A Multi biometric system based on Hybrid Densenet 201-3D CNN classifier and Aquila optimization algorithm for Fingerprint-Iris-Face

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CANDIDATE'S DECLARATION

I, Shipra Shand, Roll No. 2K20/SWE/21 student of M.Tech (Software Engineering), hereby declare that the project Dissertation titled **"A Multi biometric system based on Hybrid Densenet 201-3D CNN classifier and Aquila optimization algorithm for Fingerprint-Iris-Face"** which is submitted by me to the Department of Software Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the Project Dissertation titled **"A Multi biometric system based on Hybrid Densenet 201-3D CNN classifier and Aquila optimization algorithm for Fingerprint-Iris-Face"** which is submitted by Shipra Shand, 2K20/SWE/21 Department of Software Engineering, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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ABSTRACT

Biometric emerging and promising technology for identifying and validating a person. It is very strong, and it is accurate. Hard to copy, model, share, it distributes and cannot be stolen or forgotten. Combining more than one biometric the feature offers a promising solution to provide additional security. The traditional method of a person's identity and identity are determined through use of Biometric-Technology. The main purpose of this research project is to design and suggest an in-depth learning model: 3D convolutional neural network (3D-CNN) a category based on multiple biometric fingerprints, face recognition system and iris. To remove the feature, Densenet-201 was used. To improve functionality, feature level integration is used. Suggested Aquila Optimizer tuning separator parameter to determine the efficiency of the proposed model. Test results look at different parameters like this Equal Error Rate (EER), False Acceptance Rate (FAR), False Rejection Rate (FRR) and Accuracy showing the performance of the proposed model better there are other development models, which prove that the required identity is real or fake.

Keywords-

3D-CNN, Aquila-Optimization-Algorithm, Multimodal-Biometric, Densenet-201

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Table I: Consists the concise summary of the recent related works.

LIST OF ABBREVIATIONS AND NOMENCLATURE

1. CNN- Convolutional Neural Network
2. BR- Biometric Recognition
3. HBR- Hybrid Biometric Recognition
4. ML- Machine Learning
5. DL- Deep Learning
6. MBS- Multimodal Biometric System
7. TBIS- Token Based Identification System
8. KBIM - Knowledge-Based Identification Methods
9. BI- Biometric Identification
10. PCA- Principal Component Analysis
11. AOA- Aquila Optimisation Algorithm
12. 3DCNN- 3 dimensional convolution neural network
13. FRR- False Rejection Rate
14. FAR- False Acceptance Rate
15. ERR- Equal Error Rate
16. CPU- Central Processing Unit
17. RAM- Random Access Memory
18. GPU- Graphics Processing Unit

CHAPTER 1

INTRODUCTION

1.1 Overview

Biometric recognition is a technique for recognising someone based on their physical or behavioral features. Fingerprinting, iris scanning, facial recognition, and voice recognition are just a few examples of biometric recognition. Biometric recognition is frequently used for security reasons, such as confirming a person's identification before giving access to a facility or computer system. It can also be utilized for other things like employee attendance tracking and consumer behavior monitoring. Biometric recognition technology is continually improving and changing. It is likely to have a significant impact on our lives as it becomes more pervasive.Verification, identification, and authentication are all possible with this technology.

The following are some of the advantages of biometric recognition:

1. Increased security: Biometric recognition can be used to verify and confirm the identity of persons. Individuals can be tracked and monitored with this technology.

2. Increased efficiency: Biometric recognition can be utilized to speed up and eliminate errors in procedures.

3. Greater convenience: Biometric recognition can make it easier for people to access services and conduct transactions.

4. Increased privacy: Biometric recognition may be used to preserve people's privacy by guaranteeing that only authorized people have access to their personal information.

1.2 Scope Of Project

Identification and authentication are accomplished using biometric recognition technologies. Individuals can be identified in a variety of circumstances, including airports, border crossings, and other security checks. It can also be used to verify people's identities when they access sensitive data or systems.

Deep learning is a subclass of machine learning that excels at processing huge and complicated datasets. Deep learning techniques use a large number of hidden layers in a neural network to learn high-level features from data.Image categorization, object detection, and speech recognition are just a few of the tasks that deep learning has been found to be good for. Deep learning's capacity to learn complicated features from data makes it a viable biometric detection method.Deep learning has been shown to be useful for fingerprint identification in several studies. Zhang et al., for example, demonstrated that a deep learning algorithm could reach 99.3 percent accuracy on a dataset of 4 million fingerprints.Iris identification has also been found to benefit from deep learning. On a dataset of 2 million irises, Daugman et al. found that a deep learning algorithm could attain an accuracy of 99.28 percent.Face recognition is also a good fit for deep learning. On a dataset of 3 million faces, Sun et al. found that a deep learning algorithm could reach an accuracy of 99.63 percent.

Deep learning is a promising biometric recognition method. Deep learning's capacity to learn complicated features from data makes it an effective tool for this purpose.

1.3 Problem Statement

Biometrics is a measure of biological markers used to identify or prove a person based on some of his or her characteristics. This method is increasingly being used to build public awareness on a variety of applications today. Although biometric recognition techniques seem to be very effective, we cannot now guarantee that unimodal biometric systems based on a single biometric signature will have a high level of recognition. In addition, concerns such as sensory, abnormal, personality and consistent representation, and sensitivity to attacks hinder these systems. Due to all these practical challenges, unimodal biometric systems have relatively high error rates, making them unsuitable for use. submission of important security requests. To address these issues, MBS is a solution used for all biometric methods in the same system. A multimodal diagnostic system that combines information from the face, iris, and fingerprints is described in this study. Because they work better and provide stronger security in applications when integrated, they are more reliable and robust in real-world applications. Results were obtained to improve individual identification.

1.4 Objective

The following aims are mentioned in the supplied research project work.

- To design and construct a multimodal biometric identification system that fuses fingerprint, face, and iris inputs at the feature level.
- To create a Densenet 201 for feature extraction from fingerprint, face, and iris input features.
- To present a parallel system for integrating fingerprint, face, and iris input information.
- The deep learning model 3D-CNN classifier is proposed for classification.
- The Aquila optimization algorithm is presented to improve system performance.

1.5 Organization Of Dissertation

The following is the dissertation's structure. The necessity and significance of this project effort are addressed in detail in Chapter 1. In Chapter 2, you'll find background information on traditional methods of biometric identification methods. A full literature review has been done in Chapter 3 to describe all of the main work that has already been done in this topic. Sections 3.1 discuss the previous work in detail.. The proposed method is described in Chapter 4, where section 4.1 discusses the Densenet-201 model, section 4.2 shows the architecture of CNN, section 4.3, 4.4, 4.5 discusses 3DCNN, PCA and AOA. The hardware, software, and data set utilized in training are depicted in Section 5.1, 5.2 ,5.3 and the model's testing is described along with a description of the comprehensive implementation approach. All of the implementation steps are covered in section 5.4. The implemented approach was then thoroughly examined and reviewed in Chapter 6. The implementation results are shown in Section 6.3. The conclusion is summarized in section 6.4. Then, in Chapter 7, there are references to all of the resources that were used to obtain data for this project.

CHAPTER 2

BACKGROUND

Before the evolution of hybrid biometric recognition, we will describe the background information of the methodologies employed in BR in this chapter. We will first discuss the traditional means of identification. They are as follows:

2.1 Token-Based Identification System(TBIS)

An identifying system that employs a token to authenticate the identity of a person or a thing is known as a token-based identification system. The token can be a physical thing like a key, a card, or a badge, or a digital entity like a code, or a password. It is the one that allows you to log into your favorite services without having to re-enter your credentials every time. This saves time and is easy, but it also poses a security concern, since hackers might use your token to get access to your accounts.

The use of a token-based identifying method has a few drawbacks:

1. A token can be used to get access to the system if it is lost or stolen.
2. The token can be hacked if it is not adequately secured.
3. Replacing tokens can be costly.
4. Managing token-based systems can be problematic.

2.2 Knowledge-Based Identification Methods(KBIM)

There is no one-size-fits-all solution for identifying people based on their knowledge. However, there are a number of strategies that can be employed to improve identification accuracy. Incorporating numerous data sources, confirming information through third-party sources, and using biometric data are all examples of these strategies. Knowledge-based person identification has numerous advantages. The most obvious benefit is that it can aid in the identification of the correct person. This is critical in a number of instances, including when someone is attempting to gain access to sensitive information or when law enforcement is attempting to identify a suspect. Knowledge-based person identification has the ability to improve accuracy as well as speed up the identification process. This is due to the system's ability to quickly filter down the pool of potential candidates by taking into account criteria such as age, gender, and geography. Finally, knowledge-based person identification can aid in the improvement of identification system security. Because the system can be set up to require numerous bits of information before a person can be appropriately identified, this is the case. This can make gaining unauthorized access to a system or impersonating another person more difficult.

There are a few potential disadvantages to using knowledge-based systems for personal identification. First, if the knowledge base is not complete or up-to-date, the system may not be able to correctly identify individuals. Second, knowledge-based systems can be susceptible to error if the data used to populate the knowledge base is inaccurate or if the system itself is not configured correctly. Finally, knowledge-based systems can be slow to respond if the system is overloaded with requests or if the knowledge base is large and complex.

