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AN ENHANCED MULTI-MODAL BIOMETRIC AUTHENTICATION SYSTEM USING MODIFIED DEEP LEARNING MODEL

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ABSTRACT

The acceleration of the emergence of modern technological resources in recent years has given rise to a need for accurate user recognition systems to restrict access to the technologies. The biometric recognition systems are the most powerful option to date. Biometrics is the science of establishing the identity of a person through semi or fully automated techniques based on behavioural traits, such as voice or signature, and/or physical traits, such as the iris and the fingerprint. The unique nature of biometrical data gives it many advantages over traditional recognition methods, such as passwords, as it cannot be lost, stolen, or replicated. Biometric traits can be categorized into two groups: extrinsic biometric traits such as iris and fingerprint, and intrinsic biometric traits such as palm. Extrinsic traits are visible and can be affected by external factors, while the intrinsic features cannot be affected by external factors. In general, the biometric recognition system consists of four modules: sensor, feature extraction, matching, and decision-making modules. There are two types of biometric recognition systems, unimodal and multimodal. The unimodal system uses a single biometric trait to recognize the user. While unimodal systems are trustworthy and have proven superior to previously used traditional methods, but they have limitations. These include problems with noise in the sensed data, non-universality problems, vulnerability to spoofing attacks, intra-class, and inter-class similarity. Basically, multimodal biometric systems require more than one trait to recognize users. They have been widely applied in real-world applications due to their ability to overcome the problems encountered by unimodal biometric systems. In multimodal biometric systems, the different traits can be fused using the available information in one of the biometric system's modules. The advantages of multimodal biometric systems over unimodal systems have made them a very attractive secure recognition method.Therefore, with the increasing demand for information security and security regulations all over the world, biometric recognition technology has been widely used in our everyday life. In this regard, multimodal biometrics technology has gained interest and became popular due to its ability to overcome several significant limitations of unimodal biometric systems. In this project, an enhanced multi-modal biometric authentication system is presented using modified deep learning model to authenticate persons using different biometric features such as Face, Iris, Finger, Palm and Ear.

Keywords: Modified Deep Learning Model, Biometric Authentication, Enhanced Multi Model,KLDA.

1. INTRODUCTION

Individual biometric personalities like iris, DNA, Voice recognition, fingerprint, retina, and finger vein can be labeled as unibiometric systems because it relies on a single biometric source for recognition. Unibiometric systems have some disadvantages like erratic biometric basis due to sensor, low quality of specific biometric trait of the authentic user. In addition, high-security applications and large-scale civilian recognition systems place stringent accuracy necessities that cannot be met by obtainable unibiometric systems. To deal with the requirements of such applications, it is necessary to move, beyond the traditional pattern of biometric recognition usually based on a single source of biometric information and consider systems that consolidate evidence from multiple biometric sources for recognition. However, the consolidation of information presented by these multiple cures can result in a more accurate determination or certification of individuality. Hence biometric systems are designed to recognize a person based on information acquired from multiple biometric sources. Such systems are referred as multibiometric systems are expected to be more accurate compared to unibiometric systems that rely on a particular segment of biometric affirmation. Accuracy enhancement, which is the primary motivation for using multibiometric systems happens due to two reasons. Firstly, the fusion of multiple biometric sources effectively increases the dimensionality of the feature space and reduces the overlap between the feature distributions of dissimilar individuals. In addition to that, a combination of multiple biometrics is more exclusive to an individual than a single biometric trait. Due to noise, imprecision, or inherent drift (caused by factors like ageing) in a subset of the biometric sources can be compensated by the discriminatory information provided by the remaining sources. In addition to accuracy, multimodal biometric systems may also offer the following advantages over unibiometric systems viz., alleviate the non-universality problem and reduce the failure to enrol errors, provide a degree of flexibility in user authentication, enable the search of a large biometric database in a computationally efficient manner and increase the resistance to spoofing attacks. Multimodal biometric implemented based MLCNN. Proposed biometric traits like fingerprint, retina and finger vein were combined.

