School of Computer science Engineering and Information Systems

Winter Sem – 2023 - 2024

Review - 1

Programme: M.Tech (SE)

Course Title : Biometric Systems **Course Code : SWE1015**

Date of Submission: 30.4.24

Reg.no: 21MIS0123, 21MIS0143

Title : Study on Face And Fingerprint Multimodal Biometric System

Abstract

Abstract: Multimodal Face and Fingerprint Recognition Systems - Recent developments in mixed biometric recognition systems are reviewed in the current paper, with an emphasis on the fusion of face and fingerprint modalities. In the current document fifteen scholarly articles examining diverse facets of these systems, comprising Benefits and challenges, Compared to unimodal systems, combining face including fingerprint data improves accuracy and robustness, but it also presents issues with complexity, privacy, and computing expense. Preprocessing or feature extraction. For best results, each modality's unique set of techniques for reducing noise, normalization as well as and feature extraction is essential. Fusion strategies, Various methods, such as feature-level, score-level, with decision-level fusion, are investigated for merging face and fingerprint features. Deep learning - Although it demands a thoughtful evaluation of computational resources, deep learning architectures are becoming more and more popular for feature extraction and classification. They offer notable improvements in accuracy.The paper highlight the potential of multimodal face and fingerprint recognition for secure and reliable identification. However, addressing challenges

related to complexity, privacy, and computational efficiency is essential for broader adoption.

Keywords

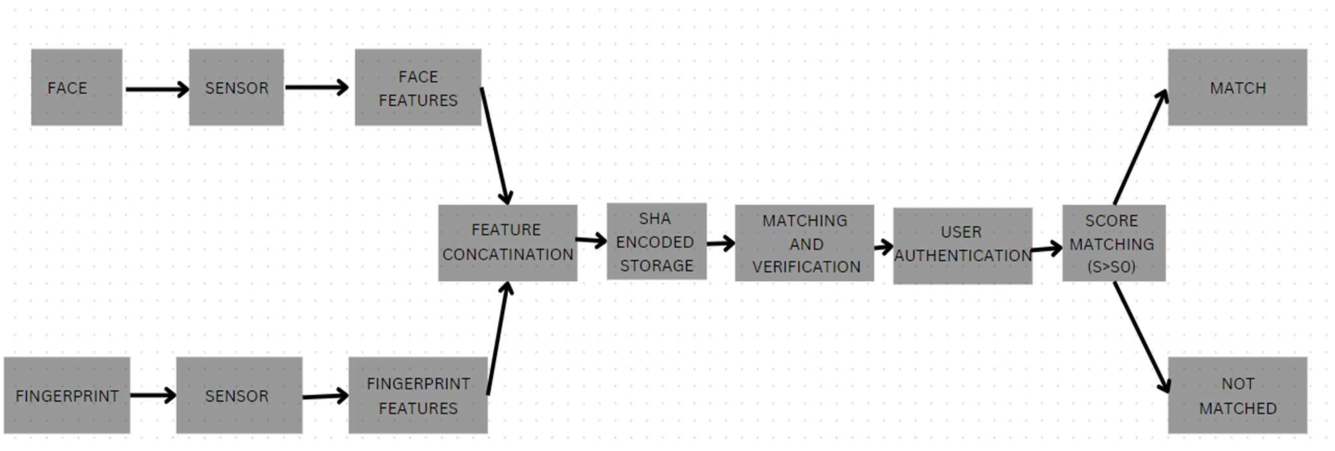
Multimodal biometrics, Face recognition, Fingerprint recognition, IoT-based biometrics, Quality-aware fusion, Template protection, Distributed applications, Android-based systems

Introduction

In a wide range of applications, including financial transactions, border control, access control systems, and personal gadgets, there is an increasing need for trustworthy and secure personal identity. Multimodal biometric identification systems, which integrate data from several biometric methods, have emerged as a viable answer in this changing environment. Compared to single-modality techniques, these systems offer improved accuracy, reliability, and security by utilizing the strengths of many modalities, including face and fingerprint. The current document study examines the fascinating developments and difficulties in multidimensional biometric recognition networks, gleaned from a wide range of current research publications.