2.3 Biometric identifiers (BI)

A biometric identifier is a measurement of a physical or behavioral trait that allows an individual to be positively identified. Measurements of hand geometry, fingerprints, DNA, or facial traits, as well as an iris or retinal scan, are examples of physical biometrics. Behavioral biometrics include, but are not limited to, gait, speech, and typing rhythm assessments. Biometric data is information created by automatic measurements of a person's biological or behavioral traits that can be used to uniquely identify that person. Fingerprints, DNA, voice, and facial traits are only a few of the examples. They came to the rescue since they are more trustworthy than traditional person identifying techniques. There are a number of reasons why biometric identifiers are important. First, they can provide a very high level of security. This is because it is very difficult to fake a biometric identifier, such as a fingerprint or iris scan. Second, biometric identifiers can be used to quickly and easily identify individuals. This can be useful in a number of situations, such as when checking in at a hotel or airport. Finally, biometric identifiers can be used to track an individual's movements. This can be useful for security purposes, or to simply keep track of someone's whereabouts.

CHAPTER 3

LITERATURE REVIEW

Technology advances at a breakneck pace, and one of the most important things we must remember when dealing with it is that we must stay current with the latest developments. Today we'll talk about a future technology that will revolutionize the way we think about security. The multi-biometric system is its name. It is an authentication method that employs various biometrics. Fingerprint, iris, and face are the most popular biometrics utilized in this system. However, other biometrics such as voice, signature, and hand geometry can be utilized in this system. The multi-biometric system is extremely safe and tough to break into. Because the system uses various biometrics for authentication, this is the case. This means that even if one biometric is compromised, the user can still be authenticated using the other biometrics.

3.1 Previous Research

Now I'd like to go through some of the previous research from the year 2018 -2022 in this area.

1. Alaa S. Al-Waisy and Rami Qahwaji in their paper propose a multi-functional and real-time biometric system based on creating in-depth presentation of images of right and left human irises, and then incorporates results in a standardized approach [1]. The proposed in-depth learning program is called IrisConvNet, and its design is based on a combination of Convolutional and Recurrent Neural Networks. Softmax classifier with Neural Network (CNN) without removing the discriminatory features from the input image or any background information including the input image and split the rated iris

region into one of the N-subjects. CNN's discriminatory training method is used in this study. Based on a combination of back-distribution algorithm and the AdaGrad mini-batch optimization approach is suggested to update weights and adapt to the level of learning, accordingly [1]. Other forms of training (for example, how to quit school) are also available. For testing, data additions are also provided with various CNN properties. The performance of the proposed system is tested using three public data sets collected under various conditions: SDUMLA-HMT, CASIA-Iris-V3 Interval, and IITD iris database. The proposed system surpasses modern algorithms (e.g., Wavelet transform, Scattering transform, Local Binary Pattern, and PCA) by obtaining a Rank-1 identification rate of 100% on all used websites and recognition time less than one second per person [1].

2. Sobhan Soleymani, Amirsina Torfi in his paper “Generalized Bilinear Deep Convolutional Neural Networks For Multimodal Biometric Identification” suggested the use of modality-specific Convolutional Neural Networks (CNNs) in classification, integration, training, and integration activities. In each mode, a specific CNN is used to extract specific information of a particular method [2]. They suggest that, instead of performing convolutional layer integration, merging can be done on fully integrated CNN-based modality layer effects, without loss of functionality and significant reduction in the number of parameters. They show that systems that use single representation work much better than systems that use multiple CNNs with multimodal integration at the element level. In order to obtain biometric multimodal bias, they investigated the weight-bearing, bilinear factor, and the combined bilinear-level compounds [2].
3. Sobhan Soleymani, Ali Dabouei in his paper provides a comprehensive multimodal fusion network that identifies a variety of methods (face, iris, and fingerprints) [3].

Multiple broadcasts of modality-specific Convolutional Neural Networks (CNNs) have been integrated and upgraded to multiple levels of feature drag on the proposed multimodal integrated integration system. With the combination of integrated feature, configuration, and segmentation, a few features from CNN per capita are released for several different conversion layers [3]. Inputs are represented at different levels of invisible presentations with features released in different CNN layers that are specific to a particular mode. Demonstrating that by using these intangible multi-level presentations produced across all modN-specific CNNs, effective multimodal segregation can be achieved by a significant reduction in the number of network parameters. They show that their CNNs with more in-depth features with multimodal integration can surpass the accuracy of consistent representation at different target temperature levels. They also show that the points and integrated decision-making level of CNNs developed separately work very well with the joint preparation of all CNN-specific mechanisms [3].

4. Racial data is an integral part of personal identity and can be used for a variety of purposes, including video surveillance, targeted advertising, and social media profiles. Convolutional Neural Networks (CNNs) have recently demonstrated the modernization of various visual cues [4]. There are now a number of racist segregation strategies based on CNN. However, these methods have the following drawbacks: I Most facial data sets do not include racial information, and those that do are usually small in medium size, leading to the influx of CNN training samples from the beginning, and (ii) CNN methods are usually racist. divided into separate categories, which may be the label for each category produced [4]. However, it does not use CNN's centralized operations, which provide comprehensive classification features to assist with racial segregation. As a result, in their paper, authors Zhao Heng; Manandhar Dipu; Kim-Hui Yap introduces a

new integrated curated reading method that uses both CNN capabilities and rich network features [4]. The method combines the soft chance of a CNN class output with an image-based search engine that integrates between query and data set images. In order to train vectors of the integrated element to perform racial segregation, a hybrid version of Support Vector Machine (SVM) was developed. [4].

5. Identifying people with camera-based surveillance systems is a difficult subject, especially if the person's face is not visible to cameras and / or when photographers do not have a clear visual identity due to low light conditions [5]. With the development of in-depth learning, Convolutional neural networks used to learn algorithms and lessons based on human mobility to identify a person, both CNN and long-term and short-term memory (LSTM) have shown promise. However, CNN and LSTM-based algorithms have the drawback of large loss of temporary and local information [5]. A few studies have also been conducted on walking-based identification using front and rear view images of people captured under low light conditions. This makes traditional features difficult to remove, such as skeletal joints, cycling, cadence, and walking distance. To address these issues, GANBAYAR BATCHULUUN, HYO SIK YOON, JIN KYU KANG, AND KANG RYOUNG PARK, in their paper using front and rear viewing images recorded at both high and low light points [5]. The results of the experiments using a compiled website and open source mean that the Gait C Institute of Automation data from the Chinese Academy of Sciences show that the proposed method works better than the previous methods [5].
6. Multibiometric systems, which incorporate data from several biometric sources, have been shown in literature to significantly improve performance by overcoming limitations such as non-universal, noisy sensory data, and large intra-class variations [6]. Combining

multibiometric data for personal verification, there are a number of integrated and based learning methods. Ajita Rattani; Narsi Reddy; Reza Derakhshani in their paper create convolutional neural network (CNN) structures to integrate biometric data from multiple sources [6]. The CNN-based multibiometric compound has the advantages of being able to integrate pre-, intermediate, and later, as well as the ability to learn architectural fusion during network training. Examination of a large VISOB data set shows that CNN multibiometrics work better than conventional integration methods [6].

7. Many hybrid and multimodal biometric detection techniques, which include both soft and solid biometric schemes, have been introduced to create secure and authentic systems. "CNN-tier multi-factor multi-factor authentication system" written by Muhammad Sajjada and Sung WookBaik introduces a new mixed method that verifies user authentication in the system while also checking if the user has successfully biometric system as a rule . or counterfeit [7]. Phase I includes fingerprints, palm vein printing, and facial recognition to match related websites, while Tier II detects fraud using fingerprints, palm vein printing, and anti-spoofing convolutional neural (CNN)-based models [7]. The hash of the fingerprint is compared to the database of fingerprints in the first step.The same procedure is followed on the palm and face, and the system allows the user to log in using integrated evidence [7]. The effectiveness of the proposed method in providing effective and robust authentication, exceeding standard verification limits and fraud procedures, validated test results across all five benchmark data sets [7].

8. Biometric detection technology has become increasingly popular as the need for information security grows. Multimodal biometric recognition has increased in popularity due to the limitations of unaltered biometric systems.Hui Xu's Two-Layer

Fusion; Miao Qi; Yinghua Lu provides a biometric detection method based on three biometric types of face, iris, and palmprint within the framework of in-depth learning, in-depth light learning theory and practical application of many cognitive functions [8]. To begin with, they have developed several Convolution Neural Network (CNN) structures for unaltered biometric recognition to assess the impact of model structure on recognition accuracy [8]. Then, using different recognition results, they created a CNN model for multimodal biometric recognition based on a combination of two layers. A number of feature integration strategies are introduced to investigate the impact of integration methods and approaches on cognitive performance [8]. Finally, three common data are used to perform multiple experiments. The test results suggest that the proposed multimodal recognition method exceeds the same recognition in terms of the accuracy of the recognition. In addition, the process of combining the two layers can increase the performance of multimodal recognition even further [8].

9. Uni-modal diagnostic systems are more prone to misdiagnosis due to errors in data collection [9]. For example, relying entirely on data from an RGB face camera can lead to problems in dimly lit areas or when people are not looking at the camera. Other diagnostic methods, such as electrocardiograms (ECG), have concerns about improper skin plumbing [9]. The integration of information from both of these models reduces diagnostic errors. Using Part A of the BioVid Heat Pain Database, which contains RGB-video and ECG synchronized data for 87 participants. Thomas Truong; Jonathan Graf; Svetlana Yanushkevich introduced the combination of the findings of facial data identification and ECG [9]. Facial recognition was 98.8% accurate using 10-fold confirmation, while ECG detection was 96.1 percent accurate. By combining different facial models with ECG models and non-compliant methods, their proposed method

improves the accuracy of the detection significantly [9].