2. LITERATURE SURVEY

Ryu et al. provided a systematic survey of existing literature on CMBA systems, followed by analysis to identify, and discuss current research and future trends. The study has found that many diverse biometric characteristics are used for multimodal biometric authentication systems. Many of the studies in the literature reviewed apply supervised learning approaches as a classification technique, and score level fusion is predominantly used as a fusion model. The review has determined however that there is a lack of comparative analysis on CMBA design in terms of combinations of biometric types (behavioural only, physiological only, or both), machine learning algorithms (unsupervised learning and semi-supervised learning), and fusion models.

Hammad et al. proposed a secure multimodal biometric system that uses convolution neural network (CNN) and Q-Gaussian multi support vector machine (QG-MSVM) based on a different level fusion. This framework developed two authentication systems with two different level fusion algorithms: a feature level fusion and a decision level fusion. The feature extraction for individual modalities is performed using CNN. systems were tested on several publicly available databases for ECG and fingerprint.

Sengar et al. projected rich neural community (DNN). The confinements of unimodal biometric structure lead to substantial False Acceptance Rate (FAR) along with False Rejection Rate (FRR), limited splitting up skill, top bound within delivery therefore the multimodal biometric product is designed to satisfy the strict delivery demands. For minutiae corresponding, values of Euclidean distance are used. The better identification pace is attained throughout the suggested procedure & it's extremely safe only in loud problem.

Joseph et al. proposed a multimodal authentication system by fusing the feature points of fingerprint, iris, and palm print traits. Each trait has undergone the following procedures of image processing techniques such as pre-processing, normalization and feature extraction. From the extracted features, a unique secret key is generated by fusing the traits in two stages. False Acceptance Rate (FAR) and False Rejection Rate (FRR) metrics are used to measure the robustness of the system. This performance of the model is evaluated using three standard symmetric cryptographic algorithms such as AES, DES, and Blowfish. This proposed model provides better security and access control over data in cloud environment.

Choudhary et al. given an overview of multiple biometrics used for authentication. Focusing on challenges in multimodal biometrics practiced through various fusion levels and different algorithms, this paper discussed scope of further research in this field. Majorly, the template security issue of multimodal biometrics is emphasized with various techniques to protect the crucial asset of human identity.

Wu et al. proposed and implemented LVID, a multimodal biometrics authentication system on smartphones, which resolved the defects of the original systems by combining the advantages of lip movements and voice. LVID simultaneously captures these two biometrics with the built-in audio devices on smartphones and fuses them at the data level. The reliable and effective features are then extracted from the fused data for authentication. LVID is practical as it requires neither cumbersome operations nor additional hardware’s but only a speaker and a microphone that are commonly available on smartphones.

Zhang et al. implemented DeepKey with a live deployment in the university and conduct extensive empirical experiments to study its technical feasibility in practice. DeepKey achieved the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) of 0 and 1.0%, respectively. The preliminary results demonstrated that DeepKey is feasible, showed consistent superior performance compared to a set of methods, and has the potential to be applied to the authentication deployment in real-world settings.

Rahiem et al. adopted Multi-Canonical Correlation Analysis (MCCA). This framework combined the two biometric systems based on ECG and finger vein into a single multimodal biometric system using feature and score fusion. The performance of the proposed system is tested on two finger vein (TW finger vein and VeinPolyU finger vein) databases and two ECG (MWM-HIT and ECG-ID) databases. Experimental results revealed the improvement in terms of authentication performance with Equal Error Rates (EERs) of 0.12% and 1.40% using feature fusion and score fusion, respectively. Therefore, the proposed biometric system is effective in performing secure authentication and assisting the stakeholders in making accurate authentication of users.

Zhang et al. designed and developed an efficient Android-based multimodal biometric authentication system with face and voice. Considering the hardware performance restriction of the smart terminal, including the random-access memory (RAM), central processing unit (CPU) and graphics processor unit (GPU), etc., which cannot efficiently accomplish the tasks of storing and quickly processing the large amount of data, a face detection method is introduced to efficiently discard the redundant background of the image and reduce the unnecessary information. Furthermore, an improved local binary pattern (LBP) coding method is presented to improve the robustness of the extracted face feature. We also improve the conventional endpoint detection technology, i.e., the voice activity detection (VAD) method, which can efficiently increase the detection accuracy of the voice mute and transition information and boost the voice matching effectiveness.

