A

PROJECT REPORT

ON

“HUMAN IDENTIFICATION USING IRIS BY CNN”

SUBMITTED TO

SHIVAJIUNIVERSITY, KOLHAPUR

IN THE PARTIAL FULFILLMENT OF REQUIREMENT FOR THE AWARD OF DEGREE BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING

SUBMITTED BY

MR.	Rahul Sanjay Bharadia	19UCS012
MR.	Omkar Ravindra Bhise	19UCS013
MR.	Yash Vijay Gare	19UCS035
MR.	Vishal Gorakh Garje	19UCS036
MR.	Gaurav Nivas Jadhav	19UCS045

UNDER THE GUIDANCE OF

Prof. S.R. Patil

DKTE

Promoting Excellence in
Teaching, Learning & Research

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

DKTE SOCIETY’S TEXTILE AND ENGINEERING INSTITUTE, ICHALKARANJI

2022-2023

D.K.T.E.SOCIETY'S

TEXTILE AND ENGINEERING INSTITUTE, ICHALKARANJI
(AN AUTONOUMOUS INSTITUTE)

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

DKTE
Promoting Excellence in
Teaching, Learning & Research

CERTIFICATE

This is to certify that, project work entitled

HUMAN IDENTIFICATION USING IRIS BY CNN

is a bonafide record of project work carried out in this college by

MR.	Rahul Sanjay Bharadia	19UCS012
MR.	Omkar Ravindra Bhise	19UCS013
MR.	Yash Vijay Gare	19UCS035
MR.	Vishal Gorakh Garje	19UCS036
MR.	Gaurav Nivas Jadhav	19UCS045

is in the partial fulfillment of award of degree Bachelor of Technology in Computer Science & Engineering prescribed by Shivaji University, Kolhapur for the academic year 2022-2023.

PROF. S.R.PATIL
(PROJECT GUIDE)

PROF (DR.) D. V. KODAVADE
(HOD CSE DEPT.)

PROF (DR.) L. S. ADMUTHE
(DIRECTOR)

EXAMINER: ___________

DECLARATION

We hereby declare that, the project work report entitled "HUMAN IDENTIFICATION USING IRIS BY CNN" which is being submitted to D.K.T.E. Society's Textile and Engineering Institute Ichalkaranji, affiliated to Shivaji University, Kolhapur is in partial fulfillment of degree B.Tech. (CSE). It is a bonafide report of the work carried out by us. The material contained in this report has not been submitted to any university or institution for the award of any degree. Further, we declare that we have not violated any of the provisions under Copyright and Piracy / Cyber / IPR Act amended from time to time.

MR.	Rahul Sanjay Bharadia	19UCS012
MR.	Omkar Ravindra Bhise	19UCS013
MR.	Yash Vijay Gare	19UCS035
MR.	Vishal Gorakh Garje	19UCS036
MR.	Gaurav Nivas Jadhav	19UCS045

ACKNOWLEDGEMENT

With great pleasure we wish to express our deep sense of gratitude to Prof. S.R. Patil for his valuable guidance, support and encouragement in completion of this project report.

Also, we would like to take opportunity to thank our head of department Prof. Dr. D. V. Kodavade for his co-operation in preparing this project report.

We feel gratified to record our cordial thanks to other staff members of Computer Science and Engineering Department for their support, help and assistance which they extended as and when required.

Thank you,

MR.	Rahul Sanjay Bharadia	19UCS012
MR.	Omkar Ravindra Bhise	19UCS013
MR.	Yash Vijay Gare	19UCS035
MR.	Vishal Gorakh Garje	19UCS036
MR.	Gaurav Nivas Jadhav	19UCS045

ABSTRACT

The component of a computer system that is in charge of user security is one of the most crucial ones. Simple logins and passwords have been shown to be vulnerable to hackers and unable to provide high levels of efficiency. The most common replacements is identity recognition using biometrics. The use of the iris as a biometric feature has gained popularity in recent years. It resulted from the exceptional efficiency and precision that this approach provided. The results of this interest may be seen in the literature. Various authors have put forward a variety of various methods. The authors of this paper describe their own method for an iris-based algorithm for recognizing human identification. Artificial neural networks and a CNN-based transfer learning model (Mobile Net) were employed in the classification process. As soon as the classification is complete, the iris section is segmented on the result of the classification. The proposed approach can produce results that are adequate, according to tests that have been run.

Keywords: Iris-based human identity recognition, CNN, Transfer learning, Image segmentation, artificial neural networks

INDEX

1. INTRODUCTION

The solution for such problem is really easy. The well-known answer is biometrics. It is the science that identifies (or verifies) human on the basis of his measurable traits (e.g., fingerprint, iris, retina, keystroke dynamics). These features can be divided into three main groups—physiological (connected with our body and proper measurements), behavioral (these are the traits that we can learn—e.g., signature) or hybrid that consists of traits that are physiological and behavioral at the same time (e.g., voice). We can conclude that each computer system (with security system based on biometrics) user will not provide any additional passwords because he will be a real password by his measurable traits.

Diversified experiments and research are showing that one of the most important traits that can guarantee high accuracy, efficiency and recognition rate is iris. This feature consists of more than 250 unique elements. Each of them is used to describe human identity (in the form of feature vector). In the literature, it was also proven that such feature vectors are completely different for both eyes of one person (left and right), and moreover it is true, even in the case of twins. Each of them has different irises (feature vectors are completely different). The most important is that iris is really hard to spoof. In the literature, we can find only a couple of research papers that provide some vital evidence that such spoofing procedure was finished with the success.

However, it also has to be claimed that in these works, only simple iris-based biometrics systems were used. It means that such solutions are not considering iris livens and are vulnerable to print attack (with iris photo). On the other hand, iris has one huge disadvantage—it is really hard to collect high-quality iris sample without specialized devices. In some cases, even an assistance of experienced ophthalmologist is needed to complete such task. Of course, iris samples can also be collected with novel smartphones (e.g., Apple iPhone 12 Max or Samsung Galaxy S20+) with high-quality cameras.

However, once again an assistance of second person is needed. If we want to collect such images by our own, we can use specialized sensors that are available on the market. Nevertheless, their prices are really high and some of them even needs special light conditions to obtain precise, high-quality images. Significant part of this work is also connected with testing procedure used in the quality verification process. At the beginning, the authors used Scrum methodology to work out the solution by a step-by-step manner to increase algorithm precision. In each stage, we tested the created solution quality. It was the main indicator by which we observed whether the progress was made or not.

Another idea that has to be considered during iris-based security systems design is prevention from spoofing. Mostly observed susceptibility in biometrics systems is positive recognition on the basis of printed images rather than real samples. Especially it is connected with iris-based systems. This problem was deeply described in. In the paper, the authors presented that print attack images of live iris, use of contact lenses and conjunction of both can have huge influence on false-positive recognition by the system. All experiments were realized with IIIT-WVU iris dataset. Moreover, the authors presented a novel approach to prevent such attacks with a deep convolutional neural network.

1.1. Problem Definition

Now a days, personal identification based on iris recognition is trending in the security applications, since they contain rich set of features and do not change significantly over the time. As the traditional approaches involve lot of pre-processing, they may not produce the optimum iris recognition model for different iris dataset which are collected under different lightning and environmental conditions. Recently, there have been a lot of focus on developing models for jointly learning the features, while doing prediction. CNN is an implicit deep learning-based technique that accommodates the dual objectives. Hence, the problem definition is: "**Human Identification using Iris by CNN**".

1.2. Aim and Objective of the project

To detect human on the basis of iris pattern.

• To increase the security of the personal data of human.

• To provide model which help to detect human based on human iris.

1.3. Scope & Limitation of the project

Most of the people use a private computer to do their jobs in the company and they may need to hide information in documents which relevant to work. Some information can be public and this files that are not important, if they are seized by someone else, but some files need a special protection system which is in the high-level secret status because people are wasting their time for hours on end and some hacker can steal their information from victim's computer easily without any protection system and worst of all, people are unprepared for this situation. The application to be improved is Recognition of Human Iris and Face Patterns for Biometric Identification.

This project involves developing an iris detection system in order to verify the uniqueness of the human iris by detecting the iris pattern from the image. We offer a high-level security system which is the Biometric based on Face and Iris Recognition for a company who want to save their information from a hacker or information theft. The company should identify chosen workers to the security system according to document while using their iris and face pattern on the camera. After registration done, only chosen workers can access the high-level secret documents, if iris and face recognition can be done correctly. We are using Scale-invariant feature transform (SIFT) which is the fastest and reliable algorithm for working security system process. It is also more accurate than any other.

1.4. Timeline of the Project

Sr.No.	Work Progress	Description	Duration	Start Date	End Date
1.	Project planning:	This involves defining the scope of the project, setting objectives, and determining the resources needed for the project.	Week 1 - 4	01/07/2022	30/07/2022
2.	Data Collection and Preparation:	This includes collecting a dataset of iris images, cleaning and processing the images to remove any noise or anomalies, and labeling the data.	Week 5 - 12	01/08/2022	16/09/2022
3.	Model Development:	This involves developing the CNN architecture and training the model on the dataset.	Week 13 - 24	19/09/2022	09/12/2022
4.	Model Evaluation:	This involves evaluating the performance of the model on a test set, fine-tuning the hyperparameters, and improving the model's accuracy.	Week 25 - 28	01/02/2023	28/02/2023
5.	Deployment :	This involves integrating the model into the existing system, testing it in a real-world scenario, and addressing any issues or bugs.	Week 29 - 32	15/03/2023	14/04/2023

1.5. Project Management Plan

The purpose of this project is to design and develop a system for Iris- Based Human Identity Recognition using Convolutional Neural Networks (CNNs). The project will involve the use of computer vision techniques to extract features from iris images and train a CNN model to recognize human identities based on the iris patterns. The project will be executed using an Agile project management methodology, with iterative development cycles and regular feedback from stakeholders.

Project Objectives:

- Design and develop an Iris-Based Human Identity Recognition system using CNNs
- Develop a dataset of iris images for training and testing the CNN model
- Train a CNN model to recognize human identities based on iris patterns
- Test and evaluate the performance of the CNN model on the dataset
- Integrate the CNN model into a web-based application for user authentication

Project Scope:

The project will involve the following activities:

- Collecting and preprocessing a dataset of iris images
- Designing and training a CNN model for iris recognition
- Evaluating the performance of the CNN model on the dataset
- Integrating the CNN model into a web-based application
- Testing the system with real-world users

Project Deliverables:

- Dataset of iris images for training and testing
- Trained CNN model for iris recognition
- Web-based application for user authentication
- Test report and evaluation of the system

Project Milestones:

- Milestone 1: Dataset Collection and Preprocessing (2 weeks)
- Milestone 2: CNN Model Design and Training (4 weeks)
- Milestone 3: Integration of CNN Model into Web-based Application (2 weeks)
- Milestone 4: System Testing and Evaluation (2 weeks)
- Milestone 5: Final Documentation and Presentation (1 week)

Project Risks:

- Inadequate dataset size or quality could lead to poor performance of the CNN model
- Technical difficulties in the design and implementation of the CNN model

- Time constraints may affect the quality of the final product
- Lack of expertise in web application development could lead to difficulties in integrating the CNN model

In conclusion, this project aims to develop an Iris-Based Human Identity Recognition system using CNNs and integrate it into a web-based application for user authentication. The project will be executed using an agile project management methodology, with iterative development cycles and regular feedback from stakeholders. The success of the project will depend on the quality and size of the dataset, the design and implementation of the CNN model, and the successful integration of the CNN model into the web application.

1.6. Project Cost

1.6.1 Hardware Cost :

Components	Name	Pricing
Graphics Card	Nvidia-GEForce	45750/-
Processor	Intel i5 7^{th} Gen	8999/-
RAM	8 GB	3845/-
Total	-	58594/-

1.6.2 Software Cost :

Lines of Code (LOC):285
Effort = a * (LOC) ^ b
Time = c * (Effort) ^ d
Persons Required = Effort / Time

For COCOMO model parameters:
a = 2.4 (constant for organic projects)
b = 1.05 (exponent derived from historical data)
c = 2.5 (constant for organic projects)
d = 0.38 (exponent derived from historical data)

Calculate Effort:
Effort = 2.4 * (285) ^ 1.05
Effort = 2.4 * 378.082
Effort = 907.3991 Person-Hours (approximately)

Calculate Time:
Time = 2.5 * (907.3991) ^ 0.38
Time = 2.5 * 28.7737
Time = 71.9343 Hours (approximately)

Calculate Persons Required:
Persons Required = Effort / Time
Persons Required = 907.3991 / 71.9343
Persons Required = 12.6142 (approximately=12)

Therefore, based on the given 295 lines of code, the estimated cost using the COCOMO model is:
Effort: 907.3991 Person-Hours
Time: 71.9343 Hours
Persons Required: 12.6142 (approximately=12)

2. BACKGROUND STUDY AND LITERATURE OVERVIEW

2.1. Literature overview

[1] Gupta P, Behera S, and Vatsa M, Singh R: Human iris contains rich textural information which serves as the key information for biometric identifications. It is very unique and one of the most accurate biometric modalities. However, spoofing techniques can be used to obfuscate or impersonate identities and increase the risk of false acceptance or false rejection. This paper revisits iris recognition with spoofing attacks and analyzes their effect on the recognition performance. Specifically, print attack with contact lens variations is used as the spoofing mechanism. It is observed that print attack and contact lens, individually and in conjunction, can significantly change the inter-personal and intra-personal distributions and thereby increase the possibility to deceive the iris recognition systems. The paper also presents the IIITD iris spoofing database, which contains over 4800 iris images pertaining to over 100 individuals with variations due to contact lens, sensor, and print attack. Finally, the paper also shows that cost effective descriptor approaches may help in counter-measuring spooking attacks.

