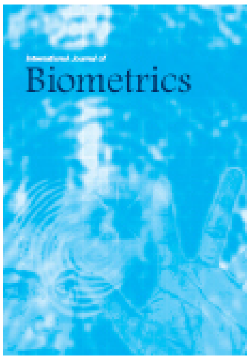

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Smita Khade, Sudeep D. Thepade, Swati Ahirrao

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Machine learning-based iris liveness identification using fragmental energy of cosine transformed iris images

Smita Khade

Symbiosis Institute of Technology,
Symbiosis International University,
Pune, India
Email: ambedkar.smita@gmail.com

Sudeep D. Thepade*

Department of Computer Engineering,
Pimpri Chinchwad College of Engineering,
Savitribai Phule Pune University,
Pune, India
Email: sudeepthepade@gmail.com
*Corresponding author

Swati Ahirrao

Symbiosis Institute of Technology,
Symbiosis International University,
Pune, India
Email: swatia@sitpune.edu.in

Abstract: Iris biometric identification provides a contactless authentication preventing the spread of COVID-19 like diseases. These systems are made vulnerable and unsafe because of the spoofing attacks attempted with the help of contact lenses, video replays and print attacks. The paper proposes the iris liveness detection method to mitigate spoofing attacks, taking fragmental coefficients of cosine transformed iris image to be used as features. Seven variants of feature formation are considered in experimental validations of the proposed method, and the features are used to train eight assorted machine learning classifiers and ensembles for iris liveness identification. Recall, F-measure, precision and accuracy are used to evaluate performances of the projected iris liveness identification variants. The experimentation carried out on four standard datasets have shown better iris liveness identification by the fragmental coefficients of cosine transformed iris image with size $4 * 4$ using random forest algorithm having 99.18% accuracy immediately followed by an ensemble of classifiers.

Keywords: iris images; liveness identification; discrete cosine transform; machine learning; classification; biometric; feature formation.

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Biographical notes: Smita Khade received a Master's degree in Computer Science and Engineering from the Pimpri Chinchwad College of Engineering, Pune. She is currently pursuing a PhD degree from Symbiosis International (Deemed University). Her research interests include vision computing, image processing, machine learning, and deep learning.

Sudeep D. Thepade is currently a Professor in the Computer Engineering Department at Pimpri Chinchwad College of Engineering affiliated with Savitribai Phule Pune University, Pune, Maharashtra, India. He has completed his PhD in 2011. He has more than 350 research papers to his credit published in international/ national conferences and journals. His domain of interest is image processing, image retrieval, video analysis, video visual data summarization, biometrics, and biometric liveness detection. He is a member of the International Association of Engineers (IAENG) and the International Association of Computer Science and Information Technology (IACSIT). He has served as a technical program committee member and reviewer for several international conferences and journals.

Swati Ahirrao received her PhD degree from the Department of Computer Science and Information Technology Symbiosis Institute of Technology (SIT), Symbiosis International (Deemed University), Pune, India. She is currently an Associate Professor with SIT. She has published over 29 research papers in international journals and conferences. According to Google Scholar, her articles have 60 citations, with an H-index of three and an i10-index of two. Her research interests include big data analytics, machine learning, and deep learning.

1 Introduction

The automatic access to the system by the genuine person has become very trivial in the information era. For automated system access, validation of the user identity is very important. Biometric authentication systems are computer-based identity verification of users, using biometric traits of users. The biometric authentication system is advantageous over other password-based conventional authentication mechanisms, as in the biometric system remembering a password, pin, or keeping a card in possession is not needed. The conventional security system cannot differentiate between real person and imposters, those who unethically have exposure to the program. For security-critical cyber applications, biometric authentication also may be thought of as one additional layer of authentication along with existing conventional authentication modes. As iris has complex textures and unique features, it is widely used in the identification of a person and authentication in most of the applications (Su and Shimahara, 2019), for example, in the Aadhar Card Project for the identification of citizens in India, on Amsterdam Airport and USA-Canadian border (Kaur et al., 2019). Compared to fingerprint and face, the iris-based authentication provides stronger contactless identification of the user. The contactless approach helps to prevent the spread of viruses and diseases like COVID-19. Even though the iris has a unique texture pattern, there is a possibility of being spoofed by the imposter.

People usually attack the biometric system to gain the privileges of other person or to hide self-identity. Iris identification system can be easily spoofed by using different contact lenses such as transparent lenses, coloured lenses, textured lenses, replayed the video and print attack (means iris texture is presented to the system by printing iris image). Print attacks (Kaur and Jindal, 2019) are done in two modes as:

1 'print and scan' – high quality printed iris pattern is scanned

2 'print and capture' – photo is captured by the scanner.

By using transparent lenses, though imposter cannot alter the texture of the iris, but can adjust the properties of the reflection (Choudhary et al., 2019) of iris to compromise the recognition system. With the help of texture colour lenses, an imposter can hide the real texture with spoof iris texture printed on it. Hence, analysing the threat and their vulnerability becomes very much important for securing the biometric system (Gupta and Sehgal, 2016). The challenging threat of spoofing of the biometric authentication system is counterfeited with the liveness identification of acquired biometric traits before authentication (Khade and Thepade, 2018).

The key contributions of the research work presented here are as follows:

- Proposing the use of fragmental coefficients of cosine transformed iris image data as features for the first time in iris liveness identification.
- Deciding upon the minimum size of fragmental coefficients which could be considered for feature formation without compromising the performance of iris liveness identification.
- Performance comparison of machine learning classifiers and ensembles to decide which classifier is better for iris liveness identification.
- Validating the performance of the proposed approach of iris liveness identification across various existing benchmark datasets.

The paper organisation is given herewith. Section 2 elaborates an outline of prevailing methods. Section 3 elaborates the proposed approach of iris liveness identification. The experimentations performed, observed results, and inferences drawn from results are discussed in Section 4. The ultimate observations and forthcoming research guidelines are discussed in Section 5. Finally, the conclusions of the paper in Section 6.

