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Features Recognition on Retinal Fundus Image – A Multi-Systemic Comparative Analysis

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Abstract* — This Article describes the perspective analysis and study on Pattern Recognition of the Retinal Nerve Fibers. The articles published in recent years are considered for observing the analytical techniques as well as approaches used for implementing the image-based processes of our Proposed System. The various Process Implementation Systems play important role for obtaining the accuracy in the performance and time-complexity based processes. Various Technical Systemic processes, approaches, methodologies, techniques are used in various articles related to retinal images published recently. The Systems such as Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are mostly used for implementing Image-based tasks. In this article the Back Propagation Technique is applied on ANN. The efficient results of the proposed processes are produced by the system named as ANFIS1 with Grid Partitioning Technique and ANFIS2 with Subtractive Clustering Technique. The Retinal Images, which are extracted from Original Retinal Fundus Image DB Set-1 and Original Retinal Fundus Image DB Set-2 have been processed by using all these systemic techniques for obtaining the Percentage of Average Classification Error, which is the core value for identifying the efficiency of a System among multiple systems.

***Key Words* — Retinal Nerve Fibers, Time-Complexity, LDA, ANN, ANFIS, Retinal Fundus Image.**

I. INTRODUCTION

Retinal Vascular Structure of a person is an unique structure can be used unique identification, wherever we use the authentication technique to provide authorization for the confidential-based private processes. In this article, the recently released article related to this retinal blood vessels' pattern recognition are studied.

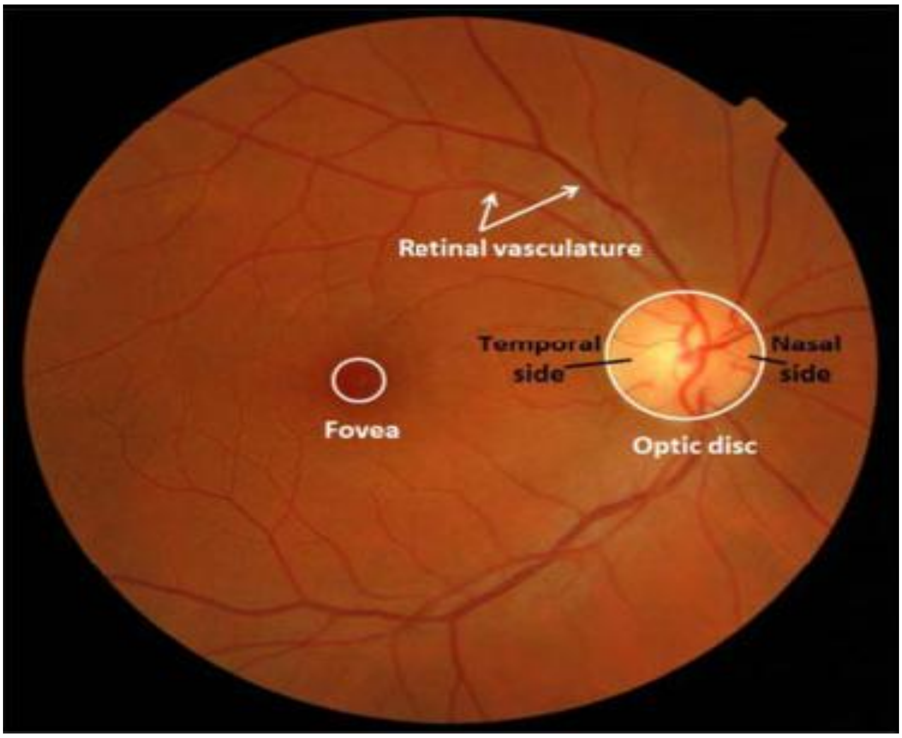

Fig. 1. The Retinal Fundus Image [34].