Ahmed et al. proposed an AI-based multimodal biometric authentication model for single and group-based users' device-level authentication that increases protection against the traditional single modal approach. To test the efficacy of the proposed model, a series of AI models are trained and tested using physiological biometric features such as ECG (Electrocardiogram) and PPG (Photoplethysmography) signals from five public datasets available in Physionet and Mendeley data repositories. The multimodal

3. PROPOSED SYSTEM

In this project we are designing Modified Deep Learning Neural Networks (MLDNN) algorithms to authenticate persons using different biometric features such as Face, Iris, Finger, Palm and Ear. Hence this algorithm is called as Multimodal. To implement this algorithm, we have applied KLDA features reduction algorithm to reduce biometric image features and then input to MLDNN algorithm to train a model to authenticate persons. MLDNN algorithm will further extract FSL features while training itself.

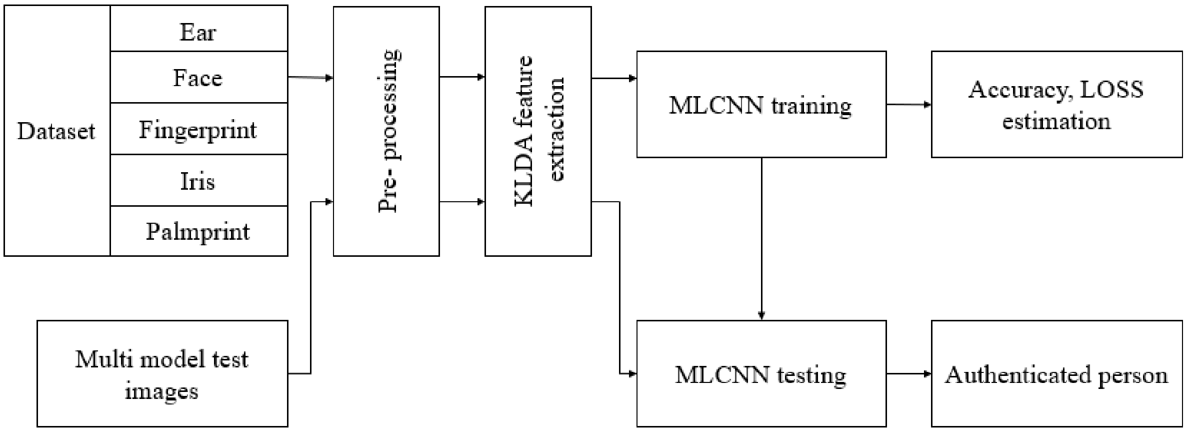


Fig. 1: Block diagram of proposed system.

Overview

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model.

When creating a project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task.

Why do we need Data Pre-processing?

A real-world data generally contains noises, missing values, and maybe in an unusable format which cannot be directly used for machine learning models. Data pre-processing is required tasks for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model.

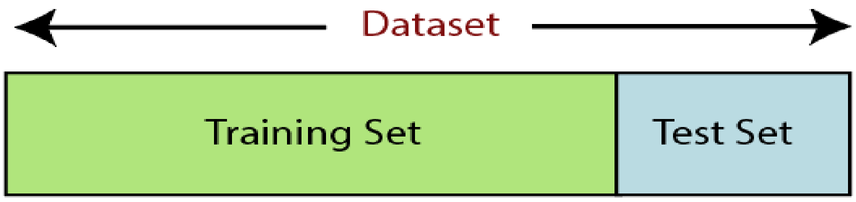
- Getting the dataset
- Importing libraries
- Importing datasets
- Finding Missing Data
- Encoding Categorical Data
- Splitting dataset into training and test set
- Feature scaling

Splitting the Dataset into the Training set and Test set

In machine learning data pre-processing, we divide our dataset into a training set and test set. This is one of the crucial steps of data pre-processing as by doing this, we can enhance the performance of our machine learning model.

Supposeif we have given training to our machine learning model by a dataset and we test it by a completely different dataset. Then, it will create difficulties for our model to understand the correlations between the models.

If we train our model very well and its training accuracy is also very high, but we provide a new dataset to it, then it will decrease the performance. So we always try to make a machine learning model which performs well with the training set and also with the test dataset. Here, we can define these datasets as:



Training Set: A subset of dataset to train the machine learning model, and we already know the output.