2 Existing methods of iris liveness identification

Many attempts are being made to identify the liveness of the sensed biometric traits before getting them authenticated. Few of the prominent approaches discussed in this section (Agarwal et al., 2020) use fingerprint and iris identity for liveness identification. The basic Haralick statistical features use GLCM and NGTDM to produce a fingerprint vector function. To enhance the performance of the device, the iris texture feature is used. The author used a standard dataset to test if this model outperforms the current model in terms of efficiency. In the existing system, GLCM has a huge feature vector size (Kaur et al., 2019). A rotation-invariant feature-set consisting of Zernike moments and polar harmonic transformations is used to identify iris spoofing attacks. The spoofing attacks on various sensors also have a huge upshot on the overall competence of the system. The system can detect only print and contact lens attacks.

Thavalengal et al. (2016) developed a system using a smartphone that captures RGB and NIR images of the eye and iris. Pupil localisation techniques with distance metrics are used for identification. For feature vector generation, 4,096 elements are considered, which are large. The author claims a good liveness identification rate, but he worked on a real-time database, and no standard datasets are used.

Fathy and Ali (2018) have not considered the segmentation and normalisation phases typically used in the fake iris identification systems. Wavelet packets (WPs) are used to break down the original image into a wavelet. The author claims 100% accuracy but, it does not work with all types of attacks, and it covers only limited spoofed attacks. In Hu et al. (2016), iris liveness identification shall be done using regional features. Regional features are built based on the interaction between the characteristics of the adjacent regions. During the experiment, the author has used 144 relational measures base on regional features. Czajka (2015) designed the liveness identification system using pupil dynamics. In this system, pupil reaction is measured with the help of sudden changes in light intensity. If the eye reacts to light intensity changes, then the eye is live; otherwise, it is spoofed. In this work, linear and nonlinear support vector machine (SVM) is used to classify the natural reaction and spontaneous oscillations. The limitation of the system measures the diverse functions, which take time. The data used in this analysis does not include any measurements from older people, so there is inaccuracy in the observation.

Naqvi et al. (2020) developed a system to detect accurate ocular regions. This system is based on convolutional neural network (CNN) model with a lite-residual encoder-decoder network. The publicly available databases are considered for the evaluation of the system. Kimura et al. (2020) designed a liveness identification system using CNN, which progresses the accuracy of the model by tuning hyperparameter. For measuring performances of the system, attack presentation classification error rate (APCER) and bonafede presentation classification error rate (BPCER) performances measured are used. The hyperparameters considered in this paper are the number of epochs (max.), batch size, learning rate and weight decay hyperparameters. This system works only for print and contact lenses attack.

Lin and Su (2019) developed face anti-spoofing and liveness identification system using CNN. The image is resized to 256 * 256, and RGB and HSV colour spaces are used. The author claims better iris's liveness predictions. Long and Zeng (2019) identified iris's liveness identification with the help of the BNCNN architecture with eighteen layers. The batch standardisation technique is used in BNCNN to prevent over-fitting and gradient disappearance during learning.

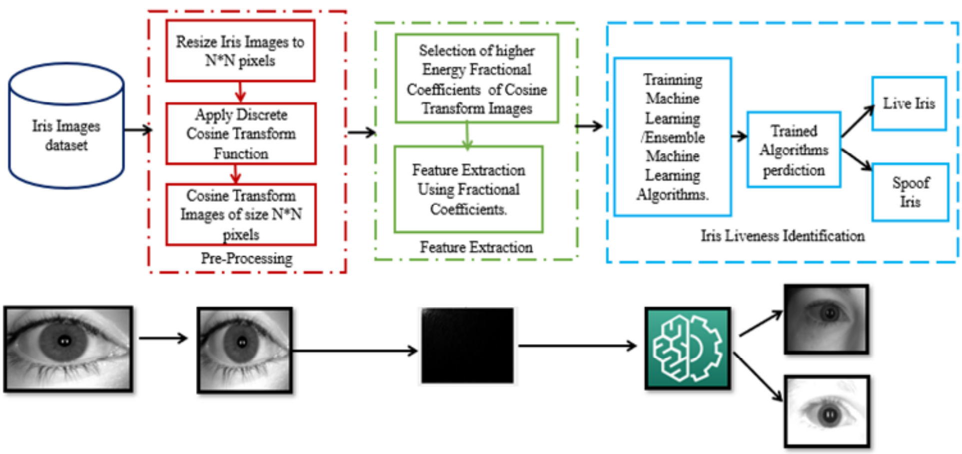
Dronky et al. (2019) observed from literature; many researchers do not identify all types of iris attacks. So, from the existing literature, it is observed that the researcher has worked on a few iris attacks, and a large feature vector size is considered.

3 Proposed iris liveness identification using fragmental energy of cosine transformed iris images

Iris recognition system is susceptible to many security challenges. These vulnerabilities do make the system less reliable for highly secured applications. The paper attempts iris liveness identification using fragmental energy of cosine transformed iris images.

These fragmental energy used as features to detect live or spoofed iris. Using these features, the proposed approach does not need any per processing like segmentation, normalisation, localisation which is conventionally being used by the methods proposed in the literature, which makes the proposed approach swifter and relatively easier (Vyas et al., 2019). The only preprocessing done in the proposed approach is resizing the iris image to square size. Figure 1 shows the block diagram of the iris liveness identification system. The proposed system is divided into three phases. Iris image resizing (preprocessing), feature formation and iris liveness identification.

Figure 1 Block diagram of the proposed iris liveness identification using fragmental energy of cosine transformed iris images (see online version for colours)



3.1 Resizing

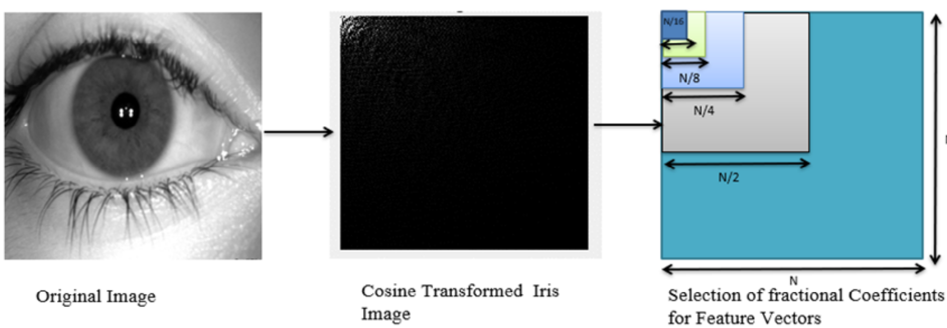
Iris preprocessing plays a very vital part in iris liveness identification. In the proposed algorithm, we follow two iris preprocessing approaches. Images are acquired using four different standard datasets, so each dataset uses a different size of images to be stored. In preprocessing, we normalised the original images of size $128 * 128$, which maintained integrity throughout the experiment. While capturing images of different datasets using different sensors like some sensors (LG, Congent, Vista) captures images in RGB format and some (LG, Dalsa) captures in greyscale format. To maintain uniqueness, we convert images into the greyscale format.

