A New Algorithmic Feature Selection and Ranking for Pattern Recognition on Retinal Vascular Structure with Different Classifiers.

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Abstract

Background: This article focuses the new algorithmic feature selection ranking along with the analysis of different classifiers for recognizing the pattern of retinal vascular structure. Problem Statement: Feature extraction of an image is the most required process in the area of image processing for its pattern recognition. In this article, an innovative algorithmic process is introduced for this core process. Methodological Processes: The mathematical morphology technique is used for acquiring and segmenting the fine fibers of blood vessels with the Region of Interest (ROI) of the retinal fundus images which are extracted from the databases diaretdb0 and diaretdb1. The retinal fibers are enhanced using the Contrast Limited Adaptive Histogram Equation (CLAHE). In this article, a new algorithmic process along with the functional features of both Gray-Level Co-occurrence Matrix (GLCM) and Wavelet Transformation (WT) . The first five high-level ranked features out of 23 from GLCM and out of 53 from WT are selected for classification process. The enhanced classification techniques such as Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN), Naïve Bayes (NB) Classifiers, K-Nearest Neighbors (KNN), Extreme Learning Machine (ELM), Artificial Neural Fuzzy Information System (ANFIS) with Grid Partitioning and ANFIS with Subtractive Clustering are used for analytical classification as well as training processes on the preprocessed images in our proposed system. Result: In this systemic process, the ANFIS with Subtractive Clustering technique is identified as the best technique than all others in accordance with the systemic core resultant measurements such as Time Complexity, Percentage of Average Classification Error and Performance Accuracy. Scope: This will be a highly required biometric system with retinal vascular traits for human identification.

Introduction

Biometric system rules the world through reliable security while allowing human being by prohibiting the hacking of any physical or logical objects from it. For this kind of biometric system based authentication process, we consider the human traits such as finger print, iris, palm, face and retinal blood vessels, etc. The frequency of acquiring the biometric traits will generally cause harmful effects. Retinal vascular structure is the most important traits than all others, not only because of its’ peculiar uniqueness, but due to the acquiring process through the equipment named ‘Fundus Camera’, which will not lead to no harmful effects and no limitation to talk images. The biometric system can be used from low to high level secured places such as Department of Defense, Government and private Research areas, Banking processes and in any kind of application.

Dr. Carleton Simon and Isodore Goldstein, during their study of eye disease, realized that the person’s retinal blood vessels have unique structure from person to person. Subsequently they published an article related to the identification of person in terms of their unique retinal blood vessel patterns (Simon and Goldstein, 1935). Dr. Paul Tower also supports their conclusions in his course of his study of identical twins which done later in the 1950s. He pointed that, of “Any two persons, identical twins would be the most likely to have similar retinal vascular patterns. However, Tower’s study showed that of all the factors compared between twins, retinal vascular patterns showed the least similarities (Tower, 1955)”. 

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System process details:

Preprocessing:
The retinal fundus images are extracted from the databases such as DIARETDB0 and DIARETDB1, which are Standard Diabetic Retinopathy Databases. The fundus images of the databases are above 1150 x 1500 sizes. This normal sized image is resized as 500 x 750 for the further systemic process through mathematical morphology of MATLAB process. The images are enhanced by Contrast Limited Adaptive Histogram Equalization (CLAHE). The image is accurately identified with the green channel rather than red channel along with the area of blood vessels (Lalli, 2014).

ROI Segmentation:
ROI stands for Region of Interest. The green channelized retinal fundus images are further enhanced with CLAHE (Contrast Limited Adaptive Histogram Equalization) technique. The morphological operations such as morphological dilation and morphological erosion are performed for image segmentation ie. for extracting the retinal blood vessels pattern (Lalli, 2013).

Feature Extraction:
The Gray Level Co-occurrence Matrix (GLCM) and Wavelet Transformation (WT) techniques are used in image features extraction.