Additionally, It examine how deep learning approaches can be integrated to increase the accuracy of recognition and examine how research like Keykhaie and Pierre are analyzing the growing significance of mobile-based authentication. Furthermore, we look into the significance of quality control in multimodal systems[8] and the use of novel modalities like ECG in addition to fingerprints. It is critical to address important issues like privacy and template protection, and we look at how academics are approaching these problems. We also take into account the creation of massive multimodal data and investigate the possibilities for apps that are distributed. This paper attempts to provide an extensive grasp of the latest developments in multimodal face and fingerprint identification by examining the usage of local and global characteristics and analyzing several fusion algorithms.

General Architecture on Topic chosen



Face Recognition Module:

Algorithm: Haar Cascade

Trains on positive and negative images to create a classifier identifying facial features like eyes, nose, and mouth.

Fingerprint Recognition Module:

Algorithm: FLANN (Fast Library for Approximate Nearest Neighbors)

Facilitates finding similar fingerprint patterns, enabling swift and precise matching against a stored fingerprint database.

Multimodal Fusion Module:

Algorithm: Feature Concatenation or Fusion

Combines feature vectors from face and fingerprint modules into a single multimodal feature vector.

Template Storage Module:

Algorithm: Secure Hashing or Encoding

Utilizes a secure hashing algorithm (e.g., SHA-256) to create a unique and irreversible template from the multimodal feature vector. Safely stores the hashed template for future matching in the database.

Matching and Verification Module:

Algorithm: Multimodal Matching

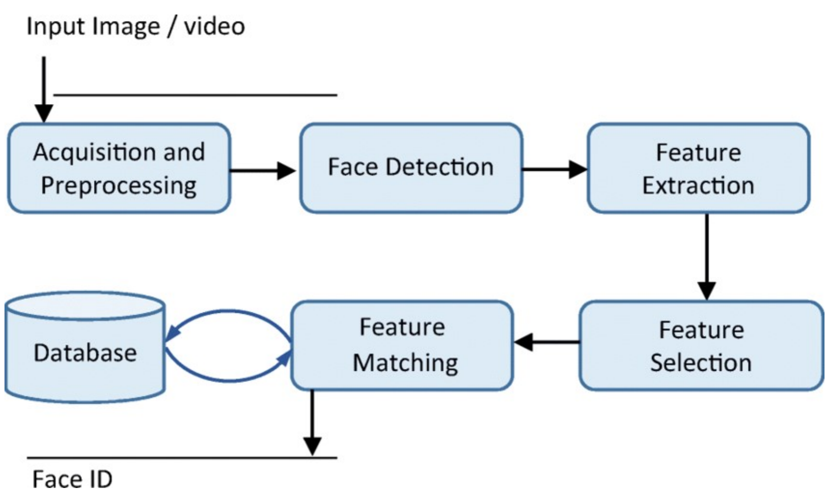
Employs a matching algorithm considering both face and fingerprint data concurrently. Utilizes similarity measures like cosine similarity or Euclidean distance for comparing multimodal feature vectors.

User Authentication Module:

Algorithm: Threshold-based Authentication

Determines an authentication threshold based on system security requirements. Authenticates users by comparing the multimodal template with stored templates in the database.

Image acquisition:



[28]

Based on the order of comparitive study of various research papers, the image datasets used for their research are as follows:

Database Name	Attributes	Purpose	Characteristics
XM2VTS multimodal data	Gray scale, 250*300, Characteristics	Facial recognition, Speaker identification	Includes Facial Images, Speech Recordings, Annotations, and Metadata
BIOMDATA multimodal database	Gray scale, 2352*1728, Characteristics	Biometric identification	Contains fingerprints, iris scans, facial images, voice recordings, palmprints, hand geometry, gait analysis
Frank dataset, Serwadda dataset	Gray scale, 224*224, Characteristics	User authentication	Captures key press duration, latency between keystrokes,

