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Performance Evaluation of Various Distance-based Data-Mining Classifiers on Typing Patterns for User Authentication / Identification

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Abstract:
User authentication or identification is the big challenges in E-Business. In this paper, we have implemented a typing biometric technique which increases the security level up to 98.1% without changing existing authentication technique. Habitual typing speed pattern is a behavioural biometric characteristic in Biometric Science can be effectively implemented to classify the users. This typing speed pattern is promising as biometric characteristics which cannot be lost or stolen in addition with inexpensive to collect. Many statistical, distance-based and machine learning algorithms are proposed on habitual typing pattern and many have obtained impressive results, but in practice, the accuracy level is not much promising, it demands higher level of security and reliability. In our experiment, we have collected press and release time of 12096 keystrokes using Java Applet programming form 12 individuals during 12 months in 4 sessions for 1440 samples then we analysed that data using R statistical programming language and obtained average Equal Error Rate (EER) of 21 different data-mining and distance-based classification algorithms and compared their performance in accuracy to search the suitable algorithms on typing patterns. But in evaluation process, a classifier's average Equal Error Rate (EER) widely jumped from 1.9% to 63%. The question may arise, which classifier is suitable on typing speed patterns, which pattern of string is suitable. To get the answer, we have started our experiment and created our own rhythmic keystroke dynamics database of different pattern of strings and executed various classification algorithms on it, so, we can compare their performance soundly.

Keywords: *Keystroke Dynamics, EER, Behavioral Biometric, Canberra , Chebyshev, Czekanowski, Gower, Intersection, Kulczynski, Lorentzian, Minkowski, Motyka, Ruzicka, Soergel, Sorensen, Wavehedges, Manhattan Distance, Euclidean Distance, Mahanobolis Distance, Z Score, KMean, SVM, NaiveBaysian, ROC Curve.*

1. Introduction

Knowledge-based user authentication technique is very popular for its simplicity characteristics and users are very comfortable on it. But today, passwords or PIN is not limited due to brute-force, shoulder surfing or key logger attack. It demands higher level of security keeping simplicity with giving better performance. Some common words, we press daily and we are habituated to press it in same rhythm which is unique, because of similar neuro-physiological factors that make written signature unique. This typing rhythm can be used in human identification / authentication.

Keystroke dynamics is a method of analysing the way a user types on a keyboard and classify the user based on their regular typing rhythm. Here, users are well-known by their typing style much like face prints, finger prints, voice prints, signature etc. It is very economic and cannot be lost or stolen in addition with it can be easily integrated in any existing knowledge-based user authentication with small alternation.

Our typing style can be easily calculated by simple key event program. In our experiment we have implemented Java Applet program to get the raw data of keystroke press and release timing pattern where get Time () function return the time of key press and release events. Then we have calculated the following features of keystroke dynamics: key hold time (KD), up-up key latency (UU), up-down key latency (UD), down-up key latency (DU), down-down key latency (DD), total time (ttime), tri-gap time (trigap), four-gap time (4gap) and total time (ttime).

Many external factors may affect the way of keystroke dynamics just like different type of keyboards. Human characteristics may change over time depending on mental state of the human or muscle pain, tiredness. Length of the string or PIN, which is used in authentication and type of that string, affects the way of regular typing rhythm. Position of the keyboard is also affect the way of typing style. In this technique, no extra security apparatus is needed to recognize the human. Here, keyboard is enough to recognize the human characteristics. It is cost effective and cannot be lost or stolen, if you watch it many times you never mimicry that pattern of typing style. It can be useful as a safe guard of password in any access control system. It can be used in cyber-criminal investigation, emotion recognition, age calculation, distance based examination and many more.
Keystroke dynamics as behavioral biometric characteristics is not new one. It is formally investigated by Bryan and Harted in 1897 as a part of study and skill gaining in telegraph operator. After that many researchers created keystroke database considering different pattern of texts or paragraphs taking different classification algorithms. Some of them obtained impressive results listed in the Table I.
We have collected press and release time of 12096 keystrokes of 1440 samples of patterns from 12 different individuals in 4 different sessions with minimum of one month interval for five different common words ("kolkata123", "facebook", "gmail.com", "yahoo.com", "123456") in our experiment. Then we have considered all 8 different features and combination of features then we have executed 8 different classifiers on that collected data. In our observation we got 2.4% of EER for the classifier OutlierCount (z-score) by taking all the features in our consideration. In second position NaïveBaysian classifier given 5.3% of EER when we have taken in our consideration all the features and all 4 strings ("kolkata123","facebook","gmail.com","yahoo.com"). So the adaptation of keystroke dynamics technique in any existing system increases the security level up to 94.7% to 96.6%.

