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# EAgeBioS: Enhanced Biometric System to handle the Effects of Template Aging

**Sunil Kumar, Vijay Kumar Lamba, Surender Jangra**

***Abstract***: ***Biometric Systems are well-known security systems that can be used anywhere for authentication, authorization or any kind of security verifications. In biometric systems, the samples are trained first and then it can be used for testing in long runs. Many recent researches have shown that a biometric system may fail or get compromised because of the aging of the biometric templates. The fact that temporal duration affects the performance of the biometric system has shattered the belief that iris does not change over lifetime. This is also possible in the case of iris. So, the main focus of this work is to analyze the effect of aging and also to propose a new system that can deal with template aging. We have proposed a new iris recognition system with an image enhancement mechanism and different feature extraction mechanisms. In this work, three different features are extracted, which are then fused to be used as one. The full system is trained on a dataset of 2500 samples for the year 2008 and testing is done in three different phases (i) No-Lapse, (ii) 1-Year Lapse and (iii) 2-Year Lapse. A portion of the ND-Iris-Template-Aging dataset [11] is used with a period of three years lapse. Results show that the performance of the hybrid classifier AHyBrK [17] is improved as compared to KNN and ANN and the effect of aging in terms of degraded performance is clear. The performance of this system is measured in terms of False Rejection Rate, Error Rate, and Accuracy. The overall performance of AHyBrK is 51.04% and 52.98% better than KNN and ANN respectively in terms of False Rejection Rate and Error Rate whereas the accuracy of this proposed system is also improved by 5.52% and 6.04% as compared to KNN and ANN respectively. This proposed system also achieved high accuracy for all the test phases.***

***Keywords***: ***Template Aging, Hybrid Classifier, Feature Extraction, Feature Fusion, Quality Enhancement***

## I. INTRODUCTION

PINs and Passwords are obsolete methods of identification. Biometric Systems are in high demand for identification due to its unique and user-friendly security features. Nowadays, various government and private sectors like aviation, banking, defense, e-commerce, and many others are opting biometrics for authentication and identification purpose. The biometric-based systems provide high-end security because almost all the biometric modalities are unique, robust, and non-invasive. Some modalities have physiological characteristics like iris, face, fingerprint, etc. and others have behavioral characteristics like signature, gait, voice, etc. In every sense, biometric traits are secure as they are intrinsic characteristics of a person; they can't be lost or forgotten. Face and fingerprints are quite popular and are in advanced stages of commercialization while iris is most secure and robust and is in advanced stages of implementation currently. The iris as a biometric is used in several applications like border control, secure transactions, and safety measures in finance and defense areas [18]. Earlier it was believed that templates of biometric traits do not change with time but as the researchers working on these modalities, they have found valid reasons that templates do get aged with time and they have a negative effect on the performance of biometric recognition systems. Template aging is an emerging covariate that shows that aging is present in fingerprints, face, iris and other biometric templates. Biometric Systems are nowadays very popular in terms of security systems, identification systems, authentication system and many more. The acceptance of the biometric systems in the field of authentication reduces the risks of threats and attacks. Many researchers proposed a technology for securing different types of systems based on the biometric modalities. Like BioTAM [15], it is a biometric authentication system based on the technology acceptance model where fingerprint modality was used. This model adds trust to achieve better performance in terms of privacy, confidence, public willingness and security. In this, the trust factor was calculated as the mean value of public willingness and confidence. Alsultan et al. [2] proposed an authentication system for user authentication where dynamic free-text keystroke approach was used for the Arabic language. The use of the Arabic language is a novel concept in this work. In this work, keystroke features were extracted from the two consecutive keys and there were five different categories of these key-pair relationships and these relationships can fall in different locations of the keyboard. To test and analyze the performance of this proposed system, twenty-one different users participated and they are native Arabic language speakers. For experimentation MATLAB® was used. We prove that this model is successful for the authentication of users on their typing for the Arabic language. The characterization of biometric template aging in fingerprints was studied by Harvey et al. [13]. Uludag et al. [30] presented a case study on template aging in fingerprints. Browning et al. [5] and Gonzalez et al. [28] studied and analyzed the effects of template aging on iris recognition.

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The other example of a biometric-based authentication system is a system that was proposed by Muley and Kute [22] for bank cards that is ATM Cards using Fingerprint. In this recognition system, fingerprint modality was used and minutiae features were extracted for matching purposes.
Similarly, a biometric security system using fingerprint modality was also proposed for Mobile Template protection by Yang et al. [31]. Telgad et al. [27] also proposed a security system using iris, fingerprint, and face modalities. All these systems provide an efficient privilege and this will increase the demand of the biometric systems for security. The performance of the different modalities was analyzed by Sabhanayagam et al. [26] and is given in Table 1.