3.2 Feature formation using fragmental energy of transformed iris

The cosine transform is applied to a resized iris image. The cosine transform enables high energy content to get accumulated in the low-frequency region in the transform domain.

The higher energy and important information are contained within the left topmost corner of the transformed iris image. This achieves the significant energy compaction in a very a smaller number of high energy coefficients. So, these are considered as the desired feature vector elements. The low-frequency high energy region of cosine transformed iris image coefficients are taken in sizes as 128 ∗ 128, 64 ∗ 64, 32 ∗ 32, 16 ∗ 16, 8 ∗ 8, 4 ∗ 4 and 2 ∗ 2 as shown in Figure 2. To form feature vectors for proposed iris liveness identification. These feature vectors taken with high energy coefficients of cosine transformed iris images support the reduction of the size of feature vectors. This is resulting in faster iris-liveness identification. The compacted high energy in these low-frequency coefficients does improve the accuracy of iris liveness identification. These high-energy feature vectors are used further to train the machine learning models used for iris liveness identification. Earlier, this fractional energy concept is used for biometric identification (Thepade and Bhondave, 2015; Thepade and Gudadhe, 2013).

Figure 2 Proposed fragmental energy-based feature formation methods from cosine transformed iris images for liveness identification (see online version for colours)



3.3 Iris liveness identification

The proposed approach of iris liveness identification uses different machine learning classifiers with ensembles combination. The machine learning classifiers employed here are SVM, naive Bayes (NB), random forest (RF), and J48, with ensembles of a few of the machine learning classifiers.

The tenfold cross-validation approach is used for training these classifiers for iris liveness identification. The tenfold cross-validation is one of the best approaches for the training of machine learning classifiers. Tenfold cross-validation gives a chance to all samples from the dataset for being part of training or test data resulting in a less biased trained classifier. The majority voting logic is used here for creating the ensembles of machine learning classifiers.

3.4 Details of machine learning algorithms used in the proposed model

In the proposed model, four machine learning algorithms and three ensembles of these algorithms are explored. The machine learning algorithms used are SVM, J48, RF, and NB with ensembles generated using majority voting logic as 'SVM + RF + NB', 'SVM + RF + RT' and 'RF + SVM + MLP'. Earlier, the machine learning algorithms are used for many image classification applications (Thepade and Kalbhor, 2015). For detailed validation across four of the popular datasets (Clarkson LivDet 2013, Clarkson LivDet 2015, IIITD Combined Spoofing Database, IIITD Contact Lens); the tenfold cross-validation method is used which divides the data randomly in ten clusters. Out of these ten, nine clusters are used for training, and remained 10th cluster is used for testing; this process gets repeated ten times each time, considering a different tenth cluster. The performance metric like accuracy, F-measures, recall, and precision are used to validate the performance of variations attempted for the proposed modal.

4 Experimental results and discussion

This section discusses the investigational results of the proposed approach of iris liveness identification. The experiments have been performed using MATLAB as a programming platform. The datasets used for experimental explorations of the proposed approach of iris liveness identification are Clarkson LiveDet2013, Clarkson LiveDet2015, IITD contact lens and IITD combined spoofing.

4.1 Description of datasets

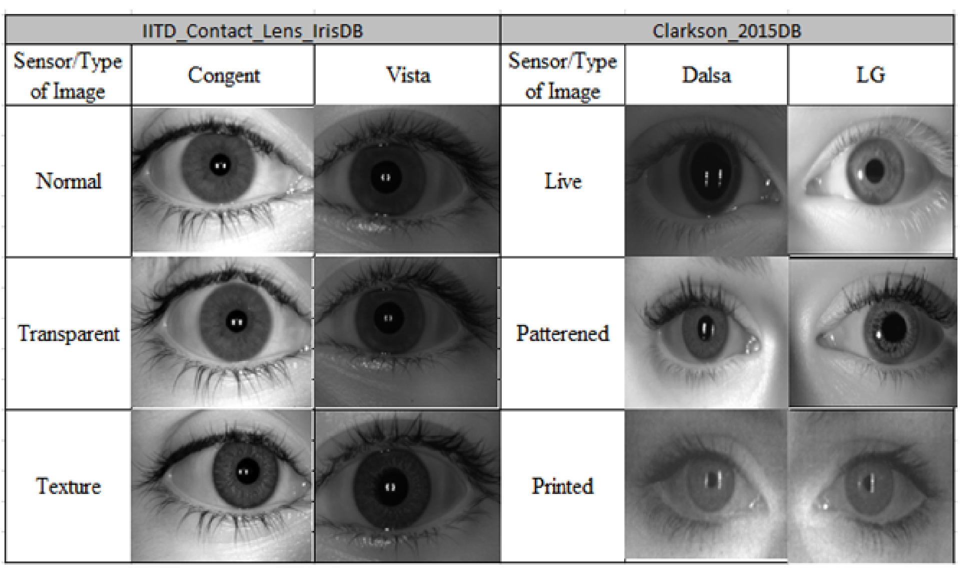
During this experiment four, publicly available and standard datasets are used. The detailed description of the dataset is as follows:

- Clarkson LivDet2013: Clarkson LivDet2013 dataset has around 1,536 iris images (Yambay et al., 2014). This dataset is separated into testing and training sets. To acquire the images, the Dalsa sensor is used. During this experiment, the training set images are used. Table 1 shows the details related to the dataset, sensors used to acquire images, and numbers of images used during this experiment.
- Clarkson LivDet2015: Images used in this dataset are captured using Dalsa and LG sensors (Yambay et al., 2015). Images are divided into three categories: live, pattern and printed. For live images, 25 subjects are used, and for pattern and printed, 15 subjects, each is used. The whole dataset has partitioned into two parts training and testing. Figure 3 shows samples of images from the dataset.
- IIITD combined spoofing database: The images used by this dataset are obtained using two iris detectors, a cogent sensor and an iris sensor (Kohli et al., 2016). Images are divided into three categories: normal, print-scan attack and print-capture attack. Table 1 shows the details related to the dataset, sensors used to acquire images, and the number of images used during this experiment.
- IIITD contact lens: The images used by this dataset are obtained using two iris detectors, a cogent dual iris sensor and Vista FA2E single iris sensor (Yadav et al., 2014; Kohli et al., 2013). Images are divided into three categories: normal, transparent and coloured. 101 objects are included, the right and left iris images of each object are collected, and thus there are 202 iris grades. Figure 3 shows the samples of images from the dataset.