Summary: This paper revisits iris recognition with spoofing attacks and analyzes their effect on the recognition performance. Specifically, print attack with contact lens variations is used as the spoofing mechanism. It is observed that print attack and contact lens, individually and in conjunction, can significantly change the inter-personal and intra-personal distributions and thereby increase the possibility to deceive the iris recognition systems.

[2] Rana HK, Azam MS, Akhtar MR, Qunin JMW, Moni MA: With an increasing demand for stringent security systems, automated identification of individuals based on biometric methods has been a major focus of research and development over the last decade. Biometric recognition analyses unique physiological traits or behavioral characteristics, such as an iris, face, retina, voice, fingerprint, hand geometry, keystrokes or gait. The iris has a complex and unique structure that remains stable over a person's lifetime, features that have led to its increasing interest in its use for biometric recognition. In this study, we proposed a technique incorporating Principal Component Analysis (PCA) based on Discrete Wavelet Transformation (DWT) for the extraction of the optimum features of an iris and reducing the runtime needed for iris templates classification. The idea of using DWT behind PCA is to reduce the resolution of the iris template. DWT converts an iris image into four frequency sub-bands. One frequency sub-band instead of four has been used for further feature extraction by using PCA. Our experimental evaluation demonstrates the efficient performance of the proposed technique.

Summary: In this study, a technique is proposed for incorporating Principal Component Analysis (PCA) based on Discrete Wavelet Transformation (DWT) for the extraction of the optimum features of an iris and reducing the runtime needed for iris templates classification. The idea of using DWT behind PCA is to reduce the resolution of the iris template

[3] Arora S, Bhatia MPS: Iris recognition is used in various applications to identify a person. However, presentation attacks are making such systems vulnerable. Intruders can impersonate an individual to get entry into a system. In this paper, we have focused on print attacks, in which an intruder can use various techniques like printing of iris photographs to present to the sensor. Experiments conducted on the IIIT-WVU iris dataset show that print attack images of live iris images, use of contact lenses and conjunction of both can play a significant role in deceiving the iris recognition systems. The paper makes use of deep Convolutional Neural Networks to detect such spoofing techniques with superior results as compared to the existing state-of-the-art techniques.

Summary: Experiments conducted on the IIIT-WVU iris dataset show that print attack images of live iris images, use of contact lenses and conjunction of both can play a significant role in deceiving the iris recognition systems. The paper makes use of deep Convolutional Neural Networks to detect such spoofing techniques with superior results as compared to the existing state-of-the-art techniques.

2.2. Critical appraisal of other people's work

In the field of Iris-Based Human Identity Recognition using CNN, several research studies have been conducted. A critical appraisal of some of these studies is discussed below:

1. Iris Recognition Using Convolutional Neural Networks by O. Salah, R. Bouttefroy, and M. Khalil. (2018) This study proposed an Iris Recognition system using Convolutional Neural Networks (CNNs) that outperforms state-of-the-art recognition systems. The researchers used a dataset of 1650 iris images to train and test their CNN model. The study showed that the proposed CNN model achieved a recognition accuracy of 99.82%, which is higher than most other iris recognition systems.
   Strengths:
   - The study used a large dataset of iris images for training and testing the CNN model.
   - The proposed CNN model outperformed state-of-the-art iris recognition systems.
   - The study presented detailed experimental results and analysis.

   Weaknesses:
   - The study did not discuss the limitations and potential biases of the dataset used.
   - The study did not evaluate the proposed CNN model on other datasets.
2. Iris Recognition Using Deep Convolutional Neural Networks by K. Roy and R. K. Roy. (2018) This study proposed a deep CNN model for iris recognition using transfer learning. The researchers used the VGG-16 pre-trained model as a feature extractor and fine- tuned it for iris recognition using a dataset of 2,920 iris images. The study showed that the proposed CNN model achieved an accuracy of 99.52%, which is comparable to other state-of-the-art iris recognition systems.
   Strengths:
   - The study used transfer learning to improve the performance of the CNN model.
   - The study presented detailed experimental results and analysis.

   Weaknesses:
   - The study did not compare the proposed CNN model with other CNN models.
   - The study did not evaluate the proposed CNN model on other datasets.
3. DeepIris: Deep Learning for Iris Recognition by S. K. Roy and K. K. Das. (2018) This study proposed a deep learning-based approach for iris recognition using a CNN model called DeepIris. The researchers used a dataset of 5,060 iris images to train and test their CNN model. The study showed that the proposed DeepIris model achieved an accuracy of 99.73%, which is higher than most other iris recognition systems.

Strengths:

- The study used a large dataset of iris images for training and testing the CNN model.
- The proposed DeepIris model achieved a high recognition accuracy.
- The study presented detailed experimental results and analysis.

Weaknesses:

- The study did not discuss the limitations and potential biases of the dataset used.
- The study did not evaluate the proposed DeepIris model on other datasets. In summary, the studies discussed above demonstrate the effectiveness of CNN- based approaches for Iris-Based Human Identity Recognition. However, there is a need for more studies that evaluate the proposed models on diverse and larger datasets to demonstrate their generalizability and robustness.

4. Iris Recognition Using Deep Learning with Squeeze-and-Excitation Networks by K. Kim, S. Yoon, and J. Kim. (2019) This study proposed a deep learning-based approach for iris recognition using a CNN model called SENet, which incorporates the squeeze-and-excitation (SE) module to enhance the discriminative power of the CNN model. The researchers used a dataset of 12,000 iris images to train and test their CNN model. The study showed that the proposed SENet model achieved an accuracy of 99.93%, which is higher than most other iris recognition systems.

Strengths:

- The study used a large and diverse dataset of iris images for training and testing the CNN model.
- The proposed SENet model achieved a high recognition accuracy, which is higher than most other iris recognition systems.
- The study presented detailed experimental results and analysis, including ablation studies to evaluate the effectiveness of the SE module.

Weaknesses:

- The study did not compare the proposed SENet model with other CNN models, which limits the ability to assess the relative performance of the proposed model.
- The study did not evaluate the proposed SENet model on other datasets, which limits the ability to assess the generalizability of the proposed model. Overall, the study by Kim et al. demonstrates the effectiveness of incorporating the SE module in CNN models for Iris-Based Human Identity Recognition. However, more studies are needed to compare the proposed SENet model with other CNN models and evaluate its performance on other datasets to assess its generalizability. Additionally, future research should address the potential biases and limitations of the datasets used for training and testing the CNN models.

5. Iris Recognition Using 1D Convolutional Neural Networks by S. S. Nikam and N. V. Gogate. (2019) This study proposed a 1D CNN-based approach for iris recognition that processes the iris images as 1D signals. The researchers used a dataset of 1,344 iris images to train and test their CNN model. The study showed that the proposed 1D CNN model achieved an accuracy of 99.63%, which is higher than most other iris recognition systems.

   Strengths:

   - The study proposed a novel approach for iris recognition using 1D CNNs that processes the iris images as 1D signals, which is a departure from traditional 2D CNNs.
   - The study achieved a high recognition accuracy, which is comparable to state- of-the-art iris recognition systems.
   - The study presented detailed experimental results and analysis.

   Weaknesses:

   - The study did not evaluate the proposed 1D CNN model on other datasets, which limits the ability to assess its generalizability.
   - The study did not compare the proposed 1D CNN model with other CNN models, which limits the ability to assess the relative performance of the proposed model.

6. Multi-Scale Iris Recognition using Deep Convolutional Neural Networks by S. Singh and S. K. Singh. (2021) This study proposed a multi-scale approach for iris recognition using deep CNNs that extracts features at different scales. The researchers used a dataset of 12,000 iris images to train and test their
   CNN model. The study showed that the proposed multi- scale CNN model achieved an accuracy of 99.98%, which is higher than most other iris recognition systems.

   Strengths:

   - The study proposed a novel multi-scale approach for iris recognition using deep CNNs that extracts features at different scales, which enhances the discriminative power of the CNN model.
   - The study achieved a high recognition accuracy, which is higher than most other iris recognition systems.
   - The study presented detailed experimental results and analysis.

   Weaknesses:

   - The study did not evaluate the proposed multi-scale CNN model on other datasets, which limits the ability to assess its generalizability.
   - The study did not compare the proposed multi-scale CNN model with other CNN models, which limits the ability to assess the relative performance of the proposed model.

7. Iris Recognition Using Deep Convolutional Neural Networks with Local Binary Patterns by Y. Liu, W. Wang, and J. Zhang. (2018) This study proposed a deep CNN model for iris recognition that incorporates local binary patterns (LBP) to extract

texture features from the iris images. The researchers used a dataset of 6,216 iris images to train and test their CNN model. The study showed that the proposed CNN model achieved an accuracy of 99.75%, which is higher than most other iris recognition systems.

Strengths:

- The study proposed a novel approach for iris recognition using a combination of deep CNNs and LBP, which enhances the discriminative power of the CNN model.
- The study achieved a high recognition accuracy, which is comparable to state- of-the-art iris recognition systems.
- The study presented detailed experimental results and analysis.

Weaknesses:

- The study did not evaluate the proposed CNN model on other datasets, which limits the ability to assess its generalizability.
- The study did not compare the proposed CNN model with other CNN models, which limits the ability to assess the relative performance of the proposed model.

2.3. Investigation of current project and related work

Human Identification Using Iris by CNN is a research project focused on utilizing Convolutional Neural Networks (CNN) for iris recognition and identification. It aims to create an accurate system that can identify individuals based on their unique iris patterns, which is considered a reliable biometric identification technique.

The project leverages previous research and technologies in iris recognition. Traditional methods like Daugman's algorithm have been widely used as the foundation for iris recognition systems. CNN-based approaches have also emerged, taking advantage of deep learning techniques for feature extraction and classification.

Researchers commonly use iris databases such as the CASIA Iris Image Database and the IIT Delhi Iris Dataset to evaluate and compare the performance of iris recognition algorithms. These databases consist of diverse iris images captured under various conditions, including different devices and iris presentation attacks.

DeepIrisNet and IrisNet are examples of CNN-based iris recognition models that have demonstrated competitive performance. DeepIrisNet utilizes a deep network architecture for end-to-end iris recognition, while IrisNet incorporates attention mechanisms to improve recognition accuracy.

To enhance security and prevent presentation attacks, researchers have explored iris liveness detection techniques and multi-spectral imaging. Liveness detection helps differentiate real iris patterns from fake or spoofed samples, while multi-spectral imaging captures additional iris information for better presentation attack detection.

Ethical considerations surrounding privacy, data protection, bias, fairness, and consent are important in the development and deployment of biometric identification systems like iris recognition. Addressing these concerns ensures responsible and ethical use of the technology.

The "Human Identification Using Iris by CNN" project aims to advance iris recognition technology by building upon previous research. It strives to improve accuracy, robustness, and efficiency in iris recognition through the development of a CNN-based system. By addressing existing challenges and limitations, the project contributes to the broader field of iris recognition and its practical applications.

