

# Multimodal Biometric Recognition System Using Face and Finger Vein Biometric Traits with Feature and Decision Level Fusion Techniques

Arjun B. C. and H. N. Prakash

**Abstract**—A lot of research is going on biometrics security systems due to the high increase in spoofing attacks. To provide enhanced security using biometric applications, researchers showed more interest in multimodal biometrics. Using Multimodal biometrics applications, the complex model structure can be designed which provides a low risk of a spoofing attack. This paper discussed a hybrid model designed using the multilevel fusion of multimodal biometrics. This model considered two biometrics modalities face and finger vein, and also two levels of fusion feature level and decision level. In this work five classifiers Ensemble discriminant, K-Nearest Neighbor, Linear Discriminant, Ensemble subspace K-Nearest Neighbor (ESKNN), and SVM for majority voting are used. In this work rich information image is created by up sampling the image using bilinear interpolation techniques. The proposed model advances the recognition rate over unimodal biometric systems.

**Index Terms**—Multimodal, biometrics, feature level fusion, decision level fusion.

## I. INTRODUCTION

A lot of terrorist activities are going on around the world. To provide a high-security system, there are a lot of limitations like noisy data, the differences in intra-class and inter-class, etc. are faced in the unimodal biometric systems. To overcome the problems faced in the unimodal biometric systems, multimodal biometric recognition is introduced. More than one biometric trait is used in this model. Multimodal provides very rich information compared to unimodal. The rich information provided by multimodal is very much useful to overcome the drawbacks of unimodal systems. The information received from multimodal biometrics can be combined at various levels of fusion. For person identification or recognition system, various types of biometrics traits can be used. All biometrics traits are grouped into physiological, behavioral, and soft biometrics [1, 2]. Under these three categories, various biometric traits are classified. Fig. 1 shows three groups of biometric traits. From these categories of biometrics, more than one biometric trait is used in the Multimodal Biometric recognition systems.

This work shows the improvement of the recognition performance of a biometric system using more than one biometric trait. This work also concentrated on the use of Multi-levels of fusion of different biometric traits.

