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A FACE SPOOFING DETECTION SYSTEM USING SURF ANALYSIS BASED ON GENETIC ALGORITHM AND ARTIFICIAL INTELLIGENCE TECHNIQUE

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ABSTRACT

Modern face biometric systems are susceptible to spoofing attacks and a secure face spoof detection system demands the capability to recognize whether a face is from a real person or a spoofed image that is created by an unauthenticated person. Inspired by the feature selection algorithm, characterization of printing artifacts, and differences in light reflection, we proposed to approach the problem of spoofing detection from a pattern analysis point of view. Indeed, face prints often contain printing quality faults that can be well detected using pattern features, the Speech up Robust Feature (SURF) descriptor. Hence, introduces a novel approach based on face pattern image analysis to find out if there is live in front of a camera or a printed face. The proposed approach analyzes the pattern and quality of the facial images using the SURF descriptor as a feature extraction algorithm. Compared to a lot of previous works, our proposed face spoofing detection approach is robust, computationally fast, and does not require user-cooperation. In addition, the feature optimization technique is used for the selection of a unique feature set from the ROI of face images. Convolutional Neural Network (CNN) classifier is used for the training of the proposed spoof detection system. It is seen that the designed hybrid system face spoof detection achieves high performance than the existing system and execution time is also well. The proposed method is assessed using the MATLAB simulator in computer vision and image processing toolbox. The experimental analysis on a publicly accessible database presented brilliant results compared to existing works by using the concept of feature optimization and artificial intelligence technique.

KEYWORDS: Biometric System, Face Spoofing, SURF, Genetic Algorithm, CNN.

1. INTRODUCTION

Biometrics technology implies techniques for measuring and analyzing human characteristics. Biometrics will be divided into 2 categories, in particular physical features such as fingerprints, facial or iris patterns, and activity features such as speech, signature, or walk patterns (steps) [1]. That's because it may be one of the most prominent major issues in various biometric systems, namely the possibility of fraud. This is identified as a Spoofing attack. The pirated data will be effectively used and imitated by pirates to achieve unauthorized access to the biometric identification system, rather than the accord of the actual user. Efforts to check the identification of fraudulent attacks produce a completely different view. In a part of the work, a progressive deception recognition technology was given to the physiological properties to detect light-weight facial statistics [2]. In general, there are two types of masks: positive and negative. The positive category (also known as the real face) limits the change, but the negative category adds a bad face to the picture, virtual or recorded video. The face recognition (FR) system with spoofing detection is illustrated in Fig. 1.

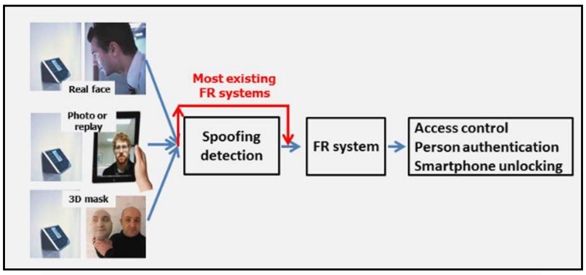

Fig 1: FR System with Spoofing Detection Module

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The popularity of face recognition has lifted the issue of face-spoofing attacks (also referred to as biosensor rendering attacks) in which pictures or videos of authorized faces can be used to acquire facilities or services [3]. Although many face deception detection techniques have been introduced, their generalization capabilities have not yet been fully resolved. With the approach of electronic medium, society is progressively reliant on PC for handling. With expanding innovation, man gets to be included with PC as the pioneer of this innovative age [4]. It has opened another age for humanity to go into the world. A standout amongst the most imperative objectives of PC vision is to accomplish visual acknowledgment.