Feature Selection:
Gray Level Co-occurrence Matrix:
There are 23 features in GLCM technique. They are Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade, Dissimilarity, Energy, Entropy, Homogeneity, Homogeneity, Maximum probability, Sum of squares, Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation1, Information measure of correlation2, Inverse difference (INV), Inverse difference normalized (INN), Inverse difference moment normalized. Out of them, the features such as Autocorrelation, Sum Entropy, Inverse-Difference Normalization (INN), Inverse-Difference Moment Normalized and Homogeneity are selected as the top high rated features for our image processing. The following graph represents the ranks of all 23 features of GLCM.
Wavelet Transformation:
Similarly there are 53 features defined in WT technique. The functions of WT are haar, db1, db2, db3, db4, db5, db6, db7, db8, db9, sym2, sym3, sym4, sym5, sym6, sym7, sym8, coif1, coif2, coif3, coif4, coif5, bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8, rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.3, rbio3.7, rbio3.9, rbio4.4, rbio5.5, rbio6.8, dmey. Out of them, rbio1.1, rbio1.3, bior3.7, bior1.3 and coif1 are considered for the image processing of our proposed system. The following graph represents the ranks of all 53 features of WT.

Feature Ranking:
The five features out of twenty three features of GLCM and five features out of fifty features of WT are extracted. Totally ten features out of seventy six combined features of both GLCM and WT are considered. The selected ten features as per mentioned in previous section, they are again ranked to select the five top-ranked features for the enhancement of the image to be processed in our proposed system. The following graphical representation clearly illustrates the rank all selected ten features. According to that, the Hybrid Feature Set with the top-ranked features named Autocorrelation, Homogeneity, Sum Entropy, bior1.3 and rbio1.1 are selected from both GLCM and WT are considered.


Classification Process:

The enhanced classification techniques such as Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN), Naive Bayes (NB) Classifiers, K-Nearest Neighbors (KNN), Extreme Learning Machine (ELM), Artificial Neural Fuzzy Information System (ANFIS) with Grid Partitioning and ANFIS with Subtractive Clustering are used for analytical classification as well as training processes on the preprocessed images in our proposed system.

Support Vector Machine (SVM):

In machine learning, support vector machines (SVMs, also support vector networks (De Schaepdrijver, 1989) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

Linear Discriminant Analysis (LDA):

In classification and other data analytic tasks it is often necessary to utilize pre-processing on the data before applying the algorithm at hand and it is common to first extract features suitable for the task to solve. Feature extraction for classification differs significantly from feature extraction for describing data. For example PCA finds directions which have minimal reconstruction error by describing as much variance of the data as possible with m orthogonal directions. Considering the first directions they need not reveal the class structure that we need for proper classification.

Artificial Neural Networks (ANN):

Artificial neural networks (ANNs) are non-linear mapping structures based on the function of the human brain. They have been shown to be universal and highly flexible function approximations for any data. These make powerful tools for models, especially when the underlying data relationships are unknown.

Naive Bayes (NB) Classifier:

A Naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions. A more descriptive term for the underlying probability model would be “independent feature model”.

In probability theory and statistics, Bayes’ theorem (alternatively Bayes' law or Bayes' rule) is a result that is of importance in the mathematical manipulation of conditional probabilities. Bayes rule can be derived from more basic axioms of probability, specifically conditional probability.

Our goal is to calculate the probability in our notation, \( P(W|L) \) using the formula for Bayes’ Theorem.

The Formula followed in NB Theorem is:

\[
P(W|L) = \frac{P(L|W)P(W)}{P(L)}
\]

--Eq. (1)

where, we have used the law of total probability to expand \( P(L) \).

K-Nearest Neighbor (KNN) Classifier:

The 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 (Altman, 1992).

Both for classification and regression, it can be useful to weight 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 (Coomans and Massart, 1982).

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.

Extreme Learning Machine (ELM):

ELM works for the “generalized” Single-hidden-layer Feed-Forward Networks (SLFNs) but the hidden layer (or called feature mapping) in ELM need not be tuned. Such SLFNs include but are not limited to support vector machine, polynomial network, RBF networks, and the conventional (both single-hidden-layer and multi-
hidden-layer) feedforward neural networks. Different from the tenet in neural networks that all the hidden nodes in SLFNs need to be tuned, ELM learning theory shows that the hidden nodes/neurons of generalized feed forward networks needn’t be tuned and these hidden nodes/neurons can be randomly generated. All the hidden node parameters are independent from the target functions or the training datasets.

