

MULTIMODAL BIOMETRIC RECOGNITION MODEL USING GWPEAO AND MULTI-SVNN CLASSIFIERS

M Ephin

Computer Science & Engineering

Dr. Pratap Singh Patwal (Professor)

Glocal School of Technology and Computer Science

ABSTRACT

Encryption is an essential measure in contemporary society to safeguard crucial data from unauthorized access by those with malicious intentions, like criminals. The encryption standards have diverse applications, spanning from online banking to the internet of things. Given the increasing prevalence of the Internet of Things (IoT), it is imperative to verify the identity of the connected devices. The primary objective of this study is to investigate a research on a multimodal biometric recognition model utilizing GwPEAO and multi-SVNN classifiers. The development of a biometric recognition model involves considering many modalities using a Multi-Support Vector Neural Network (Multi-SVNN). GwPEAO is an outcome of combining the Glowworm Optimization Algorithm (GOA) and the Penguin Search Optimization Algorithm (PeSOA), both of which are algorithms designed for Search Optimization. The approach integrates two distinct modalities, namely the ear and the finger vein. Based on this investigation, this strategy provides a high degree of accuracy and is very efficient in quickly recognizing true negatives in comparison to other currently available methods.

Keywords: *Multimodal Biometrics Recognition Model, GwPEAO, Multi-SVNN, Finger Vein, Ear.*

INTRODUCTION

A state-of-the-art multimodal biometric recognition model is developed using GWPEAO and Multi-SVNN classifiers to provide robust and accurate identification/authentication. GWPEAO is a highly effective method for extracting important characteristics from many biometric modalities, including fingerprints, face photos, iris patterns, and voice data. This method ensures a thorough representation of individual attributes (Sarhan et al., 2017; Kothari & Indira, 2019). These characteristics are smoothly combined utilizing sophisticated fusion techniques to form a uniform feature vector. The Multi-SVNN classifier, which integrates the capabilities of Support Vector Machines and Neural Networks, is subsequently trained on this merged feature space to acquire knowledge of intricate patterns and correlations, hence facilitating dependable categorization (Bianco & Napoletano, 2019; Donida Labati et al., 2016). By conducting thorough assessment and meticulous adjustments, the model attains exceptional performance metrics, such as elevated accuracy and resilience against diverse environmental conditions and attacks (Sumathi et al., 2018). Once implemented, this paradigm guarantees to improve security and simplify authentication procedures across many applications, ranging from access control to border security (Supreetha Gowda et al., 2019).

LITERATURE REVIEW

The subsequent section provides a detailed analysis of previous literature on the topic of multimodal biometric recognition model with GWPEAO and multi-SVNN classifiers.

Table 1: Related works

AUTHORS AND YEARS	METHODOLOGY	FINDINGS
Shyam and Singh (2015)	Four combinations of these approaches are possible: Eigenfaces and local binary pattern (LBP), Fisherfaces and LBP, organics' and augmented LBP, and Fisherfaces and A-LBP. Publicly accessible face databases and the Labeled Faces in the Wild are used to test multimodal face recognition systems using a new Bray Curtis dissimilarity metric.	The results show that numerous multimodal face recognition systems have improved in accuracy.
Choudhary et al. (2017)	The multi-modal biometric system uses ICA and GTCC algorithms for speech and facial recognition. Operation data was fused using score-level, feature-level, and sensor-level fusion. Every system calculates its own matching score.	Use the Training and Testing Section to apply a categorization method like Convolutional Neural Network. These systems were outfitted with MATLAB 2016a Simulation to improve false acceptance, rejection, accuracy, precision, and recognition.
Prabu, Lakshmanan, and Mohammed (2019)	A new algorithm called Hybrid Adaptive Fusion (HAF) aims to achieve this. HAF uses hybrid fusion to combine user features like iris and hand shape.	Extreme Learning machines use stored features to identify confirmed users. Neural Networks and Baiyes Networks were also used to test this concept. We also used CASIA Image Datasets. The ELM algorithm has 98.5% accuracy, higher than other machine learning methods.