**Table 1: Performance Analysis of Different Modalities [26]**

| Modalities | Measures | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Socially Introduced | Popularity | Safety | Speed | Cost | Accuracy | Stability | Ease of use |
| Iris | 1995 | M | H | M | H | H | M | M |
| Fingerprint | 1981 | H | M | H | L | M | H | H |
| Hand Geometry | 1986 | L | M | H | H | M | M | H |
| Face | 2000 | H | M | M | M | L | M | H |
| Voice | 1998 | H | H | H | L | L | M | H |
| Signature | 1970 | H | H | H | M | M | M | H |
| Keystroke | 2005 | L | L | M | M | L | L | L |

Table 1 shows that both the accuracy and safety are high in case of iris modality, however, its cost is also high but it does not affect the system because cost factor can be compromised if accuracy and factor will be high. This is the reason that iris modality is widely accepted by various organizations for security and identification systems. In Table 1, L is Low, M is Medium, and H is High.
In this era of technology, the systems with high accuracy of recognition are greeted to provide auxiliary preservation and are admired by various organizations and technologies. The systems with iris modalities have been used eminently but a lot of challenges are faced during its usage. These issues need to be handled and rectified for the development of efficient and secure biometric systems. In this paper, the effect of the template aging on the iris template is discussed and an enhanced biometric system is proposed to handle this issue and to achieve high recognition accuracy. For this, a dataset of 3 years is used for analysis. The next section of this paper will discuss the effect of template aging on iris-based biometric systems. Further, the design of the proposed system will also be described along with simulations and results.

## II. EFFECT OF TEMPLATE AGING ON IRIS BASED BIOMETRIC SYSTEMS

Biometric technologies overtook the traditional methods that were dealing with the problems of security, and different modalities are nowadays used for security purposes as discussed in the previous section. Some of the factors of the different modalities are also discussed in the previous section from where we come to know that the iris modality is widely accepted for security and authentication. Different challenges have been tackled by researchers while the use of the iris recognition system increases. One of the main challenges is Template Aging, which was not expected as a challenge for a long time because it was a belief that the features of the iris are stable for a lifetime of a human being [9] which was proved wrong by many researchers in their recent researches. Baker et al. [3] done the experimentation for the first time to analyze the degradation in match-score for Iris Template with increased time-lapse. They collected a dataset of images with 4 years' time-lapse that is 2004-2008 from 13 persons. Each person contributed 2 images and these images were acquired using LG 2200. They collected 6 samples at one time and select only 2 from them that have high quality. They analyzed performance by conducting experiments and comparing two different matches, (a) recognition/matching of the two images that are collected in the same semester but not on the same day and (b) matches between one image from 2004 and one from 2008. Experimentations conclude that there was a drastic increase in false rejection rate and that is about 75% when images were taken with a long-time-lapse. So, it is clear from the investigation that "one enrolment for protection" is not sufficient for iris-based recognition systems. Research was not stopped here for the collection of evidence on the effect of aging on Iris templates. Fenker and Bowyer [10, 11] along with Baker et al. [3] and Bowyer et al. [4] studied the template aging effect and analyzed the performance taking different duration gaps into consideration. For this, they used two different iris recognition algorithms along with a larger number of subjects and a more advanced imaging system (LG 4000) over a shorter time-lapse of 2 years. They analyzed the performance on different controlling factors like difference in pupil dilation between compared images and the presence of contact lenses. Authors again investigated on the same factor but with a large dataset and increased time-lapse time [11]. They found the evidence for the effect of template aging and concluded that the changes will be visible at one year and increases with an increase in time. In this analysis, they had noticed that more than 50% of false matches were found with two years' time-lapse whereas near about 150% with three years lapse as investigated [12].
Trokielewicz et al. [29] did a linear regression analysis of the iris template aging on 29 regression models.
To analyze the effect of aging and the other factors that change the iris template, Mehrotra et al. [21] also did experiments with the "ND-Iris-TemplateAging-2008–2010" and ND-TimeLapseIris-2012" datasets which are publicly available. For matching, they used VeriEye [23] which is a commercial matcher. To know the effects of changes, they performed their experimentation with these datasets in the presence of different covariates like noise, pupil dilation, blur, and occlusion. They observed that the performance of the iris recognition systems was not degraded only because of aging but also because of the presence of various other factors.

These are the few works that were done for iris-based recognition system that analyzed the effect of the aging on the performance of the system and all the works proofed that performance degraded with a large time-lapse. So, there is a need to develop an efficient framework that can deal with aging and improve the recognition rate because iris-based recognition systems are required due to its better performance with respect to security.

Komogortsev et al. [16] found with different experiments that the aging effects are evident as early as two weeks after initial template collection, with an average 28% increase in equal error rates and 34% reduction in rank-1 identification rates. At seven months, they observed an average 18% increase in equal error rates and a 44% reduction in rank-1 identification rates. The comparative results at two-weeks and seven-months suggested that there is little difference in aging effects between the two intervals; however, whether the rate of decay increases more drastically in the long-term remains to be seen.

Mamdouhi et al. [20] provided a solution for the extraction of the features of Iris Patterns and its classification based on neural network and achieves 95% in normal conditions whereas accuracy decreased in noisy conditions and it is 88%.

Carls et al. [6, 7] presented a match score analysis model for the facial template aging system with different methods of modeling. They used datasets that are publicly available and these databases are ND 'B' and MORPH. Prediction Estimation is done by using a linear approach along with Error Score Matrix (ESMs) and this can be further used for training and prediction purpose and the rest is used for Template Renewal Prediction Algorithm (TRPA) for Decay Error Estimation (DE). Next Error Score can be analyzed using this DE and Template renewal can be determined that provides a baseline towards achieving an optimum solution to minimize resources and system utilization.

Lantis et al. [19] have done a survey on the aging effect to identify the performance of biometric authentication systems and determines that it is affected by the variations in the template because of aging. He discussed the effect of aging on different biometric traits and on its different features and also discussed the need for the elimination of this in the form of the renewal of the template. He suggested that the modern machine learning algorithm can help to reduce this effect on the recognition systems.

