SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V10I5P102

Volume 10 Issue 5, 14-22, May 2023

Original Article

Design and Development of an Improved Multimodal Biometric Authentication System using Machine learning Classifiers

R. Nanmaran[1], V. Velmurugan[2], Babushanmugham[3], Sivachandar Kasiviswanathan[4], S. Srimathi[5]

[1, 2]Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Chennai, Tamilnadu, India.
[3]Department of Biomedical Engineering, Rajiv Gandhi College of Engineering and Technology, Pondicherry, India
[4]Department of Electronics and Communication Engineering, RMK College of Engineering and Technology Puduvoyal, Thiruvallur, Tamilnadu, India.
[5]Department of Bio-Technology, Saveetha School of Engineering, SIMATS, Chennai, Tamilnadu, India.

[2]Corresponding Author : drvelmuruganv@veltech.edu.in

Received: 28 February 2023 Revised: 07 April 2023 Accepted: 02 May 2023 Published: 29 May 2023

Abstract - *A multi modality biometric authentication system can combine information from various modalities and provides accurate results compared to biometric systems used individually. A novel ensemble classifier-based multimodal biometric authentication system has been proposed in this work. The performance of the proposed multimodal authentication system is measured using parameters such as Accuracy, Sensitivity and Specificity and compared with the SVM classifier, Decision tree classifier when fingerprint, Iris, and Face features are used. The results of the multimodal biometric system are also compared with the biometric authentication system when fingerprint features are used and combined with Fingerprint & Iris features. The proposed ensemble classifier-based multimodal biometric authentication system provides an accuracy of 96.75%, Sensitivity of 94.74%, Specificity of 98.95%, FAR of 1.04 and FRR of 5.26. The proposed ensemble classifier outperforms SVM and decision tree classifiers regarding performance measures.*

Keywords - *Authentication, SVM classifier, Decision tree classifier, Ensemble classifier.*

1. Introduction

Biometric authentication is a security process that allows only authorized users or persons to access the system or digital sources. It uses biometrics such as Fingerprints, Iris, Retina, Face, ECG, DNA, etc., to verify the authorized persons [1-3]. The biometric authentication system compares the features the designer stores to those claiming ownership or authentication. If both data match, it provides access to the users and will block them from accessing if the data does not match [4-6].

Multimodal biometric authentication systems improve security by a certain margin. Unlike conventional biometric authentication systems, it uses multiple features from multiple modalities or sources of input; as a result, better accuracy can be expected [7-11]. Even though many researches were conducted on biometric authentication systems, few researchers focus on multimodal authentication systems.

2. Literature Review

The research conducted in biometric authentication using multimodal biometrics attempted to find the results in this area [12-16]. They used fingerprints, finger veins and retina as biometrics and fused using feature level fusion method. The modified MDRSA method was used for biometric authentication. The model acheived an actual acceptance rate of 95.3% and a False acceptance rate of 0.01%. [17, 18]

The main drawback is that performance measures were insufficient to conclude the results, and the sample size was also shallow. The similar research using a Modified support vector machine classifier (MSVM), and the Convolution neural network method was used for extracting features [19-22]. They used to fingerprint and ECG signals and fused those features using different level fusion methods. Accuracy, FAR, and FRR were calculated for the simulated model.

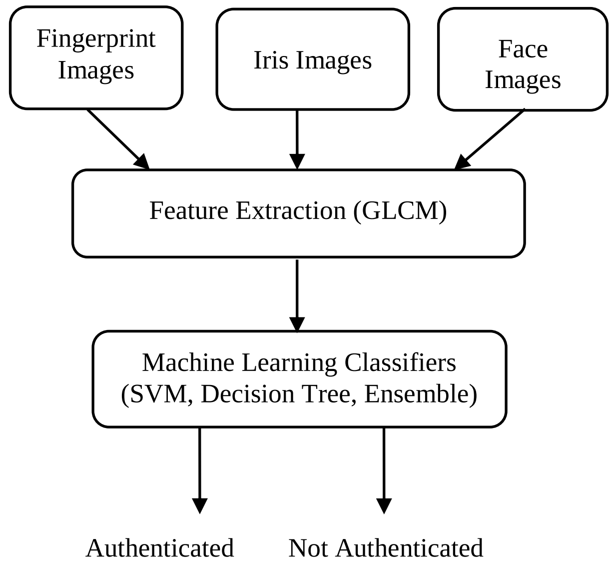

Fig. 1 Proposed ensemble classifier-based multimodal biometric authentication system

It is found that the Authentication time takes only 0.123 seconds, and the computational cost is relatively low, which is a significant advantage of this model. Accuracy loss due to poor data augmentation is the major concern of this model. Manju Dhanraj Pawar et al. designed an authentication system using face and fingerprint biometrics with a low classification error rate.