Among numerous acknowledgment subjects, face spoofing detection has drawn significant interest and consideration from numerous analysts, for example, in the territories of reconnaissance, Closed Circuit Television (CCTV) control, client confirmation, HCI human PC interface, insightful robot et cetera. Various face spoofing strategies have been proposed for face detection, which is quick [5]. The proposed methodologies have focal points over the other face spoofing plots in its speed and effortlessness. We have presented a face spoofing detection scheme by using artificial intelligence. In the proposed work, a face spoofing detection system using Convolutional Neural Network (CNN) has been proposed. In the case of CNN, the first part is training and the second is classification, and CNN has been trained by appropriate feature sets, so, in classification, they can easily classify test images with the help of trained structure. But problems may occur in the case of feature optimization, if the optimization technique is not used then training and testing will create problems. So, for feature optimization in the proposed work, a genetic algorithm (GA) has been used. The main improvement in the proposed work is the use of a Genetic Algorithm to optimize the feature to increase accuracy [6]. Face spoofing detection, countermeasures for facial spoofing assaults, face liveness detection, and face anti-spoofing are the sorts that are utilized reciprocally for signifying the methods for distinguishing a faker that attempts to imitate as a real client in the face acknowledgment framework. These frameworks for the most part used the accompanying sorts of spoofing assaults [7].

Table I: Types of Spoofing Attacks

Fig 2: Spoofing Attacks	**Flat printed photo**  (a) (b)	**The use of a flat printed image is illustrated in Fig. 2, where Fig. (a) Shows the original picture and Fig. (b) considered as the internet (social media) or fraudster can take a picture without permission or in partnership.**
	Eye cut photo attack  (c)	**In this, the regions of the eye for the printed photo are cut off to illustrate the blink deeds of the imitator as portrayed in Fig. 2 (c).**
	Warped photo attacks	**These consist of the bending of the printed photo in some direction for simulating the facial motions as portrayed in Fig. 2 (d)**

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	 (d)	
	Video playback  (e)	**This attack occurs because video playback shows each action as a real face with key features of the active user as shown in Fig. 2 (e).** **This type of attack has physical symptoms that are not in the pictures, that is. facial expressions, blinking of eyes, and movement of the head and mouth.** **It can be effortlessly executed by large tablets or smartphones.**
	Mask attacks  (f) (g)	**Mask attacks have two types as illustrated in Fig. 2 (f) and 2 (g). These types of attacks are provided by an anti-spoofing system that analyzes 3-D facial structures and is known as another combination of detection attack.** **Production of masks is very difficult and expensive compared to other attacks by certain 3-D printing and scanning devices.**

Motivation & Contributions: Nowadays, facial recognition as a biometric authentication system is often used from face image but there is a problem that occurred during the classification of faces from facial images by using accessible existing feature extraction techniques. The major causes of the problem in the face recognition system are the extraction of best and selection of a set of appropriate features from the faces and due to this face spoofing system able to attack the model. The main motivation behind developing an FSD system. To diminish these types of problems from the face recognition system by utilizing the concept of SURF descriptor with GA because it is the finest approach according to the survey. Here, CNN is used as a classifier or deep learning approach, and the main contributions are given as:

- We present a survey on the existing face recognition or spoofing system using face images of any dimension.
- We present appropriate pre-processing steps for face detection technique for the face recognition part to make feature extraction easy and best.
- To find out the suitable and appropriate feature set to form the face images using the SURF descriptor as a feature extraction technique.
- To achieve better accuracy in face recognition systems, CNN with optimized feature sets as a classifier is proposed.
- Calculate the accuracy of proposed work based on performance metrics like False Acceptance Ratio, False Rejection Ratio, and Accuracy.

In this section, we provide a brief introduction about the proposed Face Spoofing Detection (FSD) System based on the SURF descriptor with GA and ANN as a classifier and the main focus of research is to introduce a hybrid feature descriptor mechanism with a novel finesse function of GA, and the rest of paper is organized as: in Section 2 existing work related to the face spoofing modules are analyzed where the designed framework is discussed in Section 3 with experimental setup scenario. In Section 4, the simulation results of the proposed FSD system are discussed where Section 5 presents the overall conclusion with future possibilities.