2. Background Details

In 30+ years of ongoing research, many have obtained impressive results. But parameter to measure the performance in Biometric Science (EER) is widely varied because of considering the pattern of texts, length of the strings, number of subjects in the experiment, selection of features, classification algorithms etc. as the table given below.

Classification Methods	Features	EER	FAR	FRR
Likelihood ratio test [1]	Digraph		5%	5.50%
Mahalanobis distance [2]	Digraph		0%	50.00%
Minimum Distance Bayes [3]	Latency		2.80%	8.10%
Mean & Standard Deviation [4]	Digraph & Latency		0.25%	16.36%
K-Nearest Neighbour [5]		7.90%		
auto associative MLP [6]	Key Duration & Latency	1%	0%	1%
GA-SVM Wrapper feature subset [7]	Key Duration & Latency	0.81%	0%	3.69%
Distance-based Algo [8]	Latencies		1.89%	1.45%
Nearest Neighbour classifier, using Euclidean [9]	Latencies	.5-6.7%		
Fuzzy and Markov Mode [10]l	Key Duration & Latency	8.6-18.5%		
probabilistic neural networks, MLFN back-propagation [11]			0-0.4%	0-0.8%
Direction Similarity Measure (DSM) [12]	Key Duration & Latency	6.36%		
voting mechanism (of three closest distance) [13]	Key Duration & Latency	24.42%		
Direction Similarity Measure (DSM) [14]	Key Duration & Latencies	6.36%		
random forest [15]	Key Duration & Latencies		1.51%	
statistical measurement, measure of disorder, and Direction Similarity measure and combined [16]		8.22%		
k-nearest-neighbour [17]	Keystroke-stylometry	0.50%		
Support Vector Machine [18]	Key Duration & Latencies	15.28%		
Nearest Neighbour classifier, Gaussian Model and One class SVM [19]	Key Duration & Latency	11.83%		
Median Vector [20]		8.00%		
Euclidean Manhattan Mahanoboli Manhattan wt Standard Deviation [21]	Key Duration & Latencies	7%		
MLP [22]	Key Duration & Latencies	5%		
Principal Component Analysis & Neural Network [23]	Key Duration, Latencies & Total Time		6%	24%
GMM i-vector GMM-UBM DNN [24]		8.7% 6.2% 5.5% 3.5%		
Euclidean Manhattan [25]	Key Duration & Latencies	80% accuracy 70% accuracy		

Table 1: Background of keystroke dynamics

3. Definition of Data-mining Algorithms

We have defined all the algorithms, where P refers to the training set and Q refers to the test set. Mean and standard deviation is represented by μ and α respectively [26].

A. Canberra:

$$D_{car}=\sum_i^n \frac{|P_i-Q_i|}{P_i+Q_i} \quad (1)$$

B. Chebyshev:

$$D_{cheb}=\sum_i^n \max|P_i-Q_i| \quad (2)$$

C. Czekanowski:

$$D_{cze}=\frac{\sum_i^n \; |P_i-Q_i|}{\sum_i^n \; (P_i+Q_i)} \quad (3)$$

D. Gower:

$$D_{gow}=\frac{1}{n}\sum_i^n |P_i-Q_i| \quad (4)$$

E. Intersection:

$$D_{ins}=\frac{1}{2}\sum_i^n |P_i-Q_i| \quad (5)$$

F. Kulczynski:

$$D_{kuld}=\frac{\sum_i^n \; |P_i-Q_i|}{\sum_i^n \; min(P_i,Q_i)} \quad (6)$$

G. Kulczynskis:

$$D_{kuld}=\frac{\sum_i^n \; min(P_i,Q_i)}{\sum_i^n \; |P_i-Q_i|} \quad (7)$$

H. Lorentzian:

$$D_{lor}=\sum_i^n \ln(1+|P_i-Q_i|) \quad (8)$$

I. Minkowski:

$$D_{mink}=\sqrt[p]{\sum_i^n |P_i-Q_i|^p} \quad (9)$$

J. Motyka:

$$D_{mot}=\frac{\sum_i^n \; \max(P_i,)|}{\sum_i^n \; (P_i+Q_i)} \quad (10)$$

K. Ruzicka:

$$D_{ruz}=1-\frac{\sum_i^n \; min(P_i,Q_i)}{\sum_i^n \; max(P_i,Q_i)} \quad (11)$$