			typing rhythm for authentication
CYBHi database, LivDet2015 database, FVC 2004 database	Gray scale, 25*20, Characteristics	Liveness detection	Liveness detection photographs
FVC and UBIRIS dataset	Gray scale, 3200*3200, Characteristics	Biometric identification	Grayscale images of specific dimensions
ORL dataset, FERET database	Gray scale, 1028*720, Characteristics Characteristics	Facial recognition	Grayscale images of specific dimensions, includes details like eyes opened/closed, smiling/not smiling, glasses/no glasses
XJTU multimodal database	Gray scale, 65*75, Characteristics	Biometric system performance evaluation	Includes biometric images of fingerprints, iris scans, facial images, and possibly voice recordings. May include age, gender, or ethnicity information
CASIA Iris Distance Database	Gray scale, 55*55, Characteristics	Iris recognition	Grayscale JPEG files of iris images
SDUMLA-HMT multimodal database	Gray scale, 2352*1728, Characteristics	Multimodal biometric recognition	Multiple biometric modalities with unspecified characteristics, based on benchmark databases
BANCA database	Gray scale, 256*512, Characteristics	Biometric identification, Vein recognition	Images from 500 individuals, covering different ethnicities and age groups, dorsal and

			palmar veins captured, experiments conducted on benchmark databases
Private database (unspecified)	Gray scale, 3200*3200, Characteristics	Biometric identification	Details not specified
UTMIFM	Gray scale, 250*300, Characteristics	Multimodal biometric recognition	Self-established dataset consisting of iris and face modalities

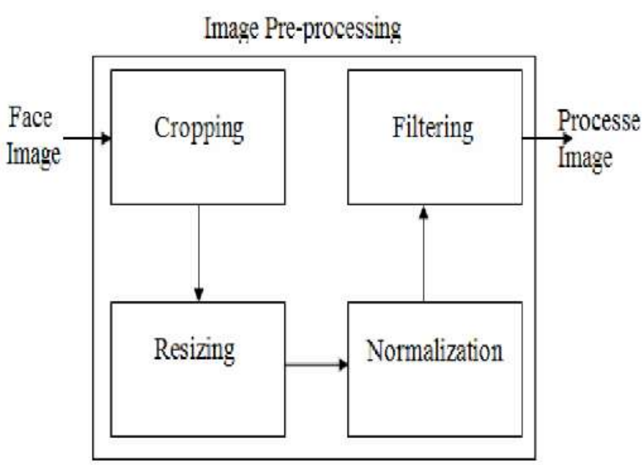
Fig. 2. Captured sample fingerprint images of a person.

[28]

Fig. 3. Original and encoded face images of a subject: (a) sample face images from ORL face database and (b) encoded face images of subject from ORL face database.

[28]

Image Pre-processing:

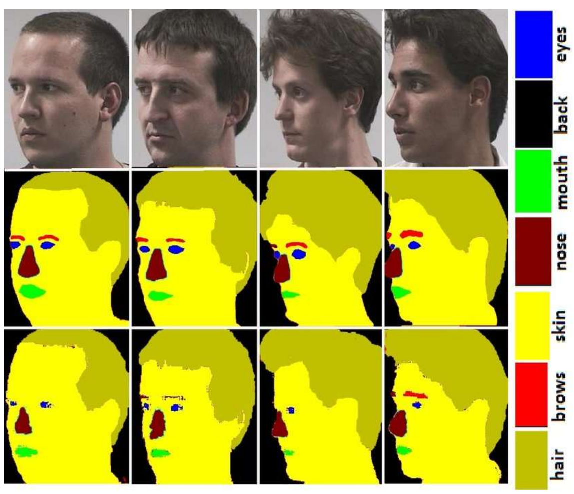


[15]

S.No	Technique Name	Methodology
1	Adaptive Dual Threshold	Analyzes local image characteristics around each pixel to determine if it's likely corrupted by salt-and-pepper noise.
2	A Multi-Abstract Network	Combines multiple modalities (face, iris, and fingerprint) to handle spatial mismatch problem with reduced network parameters.
3	Normalization, Grayscale Conversion, Histogram Equalization, Rotation and Scaling	Resizes and normalizes images to a common size and pixel intensity range for consistent input in deep learning models.
4	Bio-Hashing Method	Enhances security of derived features and improves authentication.
5	Fusion Techniques	Internal fusion, concatenation, or binary operations like AND, OR, and XOR at the feature-level to combine biometric data.
6	ICA	Utilized ICA (Independent Component Analysis) for dimensionality reduction.
7	SCER	Utilized Sparse Coding Error Ratio (SCER) to quantify the impact of various factors on query sample reliability.
8	SD based Normalization approach	Utilized Standard Deviation based Normalization Approach (DNA) for improving identification accuracy.
9	Gabor filters and SRKDA	Used Gabor Filters and SRKDA Feature Reduction for preprocessing.
10	DCT, PCA	Employed DCT, PCA, and PCA in DCT domain methods without mentioning specific preprocessing technique.