Another work to analyze the effect of aging on the biometric template was done by Ryu et al. [25]. They used fingerprint samples from the KFRIA database for their research work. They said that variation in the sample can also be the part of aging and to cope up with these different matrices and block measures can be utilized.

Johnson et al. [14] studied the impact of aging on the dataset of young children. They evaluated their mechanism on the sample from 12 months gap and concluded that a child's iris does not change significantly in the span of one year.

This work is to propose an enhanced biometric system that can deal with the iris template aging and improve the recognition rate. The motivation to work on this field comes because of the lack of research work done in this field and also the work which was already done they had just analyzed the performance of the existed systems. The other most important motivation is the requirement of the authentication systems based on biometric templates like iris as iris has a high recognition system.

## III. PROPOSED BIOMETRIC SYSTEM

This Iris based Biometric system is proposed to reduces the effect of template aging which was the major cause of the reduction in the accuracy of the recognition system while used for the samples with large time-lapse. Due to this, no one can rely on the recognition systems for the long term. To cope up with this problem, this recognition system is proposed where firstly samples are enhanced to provide the qualitative sample that can help to remove some of the unwanted factors and helps to improve the samples before segmentation. Then after the segmentation, different features of each segmented part will be extracted and then fused together to generate a large set of features which further classified using different classifiers. The performance of the classifiers is analyzed and then a hybrid classifier is generated with the combination of two different classification schemes which will improve the accuracy/ recognition rate for the proposed system.

The methodology followed in this proposed work is explained as follows:

***Step-1: Data Acquisition***

This is the first step where data is collected from different sources to perform analysis. For this work, a dataset of ND-Iris-Template-Aging [8] is used with a period of three years lapse. This dataset contains samples with short and long time-lapse with three different years 2008, 2009 and 2010. Samples have the same number of matches for all time-lapses like 2008-2009, 2009-2010 and 2008-2010. We have tested this proposed system using 500 samples from this database for training and 5 different matches in long and short time-lapse for testing. Experimentation is performed using MATLAB using the following steps.

***Step 2: Image Enhancement and Segmentation***

It is an important step in the field of digital image processing and also in the recognition systems because this helps in reducing the other interferences which might become the cause for degraded performance. In this proposed system different step are followed for enhancement and segmentation [24] as shown in fig. 1 and described below:

**2D finite impulse response (FIR) filter:**

Filters are used to remove the noise from the images because noise also becomes the cause of poor performance. So, in this work, a 2D-FIR Filter is used that is a spatial domain method that helps to remove the noise and improve the quality of the image. This step is important because noise can also affect the segmentation step which is an important step of the recognition system.

**Illumination Removal:**

Illumination means the effect of light on the image and generally, the bright pixels of the samples have value in the range of 240-255. This also affects the performance of segmentation and its removal is important. So, in this work to provide quality samples at the segmentation phase, default illumination removal function from MATLAB® is used which only works on binary image and converts 0's to 1's and 1's to 0's.

**Logarithmic and Power Law Transformation:**
To reduce the contrast of the brighter regions, Logarithmic Transformation (LT) is used in this work. This can also help to remove the other external elements like eyebrow, part of eyelid and sclera. Power Law Transformation (PLT) is used to enhance the contrast of the brighter regions to correctly identify the region of interest.

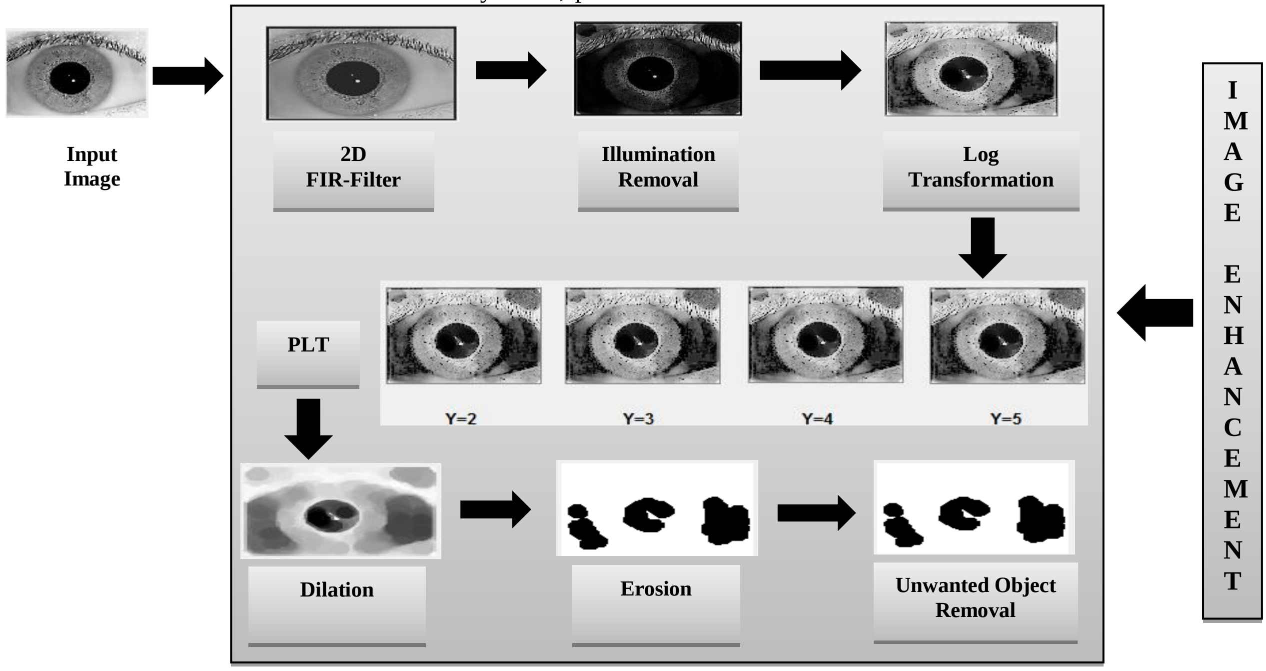


**Fig 1: Image Enhancement**

**Dilation and Erosion:**
This step helps to remove the pixels from boundaries like in this work it is used to remove the eyebrows from the black and white Iris sample after the above steps.