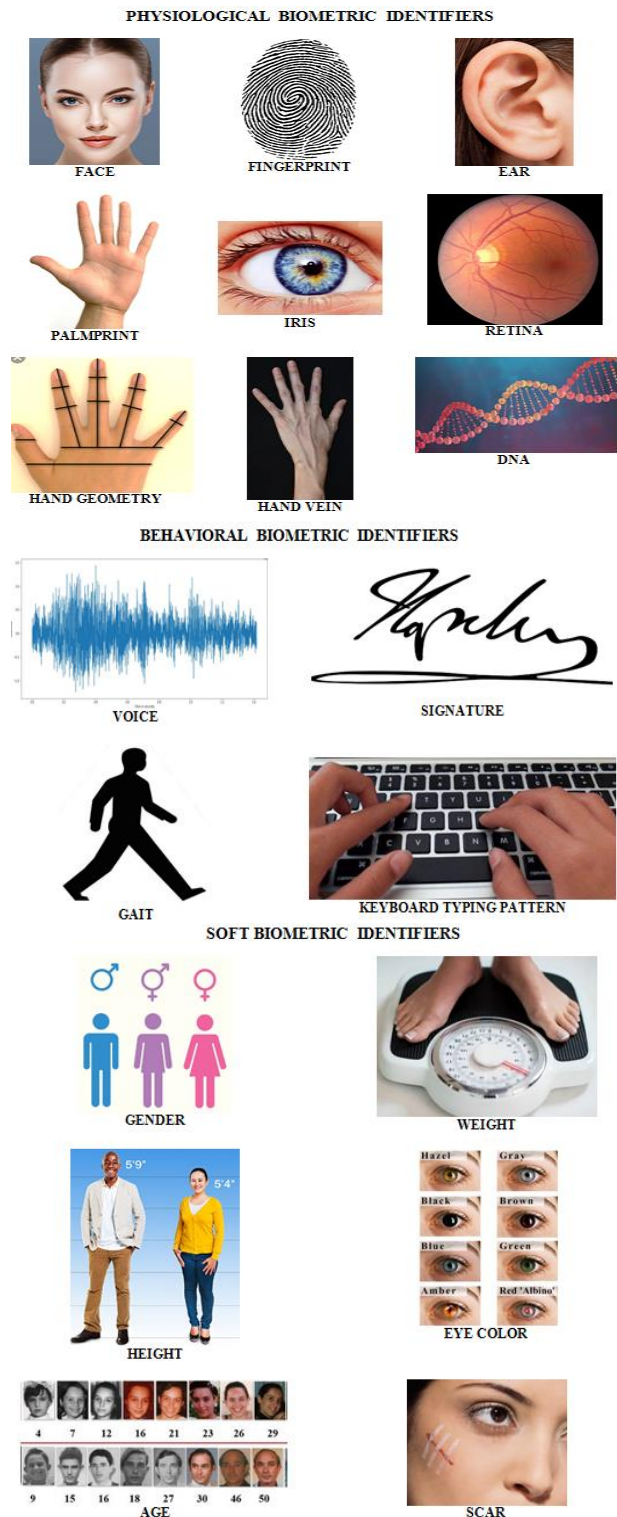


Fig. 1. Physiological, behavioral and soft biometric traits (sources: Google Image [ImaG]).

Manuscript received March 1, 2021; revised June 1, 2021.

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## II. RELATED WORK

Mohammad *et al.* [3] discussed feature level fusion using Discriminant Correlation Analysis for multimodal biometrics and obtained good results. Madasu *et al.* [4] used three different biometric traits and applied score level fusion and obtained FAR of 0.01%. Chaudhary *et al.* [5] showed using multilevel fusion recognition rate can be increased. Sangeetha *et al.* [6] and Anil jain *et al.* [7] created their own data set and explored different fusion levels. Arjun *et al.* used bilinear enhanced data samples for feature level fusion and

obtained good results [9]. Arjun *et al.* discussed SNBI samples 1:4 up-sampled data concatenation which gave a high recognition rate at feature level fusion [10]. Table I shows the survey of algorithms and fusion methods used at various levels on different biometric traits.

From the above literature survey, it has been observed that using different levels of fusion biometric recognition rates can be increased, and also not much work is done in multilevel fusion with the combination of face and finger vein for standard data sets.

TABLE I: SURVEY ON BIOMETRIC FUSION LEVEL

References	Biometric Traits used	Used Algorithms	Dataset	Methods of Fusion
[3]	Face and Ear	DCA	WVU	Feature level
[4]	Hand geometry, Palm-print , Hand vein	Frank t-norm	IITD PolyU XM2VTS	Score level
[5]	Palmprint , dorsal hand veins	Sum rule, product rule, hamacher t-norm, frank t-norm	I.I.T. Delhi, Bosphorus	Feature level & score level
[6]	Iris, Fingerprint	Gabor wavelets, Chain Code based feature extractor with contour following to detect minutiae	Own created	Score Level
[7]	Fingerprint, Face, Speech	Minutia, Eigen face, HMM and LPC	Own dataset created	Decision Level
[8]	Finger knuckle, finger vein	FFF Optimization, Repeated line tracking, k-SVM	I.I.T. Delhi, SDUMAL-HMT	Feature level & score level
[9]	Face and Signature	Bilinear enhanced data Concatenation	SDUMLA-HMT	Feature Level
[10]	Finger Vein and Iris	SNBI samples 1:4 up sampled data concatenation	SDUMLA-HMT	Feature Level

## III. DATA BASES

Data sets of a face used are AT& T Cambridge standard databases. Faces of six different poses of each individual of forty persons are considered. A total of 240 samples are used.



Fig. 2. AT& T Cambridge standard face database samples.

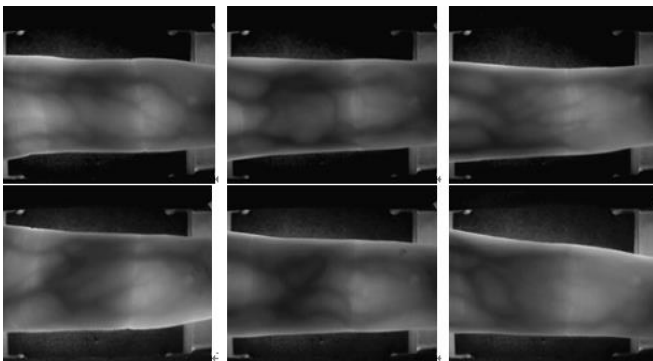


Fig. 3. Shandong University (SDUMLA) finger vein standard database samples.

Data sets images are in .pgm format shown in Fig. 2. Three samples are used for training and 3 samples for testing each individual.

