EEG Analysis in Biometric Identification and Authentication

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Abstract: This article demonstrates that EEG (Electroencephalogram) signals can be used as a biometric identifier to authenticate the person. The patterns of brainwave signals are unique for every individual and it is very difficult to use these patterns for person identification and authentication purpose. Although the brainwaves signals are much complicated to study, there are very little studies have been done on the brain wave signals based biometrics. The biometric based on these physiological traits are resistant to frauds in sensitive applications domains. In confidential areas like military organizations, government agencies secrete potential domains and likewise highly restricted areas, the biometric facility based on EEG signals can be very useful. This article represents the strategy behind implementation of EEG based biometric. Here we have achieved success in authenticating the person with the help of wavelet transform. We used 5 channels of EEG waveform as features to authenticate person. The classification results give us approximately 90% accuracy in authenticating individuals.

Index Terms **- EEG (Electroencephalogram), alpha, theta, delta, gamma, biometric system.**

I. INTRODUCTION

Human brain have more than millions of neurons which plays an important role for monitoring performance of human body with respect to inside/outside motor/sensory provocations. These neurons will deed as information shippers between human body and brain. Understanding perceptive activities of brain can be done by examining either images or signals from the brain. Human activities can be pictured in terms of motorized and sensory conditions for example, eye blinking, lip movement, remembrance, attention, hand clamping etc. These conditions are associated with precise signal frequency which helps to know purposeful performance of composite brain structure. The human brain is one of most complex structure to study and as we know well that brain signals are very confidential, the advantage of these signals is that they are very difficult to mimic also they can't be stolen by any unauthorized user to perform criminal activity as they are unique to every individual. The brain signals generated at every condition are different.

Typical waveform that represents EEG signal is as shown in following fig. 1.