**Removal of unwanted object:**
Opening operation is used to remove the unwanted objects which still exist after the implementation of the above steps. It finds the connected components and removes the components having a value less than the threshold.

**Segmentation:**
The above-obtained image is segmented further and used as a mask to remove the unwanted regions of the images.

***Step3: Feature Extraction and Fusion***
Feature Extraction is an important step in the Iris Recognition System because it helps to extract the important components from the sample which further used to recognize the identity of the sample. In this work, three different feature extraction techniques have been utilized and then all the features will have fused together and treated as one feature set. This will increase the protection means reduces false acceptance. The feature extraction techniques that are used in this work are given below:

**Histograms of Oriented Gradients (HOG):**
In this feature extraction mechanism, an input image is divided and formed square cells and these are the intensity gradients that are used to represent the object within an image. These histograms are then compiled and represent the descriptors in each direction. Furthermore, normalization is performed with the computation of intensity of a larger region of the image and is called a block and then normalization is performed within that block. This improves the accuracy of the system. Window Size, Block Size and Cell size for HOG is 64x128, 16x16 and 8x8 respectively.

**Grey Level Co-Occurrence Matrix (GLCM):**
This method is very much familiar with the extraction of features from the patters and generally the texture features. These are the statistical features that are defined in terms of contrast, correlation, energy and many more. There are a total of 22 statistical features that are extracted in this work.

**Local Binary Pattern (LBP):**
This approach is very efficient and also very simple. In this, pixels are labeled using the threshold of the neighbor pixels and provide binary values. This approach can also have the ability to control the changes in the greyscale images.
After the extraction of all the features, it is then normalized and combined in a single matrix. This fusion is done using the SUM method and formed an output feature vector.

***Step 4: Classification***
Classification is an important step for the recognition system which defines the accuracy of the system. Classifiers are the one which helps to recognize or classify the data and find out whether it belongs to the input or not. There are a number of classifiers which are used for classification purpose in various fields with good performances. These days with advancing mechanisms, classifiers are also fused with each other for more enhanced performance. In this work, we proposed a hybrid classifier using KNN and ANN and named as AHyBrK Classifier [17].

***AHyBrK Classifier***
In this work, Hybrid Classifier is used and named as AHyBrK Classifier. This classifier is a combination of two base classifiers i.e., K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN).

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In this, ANN is based on the principle of the human brain where neurons and dendrites make a connection and make the decision on the questions asked.
Similarly, the ANN classifier decides whether the input passed to it produces output or not. This classifier is composed of a number of nodes where each node is linked with each other to produce output.
These links which connect the nodes are associated with weights. In this, the input data is taken by the nodes and performs an operation on it then further this output will be passed to other neurons/nodes and forms some output. This classifier work in the same way that the human brain works and the output generated at each node is known as its activation value. ANN follows the procedure of learning and is capable to change the behavior of processing on the basis of its knowledge. The Other Classifier i.e., KNN is a very simple method [1] that classifies objects under supervision. The implementation of the KNN classifier is very simple and also provides efficient results. The basic concept working behind this classifier is to deal with the neighbor value from its entire feature space. Moreover, it doesn't work on the assumptions of the probability distribution for different variables, so it is also known as non-parametric statistics. For KNN, its output is considered as membership of the class and the classification of the objects is dependent on its neighbor. If for any $k^{th}$ neighbor, the value of k is equal to 1, it means that the object belongs to only one neighbor class. For this work, first inputs will pass to the ANN and after processing the output of ANN is passed to KNN where it is treated as an input for KNN and after this, the generated output is a final result.

## IV. EXPERIMENTATION AND RESULT ANALYSIS

The proposed system will be examined to test the effect of aging on the samples. For this analysis, the dataset of 2500 samples are trained with this proposed system and then for testing purpose we divided the system into three different phases with no-lapse, Short-Time-lapse, and Long-Time-lapse. The measurement of the effectiveness of the biometric system cannot be achieved with a single value, but some parameters are there which defines the accuracy under the same data with the same set of rules. Some of these parameters are False Acceptance Rate (FAR), False Rejection Rate (FRR), Error rate, Accuracy, etc.
***FAR:*** It is the probability of the fake users that are accepted accidentally and this can be calculated as the ratio of a number of imposters who were able to enter the system to the total no. of imposters.

$$FAR = \frac{FA}{FA + TR}$$

***FRR:*** It is the probability of the valid users that are denied accidentally and this can be calculated as the ratio of the falsely rejected and the truly accepted (TA) samples.

$$FRR = \frac{FR}{FR + TA}$$

The performance of the classification system determines the effectiveness of the system and it can be measured in terms of Error Rate and Accuracy. The ratio of the number of misclassified samples and the total no. of images in the test set is defined as Error Rate whereas accuracy is the percentage of the correctly classified samples and is opposite to error rate.