Table 1 Number of images used for an experiment from each dataset across different sensors

Database	*Sensor*	*Image category*	*No. of images used for experiment*
Clarkson 2013	Dalsa	Off (live)	350
		Pattern (contact)	440
		Live	378
	Dalsa	Pattern	356
		Printed	1,416
Clarkson 2015	LG	Pattern	433
		Live	258
		Printed	844
		Normal	2,024
	Congent	Print-capture	1,113
		Print-scan	980
		Normal	2,024
IITD_Iris_Sproffing	Vista	Print-capture	1,092
		Print-scan	1,196
		Normal	422
	Congent	Transparent	1,131
		Textured	1,150
		Normal	1,010
IIITD_Conact	Vista	Transparent	1,010
		Textured	1,010

Figure 3 Sample iris images from IITD contact lens IrisDB and Clarkson 2015 dataset images



4.2 Performance measures

To evaluate the performance of all the experimented discrepancies of the proposed approach of iris liveness identification, the accuracy, recall, F-measure, and precision are used as performance metrics.

Let *tP*, *tN*, *fP*, and *fN* respectively be the true positive, true negative, false positive, and false negative of the iris liveness identification. The *tP* indicates the data samples, which are predicted as live iris and are live samples. The *tN* gives the data samples detected as spoofed iris and also are spoofed iris samples. *fP* indicates the samples identified as live but is spoofed ones. *fN* shows the data samples detected as spoofed but are live iris samples. The performance metrics are shown in equations (1), (2), (3) and (4). Equations (1), (2), (3) and (4), respectively, give the formula for accuracy, precision, recall and F-measure.

$$Accuracy = \frac{tP + tN}{fP + fN + tP + tN} \tag{1}$$

$$Precision = \frac{tP}{fP + tP} \tag{2}$$

$$Recall = \frac{tP}{fP + tN} \tag{3}$$

$$F\text{-}measures = 2 * \frac{Precision * Recall}{Precision + Recall}. \tag{4}$$

5 Results and observations

The proposed approach of iris liveness identification has experimented with the benchmark datasets for all feature size variants. The accuracy, precision, recall, and F-measure are used as performance metrics to evaluate variants of the proposed approach of iris liveness identification.

Figure 4 gives the performance comparison of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification tested on the Clarkson 2013 dataset.

Here, it can be observed that for all classifiers, 8 ∗ 8 and 4 ∗ 4 fragmental coefficients outperform other fragmental coefficients combinations for Clarkson 2013 dataset. From results, it can be observed that as you go on reducing the number of higher energy coefficients to be considered as features from 128 ∗ 128 till 8 ∗ 8 or 4 ∗ 4, indicating the common part is getting eliminated and more discriminative part from less number of higher energy coefficients gets better iris liveness identification up to certain extent. Further, if the reduction is attempted in number of higher energy coefficients to be taken as feature vector from 4 ∗ 4 to 2 ∗ 2; the discriminative part starts getting eliminated showing declining of the performance.

The performance investigation of the proposed approach of iris liveness identification done with the help of percentages iris liveness identification accuracy for Clarkson 2013 dataset is given in Table 2 for specific machine learning classifiers.

Figure 4 Performance evaluation of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification for Clarkson 2013 dataset using percentage accuracy (see online version for colours)

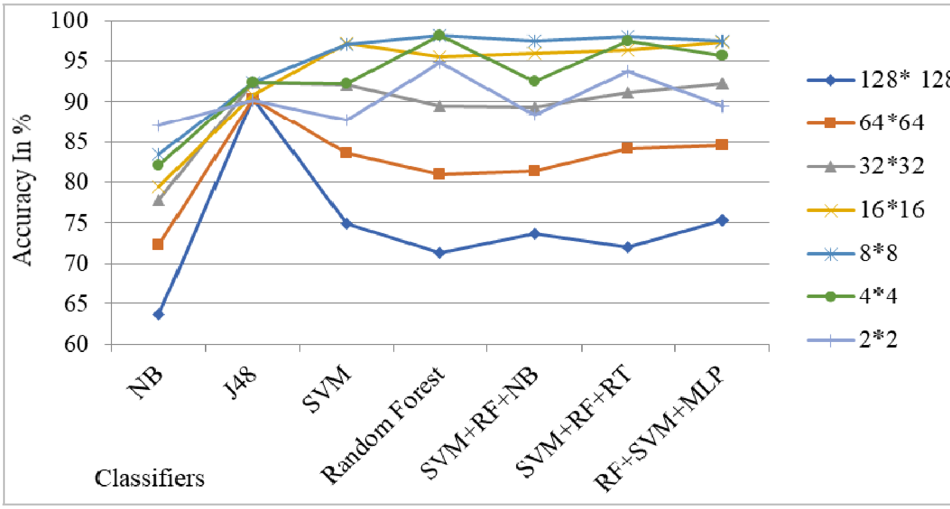


Table 2 Performance evaluation using accuracy for variants of proposed approach of iris liveness identification with various feature vector sizes and machine learning classifiers experimented on Clarkson 2013 dataset

Classifiers/ensembles of classifiers	*Fragmental coefficients*						
	128 128*	*64*64*	*32*32*	*16*16*	*8*8*	*4*4*	*2*2*
NB	63.7	72.3	77.84	79.44	83.38	82.07	87.02
J48	90.37	90.37	92.41	90.81	92.41	92.41	90.23
SVM	74.92	83.52	92.12	97.23	97.08	92.27	87.75
Random forest	71.42	81.04	89.5	95.48	98.1	98.1	94.89
SVM+RF+NB	73.76	81.34	89.35	95.91	97.52	92.56	88.33
SVM+RF+RT	72.01	84.11	91.1	96.35	97.95	97.52	93.73
RF+SVM+MLP	75.36	84.54	92.27	97.37	97.52	95.62	89.5

Here in Table 2, it is observed that the performance becomes better with the reduced feature vector size from 128 $*$ 128 till 4 $*$ 4 and then starts getting declined with feature vector size 2 $*$ 2. This shows the fragmental coefficients of cosine transformed iris images give better iris livened identification capability with the compact feature vector size evidencing the worth of the proposed approach. The highest observed iris liveness identification accuracy comes around 98.1% with 4 $*$ 4 and 8 $*$ 8 fragmental coefficients using RF classifier followed by ensembles of classifiers (RF + SVM + MLP).