10. Many applications use biometric recognition and secure human identification. Several studies have been conducted to increase the security algorithms that allow for secure identification [10]. With this goal in mind, a new algorithm known as Hybrid Adaptive Fusing (HAF) was introduced by S. Prabu, M. Lakshmanan & V. Noor Mohammed created a paper based on the theory of a combination of two factors such as the shape of the user's hand and the iris [10]. As mentioned earlier, the proposed method involves the removal of the element and the precise machine learning phase in the form of a novel and a combination. The database maintains Active Binary Patterns (ELBP) and the Scale Invariant Fourier Transform (SIFT) for further testing [10]. Saved features are integrated into Extreme Learning machines, which identify real users. This method was tested using CASIA Image Datasets and segment dividers, including Neural Networks and Bayes Networks. Compared to existing machine learning algorithms, the proposed ELM method has a 98.5 percent accuracy [10].

Table I: Consists the concise summary of the recent related works[34]

Author	**Year of Publication**	**Algorithm Used**	**Dataset Used**	**Remarks**
Patro, Kiran Kumar, [26]	2017	SVM, KNN, ANN	MIT-BIH, ECG-ID	SVM gives an accuracy of 93.709%

Ahmadi, N. and Akbarizadeh ,G[27]	2017	MLPNN, PSO	UCI, CASIA V3	Performs better as compared to other BR technique
Bora, A., Vajpai, J. and Gaur, S[28]	2018	LPC; MFCC; MFLPC; PCA	Voice is taken as a dataset.	LPC-with MFCC gives optimum accuracy.
Oloyede, M.O., Hancke, G.P. and Myburgh, H.C[29]	2018	SOA, CNN	Standard dataset of face images.	The proposed algorithm increases the efficiency of recognition.
Prabu, S., Lakshmanan , M. and Mohammed, [10]	2019	HAF, ELBP, SIFT, NN, BN	CASIA Image Dataset	Accuracy of 98.5% was achieved.

Mohsin, A.H, Zaidan.[30]	2019	PSO, AES, RFID,CIA	Finger Vein Images	Accuracy of 100% in FV identification.
M. Ilham Rizqyawan, Ulfah Nadiya [31]	2021	DT, SVMRF, Ada-Boost	Facial dataset taken as input	SVM gives the best accuracy of 98%.
Zhang, Liping, et al.[32]	2021	Attention-Network, Features -Network	Facial -Dataset	Proposed algorithm is better than others.

11. Despite the fact that there is a lot of current research on facial recognition, there are still many problems due to differences in factors including aging, positions, closing, adjustment, and appearance. Leslie Ching Ow Tiong, Seong Tae Kim and Yong Man Ro proposed the creation of a Multi-feature Deep Learning Network (MDLN) in paper written by them which incorporates approaches from face areas and times, as well as texture descriptions, to enhance the recognition functionality [11]. MDLN, in particular, is a feature-level integration program that integrates multimodal biometrics data with texture definitions to form a new representative element [11]. As a result, the proposed MLDN model provides more information on feature representation, which leads to

improved performance while overcoming the limitations of standard single-reading models [11]. We have shown that our elevated MDLN has better biometric detection performance under strict settings, including light fluctuations, appearance, and ambiguity, in our experiments [11].

12. The need for data protection has become more critical in recent years. In this case, a multibometric-based diagnostic system is the best way to significantly improve and obtain high performance accuracy [12]. The main objective of this paper is to develop a "Convolutional neural networks system for biometric multimodal diagnostics using a combination of fingerprints, fingerprints and facial images" by El mehdi Cherrat, Rachid Alaoui, Hassane Bouzahir [12] to provide a mixed program . based on multiple fingerprints, finger-vein, and face recognition programs that include the impact of three effective models: Convolutional neural network (CNN), Softmax, and random forest separators (RF). Pre-image processing is used in standard fingerprint systems to distinguish front and back regions using K-means and DBSCAN algorithms [12]. Features are also available using CNNs and the stop method, and Softmax then acts as an observer. To differentiate, an RF classifier is also provided. In order to generate facial feature vectors and separate personal recognition from the traditional face system, the architecture of CNNs and Softmax is required. These system points are integrated to improve demographic identification. Using a GPU-based implementation, the proposed method was tested on a publicly available SDUMLA-HMT biometric virtual reality biometric [12]. Test results in data sets reveal the great potential for identifying a biometric system. Compared to existing systems based on unimodal, bimodal, and multimodal features, the proposed function can provide accurate and efficient matching [12].

13. In this paper titled by Essam Abdellatef, Nabil A. Ismail, Salah Eldin S. E. Abd Elrahman, Khalid N. Ismail, Mohamed Rihan & Fathi E. Abd El-Samie canceling a biometric detection method that removes deep features in different facial areas using multiple convolutional neural networks (CNNs) [13]. The new CNN structure based on batch normalization, depth of concatenation, and residual learning framework is also proposed. Faces, eyes, nose, and mouthpieces are seen in real-life facials using a strategy based on the location of the proposed route. Many CNNs are used to extract deep features in each region, which are then integrated using an integration network [13]. In addition, the canceled biometric method using bio-convolving encryption was performed in the final facial definition to provide user privacy and increase system stability in malicious attacks. , LFW, and the PaSC database produce better and more competitive results compared to standardized methods [13].
14. The increasing size and number of biometric distributions worldwide requires research on systems that allow for rapid identification questions with high discriminatory capabilities [14]. In this regard, the study by Pawel Drozdowski; Christian Rathgeb; Benedict-Alexander Mokroß; Christoph Busch describes a biometric diagnostic system that combines the measurement of weight-level information with the previous sequential candidate list sequences that can be used using a few biometric methods [14]. The standard identifier is determined by a registration site that combines 1,000 chimeric implants, and the proposed method is tested in a series of experiments using an integrated database built from multiple publicly available databases [14]. This study demonstrates that the proposed system significantly improves biometric performance compared to a base point-based or level-based system, while reducing the workload of the computer in terms of entry level [14]. found, the proposed method can be applied randomly to any

biometric identification system [14].

15. In uncontrolled cases, face recognition of surveillance applications is still difficult, especially with the appearance of masks / veils and racial effects [15]. One of the key lessons in solving such problems is to identify multimodal face biometrics. However, many modern deep learning networks rely on feature combination or weight integration to produce a representation layer to complete their desired recognition goal when working with multimodal facial biometrics [15]. This integration does not work well as it does not work well with multimodal data to maximize recognition performance. For this reason, in dual-stream convolutional neural networks, the paper by Leslie Ching Ow Tionga, Seong Tae Kimb, Yong Man Ro suggests use. Layers to integrate the many features of multimodal facial biometrics, leading to the study of large and useful data [15]. . They show that the proposed network has the representation of a discriminatory factor and that multi-component integration layers improve accuracy and performance [15]. They also present and provide an ethnographic database for measurement, a set of novel biometric data for multimodal faces. In addition, the proposed network is tested using four publicly available data sets: AR, FaceScrub, IMDB WIKI, and the YouTube Face database. The proposed network works much better than most competing networks in these databases for both monitoring and verification functions, according to our analysis [15].
16. This network is made up of two continuous components that use different integration algorithms to integrate RGB data and texture definitions. Biometric detection technology has become very common in our daily lives as the need for safety and security legislation grows around the world [16]. Because of its ability to overcome a number of important biometric system differences, multimodal biometrics technology has gained interest and

popularity in this regard [16]. A new multimodal biometric identification system based on an in-depth learning algorithm to detect people using biometric methods of the iris, face, and artery is proposed in this study by Nada Alay and Heyam H. Al-Baity [16]. The system is built next to convolutional neural networks (CNNs), which extract features and use a softmax separator to identify images [16] .Three CNN models are integrated to create a system: one for the iris, one for the face, and one for the finger. The CNN model was built using a VGG-16 model based on the well-known model, Adam's performance model, and categorical cross-entropy as a loss function. Add image and stopping methods, for example, were used to avoid excessive immersion [16]. Different combinations of methods have been used to integrate CNN models to investigate the effect of merging methods on recognition performance, and therefore the merging methods and the level of results have been used. Several tests using the SDUMLA-HMT data set, a set of various biometrics data, were used to intensify the performance of the proposed system [16]. The results showed that using three biometric features in biometric screening programs produced better results than using two or one [16]. The results also showed that our strategy is more accurate than existing methods, in the form of aggregate component obtaining 99.39 percent accuracy and multiple methods for combining point scores to achieve 100 percent accuracy [16].

17. The use of multimodal biometrics in real-world systems has necessitated extensive research in the field of multimodal biometrics in the scientific community and the introduction of modern technology [17]. One-way biometric systems based on a variety of limitations, including noise, universal reduction, internal class variation, and intelligent attack are all factors to consider. Multimodal, on the other hand, due to improved accuracy and improved reliability, biometric technology is gaining more

attention and improved security [17]. Mehwish Leghari, Shahzad Memon, Lachhman Das Dhomeja, Akhtar Hussain Jalbani and Asghar Ali Chandio created a model (CNN) model of fingerprints and the level of online signature feature. This study uses two types of component-level algorithms for online fingerprints and online signatures [17]. The first method, known as premature fusion, incorporates fingerprints and online signature features before fully connected layers, and the second system, known as late merging, integrates features after fully connected layers. A new multimodal database of 1400 samples of fingerprints and 1400 samples of online signatures from 280 participants was obtained for training and testing of the proposed algorithm [17]. The size of the training data is expanded using augmentation techniques to make the proposed model more efficient. Test results show that the previous feature integration strategy achieved 99.10 percent accuracy, while the latest feature integration program achieved 98.35 percent accuracy [17].