$$Error\ Rate = \frac{misclassified\ samples}{Total\ Samples} * 100$$

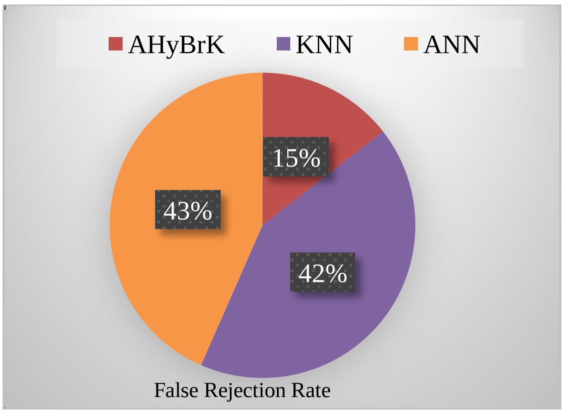
$$Accuracy = 100 - Error\ Rate$$

Table 2 describes the results achieved with the simulation of different phases. In this work, no forged sample is used because the main focus of this work is to measure the effect of aging.

**Table 2: Results using Different Parameters (using AHyBrK)**

| Parameters | Test Phase-1 | Test Phase-2 | | Test Phase-3 |
|---|---|---|---|---|
| | 2008-2008 | 2008-2009 | 2009-2010 | 2008-2010 |
| FAR | 0 | 0 | 0 | 0 |
| FRR | 0.027 | 0.048 | 0.057 | 0.067 |
| Error Rate | 2.68% | 4.84% | 5.72% | 6.72% |
| Accuracy | 97.32% | 95.16% | 94.28% | 93.28% |

Results show that the False Acceptance Rate is '0' because no forged samples are used in this wok. The values of FRR, Error Rate and Accuracy are calculated with the Hybrid Classifier as shown in Table 2. The individual analyses of all the test phases are given below:
***Test Phase 1:*** Testing dataset is the same as the training dataset means all 2500 samples are taken as test dataset with which this system was already trained. The results are calculated in terms of different parameters and using three different classifiers. As shown in Table 2, FAR is 0 in the case of the AHyBrK classifier similarly in the case of KNN and ANN individually it stays zero. The other calculated parameters are:

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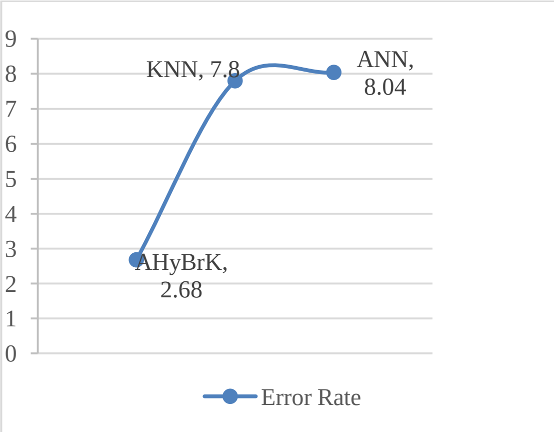
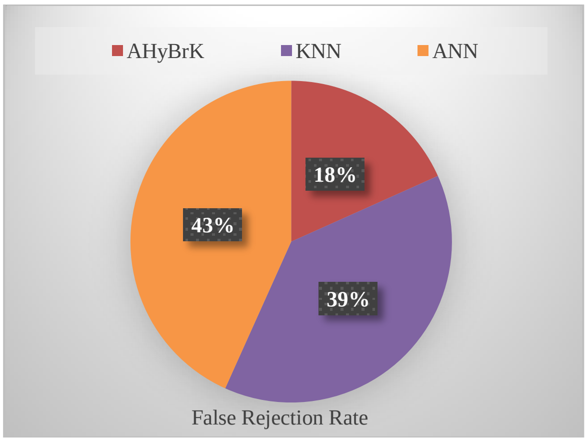


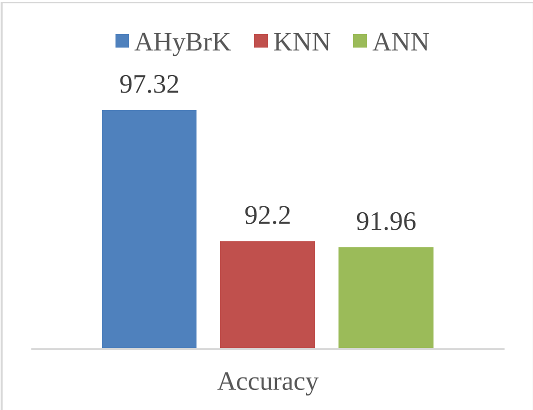
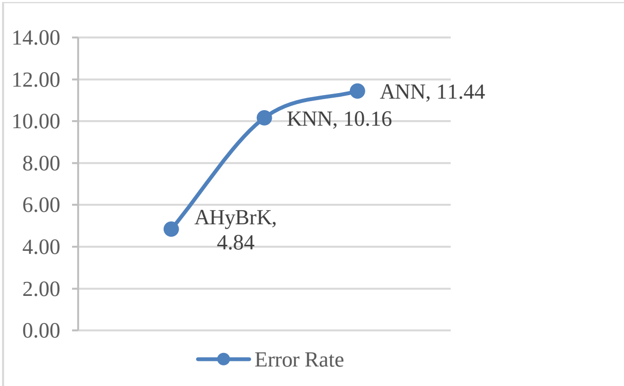




**Fig. 2: Parameter Calculation for Test Phase 1 (a) FRR, (b) Error Rate, (c) Accuracy**

Results in Fig 2 shows that the performance of this proposed AHyBrK classifier is better than both KNN and ANN. In terms of FRR and Error Rate, AHyBrK performed 65% better than KNN and 66% better than ANN whereas in terms of accuracy its performance is improved by 5.2% from KNN and 5.5% from ANN. It means the performance of ANN is poor than KNN and hence its combination resolves the deficiencies of ANN and enhanced its performance.

