Face Anti-Spoofing Using Block Average Local Binary Pattern

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ABSTRACT:

Nowadays the face biometric system is gaining popularity for authentication in access control applications. At the same time, the threats to authentication systems are also increased in terms of spoofing or presentation attacks (PA) where an intruder attempts to spoof the face recognition system by using genuine user photos or video to gain access. To effectively secure the secrecy of a genuine user, there is an urgent need for building a face authentication system with anti-spoofing countermeasures. In this paper, we introduced a novel face anti-spoofing approach, which is mainly based on contrast and texture features of both real and spoof photos. We developed a novel descriptor called Block Average Local Binary Pattern (BALBP) for face anti-spoofing system. The publicly available NUAA, MSU-MFSD, REPLAY-MOBILE and REPLAY-ATTACK are photo-impostor datasets are tested on the approach, which includes images with different illumination and area of the face. The accuracy of the proposed approach is evaluated using different metrics. The results show that our proposed method is superior to other state-of-the-art (SOTA) practices when tested on different photo-impostor datasets.

Keywords: Face anti-spoofing; Local Binary Pattern; Block Average Local Binary Pattern; Texture analysis; Information security.

1.Introduction

Face anti-spoofing is a method used to detect whether the face is real or spoof. The spoofing attack occurs when an intruder tries to deceive a facial recognition system using fake photo, video or 3D mask to impersonate genuine users. The face anti-spoofing task is formulated as a two class problems Raghavendra et al., [1]. The first class is the real image class, which captures photo of a live person and the second class is the spoof image class, which consist the photo of a real face.

Face anti-spoofing technology is extensively used in areas such as mobile security, banking, surveillance systems to prevent unauthorized access in automated teller machines (ATMs), mobile phones, entrance guard systems. The eyeblink detection approach can be applied to a wide range of applications, including fatigue monitoring, psychological experiments, medical testing, and interactive gaming.

Face anti-spoofing methods generally fall into three categories: sensor-level, feature-level, and score-level approaches as suggested by Galbally et al., [2]. Sensor-level technique often called hardware level technique, these methods involve adding specialized devices to sensors to detect distinct features of living traits, such as thermal patterns in the face, blood pressure, fingerprint moisture, or specific reflections from the eye. Feature level technique often called software level technique which captures the biometric sample from standard sensors and then extract the distinct features from that sample to detect the fake traits. Finally, the score level technique is a third group of protection methods in the context of fingerprint anti-spoofing falls outside traditional software- and hardware-based techniques. Score level technique is less common than other two techniques, which focus on analysing biometric systems at score level.

Face recognition technology has evolved over the years, widely used in various sectors such as authentication and access control. Face attacks may be classified into one of the two group: 2D surfaces (e.g., photo, video) and 3D volumes (e.g., masks).Photo attacks refer to attempts to access recognition system by using a printed photo of a genuine user. The photo may be captured by the intruder using digital camera or obtained from the internet often uploaded by the user on social media platforms. Video attacks sometimes called as replay attacks where attacker does not use a still image instead of the replays a video of genuine user through mobile phone, laptop or tablet, these attacks are an evolution in face spoofing, which makes face recognition systems hard to detect as they not only mimic facial features but also the movements of the face. Another type of attack is a mask attack, where the spoofing artefact is 3D mask of genuine user's face making it harder to detect as it replicates the complete 3D structure of the face. The use of depth cues which could prevent the previous two types of attacks, becomes inefficient in this case.

2. Literature Review

In this section, different types of face anti-spoofing methods such as texture-based method, motion-based method, optical flow-based analysis, image quality-based method, approach based on other cues, hardware-based method and frequency-based approaches are reviewed.

In texture-based method, texture is a key characteristic of images. This method detects textural differences between real and spoofed faces by analyzing surface irregularities and imperfections in the media. Tan et al., [3] introduced techniques where they calculated luminance and reflectance of images and classified them using sparse low rank bilinear logistic regression techniques. Further, Peixoto et al., [4] expanded this idea by incorporating metrices that are suitable for varying lighting condition. Maatta et al., [5] employed LBP for spoofing detection while Schwartz et al.,[6] combined color, texture and shape. Chingovska et al., [7] introduced variations of LBP.Kose et al., [8] utilized reflectance-based techniques to detect spoofing.

Motion-based methods analyze involuntary facial actions such as eye blinking to detect spoofing attacks. Tronci et al., [9] introduced a method that combines static features such as colors, edges and textures with video-based analyses such as eye blinks, mouth movements and facial expression changes to extract motion cues. Anjos et al., [10] used motion intensity between face and background, to find attack attempts which show stronger motion correlations. In contrast, Pinto et al., [11] introduces a new anti-spoofing approach that analyzes the temporal changes in noise signal frequencies from videos, representing the first use of visual codebooks for face spoofing detection.Kollreider et al., [12] uses optical flow method to detect face motion for liveliness verification, but it does not work well with photo distortion or when depth changes. Frischholz et al., [13] introduced a method involving head movement of the user. Improvised methods like Hsieh et al., [14] detects motion more accurate by using regularization. For face tracking Ranftl et al., [15] use likelihood maps. Gao et al., [16] and Ming et al., [17] both use optical flow better face detection and distinguish real faces. However, some of these methods rely on user involvement and face challenges with spoofing. Therefore, in order to overcome this problem, Yin et al., [18] introduced the displacement of optical flow vector (DOVF) model, which uses dense optical flow and KNN for classification. This method is more reliable as it does not require user involvement, but unlike other methods, it is inefficient when there are unstable light conditions.