Research Gap: Multimodal biometric recognition models have advanced, although GWPEAO and Multi-SVNN classifier integration is still lacking. Both components have shown efficacy in feature extraction and classification tasks, but their combined use in multimodal biometrics is unknown. These advanced algorithms' synergies are often overlooked in investigations of single-modal or simpler fusion methods. Addressing this gap could improve biometric recognition accuracy, resilience, and scalability, especially when several modalities must be seamlessly integrated for security and user experience. More study is needed to determine the best fusion procedures, training methods, and performance evaluation measures for this integrated framework to improve multimodal biometric systems.

METHODOLOGY

When employing multimodal detection, it is imperative to tackle issues that arose from utilizing unimodal detection. Utilizing multimodal recognition techniques, the accuracy of recognition is often high. By incorporating finger vein and ear photos, it is possible to overcome the difficulties posed by variations in skin texture and aging. Hence, the constructed multimodal identification model utilizes images of the veins in the finger and the ear for the goal of detection. The Multi-SVNN, based on GwPeSOA, is trained using features obtained from photos recovered by feature extraction.

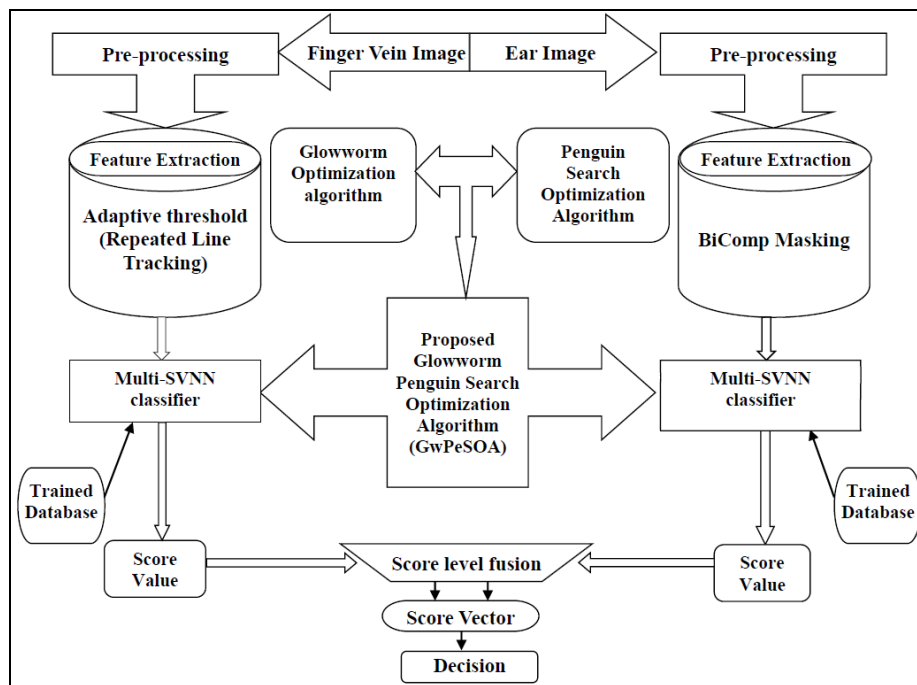


Figure 1: Biometric model of the developed GwPeSOA-based multi-SVNN

The output of the classifier, which was trained using images of the ear and the finger, is mixed by considering the appropriate weights. It is feasible to distinguish between the score output and the ultimate output for each individual. To ascertain the recognized individual, the person with the highest score is selected. The figure above displays the architecture of multimodal biometrics, which is built on the GwPeSOA-based multi-SVNN.