L. Soergel:

$$D_{soe}=\frac{\sum_i^n \; |P_i-Q_i|}{\sum_i^n \; max(P_i,Q_i)} \quad (12)$$

M. Sorensen:

$$D_{sor}=\frac{\sum_i^n \; |P_i-Q_i|}{\sum_i^n \; (P_i+Q_i)} \quad (13)$$

N. Wavehedges:

$$D_{wv}=\frac{\sum_i^n \; |P_i-Q_i|}{\sum_i^n \; max(P_i,Q_i)} \quad (14)$$

O. Manhattan Distance:

$$M=\sum_{i=1}^n (|P_i-Q_i|) \quad (15)$$

P. Scaled Manhattan Distance:

$$M=\sum_{i=1}^n (|P_i-Q_i|)/\alpha_i \quad (16)$$

Q. Euclidean Distance:

$$E=\sqrt[2]{\sum_i^n (|P_i-Q_i|)^2} \quad (17)$$

R. Mahanobolis Distance:

$$Eh=\sqrt[2]{\sum_i^n ((|P_i-Q_i|)/\alpha_i)^2} \quad (18)$$

S. Z Score:

$$Z=\sum_{i=1}^n (|P_i|-\mu(|Q_i|))/\alpha_i \quad (19)$$

4. Experimental results

We have implemented Java Applet program to collect the raw data of keystroke dynamics. We have collected press and release time of all keys for different pattern of texts ("kokata123", "facebook", "gmail.com", "yahoo.com", "123456") and extracted the features key duration, latency times of sequences of up and down keys. We have also collected the data from CMU database for the text ".tie5Roanl". Then we have used R Statistical programs to analyse the obtained results and evaluated and compared the performance.We have applied 21 classification algorithms on different pattern of texts and obtained average EERs. We have also applied all the algorithms on our collected database considering all 5 texts. The recorded results are in Table II (taking means of the samples) and Table III (taking medians of the samples). Obtained results are impressive when we choose 5 texts and an applied algorithm is Lorentzian in Table III.

Classification Algorithms	all 5 strings	"kolkata123"	"facebook"	"gmail.com"	"yahoo.com"	"123456"	".tie5Roanl" [15]
OutlierCount	**2.40**	**8.93**	**7.88**	**11.36**	**11.26**	**15.46**	**17.68**
Lorentzian	**4.36**	**12.31**	**10.16**	**12.34**	**16.10**	**15.44**	**32.11**
Canberra	7.07	12.22	11.52	12.31	16.73	14.05	36.98
ScaledManhattan	8.81	11.33	8.05	10.83	14.49	14.61	16.92
Czekanowski	12.91	16.48	16.76	18.40	19.67	17.99	40.72
Kulczynski	12.91	16.48	16.76	18.40	19.67	17.99	40.72
Kulczynskis	12.91	16.48	16.76	18.40	19.67	17.99	40.72
Motyka	12.91	16.48	16.76	18.40	19.67	17.99	40.72
Ruzicka	12.91	16.48	16.76	18.40	19.67	17.99	40.72
Soergel	12.91	16.48	16.76	18.40	19.67	17.99	40.72
Sorensen	12.91	16.48	16.76	18.34	19.67	17.99	40.57
Wavehedges	12.91	16.48	16.76	18.40	19.67	17.99	40.72
Cheby	14.36	15.56	15.81	16.60	20.27	17.86	32.38
Manhattan	14.36	15.56	15.81	16.60	20.27	17.86	32.38
SVM	18.21	15.06	11.40	14.27	16.82	16.16	17.03
KMeans	18.40	14.99	13.19	13.89	16.98	17.96	16.73
Euclidean	20.49	17.49	19.51	19.48	21.15	18.88	34.42
Minkowski	21.88	20.27	19.98	21.43	21.21	19.92	35.45
Mahalanobis	25.98	13.95	16.86	16.26	24.87	30.62	26.37
Gower	51.45	52.43	53.41	53.63	53.54	50.00	62.54
Intersection	57.89	61.62	51.80	52.53	51.99	54.39	39.68

Table 2: Average equal error RATE for all classification models taking Mean of samples