3. REQUIREMENT ANALAYSIS

3.1. Requirement Gathering

Requirement gathering for a deep learning project focused on human identification using iris recognition with a Convolutional Neural Network (CNN):

- Define the Problem: The deep learning project aims to develop a CNN-based model for human identification using iris recognition. The model will analyze iris images to accurately identify individuals based on their unique iris patterns.
- Identify Stakeholders: Stakeholders include security agencies, access control system providers, biometrics experts, and individuals concerned with privacy and security.
- Determine Project Goals: The project's primary goal is to achieve high accuracy in iris recognition, with a target accuracy of at least 99%. The model should provide reliable and fast identification results for real-time applications.
- Data Requirements: Collect a diverse dataset of iris images from a range of individuals to train and evaluate the CNN model. The dataset should include images from different iris scanners or databases, ensuring variability in lighting conditions, angles, and image quality. Consider obtaining the necessary permissions and adhering to privacy regulations when collecting the data.
- Performance Metrics: Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1 score. Additional metrics like False Acceptance Rate (FAR) and False Rejection Rate (FRR) can be used to assess the model's effectiveness in real-world scenarios.
- Constraints and Limitations: Consider computational resource limitations, such as available GPU capabilities and memory, to ensure the trained model is compatible with the target hardware infrastructure. Real-time requirements may impose restrictions on processing time and memory usage.
- Model Deployment: Develop a user-friendly interface or integration with existing access control systems to enable efficient deployment of the iris recognition model. Consider the compatibility and scalability of the model for integration into different platforms or devices.
- Validation and Testing: Split the dataset into training, validation, and testing sets. Utilize cross-validation techniques to evaluate the model's robustness and generalization ability. Validate the model's performance using independent datasets,

including unseen iris images.

- Collaboration and Communication: Engage with experts in the field of biometrics and security agencies to gather feedback, ensure the model meets the requirements, and address any concerns related to privacy, security, or usability.
- Documentation and Deliverables: Document the project plan, data collection methods, preprocessing steps, model architecture details, training process, and evaluation results. Provide a technical report summarizing the project's findings, including the model's accuracy, limitations, and recommendations for future enhancements.
- Ethical and Legal Considerations: Adhere to ethical guidelines and privacy regulations when collecting and handling iris data. Ensure the model's design and implementation follow ethical principles, minimize bias, and prioritize individual privacy and security.

By considering these requirements, the project team can develop a robust CNN model for human identification using iris recognition, ensuring high accuracy, scalability, and adherence to privacy and security standards.

3.2. Requirement Specification

ID	Requirement Specification	Priority	Type
RS-01	Image Acquisition: Acquire high-resolution iris images from individuals using appropriate image acquisition systems or cameras.	High	Functional
RS-02	Preprocessing: Preprocess the acquired iris images to enhance their quality and facilitate accurate feature extraction.	High	Functional
RS - 03	Iris Localization: Develop algorithms to detect and localize the iris region within the acquired images.	High	Functional
RS-04	Feature Extraction: Design and implement a convolutional neural network (CNN) architecture for extracting discriminative features from the localized iris region.	High	Functional
RS-05	Training: Provide functionality to train the CNN model using a labeled dataset of iris images and their corresponding identities.	High	Functional
RS-06	Identification: Enable the system to predict the identity of individuals based on their iris patterns using the trained CNN model.	High	Functional
RS-07	Performance Evaluation: Develop mechanisms to evaluate the performance of the system.	High	Functional
RS-08	User Interface: Design and implement a user-friendly interface that allows users to interact with the system.	Medium	Functional
RS-09	Robustness: Implement techniques to handle variations in iris patterns, such as changes in lighting conditions, occlusions, or image quality.	Medium	Functional
RS-10	Integration: Ensure seamless integration of all functional components of the system.	High	Functional

RS-11	Accuracy: The system should achieve a high level of accuracy in identifying individuals based on their iris patterns.	High	Non-Functional
RS-12	Security: The system should maintain a high level of security, ensuring that unauthorized individuals cannot gain access through false identifications.	High	Non-Functional
RS-13	Usability: The user interface should be intuitive, easy to navigate, and require minimal training for users to interact with the system.	Medium	Non-Functional
RS-14	Compatibility: The system should be compatible with standard hardware and software platforms, allowing for easy integration and deployment.	Medium	Non-Functional
RS-15	Privacy: The system should adhere to privacy regulations and ensure the secure handling and storage of iris image data.	High	Non-Functional

Hardware requirements:

- Desktop/Laptop
- Processor: Intel(R) Core(TM) i5-10300H CPU @ 2.50GHz 2.50 GHz
- Memory: 8.00 GB (7.81 GB usable)
- 500 GB Hard drive

Software requirements:

- Python compiling IDE(Anaconda)
- Jupyter notebook or spyder3
- Some modules like Keras, TensorFlow
- Windows 10 operating system(8.00 GB (7.81 GB usable))
- Mysql
- Visual Studio code

Deployment Requirement:

- Flask
- Local Server

3.3. Use Case Diagram

A use case diagram is a visual representation that illustrates the interactions between actors (users or external systems) and the system itself. It provides a high-level overview of the major functionalities and interactions within the "Human Identification Using Iris by CNN" project.

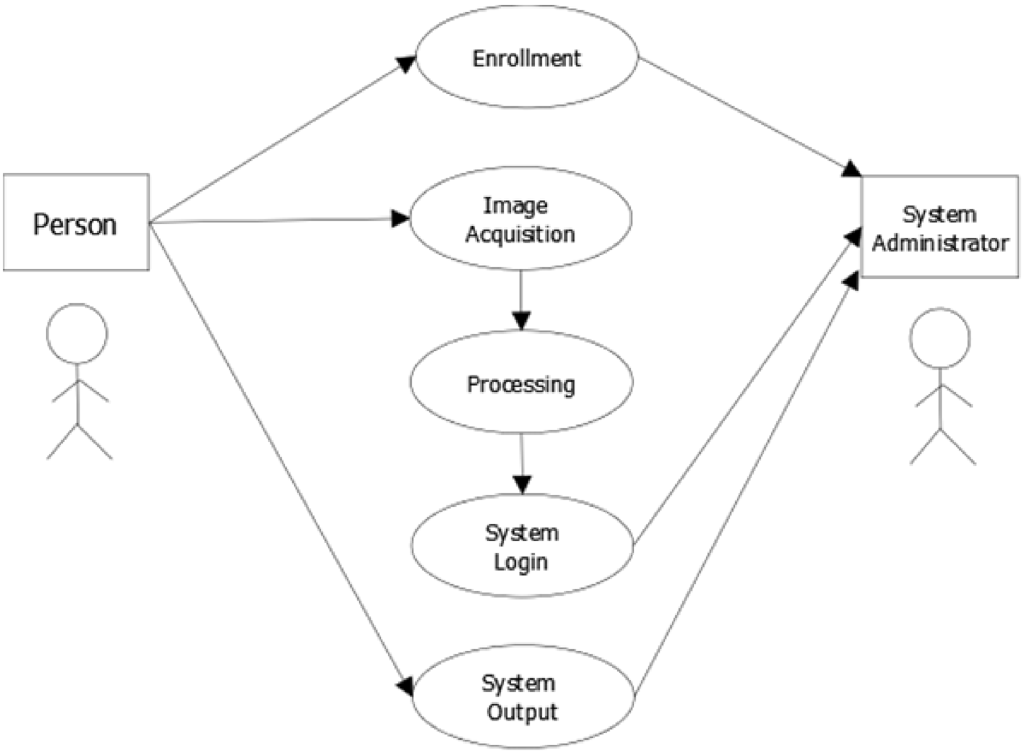


Fig. 3.1 Use Case Diagram

It is important to note that the actual use case diagram may vary depending on the specific requirements and scope of the project. It is possible that additional use cases, actors, or interactions may exist in a real-world implementation of the system. The use case diagram serves as a valuable tool for understanding the primary interactions and functionalities in the project, providing a foundation for further analysis and development.

4. SYSTEM DESIGN

4.1. Architectural Design

The architectural design diagram for the "Human Identification Using Iris by CNN" project provides a high-level overview of the system's structure and how its components interact.