SIFT biometric features such as entropy, average intensity, maximum intensity, contrast, and centroid were extracted for face and ridges, and minute extraction was done for fingerprint biometrics. 93% accuracy is obtained when face features or fingerprint features are used individually, but 98% accuracy is obtained when both features are used together [23-26]. The method's main drawback is less sample size; only 30 sample images were used for testing. A multimodal authentication system using deep learning was proposed. They used to fingerprint and palm print biometrics for the multimodal authentication system. Palm print features such as Edges, centre lines, and wrinkles are extracted and used for deep learning algorithms for authentication. The proposed system is not validated, which is a main drawback of the model [27-29].

3. Methodology

A biometric authentication system using various machine learning classifiers has been proposed and developed in this work, and the methodology for achieving authenticity is shown in Figure 1. This proposed work will eliminate authentication accuracy loss and exposure to spoof attacks. Fingerprint, Iris and Face biometrics are considered, and multiple features from these three types of input images are extracted and given as input to the ensemble classifier [30].

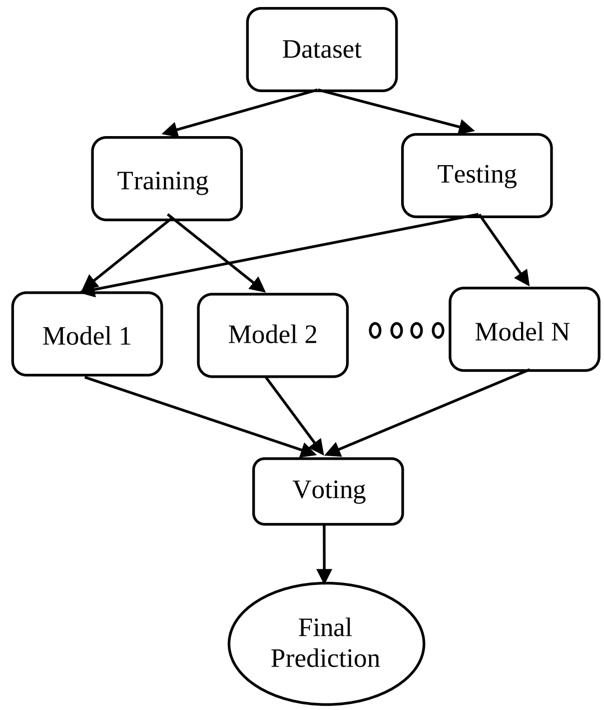

Fig. 2 Ensemble classification methodology

Accuracy, Sensitivity, Specificity, FAR and FRR are the parameters which measure the classifier's performance. The fingerprint minute is extracted using the following steps, image enhancement, binarization, thinning, or skeletonization. For face and iris biometrics, the SIFT features such as contrast, correlation, entropy, and energy are calculated using GLCM [31-36]. Then the features are applied to the proposed ensemble classifier and SVM, Decision tree classifiers for comparison.The methodology of the proposed ensemble classifier and the performance measures are explained in this section.

3.1. Proposed Ensemble Classification (Boosted Tree)

Ensemble classification is a method of generating a new base classifier that performs better than any constituent classifier. They use different training data sets and hyperparameters in classification [37-39]. The methodology of ensemble classification is shown in Figure 2.

Ensemble classification can be done in four methods: stacking, blending, bagging and boosting. The way of training the models differs for all these four methods. Boosted tree method of classification is used in this proposed work. Boosting algorithm is a self-learning technique in which the same weights will be assigned initially to all the models involved. The weights will be adjusted later based on the performance [40-41]. In order to give more focus on misclassified data, it will be assigned.

The Equation defines the final model (1) using the weighted average method.

$$C = \frac{\left(\frac{\sum P_i n_i}{\sum n_i}\right)}{m} \quad (1)$$

Where,

$P_1, P_2 \ldots P_m$ = Base Classifier

$n_1, n_2 \ldots n_m$ = Weights

m = model number

C = Final Classifier

3.2. Performance Measures of Multimodal Authentica-tion System

To analyze the performance of classifiers the, parameters like accuracy, Sensitivity, Specificity, FAR, and FRR can be very useful and are defined in this section with mathematical expression.

3.2.1. Accuracy

The amount of authorized persons correctly authenticated is called true positive (TP), and authorized persons wrongly authenticated is called False Positive (FP). The amount of unauthorized persons correctly authenticated is called True negative (TN), and unauthorized persons wrongly authenticated is known as False negative (FN) [42-46]. The accuracy of the classifier is given in Equation (2).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

3.2.2. Sensitivity

Sensitivity is the ratio of correctly authenticated authorized persons to the overall authorized persons defined in Equation (3).

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

3.2.3. Specificity

Sensitivity is the ratio of correctly authenticated unauthorized persons to the overall unauthorized persons defined in Equation (4).

$$specificity = \frac{TN}{TN+FP} \quad (4)$$

3.2.4. False Acceptance Rate (FAR)

The number of unauthorized persons correctly accepted or authenticated is called the false acceptance rate, given in Equation (5).

$$FAR = \frac{FP}{FP+TN} \quad (5)$$

3.2.5 False Rejection Rate (FRR)

The amount of unauthorized persons correctly accepted or authenticated is called the false acceptance rate in Equation (6).

$$FRR = \frac{FN}{FN+TP} \quad (6)$$

4. Result and Discussion

Two hundred samples of fingerprint, Iris & Face images are considered input images and features from those images are extracted. The results of minutia extraction from fingerprint images are shown in Figure 3(a) and Figure 3(b). Edge detection using the Hough circle for the iris image is shown in Figure 3(c) and Figure 3(d). Figure 3(e) and Figure 3(f) show edge detection using Hough circle for the face image.