Classification Algorithms	all 5 strings	"kolkata123"	"facebook"	"gmail.com"	"yahoo.com"	"123456"	".tie5Roanl" [15]
Lorentzian	1.86	9.09	9.94	10.64	13.10	16.38	25.27
OutlierCount	2.33	9.85	9.97	13.42	12.15	16.30	17.12
Canberra	3.69	8.93	10.83	12.47	12.92	15.18	29.74
ScaledManhattan	8.87	11.77	9.75	11.90	14.74	17.61	15.45
Sorensen	11.33	14.36	14.61	15.88	19.26	18.53	30.72
Czekanowski	11.40	14.36	14.61	15.88	19.26	18.53	30.77
Kulczynski	11.40	14.36	14.61	15.88	19.26	18.53	30.77
Kulczynskis	11.40	14.36	14.61	15.88	19.26	18.53	30.77
Motyka	11.40	14.36	14.61	15.88	19.26	18.53	30.77
Ruzicka	11.40	14.36	14.61	15.88	19.26	18.53	30.77
Soergel	11.40	14.36	14.61	15.88	19.26	18.53	30.77
Wavehedges	11.40	14.36	14.61	15.88	19.26	18.53	30.77
Cheby	12.53	13.48	15.85	16.16	20.04	19.24	25.68
Manhattan	12.53	13.48	15.85	16.16	20.04	19.24	25.68
SVM	18.18	15.06	11.30	14.49	16.24	16.82	17.16
KMeans	18.40	15.21	13.19	13.89	16.98	17.96	16.62
Euclidean	22.82	16.00	18.88	19.07	22.38	20.20	29.11
Minkowski	23.99	18.78	19.07	22.89	21.40	20.49	31.99
Mahalanobis	26.17	15.40	16.29	16.32	26.77	31.72	26.77
Gower	51.36	52.56	53.25	53.82	53.25	49.94	62.32
Intersection	60.21	63.67	54.04	54.67	55.49	59.12	41.44

Table 3: Average equal error RATE for all classification modelstaking Median of samples

5. Evaluation and Analysis

After getting all the average EERs for different classification models, we analysed the results by R statistical programs and we observed that all the models are suitable to recognise the keystroke pattern except 2 to 4 classification models for different pattern of string, but Lorentzian model is the better where obtained results is 98.1% accurate.