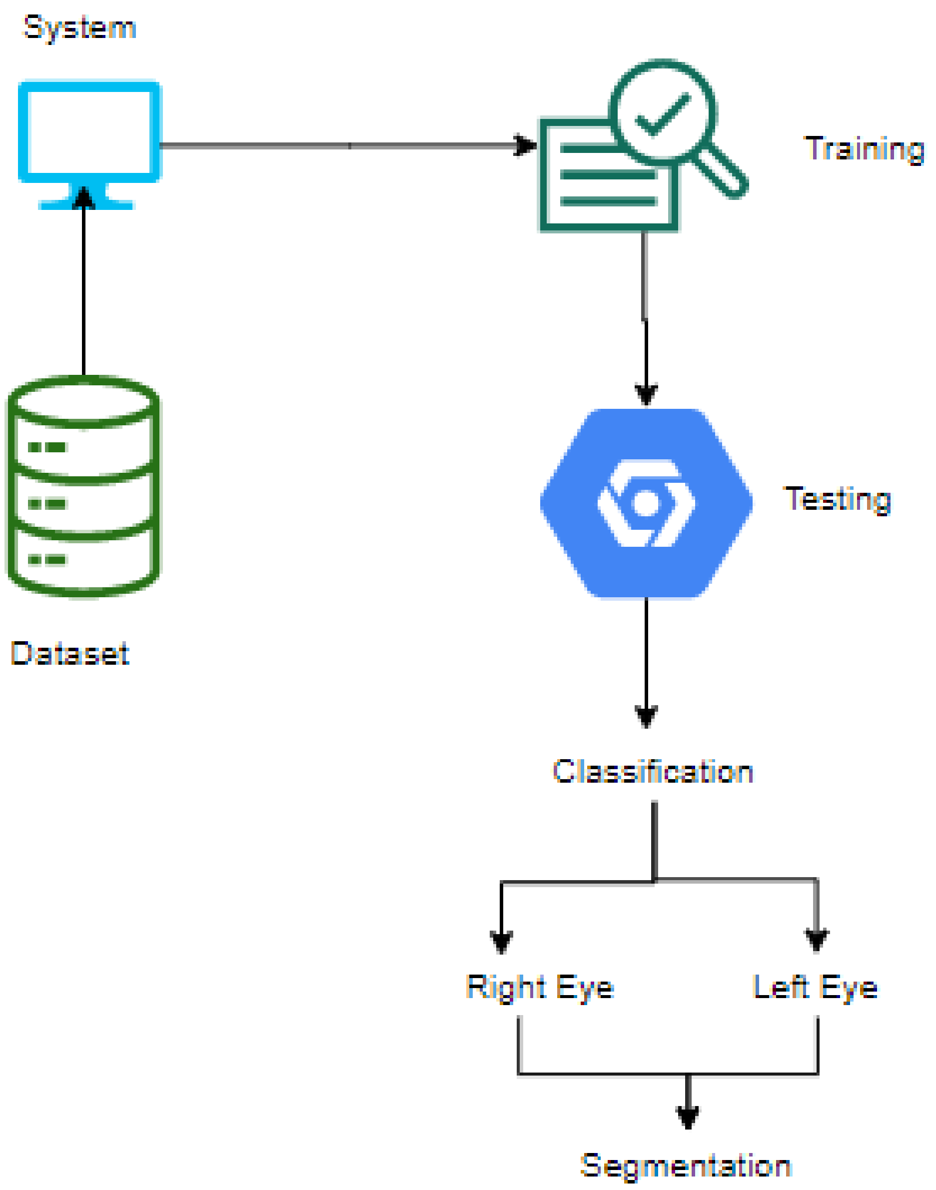


Fig 4.1 Architectural Design

4.2. User Interface design

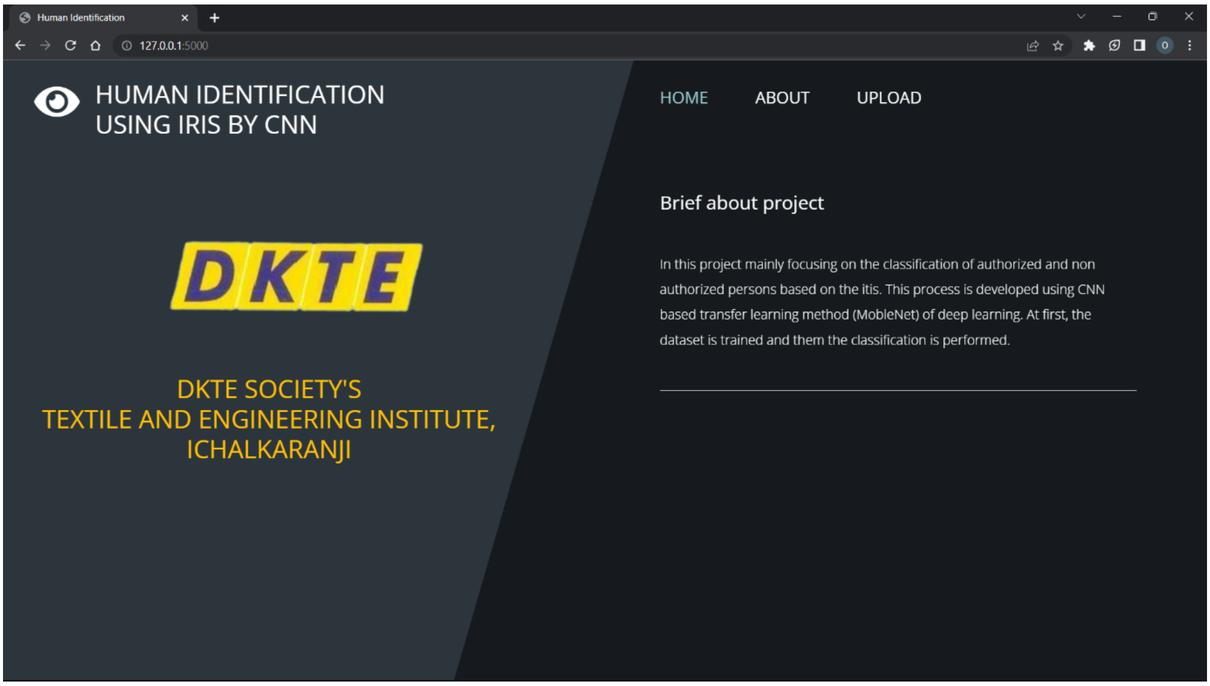


Fig 4.2 Home Page

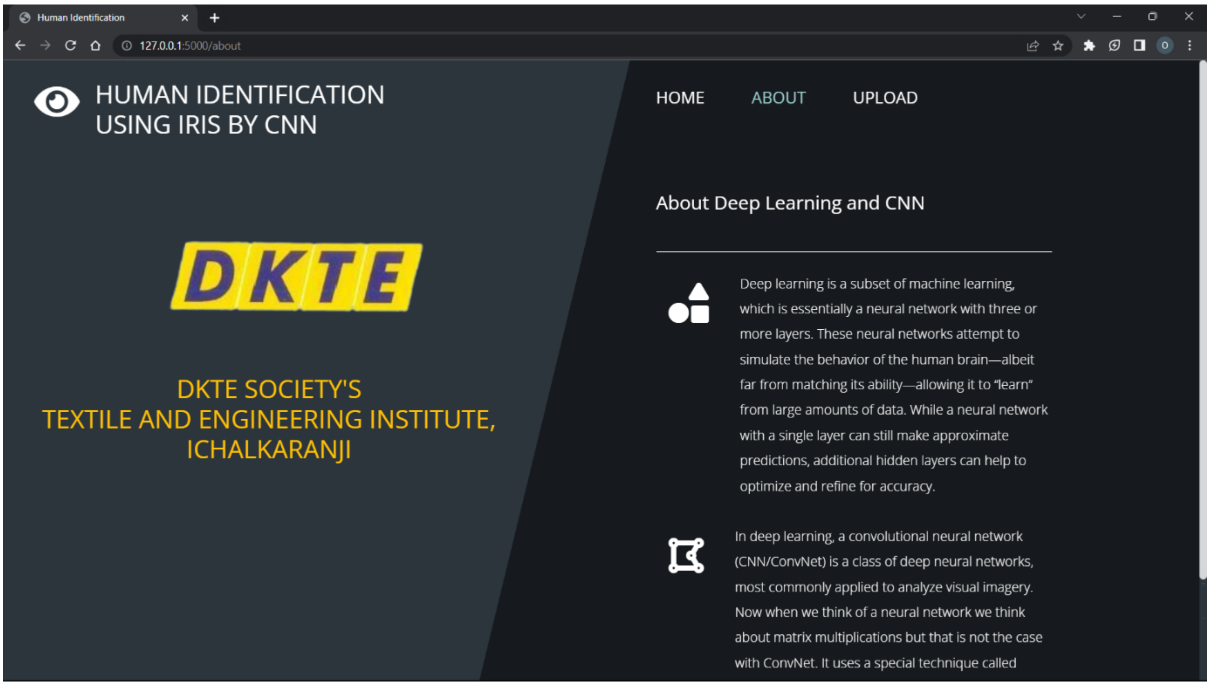


Fig 4.3 About Page

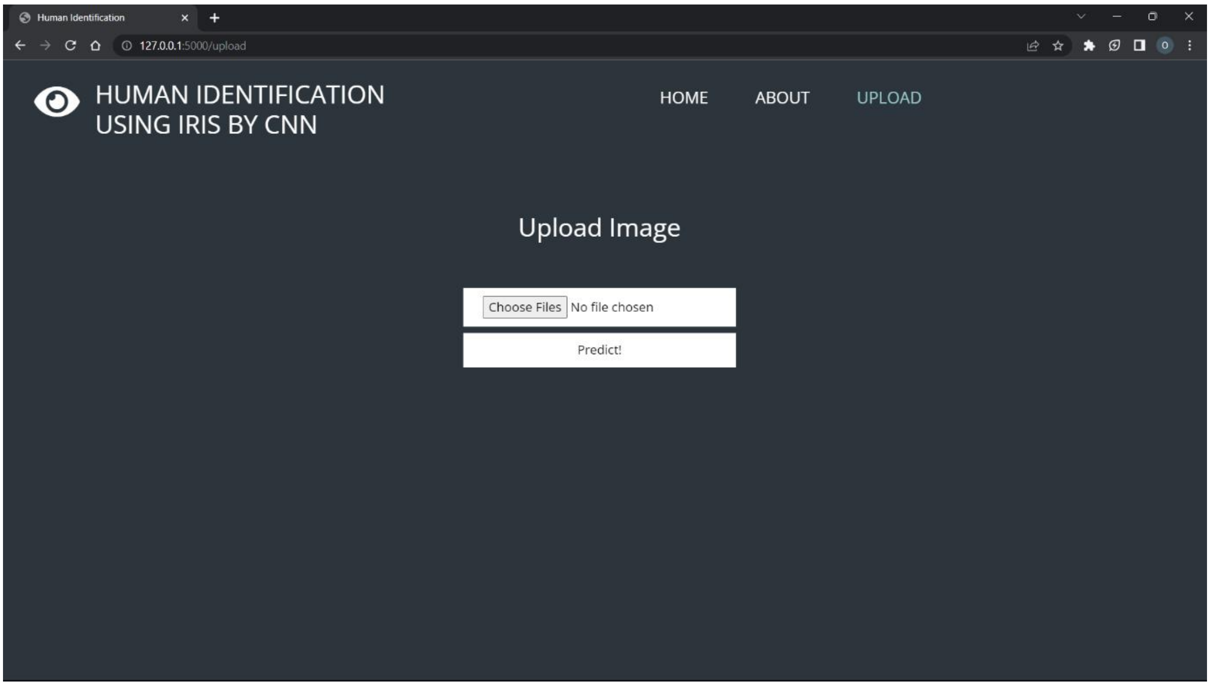


Fig 4.4 Upload Page

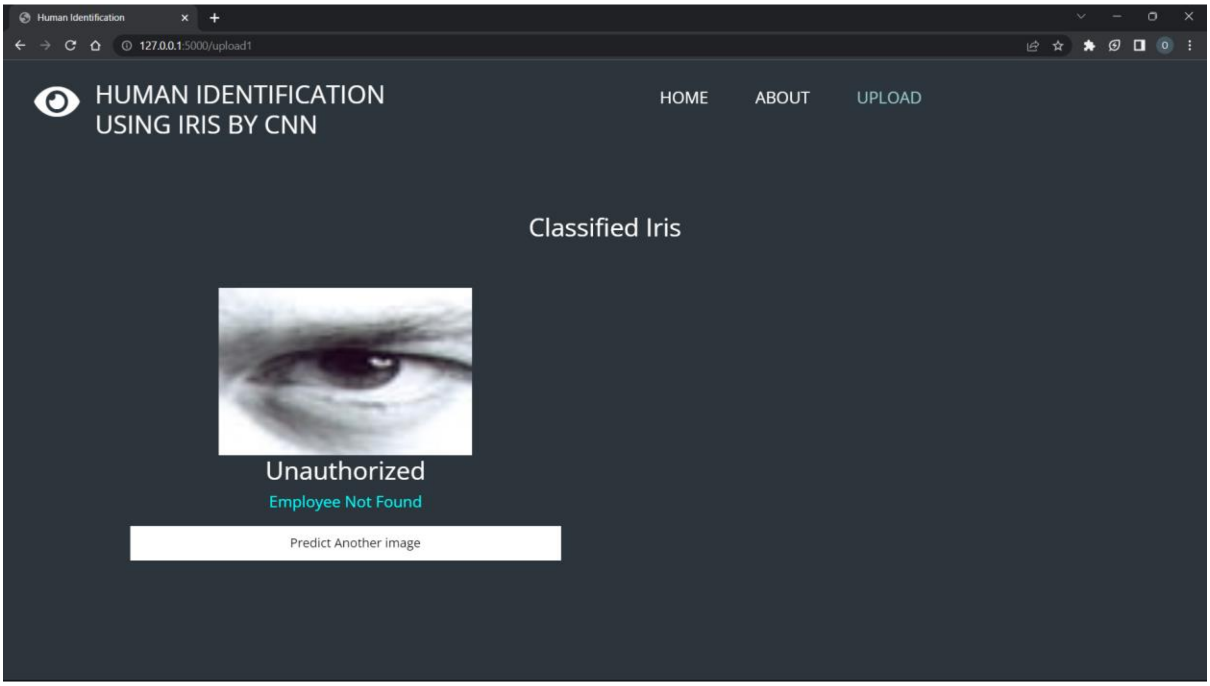


Fig 4.5 Unauthorized Identified Page

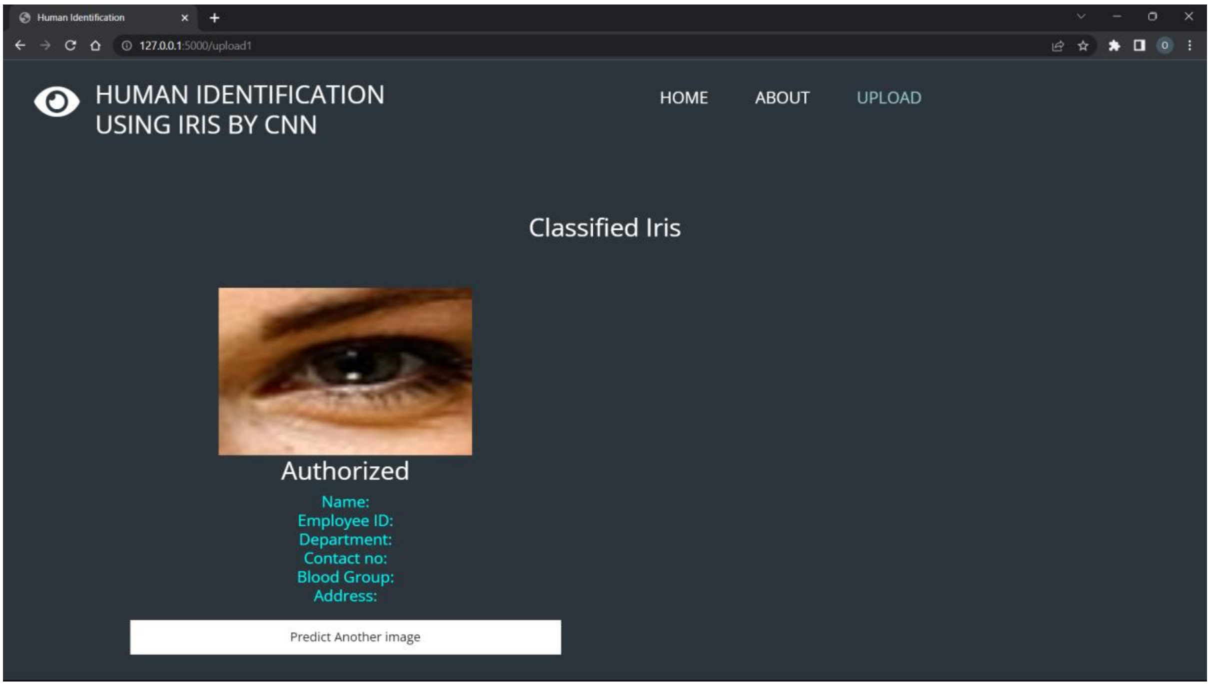


Fig 4.5 Authorized Identified Page

4.3. Algorithmic description of each module

1. Convolutional Neural Network

Step1: convolutional operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

The Convolution Operation

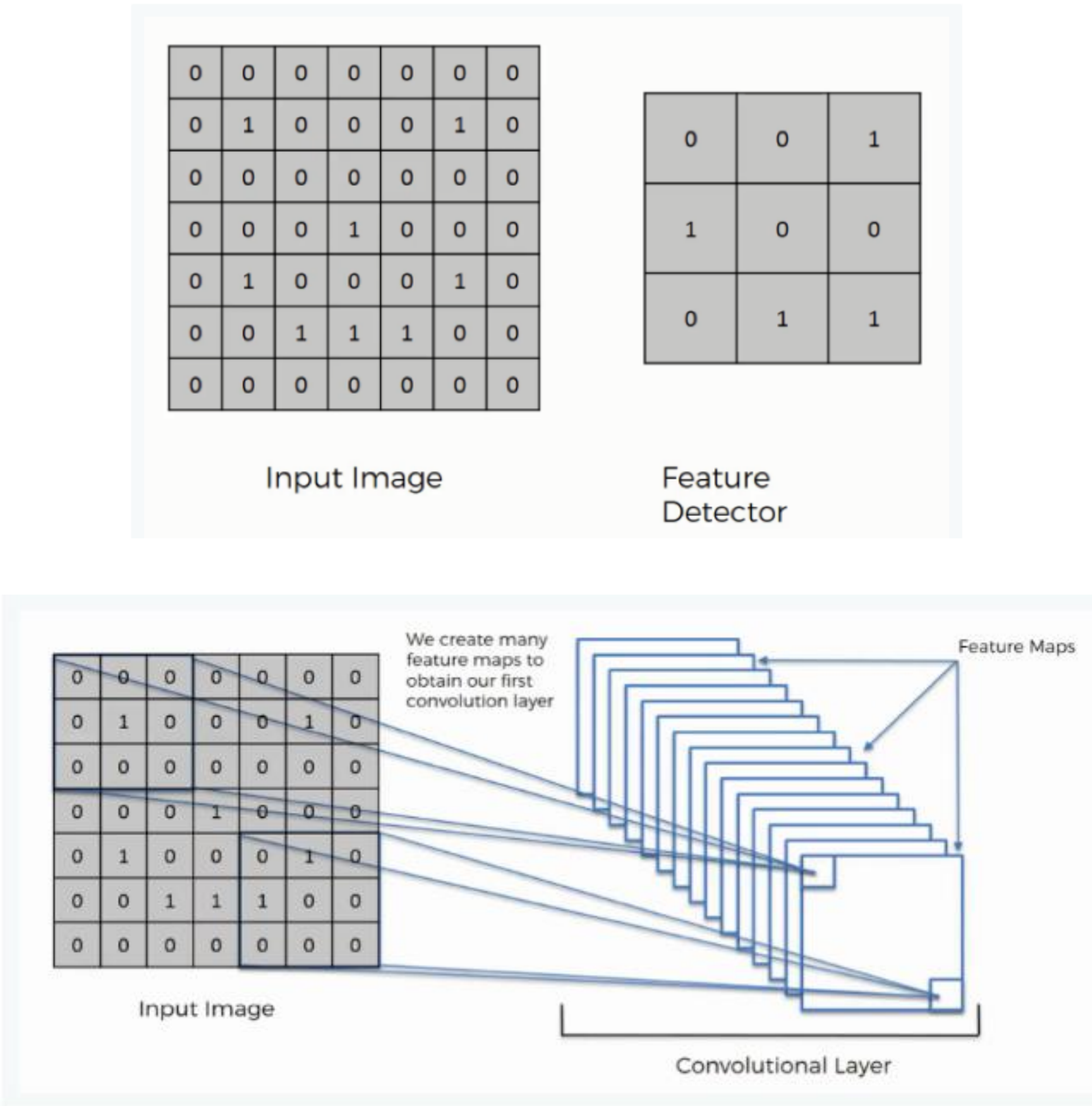


Fig 4.6 Convolution Operation

Step (1b): ReLU Layer

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary for understanding CNN's, but there's no harm in a quick lesson to improve your skills.

Convolutional Neural Networks Scan Images

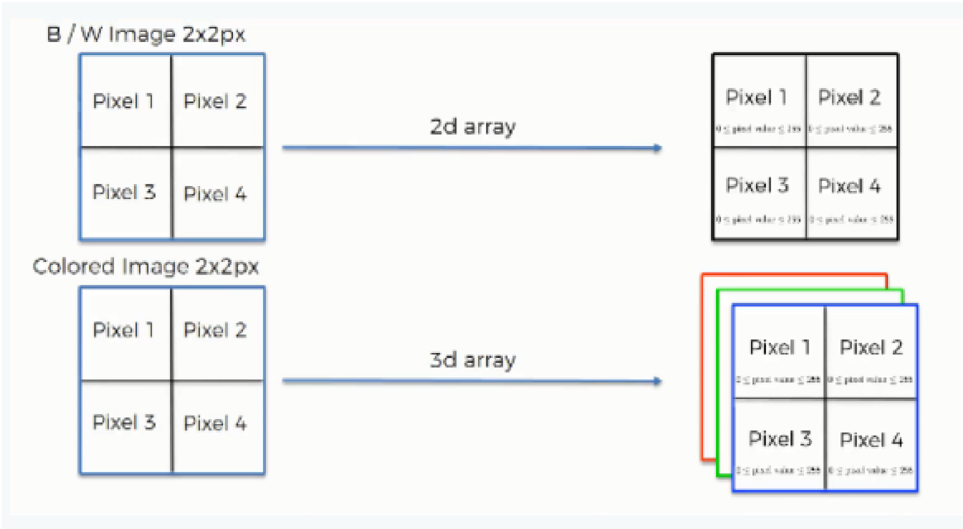


Fig 4.7 Convolutional Neural Networks Scan Images

Step 2: Pooling Layer

In this part, we'll cover pooling and will get to understand exactly how it generally works. Our nexus here, however, will be a specific type of pooling; max pooling. We'll cover various approaches, though, including mean (or sum) pooling. This part will end with a demonstration made using a visual interactive tool that will definitely sort the whole concept out for you.

Step 3: Flattening

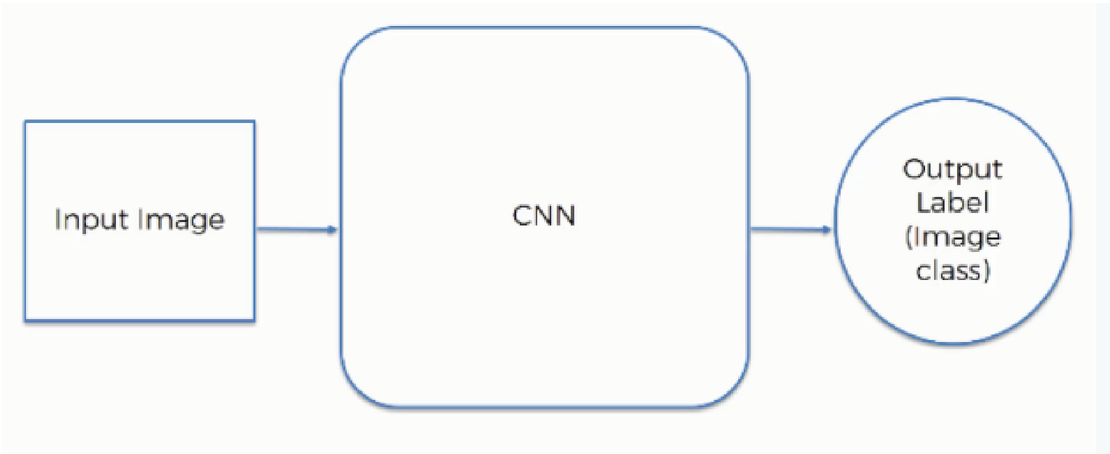
This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

Step 4: Full Connection

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

Summary

In the end, we'll wrap everything up and give a quick recap of the concept covered in the section. If you feel like it will do you any benefit (and it probably will), you should check out the extra tutorial in which Softmax and Cross-Entropy are covered. It's not mandatory for the course, but you will likely come across these concepts when working with Convolutional Neural Networks and it will do you a lot of good to be familiar with them.