Data sets of finger vein used are Machine Learning and Data Mining Lab, Shandong University (SDUMLA) standard databases. Finger vein of six left indexed finger with different position of each individual of forty persons is considered. A total of 240 samples is used. Data sets images are in .bmp format shown in Fig. 3. Three samples are used for training and 3 samples for testing each individual.

## IV. METHODOLOGY

In this work face and finger vein, Biometric data sets are used. Initially, uniform local binary pattern features are extracted from each data set of face and finger vein. For Unimodal Biometric system after extracting Local Binary Pattern of both face and finger vein data sets are trained and tested separately using ensemble subspace discriminant and K-nearest neighbor classifier using decision level fusion AND and OR operations as shown in Fig. 4. The same procedure is applied for bilinear interpolated up-sampled data sets and results are compared.

In the proposed model both standard data sets and 1:2 ratio up-sampled datasets are trained separately and tested in unimodal. And for Multimodal biometrics standard data sets and 1:2 ratio up-sampled are fused at feature level using concatenation technique.

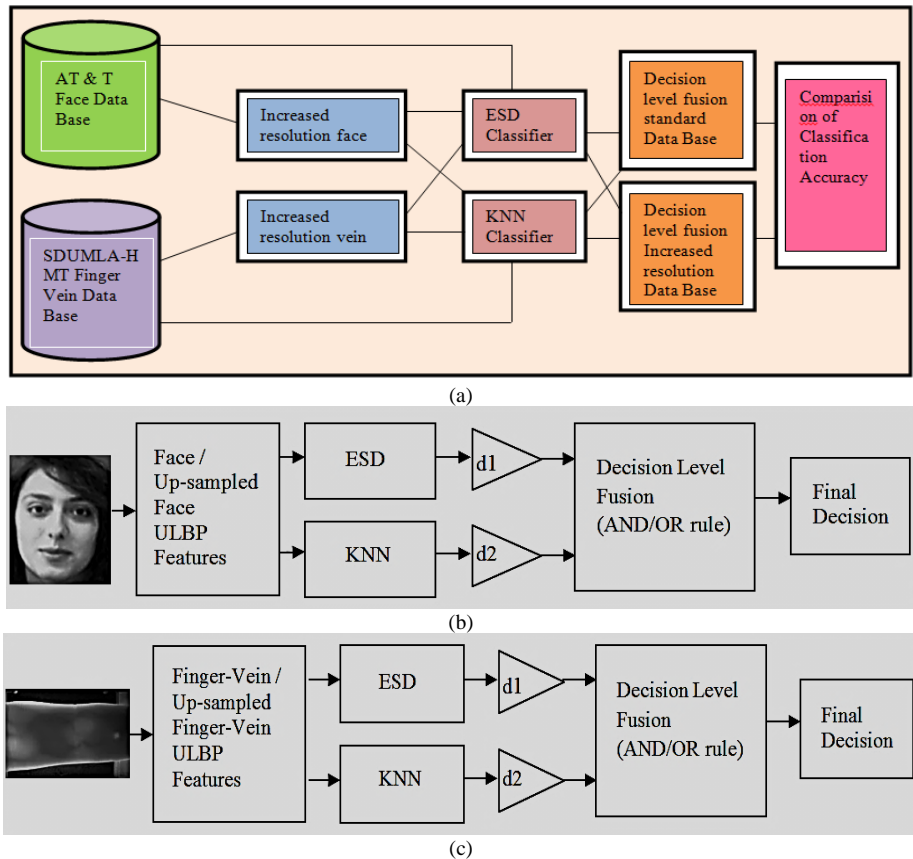


Fig. 4. Proposed research work modal for unimodal biometrics using Decision level fusion (a) General model (b) face biometric model (c) finger vein model.