Different methods are used to spot fake faces in facial recognition. Feng et al., [19] introduced a neural network that combines shearlet-based image quality features and dense optical flow for motion cues in liveness detection. Methods like Local Binary Pattern (LBP) and difference of Gaussian (DOG) are used to detect micro-texture and frequency differences between real and fake faces. Menotti et al., [20] proposed framework, that combines shearlet-based image quality features (SBIQF) and outperformed most advanced techniques in distinguishing real face from spoofing attacks. Raghavendra et al., [21-31] proposed many texture descriptors for face anti-spoofing.

Alternative face anti-spoofing methods utilize the additional information, such as 3D depth analysis Wang et al., [32] and spoofing context detection Komulainen et al., [33] to enhance face anti-spoofing techniques. Liu et al., [34] introduced CNN-RNN model to estimate face depth through pixel level supervision. However, real faces and masks both have similar depth and structural characteristics. These methods find it hard to detect 3D mask attacks.

Non-traditional hardware like depth sensors, multi-spectral and light field cameras, and thermal imaging help detect spoofing by analyzing face shape and reflectance. Depth data identifies flat surfaces like video displays or printed images by Erdogmus et al., [35], while multi-spectral imaging distinguishes 3D masks and 2D artifacts from skin by Zhang et al., [36]. Thermal imaging detects cold spots from plastic surgery Pavlidis et al. [37], light field cameras capture depth from a single image Raghavendra et al., [38–40]. While hardware-based methods face challenges like sunlight interference, thermal radiation, and difficulties distinguishing real faces from 3D masks suggested by Zhang et al., [36]. Despite these limitations, affordable sensors like light field cameras and multi-camera smartphones offer opportunities to improve anti-spoofing techniques.

Li et al., [41] analyzed the smaller size and invariant expressions of faces in photo to detect photo-based spoofing attacks. Pedrini et al., [42] isolated the noise using low-pass filter to detect video spoofing attacks. Lee et al.,[31] proposed a frequency entropy-based method for image sequences, using face detection, RGB normalization, and independent component analysis (ICA) to remove noise, analyzing power spectrum and entropy to distinguish real from synthetic samples.

3.Methodology

3.1 System Architecture

Figure 1 depicts the architecture of the proposed method contains Block Average Local Binary Pattern (BALBP) descriptor which is essential in any biometric system as it assists in detecting live face from the attacks like a photograph, a mask or videos of a real face.

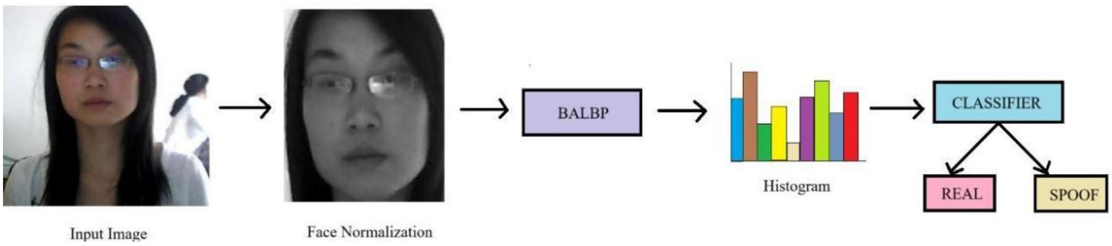

Fig. 1. Architecture of proposed method

The process begins with capturing an image using a camera, but face normalization is the critical step that ensures the facial image is adjusted based on some key features for further analysis. During face normalization, the orientation of the face is aligned, the size is standardized, and lighting variations are corrected. This ensures uniformity across images, making subsequent processing more accurate and reliable.

After the normalization process is completed, BALBP a texture descriptor is applied to extract the texture feature, by dividing the face into segments to assess local texture patterns, averages the data, fed into a histogram to extract the required features, and uses a classifier to determine whether the face is real or spoofed based on learned texture features. In this way, BALBP improves the security in FR systems and decreases the chances of unauthorized access by increasing systems ability to identify spoofing attempts.

Algorithm

Input: face image; Output: Spoofing outcomes

1. Input the face images from the database are loaded and converted into gray-scale images.

2. Traverse the image and extract all possible 4x4 matrices.

3. In 4x4 matrix, divide the matrix into 9 subblocks of 2x2 matrix of each and calculate the average in sub-blocks to form a new 3x3 matrix.

4. Resultant 3x3 matrix, further apply LBP (Local binary pattern) descriptor to obtain a new LBP value.

5. Apply BALBP descriptor to whole image to produce final BALBP image.

6. Extract 59 features by applying histogram on BALBP image.

7. Trained classifier will classify given a test image as real/spoof.

3.2 Block Average Local Binary Pattern (BALBP)

In this work, we have developed a new texture descriptor called Block Average Local Binary Pattern (BALBP), which is another variant of the Local Binary Pattern (LBP) operator used for extracting texture features from images.