18. To overcome the barriers of unimodal biometric systems, multimodal biometric systems integrate more than one biometric system into a single process [18]. The use of different rendering techniques, feature-level integration, and multimodal biometrics systems add complexity and make the combined biometrics features even larger. Lawrence Omotosho, Ibrahim Ogundoyin, Olajide Adebayo, Joshua Oyeniyi, provides a face-iris multimodal biometric recognition system based on convolutional neural networks for feature extraction, feature fusion, training , and match. , with the goal of reducing size, error rate, and improving visual accuracy of access control [18]. The program was trained, categorized, and evaluated using the Convolutional Neural Network based on a deeply monitored learning model. Images go through a normal acquisition process before being given two flexible layers [18]. The created system of multimodal biometrics was

tested in a database of 700 iris and facial images, including 600 irises and facial images on a training site and 100 images of iris and facial images on a test site [18]. The multimodal system has a performance recognition rate (RA) of 98.33 percent and an average error rate (ERR) of 0.0006 percent when reading at a value of 0.0001 [18].

19. Boucetta Aldjia's , Boussaad Leila proposes a new multimodal biometric diagnostic system based on the Convolutional neural network (CNN), where we perform premature integration (fusion level fusion) of the face, palmprint, and iris by packing three biometric channels of the RGB image, and then used as input to CNN. To build strong and fast segregation, this approach uses four pre-trained models deep-convolutional neural network (CNN): Inceptionv3, GoogleNet, ResNet18, and SqueezeNet. It also ends up creating a new model from scratch, which requires a lot of data and statistics [19]. As a result, we used two methods to investigate a well-trained deep-convolutional neural network: feature detection and fine-tuning [19]. Pre-trained deep-convolutional neural network (CNN) models are used as feature codecs in the first strategy, while the pre-trained SqueezeNet model is used instead of the Imagenet division by 1000 classes in the second method. The proposed multimodal biometric test results show promising accuracy [19].

20. Biometric recognition systems are used in a variety of applications, including security, data protection, and remote access. Biometric recognition could employ physiological cues like the electrocardiogram (ECG)[20]. ECG leads have structural and functional relationships from a medical standpoint. Precordial ECG leads look at the heart from various axial angles, whereas limb leads look at it from various coronal angles[20]. By predicting these latent medical variables, this work by Majid Sepahvand, Fardin

Abdali-Mohammadi attempted to build a personal biometric recognition system based on ECG signals[20]. Within-correlation and cross-correlation in the time-frequency domain between ECG leads were determined and expressed in the form of extended adjacency matrices to evaluate functional relationships[20]. After that, genetic programming was used to develop CNN trees for the automatic estimate of structural relationships in extended adjacency matrices. The deep feature learning procedure is carried out using CNN trees utilizing structural morphology operators[20]. The proposed system was created for closed-set identification as well as verification. It was then put to the test on two datasets, PTB and CYBHi, to see how well it performed. When compared against existing approaches, the new method outscored them all[20].

21. A multimodal biometric system employs multiple biometric approaches to address some of the shortcomings of a unimodal biometric system and increase accuracy, security, and other factors[21]. This study by Santham Bharathy Alagarsamy & Kalpana Murugan employs pre-processing, ring projection, data normalization, AARK (Adaptive Approach Runge–Kutta) threshold segmentation, DWT (Discrete Wavelet Transform) feature extraction, and classifiers to provide an integrated multimodal biometric system for the identification of people using ear and face as input. Individual scores are then computed based on unique matches obtained from multiple modalities[21]. The proposed method outperformed the individual ear and facial biometrics that were examined in the study. The final results are then utilized to establish whether or not the person is real. Using the IIT (Indian Institute of Technology) Delhi ear dataset and ORL (Our Database of Face) face dataset, the suggested approach demonstrated individual exactness of 96.24 percent[21].

22. Border criminals and undocumented immigrants have increased considerably in recent

years due to a lack of effective authorisation processes at border crossing points[22]. Passengers are usually checked at the border by professional immigration agents who compare their passports to their physical appearance, while some nations use automated border control (ABC) systems. ABC is a real-world biometric application that typically uses fingerprint and face (multimodal) biometric authorization[22]. Choosing an acceptable categorization method, on the other hand, is a difficult issue at the decision-making stage. This study by Susara S Thenuwara, Chinthaka Premachandra ,Hiroharu Kawanaka offers a unique architecture for multimodal biometric authorisation that uses the multi-agent system's (MAS) co-features, such as coordination, cooperation, and negotiation, to arrive at the best solution[22]. The experiment was carried out with four multimodal datasets, namely the NIST multimodal, SDUMLA-HMT multimodal, BANCA, and PRIVATE databases, to illustrate the efficacy of the suggested strategy. The experimental outcome compares favorably to earlier ABC systems in the authentication step and is computationally efficient[22].

23. Recent advances in biometrics based on artificial intelligence have drawn great attention to safety issues [23]. Hybrid techniques are inspired by the fact that they combine the same strengths and overcome weaknesses. Biomedical engineering is one area where such methods are used. For individual identification, the biometric system uses behavioral or physiological features [23]. The combination of two or more of these unique biometric features enhances security and overcomes the shortcomings of unimodal biometric-based security systems. Named Chahreddine Medjahed, a comprehensive multimodal biometric learning program based on score fusion ”, Abdellatif Rahmoun, Christophe Charrier, Freha Mezzoudj provides effective facial, left, and hand based biometric programs. Convolutional neural networks (CNN) and its

closest neighbors to k (KNN) based on biometric multimodal identification systems are promoted and trained to identify people using biometric multimodal points.Fe facial data and the IITD palm printing site is used as raw data to train biometric algorithms in order to develop a robust and secure system / verification system [23]. The testing of sound data sets is used to evaluate the performance of the proposed model in difficult situations. CNN and KNN are multi-dimensional biometric systems that defeat many of the most popular current biometric authentication methods, based on computer simulation data [23].

24. The implementation of in-depth study methods based on the use of biometrics is briefly discussed in this paper by J. Jenkin Winston, D. Jude Hemanth, Anastassia Angelopoulou & Epaminondas Kapetanios [24]. The iris perception problem is investigated in this study using a convolutional neural network model and a combination of deep learning models [24]. This study also shows the enhancements used to complete the database and its results. To help understand the process, diagram of learning curves and the effects of intermediate network layers such as flexibility layer, standardization, and activation layer are displayed. The accuracy and curve of the receiver performance feature are used to analyze network performance [24]. Their experiments suggest that Adam-based preparation works best when studying the features of the iris with in-depth study [24]. In addition, with a high accuracy of 97.8%, an in-depth mixed reading network with SVM works best on iris recognition. These tests also showed that not all hybrid networks will perform better, as a deep-rooted learning network with KNN has produced much worse accuracy [24].
25. Biometrics is now the preferred technology for identifying, authenticating, and verifying people in a variety of applications and industries. Unfortunately, this ubiquitous finding

has exacerbated criminal acts to undermine the integrity of these methods [25]. This paper, by Basma Abd El-Rahiem, Mohamed Amin, Ahmed Sedik, Fathi E. Abd El Samie & Abdullah M. Iliyasu offers the cancellation of The multi-biometric biometric scheme (MBCS) uses a pre-trained Inspection V3 model to create a non-invalid template for complete evidence, using a proven application of in-depth learning models to integrate fingerprints for multiple exposure, fingerprint, and iris biometrics [25]. Use comprehensive testing that includes visual, quantitative, qualitative, and weight analysis, to validate our MBCS, with average results of 99.158, 24.523 dB, 0.079, 0.909, 59.582, and PSN, 627 PSN, 627 SIM for PSN, 627 for SIM, UIQ, SD, and UACI, respectively [25]. These quantitative results indicate that the proposed process exceeds the modern methods published in the literature. We refine the proposed MBCS to make it easier to produce seamless templates of real-time biometric applications that verify human authenticity at airports, banks, and elsewhere [25].

CHAPTER 4

PROPOSED APPROACH

To test the proposed framework, we used three biometric features: Face, Fingerprints and Iris. In this study, we aim to integrate three different biometric features and improve system accuracy. Fig. 1 shows a block diagram of the proposed biometric system based on the combination of face, Iris and fingerprints. The first step is to think ahead. Then, the proposed system removes facial features, Iris and fingerprints separately using the PCA algorithm and extracting the best feature. Then, the extracted features are integrated. Finally, the hybrid -based -classifier Densenet 201-3DCNN is used to perform the separation process. Aquila's algorithm has been proposed to determine the performance of the partition model.

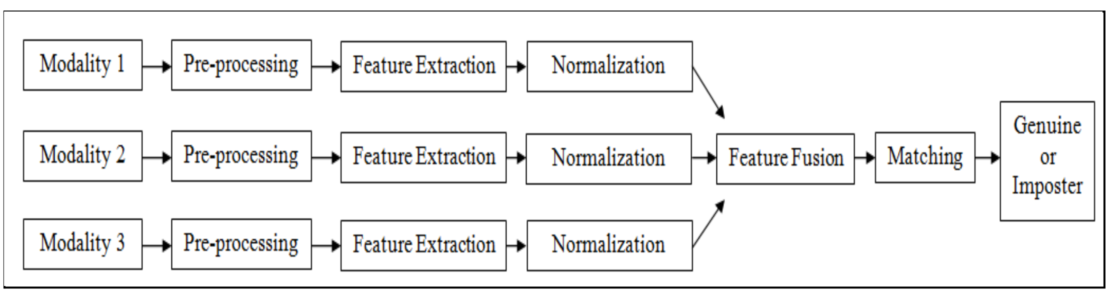


Fig. 1: Proposed Methodology

4.1 DENSENET-201

DenseNet-201 is a neural convolutional network trained with over a million images from the ImageNet website. The network is made up of a series of flexible and fully integrated layers. Network input is 224x224x3 image size. Network output is a 1000-dimensional vector representing the image possibilities for each of the 1000 categories.