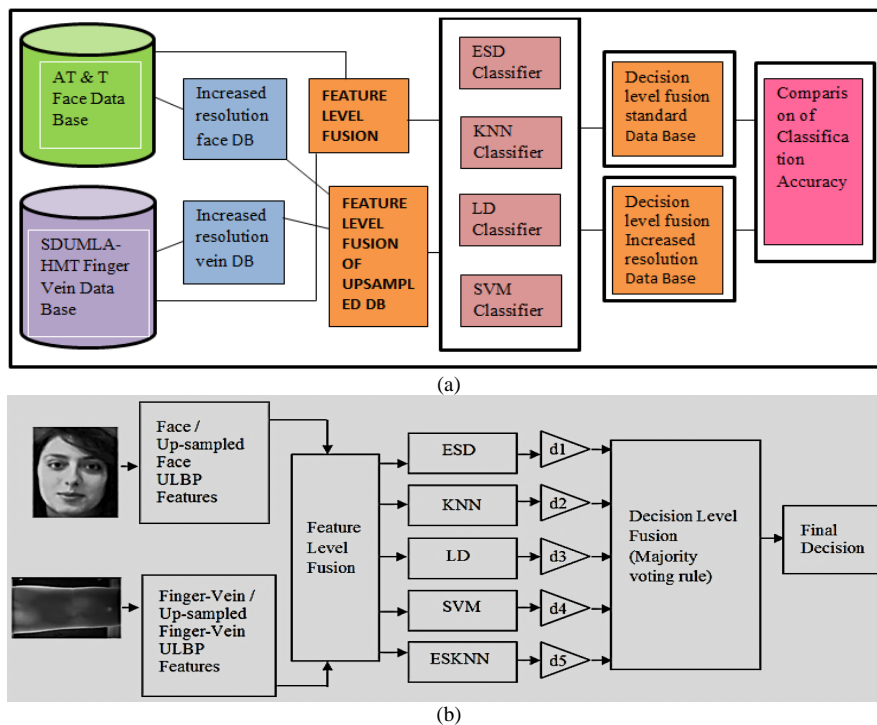


Fig. 5. Proposed research work modal for multilevel fusion of Feature and Decision level fusion (a) General model (b) face and finger vein multi model.

Above experimentation falls under three major steps features extraction, feature level fusion, and decision level fusion.

Fig. 5. shows the proposed research model for a multilevel fusion of Feature and Decision level fusion where decision rule is AND and OR is used. And further research work is extended to Decision level fusion where majority voting decision rule is used with different machine learning

algorithms.

A novel framework modal is designed of face and finger vein data sets with Uniform Local Binary pattern features of Bilinear interpolated data sets are fused in feature level and decision level using five classifiers for majority voting.

Fig. 4 shows the proposed research modal for with only decision level fusion. The data base samples are enhanced using bilinear interpolation technique and from enhanced

sample local binary patterns are extracted. These features of face and finger vein are trained and tested separately as shown in Fig. 4. In decision level AND and OR techniques are used.

Fig. 5 shows the proposed research modal for a multilevel fusion of Feature and Decision level fusion. In this proposed model both feature level and decision level techniques are applied. After extracting features of face and finger vein, using feature level fusion technique face and finger vein features are combined to obtain new feature vector. This new feature vector is used in decision level fusion as shown in Fig. 5.

The proposed research model for multilevel fusion is further extended to Decision level fusion where majority voting decision rule is used with different machine learning algorithms.

Above experimentation falls under three major steps features extraction, feature level fusion, and decision level fusion.

A. Feature Extraction

Local binary pattern features are extracted from individual data samples of face and finger vein separately. The Same method is applied for up-sampled bilinear interpolated data samples. Up-sampled data means an increased resolution by two times of the actual image [9, 10].

B. Feature Level Fusion

Using the concatenation feature level method all the features are joined together which results in a single vector of each sample of both face and finger vein [9, 10].

C. Decision Level Fusion

Fused data is set as an input to five classifiers Ensemble subspace discriminant (ESD), K-Nearest Neighbor (KNN), Linear Discriminant (LD), Ensemble subspace K-Nearest Neighbor (ESKNN) and Support Vector Machine (SVM), After obtaining the results of classifier AND and OR decision level method [11] and Majority voting decision level method [11] is applied and results are plotted.

V. EXPERIMENTAL RESULTS

The unimodal experiments results are shown in Table II where experiments are conducted by applying decision level fusion technique. The four models were designed and explored, in 1st model and 2nd model only face biometric is used, classification accuracy showed better results for enhanced images. From the model 3 and 4 it is observed that original data base image showed better results for finger vein samples.

From the Table II, it has been observed that Up-sampled data sets using bilinear interpolation technique data samples got good results compared to standard data sets for Face biometrics. Classification accuracy of ensemble subspace discriminant classifier showed more accuracy for up-sampled Finger vein data sets compared to standard data sets.

Overall for unimodal biometric proposed modal multi-level fusion at feature level concatenation technique and decision level OR technique showed better classification accuracy, results are shown in Table II and Fig. 6.