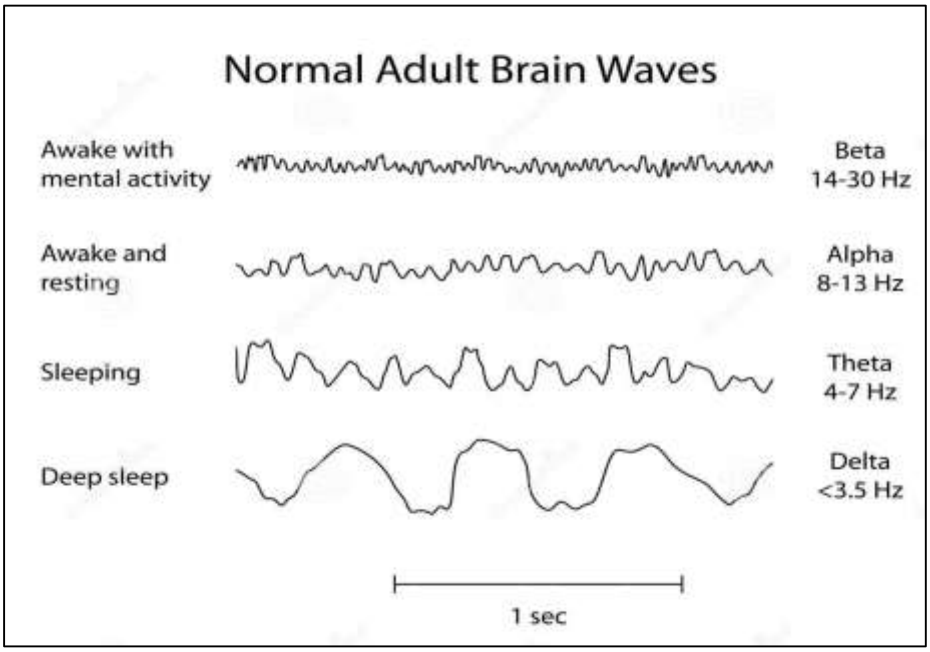

Fig 1. Typical EEG waveform

The arrangement of electrical brain activities generated from brain is known as the brainwave patterns. The process of authentication involves one to one matching of the users whereas in identification the process involves one to N matching. Authentication either accepts the identity of user or denies it. In contrast identification simply states the user is valid or not. EEG signal patterns based biometric are emerging these days to make security traits stronger than before. In recent years, enormous technologies have been developed to capture the brain wave records. Various mechanisms are implemented to record and study the patterns emitted by brain signals. Here in this paper we used electroencephalogram(EEG) signals to authenticate the user based on some features obtained after applying some feature extraction and classification techniques, such as wavelet transform.

II. LITERATURE REVIEW:

Table 1 describes the literature review done on EEG based biometric authentication.

TABLE 1. LITERATURE REVIEW

Author	Method	Result
Nagsen S. Bansod, Siddharth B. Dabhade, M. M. Kazi, Yogesh S. Rode & K. V. Kale. 2016 "Single Electrode Brain Signal Data Fusion for Security" [1]	Used 13 features of EEG signal data and pattern recognition technique for EEG feature classification.	Got 61% classification and recognition rate using Manhattan Distance Metric.
C. Ashby, A. Bhatia, F. Tenore, and J. Vogelstein. April 2011 [2]	Mined the PSD, spectral power (SP), AR, IHPD and IHLC from 14 EEG channels and applied the linear support vector machine (SVM) classifier for authentication on 5 subjects.	Acquired the false rejection rate (FRR) of 2.4% to 5.1%, and the false acceptance rate (FAR) of 0.7% to 1.1%.
Katharine Brigham and B. V. K. Vijaya Kumar. Sept 2010 [3]	For classification applied the linear SVM only on AR	Obtained accuracy 98.96% with the 122 subjects test 99.76% with the 6 subjects test and.
P. Nguyen, D. Tran, X. Huang, and D. Sharma. 2012 [4]	Made the use of linear SVM to check some databases which had subjects of 3, 9, 40, 20, and 122.	From these features of speech recognition applied in EEG signal verification, the accuracies wide-ranging from 18.36% to 100%.
D. Zhu, X. Zhou, and Q. Guo. 2013. [5]	Made use of polynomial kernel SVM which is established on wavelet transform (WT) and AR from single channel.	Got usual precision was 85% on 13 subjects.
A. Ferreira, C. Almeida, P. Georgieva, A. Tome, and F. Silva. 2010. [6]	Applied the linear and radial basis function (RBF) Support Vector Machine to categorize 13 individuals on the gamma band SP.	The method One against one acquired an error rate of 15.67% to 38.21% and another method one against all acquired an error rate from 17.43% to 30.57%.
N.-Y. Liang, P. Saratchandran, G.-B. Huang, and N. Sundararajan. 2006. [7]	Made use of the back-propagation NN to categorize 7 subjects on AR from 6 channels.	Acquired correctness of 42.87% to 50.14%.
M. Poulos, M. Rangoussi, V. Chrissikopoulos, and A. Evangelou. 1999. [8]	Made use of back-propagation NN to detect AR and fisher distance from 6 channels on 3 individuals.	Caught an precision of 80.7% to 86.7%.
C. R. Hema and A. Osman. [9]	Applied PSD and feed forward NN	Had correctness of 79.9% to 89.95%.
C. He, X. Lv, and J. Wang. [10]	Naive Bayes model is used for validation of 4 individuals depend on mAR features.	Obtained half total error rate (HTER) of 6.7%

C. He and J. Wang [11]	Naive Bayes model is used for validation of 7 subjects	Obtained HTER from 2.2% to 7.3%.
T. Kathikeyan and B. Sabarigiri [12]	Here also Naive Bayes model depend on AR and power spectral density (PSD)	Had an equal error rate (EER) of 4.16%.
Gui, Qiong, Zhanpeng Jin, and Wenyao Xu 2014. [13]	Reduced the noise level through ensemble averaging and low-pass filter, Used wavelet packet decomposition and artificial neural network.	Found classification rate up to 90% for distinguishing subjects or small group of individuals.