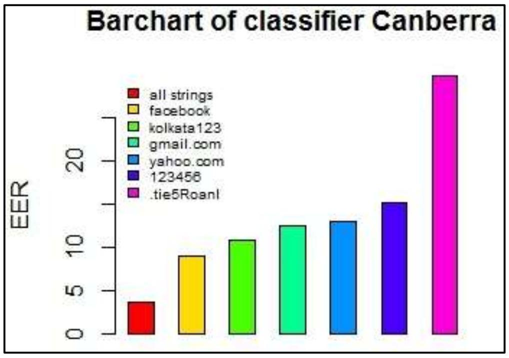

Figure 1: Barchart of the model Canberra for different pattern of texts

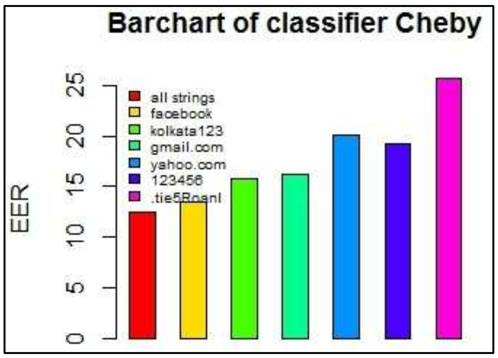

Figure 2: Barchart of the model Cheby for different pattern of texts

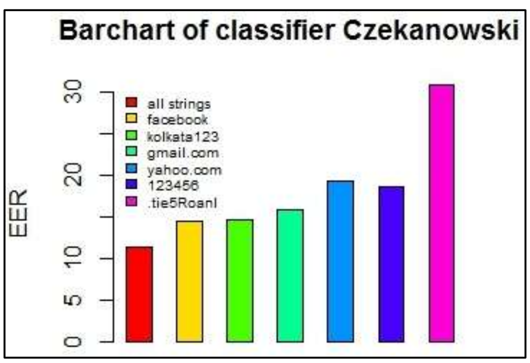

Figure 3: Barchart of the model Czekanowski for different pattern of texts

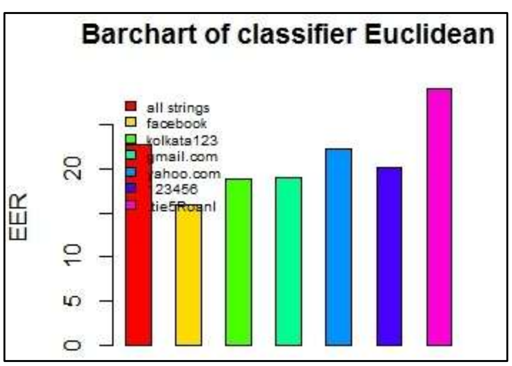

Figure 4: Barchart of the model Euclidean for different pattern of texts

Figure 5: Barchart of the model Gower for different pattern of texts

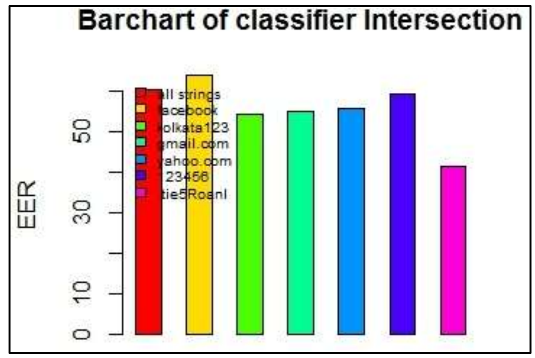

Figure 6: Barchart of the model Intersection for different pattern of texts

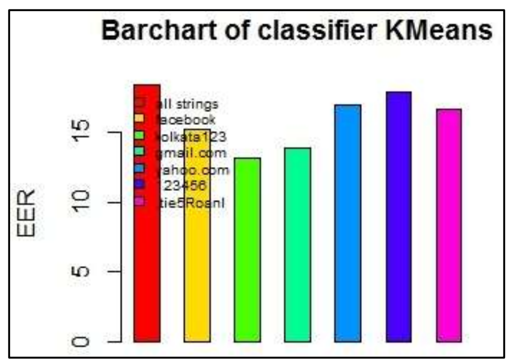

Figure 7: Barchart of the model KMeans for different pattern of texts

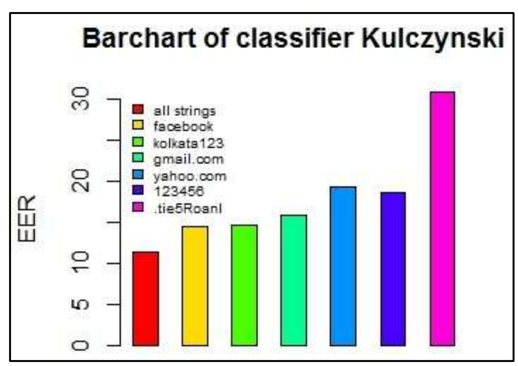

Figure 8: Barchart of the model Kulczynski for different pattern of texts

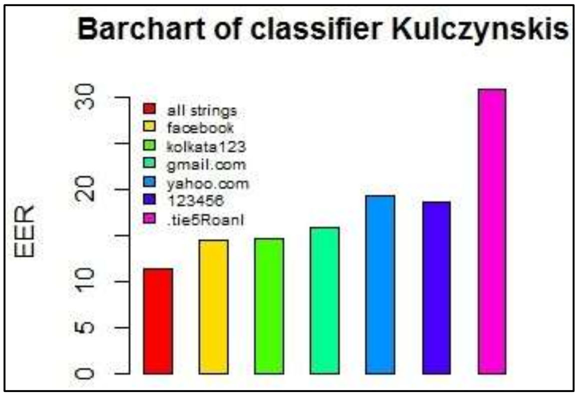

Figure 9: Barchart of the model Kulczynskis for different pattern of texts

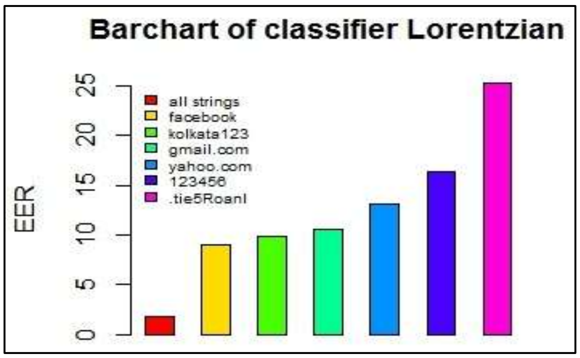

Figure 10: Barchart of the model Lorentzian for different pattern of texts