Figure 5 shows an analysis of the performance of the proposed fragmental coefficients used with the specific fragmental coefficients for the planned method of iris liveness identification explored on the Clarkson 2013 dataset.

Figure 6 gives the performance comparison of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification tested on the Clarkson 2015 dataset. Here, it can be observed that for all classifiers 4 ∗ 4, fragmental coefficients outperform other fragmental coefficients combinations for Clarkson 2015 dataset. The analysis of results show here the reduction in number of higher energy coefficients from 128 ∗ 128 till 4 ∗ 4 is giving the performance improvement as the common part is getting curtailed and discriminative is getting focused more. Further, if reduction is attempted form 4 ∗ 4 to 2 ∗ 2, the discriminative part is getting deleted and hence performance gets deteriorated.

Figure 5 Performance evaluation of machine learning classifiers for specific fragmental coefficients in the proposed approach of iris liveness identification for Clarkson 2013 dataset using percentage accuracy (see online version for colours)

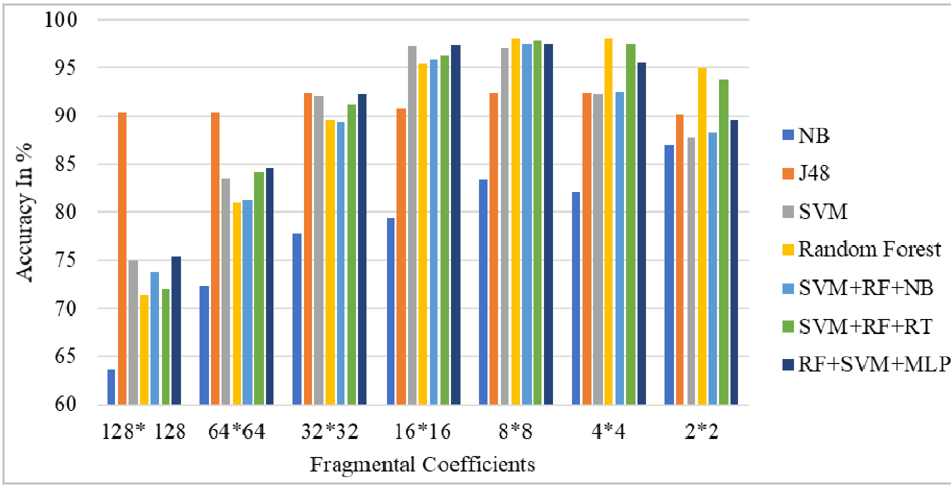
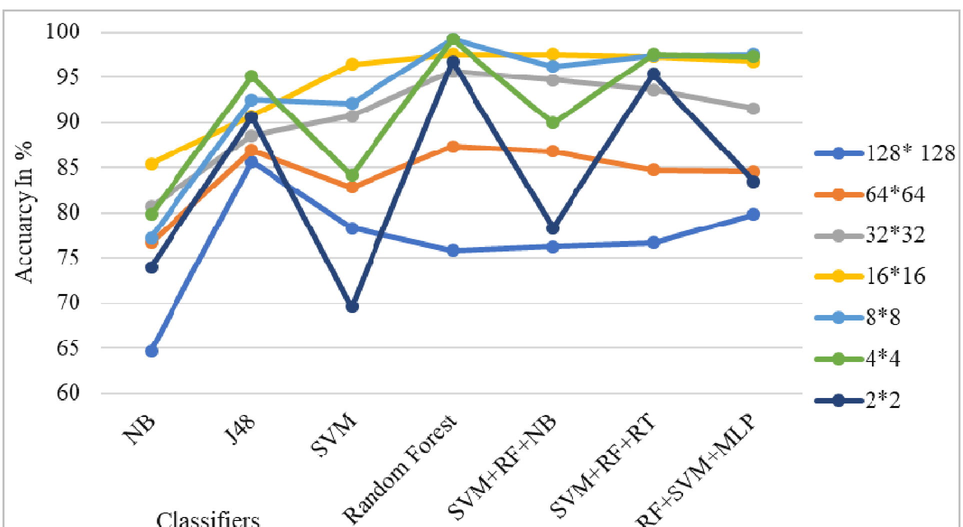


Figure 6 Performance evaluation of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification for Clarkson 2015 dataset using percentage accuracy (see online version for colours)



The performance investigation of the proposed approach of iris liveness identification done with the help of percentages iris liveness identification accuracy for the Clarkson 2015 dataset is given in Table 3 for specific machine learning classifiers. Here in Table 3, it is observed that the performance becomes better with the compact feature vector size from 128 ∗ 128 till 4 ∗ 4. The highest observed iris liveness identification accuracy comes around 99.18% with 4 ∗ 4 fragmental coefficients by using RF classifier.

Table 3 Performance evaluation using accuracy for variants of proposed approach of iris liveness identification with various feature vector sizes and machine learning classifiers experimented on Clarkson 2015 dataset

Classifiers/ensembles of classifiers	*Fragmental coefficients*						
	128 128*	*64*64*	*32*32*	*16*16*	*8*8*	*4*4*	*2*2*
NB	64.71	76.70	80.65	85.42	77.24	79.83	73.97
J48	85.69	86.92	88.55	90.73	92.50	95.09	90.59
SVM	78.33	82.83	90.73	96.45	92.09	84.19	69.61
Random forest	75.88	87.32	95.64	97.54	99.18	99.18	96.73
SVM+RF+NB	76.29	86.78	94.68	97.54	96.18	89.91	78.33
SVM+RF+RT	76.70	84.74	93.59	97.27	97.41	97.54	95.36
RF+SVM+MLP	79.83	84.60	91.55	96.73	97.54	97.27	83.51

Figure 7 shows an analysis of the performance of the proposed fragmental coefficients based features formation methods used with the specific fragmental coefficients for the planned method of iris liveness identification explored on Clarkson 2015 dataset.