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2. RELATED WORK

Lots of face recognition or spoofing system are proposed by the researchers in the previous ten years, to find out the exact existing problems that help to design improved FSD systems. In 2019, ***M. Khammari*** presented an anti-face spoofing using CNN with Local Binary Pattern (LBP) and Simplified Weber Local Descriptor (SWLD). In this research, the authors combined the WLD and LBP features to ensure the preservation of the image information and the orientations of the edges in a face image. The author used the publicly available databases REPLAYATTACK and CASIA for the experimental analysis and compare it with the lots of state-of-the-art methods. Due to lack of optimal feature sets, designed model produce near to 3% error and need to enhance for security purpose by utilizing the optimization techniques [8]. ***Kudzaishe Mhou et.al***, 2017 have implemented a system with Gabor filters, Laplacian blur detection, color moments, and LBP that measures the light reflection on varied material and the classification has been done with the provided face being fake or real. The authors noted an improvement in results with a system that works better in a lightning environment compared to a few related systems. In particular, the light source while the sample was photographing the previous processing provided excellent results. Investigators also extracted a 40-person data set with different cameras that could serve as other related sources CASIA-FASD and the MSU MFSD public datasets [9]. In 2016, ***Z. Boulkenafet et al.*** have describe a new way to get facial smoothness through color analysis. The author has used color-coded knowledge to share chrominance channels with the removal of low-level corresponding descriptions from various color spaces. Feature histograms are calculated from all individual photo bands. The implementation of the three most popular database repositories was called, Replay-Attack Database, CASIA Face Anti-Spoofing Database with MSU Mobile Face Spoof Database, and it produced better results compared to existing work [10]. Before that in 2015, ***S. Tirunagari et al***. has introduced DMD (Dynamic Mode Decomposition), LBP, and SVM (Support vector Machine) and histogram kernel of the intersection editing infrastructure. A single DMD property can display full temporary image details as a single image of the same size embedded in the video. The integration of the stated algorithms has already proved to be effective, accessible, and efficient. The effectiveness of this method has been evaluated by the data used (re-attack, print-attack, and (CASIA-FASD) and the proposed function has improved compared to the existing ones [11]. ***D. Wen et al.*** in 2015 has introduced an effective algorithm and a powerful face algorithm for the spoofing of IDA (Image distortion analysis). Four different components have been developed to produce the IDA feature vector. The ensemble classifier has a variety of SVMs that are trained for various face attacks used to distinguish between spoof and real faces. The presented method has been extended to video access using the based voting system. Investigators have collected a face spoofing database consisting of two mobile devices with three types of spoof attacks. Investigators have led to two details of two public domains and the MSU MFSD database has demonstrated that the introduced way performs better than the means of detecting spoof. The conclusion has also shown the separating genuine difficulty mostly in the cross-database and cross-device scenarios [12].

Face recognition as a biometric program is another way to authenticate a person to various access control applications but still, various attacks such as photos, 3D masks, and video replay attacks have affected these systems. Because of these attacks, the system must require an FSD system that can detect whether the face is from a real person or a false image. Therefore, in the proposed work, the SURF descriptor is used to extract key points from the facial image after preliminary consideration. There is another problem with the spoofing face detection system, i.e. if the feature sets are not fixed where it is possible that the error value is higher, therefore, overcoming the error correction is necessary for the purpose of the novel purpose. To optimize the output of the extracted feature, a genetic algorithm will be used and the feature sets will not have to be completed, so the accuracy of the proposed function will be increased. In the proposed activity, the face recognition system uses the SURF and GA descriptors. CNN is used as a classifier to train the face recognition system. In CNN, the first part is training and the second is classification, and CNN would be trained by appropriate feature sets, so, in the classification section, test data can be easily classified with the help of trained structure.

3. FSD FRAMEWORK

This research work has dealt with proposing a technique of efficient face spoofing technique with face images of any dimension. An appropriate face segmentation technique for the face recognition part to make feature extraction easy and best has been presented. The suitable and appropriate features set from the face images SURF feature are used. For achieving better accuracy in authentication systems, an artificial neural network as a classifier has been proposed. The methodology of the proposed work is specified below:

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Step 1: Design and develop a appropriate GUI for the proposed facial emotion recognition system.
Step 2: Upload the face images for the Training and Testing of the proposed facial spoofing detection system.
Step 3: Apply pre-processing on uploaded face images in both sections. The proposed pre-processing algorithm is given as:

Algorithm 1st: Pre-Processing Algorithm

Upload Images
Apply pre-processing algorithm on uploaded image
For I = 1 to all sets
  $RESIZE_{IMAGE}$ = Resize (I)
  $FACE_{DETECTION}$ = $FACE_{DETECTOR}$ ($RESIZE_{IMAGE}$)
  Threshold = Threshold ($FACE_{DETECTION}$)
  $GRAY_{FACE}$ = Gray ($FACE_{DETECTION}$, Threshold)
  ROI = Crop ($GRAY_{FACE}$, $FACE_{REGION}$)
End

Save all ROI data as an input of the SURF feature extraction technique.
Step 4: Develop code for the face spoofing detection from the pre-processed face images in the training and testing section.
Step 5: Apply SURF Descriptor for the feature extraction from the detected face. The SURF algorithm is given as;

Algorithm 2nd: SURF Descriptor

Load ROI data of face images
For I = 1 to all sets
  $EXTREMA_{DETECTION}$= $GRAY_{FACE}$ (I)
  $KEYPOINT_{LOCALIZATION}$= $EXTREMA_{DETECTION}$ (I)
If localization need orientation
  Orientation= $KEYPOINT_{LOCALIZATION}$ (I)
End
  $KEYPOINT_{DESCRIPTOR}$=All best Feature
End

Save $KEYPOINT_{DESCRIPTOR}$ of proposed work for the next phase and we apply the Genetic Algorithm on the $KEYPOINT_{DESCRIPTOR}$ and fin the optimal solution of proposed work.
Step 6: Initialize the Genetic Algorithm to optimize SURF features and remove the unwanted feature sets using the novel objective function. The used algorithm of feature optimization is given as:

Algorithm 3rd: Genetic Algorithm

Define the population size of the GA (50)
Initialized the GA in Model
Set all initialization parameters
Load $KEYPOINT_{DESCRIPTOR}$
For I = 1 to all $KEYPOINT_{DESCRIPTOR}$
  For r=1 to all rows
  For c=1 to all columns
Define Ft (Threshold) = Average of Key points
Define Fs = $KEYPOINT_{DESCRIPTOR}$ (r, c)
Call fitness function

$$Fitness\ Function = \begin{cases} True, & if\ Fs > Ft \\ False, & otherwise \end{cases}$$

  If fitness functions==True
   Consider as best solution as GA_{DATA}
  End
 End
 End
End

Save GA_{DATA} of proposed work and pass it as an input of ANN for training in the training part and classification in the classification part.

Step 7: Apply CNN on optimized data to train the database and train the data using the succeeding phases:

- **a.** Select an optimized feature as an input of CNN for training and testing data.
- **b.** Compute the complete categories which are created by the training of optimized data using CNN.

Step 8: After that in the classification section, the test data has been classified according to the trained CNN structure. The CNN algorithm is given as:

Algorithm 4th: CNN Classifier

Load GA_{DATA}
$TRAINING_{DATA} = GA_{DATA}$
Initialize CNN
Generate group of data = group
Set iteration = 50
For I = 1 to iteration
    Weight = GA_{DATA} (i)
    $HIDDEN_{NEURONS}$ = [10] (TANSIG)
    Net_algo = TRAINLM
    Generate Net structure of CNN (net)
    Net = train (Net, $TRAINING_{DATA}$, group)
End
Save Net of proposed work as a structure and classify the test face based on Net.

Step 9: At last of the module, the performance parameters of the proposed spoof detection system like FAR, FRR, Execution time, Error rate, and Accuracy are calculated.

There are two sections of proposed work, first is training and the second is the classification of test face data. For the classification of the proposed image, we used images from the below-described database.