TABLE II: UNIMODAL BIOMETRIC SYSTEM COMPARISON OF CLASSIFICATION ACCURACY

Sl. no	Biometric	Features	Classifiers Individual Accuracy	Fusion level	Fusion Technique	Classification Accuracy
1	Face	UBLP	ESD – 65.83%	Decision Level	AND	57.5
			KNN- 57.50%		OR	75
2	Face	Up sampled 1:2 ratio UBLP	ESD – 70%	Decision Level	AND	62.5
			KNN- 68.33%		OR	75.83
3	Finger Vein	UBLP	ESD – 85.83%	Decision Level	AND	79.16
			KNN- 84.16%		OR	90.83
4	Finger Vein	Up sampled 1:2 ratio UBLP	ESD – 88.33%	Decision Level	AND	84.16
			KNN- 85%		OR	89.16

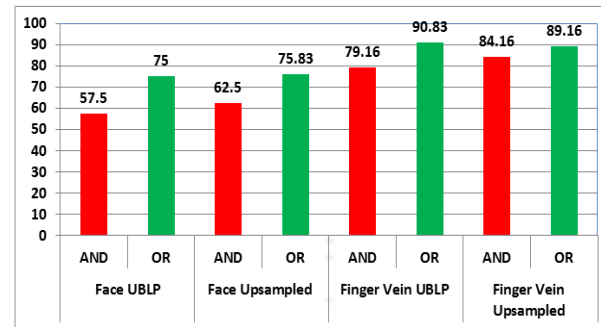


Fig. 6. Classification accuracy of unimodal biometric system.

From the Fig. 6 we can observe that finger vein samples shows better performance when compared with face samples, when unimodal experiments are conducted. And also in Fig. 6. Finger vein unimodal experiment with OR technique showed more classification accuracy.

The Table III shows the experiments results of multimodal biometrics with multilevel fusion. Two models were developed, model 1 for standard database and model 2 for enhanced data base. The enhanced samples after interpolation technique performed well over standard database. From the Table III we can observe that multimodal fusion of face and finger vein for enhanced samples showed better results. That is model 2 performed well over model 1 listed in Table III.

TABLE III: MULTIMODAL MULTI LEVEL FUSION BIOMETRIC SYSTEM COMPARISON OF CLASSIFICATION ACCURACY

Sl. no	Biometric	Features	Classifiers Individual Accuracy	Fusion level	Fusion Technique	Classification Accuracy
1	Face and Finger vein	UBLP	ESD – 96.66%	Feature Level, Decision Level	AND	82.5
			KNN- 87.50%		OR	97.5
2	Face and Finger vein	Up sampled 1:2 ratio UBLP	ESD – 92.5%	Feature Level, Decision Level	AND	85
			KNN- 87.5.33%		OR	99.16

From the Fig. 7 we can observe that multimodal biometric face and finger vein enhanced samples shows better performance when compared with standard samples, when multimodal experiments are conducted. And also in Fig. 7, Face and Finger vein multimodal experiment with OR technique showed more classification accuracy.

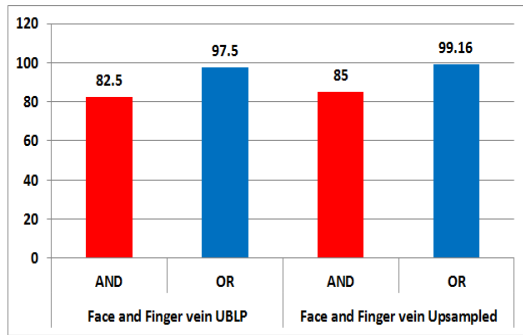


Fig. 7. Classification accuracy of Multimodal biometric system.

Experiments conducted on the multimodal biometric system for ensemble and KNN classifier in this case both feature level and decision level technique is used. AND and OR decision level technique is applied. OR operation showed

good results shown in Table III and Fig. 7.

The proposed Multimodal Multi-level fusion Biometric system using feature level and Majority Voting decision level fusion showed good results after experimentation at various levels. Experiments are setup for choosing variation in classifiers at decision level. Initially three classifiers are used for decision making, in the next stage 4 classifiers are used and in the last stage 5 classifiers are used. Majority voting of 2 when 4 classifiers are considered accuracy rate is increased, for the same model up-sampled data sets are used which shows improvement. All the experiment variations and results are shown the Table IV and Fig. 8. In all the cases ensemble subspace discriminant classifier showed better result.