4.2 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a type of neural network that has been shown to work very well in areas such as image recognition and segmentation. CNNs are similar to normal neural networks because they are made up of neurons with readable weight and bias. Each neuron receives a specific input, produces a dot product and voluntarily follows it indirectly. The whole network still produces one distinct function: from pixels of raw image on one side to class points on the other. They also have a loss function (e.g. SVM / Softmax) in the final (fully connected) layer and all the tips / tricks we have developed for emotional networks are still in use. It is easy to train. You only need about a day of GPU training for a large network. It's at a high level. ConvNet architecture has gone beyond the roof over the past few years, achieving record-breaking performance on standard vision benchmarks. But ConvNets has a few advantages over traditional neural networks. One of these benefits is that they are able to automatically learn the most relevant aspects of the convolution process. Convolution is a mathematical operation in two tasks that produces a third function that reveals how the shape of one is adjusted by the other. Convolutional Neural Networks takes the opportunity that the input includes images and can connect input regions instead of connecting all neurons in a fully connected way. In this way, the network can learn features in the first layer that get edges, shapes, etc. The elements learned in the first layer can be used in the second layer to study complex features, and so on. This allows the network to successfully detect complex patterns in images with just a few layers. Thus, CNN is able to take a captured image, process it through a series of hidden layers, and issue a photo label. CNN's simple image classification can be made into an input layer, a flexible layer, a merge layer, a fully integrated layer, and an output layer. The insertion layer can take a picture and feed it to a convolutional layer. The convolution layer will then apply a number of convolutional filters to the image. Each filter will produce a modified version of the image. The integration layer will then take out the convolution layer output and reduce the image size. A fully integrated layer can take the output of the integration layer and use it to split the input image into one of several classes. CNN will then release the photo class label. CNN has been successful in many photographic functions, such as image recognition and face recognition.Fig. 2 shows a typical CNN architecture.

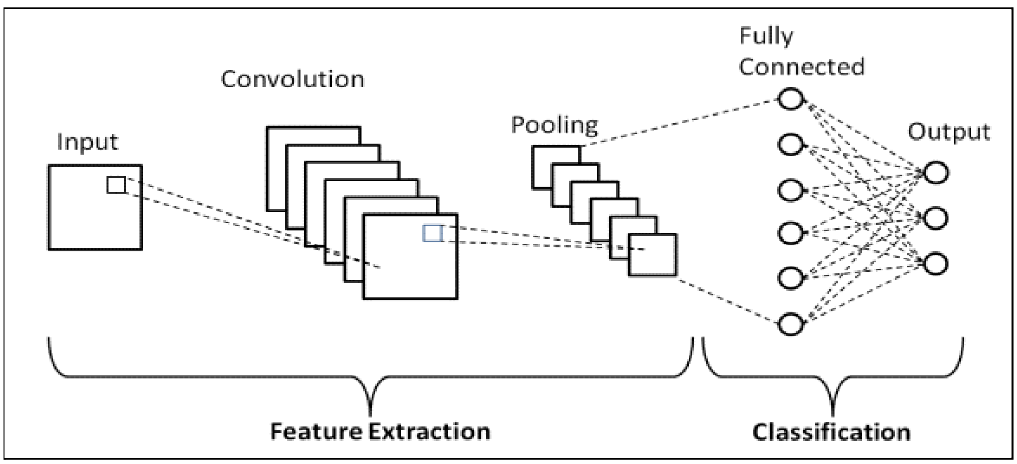


Fig 2. CNN architecture

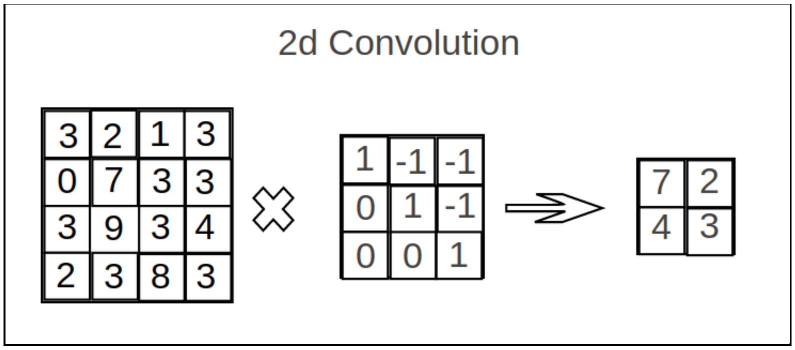
4.3 3D Convolutional Neural Network(3DCNN)

Whatever we say, a 3d CNN is still a CNN that is extremely comparable to a 2d CNN. Except for the following differences (which are not exhaustive):

4.3.1 Layers of 3D Convolution

Originally, a 2d Convolution Layer was a multiplication of the input and the various filters on an entry-by-entry basis, with the filters and inputs being 2d matrices. (Fig.3).

Fig. 3. Matrices of 2d Convolution



The same operations are employed in a 3d Convolution Layer. These procedures are performed on several pairs of 2d matrices. (Fig.4).Options for padding and slides step function in the same way.

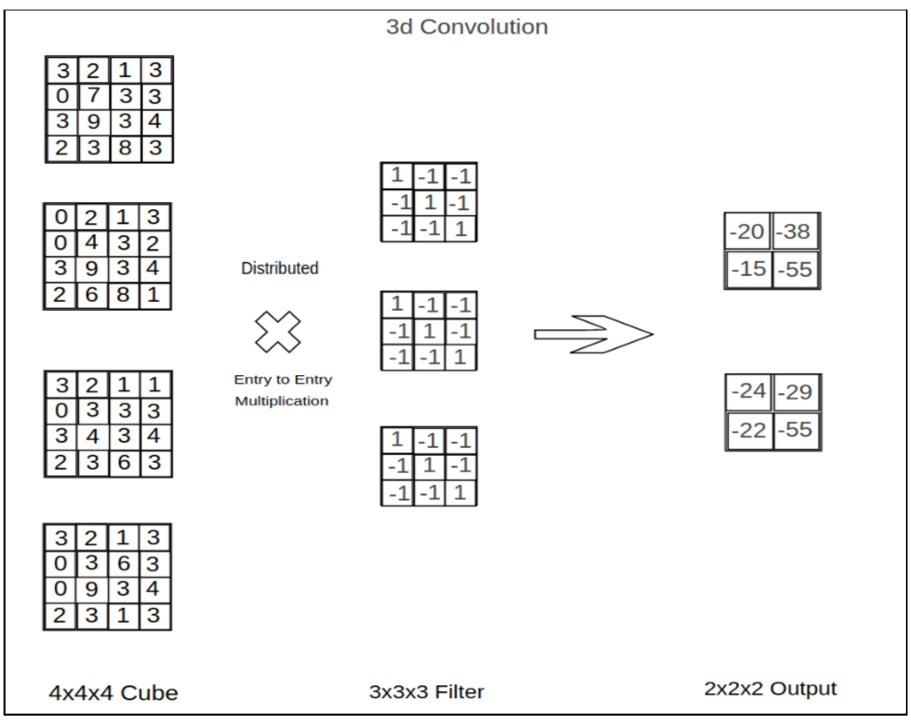


Fig. 4. Matrices of 3d Convolution

4.3.2 MaxPool Layers in 3D

The greatest element of a small 2x2 square that we delimitate from the input is taken by 2d Maxpool Layers (2x2 filter) is shown in Fig.5.

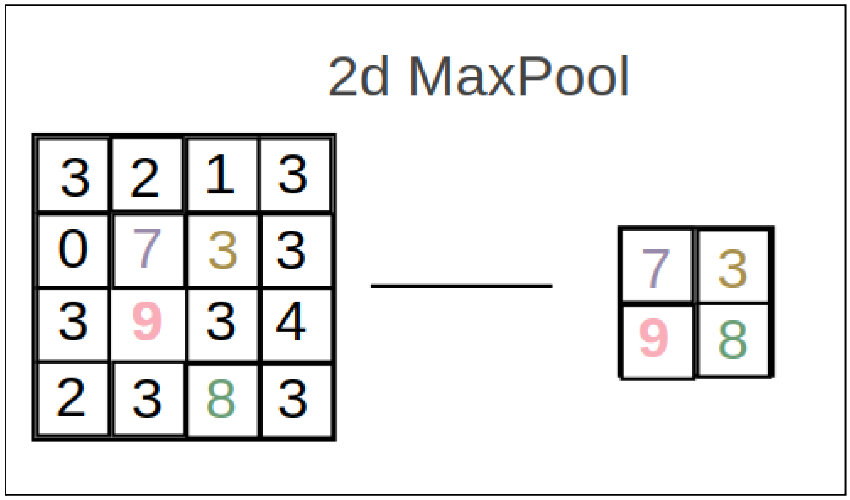


Fig. 5. 2d MaxPool

We now look for the maximum element in a width 2 cube in a 3d Maxpool (2x2x2 kernel). The space restricted by the 2x2x2 zone from the input is represented by this cube shown in Fig.6..