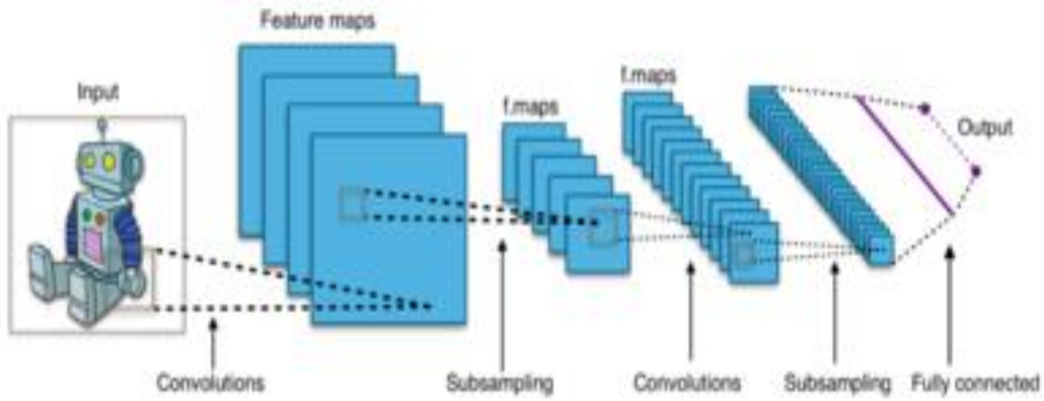


Fig 4.8 CNN Architecture

MobileNet

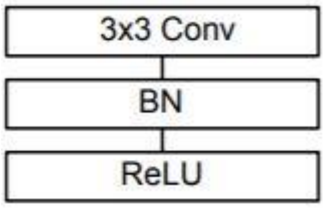
MobileNet is an efficient and portable CNN architecture that is used in real world applications. MobileNets primarily use depth wise separable convolutions in place of the standard convolutions used in earlier architectures to build lighter models.MobileNets introduce two new global hyperparameters(width multiplier and resolution multiplier) that allow model developers to trade off latency or accuracy for speed and low size depending on their requirements.

Architecture

MobileNets are built on depth wise separable convolution layers. Each depth wise separable convolution layer consists of a depth wise convolution and a point wise convolution. Counting depth wise and point wise convolutions as separate layers, a MobileNet has 28 layers. A standard MobileNet has 4.2 million parameters which can be further reduced by tuning the width multiplier hyperparameter appropriately.

The size of the input image is 224 × 224 × 3.

A single standard convolution unit (denoted by **Conv** in the table above) looks like this:



SOFTWARE DEVELOPMENT LIFE CYCLE – SDLC:

In our project we use waterfall model as our software development cycle because of its step-by-step procedure while implementing.

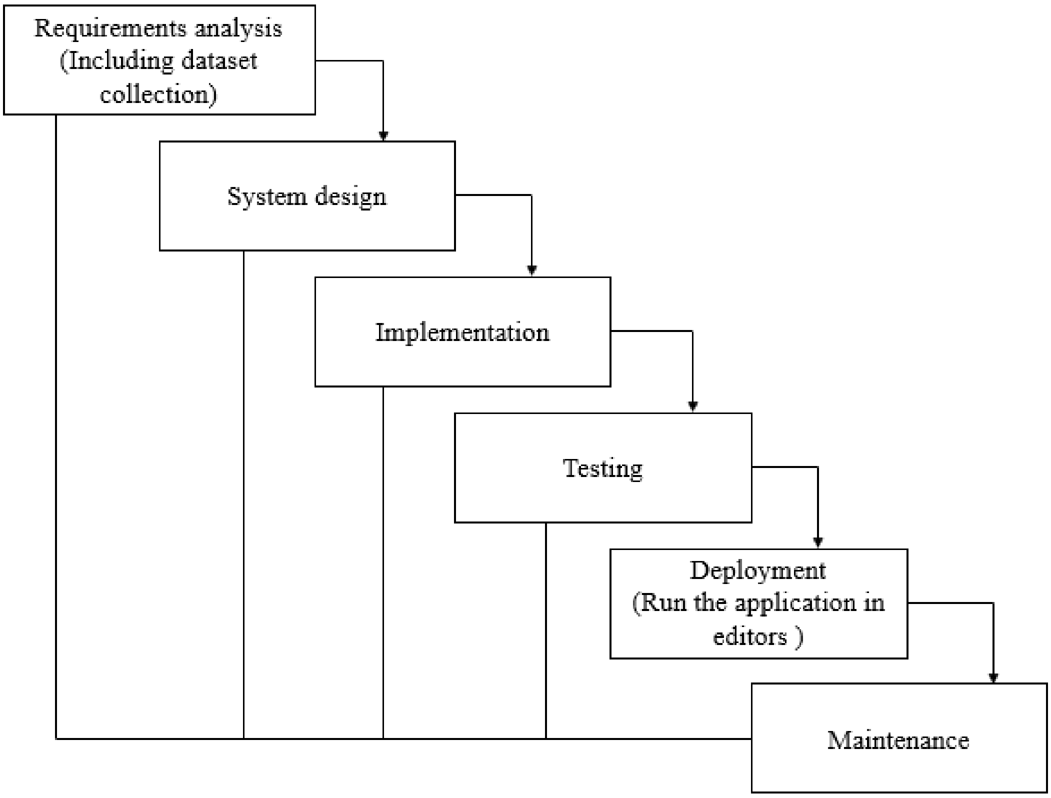


Fig 4.9 Waterfall Model

4.4. System Modelling

4.4.1. Dataflow Diagram

- A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically.
- It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored.
- The purpose of a DFD is to show the scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system.