III. Material and Methods

Mindwave Mobile Sensor:

To collect the dataset of EEG we have used the MindWave Mobile sensor. It reports the wearer's mental state in the form of NeuroSky's proprietary Attention and Meditation eSense algorithms, along with raw wave and information about the brainwave frequency bands. The NeuroSky MindWave Mobile can be used with supported video games, research software, or a number of other applications for an enhanced user experience. Table 2 depicts the minimum system requirements for IOS and Android.

TABLE 2. Minimum System Requirements for IOS/Android

Operating system	**iOS**	**Android**
	iOS 4.3.3 or later	**Android 2.2 or later**
Hardware	at least iPhone, iPad, or iPod Touch 3 (3rd gen 32GB or later)	Compatible Android phone or tablet
Wireless	Bluetooth	

3.1 Dataset Used:

The table 3 below gives a general synopsis of some of the commonly-recognized frequencies that tend to be generated by different types of activity in the brain:

TABLE 3. Some of the commonly-recognized frequencies

Brainwave Type	**Frequency range**	**Mental states and conditions**
Delta	0.1Hz to 3Hz	Deep, dreamless sleep, non-REM sleep, unconscious
Theta	4Hz to 7Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha	8Hz to 12Hz	Relaxed (but not drowsy) tranquil, conscious
Low Beta	12Hz to 15Hz	Formerly SMR, relaxed yet focused, integrated

Midrange Beta	16Hz to 20Hz	Thinking, aware of self & surroundings
High Beta	21Hz to 30Hz	Alertness, agitation

The experimental data is collected using Mindwave Mobile Sensor. The dataset used in the experiment is collected for total 10 subjects where 5 female and 5 male subjects are there among 10. The dataset may contain numeric data as shown in table 4 and the data is stored in a .csv file. Each sample is of 30 seconds duration and likewise 25 samples per subject are collected. Dataset was collected in the conditions while subject is performing following tasks/activities:

1. Subject is in relaxed, sleeping state with eyes closed.
2. Subject is imagining the rotational conditions of given figure.
3. Subject is given mental activity of counting and writing numbers on board.
4. Subject is given mental activity of writing and rubbing alphabets or vowels on board.
5. Subject is performing mathematical calculations orally in mind.

TABLE 4. SAMPLE DATA COLLECTED USING MINDWAVE MOBILE SENSOR

Delta	**Theta**	**Alpha low**	**Alpha high**	**Beta low**	**Beta high**	**Gamma low**	**Gamma mid**
13026	19178	83616	19583	12517	12450	18476	11686
7395	8026	14105	7060	8924	20083	12024	2976
11713	14797	32009	25462	11936	28866	13166	5391
223172	69469	3953	2654	2587	7775	4300	1797
151697	75771	14067	19070	17861	16746693	18111	12197
41937	16756343	7295	9305	5947	5398	3081	3069
4281	5971	83781	20331	11935	28752	11705	8266
1163300	69554	16763625	73733	20835	18305	21308	6610
357172	16748258	16760080	16745301	6829	14421	16747776	10703
9036	16747868	19976	31513	8471	16753639	19977	23379
16763971	16744931	69374	16760472	4745	18871	26090	4828
…	…	…	…	…	…	…	…

3.2 Preprocessing

Raw EEG signals are very noisy and they are not stable to analyze them as it is - correctly. EEG signals must need to preprocess before using it in actual operations. Wavelet function formulates some of mathematical tools to perform preprocessing and feature extraction on raw EEG brainwave signals [14]. The following figure 2 is identical to the EEG signals that are preprocessed in MATLAB.