Figure 7 Performance evaluation of machine learning classifiers for specific fragmental coefficients in the proposed approach of iris liveness identification for Clarkson 2015 dataset using percentage accuracy (see online version for colours)

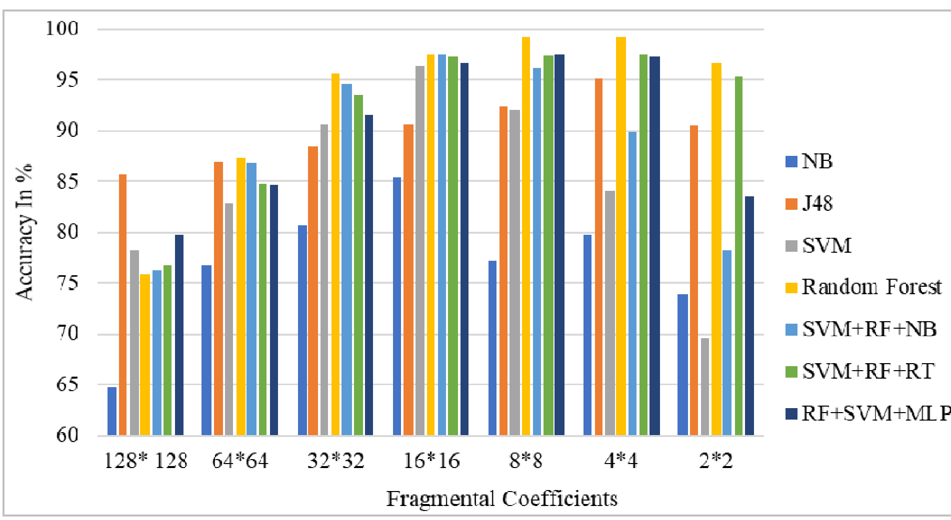


Figure 8 gives the performance comparison of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification tested on the IIITD Contact dataset. Here, it can be observed that 4 ∗ 4 fragmental coefficients outperform other fragmental coefficients combinations for the IIITD contact dataset for all classifiers. Here also, the performance improvement is observed from 128 ∗ 128 size of higher energy coefficients till the size of 4 ∗ 4, as this reduction enhances discriminative part more and eliminates the common part of information across samples. Further if more reduction in feature vector size is attempted from 4 ∗ 4 to 2 ∗ 2, as the discriminative part is also getting curtailed; the performance deteriorates.

Figure 8 Performance evaluation of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification for IIITD contact dataset using percentage accuracy (see online version for colours)

Table 4 Performance evaluation using accuracy for variants of proposed approach of iris liveness identification with various feature vector sizes and machine learning classifiers experimented on the IIITD contact dataset

Classifiers/ensembles of classifiers	*Fragmental coefficients*						
	128 128*	*64*64*	*32*32*	*16*16*	*8*8*	*4*4*	*2*2*
NB	54.21	63.61	64.09	68.67	66.98	59.63	51.68
J48	58.19	61.32	65.9	67.59	71.8	68.91	60
SVM	56.62	56.62	62.16	66.9	64.21	55.18	52.53
Random forest	60.12	64.69	73.85	78.07	83.97	84.69	75.66
SVM+RF+NB	58.31	66.02	70.24	72.4	69.75	57.22	55.42
SVM+RF+RT	58.43	60.96	70	74.45	78.31	79.27	71.56
RF+SVM+MLP	56.98	58.55	63.25	70.6	70.36	59.15	55.18

The performance investigation of the proposed approach of iris liveness identification done with the help of percentages iris liveness identification accuracy for IIITD contact dataset is given in Table 4 for specific machine learning classifiers. Here in Table 4, it is observed that the performance becomes better with the compact feature vector size from 128 ∗ 128 till 4 ∗ 4 and then starts getting declined with feature vector size 2 ∗ 2. The highest observed iris liveness identification accuracy comes around 84.69% with $4 * 4$ fragmental coefficients using the RF classifier. The discriminative part gets more focused when the feature vector size is reduced from $128 * 128$ till $4 * 4$, showing highest performance at $4 * 4$.

Figure 9 shows an analysis of the performance of the proposed fragmental coefficients-based feature formation methods used with the specific fragmental coefficients for the planned method of iris liveness identification explored on the IIITD contact dataset.

Figure 9 Performance evaluation of machine learning classifiers for specific fragmental coefficients in the proposed approach of iris liveness identification for IIITD contact dataset using percentage accuracy (see online version for colours)

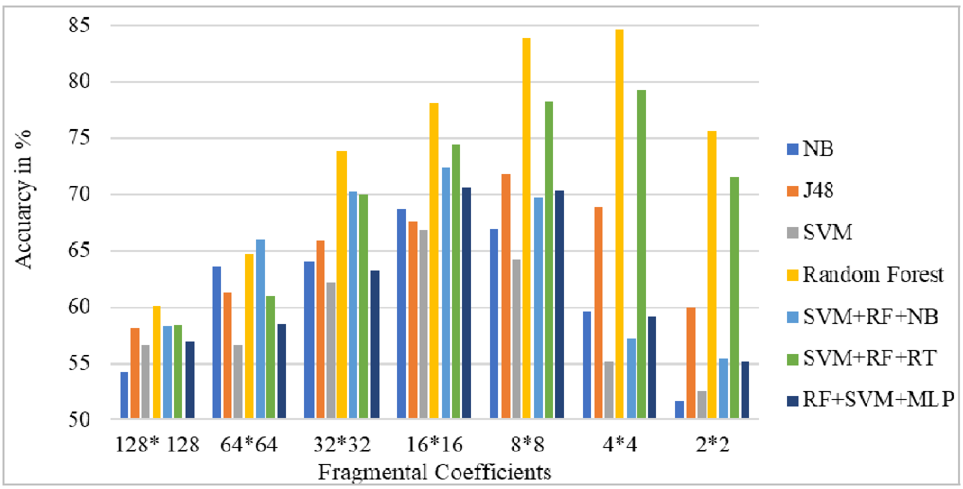


Figure 10 Performance evaluation of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification for IIITD combined spoofing dataset using percentage accuracy (see online version for colours)