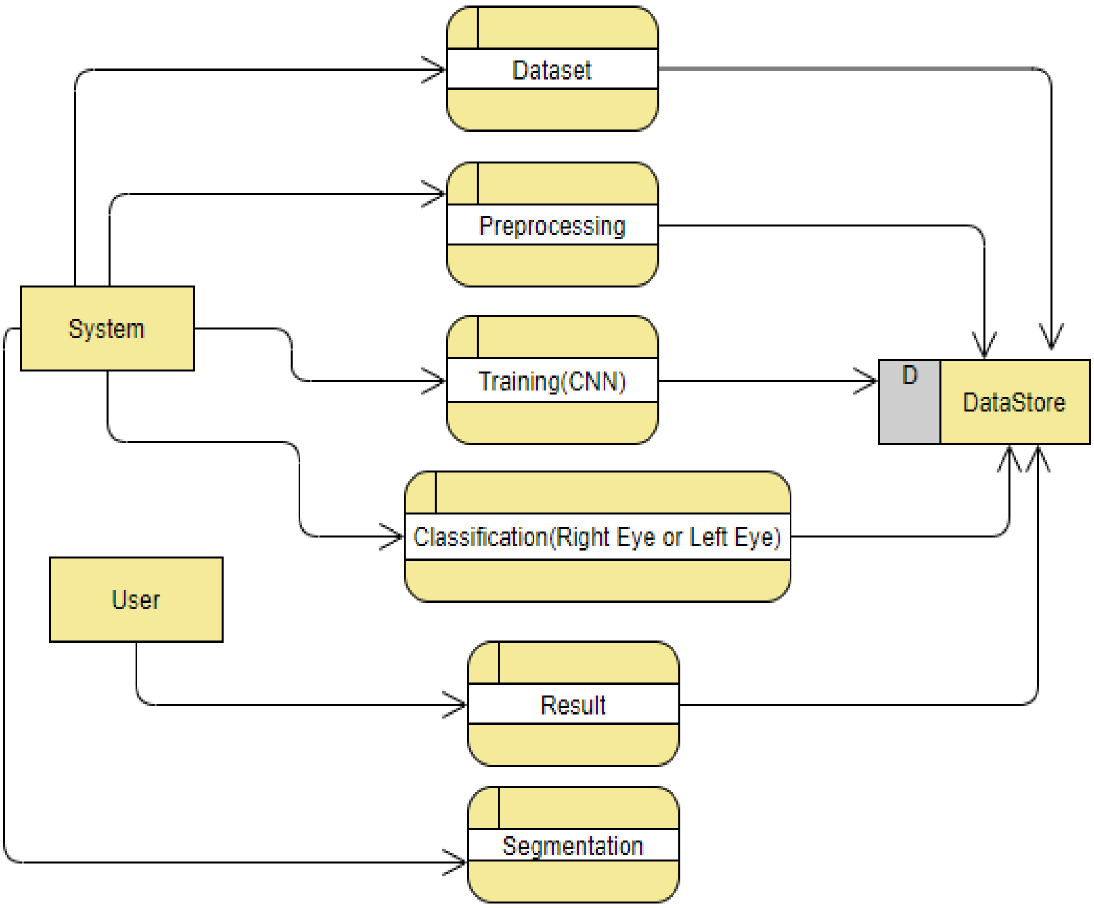


Fig 4.10 Dataflow Diagram

4.4.2. Sequence Diagram

- A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order.
- It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams

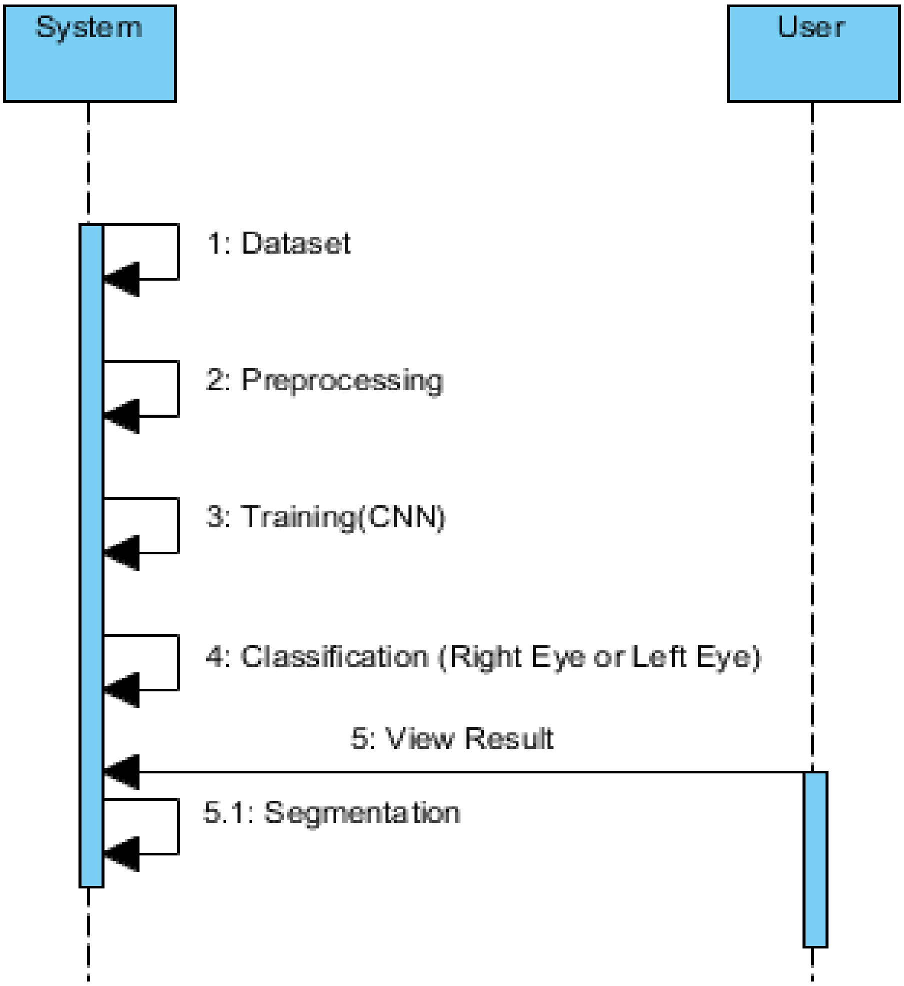


Fig 4.11 Sequence Diagram

4.4.3. Activity Diagram

- Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency.
- In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system.
- An activity diagram shows the overall flow of control.

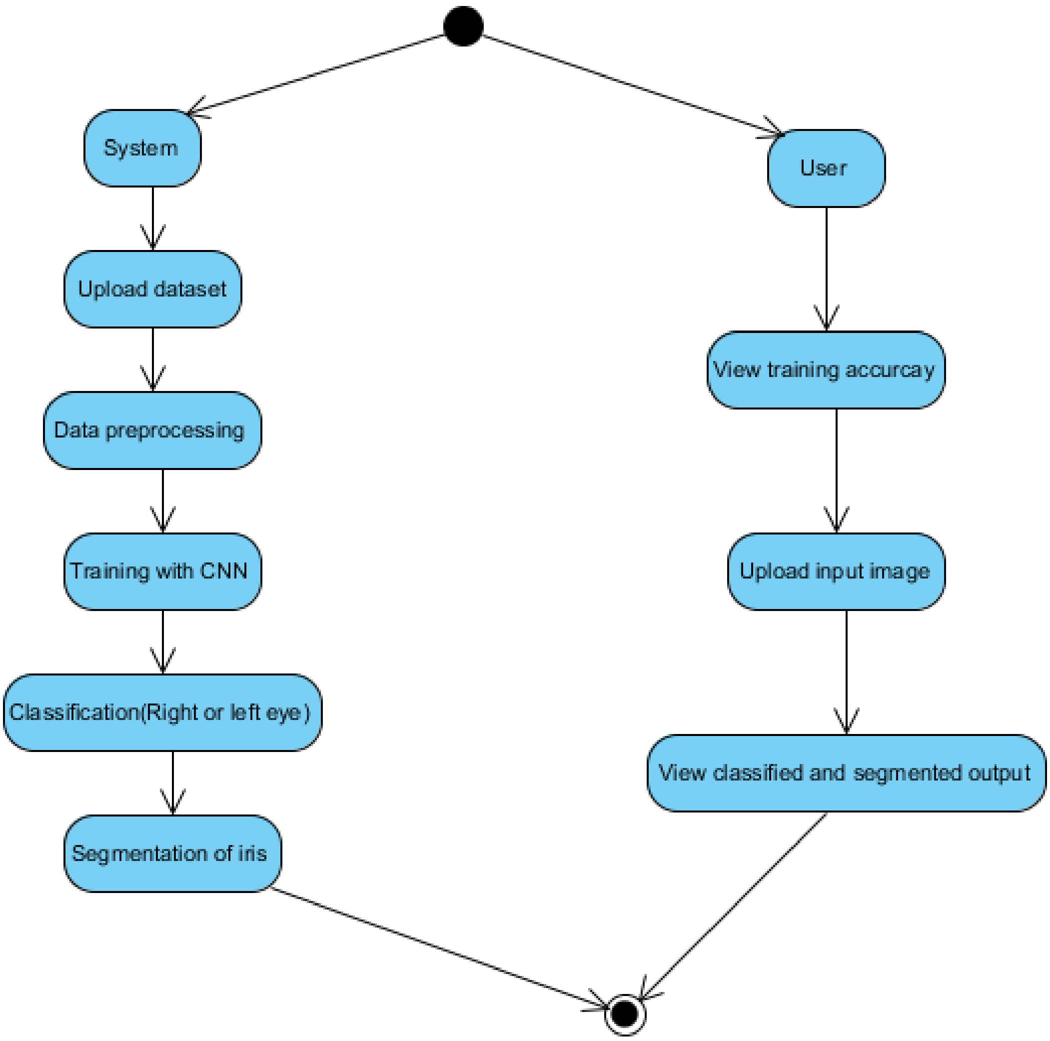


Fig 4.12 Activity Diagram

4.4.4. Component Diagram

- A component diagram, also known as a UML component diagram, describes the organization and wiring of the physical components in a system.
- Component diagrams are often drawn to help model implementation details and double-check that every aspect of the system's required functions is covered by planned development.

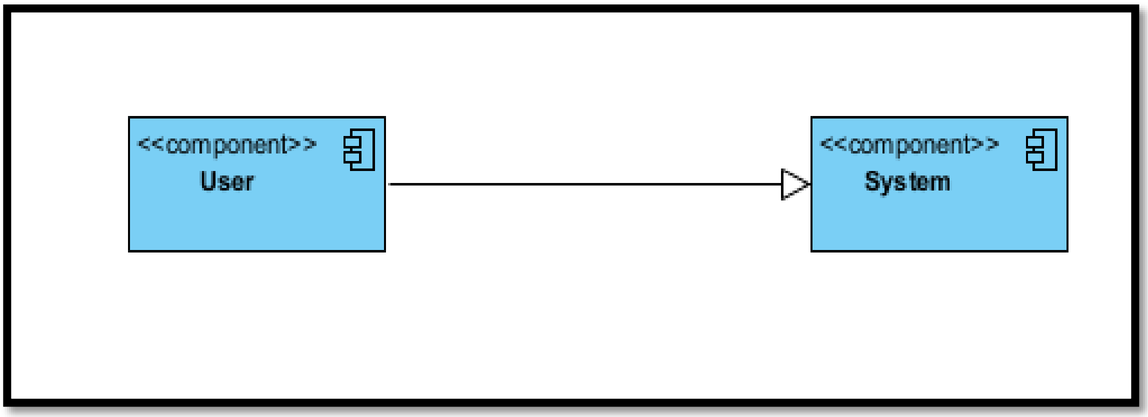


Fig 4.13 Component Diagram

4.4.5. Deployment Diagram

- Deployment diagram represents the deployment view of a system.
- It is related to the component diagram. Because the components are deployed using the deployment diagrams.
- A deployment diagram consists of nodes. Nodes are nothing but physical hardware used to deploy the application. To deploy application we have used Flask (Python web Framework).