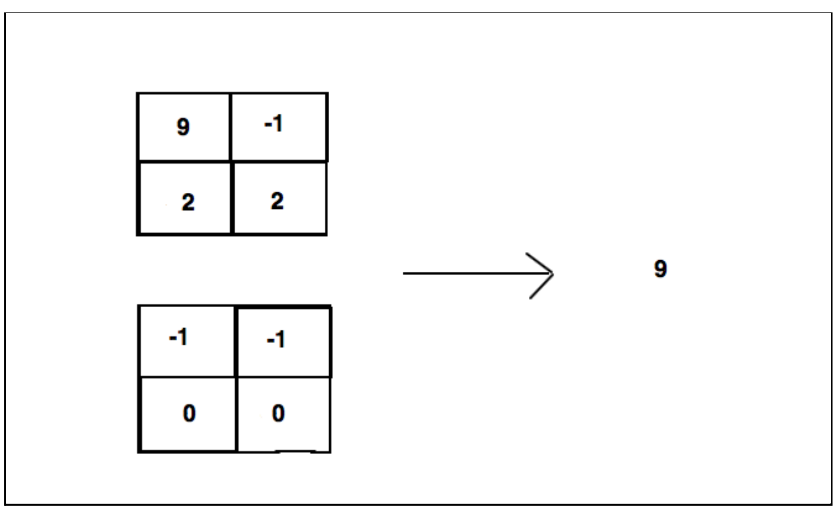


Fig. 6. 3d Max Pool

Note that the number of operations (when comparing 2d CNN layers) is multiplied by the size of the filters used (whether the layer is Maxpool or Convolution) as well as the size of the input itself.

4.4 Aquila Optimisation Algorithm (AOA)

The deep learning algorithm Aquila is used to improve the performance of deep neural networks. It works on the idea of reinforcement learning and can alter the settings of the neural network automatically to increase its performance. In terms of accuracy and efficiency, Aquila has been found to outperform other optimization methods.

The Aquila Optimization Algorithm is an optimization algorithm for determining a function's global optimum. It's a derivative-free algorithm, which means it doesn't involve optimizing the function's derivatives. The method is built on the concept of moving a population of potential solutions, known as "agents," throughout the search area. The agents are relocated according to a set of rules that urge them to move to areas of the search space where the global optimum is more likely to exist. Marco Laumanns and Thomas Weise proposed the Aquila Optimization Algorithm in their paper "The Aquila Optimization Algorithm: A Metaheuristic for Global Optimization."

What exactly is the Aquila Optimization Algorithm?

- The Aquila Optimization Algorithm keeps a population of agents in the search space. The agents are moved around according to a set of rules that urge them to move to areas of the search space where the global optimum is more likely to exist.
- The algorithm operates by incrementally improving the population of agents. The agents are tested in each iteration, and the best performing agent is chosen. After that, the chosen agent is utilized to create a new agent, which is then added to the population.

- The selected agent is mutated to create the new agent. The mutation is a change in the position of the agent in the search space at random. The new agent is then tested, and if it outperforms the prior best agent, it is promoted to the top spot.
- The process continues until a termination requirement, such as a maximum number of iterations or a specific goal value for the function being optimized, is satisfied.

What are the benefits of using the Aquila Optimization Algorithm?

- The Aquila Optimization Algorithm is a derivative-free algorithm, which means it doesn't optimize the function's derivatives. This makes it ideal for optimizing difficult-to-differentiate functions, such as discontinuous functions.
- The algorithm can also escape local optima, which means it is more likely to locate a function's global optimum.
- Finally, the algorithm is simple to use and may be used to solve a variety of optimization issues.

When should you not utilize the Aquila Optimization Algorithm?

- The Aquila Optimization Algorithm is a stochastic algorithm, which means it is determined by chance. As a result, finding the global optimum of a function is not guaranteed by the method.
- The algorithm's convergence to the global optimum in a finite amount of time is likewise not guaranteed. The algorithm may become "stuck" in a local optimum and never locate the global optimum in some instances.
- Finally, the algorithm could be computationally costly for large computational problems.

4.5 Principle Component Analysis (PCA)

Key Component Analysis is an unregulated learning method used in machine learning to reduce size. It is a mathematical process that uses orthogonal conversion to convert a related element's visibility into a set of unrelated feature lines. Key components are newly modified features. It is one of the most widely used tools for analyzing test data and predictable modeling. It is a way of extracting solid patterns from the database by reducing variability.

PCA is looking for a low-dimensional environment where it will process high-resolution data.

PCA reduces size by examining the variability of each feature because the top attribute shows the appropriate differences between classes.

Image processing, movie recommendation systems, and enhanced power sharing on multiple communication channels are examples of using a real-world PCA. Because it is a method of extracting a feature, it retains important variables while discarding less important ones.

The PCA algorithm is based on the following mathematical concepts:

Covariance and Diversity

Eigenvectors and Eigenvalues

CHAPTER 5

IMPLEMENTATION DETAILS

Below in this section, the hardware requirements, software requirements and data set used in training and testing of model is listed along with the description of detailed procedure of implementation.

5.1 Hardware Requirements

The proposed model is used for the following hardware requirements.

1. PC integrating Windows 10 operating system
2. Intel core i5 eighth generation quad-core CPU
3. NVIDIA GeForce-GTX 1050 GPU
4. RAM size 8 gigabytes
5. It also requires extremely high speed.

5.2 Software Requirements

The proposed model is used for the following software requirements.

We have used the MATLAB environment. MathWorks has developed MATLAB, a programming language with a variety of paradigm and multitasking environment. Matrix functionality, function and data recognition, algorithm implementation, building user interaction, and interaction with programs written in other languages are all possible with MATLAB.

JSON is a standard open file format and data exchange format that stores and transmits responsible pear-shaped data objects - the same number of frames using human-readable text. It is a widely used data format for data transmission, which includes web applications and servers.

5.3 Dataset Used

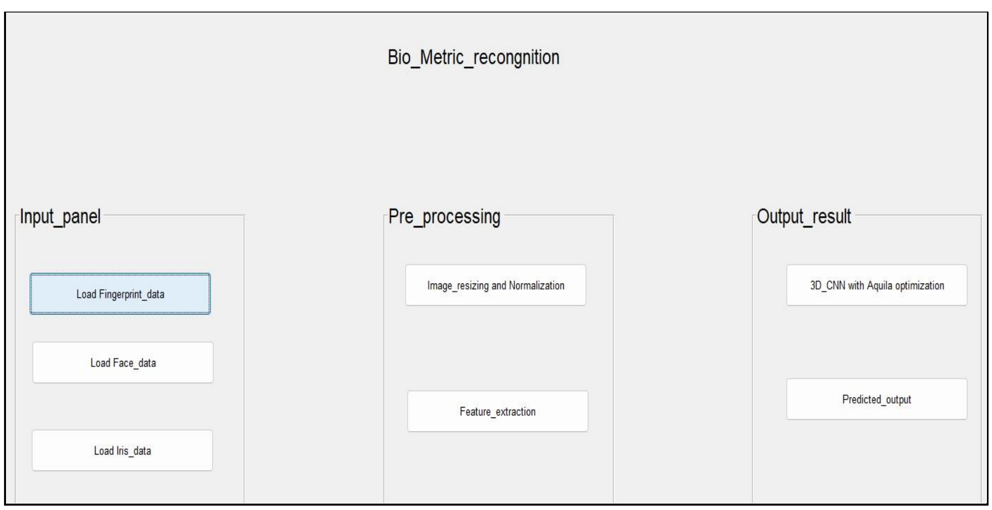
The proposed model is implemented with the following Data Set requirements.

During the training of the model,we have used finger-print, iris and face images as a dataset from kaggle and MMU iris database. There are 960 fake face images ,1081 real face images , 490 fake left finger print images , 472 fake right finger print images , 480 left real fingerprint images , 480 right real fingerprint images, and 460 iris images which contain a combination of fake and real images.

5.4 Description of Implementation

Below in this section, the description of implementation of the proposed model, its training and testing is explained. Fig. 7 shows the GUI.

Fig.7. Graphic User Interface



1. First we loaded datasets of face, iris and fingerprint images.This task is shown in Fig. 8.

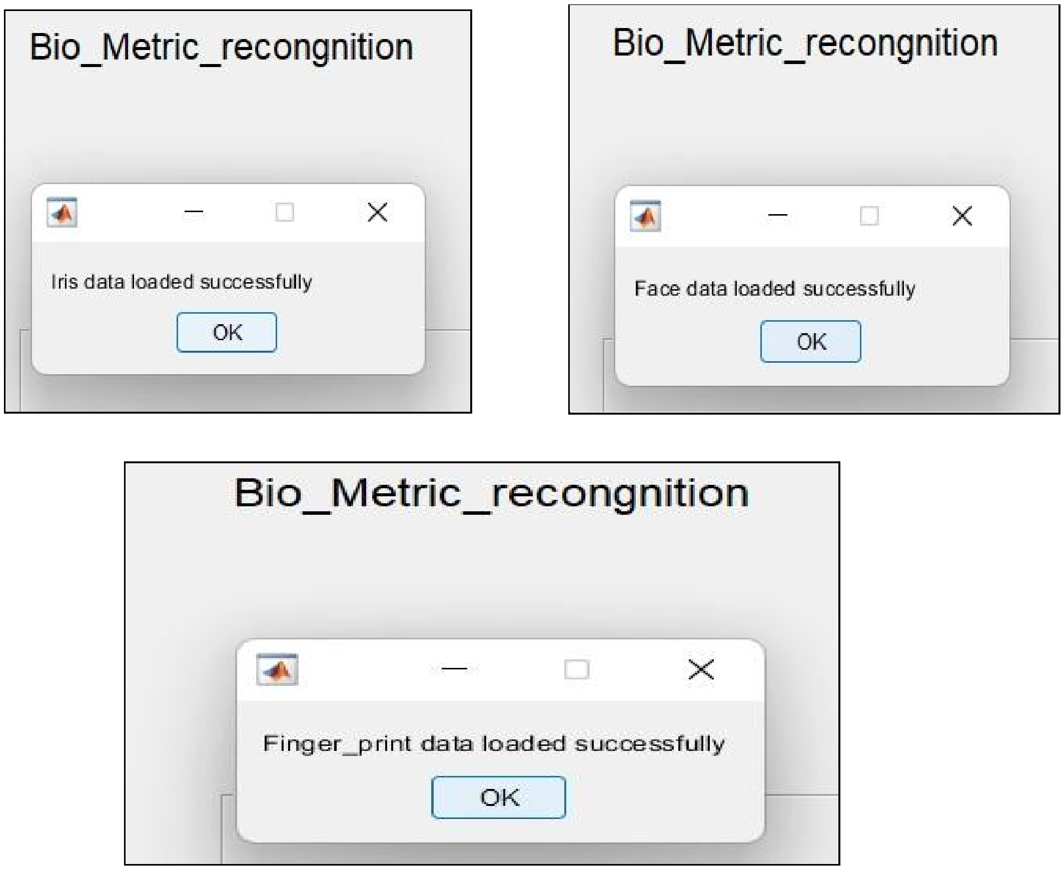


Fig.8. Loading Data

2. Then we have done data pre-processing steps which are as follows:

A. Image resizing-Resizing photographs before feeding them into a machine learning system is typically advantageous. This is because resizing can increase the quality of the input data while also lowering the amount of processing the method requires.Fig.9 shows this process.