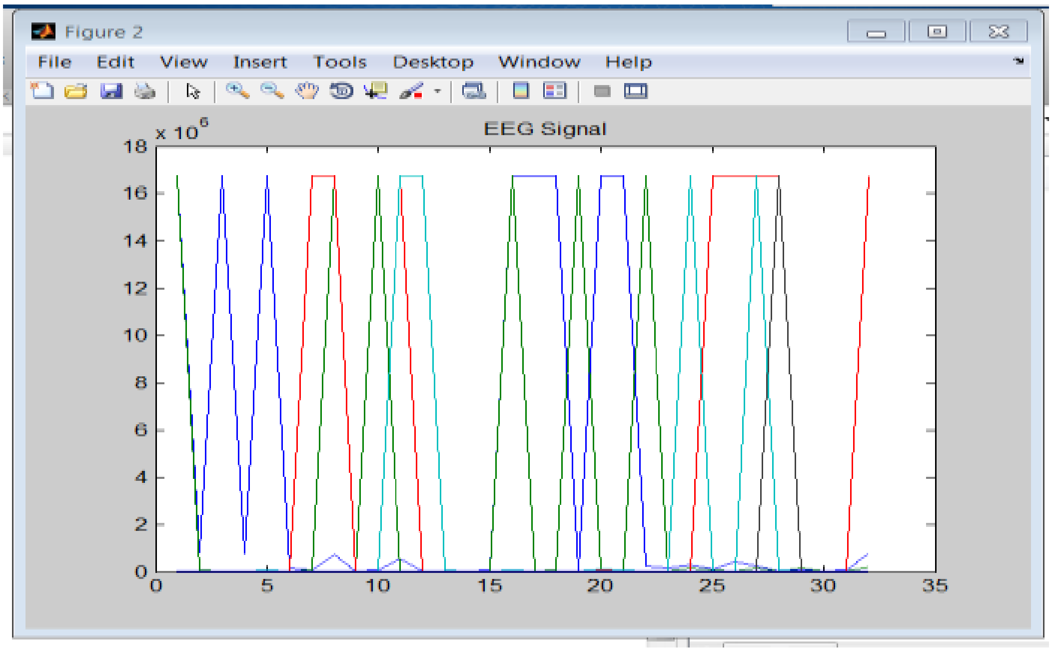

Fig 2. Preprocessed EEG signal

3.3 Feature Extraction

The following table demonstrates the features extracted with the help of wavelet transform. Features that are generally used to process are as follows: eegRawValues, eegRawValueVolts, attention level, meditation level, blinkStrength, delta (1-3 Hz), theta (4-7 Hz), alphaLow (8-9 Hz), alphaHigh (10-12 Hz), betaLow (13-17 Hz), betaHigh, gammaLow (31-40 Hz), gammaMid (41-50 Hz), etc. Among these features we are going to use Gamma, Beta, Alpha, Theta and Delta channels. The wavedec() function is used as feature extraction technique.

For a sampling signal given, initially imprecise *f* and *fj* with *f*, using the decomposition statement, it is decomposed *ck* into *fj* and *dk*,

Set,

$$f_j(x) = \sum_{k \in z} C_k^j \varphi(2^j x - k) \in v_j \quad (1)$$

fj can be broken down into $f_j = w_{j-1} + f_{j-1}$ in which

$$w_{j-1} = \sum_{k \in z} d_k^{j-1} \psi(2^{j-1} x - k) \in w_{j-1} \quad (2)$$

$$f_{j-1} = \sum_{k \in z} C_k^{j-1} \varphi(2^{j-1} x - k) \in v_{j-1} \quad (3)$$

Features are saved in .csv file to use in the testing with training dataset.