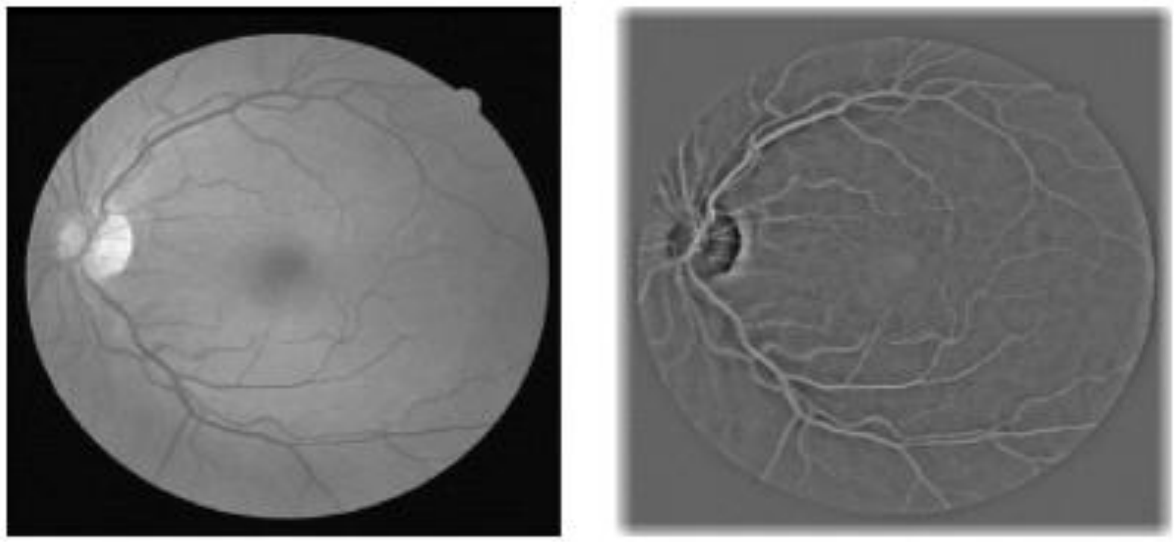

Fig. 2. (a) Gray Level Intensity Image Obtained from an Original Color Fundus Image. (b) Background Normalized Image [8].

II. PERSPECTIVE OF PUBLISHED ARTICLES

In the article entitled "Locating Blood Vessels in Retinal Images by Piecewise Threshold Probing of a Matched Filter Response", the Matched Filter Response (MFR) technique is used with the description that the MFR method-based segments roughly 3/4 of the vessels in a retinal fundus image at a false positive rate comparable to a human observer. Compared to basic thresholding of an MFR, this method reduces the false positive rate by a factor of 15 times [1].

The Mathematical Morphology technique based processes used in the construction of a synthetic adaptive contrast function from regional maxima and minima and by considering the connected components of the set and the semi-automatic method to measure and quantify the geometrical and topological properties of retinal blood vessels. The semi-automatic labeling of the skeleton trees is described followed by an automatic procedure to measure length, area and angles, and the connectivity between branches of retinal blood vessels [2-3]. The Active Contour technique to perform accurate segmentation on a reference frame and uses fast registration to compute the segmented images of the sequence of images acquired during the treatment. It enables fast tracking of retinal structures and ensures proper administration of the treatment in case of eye movement [4]. The inclusion of a shape prior constraint improves performance on regions with intensity in homogeneity [26]. The Fuzzy Convergence technique can be used for the convergence of the blood vessel network as the primary feature for detection, in conjunction with the brightness of the nerve as a secondary feature [5]. This method can classify a pixel-based process. The initial step of vessel centerline detection combines local information, used for early pixel selection, with structural features, as the vessel length [8]. An effective retinal vessel segmentation technique based on supervised classification using an ensemble classifier of boosted and bagged decision trees with 9-D feature vector which consists of the vessel map obtained from the orientation analysis of the gradient vector field, Morphological transformation; line strength measures and the Gabor filter response which encodes information to successfully handle both normal and pathological retinas [36]. The Adaptive Local Thresholding technique uses a general framework of adaptive local thresholding based on a verification-based multi-threshold probing scheme. The application-dependent verification procedure can be designed to fully utilize all relevant information about the objects of interest [6]. The Early Treatment Diabetic Retinopathy Study standard based paper presents an ETDRS retinal image registration algorithm that effectively combines both area-based and feature based methods into one flow [7]. GLCM-Gray level co-occurrence matrix is used for Early Treatment Diabetic Retinopathy Study Standard [9]. A new Multi-resolution Hermite model (MHM) was proposed together with an EM-like optimization scheme and statistical linking algorithm for the modeling and analysis of vascular structure from retinal fundus images [10].