ELM theories conjecture that this randomness may be true to biological learning in animal brains. Although in theory all the parameters of ELMs can be analytically determined instead of being tuned, for the sake of efficiency, in real applications the output weights of ELMs may be determined in different ways (with or without iterations, with or without incremental implementations, etc.).

Artificial Neural Fuzzy Information System (ANFIS): Adaptive neuro fuzzy inference system (ANFIS) is a type of neural network based on Takagi–Sugeno fuzzy inference system. It integrates both neural networks and fuzzy logic principles. Hence, it has potential to capture the benefits of both the neural network and fuzzy logic in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions (Jang, Sun, Mizutani, 1997). Hence, ANFIS is considered to be a universal estimator (Lalli, D., Kalamani, N. Manikandaprabu and S. Brindha, 2013).

Grid Partitioning:
Grid partitioning is the default partitioning method used in Artificial Neural Fuzzy Information Systemic processes. In a fuzzy inference system, basically there are three types of input space partitioning: grid, tree, and scattering partitioning. GENFIS1 uses the grid partitioning and it generates rules by enumerating all possible combinations of membership functions of all inputs; this leads to an exponential explosion even when the number of inputs is moderately large. For instance, for a fuzzy inference system with 10 inputs, each with two membership functions, the grid partitioning leads to $2^{10} = 1024$ rules, which is inhibitive large for any practical learning methods. The “curse of dimensionality” refers to such situation where the number of fuzzy rules, when the grid partitioning is used, increases exponentially with the number of input variables (Yager, R., D. Filev, 1994).

Subtractive Clustering:
Subtractive Clustering, [Chi94], is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. The cluster estimates obtained from the sub-cluster function can be used to initialize iterative optimization-based clustering methods (FCM) and model identification methods (like ANFIS). The sub-cluster function finds the clusters by using the subtractive clustering method. Subtractive Clustering is one among the automated data-driven based methods for organizing the core fuzzy models proposed by chiu (Lalli, G, 2013). It is an extension of the Mountain Clustering technique, which is introduced by Yager and Filev (Lalli, G, 2014). This method avoids from rule-base explosion problem. It is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data.

The main processes of subtractive clustering are as follows:

The algorithm assumes each data point is a potential cluster center and calculates some measure of potential for each of them according to the following equation.

$$p_i = \sum_{j=1}^{m} \left( \exp(-\alpha ||x_i - x_j||^2) \right)$$ \quad -- Eq. (2)

where, $\alpha = 4 / r_i^2$ and $r_i > 0$ defines the neighborhood radius for each cluster center, while it has a set of m data points $\{x_1, ..., x_m\}$ in a N-dimensional space (Nedjah, Nadia ed.).
System Process: Input and Output Data:

Input and Output Data:

Input Vector (Common Format for GLCM & WT):

\[
\text{INP} = \begin{bmatrix}
I_1 \\
I_2 \\
\vdots \\
I_N
\end{bmatrix}
\begin{bmatrix}
f_{11} & f_{12} & f_{13} & \ldots & f_{1M} \\
f_{21} & f_{22} & f_{23} & \ldots & f_{2M} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
f_{N1} & f_{N2} & f_{N3} & \ldots & f_{NM}
\end{bmatrix}
\]

where, INP indicates ‘Input Vector’, 
F indicates ‘Feature’ with M varies from 1 to 23 for GLCM and 1 to 53 for WT, 
I indicates ‘Images’ with N varies from 1 to 200.

Output Vectors:

Output Vector: GLCM / WT with Minimum Feature Value:

\[
\alpha^T = \begin{bmatrix}
\alpha_1 \\
\alpha_2 \\
\vdots \\
\alpha_N
\end{bmatrix}
\]

\( (N \times 1) \)

where, \( \alpha^T \) indicates the Output Vector with Minimum values of each Feature.

Output Vector: GLCM / WT with Maximum Feature Value:

\[
\beta^T = \begin{bmatrix}
\beta_1 \\
\beta_2 \\
\vdots \\
\beta_N
\end{bmatrix}
\]

\( (N \times 1) \)

where, \( \beta^T \) indicates the Output Vector with Maximum values of each Feature.