Test set: A subset of dataset to test the machine learning model, and by using the test set, model predicts the output.

KLDA

The principle of KLDA can be illustrated in below Fig.2. Owing to the severe non-linearity, it is difficult to directly compute the discriminating features between the two classes of patterns in the original input space (left). By defining a non-linear mapping from the input space to a high-dimensional feature space (right), we (expect to) obtain a linearly separable distribution in the feature space. Then LDA, the linear technique, can be performed in the feature space to extract the most significant discriminating features. However, the computation may be problematic or even impossible in the feature space owing to the high dimensionality. By introducing a kernel function which corresponds to the non-linear mapping, all the computation can conveniently be carried out in the input space. The problem can be finally solved as an eigen-decomposition problem like PCA, LDA and KPCA.

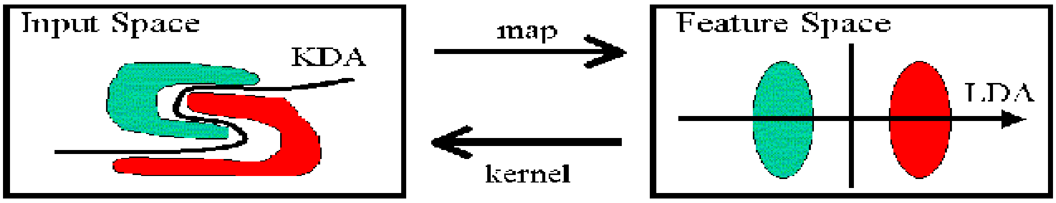


Fig. 2: Kernel discriminant analysis.

4. RESULTS AND DISCUSSION

Results description

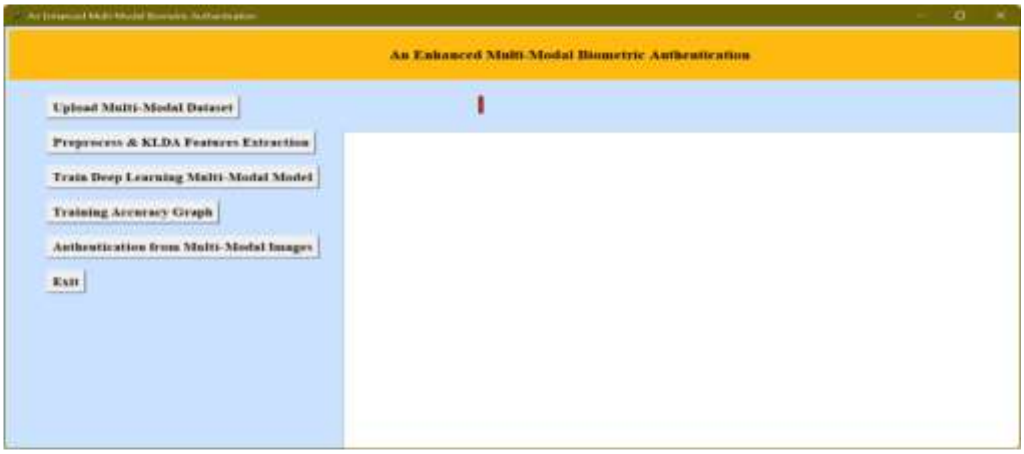


Figure 2: Main GUI application of enhanced multi model biometric authentication.

The figure 2 depicts the main interface of the application, providing an overview of the tool for exploring enhanced multi model biometric authentication. It include various features and options for users to interact with the application.