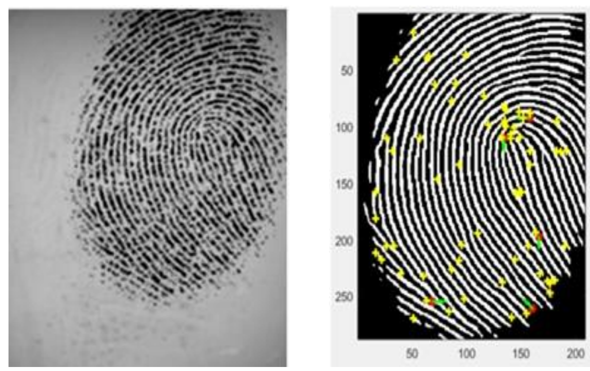

Fig. 3(a) Fingerprint image 3(b) Minutia detection after filtration

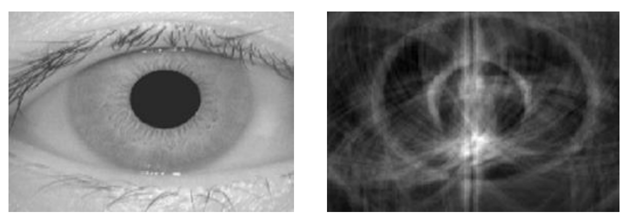

Fig. 3(c) Iris image 3(d) Edge detection using hough circle

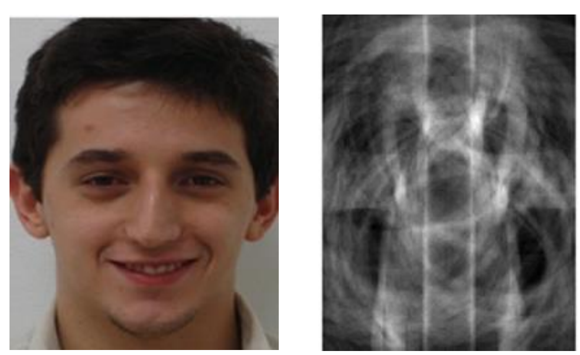

Fig. 3(e) Face image 3(f) Edge detection using hough circle

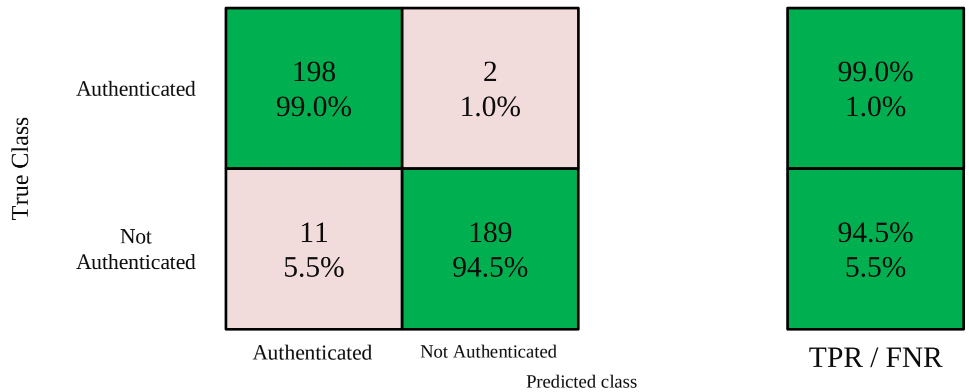

Fig. 4(a) Confusion matrix for ensemble classifier (boosted tree)