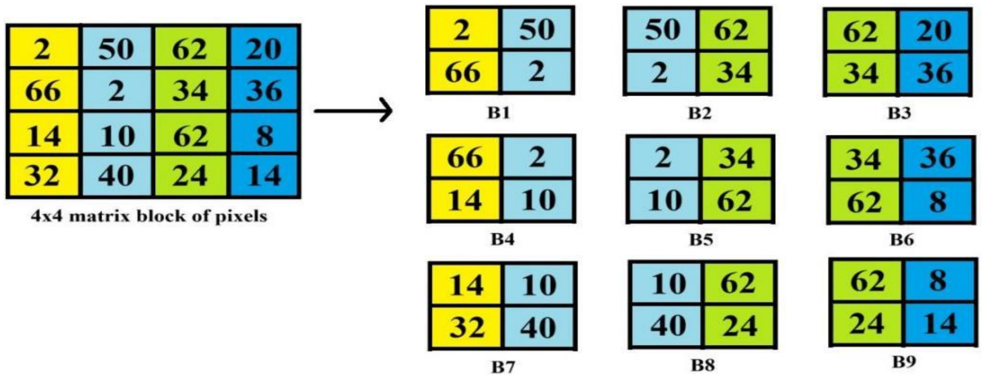

Fig. 2. 4x4 matrix is divided into 9 subblocks of 2x2 matrix

Consider a 4x4 matrix of a gray image, divide the matrix into 9 subblocks of 2x2 matrix (labelled B1 to B9) of each and calculate the average of each sub blocks to form a new 3x3 matrix using an (1) as shown in Figure 2.

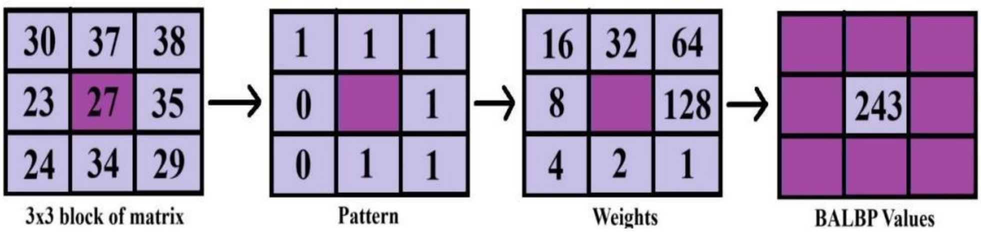

Fig. 3. Calculation process of Block Average Local Binary Pattern

Further, BALBP extracts pixel values from images. This is achieved by comparing intensity of each pixel with its neighbouring pixels, using the central pixel as the point of reference, using (2) and (3). For each comparison, a binary value is set to 1 if the neighbouring value is greater than or equal to the reference, and 0 otherwise, as shown in Figure 3.

(1) $$R(y) = \frac{1}{4}\sum_{i=1}^{2}\sum_{j=1}^{2} M(i,j)$$

R(y) is a matrix that holds the average of the subblocks

$$(2) \quad BALBP_{P,R} = \sum_{m=0}^{m-1} f(R_m(y) - E_c)2^m$$

$$(3) \quad f(y) = \begin{cases} 1, & y \geq 0 \\ 0, & otherwise \end{cases}$$

where E_c is the center pixel, () is the average of the each block, P is the total number of neighbourhood pixels on a circle of radius R, and f defines a function of thresholding.

For the given image, the BALBP image pattern was calculated, histograms of BALBP was constructed using the following (4) and (5).

$$(4) \quad HG_{BALBP} = \sum_{i=1}^{N1} \sum_{j=1}^{N2} h_4(BALBP(i,j), S) \ , \quad S \in (0, \ \ 2^{p-1} - 1)$$

$$(5) \quad h_4(X,Y) = \begin{cases} 1 & X = Y \\ 0 & else \end{cases}$$

Where, N1 x N2 is the size of the BALBP output image.

4. Results and Discussions

To evaluate the performance of the developed method for face anti-spoofing, different experiments were conducted on different databases such as NUAA, MSU-MFSD, REPLAY-ATTACK, REPLAY-MOBILE ATTACK.

4.1 Experiment 1: BALBP Comparison with Different Classifiers.

This experiment involves the use of four datasets such as NUAA, MSU-MFSD, Replay-Attack, and Replay- Mobile. Here images of size 40x40 pixels were used. From each image 59 features were extracted using BALBP descriptor. Images of different types were used from all datasets, and their accuracies were measured using both SVM and KNN classifiers.

In the Experiment, the Block Average Local Binary Pattern (BALBP) descriptor is used to effectively capture texture features while reducing noise. Unlike standard LBP, BALBP calculates the average pixel values within blocks, which helps in minimizing the influence of minor variations and illumination changes. This averaging process enhances the descriptor's robustness by preserving only the most significant texture patterns. As a result, it becomes easier to distinguish between real and spoofed faces due to the reduced sensitivity to small distortions. The regional block-wise approach further ensures better spatial representation of facial features, improving classification accuracy.