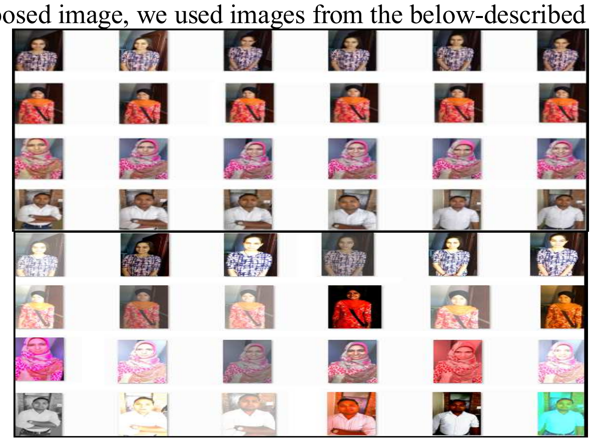

Fig 3: (a) Original and (b) Spoof Face Images

The above figure represents the database of proposed work for the detection of a spoof image. We have constructed a face spoof database using the cameras with a non-compression technique and the format of database images is ".JPEG". In the figure, (a) is the set of the original image and (b) is the set of spoof images. Below Fig. 4 described the structure of the proposed FSD system which is developed using the concept of CNN as a classifier.

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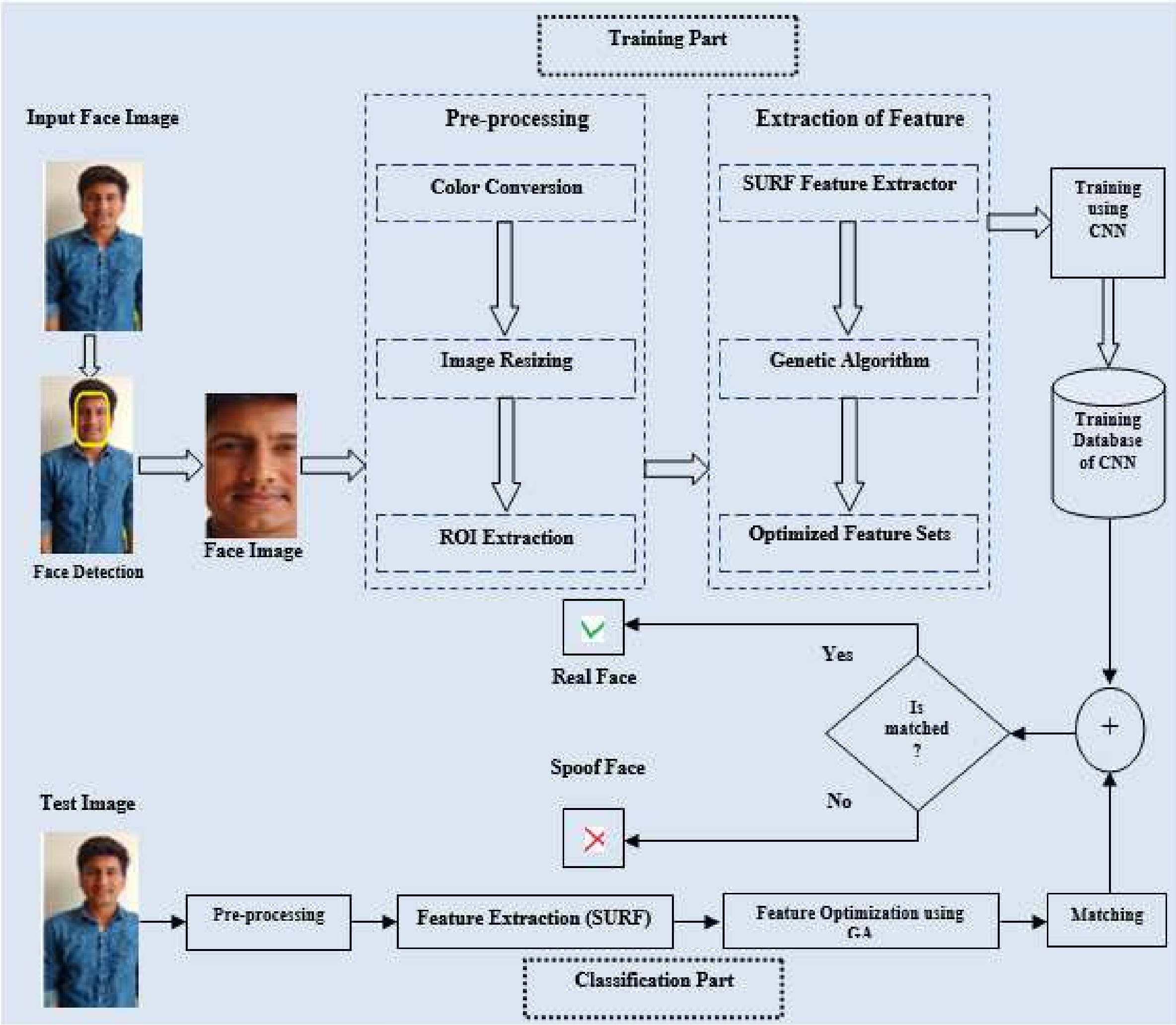