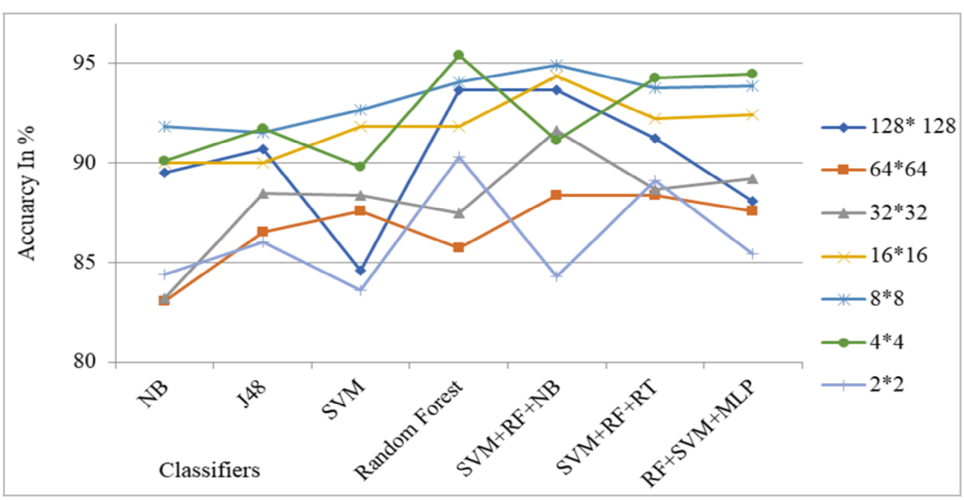


Figure 10 gives the performance comparison of considered fragmental coefficients for specific machine learning classifiers in the proposed approach of iris liveness identification tested on IIITD combined spoofing dataset. Here, it can be observed that for all classifiers, 4 ∗ 4 fragmental coefficients outperform other fragmental coefficients combinations for IIITD combined spoofing dataset.

The performance investigation of the proposed approach of iris liveness identification done with the help of percentages iris liveness identification accuracy for IIITD combined spoofing dataset is given in Table 5 for specific machine learning classifiers. Here in Table 5, it is observed that the performance becomes better with the compact feature vector size. The highest observed iris liveness identification accuracy comes around 95.41% with 4 ∗ 4 fragmental coefficients by using RF classifier.

Table 5 Performance evaluation using accuracy for variants of proposed approach of iris liveness identification with various feature vector sizes and machine learning classifiers experimented on IIITD combined spoofing dataset

Classifiers/ensembles of classifiers	*Fragmental coefficients*						
	128 128*	*64*64*	*32*32*	*16*16*	*8*8*	*4*4*	*2*2*
NB	89.5	83.07	83.18	90.01	91.84	90.11	84.4
J48	90.72	86.54	88.48	90.01	91.53	91.74	86.03
SVM	84.6	87.56	88.37	91.84	92.66	89.8	83.58
Random forest	93.67	85.72	87.46	91.84	94.08	95.41	90.31
SVM+RF+NB	93.67	88.37	91.64	94.39	94.9	91.13	84.3
SVM+RF+RT	91.23	88.37	88.68	92.25	93.78	94.29	89.09
RF+SVM+MLP	88.07	87.56	89.19	92.45	93.88	94.49	85.42

Figure 11 shows an analysis of the performance of the proposed fragmental coefficients-based feature formation methods used with the specific fragmental coefficients for the planned method of iris liveness identification explored on IIITD combined spoofing dataset.

Figure 11 Performance evaluation of machine learning classifiers for specific fragmental coefficients in the proposed approach of iris liveness identification for IIITD combined spoofing dataset using percentage accuracy (see online version for colours)

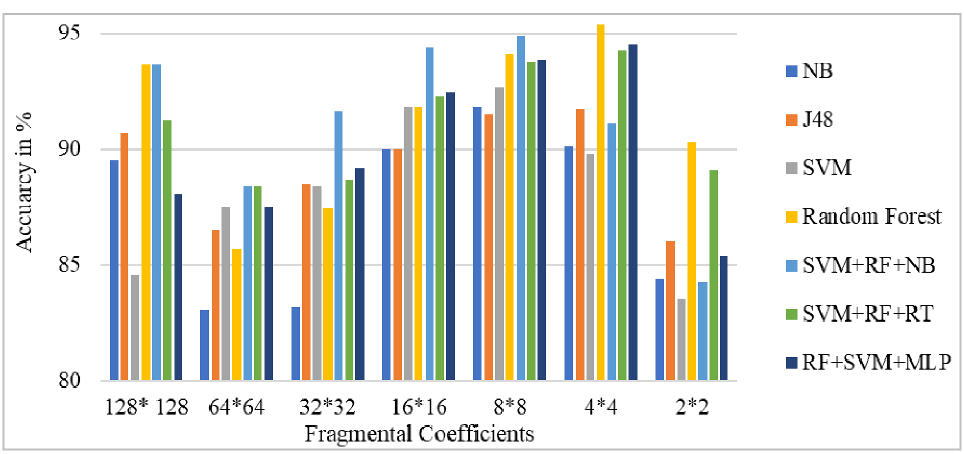


Table 6 Performance comparison of fragmental coefficients using an average of % accuracy, % precision, % recall and % F-ratio values