B. Normalization - For normal machine reading, there are a few ways to make the data normal, but the most common is to re-measure the data so that the values lie within a given range, usually between 0 and 1. This is usually achieved by dividing each value by the database to a very large number. Setting (re-measuring data so that the average is 0 and the standard deviation is 1) and the standard deviation is two additional modes of normalization (re-measuring data so that the minimum value is 0 and the maximum value is 1).

C. Feature Extraction- is a process of minimizing size when the original raw data set is reduced to a small set of features that still contain important information from the actual data. This can be done in a variety of ways, such as key component analysis, independent component analysis, and non-negative matrix factorization. Here we have used PCA for this purpose.This task is shown in Fig.10.

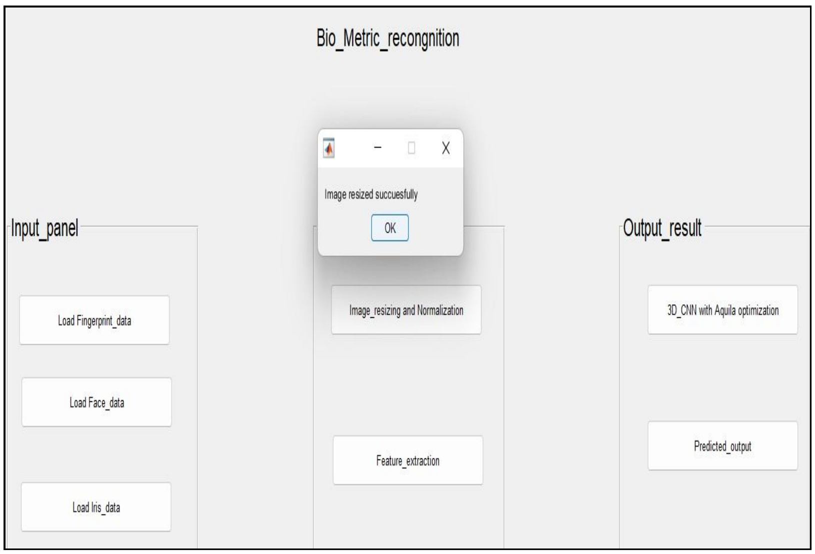


Fig. 9. Image Resizing

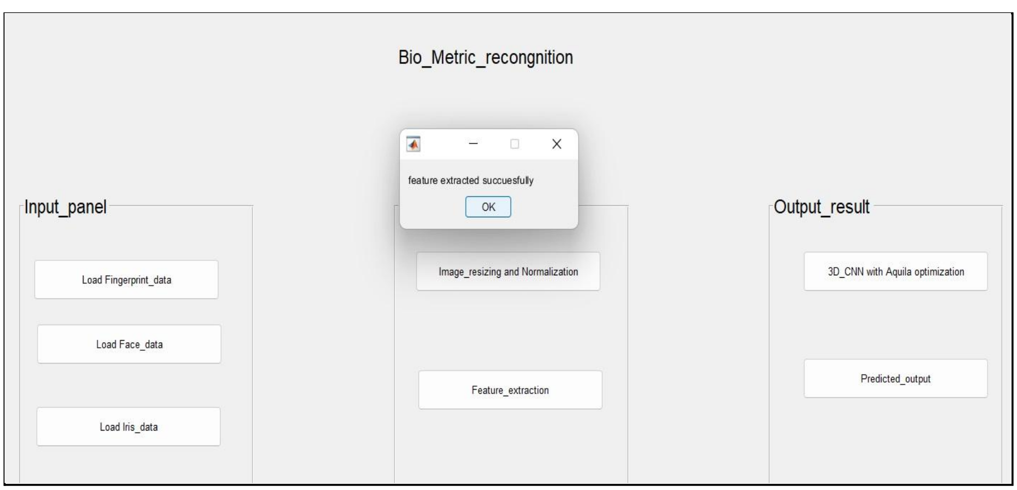


Fig. 10. Feature Extraction

3. We applied Hybrid Densenet-201 3D-CNN along with the Aquila Optimisation algorithm for training ,testing and reducing the value of loss function as shown in Fig.11..

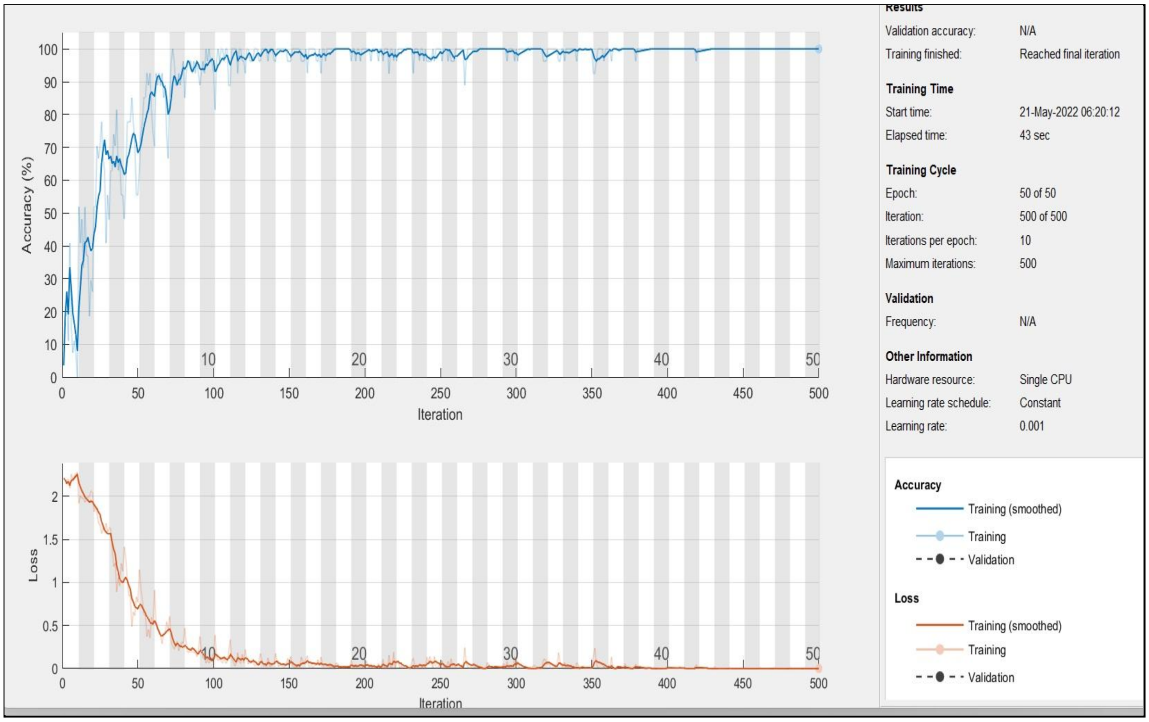


Fig. 11. Training Model

4. Uploaded the image to check whether it is real or fake as shown in Fig.12.

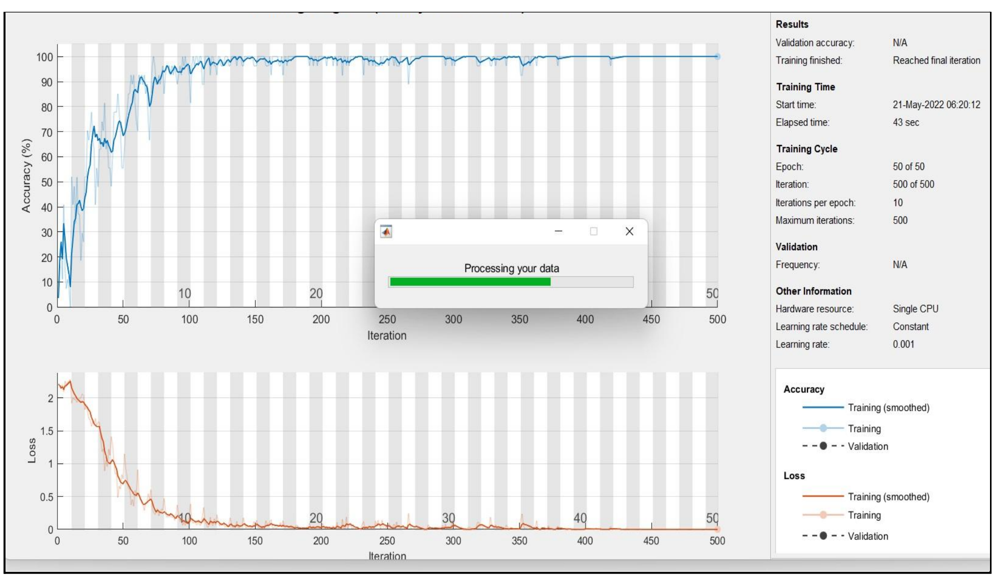


Fig. 12. Uploading image to check the authenticity.