The below experimental results shows that the performance of developed method is improved with increase in the number of training images. The results of the accuracy are given in Table 1 and Table 2. It is observed maximum accuracy of 92.77% is achieved using SVM classifier, whereas the KNN classifier reached an accuracy of 94.77% in identifying whether the given face image is real or spoof. Figure 4 and Figure 5 show the performance of BALBP descriptor over NUAA, MSU-MFSD, Replay-Attack and Replay-Mobile datasets. It was evident from the results that the BALBP descriptor performing very well.

Table 1: Performance of BALBP Descriptor with SVM Classifier in Terms of Recognition Rate

CLASS	NUAA	MSU-MFSD	Replay Attack	Replay-Mobile
1	77.32	81.51	68.13	81.36
2	86.71	82.26	68.25	81.65
3	87.42	82.48	68.69	82.33
4	87.80	82.86	69.31	82.52
5	88.03	82.91	70.81	82.72
6	90.09	83.23	71.38	82.72
7	91.29	83.29	71.94	82.91
8	92.16	83.56	72.19	83.01

9	92.45	84.04	72.38	84.37
10	92.77	84.47	74.38	85.24

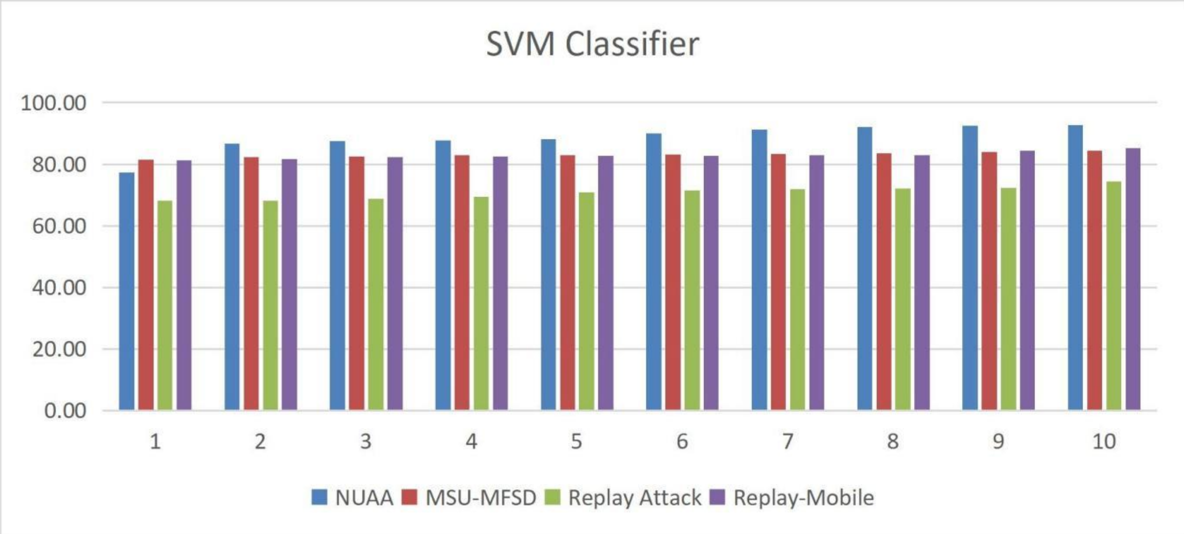

Fig. 4. Recognition Rate Performance of BALBP Descriptor with SVM Classifier

Table 2: Performance of BALBP Descriptor with KNN Classifier in Terms of Recognition Rate

CLASS	NUAA	MSU-MFSD	Replay Attack	Replay-Mobile
1	85.32	85.66	71.38	77.37
2	86.71	85.77	72.19	79.72
3	87.42	85.88	72.89	81.36
4	87.80	86.09	74.38	81.65
5	88.03	86.47	74.76	82.33
6	90.09	87.01	75.89	82.52
7	91.29	87.28	77.13	82.72
8	92.16	87.65	79.56	82.91
9	92.45	88.03	80.67	83.01
10	94.77	88.41	82.45	85.24

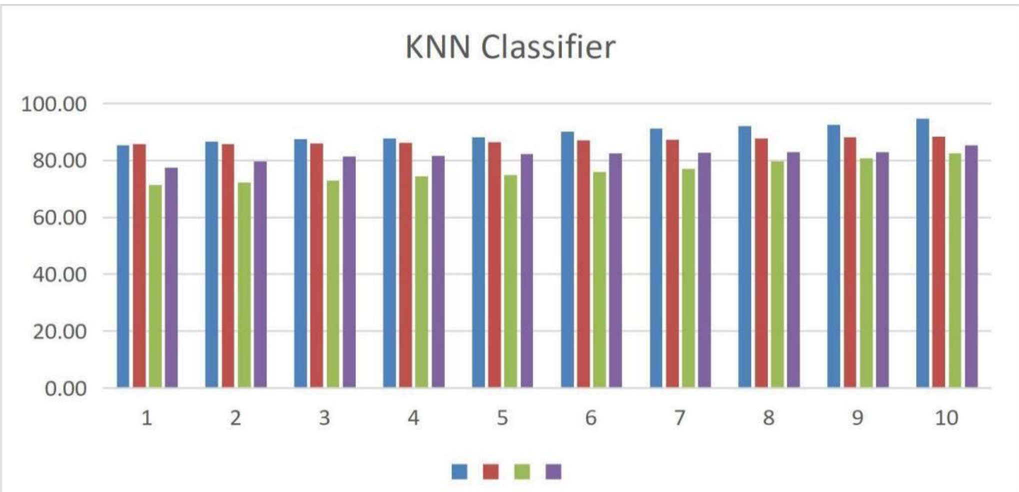

Fig. 5. Recognition Rate Performance of BALBP Descriptor with KNN Classifier.