	Performance measures classifiers	*Avg of (accuracy, precision, recall, and f-ratio) fragmental coefficients*							
		*128*128*	*64*64*	*32*32*	*16*16*	*8*8*	*4*4*	*2*2*	*AVG*
Clarkson_2013	NB	63.7	72.3	77.84	79.44	83.38	82.07	87.02	*77.96429*
	J48	90.37	90.37	92.41	90.81	92.41	92.41	90.23	*91.28714*
	SVM	74.92	83.52	92.12	97.23	97.08	92.27	87.75	*89.27*
	Random forest	71.42	81.04	89.5	95.48	98.1	98.1	94.89	*89.79*
	SVM+RF+NB	73.76	81.34	89.35	95.91	97.52	92.56	88.33	*88.39571*
	SVM+RF+RT	72.01	84.11	91.1	96.35	97.95	97.52	93.73	*90.39571*
	RF+SVM+MLP	75.36	84.54	92.27	97.37	97.52	95.62	89.5	*90.31143*
	AVG	*74.50*	*82.46*	*89.22*	*93.22*	*94.85*	*92.93*	*90.20*	-----
Clarkson_2015	NB	64.71	76.7	80.65	85.42	77.24	79.83	73.97	*76.93143*
	J48	85.69	86.92	88.55	90.73	92.5	95.09	90.59	*90.01*
	SVM	78.33	82.83	90.73	96.45	92.09	84.19	69.61	*84.89*
	Random forest	75.88	87.32	95.64	97.54	99.18	99.18	96.73	*93.06714*
	SVM+RF+NB	76.29	86.78	94.68	97.54	96.18	89.91	78.33	*88.53*
	SVM+RF+RT	76.7	84.74	93.59	97.27	97.41	97.54	95.36	*91.80143*
	RF+SVM+MLP	79.83	84.6	91.55	96.73	97.54	97.27	83.51	*90.14714*
	AVG	*76.77*	*84.27*	*90.77*	*94.52*	*93.16*	*91.85*	*84.01*	-----
IIITD_Contact	NB	54.21	63.61	64.09	68.67	66.98	59.63	51.68	*61.26714*
	J48	58.19	61.32	65.9	67.59	71.8	68.91	60	*64.81571*
	SVM	56.62	56.62	62.16	66.9	64.21	55.18	52.53	*59.17429*
	Random forest	60.12	64.69	73.85	78.07	83.97	84.69	75.66	*74.43571*
	SVM+RF+NB	58.31	66.02	70.24	72.4	69.75	57.22	55.42	*64.19429*
	SVM+RF+RT	58.43	60.96	70	74.45	78.31	79.27	71.56	*70.42571*
	RF+SVM+MLP	56.98	58.55	63.25	70.6	70.36	59.15	55.18	*62.01*
	AVG	*57.55*	*61.68*	*67.07*	*71.24*	*72.19*	*66.29*	*60.29*	-------
IIITD_Spoofing	NB	89.5	83.07	83.18	90.01	91.84	90.11	84.4	*87.44429*
	J48	90.72	86.54	88.48	90.01	91.53	91.74	86.03	*89.29286*
	SVM	84.6	87.56	88.37	91.84	92.66	89.8	83.58	*88.34429*
	Random forest	93.67	85.72	87.46	91.84	94.08	95.41	90.31	*91.21286*
	SVM+RF+NB	93.67	88.37	91.64	94.39	94.9	91.13	84.3	*91.2*
	SVM+RF+RT	91.23	88.37	88.68	92.25	93.78	94.29	89.09	*91.09857*
	RF+SVM+MLP	88.07	87.56	89.19	92.45	93.88	94.49	85.42	*90.15143*
	AVG	*90.20*	*86.74*	*88.14*	*91.82*	*93.23*	*92.42*	*86.16*	-------

Table 6 represents performance comparison of fragmental coefficients using an average of % accuracy, % precision, % recall, and % F-ratio values across all datasets used for implementation. The highest performances for specific datasets are shown in Table 7.

Table 7 Performance evaluation using accuracy for the proposed approach of iris liveness identification for all various datasets used during implementation

Datasets	*Classifiers/ensembles of classifiers*	*Fractional coefficients*	*Accuracy in %*
Clarkson 2013	RF	4*4	99.1
Clarkson 2015	RF	4*4	99.18
IIITD_Contact	RF	4*4	84.69
IIITD_Combined_Spoofing	RF	4*4	95.41

It is observed from Table 7, that RF gives the highest accuracy of 99.18% using $4 * 4$ fragmental coefficients in the proposed approach of iris liveness identification experimented over the Clarkson 2015 dataset.

The use of fragmental energy cosine transforms to distinguish between live and faked artefacts and offer improved outcomes compared to the latest state-of-the-art approaches. The findings show that our suggested approach decreases classification error and improves accuracy relative to the previous approaches used to detect presentation attacks iris identification system. This has been tabulated in Table 8. The proposed approach is compared to the recent research done in this area, and it has already been concluded that the proposed approach outperforms other methods.

Table 8 The comparative analysis/study of the proposed approach and prevailing methods

Authors	*Dataset*	*Performance measure*	*Classifiers*	*Accuracy (%)*
A		Accuracy	VGGNet	97.98
	IITD	FAR	LeNet	89.38
			ConvNet (SVM)	98.99
B	IITD	Accuracy, precision	KNN, NB, DT	96.43
C	IITD	Accuracy	R-CNN, CNN	98.9
D	PolyU bi-spectra	Accuracy	CNN, SDH	90.71
E	CASIA-Iris-L	Accuracy	Hadamard+ CNN	97.41
F	ATVS	Accuracy	DWT + ResNet	92.57
	Clarkson 2013		RF	99.1
G	Clarkson 2015	Accuracy, precision, recall, and F measure	RF	99.18
	IIITD_Contact		RF	84.69
	IIITD_Combined_Spoofing		RF	95.41

Notes: A – Arora et al. (2021), B – Omran and Alshemmary (2020), C – Zhao and Kumar (2019), D – Wang and Kumar (2019), E – Cheng et al. (2019), F – Chatterjee et al. (2019), G – proposed approach and RF – random forest.

6 Conclusions

The paper projected a novel method of iris liveness identification for the sustenance against iris spoofing by textured lenses and print attacks. The proposed approach identified both kinds of print attacks (capture/scan) and detected iris spoofing attempted using different sensors. Till now, many approaches have used preprocessing as iris segmentation, normalisation, and localisation; which, is tolling computationally on the method of iris liveness identification. To overcome this drawback, in the proposed approach, discrete cosine transforms apply directly to iris images and extracting fragmental coefficients as feature vectors. Various machine learning algorithms and their ensemble combinations are trained using these cosines transformed iris fragmental coefficients. The experiential validation of the proposed liveness identification approach is done on four benchmark datasets. The performance comparison of variants of the proposed approach is done using four metrics alias accuracy, precision, recall and F-measure. For Clarkson 2013 dataset, fake images are identified with 98.1% accuracy. Clarkson 2015 the highest accuracy of a dataset of 99.18% is achieved by RF with $4 * 4$ fragmental coefficients. In IIITD spoofing get 99.15%, and IIITD contact got 87.68% accuracy. The experimental result displays that the proposed approach efficiently identified iris spoofing attacks using diverse sensors.

In future work, may extend this framework with the best performance features, a level fusion of fragmental coefficients of cosine transforms. We will apply this and extended framework to other biometric traits.

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