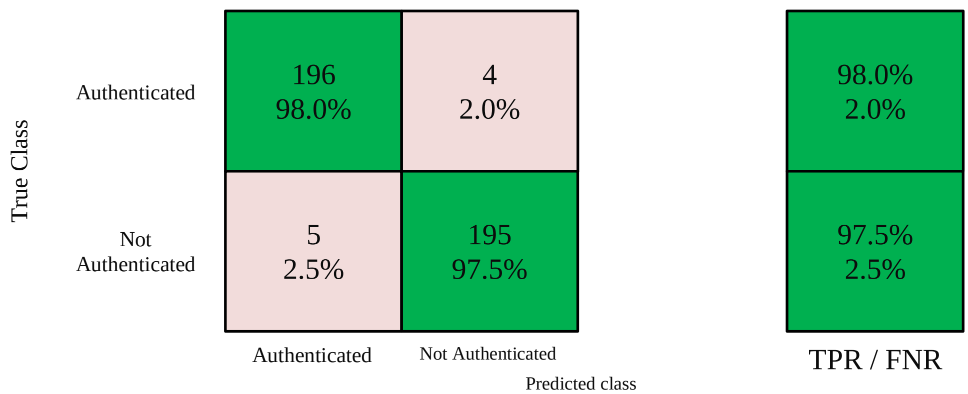

Fig. 5(a) Confusion matrix for SVM classifier

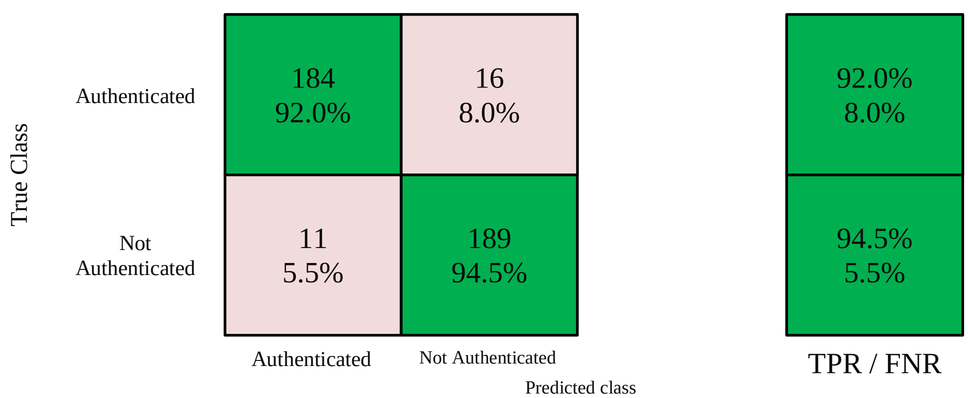

Fig. 6(a) Confusion matrix for decision tree classifier

The features extracted from fingerprint, Iris, and Face images are given as input to the proposed boosted tree classifier, an ensemble classifier. Decision tree classifiers considered and implemented with these multi modal input features for comparison classifiers such as SVM. When these three classifiers are tested with sample testing images, the response of classifiers is given as a confusion matrix as below. The confusion matrix, ROC curve of the proposed ensemble classifier, SVM, and Decision tree are shown in Figure 4(a), Figure 4(b), Figure 5(a), Figure 5(b), Figure 6(a) and Figure 6(b) respectively.

In all three classifiers, the ROC curve approaches towards which indicate better classification. The area under the curve for the ensemble classifier is higher than the other two classifiers, which shows the superior performance of the ensemble over other classifiers.

TP, TN, FP, and FN values obtained from the confusion matrix are used for calculating performance measures, and the results are tabulated. Classifier results when fingerprint features alone are used are tabulated in Table 1.

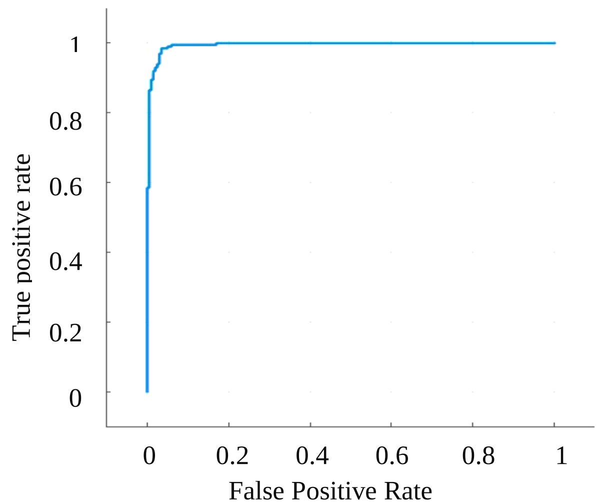

Fig. 4(b) ROC for ensemble classifier (boosted tree)