***Test Phase 2:*** Testing with a Short-Time-lapse where testing dataset is taken from the years 2009 and 2010. In this, the size of the test dataset is 500x5 for each time-lapse. It means testing is done using a total of 5000 samples for this phase. This phase works into two sub-phases:

***Test Phase 2.1****:* In the first sub-phase data samples of the year 2008 are used as a training dataset and 2009 as a test dataset. The results are calculated in terms of different parameters and using three different classifiers. As shown in Table 2, FAR is 0 in the case of the AHyBrK classifier similarly in the case of KNN and ANN individually it stays zero. The other calculated parameters are:



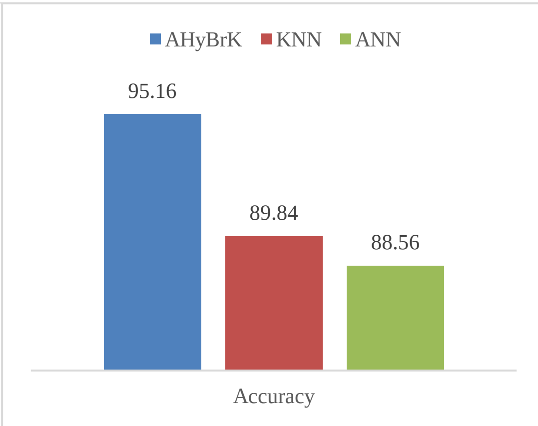




**Fig. 3: Parameter Calculation for Test Phase 2.1 (a) FRR, (b) Error Rate, (c) Accuracy**

Results in Fig 3 are calculated on Short-Term-Lapse and it is identified that the performance of the proposed AHyBrK classifier is improved with the combination of KNN and ANN. In terms of FRR and Error Rate, AHyBrK performed 52% better than KNN and 57% better than ANN whereas in terms of accuracy its performance is improved by 5.5% from KNN and 6.9% from ANN.

***Test Phase 2.2****:* In the second sub-phase, data samples of the year 2009 are used as a training dataset and 2010 as a test dataset. The results are calculated in terms of different parameters and using three different classifiers. As shown in Table 2, FAR is 0 in the case of the AHyBrK classifier similarly in the case of KNN and ANN individually it stays zero. The other calculated parameters are:

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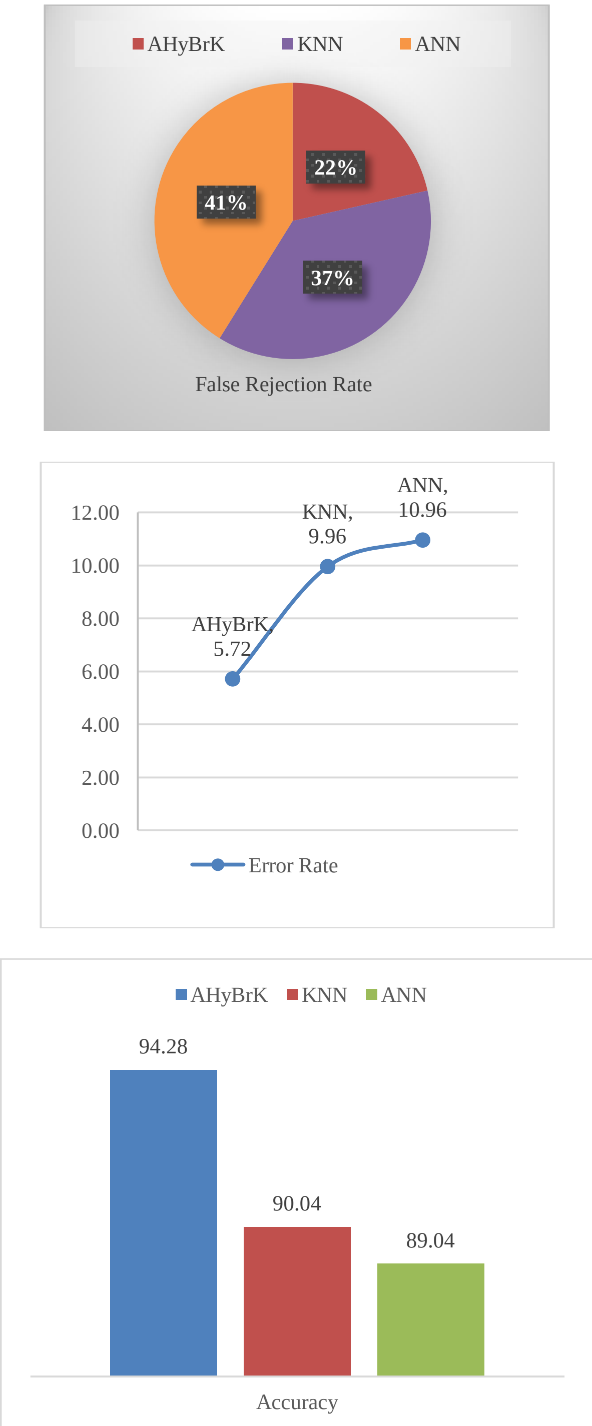