Output Vector: GLCM / WT with Feature Difference Value:

\[
\gamma^T = \begin{bmatrix}
\gamma_1 \\
\gamma_2 \\
\vdots \\
\gamma_N
\end{bmatrix}
\]

\( (N \times 1) \)

where, \( \gamma^T \) indicates the Output Vector with Difference of Minimum and Maximum Features of each Image.
Output Vector: GLCM with First 5 Best Ranked Feature Value:

\[
\gamma_{1G} = \begin{pmatrix}
g_1 \\
g_2 \\
g_3 \\
g_4 \\
g_5 \\
\end{pmatrix}_{N \times 1}
\]

where, \( \gamma_1 \) indicates the Output Vector with First 5 Best Featured Values of GLCM and ‘g’ indicates the GLCM.

Output Vector: WT with First 5 Best Ranked Feature Value:

\[
\gamma_{2W} = \begin{pmatrix}
w_1 \\
w_2 \\
w_3 \\
w_4 \\
w_5 \\
\end{pmatrix}_{N \times 1}
\]

where, \( \gamma_2 \) indicates the Output Vector with First 5 Best Featured Values of WT and ‘w’ indicates WT.

Proposed Algorithm: Feature Selection & Ranking:

Algorithm: GLCM Features:

The Algorithmic format with GLCM Features is as follows.

Procedure GLCM (INP[]):

// Passed INP[] consists of the Features of all the Preprocessed Retinal Images through GLCM Classifier.
// Declare the Arrays \( \alpha_1[ ] \), \( \beta_1[ ] \), \( \gamma_1[ ] \) and \( \gamma_{1G}[ ] \)

Step 1: // Input Process:

// Read the Preprocessed Retinal Images from INP[] to be considered as Input Images.
Read each Feature of Image from Vector INP

Step 2: // Image: Feature Extraction & Selection:

// Extraction of Features from each of 200 Images
// Variable F indicates ‘Feature’
// Variable I indicates ‘Image’
// GLCM has 23 Function-based Features

k = 0

for j in F_1 to F_23
{
    for i in I_1 to I_300
    {
        // Variable \( \alpha \) to have minimum feature value
        // Variable \( \beta \) to have maximum feature value
        // Variable \( \gamma \) to have difference of \( \alpha \) and \( \beta \)
        \( \alpha_{1}[k] = \min \left( INP(i,j) \right) \)
        \( \beta_{1}[k] = \max \left( INP(i,j) \right) \)
        \( \gamma_{1}[k] = \alpha - \beta \)
        k = k+1
    }
}
Step 3: // Image: Feature Ranking:
// Order γ values in Ascending Level and store it in γ₁
\[
\gamma_1[ ] = \text{asc}[\gamma]
\]

Step 4: // Image: Ranked Feature:
// Select Best 5 featured values from γ₁
\[
\gamma_{1\text{G}} = \{ 1:5 \}
\]

Algorithm: WT Features:
The Algorithmic format with WT Features is as follows.

Procedure WT (WT-Features):
// Passed INP[] consists of the Features of all the Preprocessed Retinal Images through WT Classifier.
// Declare the Arrays α₂[ ], β₂[ ], γ₂[ ] and γ₂W[ ]

Step 1: // Input Process:
// Read the Preprocessed Retinal Images from INP[] to be considered as Input Images.
Read each Feature of Image from Vector INP

Step 2: // Image: Feature Extraction & Selection:
// Extraction of Features from each of 200 Images
// Variable F indicates ‘Feature’
// Variable I indicates ‘Image’
// Wavelet Transform has 53 Function-based Features
\[
k = 0
\]
for j in F₁ to F₅₃
{
    for i in I₁ to I₂₀₀
{
        // Variable α to have minimum feature value
        // Variable β to have maximum feature value
        // Variable γ to have difference of α and β
        \[
        \alpha_2[k] = \min(\text{INP}(i,j))
        \]
        \[
        \beta_2[k] = \max(\text{INP}(i,j))
        \]
        \[
        \gamma_2[k] = \alpha - \beta
        \]
        k = k+1
    }
}

Step 3: // Image: Feature Ranking:
// Order γ values in Ascending Level and store it in γ₂
\[
\gamma_2[ ] = \text{asc}[\gamma]
\]