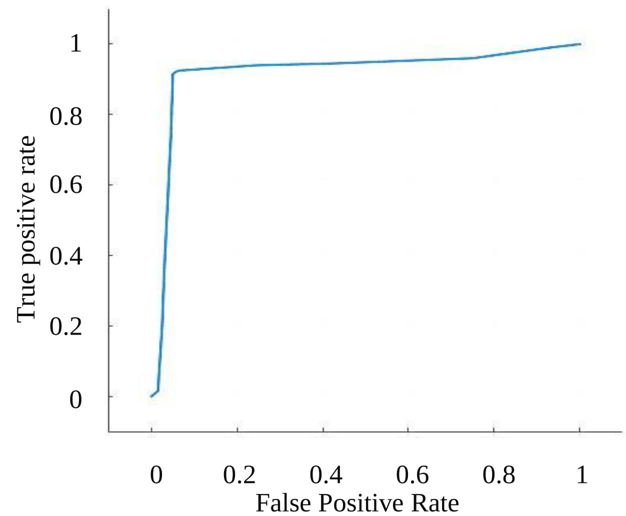

Fig. 6(b) ROC for decision tree classifier

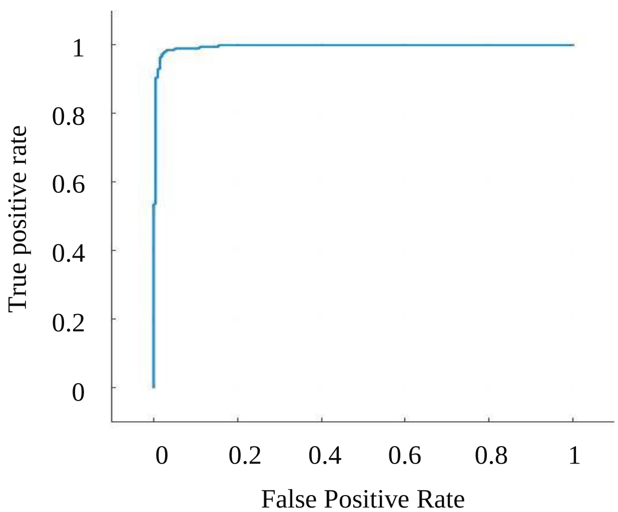

Fig. 5(b) ROC for SVM classifier

Classifier results when Fingerprint & Iris features combined are tabulated in Table 2. Classifier results and multimodal Fingerprint, Iris, & Face features are tabulated in Table 3. Based on the simulation results and results from Table 1, it is found that the ensemble classifier-based multimodal biometric authentication system performs better than the decision tree and SVM classifier when fingerprint features alone are given as input to classifiers. It achieves the highest accuracy of 94%, Sensitivity of 91.51%, Specificity of 96.8%, lowest FAR of 3.19%, and FRR of 3.49%. Ensemble classifier outperforms the other two classifiers when fingerprint & Iris features are jointly given, shown in Table 2 and Figure 7 and Figure 8. When three modalities, namely fingerprint, Iris and face features combined and given as input to classifiers, the ensemble classifier performs excellently, which is evident from Table 3.

Table 1. Performance measures of SVM, decision tree, ensemble classifiers (finger print)

S.No	Classifiers Used	TP	FP	TN	FN	Accuracy (%)	Sensitivity (%)	Specificity (%)	FAR (%)	FRR (%)
1.	SVM Classifier	191	9	192	8	92.75	90.57	95.52	4.48	4.02
2.	Decision Tree Classifier	181	19	180	20	90.25	90.05	90.45	9.55	9.95
3.	Ensemble Classifier	194	6	182	18	94	91.51	96.80	3.19	3.49

Table 2. Performance measures of SVM, decision tree, ensemble classifiers (finger print + iris)

S.No	Classifiers Used	TP	FP	TN	FN	Accuracy (%)	Sensitivity (%)	Specificity (%)	FAR (%)	FRR (%)
1.	SVM Classifier	194	6	193	7	94.75	91.51	96.98	3.02	3.48
2.	Decision Tree Classifier	182	18	184	16	91.50	91.92	91.08	8.91	8.08
3.	Ensemble Classifier	196	4	185	15	95.25	92.89	97.88	2.11	3.41

Table 3. Performance measures of SVM, decision tree, ensemble classifiers (finger print + iris + face)

S.No	Classifiers Used	TP	FP	TN	FN	Accuracy (%)	Sensitivity (%)	Specificity (%)	FAR (%)	FRR (%)
1.	SVM Classifier	196	4	195	5	94.75	93.51	97.98	2.01	2.48
2.	Decision Tree Classifier	184	16	189	11	93.25	94.36	92.19	7.80	5.64
3.	Ensemble Classifier	198	2	189	11	96.75	94.74	98.95	1.04	2.26