RESULTS AND DISCUSSIONS

The investigation makes use of the SDUMLA HMT Finger 2017 finger vein database and the AMI ear 2017 ear database. The effectiveness of this biometric model can be evaluated through an examination of its sensitivity, accuracy, and specificity using these two datasets.

Facial photographs, finger vein images, locomotion videos, view angles, iris images, and fingerprint images are all stored in the SDUMLA-HMT database. Additionally, videos of gait are included in the database. Authentic multimodal data submitted by 106 unique individuals is comprised in the database. The Joint Laboratory of Intelligent Computing and Intelligent Systems, located at Wuhan University, has been assigned the responsibility of creating a prototype of the apparatus employed for vein imaging in the fingertips. The participants supplied photographic documentation of the veins on their ring finger, middle finger, and index finger, taken from both palms. In order to acquire an exhaustive collection of finger vein images for every volunteer, the data collection procedure was duplicated six times on each of the six digits, for a cumulative count of 36 photographs per subject. The finger vein database comprises 3,816 photographs in total.

In order to carry out the research, the training data is modified to varying degrees (40–90%), taking into account distinct quantities of neurons. On a scale of five, the research examines between five and twenty-five neurons in total. A 25-neuron model utilizing 90% of the training data achieves an accuracy of 94.1%. An equivalent relationship can be observed between the specificity (96.7%) and sensitivity (92.1%).

Table 2: Results of the proposed GwPeSOA-MSVNN method on SDUMLA-HMT dataset

SDUMLA DATASET	HMT	Training percentage =90% and Neurons = 25			
		IMAGE SIZE	Accuracy (%)	Specificity (%)	Sensitivity (%)
		(128 X 128)	94.1	92.1	96.7

Most multimodal biometric systems process biometric parameters in isolation without considering their mutual dependence in modules. The reciprocal reliance of features is ignored by multimodal databases. Yang et al. (2015) state that there is no analysis that shows whether such combinations at the feature, classification, or decision levels affect system performance. The features obtained during feature extraction include significant personal information, according to the work suggested. Neural network design generates feature maps for human identification. The classifier can accurately identify the individual. Unlike the methodologies discussed above, the classifier and optimization algorithm produce higher performance metrics than other research. GwPeSOA-MSVNN helps choose weights, improving model performance. Contrary to the Robust Intra-Class Distance-Based Approach, which lacks confidence in weight selection.