Table 3 : Comparison of BALBP in Terms of Precision.

DATA SET	Precision		
	160x160	80x80	40x40
NUAA	91.41	87.47	82.76
MSU-MFSD	92.38	88.58	88.58
Replay Attack	82.28	82.28	82.28
Replay Mobile	92.16	89.29	88.32

4.2 Experiment 2: Comparison of BALBP with Precision and Recall.

This experiment involves the use of four datasets such as NUAA, MSU-MFSD, Replay-Attack, and Replay- Mobile. In this experiment, we used both real and attack images of three different sizes for training. Each image was split into four non-overlapping sub-images of 80x80, sixteen sub-images of 40x40, and the original full-sized image of 160x160. We use the segmented images to extract 59 features with the BALBP descriptor. Experiments were then carried out on different types of images from all the datasets.

In the Experiment improves performance in face anti-spoofing tasks when compared using precision and recall metrics. BALBP shows higher precision by effectively filtering out noise and false positives, thanks to its block-wise averaging mechanism that captures only the most relevant texture details. It also achieves better recall since important spoofing cues across facial regions are preserved through regional averaging, reducing missed detections. Compared to standard LBP, BALBP provides a more stable and discriminative feature set, improving both detection accuracy and robustness. The balanced precision-recall performance makes BALBP a suitable choice for real-time spoof detection systems.

Table 3 and Figure 6 shows the performance of the BALBP descriptor in terms of average precision, tested on three different image sizes across all datasets. Specifically, the a precision for 40x40 segmented face images of the NUAA dataset was 82.76%, for the MSU-MFSD dataset it was 88.58%, for the reply-attack dataset it was 82.28% and for the reply mobile dataset it was 84.15%.

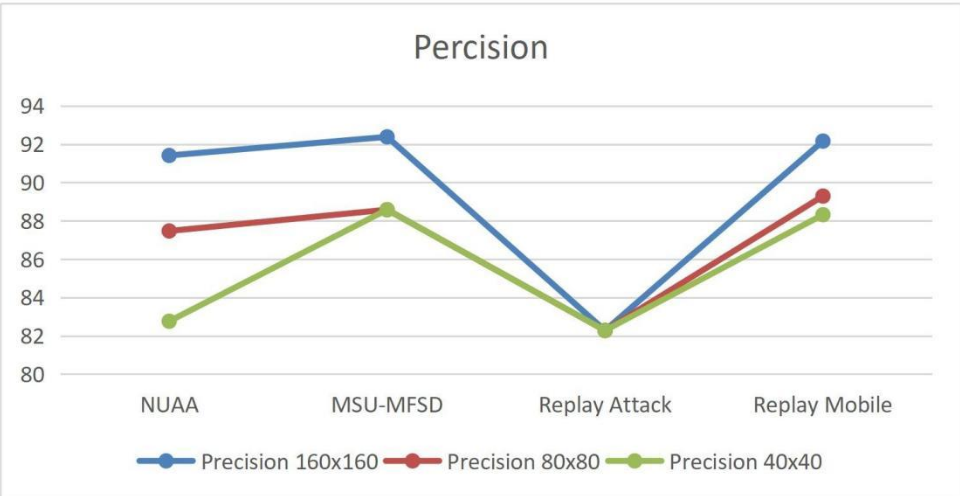

Fig . 6. Comparison of BALBP with Metric Precision.

Table 4: Comparison of BALBP in Terms of Recall.

DATA SET	Recall		
	160x160	80x80	40x40
NUAA	88.87	85.04	51.41

MSU-MFSD	80.7	80.02	60.77
Replay Attack	62.13	62.13	60.01
Replay Mobile	80.36	80.36	59.03

Table 4 and Figure 7 show the performance of the BALBP descriptor in terms of recall, tested on three different image sizes across all datasets. Specifically, recall for segmented face images of the different datasets was outperformed in all four datasets.

4.3 Experiment 3: Comparison of BALBP with F1-Score

This experiment involves the use of four datasets such as NUAA, MSU-MFSD, Replay-Attack, and Replay- Mobile. In this experiment, we used both real and attack images of three different sizes for training. Each image was split into four non-overlapping sub-images of 80x80, sixteen sub-images of 40x40, and the original full-sized image of 160x160. We use the segmented images to extract 59 features with the BALBP descriptor. Experiments were then carried out on different types of images from all the datasets.