The Support Vector Machine (SVM)'s Reliable identification of arteries and vessels from retinal images can be useful in an automatic analysis of the changes in artery and vein diameters, retinal vessel oximetry and change analysis, and automatic detection of abnormalities such as branch retinal vein occlusions (BRVO). Retinal oximetry has added to the understanding of the patho-physiology of retinal disorders, including diabetic complications in the retina and altered oxygen delivery in glaucoma [11]. Detection of new vessels on the optic disc may similarly improve the detection of proliferative disease. However, the high sensitivity achieved using microaneurysm detection alone, coupled with the low prevalence of new vessels imply that a very large study would be required to reveal any potential improvement [27]. Line vector and Support vector machine focuses the averaging implicit in the line strength computation reduces noise but it is simpler than a convolution with a two-dimensional kernel. Since no hypothesis is assumed on the cross-section profile, we obtain robust detection in presence of vessels with different size. Moreover, the one-pixel width of the rotating line gives good edge localization and increased selectivity between inside and outside pixels [12]. Matched Filter Technique with the OD detection algorithm is based on matching the expected directional pattern of the retinal blood vessels. Hence, a simple matched filter is proposed to roughly match the direction of the vessels at the OD vicinity. The retinal vessels are segmented using a simple and standard 2-D Gaussian matched filter. Consequently, a vessels direction map of the segmented retinal vessels is obtained using the same segmentation algorithm [13]. In the Laplacian operator and normalized gradient vector field, the problem by detecting the blood vessel-like objects in the image using the Laplacian operator and the noisy objects are pruned according to the detected centerlines, which are extracted using the normalized gradient vector field [14]. The Generalized Dual-Gaussian model focuses the inclusion of the generalized dual-Gaussian cross-sectional profile results in an improvement in detection as compared to the single-Gaussian profile in the context of dual-wavelength retinal oximetry data. The estimation of the parameters of the intensity profile could also be used potentially to differentiate between veins and arteries reliably [15].

The High frequency ultrasound (HFUS) beyond 40 MHz has been used for imaging the surface layer of skin and the anterior segment of the eye due to its shallow penetration depth. This shallow imaging depth is the main bottleneck to us. Using of ultrasound in this frequency range for imaging of deep-lying tissues [16]. Active Contour Model algorithm uses a simple "tramline" vessel pixel detection algorithm, a "Ribbon of Twins" active contour model grown along vessels for detection and integrated measurement, and an auxiliary algorithm to identify the network topology [17]. An *ad hoc* parallel implementation used for the segmentation on high-resolution images. This implementation is based on a data partitioning, which allowed a faster processing of these images [18]. Bayesian segmentation with the Maximum a posteriori (MAP) Probability has the advantages of performing segmentation based on vessel diameter: first the main vessels are detected then vessels of smaller diameter. This technique might be improved by using a more advanced model (mixture of Gaussians together with other geometric parameters like curvature) and needs to be evaluated using a larger image database [19]. Multiconcavity modeling approach has been used to present a novel regularization-based multiconcavity approach for effectively segmenting blood vessels in both normal and pathological retinas with bright and dark lesions in a single system. perceptive transform derived from Weber's law is proposed to map an input image into a perceptive space for robust vessel segmentation [20].

AdaBoost algorithm with the strength for capturing a rich collection of shape and structural information, in addition to local information at multiple spatial scales, in the feature vector. The quality of the vessel map decreases as vessels become very thin. This is a feature of any current vessel detection algorithm, and defines the applicability boundaries of the current technology [21]. The OCT layer segmentation technique first detects the retinal blood vessels and accordingly cuts an OCT image into multiple vessel sections and nonvessel sections. The nonvessel sections are then smoothed by a bilateral filter and a median filter. Retinal layer boundaries of the smoothed nonvessel sections are detected and the complete retinal layer boundaries are determined through interpolation [22]. Using Fast Localization two features are selected for projection. The first one is the directionality of the retinal vessels (represented by the horizontal and vertical edge maps of the image).The second feature is the intensity profile of the OD (a bright circular region with a thin dark slab in the middle) [23]. Neural Network scheme for pixel classification, being the feature vector representing each pixel composed of gray-level and moment invariants-based features. To the best of our knowledge, although moment invariants have been widely used over the years as features for pattern recognition in many areas of image analysis (typical examples include optical character recognition and shape identification), they have never been applied within this framework [24]. Automatic vessel segmentation of retina images is essential for computing fractal dimension based on box-counting technique. The novelty of Gabor wavelet transforms and Fractal dimensions technique lie in the use of FFD on grayscale retina images, eliminating the binary segmentation of the vessel network which is prone-to-error whether carried out by human expert or by automated algorithms [25]. Curve-let Transform Specify characteristics of retinal images make the vessel detection more difficult. Regarding the high ability of FDCT in representing images containing edges, using modification of curvelet transform coefficients, the retinal image contrast was improved and prepared better for segmentation step. Due to high sensitivity of multistructure elements to edges in all directions, multistructure elements morphology was capable of detecting the blood vessel edges successfully [28]. Graph-based segmentation for retinal vessel boundary detection based on graph search and validated it on a publicly available dataset of expert annotated vessel widths. The advantage is that this method detects both boundaries simultaneously, and is therefore more robust than methods which detect the boundaries one at a time. The simultaneous detection of both borders makes the accurate detection possible even if one boundary is of low contrast or blurred [29]. Ellipse fitting algorithm presented solution for glaucoma assessment was in the form of two segmentation methods for OD and cup. A novel,active contour model is presented to get robust OD segmentation. This has been achieved by enhancing the C-V model by including image information at the support domain around each contour point. An attractive aspect of the extension is the strengthening of region-based active contour model by the integration of information from multiple image feature channels [30].