11	Geometric calibration	Utilized geometric calibration and direct least square ellipse for face recognition, and PCA for generating eigenfaces.
12	Encoding and Decoding	Encoded fingerprint templates into face images and performed subsequent decoding process.

Image Segmentation:



[20]

Deep learning

Technique	Salient Features
Convolutional Neural Networks (CNN)	Utilizes deep learning to automatically learn and extract features for segmentation tasks
Deep Belief Networks (DBN)	Hierarchical probabilistic models used for unsupervised feature learning, useful for image segmentation
Recurrent Neural Networks (RNN)	Processes sequential data to capture temporal dependencies, useful for segmentation in video or time-series data

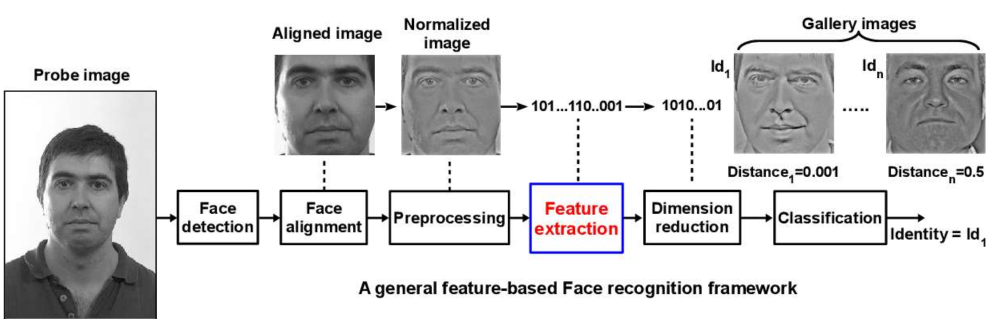
Convolution based

Technique	Salient Features
Fully Convolutional Networks (FCN)	Adapts CNNs for end-to-end segmentation, useful for pixel-wise labeling tasks
U-Net	Architecture with symmetric encoder-decoder structure, useful for biomedical image segmentation

Hybrid

Technique	Salient Features
CNN + Conditional Random Fields (CRF)	Integrates deep learning features with probabilistic graphical models for segmentation tasks
CNN + Graph Regularization	Combines CNN-based feature extraction with graph-based regularization for improved segmentation performance

Feature Extraction:



A general feature-based Face recognition framework

[22]