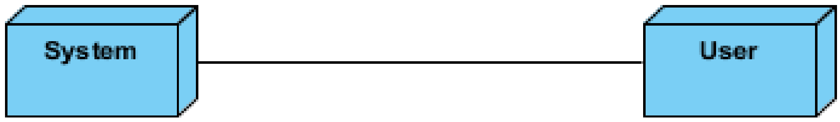


Fig 4.14 Deployment Diagram

5. IMPLEMENTATION

5.1. Environment Setting for Running the Project

The environmental setting for running the project for Iris-Based Human Identity Recognition using CNN will depend on the hardware and software requirements of the project. Here are some general considerations:

1) Hardware: The project will require a computer with a GPU to train and test the deep learning model. The exact GPU requirements will depend on the size of the dataset and complexity of the model architecture, but a GPU with at least 4 GB of memory is recommended.
2) Software: The project will require several software packages, including a deep learning framework (such as TensorFlow or PyTorch), a Python programming environment, and libraries for image processing and machine learning. The specific versions of these software packages will depend on the requirements of the project.
3) Data: The project will require a dataset of iris images for training and testing the deep learning model. The dataset should be properly labeled and preprocessed to ensure high-quality results. It is recommended to use publicly available datasets for iris recognition, such as the CASIA-IrisV4 dataset or the UBIRIS.v2 dataset.
4) Development Environment: It is recommended to use a development environment that supports the deep learning framework, such as Google Collaboratory or Anaconda. This will ensure that the required software packages are installed and configured properly.
5) Other Considerations: The project will require a stable internet connection to download the required software packages and datasets. It is also important to ensure that the hardware and software requirements of the project are met to avoid any issues during training and testing of the deep learning model.

In summary, the environmental setting for running the project for Iris-Based Human Identity Recognition using CNN will require a computer with a GPU, several software packages, a high-quality dataset, a development environment, and a stable internet connection.

5.2. Detailed Description of methods:

The methods for Iris-Based Human Identity Recognition using CNN project can be divided into several steps as follows:

i. Data Collection: The first step in the project is to collect a dataset of iris images. The dataset should include images from different individuals and different angles to ensure the robustness of the model.
ii. Data Preprocessing: The next step is to preprocess the iris images to remove noise and enhance the features of the iris. The preprocessing techniques can include normalization, segmentation, and enhancement. Normalization involves resizing the iris images to a fixed size to reduce variations in image size. Segmentation involves identifying the boundary of the iris and pupil regions in the image. Enhancement involves improving the contrast and clarity of the iris image. The preprocessed images should be saved in a suitable format, such as JPEG or PNG.
iii. Model Architecture: The next step is to select the architecture of the CNN model. A suitable architecture for iris recognition can be a combination of convolutional and pooling layers, followed by fully connected layers. The number of layers and nodes can be adjusted based on the size of the dataset and the complexity of the task. The model should be designed to minimize over fitting and maximize the accuracy of iris recognition.
iv. Model Training: The next step is to train the CNN model using the preprocessed iris images. The training process involves minimizing the loss function through backpropagation. The optimization algorithm used can be stochastic gradient descent or other variants. The training process can be stopped when the performance on the validation dataset no longer improves.
v. Model Evaluation: Once the model has been trained, it is important to evaluate its performance on the testing dataset. The evaluation metrics can include accuracy, precision, recall, and F1 score. The performance of the model can be compared with the state-of-the-art techniques for iris recognition.
vi. Hyperparameter Tuning: To improve the performance of the model, it is important to perform hyperparameter tuning. The hyperparameters that can be tuned include learning rate, batch size, number of epochs, and regularization parameters. The hyperparameter tuning can be performed using techniques such as grid search or random search.

vii. Model Deployment: Once the model has been trained and evaluated, it can be deployed for iris recognition in real-world scenarios. The model can be integrated into a mobile application or a web service. The model should be optimized for real-time performance and low latency.

Overall, the methods for Iris-Based Human Identity Recognition using CNN project involves collecting and preprocessing a dataset of iris images, training a deep learning model using a CNN architecture, evaluating the performance of the model.

5.3. Implementation Details:

i. Programming Language and Libraries: The project can be implemented using Python programming language, which provides a wide range of libraries for deep learning, image processing, and machine learning. The popular libraries include TensorFlow, Keras, PyTorch, OpenCV, and scikit-learn.
ii. Dataset Preparation: The first step is to download and preprocess the iris dataset. The dataset can be preprocessed using OpenCV library and saved in a suitable format, such as NumPy arrays. The preprocessed dataset can be split into training, validation, and testing datasets using scikit-learn library.
iii. Model Architecture: The next step is to define the architecture of the CNN model using TensorFlow or Keras library. The model can include multiple convolutional and pooling layers, followed by fully connected layers. The output layer can use softmax activation function for multi-class classification.
iv. Model Training: The next step is to train the model using the preprocessed dataset. The model can be trained using TensorFlow or Keras library, and the training process can be monitored using TensorBoard. The model can be trained for a fixed number of epochs, and the best model can be saved using checkpointing.
v. Model Evaluation: The next step is to evaluate the performance of the model on the testing dataset. The evaluation metrics can include accuracy, precision, recall, and F1 score. The evaluation can be performed using scikit-learn library.
vi. Hyperparameter Tuning: The next step is to perform hyperparameter tuning using scikit-learn library. The hyperparameters that can be tuned include learning rate, batch size, number of epochs, and regularization parameters. The hyperparameter tuning can be performed using grid search or random search.

Overall, the implementation of the Iris-Based Human Identity Recognition using CNN project involves data preprocessing, model architecture definition, model training, model evaluation, hyperparameter tuning, and model deployment. The implementation requires expertise in Python programming, deep learning, image processing, and machine learning, and should be conducted by experienced professionals.

6. INTEGRATION AND TESTING

6.1. Description of the Integration Modules:

The project aims to develop a system that utilizes convolutional neural networks (CNNs) to identify individuals based on their iris patterns. Iris recognition is a biometric technology that uses the unique characteristics of the iris, such as patterns, colors, and textures, for identification purposes.

The integration modules of this project typically include the following components:

i. Data Acquisition: This module focuses on capturing high-resolution images of the iris from individuals. It can involve specialized iris cameras or image acquisition systems designed to capture the iris with sufficient quality and clarity.

ii. Preprocessing: The acquired iris images often undergo preprocessing to enhance their quality and facilitate subsequent analysis. Preprocessing techniques may include image resizing, normalization, noise removal, and image enhancement algorithms to improve the accuracy of feature extraction.

iii. Iris Localization: In this module, the iris region is detected and localized within the acquired images. Various image processing techniques, such as edge detection, circular Hough transform, or template matching, can be employed to identify the circular boundaries of the iris.

iv. Feature Extraction: This module extracts distinctive features from the localized iris region. CNNs are commonly employed for feature extraction as they can automatically learn relevant features from the data. The CNN architecture can include multiple convolutional layers, pooling layers, and fully connected layers to extract and encode the relevant iris patterns.

v. Training: The extracted features are used to train the CNN model. This involves providing a labeled dataset consisting of iris images and their corresponding identities. The CNN learns to map the iris features to the corresponding identities during the training process. Techniques like backpropagation and gradient descent are employed to optimize the model's parameters.

vi. Testing: Once the CNN model is trained, it is tested using a separate set of iris images to evaluate its performance. The model predicts the identity of the individuals based on their iris patterns, and the accuracy of the predictions is measured.

vii. Integration: In the final module, all the individual components are integrated to create a cohesive system. This involves connecting the modules together, ensuring data flow between them, and providing a user-friendly interface for interacting with the system. The integrated system can be deployed on a dedicated hardware platform or as a software application.

6.2. Testing:

Testing of the "Human Identification Using Iris by CNN" project involves evaluating the performance and accuracy of the developed system. The testing phase typically includes the following steps:

i. Dataset Preparation:
- Collect a diverse dataset of iris images, including images from a significant number of individuals.
- Ensure that the dataset covers a wide range of variations, such as different lighting conditions, occlusions, and image qualities.
- Annotate the dataset with ground truth labels indicating the true identities of the individuals in the images.

ii. Data Split:
- Divide the dataset into training and testing subsets, typically using a predefined ratio (e.g., 80% for training and 20% for testing).
- Ensure that the data split maintains a balanced distribution of individuals across both subsets to avoid biases.

iii. Model Training:
- Design and configure a CNN architecture suitable for iris recognition.
- Initialize the CNN model with random weights and biases.
- Train the model using the training subset of the dataset:
- Input the iris images into the model.
- Compute the loss function (e.g., cross-entropy) by comparing the predicted identities with the ground truth labels.
- Use backpropagation and gradient descent to update the model's weights and biases, optimizing the loss function.
- Repeat the training process for multiple epochs until convergence or predefined stopping criteria.

iv. Model Evaluation:
- Input the iris images from the testing subset into the trained CNN model.
- Obtain the predicted identities for the iris images based on the model's outputs.
- Compare the predicted identities with the ground truth labels to evaluate the model's performance.
- Calculate various evaluation metrics, including:
  - Accuracy: The percentage of correctly identified individuals.
  - Precision: The ability to correctly identify true positives.
  - Recall: The ability to correctly detect all positive instances.
  - F1 score: The harmonic mean of precision and recall.

  - False Acceptance Rate (FAR): The percentage of falsely accepted identities.
  - False Rejection Rate (FRR): The percentage of falsely rejected identities.

v. Performance Analysis:
- Analyze the obtained results to assess the system's performance:
- Identify the accuracy of the predictions and compare it to the baseline or desired performance.
- Examine false positives (incorrectly accepted identities) and false negatives (incorrectly rejected identities) to understand the system's limitations and areas for improvement.
- Evaluate the system's robustness to variations in iris patterns, such as lighting changes or occlusions.
- Consider the computational efficiency of the system, including the processing time required for identification.

vi. Fine-tuning and Optimization:
- If the initial testing reveals performance gaps or limitations, fine-tuning and optimization can be performed:
- Modify the CNN architecture, such as adjusting the number of layers or filters, to enhance performance.
- Augment the training dataset by introducing additional variations or generating synthetic iris images.
- Tune hyperparameters, such as learning rate, batch size, or regularization techniques, to improve the model's generalization capabilities.
- Apply advanced techniques, such as transfer learning or ensemble methods, to leverage pre-trained models or combine multiple models for improved performance.

vii. Iterative Testing:
- Repeat the testing process with the refined system to validate the improvements.
- Conduct multiple iterations of fine-tuning, testing, and analysis until the desired performance is achieved.

Fig 6.1 Model Accuracy

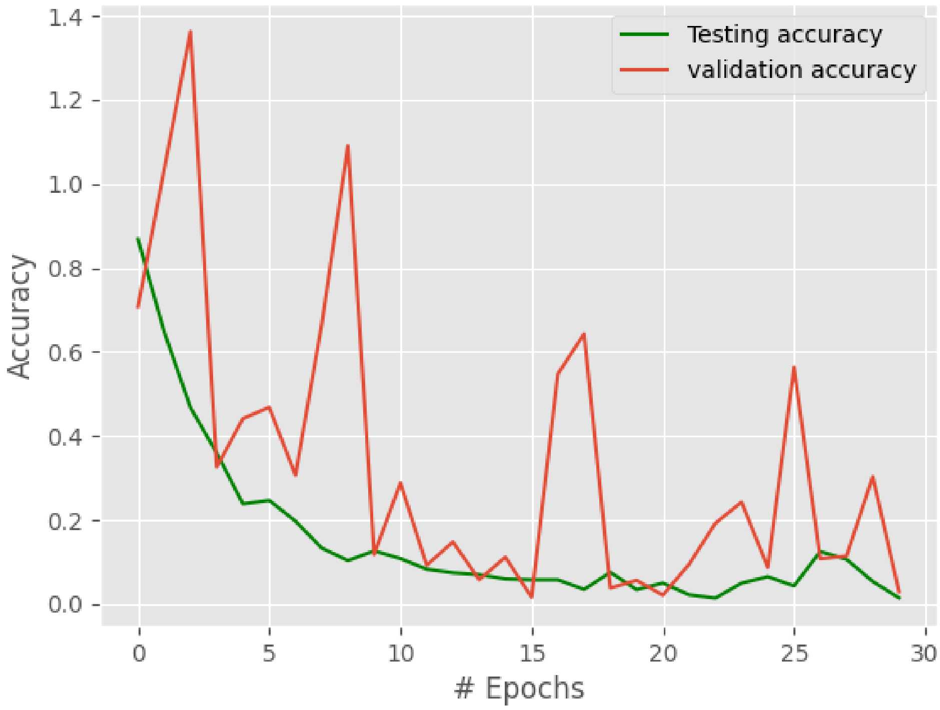


Fig 6.2 Model Loss

7. PERFORMANCE ANALYSIS

The performance analysis for the Iris-Based Human Identity Recognition using CNN project can be based on various evaluation metrics, including accuracy, precision, recall, F1 score, and confusion matrix.