Line integrals and variational optimization with the limitations of the Hessian-based vessel enhancement methods have been discussed, which stem from the fact that the Hessian matrix is a local measure sensitive to local intensity structures. A new view on the vesselness measure has been proposed [31]. Fast Localization of ROI, the automated method to estimate the AVR in retinal color images by detecting the location of the optic disc, determining an appropriate region of interest (ROI), classifying vessels as arteries or veins, estimating vessel widths, and calculating the AVR. After vessel segmentation and vessel width determination, the optic disc is located and the system eliminates all vessels outside the AVR measurement ROI [32]. The publication of numerous automated methods designed for this purpose over last years. As far as our understanding, most quality evaluation functions QEFs) applied for measuring the performance of these methods do not consider vascularity as a tree-like connected structure with specific anatomical features, which are based on the individual pixel-to pixel comparison of the resulting segmentation with an image labeled by a medical expert (reference-standard image) [33].

The OD segmentation method uses ASF and morphological reconstruction to remove vessels and bright region distracters while retaining the shape of the papillary region. The fast, hybrid level set model uses both region information and local edge vector with simple automatic initialization to achieve robust, fast, and accurate segmentation [34]. Graph-cut technique on Framework effectively combined the GS and GC methods, and employed a multi-object strategy during which two retinal layers were included as auxiliary target objects for helping the SEAD (symptomatic exudates associated derangement) segmentation. An automatic voxel classification based on the texture features was used for initialization. Probability constraints further improved the graph-based segmentation [35].

A novel registered-fundus and a novel multimodal vessel segmentation approach to help obtain better vessel profiles in the SD-OCT volumes. Overall, the two present fundus-related approaches perform better than two closest previous OCT-based vessel segmentation approaches. The multimodal approach performs better than all the three unimodal vessel segmentation approaches of the registered-fundus and the two OCT-based approaches quantitatively and qualitatively. This article used Multimodal Retinal Vessel Segmentation [37]. Extended Kalman Filter performs grouping on the extracted vessel segments to restore the topology of vascular trees with anatomical realism. If an operator can provide the tree type (artery/vein), trees extracted using our proposed system can facilitate the quantification of geometrical and topological properties of veins and arteries for the study of certainly medical conditions, such as arteriolar narrowing and hypertension [38].

The Parametric Modeling of the intensity variation method begins with fitting a mathematical model to the temporal intensity variation at each pixel. Unlike current time-intensity models, the proposed model accurately capture the temporal variation of the fluorescein leakage during the first pass and subsequent recirculations. This allowed capturing the intrinsic dynamic properties of the intensity variation and thus improved the accuracy of the segmenting and differentiating the different types of lesions. The model parameters at each pixel are then used to form a feature vector that is used to classify the different pixels into areas of classic CNV, occult CNV(Choroidal neovascularization), and background [39].

These systems focus various retinal blood vessel based image processes for its unique feature identification through various image-based processes.

III. COMPARITIVE SYSTEM PROCESS

In our proposed systemic sequential processes, we have obtained the following resultant values through various systems. The values are given in Table 1.