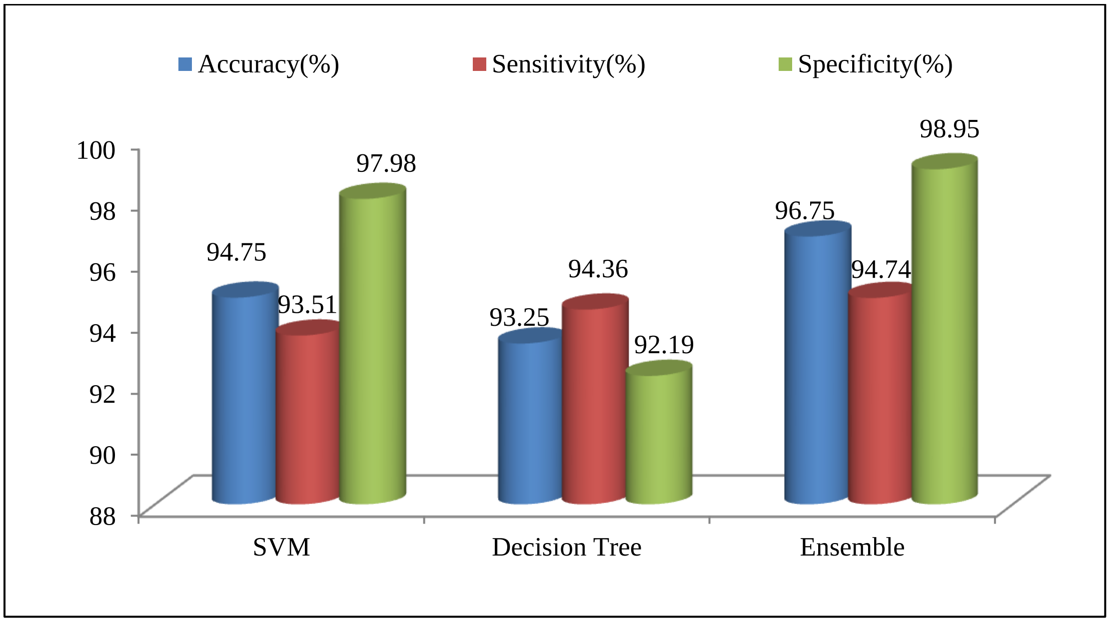

Fig. 7 Accuracy, sensitivity, specificity comparison of SVM, decision tree, ensemble classifiers on biometric authentication system (fingerprint+iris+face)

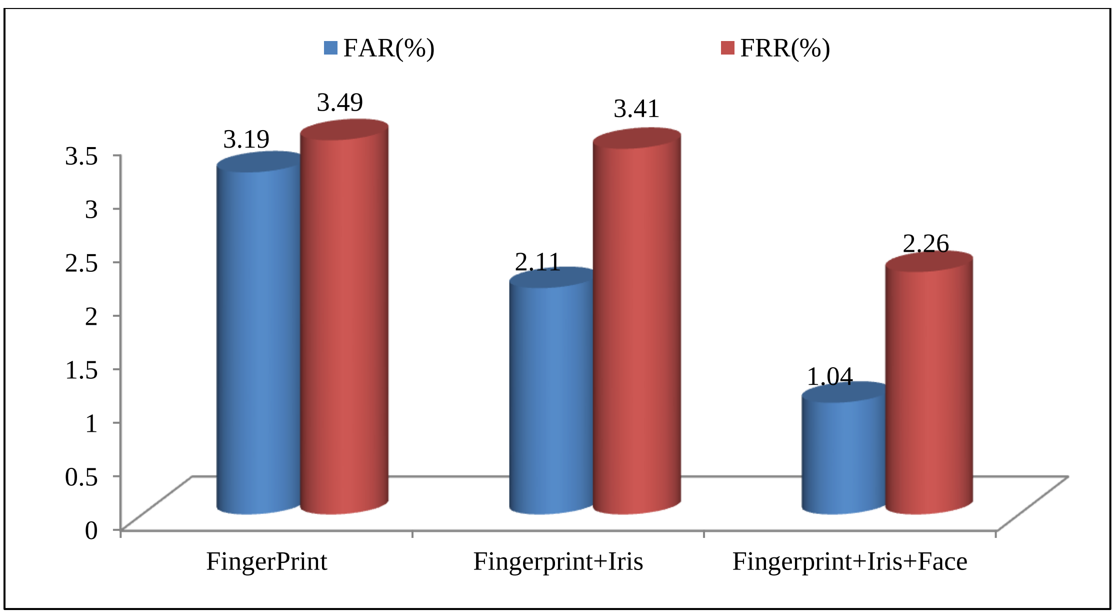

Fig. 8 Performance measures (FAR, FRR) of biometric authentication system using ensemble classifier

5. Conclusion

This work proposes a multimodal biometric authentication system using various biometrics using machine learning classifiers. Features from Fingerprints, Iris and Face are considered multimodal features and given as input to the proposed ensemble classifier and for comparison given to SVM, Decision tree classifier. The effect of multimodal fusion was analyzed by comparing various combinations of features and individually. The proposed ensemble classifier-based multimodal biometric authentication system provides better results, with high accuracy of 96.75%, Sensitivity of 94.74%, Specificity of 98.95% and low FAR of 1.04% and FRR of 2.26%.

References

[1] D. Jagadiswary, and D. Saraswady, "Biometric Authentication using Multimodal Biometric," *Procedia Computer Science*, vol. 85, pp. 109-116, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[2] Manju Dhanraj Pawar, R. D. kokatte, and V. R. Gosavi, "An Optimize Multimodal Biometric Authentication System for Low Classification Error Rates using Face and Fingerprint," *International Conference on IoT based Control Networks and Intelligent Systems*, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Sandeep Singh Sengar, U. Hariharan, and K. Rajkumar, "Multimodal Biometric Authentication System using Deep Learning Method," *2020 International Conference on Emerging Smart Computing and Informatics (ESCI)*, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Terence Sim et al., "Continuous Verification using Multimodal Biometrics," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 687-700, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[5] Ajay Kumar, Vivek Kanhangad, and David Zhang, "A New Framework for Adaptive Multimodal Biometrics Management," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 1, pp. 92-102, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[6] William Stallings, *Cryptography and Network Security*, 4th Edition, Prentice Hall, 2005. [Google Scholar] [Publisher Link]