Fig 3: FSD System using Optimized CNN

The simulation results of the proposed FSD system based on an optimized SURF feature using the concept of GA with CNN is described in the next section of this research article.

4. RESULTS AND DISCUSSION

We explain and analyze the experimental simulation results of the proposed FSD system that is based on the optimized SURF feature using GA and CNN as a classifier. We use the SURF descriptor for the feature extraction and later the feature optimization, we have classified the test image based on training of the FSD system. Afterward the classification, we have computed the performance parameters of the FSD system in terms of Accuracy, Error Rate, Execution time, and FAR, FRR. The calculated performance parameters of the FSD system are given in Table II.

Table II: Performance Parameters of FSD System

S No.	FAR	FRR	Error (%)	Accuracy (%)	Execution Time (s)
1	89.52	53.58	1.87	98.13	15.45
2	91.36	29.83	1.66	98.34	12.78
3	83.26	45.82	2.08	97.92	14.76
4	87.36	67.27	1.28	98.72	12.74
5	93.27	38.74	2.72	97.28	11.87
6	74.72	34.79	2.28	97.72	09.34

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7	**78.37**	**67.62**	**1.73**	**98.27**	**17.38**
8	**84.28**	**72.42**	**3.62**	**96.38**	**16.88**
9	**87.82**	**55.53**	**2.92**	**97.08**	**13.73**
10	**82.73**	**67.34**	**1.19**	**98.81**	**12.48**

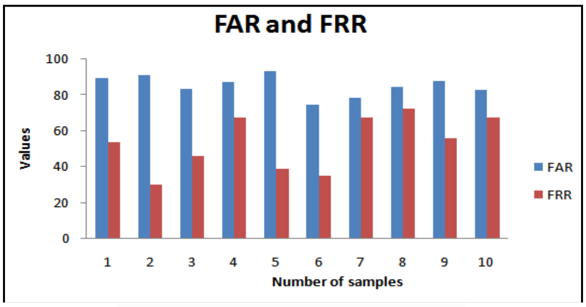

Fig 4: FAR & FRR of FSD System

The above figure signifies the result of FAR and FRR after simulation. The X-axis in the figure defines the number of samples and Y-axis defines the values attained of FAR and FRR later the simulation. The blue bar defines the result of FAR and the red bar defines the outcome of FRR. The average value of FAR is 85.26 and the average value of FRR is 53.29.

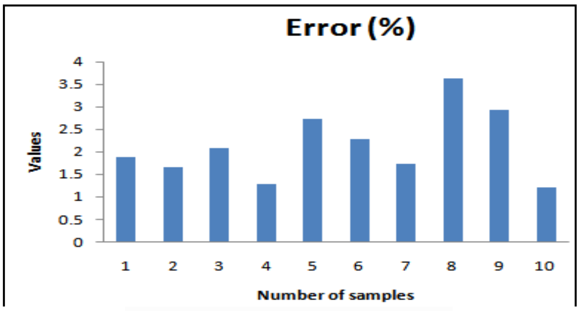

Fig 5: Error Rate of FSD System

The above figure signifies the number of errors in the presented work X-axis, defines the number of samples taken to execute the work and the Y-axis defines the values attained for Error. The presence of errors in the work is 2.13% approximately.