TABLE-I
System-based Average Classification Error Values

System(s)	(Original Retinal Fundus Image DB Set-1)	(Original Retinal Fundus Image DB Set-2)	Average Classification Error in %
SVM	18A,22UA	19A,21UA	7.5%
LDA [Linear Discriminant Analysis]	17A,23UA	18A,22UA	12.5%
ANN[Back Propagation]	20A,20UA	20A,20UA	0%
ANFIS1[Grid partition]	19A,21UA	20A,20UA	5%
ANFIS2[Subtractive Clustering-Proposed]	20A,20UA	20A,20UA	0%
ORIGINAL	20A,20UA	20A,20UA	0%

A*-Authorized(GENUNE), UA*-Unauthorized(IMPOSTER)

TABLE-II
System-based Average Classification Error Calculating Formulae

System(s)	Error calculation for Image set-1:	Error calculation for Image set-2:
SVM LDA ANN ANFIS1 ANFIS2	((18~20)/20)*100% (or) ((22~20)/20)*100% ((17~20)/20)*100% (or) ((23~20)/20)*100% ((20~20)/20)*100% (or) ((20~20)/20)*100% ((19~20)/20)*100% (or) ((21~20)/20)*100% ((20~20)/20)*100% (or) ((20~20)/20)*100%	((19~20)/20)*100% (or) ((21~20)/20)*100% ((18~20)/20)*100% (or) ((22~20)/20)*100% ((20~20)/20)*100% (or) ((20~20)/20)*100% ((20~20)/20)*100% (or) ((20~20)/20)*100% ((20~20)/20)*100% (or) ((20~20)/20)*100%

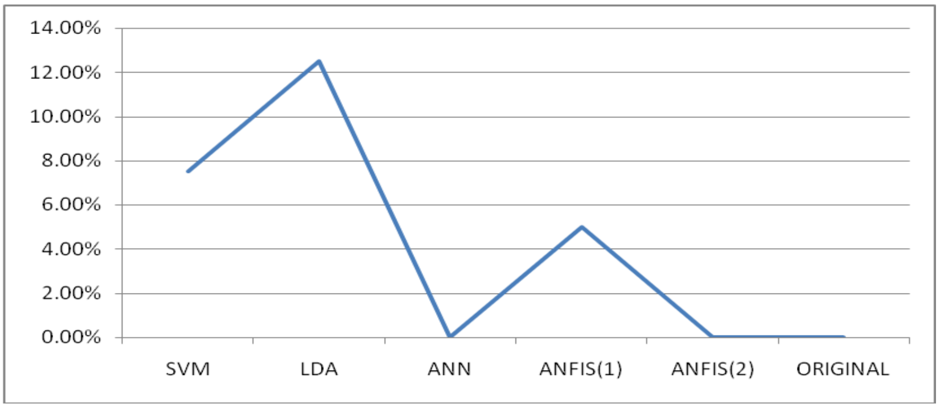

Fig. 3. Average Classification Error (in Percentage) in accord with various Systems (Ref.: TABLE-I)

TABLE-III
System-based Elapsed Time Values of Retinal Images

Image/System	SVM	LDA	ANN	ANFIS(1)	ANFIS(2)
Image1	1.045	0.973	1.583	0.625	0.45
Image2	1.118	0.875	1.259	0.918	0.358
Image3	0.779	1.458	2.35	1.855	1.418
Image4	0.862	1.058	2.081	1.528	0.601
Image5	0.919	0.958	2.118	1.72	0.725
Image6	0.833	2.007	2.251	1.561	0.893
Image7	0.875	1.025	1.25	0.428	0.552
Image8	0.797	0.932	1.005	0.793	0.871
Image9	1.321	0.698	2.312	1.972	0.785
Image10	0.997	0.932	2.591	0.921	1.821
Average	0.9546	1.0916	1.88	1.2321	0.8474

The following System generated Graph represents the Elapsed Time versus Retinal Images. The overall Time Complexity has also been represented in Pie Chart form.