[7] Alfred J. Menezes, Paul C. Van Oorschot, and Scott A. Vanstone, *Handbook of Applied Cryptography*, CRC Press, pp. 756-799, 2001. [Google Scholar] [Publisher Link]

[8] Samarth Bharadwaj, Mayank Vatsa and Richa Singh, "Biometric Quality: A Review of Fingerprint, Iris, and Face," *EURASIP Journal on Image and Video Processing*, pp. 2014-2034, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[9] Anil K. Jain, and Jianjiang Feng, "Latent Fingerprint Matching," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 33, no. 1, pp. 88-100, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[10] Diego Marin et al., "A New Supervised Method for Blood Vessel Segmentation in Retinal Images by using Gray-Level and Moment Invariants-Based Features," *IEEE Transactions on Medical Imaging*, vol. 30, no. 1, pp. 146-158, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[11] J. Ayangbekun Oluwafemi, Olowookere A. Sunday, and Shoewu Oluwagbemiga, "Two Way Mobile Authentication Security Mechanisms for an Enterprise System," *SSRG International Journal of Computer Science and Engineering*, vol. 1, no. 8, pp. 1-5, 2014. [CrossRef] [Publisher Link]

[12] Maneesh Upmanyu et al., "Blind Authentication: A Secure Crypto-Biometric Verification Protocol," *IEEE Transactions on Information Forensics and Security*, vol. 5, no. 2, pp. 225-268, 2010. [CrossRef] [Google Scholar] [Publisher Link]

[13] Ajay Kumar, and Yingbo Zhou, "Human Identification using Finger Images," *IEEE Transactions on Image Processing*, vol. 21, no. 4, pp. 2228-2244, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[14] G. R. Blakley, "Safeguarding Cryptographic Keys," *In the Proceedings of the International Workshop on Managing Requirements Knowledge*, pp. 313, 1979. [CrossRef] [Google Scholar] [Publisher Link]

[15] Pim Tuyls et al., "Visual Crypto Displays Enabling Secure Communications," *In: Hutter, D., Müller, G., Stephan, W., Ullmann, M. (eds) Security in Pervasive Computing. Lecture Notes in Computer Science*, vol. 2802, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[16] Zhifang Wang et al., "Multimodal Biometric System using Face-Iris Fusion Feature," *Journal of Computers*, vol. 6, no. 5, pp. 931-938, 2011. [Google Scholar] [Publisher Link]

[17] V. Sandhya, and Nagaratna P. Hegde, "Implementation of Fusion of Sclera and Periocular as a Biometric Authentication System using Deep Learning," *International Journal of Engineering Trends and Technology*, vol. 70, no. 3, pp. 212-221, 2022. [CrossRef] [Publisher Link]

[18] S. Brindha et al., "A Perspective of Finger Vein Pattern Based Testifying System," *International Journal of Engineering Trends and Technology*, vol. 68, no. 3, pp. 26-31, 2020. [CrossRef] [Publisher Link]

[19] Di Miao et al., "Bin-Based Classifier Fusion of Iris and Face Biometrics," *Neurocomputing*, vol. 224, pp. 105-118, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[20] Hunny Mehrotra et al., "Incremental Granular Relevance Vector Machine: A Case Study in Multimodal Biometrics," *Pattern Recognition*, vol. 56, pp. 63-76, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[21] Majid Komeili, Narges Armanfard, and Dimitrios Hatzinakos, "Liveness Detection and Automatic Template Updating using Fusion of ECG and FIngerprint," *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 7, pp. 1810-1822, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[22] Chen Xing Zhao et al., "Securing Handheld Devices and Fingerprint Readers with ECG Biometrics," *In the Proceedings of the 2012 IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems*, pp. 150-155, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[23] B. E. Manjunathswamy et al., "Multimodel Biometrics using ECG and Fingerprint," *International Journal of Computer Applications*, pp. 777-784, 2014. [Google Scholar]

[24] Yogendra Narain Singh, Sanjay Kumar Singh, and Phalguni Gupta, "Fusion of Electrocardiogram with Unobtrusive Biometrics: An Efficient Individual Authentication System," *Pattern Recognition Letters*, vol. 33, no. 14, pp. 1932-1941, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[25] O. C. Kurban, T. Yildirim, and A. Bilgiç, "A Multi-Biometric Recognition System Based on Deep Features of Face and Gesture Energy Image," *In the Proceedings of the IEEE International Conference on INnovations in Intelligent SysTems and Applications*, pp. 361-364, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[26] Disha Lobo, C. V. Anoop, and Y. Mahesha, "Securing Fingerprint Based Biometric System," *SSRG International Journal of Electronics and Communication Engineering*, vol. 3, no. 10, pp. 1-8, 2016. [CrossRef] [Publisher Link]