Step 4: // Image: Ranked Feature:
// Select Best 5 featured values from γ₁
\[
\gamma_{2\text{W}} = \{ 1:5 \}
\]
The Format of Equation for GLCM and WT Feature Ranking and Selection:
\[
Y = \sum_{F=1}^{M} \left( \sum_{I=1}^{N} \begin{bmatrix}
( \alpha = \min(F(I))) \\
( \beta = \max(F(I))) \\
( Y = \alpha - \beta ) \land \{F;N \text{ and } F1:M\}
\end{bmatrix} \right)
\]  -- Eq. (3)

where, ‘F’ indicates ‘Feature’ of either ‘GLCM’ or ‘WT’ and ‘I’ indicates ‘Image’.
Calculation of Area of Blood Vessels:

The matrix of image is labeled as a bloodvessel [500x750]. The below procedure can be used to calculate the area of blood vessels ie. the existence of the number of pixels (De Schaepdrijver, 1989).

The Equation Codes for calculating Pixel Count of Blood Vessels:

The following codes are used in MATLAB process.

```matlab
for (x=1; x<=500; x++)
    for (y=1; y<=750; y++)
        if (a_bloodvessel[x,y] == 1) then
            area=area+1.
```

System process: processed images and resultant data:

The following retinal fundus images are considered as input images for our systemic processes:

![Fig. 6: Input Retinal Images.](image)

![Fig. 7: (a) Input Fundus Image (b) Green Channel of the Fundus Image (c) Enhanced Image with Inversion. (d) Extracted Blood Vessels in Binary (e) Final Blood Vessel Pattern.](image)
Table 1: GLCM & WT Functions-based Performance Values:

<table>
<thead>
<tr>
<th>Image</th>
<th>Auto Correlation</th>
<th>GLCM Features (Ordered Best Five Performance Features)</th>
<th>WT Features (Ordered Best Five Performance Features)</th>
</tr>
</thead>
<tbody>
<tr>
<td>img1</td>
<td>0.248304</td>
<td>0.936574, 0.930945, 0.921965, 0.916235, 0.910345</td>
<td>-</td>
</tr>
<tr>
<td>img2</td>
<td>0.251265</td>
<td>0.939574, 0.933945, 0.928965, 0.923945, 0.918965</td>
<td>-</td>
</tr>
<tr>
<td>img3</td>
<td>0.256304</td>
<td>0.940945, 0.934945, 0.929965, 0.924945, 0.919965</td>
<td>-</td>
</tr>
<tr>
<td>img4</td>
<td>0.261304</td>
<td>0.941945, 0.935945, 0.930965, 0.925945, 0.920965</td>
<td>-</td>
</tr>
<tr>
<td>img5</td>
<td>0.266304</td>
<td>0.942945, 0.936945, 0.931965, 0.926945, 0.921965</td>
<td>-</td>
</tr>
<tr>
<td>img6</td>
<td>0.271304</td>
<td>0.943945, 0.937945, 0.932965, 0.927945, 0.922965</td>
<td>-</td>
</tr>
<tr>
<td>img7</td>
<td>0.276304</td>
<td>0.944945, 0.938945, 0.933965, 0.928945, 0.923965</td>
<td>-</td>
</tr>
<tr>
<td>img8</td>
<td>0.281304</td>
<td>0.945945, 0.939945, 0.934965, 0.929945, 0.924965</td>
<td>-</td>
</tr>
<tr>
<td>img9</td>
<td>0.286304</td>
<td>0.946945, 0.940945, 0.935965, 0.930945, 0.925965</td>
<td>-</td>
</tr>
<tr>
<td>img10</td>
<td>0.291304</td>
<td>0.947945, 0.941945, 0.936965, 0.931945, 0.926965</td>
<td>-</td>
</tr>
<tr>
<td>img11</td>
<td>0.296304</td>
<td>0.948945, 0.942945, 0.937965, 0.932945, 0.927965</td>
<td>-</td>
</tr>
<tr>
<td>img12</td>
<td>0.301304</td>
<td>0.949945, 0.943945, 0.938965, 0.933945, 0.928965</td>
<td>-</td>
</tr>
<tr>
<td>img13</td>
<td>0.306304</td>
<td>0.950945, 0.944945, 0.939965, 0.934945, 0.929965</td>
<td>-</td>
</tr>
<tr>
<td>img14</td>
<td>0.311304</td>
<td>0.951945, 0.945945, 0.940965, 0.935945, 0.930965</td>
<td>-</td>
</tr>
<tr>
<td>img15</td>
<td>0.316304</td>
<td>0.952945, 0.946945, 0.941965, 0.936945, 0.931965</td>
<td>-</td>
</tr>
<tr>
<td>img16</td>
<td>0.321304</td>
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<td>-</td>
</tr>
<tr>
<td>img17</td>
<td>0.326304</td>
<td>0.954945, 0.948945, 0.943965, 0.938945, 0.933965</td>
<td>-</td>
</tr>
<tr>
<td>img18</td>
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<td>0.955945, 0.949945, 0.944965, 0.939945, 0.934965</td>
<td>-</td>
</tr>
<tr>
<td>img19</td>
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<td>0.956945, 0.950945, 0.945965, 0.940945, 0.935965</td>
<td>-</td>
</tr>
<tr>
<td>img20</td>
<td>0.341304</td>
<td>0.957945, 0.951945, 0.946965, 0.941945, 0.936965</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2: GLCM & WT Best Five Selected and Ranked Functions Values:

<table>
<thead>
<tr>
<th>Image</th>
<th>GLCM &amp; WT (Best 5 Selected Features and Its Values)</th>
<th>Area of Blood Vessels</th>
<th>Count of Pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>img1</td>
<td>0.245904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img2</td>
<td>0.251904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img3</td>
<td>0.257904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img4</td>
<td>0.263904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img5</td>
<td>0.269904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img6</td>
<td>0.275904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img7</td>
<td>0.281904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img8</td>
<td>0.287904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img9</td>
<td>0.293904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img10</td>
<td>0.299904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img11</td>
<td>0.305904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img12</td>
<td>0.311904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img13</td>
<td>0.317904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img14</td>
<td>0.323904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img15</td>
<td>0.329904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img16</td>
<td>0.335904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img17</td>
<td>0.341904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img18</td>
<td>0.347904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img19</td>
<td>0.353904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
<tr>
<td>img20</td>
<td>0.359904, 1.07E-05, 1.57E-05, 1.75E-05</td>
<td>15,404.65</td>
<td>6152</td>
</tr>
</tbody>
</table>
Table 3: System-based Elapsed Time Complexity Values of Input Retinal Images.

<table>
<thead>
<tr>
<th>Particulars</th>
<th>Image Processing based Feature Extraction and Selection Classifiers (Existing &amp; Proposed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input Images</td>
<td>SVM</td>
</tr>
<tr>
<td>Img1</td>
<td>0.491392</td>
</tr>
<tr>
<td>Img2</td>
<td>0.223775</td>
</tr>
<tr>
<td>Img3</td>
<td>0.140449</td>
</tr>
<tr>
<td>Img4</td>
<td>0.099716</td>
</tr>
<tr>
<td>Img5</td>
<td>0.102106</td>
</tr>
<tr>
<td>Img6</td>
<td>0.080489</td>
</tr>
<tr>
<td>Img7</td>
<td>0.852522</td>
</tr>
<tr>
<td>Img8</td>
<td>0.070907</td>
</tr>
<tr>
<td>Img9</td>
<td>0.091714</td>
</tr>
<tr>
<td>Img10</td>
<td>0.696925</td>
</tr>
<tr>
<td>Img11</td>
<td>0.070153</td>
</tr>
<tr>
<td>Img12</td>
<td>0.082000</td>
</tr>
<tr>
<td>Img13</td>
<td>0.082000</td>
</tr>
<tr>
<td>Img14</td>
<td>0.082504</td>
</tr>
<tr>
<td>Img15</td>
<td>0.097195</td>
</tr>
<tr>
<td>Img16</td>
<td>0.099787</td>
</tr>
<tr>
<td>Img17</td>
<td>0.089062</td>
</tr>
<tr>
<td>Img18</td>
<td>0.088884</td>
</tr>
<tr>
<td>Img19</td>
<td>0.108274</td>
</tr>
<tr>
<td>Average</td>
<td>0.118167</td>
</tr>
</tbody>
</table>

Table 4: System-based Time Complexity: Average Values for Different Classifiers.