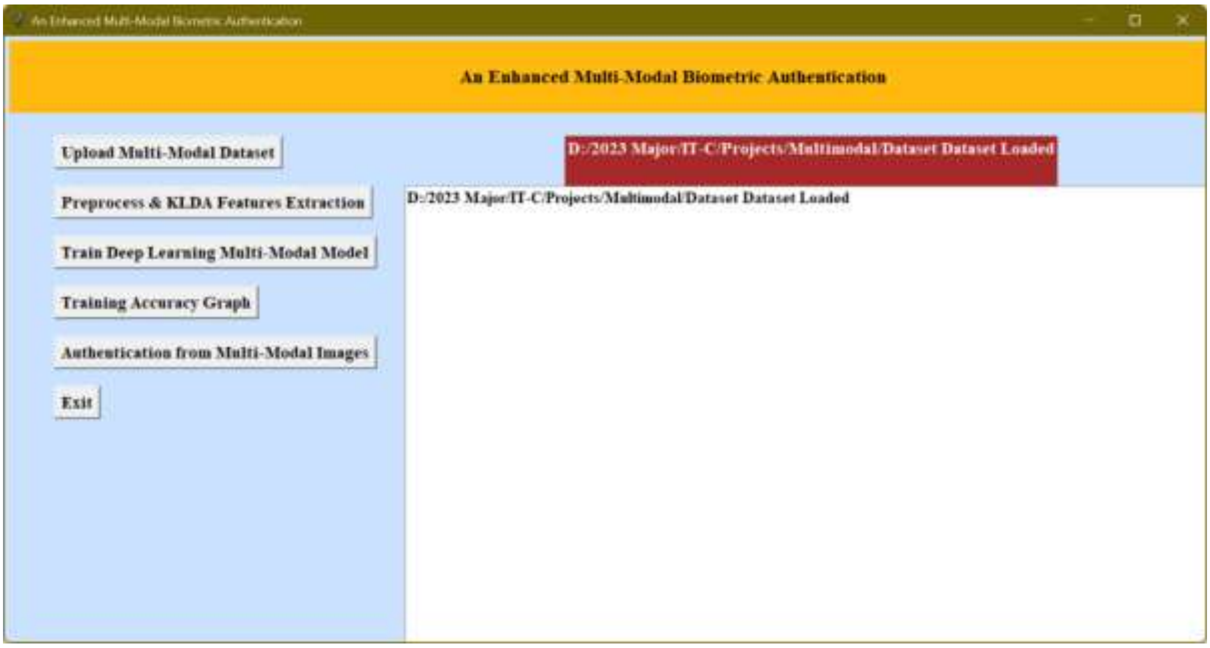


Figure 3: Displays the acknowledgement of loaded dataset in the GUI console.