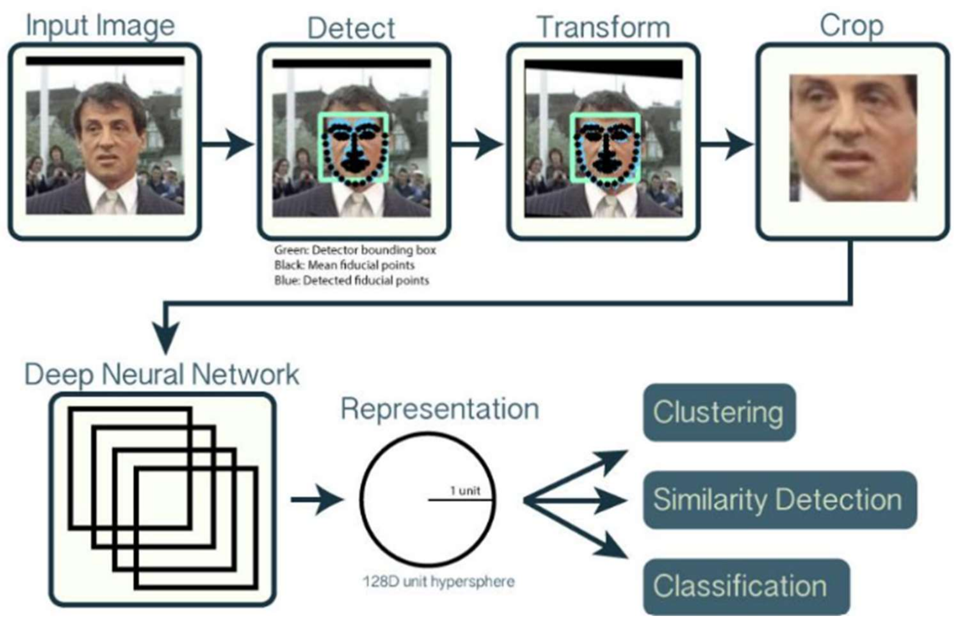
Deep learning

Technique	Salient Features
Convolutional Neural Networks (CNN)	Utilizes deep learning to automatically learn and extract features from raw data, useful for image recognition tasks
Recurrent Neural Networks (RNN)	Processes sequential data to capture temporal dependencies, useful for feature extraction in time-series data

Dimensionality reduction

Technique	Salient Features
Principal Component Analysis (PCA)	Linear dimensionality reduction technique, useful for reducing the dimensionality of feature spaces
t-distributed Stochastic Neighbor Embedding (t-SNE)	Non-linear dimensionality reduction technique, useful for visualizing high-dimensional data
Auto encoders	Neural network architecture that learns to reconstruct inputs, useful for learning compact representations

Classification:



[24]

Machine learning

Technique	Salient Features
Support Vector Machines (SVM)	Finds the hyperplane that best separates classes in feature space, useful for binary and multi-class classification tasks
k-Nearest Neighbors (k-NN)	Assigns a class label based on the majority class among its k nearest neighbors in feature space
Decision Trees	Constructs a tree-like model of decisions based on feature values, useful for both classification and regression tasks
Random Forests	Ensemble learning method that combines multiple decision trees for improved accuracy and robustness

Deep learning

Technique	Salient Features
Convolutional Neural Networks (CNN)	Utilizes deep learning to automatically learn and extract features from raw data, useful for image classification tasks
Recurrent Neural Networks (RNN)	Processes sequential data to capture temporal dependencies, useful for classification in time-series data

Long Short-Term Memory (LSTM)	Variant of RNN designed to overcome the vanishing gradient problem and handle long-range dependencies
Transformer Networks	Utilizes self-attention mechanisms to capture long-range dependencies in sequences, popular for natural language processing tasks

Statistical

Technique	Salient Features
Gradient Boosting Machines (GBM)	Builds a strong predictive model by sequentially adding weak learners that correct errors of previous models
AdaBoost	Adaptive boosting algorithm that combines multiple weak classifiers to form a strong classifier
XGBoost	Optimized implementation of gradient boosting that provides efficient and scalable tree boosting

Conclusions (Among various schemes which is best for which application)

Finally based on the comparitive study done using tables, we conclude that following are best for our research:

Face Recognition Module:

Algorithm: Haar Cascade

Trains on positive and negative images to create a classifier identifying facial features like eyes, nose, and mouth.

Fingerprint Recognition Module:

Algorithm: FLANN (Fast Library for Approximate Nearest Neighbors)

Facilitates finding similar fingerprint patterns, enabling swift and precise matching against a stored fingerprint database.

Multimodal Fusion Module:

Algorithm: Feature Concatenation or Fusion

Combines feature vectors from face and fingerprint modules into a single multimodal feature vector.

Template Storage Module:

Algorithm: Secure Hashing or Encoding

Utilizes a secure hashing algorithm (e.g., SHA-256) to create a unique and irreversible template from the multimodal feature vector. Safely stores the hashed template for future matching in the database.

Matching and Verification Module:

Algorithm: Multimodal Matching

Employs a matching algorithm considering both face and fingerprint data concurrently. Utilizes similarity measures like cosine similarity or Euclidean distance for comparing multimodal feature vectors.

User Authentication Module:

Algorithm: Threshold-based Authentication

Determines an authentication threshold based on system security requirements. Authenticates users by comparing the multimodal template with stored templates in the database.

Improved accuracy: [1]Higher rates of identification and less false accept/reject rates are regularly attained by multimodal systems over unimodal ones.

- **Robustness to variations:** [3]Limitations of individual features, including aging, ambient conditions, or sensor noise, can be compensated for by integrating many modalities.