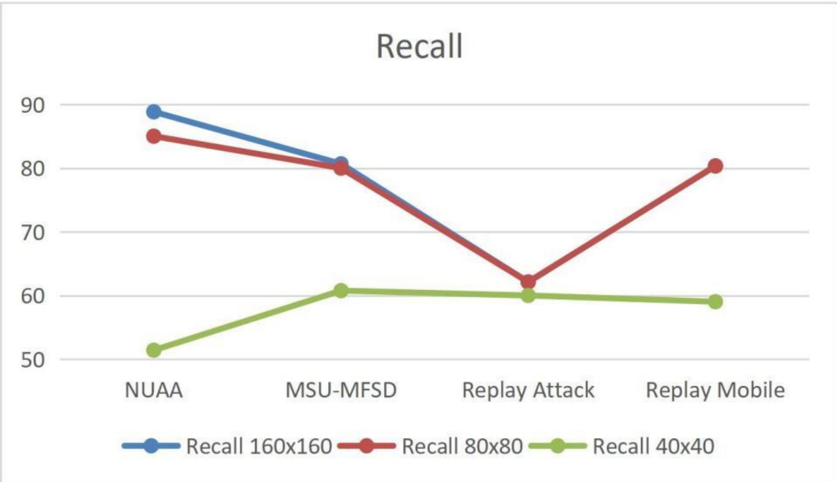

Fig . 7. Comparison of BALBP with Metric Recall

Table 5 : Comparison of BALBP with Metric F1-Score

DATA SET	**F1 score**		
	160x160	80x80	40x40
NUAA	90	51	50
MSU-MFSD	85	60	60
Replay Attack	71	62	59
Replay Mobile	85	64	64

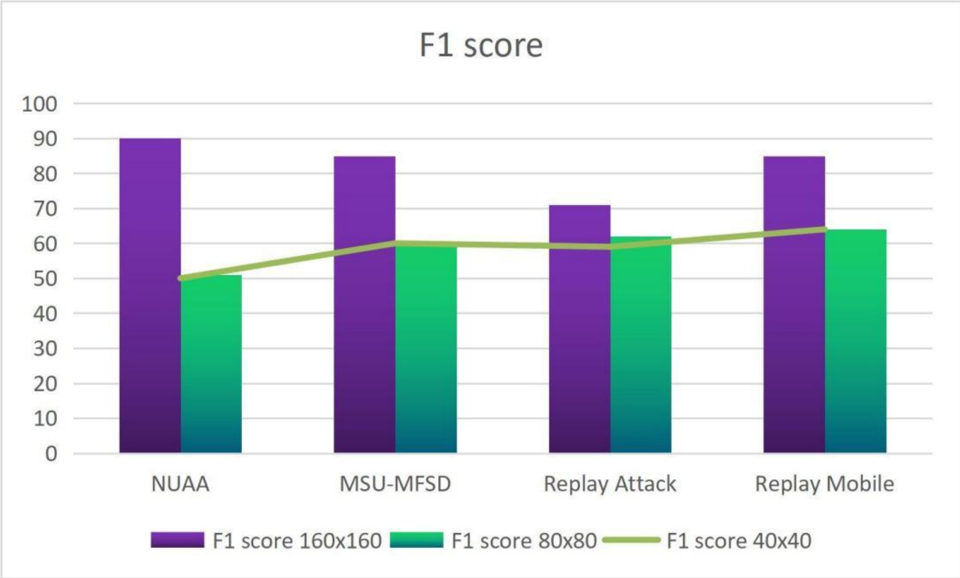

Fig . 8. Comparison of BALBP with Metric F1-Score

The Block Average Local Binary Pattern (BALBP) descriptor demonstrates strong performance in face anti- spoofing tasks when evaluated using the F1 score metric. The F1 score, which is the harmonic mean of precision and recall, is used to provide a balanced measure of a model's accuracy, especially in imbalanced datasets.

BALBP achieves a higher F1 score by maintaining both high precision—through noise reduction using block averaging—and high recall— by preserving key spoofing features across facial regions. This balance ensures fewer false positives and false negatives in detection. Therefore, the use of the F1 score highlights BALBP's effectiveness in providing reliable and consistent spoof detection.

Table 5 and Figure 8 shows the performance of the BALBP descriptor in terms of average f1-score, which were tested for three different sizes of images across all datasets. It was observed that higher f1-score indicates better performance specifically the f1-score for 160x160 segmented face images of the NUAA dataset was 90%, for the MSU-MFSD dataset it was 85%, for the Replay-Attack dataset it was 71% and for the Replay-Mobile dataset it was 85%.

4.4 Experiment 4: Comparison of BALBP with Other Descriptors

This experiment compares the BALBP descriptor with other descriptors. Figure 9 and Table 6 show that the recognition rate improves as the number of training images increases. The results demonstrate that the BALBP method outperforms with other descriptor in terms of recognition rate.

When compared to other texture descriptors like Local Block Pattern (LBP), Local Ternary Pattern (LTP), and Local Gabor Convolution (LGC), the proposed Block Average Local Binary Pattern (BALBP) achieves a higher F1 score, indicating improved overall accuracy in face anti-spoofing tasks. While LBP and LTP focus on directional and threshold-based patterns, and LGC emphasizes frequency information, BALBP uniquely combines local texture extraction with block-wise averaging, reducing noise and enhancing feature discrimination.

Using a classifier like the Hybrid Probabilistic Model (HPM), BALBP shows improved balance between precision and recall, leading to fewer misclassifications. This makes BALBP a more effective and reliable descriptor for real-world spoof detection scenarios.