TABLE IV: MULTIMODAL MULTI LEVEL FUSION BIOMETRIC SYSTEM USING FEATURE LEVEL AND MAJORITY VOTING DECISION LEVEL FUSION COMPARISON OF CLASSIFICATION ACCURACY

Sl.no	Biometric	Features	Classifiers Individual Accuracy	Majority Voting	Fusion Technique	Classification Accuracy
1	Face and Finger vein	UBLP	ESD – 96.66% KNN- 87.50% LD-89.16% SVM-73.33%	2 voting out of 4 classifier	Feature Level, Decision Level	95%
		Upsampled 1:2 ratio UBLP	ESD – 93.33% KNN- 87.50% LD-90.83% SVM-76.77%	2 voting out of 4 classifier	Feature Level, Decision Level	95.33%
2	Face and Finger vein	UBLP	ESD – 96.66% KNN- 87.50% LD-89.16%	2 voting out of 3 classifier	Feature Level, Decision Level	95%
		Upsampled 1:2 ratio UBLP	ESD – 92.50% KNN- 87.50% LD-90.83%	2 voting out of 3 classifier	Feature Level, Decision Level	93.33%
3	Face and Finger vein	UBLP	ESD – 95.83% KNN- 87.50% LD-89.16% SVM-73.3% ESKNN-87.5%	3 voting out of 5 classifier	Feature Level, Decision Level	90%
		Upsampled 1:2 ratio UBLP	ESD – 93.33% KNN- 87.50% LD-90.83% SVM-73.3% ESKNN-88.3%	3 voting out of 5 classifier	Feature Level, Decision Level	91.66%

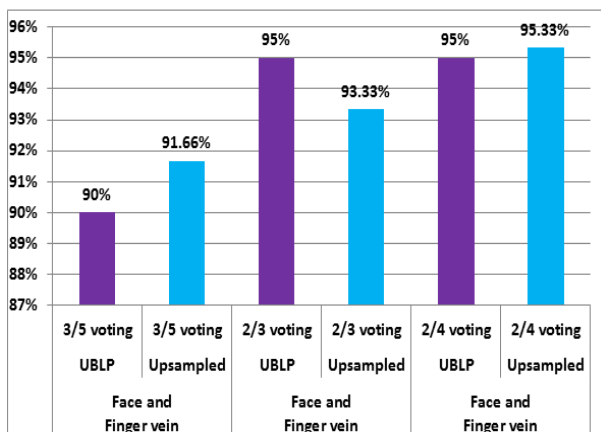


Fig. 8. Classification accuracy of Multi-level fusion biometric system.

Three models were designed as shown in Table III, for all the models two experiments were conducted both for actual images and enhanced images of face and finger vein. In first model four machine learning classifier is used and 2 out of 4 decision is considered. And in second model 2 out of 3 decisions and for last model 3 out of 5 classifier decision are considered.

From the experiments listed in Table III, we can observe that if 50% or less than 50% weightage is considered then classification accuracy will increase. But if greater than 50% weightage is given then classification accuracy will reduce.

Experiments were conducted on two levels of fusion, feature level, and decision level. Initially, the feature level concatenation method is applied and in the next stage, decision level fusion majority voting is done. Variation in the

number of classifiers is considered for majority voting and results are plotted. From the experimentation, it has been observed that 50% voting out of four classifiers for up-sampled data with both feature level and decision level fusion got good results as shown in Table IV and Fig. 8.

## VI. CONCLUSION

In this work, two biometric traits face and finger veins are considered. Both biometrics traits are considered from the standard databases, face data sets from AT&T, and finger vein data sets from SDUMLA-HMT. In this work, multilevel fusion of two biometrics with both standard data sets and up-sampled data sets are used. Bi linear method is used to up-sample the data sets. Experiments showed good results for multimodal biometrics when multilevel fusion is applied. When OR and AND method is applied at decision level for up-sampled feature level fusion of face and finger vein got high classification accuracy rate. The Majority voting at the decision level for up-sampled feature level fused image of a face and finger vein also showed a low classification error rate. The above experiment shows that the multilevel fusion of multimodal biometrics for up-sampled data sets of the face and finger vein method will give high classification accuracy. Compared to previous experimentation in this work bigger data sets are used. Further using different biometric traits and their up-sampled images in multilevel fusion techniques classification rate can be increased.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

## AUTHOR CONTRIBUTIONS

Author Arjun B. C. performed the experimentation of the work by identifying the new method for data fusion. Author Prakash H N provided guidelines for using techniques and evaluated their performance. Both have approved the final version.

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