- **Liveness detection:** [6] Enhancing liveness detection and thwarting spoofing attempts can be achieved by combining fingerprints and facial features.
- **Wider applicability:** [7] Diverse demographics and situations where only one method can be inaccessible or unreliable might be served by multimodal systems.
- **Quality-aware fusion:** [3] When using quality estimation approaches, the dependability of individual samples inside each modality is taken into account, which further improves recognition accuracy.
- **Lightweight deep learning:** [12] Creating effective structures for deep learning can help real-world deployments strike a balance between computational demands and accuracy.
- **Privacy-preserving techniques:** [9] Privacy concerns can be addressed by implementing safe and privacy-enhancing techniques such as federated learning or homomorphic encryption.
- **Multimodal fusion strategies:** [13] System efficiency and versatility can be improved by investigating new fusion techniques and the advantages of incorporating modalities other than face and fingerprint.
- **Complexity:** [8] Multiple modalities' design, implementation, and integration raise resource requirements and system complexity.
- **Privacy concerns:** [9] Biometric data collection and storage creates privacy issues that call for ethical frameworks and careful thought.
- **Template protection:** [9] It is essential to store and safeguard biometric templates securely to avoid misuse and unwanted access.
- **Computational cost:** [14] Although deep learning algorithms can yield great accuracy, their real-time implementation may be hindered by their considerable computational resource requirements.

References

Base review paper link: M. Abdul-Al, G. K. Kyeremeh, N. O. Parchin, R. A. Abd-Alhameed, R. Qahwaji and J. Rodriguez, "Performance of Multimodal Biometric Systems Using Face and Fingerprints (Short Survey)," *2021 IEEE 26th International Workshop on Computer Aided Modeling and Design of Communication Links and*

Networks (CAMAD), Porto, Portugal, 2021, pp. 1-6, doi: 10.1109/CAMAD52502.2021.9617766.

[1] E. M. Cherrat, R. Alaoui, H. Bouzahir and W. Jenkal, "High density salt-and-pepper noise suppression using adaptive dual threshold decision based algorithm in fingerprint images," *2017 Intelligent Systems and Computer Vision (ISCV)*, Fez, Morocco, 2017, pp. 1-4, doi: 10.1109/ISACV.2017.8054913.

[2] Mulyanto, B. Firmanto, A. F. O. Gaffar, B. Suprapty and A. B. W. Putra, "Multimodal biometric system based on feature source compaction and the proposed VCG (Virtual Center of Gravity) feature," 2021 International Seminar on Intelligent Technology and Its Applications (ISITIA), Surabaya, Indonesia, 2021, pp. 95-100, doi: 10.1109/ISITIA52817.2021.9502224.

[3] S. Soleymani, A. Dabouei, H. Kazemi, J. Dawson and N. M. Nasrabadi, "Multi-Level Feature Abstraction from Convolutional Neural Networks for Multimodal Biometric Identification," 2018 24th International Conference on Pattern Recognition (ICPR), Beijing, China, 2018, pp. 3469-3476, doi: 10.1109/ICPR.2018.8545061.

[4] S. S. Sengar, U. Hariharan and K. Rajkumar, "Multimodal Biometric Authentication System using Deep Learning Method," 2020 International Conference on Emerging Smart Computing and Informatics (ESCI), Pune, India, 2020, pp. 309-312, doi: 10.1109/ESCI48226.2020.9167512.

[5] S. Keykhaie and S. Pierre, "Mobile Match on Card Active Authentication Using Touchscreen Biometric," in IEEE Transactions on Consumer Electronics, vol. 66, no. 4, pp. 376-385, Nov. 2020, doi: 10.1109/TCE.2020.3029955.

[6] M. Hammad, Y. Liu and K. Wang, "Multimodal Biometric Authentication Systems Using Convolution Neural Network Based on Different Level Fusion of

ECG and Fingerprint," in IEEE Access, vol. 7, pp. 26527-26542, 2019, doi: 10.1109/ACCESS.2018.2886573.

[7] M. Rukhiran, S. Wong-In and P. Netinant, "IoT-Based Biometric Recognition Systems in Education for Identity Verification Services: Quality Assessment Approach," in IEEE Access, vol. 11, pp. 22767-22787, 2023, doi: 10.1109/ACCESS.2023.3253024.