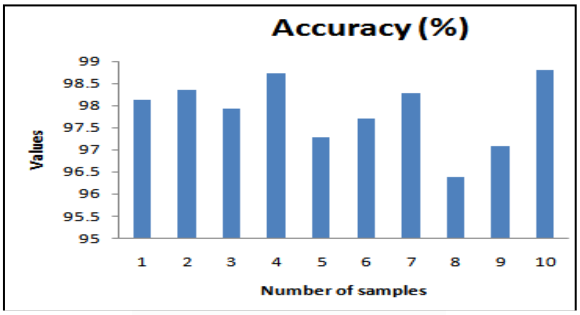

Fig 6: Accuracy of FSD System

The above figure signifies the outcome of Accuracy after simulation. The X-axis in the figure defines the number of samples and Y-axis defines the values attained of FAR and FRR after simulation. The average value of accuracy is 97.86.

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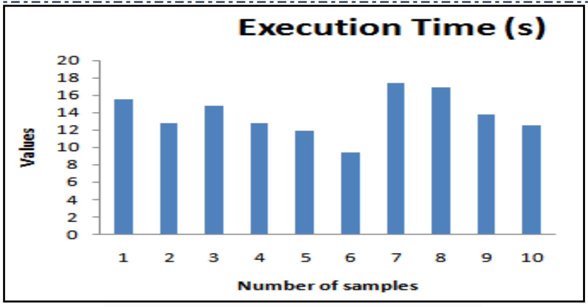

Fig 7: Execution Time of FSD System

The above figure signifies the outcome of execution time after simulation. The X-axis in the figure defines the number of samples and Y-axis defines the values obtained for execution time after simulation. The average value of accuracy is 13.741 approximately. After the simulation of experimental results, we compare the proposed FSD model with existing work by ***M. Khammari*** [8]. The error rate of the work proposed by [8] is near to the 3.15% but the error rate of the proposed FSD system is 2.135% and the execution time of the proposed FSD model is faster than the existing work.

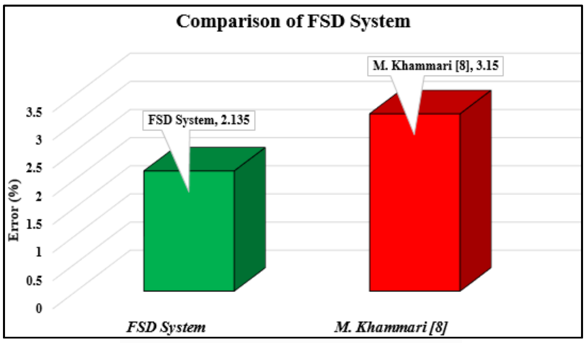

Fig 8: Comparison of FSD System

From the above figure, it is shown that the error rate of the proposed FSD system is less than the existing work presented by ***M. Khammari*** [8]. If the error rate of the system id improved then accuracy also improved and the obtained accuracy is near to 98%. So, we can say that the effect of the optimized SURF feature is a beneficial step towards the biometric authentication system that able to identify the spoof face images or other types of attacks. In this section of the research article, the results of our proposed FSD system are analyzed and compared with the state-of-the-art to validate the proposed work. The performance evaluation of the studied FSD system is measured in terms of the FAR, FRR, Error, Accuracy, and Execution time, and all of the mentioned parameters are better for the proposed FSD system and HTER. The overall conclusion and future possibilities of the FSD system are described in the below section of the article.

5. CONCLUSION AND FUTURE WORK

In this research, we have proposed an FSD system using a genetic algorithm and artificial neural network. For the feature extractions, SURF descriptor is used and once the face images are translated into a proper feature space, there are some differences between the original and spoofed images that may turn out to be evident. In this framework, it is expected that spoofing induces some distortions in the image and the image quality properties of real accesses and fraudulent attacks will be dissimilar. CNN classifier consists of optimized key points that have been trained for different spoof face and real face. The proposed solution has suggested an effective and efficient method against spoof detection. The proposed approach has also shown increment in the detection rate as compared to the existing systems by using the concept of hybridization of genetic algorithm and artificial neural network.

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The future works include developing some novel methods for attaining discriminative image patches and inclusion of temporal information in the proposed method for higher security applications in the spoof detection system. It is possible using some significant pre-processing steps in the training and classification phases.

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