNN and Naïve Bayes classifier. For the performance evaluation of DRIVE and HRF standard image dataset, iris recognition process is carried out by using blood vessel segmentation. Though the GLCM and Gabor features when considered separately, does not give promising results, the combined results shows more accuracy. The system has shown the outstanding performance using LBP features. To evaluate the performance of various classifiers, we have used the MMU dataset. The KNN classifier is found to be better as compared with SVM and Naïve Bayes.

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8. REFERENCES