**Fig. 4: Parameter Calculation for Test Phase 2.2 (a) FRR, (b) Error Rate, (c) Accuracy**

Results in Fig 4 shows that in the case of Short-Term-Lapse where the dataset of 2009 is used for training and testing is done on the dataset of 2010, the performance of this proposed AHyBrK classifier is better than both KNN and ANN. In terms of FRR and Error Rate, AHyBrK performed 42% better than KNN and 47.8% better than ANN whereas in terms of accuracy its performance is improved by 4.4% from KNN and 5.5% from ANN. It means the performance of ANN is lesser than KNN and when both of these classifiers are combined and form a new AHyBrK classifier, it resolves the deficiencies of ANN by using KNN and improved its performance.

***Test Phase 3***: Testing with a Long-Time-lapse where the testing dataset is taken from the year 2010. In this, the size of the test dataset is 500x5 from samples of the year 2010 and it means here testing is done using 2500 samples in total. The results are calculated in terms of different parameters and using three different classifiers. As shown in Table 2, the False Acceptance Rate is zero in the case of all three classifiers that are AHyBrK, KNN, and ANN. The performance of the proposed classifier and other classifier is calculated in terms of different parameters given below:

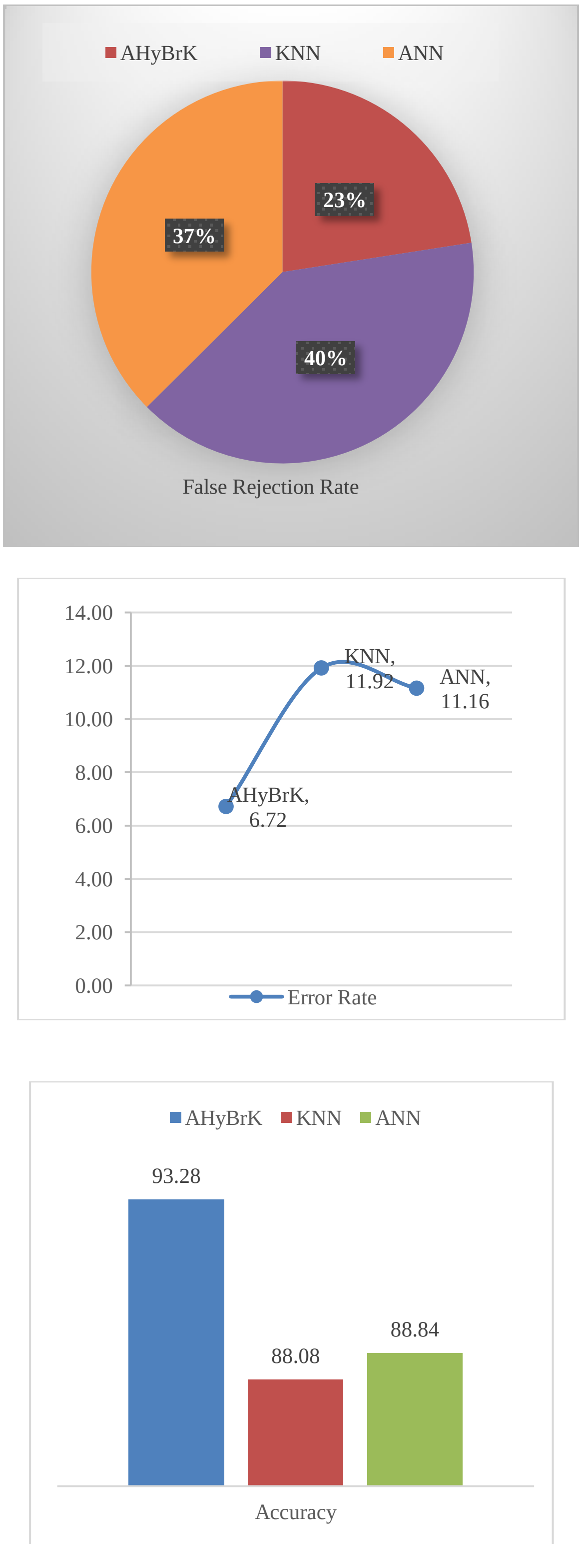


**Fig. 5: Parameter Calculation for Test Phase 3 (a) FRR,**

**(b) Error Rate, (c) Accuracy**

Results in Fig 5 shows that in the case of Long-Term-Lapse where the dataset of 2008 is used for training and testing is done on the dataset of 2010 means 2-year lapse, the performance of this proposed AHyBrK classifier is better than both KNN and ANN. In terms of FRR and Error Rate, AHyBrK performed 43.6% better than KNN and 39.7% better than ANN whereas in terms of accuracy its performance is improved by 5.5% from KNN and 4.7% from ANN. It means the performance of hybrid Classifier i.e. AHyBrK classifier is more than KNN and ANN both and it removes all the deficiencies of ANN by using KNN.

The overall performance of the hybrid classifier (AHyByK) with KNN and ANN are given below.

**False Rejection Rate:** In this work, experimentation is done in three different phases and for all phases, the performance of the AHyBrK is better than KNN and ANN. For Test Phase-1 where the same training and testing dataset is used, the performance is 65.64% better than KNN and 66.66% better than ANN. The performance of this is degraded in the next test phases because of aging but still, it is better than KNN and ANN. Results conclude that in a one year time-lapse, FRR is on an average 47.46% better than KNN and 52.75% better than ANN but in the case of two years time-lapse, FRR is 43.62% and 39.78% better than KNN and ANN respectively. Figure 5 shows that FRR is increased with increasing time-lapse and this shows that the effect of the template aging on the recognition system.