5. Predicted the output. This can be seen in Fig.13.

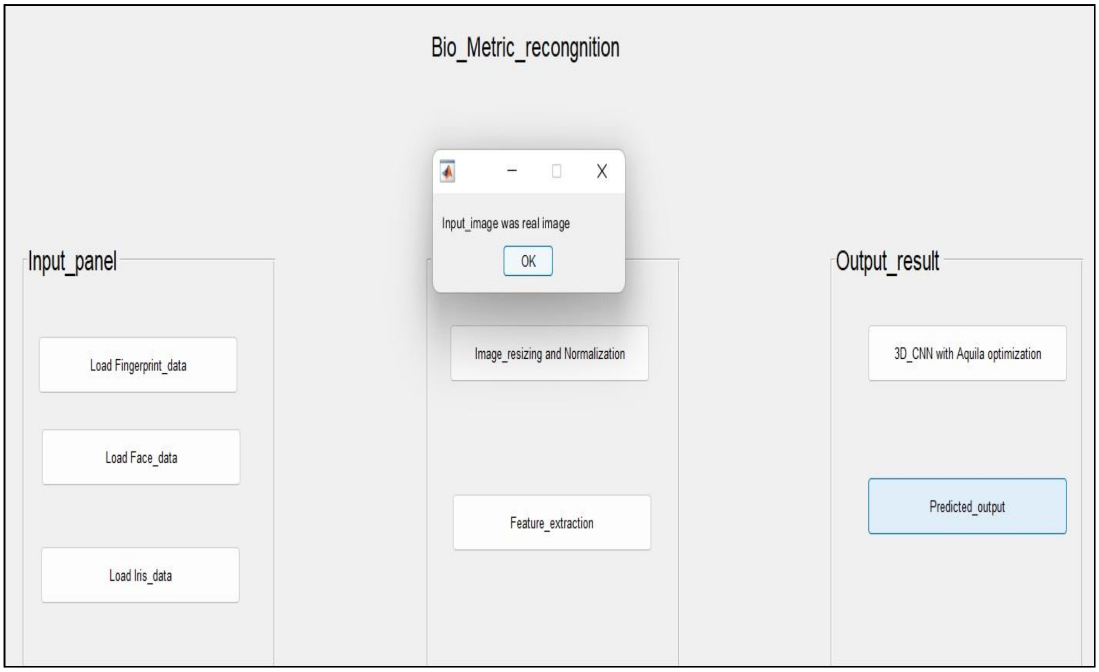


Fig. 13. Output.

CHAPTER 6

RESULTS AND DISCUSSION

In this chapter, we'll go over the results that we've gotten using the proposed model. We'll also talk about the performance metrics that might help us figure out how accurate our model is in comparison to others. We'll also talk about future projects.

6.1 Comparison of Algorithms Used for Hybrid Biometric Recognition

Figure depicts the algorithms used by different authors from the year 2017-2022. We can see that most of the authors used Neural Networks by 46.7% for Hybrid Biometric Recognition followed by Random Forest by 20%, SVM by 13.3%, Naive Bayes by 13.3% and KNN by 6.7%. Fig. 14 shows the algorithms used by different authors.

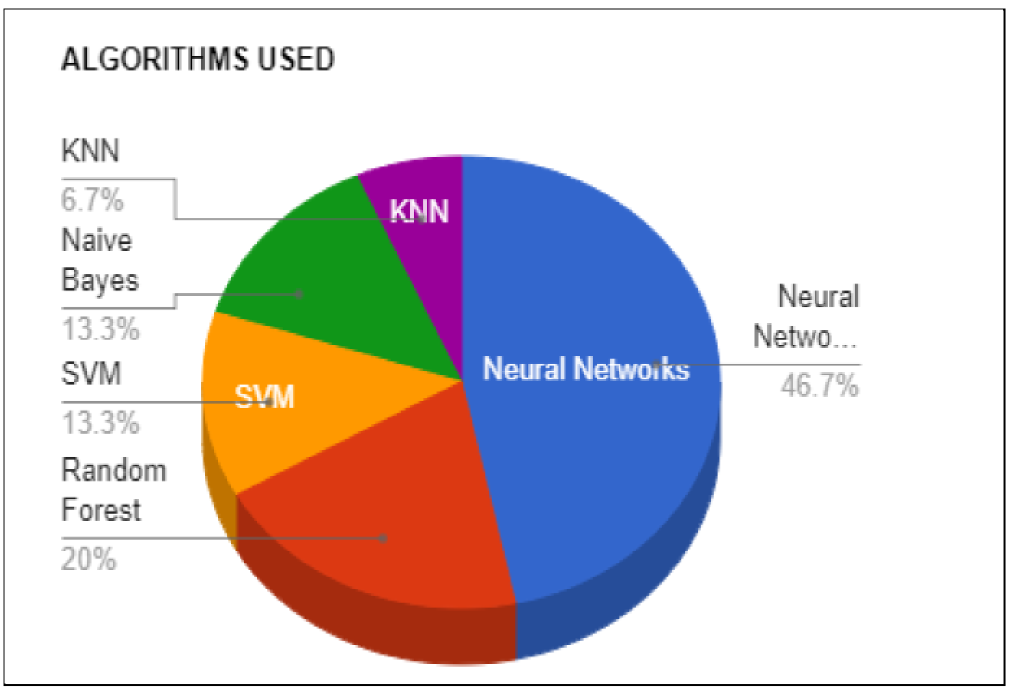


Fig. 14. Concise summary of algorithms used[34]

6.2 Performance Measures

We will now discuss the performance measures that we have used to measure the performance of our proposed model.

6.2.1 False Rejection Rate (FRR):

$No.\ of\ false\ rejection \div No\ of\ identification\ attempt$

False denial rate is a measure of how likely a biometric security system has accidentally rejected an authorized user access attempt. System FRR is usually calculated by dividing the negative rejection number by the number of attempts.

6.2.2 False Acceptance Rate (FAR)

$No.\ of\ false\ acceptance \div No\ of\ identification\ attempt$

False Accreditation Scale (FAR) is a matrix for calculating the average number of inaccuracies in a biometric security system. Determines the extent to which illegal or illegal users are verified in a particular system in order to measure and evaluate the efficiency and accuracy of a biometric system.

6.2.3 Equal Error Rate (ERR)

It is a place where your false identification and rejection rates are very low and very good. Your system will work better if your EER is low.

6.2.4 Accuracy:

One parameter for testing accuracy classification models. In excess, accuracy refers to the percentage of accurate predictions made by our model. The following is the official definition of accuracy:

Accuracy=$No.\ of\ correct\ predictions \div Total\ no.\ of\ predictions$

Accuracy can also be calculated according to the pros and cons of binary options:

Accuracy=$TP + TN \div TP + TN + FP + FN$

6.2.5 Precision :

It is the accuracy of the model's positive prediction

Precision=$TP \div TP + FP$

6.2.6 Recall:

It determines how well the model can detect positive samples. The more positive samples identified, the larger the recall.

Recall=$TP \div TP + FN$

6.2.7 F1 Score

One of the most important test steps in machine learning is the F1-score. It cleverly summarizes the performance of the model prediction by combining the two in advance contradictory metrics: accuracy and memory.

6.2.8 Specificity:

It is the percentage of true negatives predicted properly by the model.

6.3 Results Obtained

6.3.1 Confusion Matrix

Confusion matrix is a matrix used to test the performance of differentiation models in a specific set of test data. Only if the true values of the test data are known can be determined. The matrix itself is easy to understand, but related words may be confusing. It is also known as the error matrix as it shows errors in the performance of the model as a matrix.This is shown in Fig.15.

Fig. 15. Confusion Matrix.

6.3.2 Results of the Performance Parameters

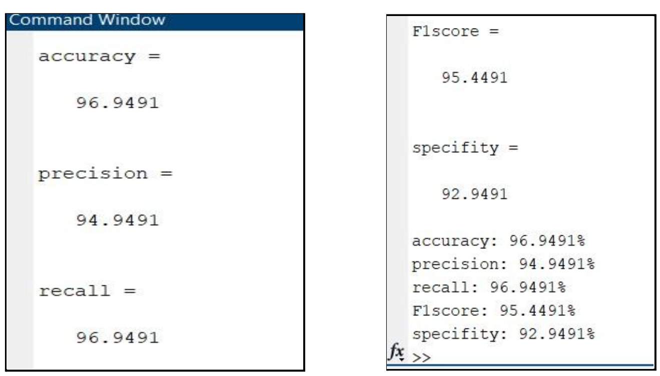


Fig. 16. Results

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

We attempted to implement a hybrid biometric recognition system that included three biometric traits: face, iris, and fingerprint in this research. We used photos from kaggle and the MMU iris database to create our dataset. The data was then preprocessed, including image resizing and normalization. The features were then extracted using the PCA technique. The 3d-cnn model, which included Densenet-201, was then trained. The photograph was then fed to ensure its authenticity. And they expected the result. We found that we had a 96.9491 percent accuracy, a 94.9491 percent precision, a 96.9491 percent recall, a 95.4491 percent F1 score, and a 92.9491 percent specificity. We'll aim to incorporate more biometric features in the future to increase the model's accuracy.

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