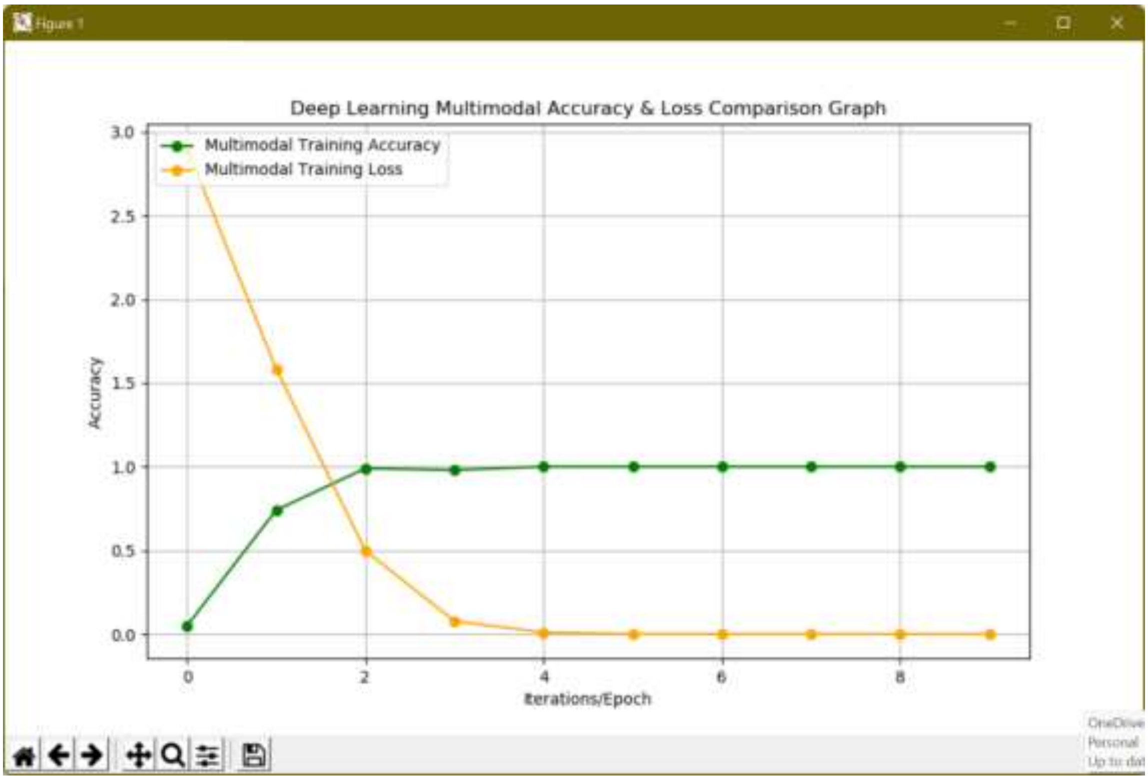


Figure 4: Displays the Accuracy and Loss Comparison graph for the Deep learning Multimodal.

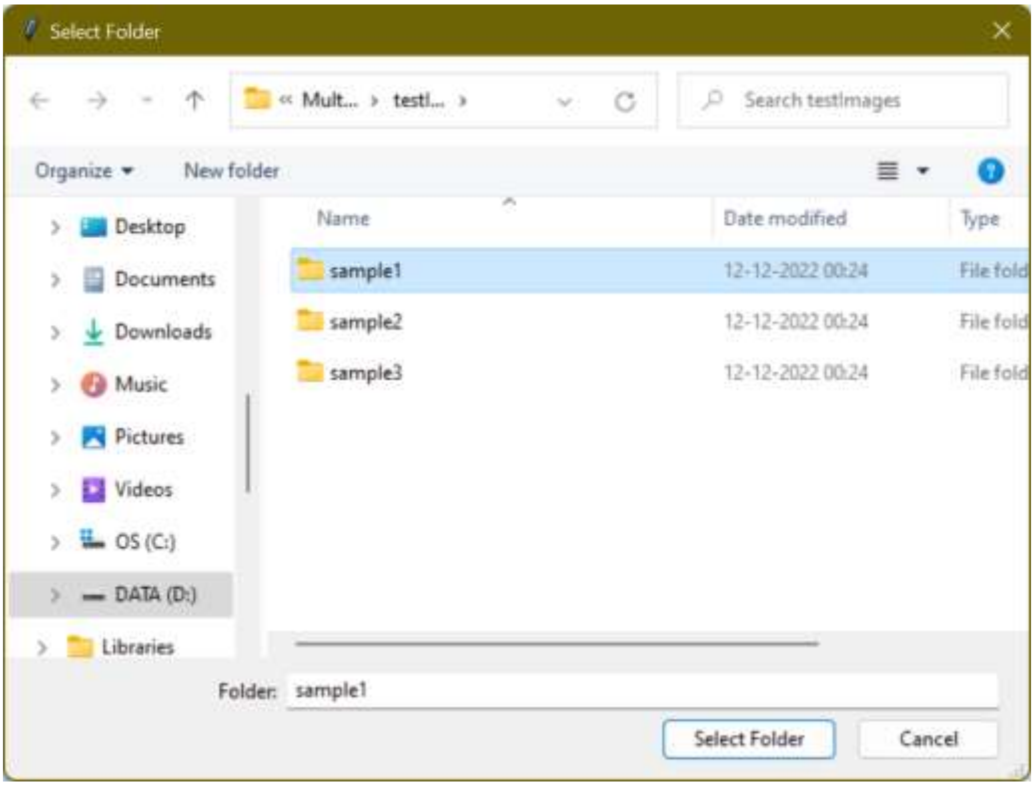


Figure 4: Displays the uploading sample1 testing folder.

The below figure shows the authentication of multi model images of face, eyes, ears, palm, fingerprint as id 4

Figure 5: Displays the authentication of multi model as id 4.

Figure 6: Displays the authentication of multi model as id 9

5. CONCLUSION AND FUTURE WORK

With the increasing demand for information security and security regulations all over the world, biometric recognition technology has been widely used in our everyday life. In this regard, multimodal biometrics technology has gained interest and became popular due to its ability to overcome several significant limitations of unimodal biometric systems. In this project, an enhanced multi-modal biometric authentication system is presented using MLCNN training and testing model to authenticate persons using different biometric features such as Face, Iris, Finger, Palm and Ear. Future work can be further extended by accurately modeling feature extraction techniques and managing the database more effectively and evaluating the matching methodology and its performance of biometric system using different level of fusion.

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