[27] Alaa S. Al-Waisy et al., "A Multi-Biometric Iris Recognition System based on a Deep Learning Approach," *Pattern Analysis and Applications*, vol. 21, pp. 783-802, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[28] Veeru Talreja, Matthew C. Valenti, and Nasser M. Nasrabadi, "Multibiometric Secure System Based on Deep Learning," *In the Proceedings of the IEEE Global Conference on Signal and Information Processing*, pp. 298-302, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[29] Alessandra Lumini, and Loris Nanni, "An Improved BioHashing for Human Authentication," *Pattern Recognition*, vol. 40, no. 3, pp. 1057-1065, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[30] P. Jennifer, and A. Muthu Kumaravel, "An Iris Based Authentication System by Eye Localization," *International Journal of Biotech Trends and Technology*, vol. 3, no. 4, pp. 9-12, 2013. [Google Scholar] [Publisher Link]

[31] H. Mohamed, and K. Wang, "Fingerprint Classification Based on a Q-Gaussian Multiclass Support Vector Machine," *In the Proceedings of the 2017 International Conference on Biometrics Engineering and Application*, pp. 39-44, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[32] R. Nanmaran et al., "Investigating the Role of Image Fusion in Brain Tumor Classification Models Based on Machine Learning Algorithm for Personalized Medicine," *Computational and Mathematical Methods in Medicine*, vol. 2022, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[33] N. Kanagathara, and R. Nanmaran, "Illustration of Potential Energy Surface from DFT Calculation Along with Fuzzy Logic Modelling for Optimization of N-Acetylglycine," *Computational and Theoretical Chemistry*, vol. 1202, pp. 113301, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[34] S. Srimathi, G. Yamuna, and R. Nanmaran, "An Efficient Cancer Classification Model for CT/MRI/PET Fused Images," *Current Medical Imaging*, vol. 17, no. 3, pp. 319-330, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[35] R. Nanmaran, and B. Luminasree, "Development of Wavelet Transform-Based Image Fusion Technique with Improved PSNR for CT and PET Images in Comparison with Discrete Cosine Transform-Based Image Fusion Technique," *ECS Transactions*, vol. 107, no. 1, pp. 13185, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[36] Deepak Singh, and Mohan Rao Mamdikar, "Identify a Person from Iris Pattern using GLCM Features and Machine Learning Techniques," *SSRG International Journal of Computer Science and Engineering*, vol. 7, no. 9, pp. 25-29, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[37] N. G. Rahul Jayanthi, and R. Nanmaran, "Extraction of Minute Fingerprint Features using Grey Level Co-occurrence Matrix Method with Improved FAR and FRR For Fingerprint Authentication in Comparison with Principal Component Analysis," *SPAST Abstracts*, vol. 1, no. 1, 2021. [Google Scholar] [Publisher Link]

[38] R. Nanmaran, and S. Hari Priya, "Design and Development of Decorrelation Stretch Technique for Enhancing the Quality of Satellite Images with Improved MSE and UIQI in Comparison with Wiener Filter," *ECS Transactions*, vol. 107, no. 1, pp. 13279, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[39] S. Srimathi, G. Yamuna, and R. Nanmaran, "Neural Networks Based Cancer Classification Model using CT-PET Fused Images," *In: Singh, M., Gupta, P., Tyagi, V., Flusser, J., Ören, T., Kashyap, R. (eds) Advances in Computing and Data Sciences, In the Proceedings of the Communications in Computer and Information Science*, vol. 1045, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[40] S. Srimathi, G. Yamuna, and R. Nanmaran, "Threshold Based Stochastic Regression Model with Gabor Filter for Segmentation and Random Forest Classification of Lung Cancer," *Journal of Computational and Theoretical Nanoscience*, vol. 16, no. 4, pp. 1666-1673, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[41] R. Nanmaran, G. Thirugnanam, and P. Mangaiyarkarasi, "Medical Image Multiple Watermarking Schemes Based on Integer Wavelet Transform and Extraction using ICA," *In International Conference on Advances in Computing and Data Sciences*, pp. 44-53, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[42] R. Nanmaran, and G. Thirugnanam, "Multiple Image Watermarking based on Hybrid Steerable Pyramid with DWT and Extraction using ICA," *International Journal of Research and Analytical Reviews*, vol. 5, no. 4, pp. 563-568, 2018. [Google Scholar]

[43] N. Rajendiran, T. Gurunathan, and M. Palanivel, "Wavelet Packet Transform-Based Medical Image Multiple Watermarking with Independent Component Analysis Extraction," *International Journal of Medical Engineering and Informatics*, vol. 12, no. 4, pp. 322-335, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[44] Nibedita Dey et al., "Nanomaterials for Transforming Barrier Properties of Lignocellulosic Biomass Towards Potential Applications - A Review," *Fuel*, vol. 316, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[45] Nibedita Dey et al., "Nanotechnology-Assisted Production of Value-Added Biopotent Energy-Yielding Products from Lignocellulosic Biomass Refinery - A Review," *Bioresource Technology PART A*, vol. 344, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[46] P. Sai Preethi et al., "Advances in Bioremediation of Emerging Contaminants from Industrial Wastewater by Oxidoreductase Enzymes," *Bioresource Technology*, vol. 359, 2022. [CrossRef] [Google Scholar] [Publisher Link]