3.4 Classification

Pattern matching

For matching the results with stored data IF ELSE condition is applied for comparison between 3 different channels. The following pseudo code is identical to the pattern matching condition:

```
FOR each subject
        IF result_channel_value == pattern_value
                Pattern Matches
        ELSE
                Compare next channel frequency
        END IF
END FOR
```

The classification stage is one of last step to process the brainwave signals for the purpose of personnel identification. In the classification phenomenon, input is taken as a features extracted in the previous stage of feature extraction. These features help to identify individual user on the basis of its occurring frequency. For the classification of EEG signals, neural network method is used by many of the researchers [14], [15]. Analysis of wavelet packet decomposition to do analysis of EEG Signals was capable to obtain the four brain measures: delta, beta, theta and alpha [16], [17].

IV. EXPERIMENTAL RESULTS

4.1 Decomposition results: Table 5 below is identical to the decomposition results obtained with the help of wavelet decomposition method.

TABLE 5. RESULT OF 8 LEVEL DECOMPOSITION METHOD

D1	D2	D3	D4	D5	D6	D7	D8
-564409	2488411	-2674859	253184	909242.2	-535135	-502746	37487.25
-193624	477995.5	-2410712	401575.6	883027	-612798	-498703	45352.96
2728899	-3164622	-1364787	539262	833288.7	-689294	-494244	53143.22
434345.5	-2931001	313487.3	655982.9	760767	-764086	-489370	60853.18
-6963656	2556489	2169462	742320.6	668358.8	-836850	-484096	68480.71
7527286	3865299	3143288	790934.4	561952.9	-907575	-478457	76027.99
-2993882	-1069830	2623703	795814	446230.1	-975985	-472474	83494.45
193604.1	-3099310	1078095	758162.5	324101.8	-1041482	-466154	90875.57
-99607.9	-596972	-883932	681921.3	197902.6	-1103274	-459495	98165.17
151079.1	887986.6	-2205425	572788.6	67423.61	-1160098	-452479	105352.2
317834.3	933648.6	-2078620	442276	-65884.6	-1210803	-445092	112427.1
-367838	815108.4	-1143024	305710.7	-195382	-1254815	-437353	119387.6
-38886.7	-174496	21015.39	185157.2	-315097	-1291338	-429270	126229.3
-272000	-810645	902633.5	112384.7	-419286	-1319413	-420846	132945.9
1111499	-169686	916979.1	108094.3	-502254	-1338323	-412089	139533.3
-865179	200685.6	568584.2	169476.5	-562610	-1347307	-402996	145984.3
-198868	-58115.6	251452.4	283173	-599064	-1345897	-393571	152294.2
297620.4	-12091.1	-83325.3	416332.7	-609465	-1334235	-383835	158463

4.2 Distance classification Matrix: Table 6 is presenting distance matrix calculated using pdist2 method.

TABLE 6. CALCULATED DISTANCE MATRIX

0	2068295	2640125	2454855	6449810	7151747	2936587	1979474	2831812	2039874	2011482	2495272
2068295	0	3842774	3252141	7101043	8132406	2952515	3045261	1773961	1100837	1169485	1629266
2640125	3842774	0	2539556	4363604	5183041	2518424	2635833	3786278	3653587	3489449	3454405
2454855	3252141	2539556	0	6799866	7698648	3939095	974892.6	2513955	2912282	2802034	2420507
6449810	7101043	4363604	6799866	0	1731409	4271711	6890632	7273576	7049334	6885137	6941514
7151747	8132406	5183041	7698648	1731409	0	5352995	7662285	8434490	8031803	7884562	8065754
2936587	2952515	2518424	3939095	4271711	5352995	0	3790774	3423222	2918486	2793433	3088171

1979474	3045261	2635833	974892.6	6890632	7662285	3790774	0	2516721	2505463	2429529	2349593
2831812	1773961	3786278	2513955	7273576	8434490	3423222	2516721	0	1365997	1294252	593384.7
2039874	1100837	3653587	2912282	7049334	8031803	2918486	2505463	1365997	0	256287.3	1130528
2011482	1169485	3489449	2802034	6885137	7884562	2793433	2429529	1294252	256287.3	0	964032.5
2495272	1629266	3454405	2420507	6941514	8065754	3088171	2349593	593384.7	1130528	964032.5	0

These feature data is identical to the single user which represents at which frequencies the values of which channel occur. In this project, we have done data collection of 10 subjects, 5 male and 5 female of which we collected 25 samples per subject and these samples are gathered in 5 different conditions in which subject is told to do the specific tasks. Features that are extracted are as shown in table 7 from which we have used combination of Gamma, Beta and Alpha specifically to identify the user.