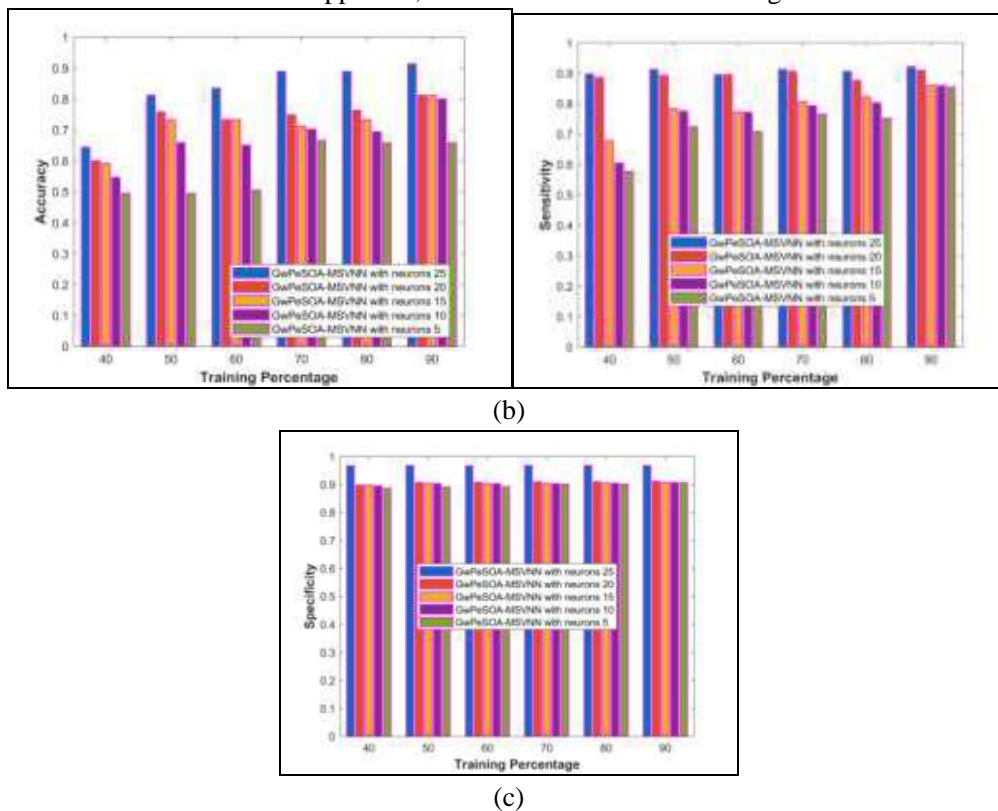


Figure 2: Graphical comparison using the SDUMLA-HMT dataset with an image of size 128X128 based on a) Accuracy b) Sensitivity c) Specificity

CONCLUSION

In conclusion, the biometric system is a promising and rapidly evolving technology used in automated systems to uniquely identify individuals without the need for IDs or passwords. Biometric authentication could alleviate various security issues. A good biometric authentication system can reduce security risks.

Passwords, smart cards, and tags have limits, as indicated. These constraints can be overcome using biometric authentication. Individuals' fingerprints, face traits, speech patterns, and iris patterns are used to collect biometric data for biometric recognition. By considering identification knowledge and possession, the biometric system has many benefits.

REFERENCES

1. Sarhan, S., Alhassan, S., & Elmougy, S. (2017). Multimodal biometric systems: a comparative study. *Arabian Journal for Science and Engineering*, 42, 443-457.
2. Bianco, S., & Napolitano, P. (2019). Biometric recognition using multimodal physiological signals. *IEEE access*, 7, 83581-83588.
3. Supreetha Gowda, H. D., Hemantha Kumar, G., & Imran, M. (2019). Multimodal biometric recognition system based on nonparametric classifiers. In *Data Analytics and Learning: Proceedings of DAL 2018* (pp. 269-278). Springer Singapore.
4. Shyam, R., & Singh, Y. N. (2015). Identifying individuals using multimodal face recognition techniques. *Procedia Computer Science*, 48, 666-672.
5. Choudhary, R., Kumar, E. K., & Monga, H. (2017). Enhanced Multi-Modal Biometric Based Security Scheme with Feature Based Machine Learning Approach. *International Journal of Computer Science and Information Security (IJCSIS)*, 15(11).
6. Prabu, S., Lakshmanan, M., & Mohammed, V. N. (2019). A multimodal authentication for biometric recognition system using intelligent hybrid fusion techniques. *Journal of medical systems*, 43(8), 249.
7. Yang, W., Hu, J., Wang, S., & Chen, C. (2015). Mutual dependency of features in multimodal biometric systems. *Electronics Letters*, 51(3), 234-235.
8. Kothari, A., & Indira, B. (2019). A unique six sigma based segmentation technique for brain tumor detection and classification using hybrid cnn-svm model.
9. Sumathi, R., Venkatesulu, M., & Arjunan, S. P. (2018). Extracting tumor in MR brain and breast image with Kapur's entropy based Cuckoo Search Optimization and morphological reconstruction filters. *Biocybernetics and Biomedical Engineering*, 38(4), 918-930.
10. Donida Labati, R., Genovese, A., Munoz Ballester, E., Piuri, V., Scotti, F., & Sforza, G. (2016). Computational intelligence for biometric applications: a survey. *COMPUTING INTERNATIONAL SCIENTIFIC JOURNAL*, 15(1), 40-49.