Table 6 Comparison of the BALBP with other Descriptors in Terms of Precision and Recall.

Descriptors	**SVM**		**KNN**	
	Precision (%)	**Recall (%)**	**Precision (%)**	**Recall (%)**
LBP[45]	74.41	63.7	74.41	63.7
LTP[45]	84.87	77.2	84.87	77.2
LGS[45]	78.62	69.04	78.62	69.04
EDDTCP[]	81.69	88.69	81.69	88.69

proposed method	91.41	88.87	91.41	88.87

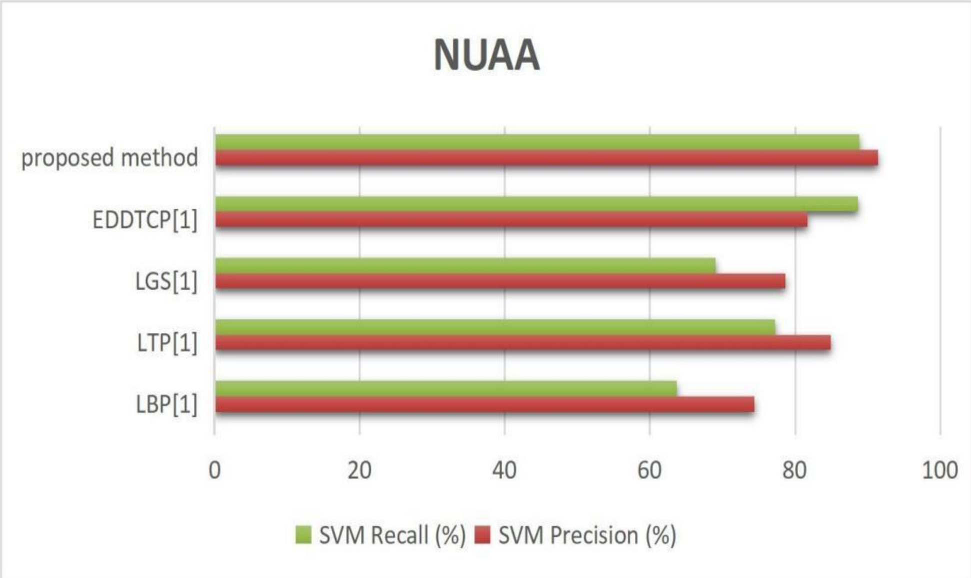

Fig . 9. Comparison of the BALBP with other Descriptors in Terms of Precision and Recall.

Table 7and Figure 10 shows the performance of the BALBP descriptor in terms of HTER and EER compared with other methods, which were tested for Replay-Attack dataset. The proposed method was outperformed over other methods in terms HTER and EER.

Table 7 Comparison of the BALBP with other Descriptors in Term of HTER and EER for Replay Attack Dataset

Descriptors	**Replay Attack**	
	HTER	**EER**
CNN[43]	41.36	42.48
CSURF (HSV+YCbCr)[44]	8.2	3.3
CSURF (YCbCr)[44]	8.9	5.2
EDDTCP[45]	7.86	1.26
LBP[45]	10.72	1.96
LTP[45]	19.99	0.75
CSURF (HSV)[44]	11.5	6.2
CSURF (RGB)[44]	13.5	11.3
SURF(Gray)[44]	21.2	19.5
LGS[45]	14.99	0.35
proposed method	0.45	0.44

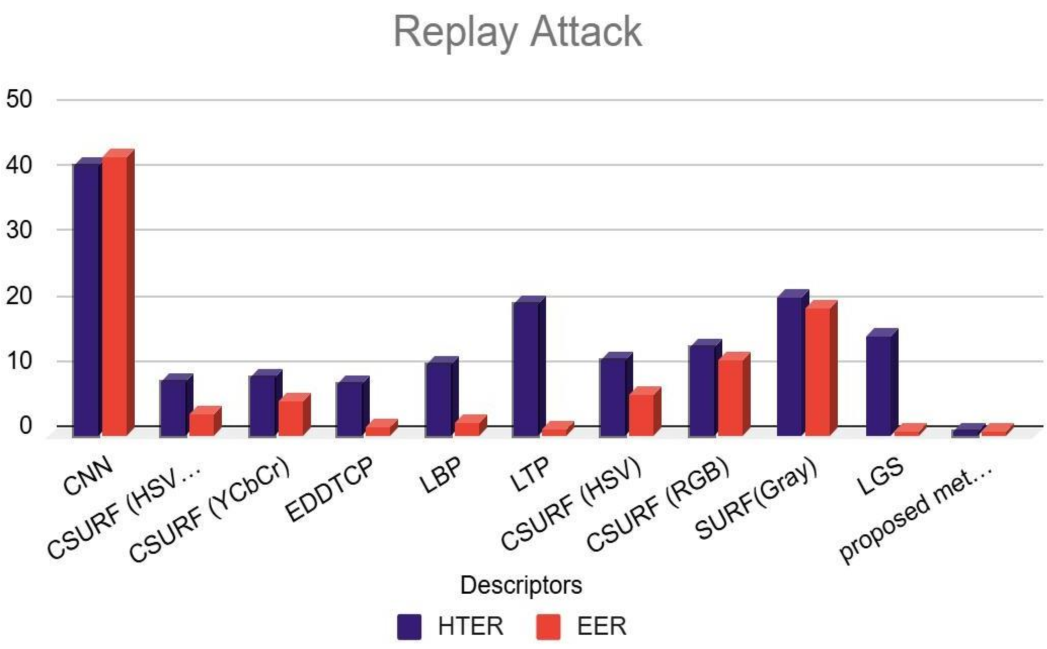

Fig . 10. Comparison of the BALBP with other Descriptors in Term of HTER and EER for Replay Attack Dataset

Table 8 and Figure 11 shows the performance of the BALBP descriptor in terms of HTER and EER compared with other methods, which were tested for NUAA dataset. The proposed method was outperformed over other methods in terms HTER and EER.