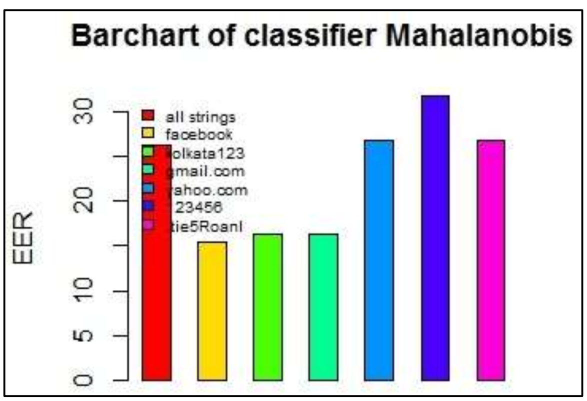

Figure 11: Barchart of the model Mahalanobis for different pattern of texts

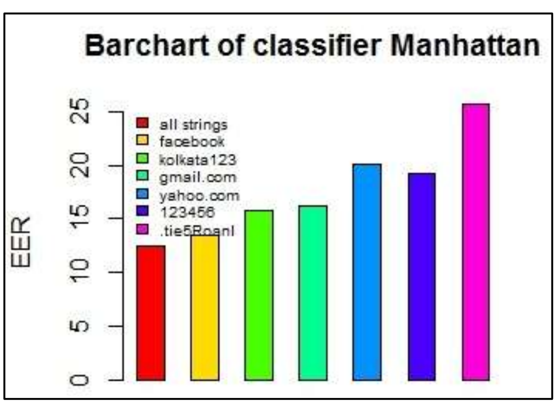

Figure 12: Barchart of the model Manhattan for different pattern of texts

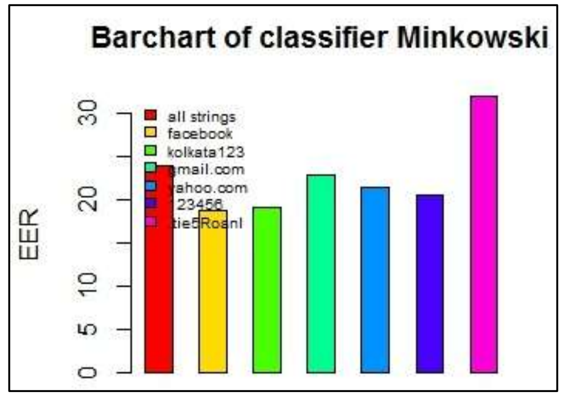

Figure 13: Barchart of the model Minkowski for different pattern of texts

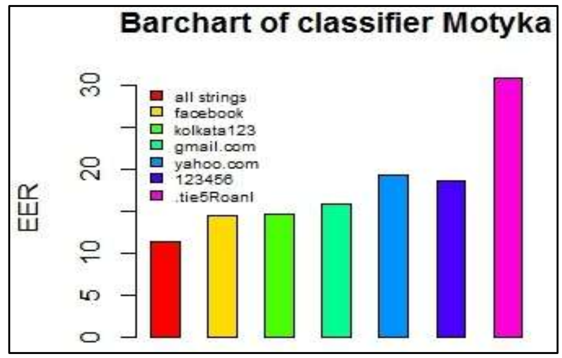

Figure 14: Barchart of the model Motyka for different pattern of texts

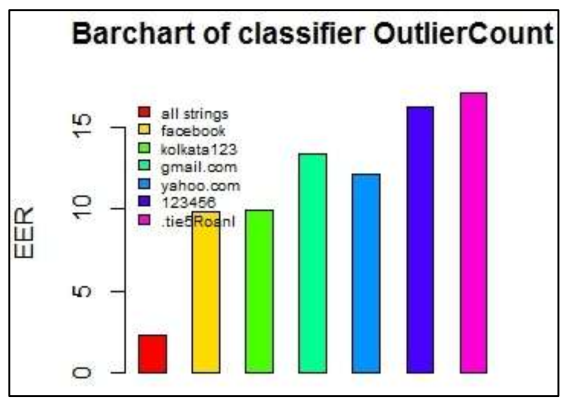

Figure 15: Barchart of the model OutlierCount for different pattern of texts

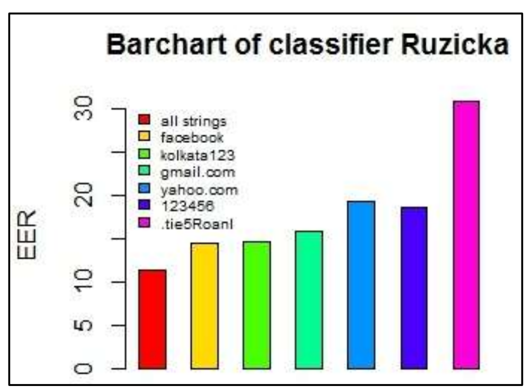

Figure 16: Barchart of the model Ruzicka for different pattern of texts

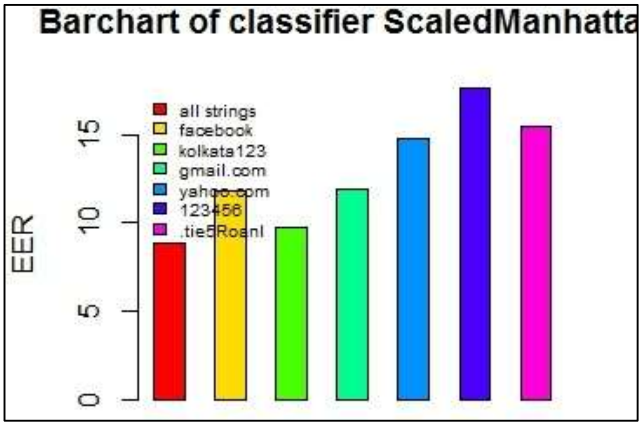

Figure 17: Barchart of the model ScaledManhattan for different pattern of texts

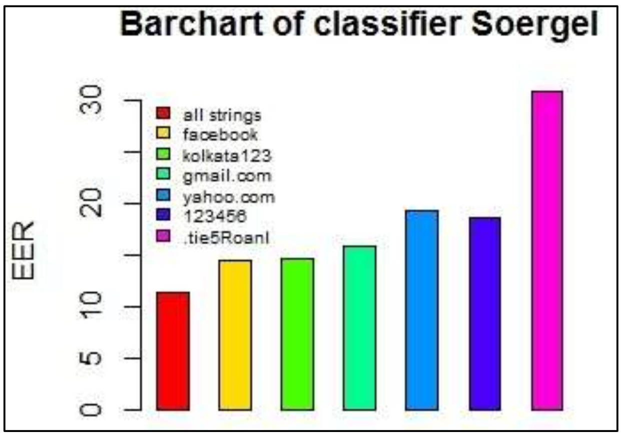

Figure 18: Barchart of the model Soergel for different pattern of texts

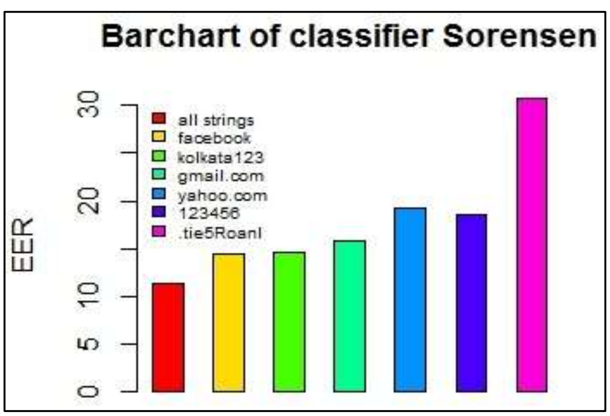

Figure 19: Barchart of the model Sorensen for different pattern of texts

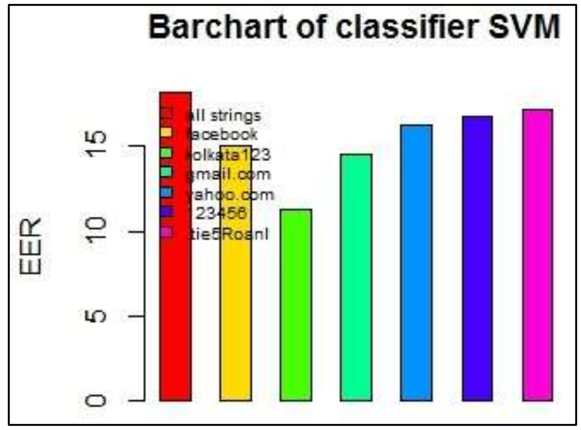