TABLE 7. FEATURES EXTRACTED WITH THE HELP OF WAVELET TRANSFORM

	A Gamma Number	B Beta Number	C Alpha Number	D Theta Number	E Delta Number
1	Gamma	Beta	Alpha	Theta	Delta
2	0.7500	0.2500	0.1250	0.1250	0.1250
3	0.5000	0.2500	0.1250	0.1250	0.1250
4	0.6250	0.3750	0.2500	0.1250	0.1250
5	1	0.3750	0.2500	0.1250	0.1250
6	0.7500	0.3750	0.1250	0.1250	0.1250
7	0.7500	0.5000	0.1250	0.1250	0.1250
8	1	0.3750	0.2500	0.1250	0.1250
9	0.8750	0.2500	0.1250	0.1250	0.1250
10	0.7500	0.2500	0.1250	0.1250	0.1250
11	0.6250	0.2500	0.1250	0.1250	0.1250
12	0.6250	0.5000	0.1250	0.1250	0.1250
13	0.8750	0.2500	0.2500	0.1250	0.1250
14	0.6250	0.3750	0.1250	0.1250	0.1250
15	0.8750	0.2500	0.2500	0.1250	0.1250
16	0.7500	0.3750	0.1250	0.1250	0.1250
17	0.7500	0.3750	0.1250	0.1250	0.1250

Classification of these features gives approximately 90% accuracy with the help of wavelet transform.

TABLE 8. CALCULATED MSE

1.07911 e-1	2.35498 e-1	2.46657 e-1	2.42395 e-1	2.46066 e-1	2.42553 e-1	2.48119 e-1
2.34574 e-1	**1.23903 e-7**	2.42715 e-1	2.37534 e-1	2.38160 e-1	2.39790 e-1	2.46672 e-1
2.39306 e-1	2.47027 e-1	**1.72449 e-7**	2.36719 e-1	2.40079 e-1	2.44190 e-1	2.42206 e-1
2.41110 e-1	2.35279 e-1	2.42064 e-1	**1.46374 e-7**	2.33373 e-1	2.43262 e-1	2.47393 e-1
2.41272 e-1	2.42688 e-1	2.45017 e-1	2.57661 e-1	**1.54482 e-2**	2.43409 e-1	2.47966 e-1
2.40178 e-1	2.57547 e-1	2.43778 e-1	2.45851 e-1	2.42662 e-1	**1.04483 e-1**	2.49150 e-1
1.41854 e-1	1.41714 e-1	1.59264 e-1	1.42538 e-1	1.62645 e-1	1.68791 e-1	**1.78176 e-3**

The receiver operating characteristics is a metric used to check the quality of classifiers. For each class of classifier, threshold values across the interval [0, 1] are applied to outputs. For each threshold, two values are calculated, the True Positive Ratio and the False Positive Ratio as shown in fig. 3.