Table 8 Comparison of the BALBP with other Descriptors in Term of HTER and EER for NUAA Dataset

Descriptors	**NUAA**	
	HTER	**EER**
EDDTCP[45]	5.74	5.3
LBP[45]	12.09	10.54
LTP[45]	11	9.7
LGS[45]	10.83	9.58
proposed method	14.58	10.66

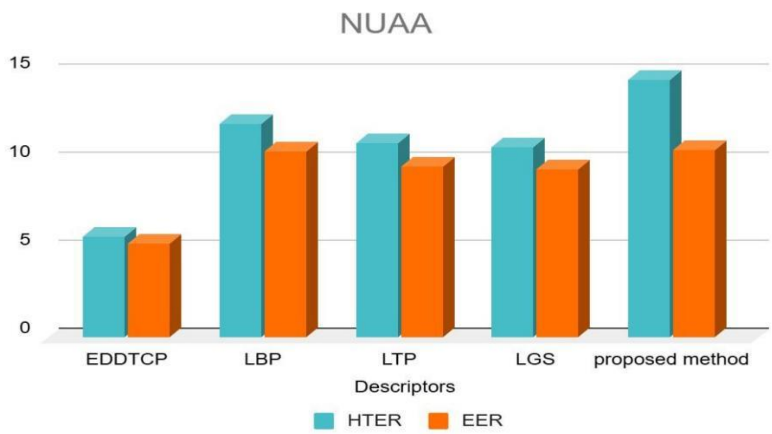

Fig . 11. Comparison of the BALBP with other Descriptors in Term of HTER and EER for NUAA Dataset

Table 9 Comparison of the BALBP with other Descriptors in Term of HTER and EER for MSU-MFSD Dataset

Descriptors	MSU-MFSD	
	HTER	EER
EDDTCP[45]	6.56	2.37
LBP[45]	12.54	3.49
LTP[45]	12.64	3.5
LGS[45]	13.13	3.65
proposed method	0.52	0.38

Table 9 and Figure 12 shows the performance of the BALBP descriptor in terms of HTER and EER compared with other methods, which were tested for MSU-MFSD dataset. The proposed method was outperformed over other methods in terms HTER and EER.

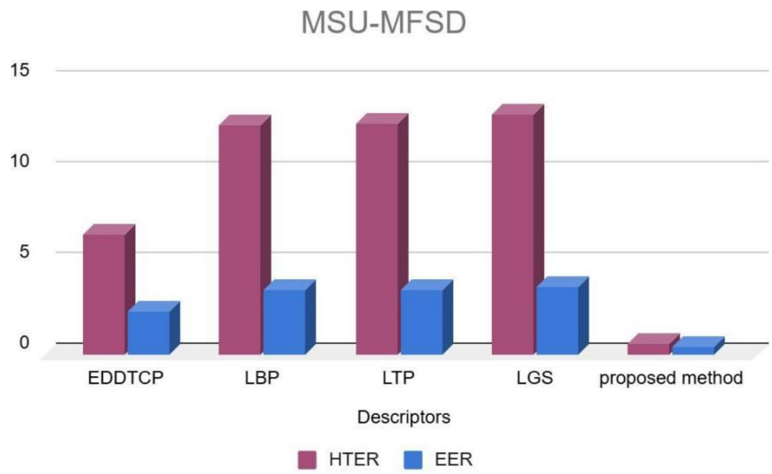

Fig . 12. Comparison of the BALBP with other Descriptors in Term of HTER and EER for MSU-MFSD Dataset

5.Conclusions

This work introduces a new method to detect face anti-spoofing. This method focuses on texture analysis using Block Average Local Binary Pattern (BALBP) descriptor. This method ensures discrimination between real and fake effectively by capturing unique texture. A Support Vector Machine (SVM) and KNN classifier is used to train the model and to ensure effectiveness in detecting real and fake image based on texture features. BALBP descriptor together with SVM and KNN classifier makes this work achieve a strong performance in identifying real and fake faces there by making significant contribution towards face recognition and security.

In this work, using BALBP descriptor texture features is extracted from grayscale images real and fake images are distinguished. Accurate classification is achieved using classifiers which helped in understanding that real images exhibits distinct textures than spoofed images. Experiments were conducted on different databases such as NUAA,MSU-MFSD, Replay-Attack, and Replay- Mobile databases shows that this method achieves high detection rates for print and replay attacks. Future work could extend this method to detect spoofing attacks involving facial masks and 3D models.

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