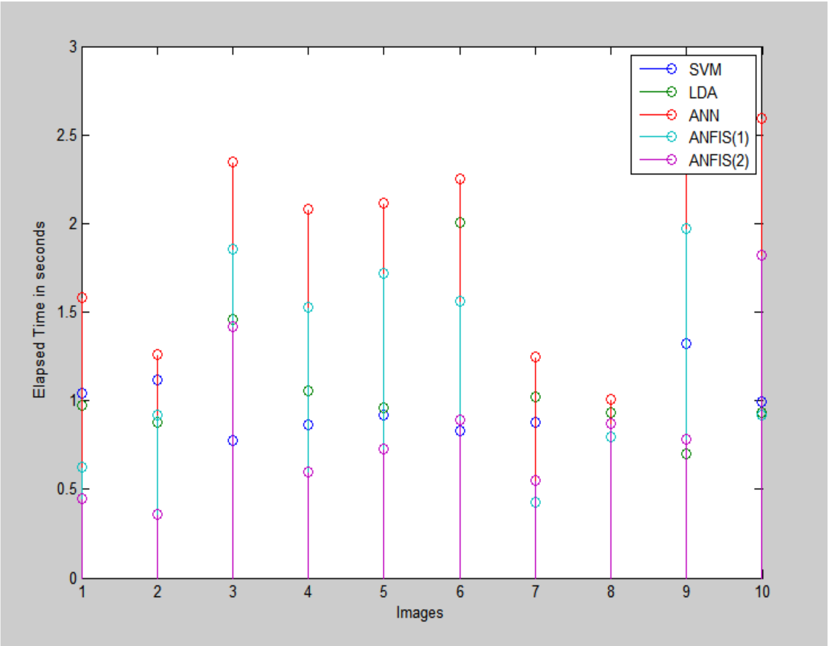

Fig. 4. The Time Plot Graph individual.

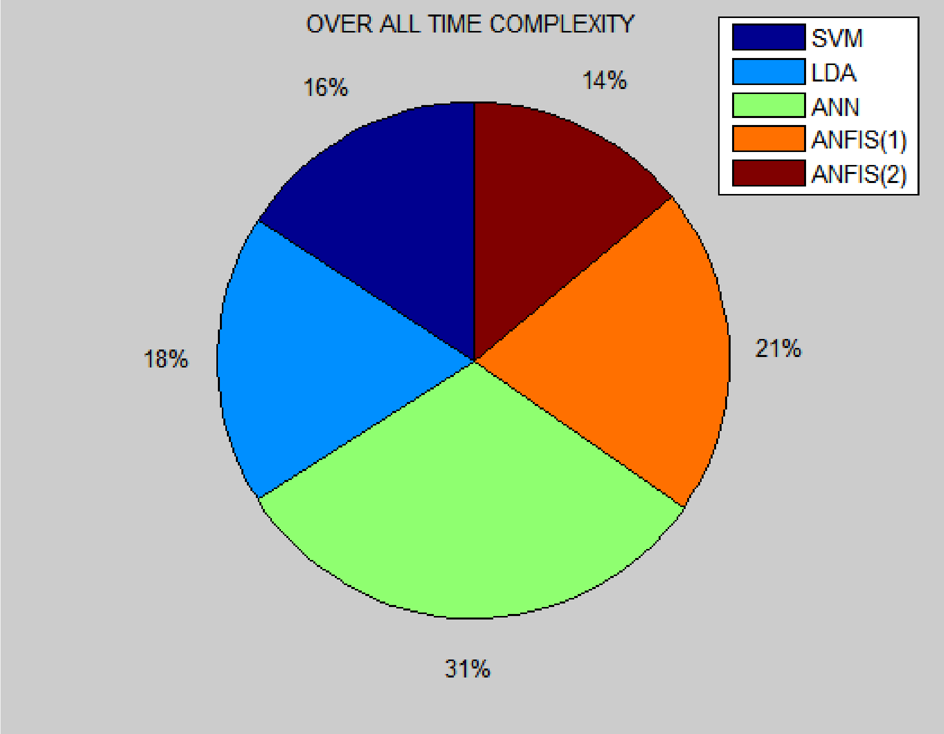

Fig. 5. The Overall Time Complexity Chart.

IV. CONCLUSION

From this Comparative Analysis on the Systems like Artificial Neural Network and ANFIS1 (Subtractive Clustering) Technique, both have better performance with regards to Classification Accuracy. On another side, the Time Complexity is an important factor to be considered for the Pattern Recognition System. Artificial Neural Network taking more time for authentication. Since ANFIS1 (Subtractive Clustering Technique) is identified and concluded the best classifier for our proposed system in both better accuracy and lesser time complexity levels.

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