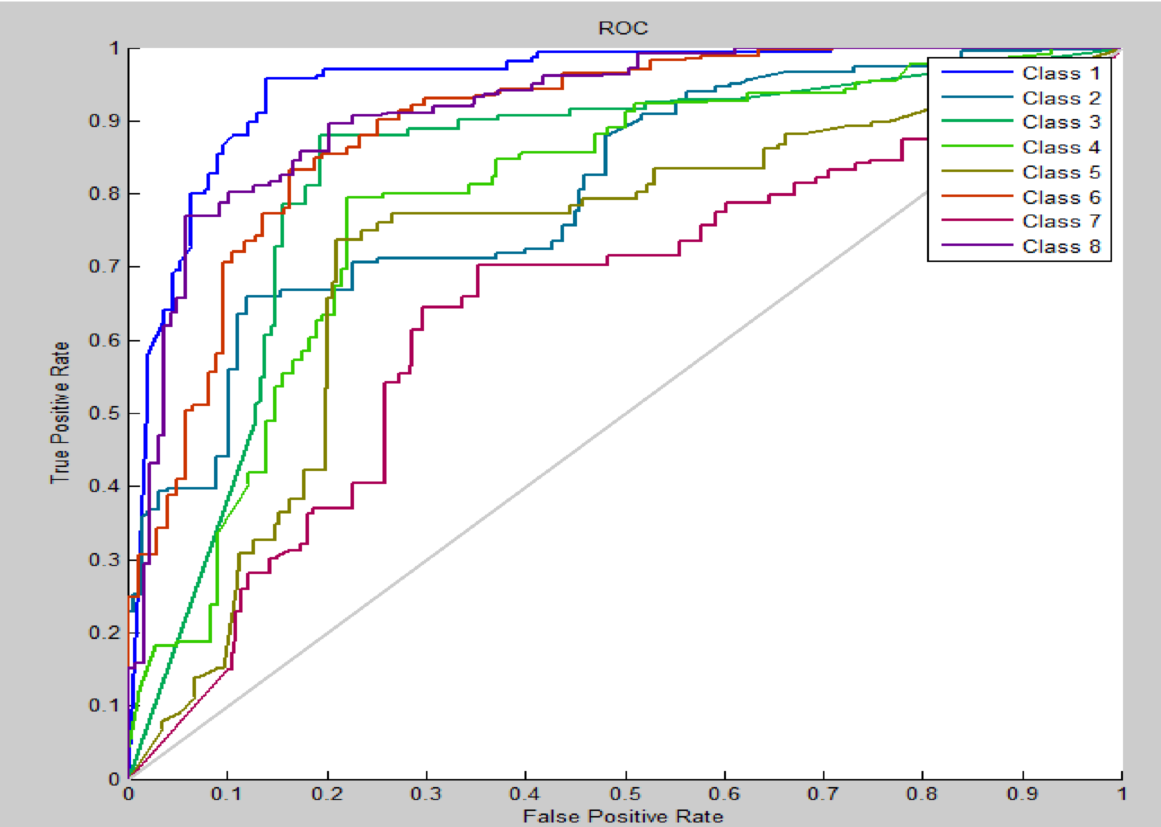

Fig 3. ROC

V. CONCLUSION

From the proposed techniques it is clarified that Electroencephalogram (EEG) signals are more secure and strong enough to identify and authenticate the individual. It provides powerful substantiation to be distinctive for an individual. As we know very well, each person has different capacities and the way of managing their brain activities. In accordance to the thoughts, brainwave signals occur at different frequency ranges for each and every second. Also the brainwave pattern for each signal wave band is different and variant. So that classification stage results in the more complicated task. It gives significant results to recognize the person based on its occurring frequencies of wavelength. Here we have developed a biometric technique, which emulates EEG signals as a biometric trait in making a personal identification , can be used to overcome limitations of typical biometrics. We have collected dataset of EEG for 10 subjects in which 5 male and 5 female subjects are involved. For every single user we got 5 samples at each of 5 conditions such as subject is in sleeping condition, subject is doing some mathematical calculations, etc. Data collection is done in the Multimodal Biometric Research Laboratory. Preprocessing on collected dataset is done with the wavelet transform for EEG data. Features are extracted for EEG signals using statistical dependencies in time domain analysis. Classification of the extracted features is done in MATLAB with the help of wavelet transform.

VI. ACKNOWLEDGMENT

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