<table>
<thead>
<tr>
<th>Name of Classifier</th>
<th>Time Complexity Average Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>0.118167</td>
</tr>
<tr>
<td>LDA</td>
<td>0.002242</td>
</tr>
<tr>
<td>ANN</td>
<td>0.001590</td>
</tr>
<tr>
<td>NB</td>
<td>0.101023</td>
</tr>
<tr>
<td>KNN</td>
<td>0.112231</td>
</tr>
<tr>
<td>ELM</td>
<td>0.140449</td>
</tr>
<tr>
<td>ANFIS (Grid Partitioning)</td>
<td>0.0981314</td>
</tr>
<tr>
<td>ANFIS (Subtractive Clustering)</td>
<td>0.002153</td>
</tr>
</tbody>
</table>

Fig. 8: Charts for Time Complexity: Average Values for Different Classifiers.

Table 5: Core Resultant Values of various Classifiers and its' implementation on Enhanced Retinal Images.

<table>
<thead>
<tr>
<th>Types of Classifier / Approach</th>
<th>Avg. Time Complexity Computation Time (in Sec.)</th>
<th>Average Classification Error</th>
<th>Performance Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>0.12</td>
<td>7.50%</td>
<td>92.50%</td>
</tr>
<tr>
<td>LDA</td>
<td>0.03</td>
<td>12.50%</td>
<td>87.50%</td>
</tr>
<tr>
<td>ANN</td>
<td>0.55</td>
<td>0%</td>
<td>100%</td>
</tr>
<tr>
<td>NB</td>
<td>0.15</td>
<td>13%</td>
<td>85%</td>
</tr>
<tr>
<td>KNN</td>
<td>0.10</td>
<td>7.50%</td>
<td>92.50%</td>
</tr>
<tr>
<td>ELM</td>
<td>0.47</td>
<td>0%</td>
<td>100%</td>
</tr>
<tr>
<td>ANFIS (Grid Partitioning)</td>
<td>0.42</td>
<td>5%</td>
<td>95%</td>
</tr>
<tr>
<td>ANFIS (Subtractive Clustering)</td>
<td>0.02</td>
<td>0%</td>
<td>100%</td>
</tr>
</tbody>
</table>
System Processes:

All the above resultant data, which are given in the above tables, are implemented through MATLAB Processes. Table 1 consists of GLCM and WT functions-based performance values of the best five functions extracted from the implemented 23 dataset functional values of GLCM as well as 53 dataset functional values of WT respectively. Table 2 has the best 5 selected and ranked featured values, which are extracted from both the datasets of GLCM and WT. On this ranked functional values, the feature extraction process is carried out by following the different classifiers such as SVM, LDA, ANN, NB, KNN, ELM, ANFIS with Grid Partitioning and ANFIS with Subtractive Clustering procedures. Theses implemented values are given in Table 3. Table 4 contains only the Time Complexity values obtained through various classifiers. The other systemic values like Average Classification Error and Performance Accuracy values of different classifiers are given in Table 5. The images given in Fig. 6 are input retinal images. Fig. 7 explains the step-by-step process sequence of the retinal fundus images undergone the processes such as (i) Inputting the retinal images, (ii) Extracting the Green Channel of the Retinal Fundus Image, (iii) Enhancement of the Image with Inversion, (iv) Extraction of Blood Vessels in Binary Format and (v) Blood Vessels Patterns needed for our further systemic processes.

Conclusion:

This proposed image processing system, which is trained by using the enhanced classifiers such as NB, KNN, ELM and ANFIS with the characteristic performance features such as Computation Time, Average Classification Error and Performance Accuracy. Through this training process, it is identified that the ANFIS is the best classifier through its efficient characteristic functionality features such as Average Classification Error, Performance Accuracy than other classifiers. Even though it consumes little bit more timing for processing than others, it is not a great variation at all. So, this proposed system is considered as the best biometric system for human identification with the retinal blood vessels, which is a wonderful biometric feature.

REFERENCES