[8] S. Soleymani, A. Dabouei, F. Taherkhani, S. M. Iranmanesh, J. Dawson and N. M. Nasrabadi, "Quality-Aware Multimodal Biometric Recognition," in IEEE Transactions on Biometrics, Behavior, and Identity Science, vol. 4, no. 1, pp. 97-116, Jan. 2022, doi: 10.1109/TBIOM.2021.3131664.

[9] Z. H. Goh et al., "A Framework for Multimodal Biometric Authentication Systems With Template Protection," in IEEE Access, vol. 10, pp. 96388-96402, 2022, doi: 10.1109/ACCESS.2022.3205413.

[10] A. Tarannum, Z. U. Rahman, L. K. Rao, T. Srinivasulu and A. Lay-Ekuakille, "An Efficient Multi-Modal Biometric Sensing and Authentication Framework for Distributed Applications," in IEEE Sensors Journal, vol. 20, no. 24, pp. 15014-15025, 15 Dec.15, 2020, doi: 10.1109/JSEN.2020.3012536

[11] X. Zhang, D. Cheng, P. Jia, Y. Dai and X. Xu, "An Efficient Android-Based Multimodal Biometric Authentication System With Face and Voice," in IEEE Access, vol. 8, pp. 102757-102772, 2020, doi: 10.1109/ACCESS.2020.2999115.

[12] A. A. Akinrinmade, E. Adetiba, J. A. Badejo and O. Oshin, "NaijaFaceVoice: A Large-Scale Deep Learning Model and Database of Nigerian Faces and Voices," in IEEE Access, vol. 11, pp. 58228-58243, 2023, doi: 10.1109/ACCESS.2023.3282618.

[13] M. Leghari, S. Memon and A. A. Chandio, "Feature-level fusion of fingerprint and online signature for multimodal biometrics," 2018 International Conference on

Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 2018, pp. 1-4, doi: 10.1109/ICOMET.2018.8346358.

[14] T. Edwards and M. S. Hossain, "Effectiveness of Deep Learning on Serial Fusion Based Biometric Systems," in IEEE Transactions on Artificial Intelligence, vol. 2, no. 1, pp. 28-41, Feb. 2021, doi: 10.1109/TAI.2021.3064003

[15] Ammour, B., Bouden, T., Boubchir, L., & Biad, S. (2017, July). Face identification using local and global features. In *2017 40th International Conference on Telecommunications and Signal Processing (TSP)* (pp. 784-788). IEEE.

[16] A multi-agent based enhancement for multimodal biometric system at border control Susara S Thenuwara , Chinthaka Premchandra , Hiroharu Kawanaka , 2022

[17] A Multimodal Hand Vein Biometric based on Score Level Fusion Maleika Heenya,Mamode khan, 2012

[18] A robust face and ear based multimodal biometric system using sparse representation Z. Huang et al. / Pattern Recognition 46 (2013)

[19] Biometric authentication using a deep learning approach based on different level fusion of finger knuckle print and fingernail Heidari and A. Chalechale,2022

[20] Designing efficient fusion schemes for multimodal biometric systems using face and palmprint R. Raghavendra et al. / Pattern Recognition 44 (2011)

[21] Enhancement of Security through Fused Multimodal Biometric System Priyanka Tekade,Priti Shende ,2017

[22] Enhancing Security for Multimodal Biometric using Hyper Image Encryption Algorithm K Nivetha,D.Saraswady,2015

[23] Face-Iris Multimodal Biometric System based on Hybrid Level Fusion Basma Ammour,Toufik Bouden,Larbi Boubchir,2018

[24] Fingerprint-Fingervein Multimodal Biometric Authentication System in Field Programmable Gate Array R.Moganeshwaran,M.Annuar Suhaini,2012

[25] Multimodal Biometric Identification System based on the Face and Iris Basma Ammour,Toufik Bouden,2017

[26] Multimodal biometric identification system based on finger geometry, knuckle print and palm print Mohamed Berkane,Mohamed C.Batouche,2014

[27] Multimodal biometrics: Weighted score level fusion based on non-ideal iris and face images Zhu le qing,Zhang san yuan,2017

[28] Multimodal face and fingerprint biometrics authentication on space-limited tokens Hiew moi sim,Hishammuddin Asmuni,2014

[29] Multimodal facial biometrics recognition: Dual-stream convolutional neural networks with multi-feature fusion layers Muhammad Khurram Khan,Jiashu Zhang,2018