Figure 20: Barchart of the model SVM for different pattern of texts

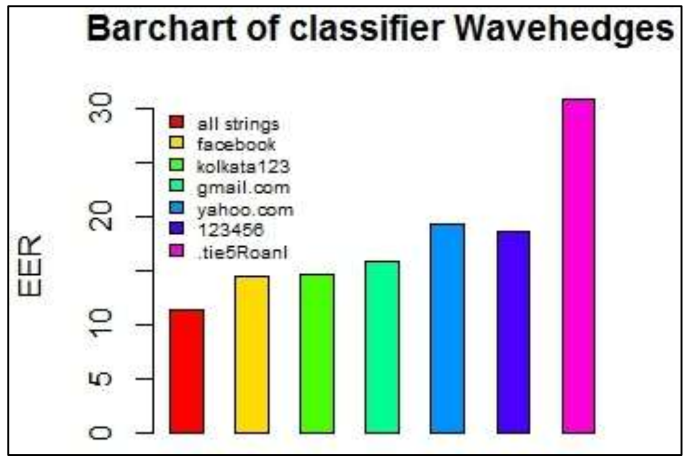

Figure 21: Barchart of the model Wavehedges for different pattern of texts

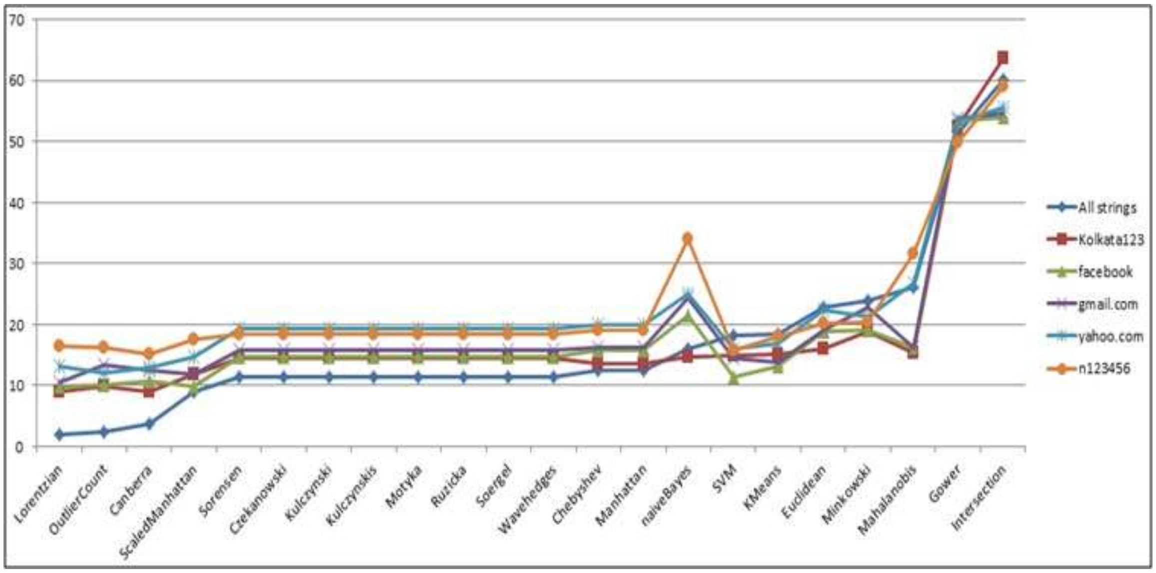

Figure 22: Linechart indicates the suitable pattern of text for different classifications

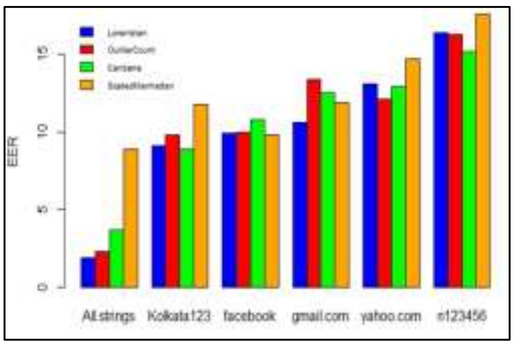

Figure 23: Best 4 classifications comparison

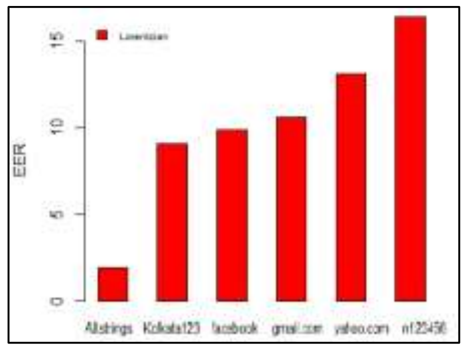

Figure 24: Best algorithms indicates the suitable pattern

Comparison of different classification algorithms and pattern of texts are represented by bar chart in the Figure 1 to 24. The observation of the obtained comparisons are some of the algorithms like Lorentizian, Outlier Count, Canberra and Scaled Manhattan are favourable compared to others where short size multiple of texts from common words are suitable than complex pattern of texts.

6. Conclusion

We have created database of keystroke pattern and also we have taken CMU dataset in our experiment to evaluate the performance of different classification algorithms on different pattern of texts and we achieved up to 98.1% of accurate result if we consider the daily used common multiple of texts as patterns of keystroke and Lorenzian, Ourlier Count, Canberra or Scaled Manhattan distance-based algorithm as classification technique we can achieve impressive results.

In literature, many researchers have obtained impressive results up to 100%. But in practice it is not possible where millions of imposters are involved and it is also not possible to type texts more than 100 times in each login session. But we can use it as safe guard of password or PIN since it is cost effective, non-sharable, easily integrated in any existing system.

Some affecting factors are emotional state of the user, keyboard type, position of keyboard and hand injuries which affect the way of Keystroke dynamics, where key pressures, areas of fingertip, finger movements are effective features also can be introduced where pressure sensitive keyboard is needed or android hand held touch screen device is effective.

7. Acknowledgment

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