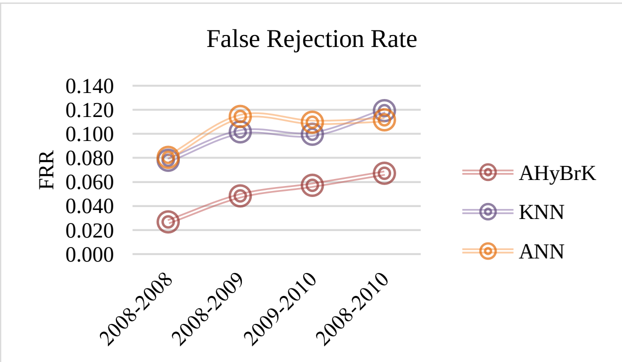


**Fig. 6: False Rejection Rate**

**Error Rate:** With the Experimentation, it is clear that the error rate is similar to the False Rejection Rate because there is no sample that is falsely accepted. So, improvement in the error rate is the same as FRR. Figure 7 shows that Error Rate is increased with increasing time-lapse and this shows that the effect of the template aging on the recognition system.

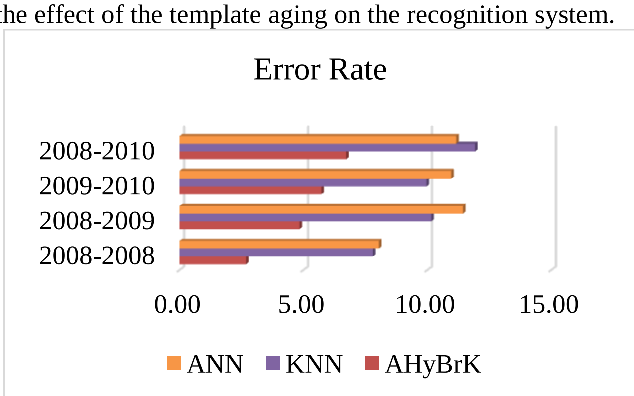


**Fig. 7: Error Rate**

**Accuracy:** Accuracy is the main parameter that tells the performance of the system. The system with high accuracy defines that its recognition rate is good and can be used in different fields. In this, as experimentation is done in three different phases along with three different classifiers, so, the comparison is done between classifiers where it is analyzed that the performance of the hybrid classifier is better than the individual classifiers as shown in fig. 8. On average, for all three phases, the performance of the hybrid classifier (AHyBrK) is better than KNN and ANN with 5.5% and 6.04% respectively. Also, it is analyzed that the accuracy decreases with increasing time lapse. For instance, Accuracy of the AHyBrK is decreased with the rate of 2.2% when time-lapse is increased by one year and it is around 4.15% decreases when time-lapse is for two years.

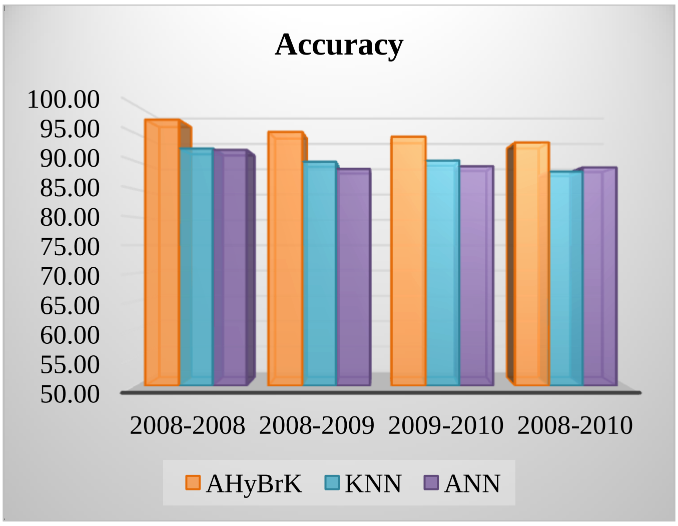


**Fig. 8. Accuracy**

## V. CONCLUSION

The main focus of this work is to analyze the effect of template aging on iris biometric systems because these systems provide high efficiency in security systems and very few works have been done for its analysis. In this work, the dataset of ND-Iris-Template-Aging is used where samples were taken for three different time-lapse i.e. 2008-2009, 2009-2010, and 2008-2010 to analyze the effect of aging.

In this work, the first quality enhancement mechanism is used to improve the quality of the sample and removal of unwanted objects then three different features were extracted and all were fused together to represent it as one. These fused features are further passed to three different classifiers i.e., KNN, ANN, and the proposed AHyBrK. The performance of this system is analyzed using different parameters. Results show that this hybrid AHyBrK performed better than ANN and KNN by 51% and 52% from KNN and ANN respectively in terms of FRR and Error Rate and Accuracy is also improved by 5% from KNN and 6% from ANN. The performance of this proposed AHyBrK is also degraded with an increase in the time-lapse but it is still better than the ANN and KNN. So, it is true that template aging has a great impact on the performance of the iris biometric system and it may be resolved with some enhanced mechanism. So, future work could go in the direction to propose an efficient biometric system that improves the performance of the system with a higher rate in the presence of aging.

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