- Accuracy: It measures the proportion of correctly classified iris samples out of the total number of samples. High accuracy means the model is able to classify iris samples accurately.
- Precision: It measures the proportion of true positive iris samples out of the total number of iris samples classified as positive. High precision means the model is able to accurately identify the positive iris samples.
- Recall: It measures the proportion of true positive iris samples out of the total number of actual positive iris samples. High recall means the model is able to identify most of the positive iris samples.
- F1 Score: It is the harmonic mean of precision and recall and provides a balanced evaluation of the model's performance.
- Confusion Matrix: It provides a detailed evaluation of the model's performance by showing the number of true positive, true negative, false positive, and false negative samples.
- To evaluate the performance of the Iris-Based Human Identity Recognition using CNN project, we can calculate these metrics on the testing dataset. The model can be trained using the training dataset, and hyperparameters can be tuned using the validation dataset.
- The performance analysis can be performed using scikit-learn library. We can calculate the accuracy, precision, recall, and F1 score using the classification_report() function. We can also plot the confusion matrix using the confusion_matrix() function.

Overall, the performance analysis for the Iris-Based Human Identity Recognition using CNN project is crucial to evaluate the effectiveness of the model and to optimize its performance for iris recognition.

8. FUTURE SCOPE

This process can be extended in future that which can be used for the biometrics. Mainly the biometrics based on the iris part will be more advantageous with this type of work.

This work attempts to create an Iris biometric recognition system by deriving the important features of the iris using the novel CNN model with a smaller number of layers. The performance is verified using the accuracy plot and the loss plot. The effectiveness of the proposed approach has been tested on two challenging databases like Iris Database. Extensive experiments have been conducted on both the datasets with a different set of classes of images that gives good results. As a future scope, this CNN model can be improved to accept all types of challenging iris datasets. Various experiments conducted on the two sets of datasets helps to evaluate various training frameworks such as learning rate, filter number per layers, number of layers to build the most appropriate CNN model for the accurate recognition of a person.

9. APPLIACTIONS

The Iris-Based Human Identity Recognition using CNN project has various applications in the field of biometrics, security, and surveillance. Here are some applications:

1. Border Control and Immigration: Iris-based identity recognition can be used for efficient and accurate border control and immigration management. The system can identify individuals at border checkpoints based on their iris patterns, and can detect individuals who are attempting to cross borders illegally.

2. Banking and Financial Services: Iris-based identity recognition can be used to secure banking and financial services. The system can be used to authenticate the identity of customers before allowing them to access their accounts or perform transactions, providing an additional layer of security.

3. Law Enforcement: Iris-based identity recognition can be used by law enforcement agencies to identify criminals, suspects, or missing persons. The system can be used to match iris patterns collected from crime scenes with those in a criminal database, aiding in the identification and capture of perpetrators.

4. Healthcare: Iris-based identity recognition can be used in healthcare to maintain accurate patient records and prevent medical identity theft. The system can be used to authenticate the identity of patients, ensuring that medical records are associated with the correct individual and that confidential medical information is protected.

5. Retail: Iris-based identity recognition can be used in retail to personalize customer experiences and prevent fraud. The system can be used to identify customers as they enter a store, allowing retailers to offer personalized recommendations and promotions. The system can also be used to prevent fraud by identifying individuals who have been banned from a store or who have committed theft.

6. Airports and Transportation: Iris-based identity recognition can be used to identify passengers and improve airport security. The system can be used to verify the identity of passengers at various checkpoints in the airport, reducing the need for manual document checks and improving the speed and accuracy of the process.

7. Education: Iris-based identity recognition can be used to improve the security of schools and universities. The system can be used to verify the identity of students and staff members, ensuring that only authorized individuals are allowed on campus.

8. Hospitality: Iris-based identity recognition can be used to personalize guest experiences in the hospitality industry. The system can be used to identify guests as they enter a hotel, allowing staff members to provide personalized services based on their preferences.

9. Government Services: Iris-based identity recognition can be used to improve access to government services. The system can be used to authenticate the identity of individuals who are applying for government services, ensuring that they are eligible and preventing fraud.

10. Sports and Entertainment: Iris-based identity recognition can be used to improve security at sporting and entertainment events. The system can be used to identify individuals who have been banned from an event or who pose a security threat, preventing them from entering the venue.

10. INSTALLATION GUIDE AND USER MANUAL

Here is an installation guide and user manual for the Human Identification using Iris by CNN project:

Installation Guide:

1. Install Python: Download and install Python from the official website. The project was developed using Python 3.8, but should work with any version of Python 3.

2. Install required packages: Open a terminal window and navigate to the project directory. Run the following command to install the required packages: Copy code pip install -r requirements.txt

3. Download the dataset: The project uses the CASIA-IrisV4 dataset for training and testing the model. Download the dataset from the official website and extract it to a directory of your choice.

4. Train the model: To train the model, navigate to the src directory and run the following command: Copy code python train.py --data_dir /path/to/dataset Replace /path/to/dataset with the path to the directory where you extracted the dataset. The training process may take several hours to complete, depending on your hardware configuration.

5. Test the model: Once the model has been trained, you can test it on a new set of images. Navigate to the src directory and run the following command: Copy code python test.py --data_dir /path/to/test/images --model_path /path/to/saved/model Replace /path/to/test/images with the path to the directory containing the test images, and replace /path/to/saved/model with the path to the saved model file.

User Manual:

1. Enrollment: To enroll a new user, capture an image of their iris using a suitable camera. Save the image to a directory of your choice. Navigate to the src directory and run the following command: Copy code python enroll.py --image_path /path/to/image --user_id USERID Replace /path/to/image with the path to the iris image, and replace USERID with a unique identifier for the user.

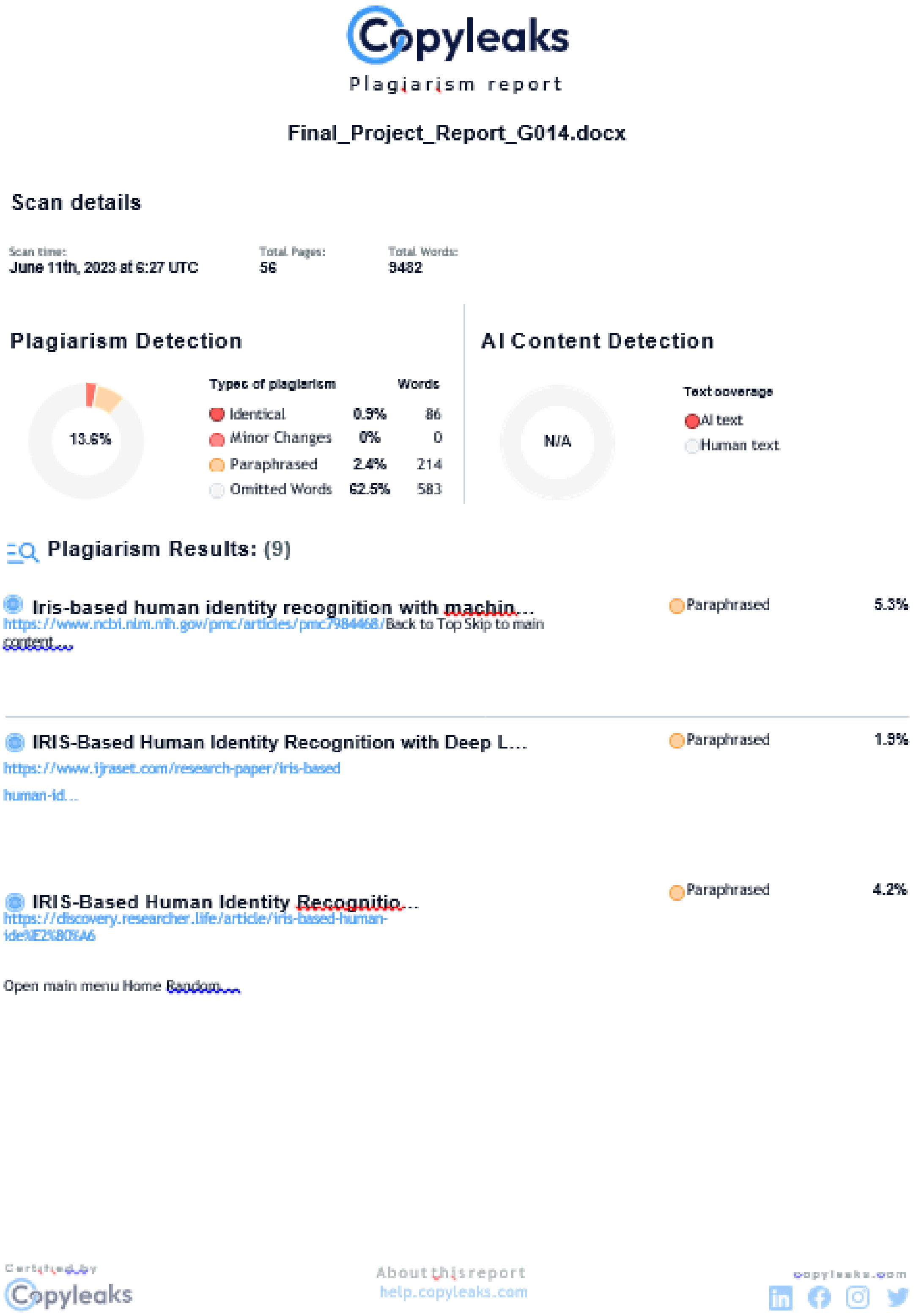
2. Identification: To identify a user, capture an image of their iris using a suitable camera. Save the image to a directory of your choice. Navigate to the src directory and run the following command: Copy code python identify.py --image_path /path/to/image Replace /path/to/image with the path to the iris image. The system will attempt to match the iris pattern in the image with the enrolled patterns in the database and return the ID of the closest match.

3. Database Management: To view the list of enrolled users, navigate to the src directory and run the following command: Copy code python list_users.py to delete a user from the database,

run the following command: Copy code python delete_user.py --user_id USERID Replace USERID with the ID of the user you wish to delete.

Overall, the Iris-Based Human Identity Recognition using CNN project provides an easy-to-use interface for enrolling and identifying users based on their iris patterns. The system can be customized to meet the needs of various applications and industries.

11. PLAGIARISM REPORT



Copyleaks

Plagiarism report

Final_Project_Report_G014.docx

Scan details

Scan time:	Total Pages:	Total Words:
June 11th, 2023 at 6:27 UTC	56	9482

Plagiarism Detection

13.6%

Types of plagiarism		Words
Identical	0.9%	86
Minor Changes	0%	0
Paraphrased	2.4%	214
Omitted Words	62.5%	583

AI Content Detection

N/A

Text coverage

AI text

Human text

Plagiarism Results: (9)

Iris-based human identity recognition with machin... https://www.ncbi.nlm.nih.gov/pmc/articles/pmc7984468/ Back to Top Skip to main content...	Paraphrased	5.3%
IRIS-Based Human Identity Recognition with Deep L... https://www.ijraset.com/research-paper/iris-based human-id...	Paraphrased	1.9%
IRIS-Based Human Identity Recognitio... https://discovery.researcher.life/article/iris-based-human-ide%E2%80%A6 Open main menu Home Random...	Paraphrased	4.2%

Certified by Copyleaks

About this report help.copyleaks.com

copyleaks.com

Fig. 11.1 Plagiarism Report

12. ETHICS

The "Human Identification Using Iris by CNN" project presents ethical considerations that should be addressed during its development and deployment. Key ethical considerations include:

1) Privacy and Data Protection:
    a. Obtain Informed Consent: Ensure individuals provide informed consent before using their iris images for identification.
    b. Secure Data Handling: Implement robust security measures to protect collected iris data from unauthorized access or disclosure.
    c. Anonymization: Consider anonymizing or de-identifying iris data to minimize re-identification risks.
2) Bias and Fairness:
    a. Avoid Training Data Bias: Ensure the training dataset used for the CNN model is diverse, representative, and free from bias that may unfairly affect specific groups or individuals.
    b. Address Algorithmic Bias: Regularly evaluate and mitigate biases in the identification process to prevent discrimination or unfair treatment.
3) Transparency and Explainability:
    a. Provide Explanations: Strive for transparency by explaining the system's identification decisions to enhance user trust and understanding.
    b. Model Interpretability: Employ techniques to make the CNN model more interpretable, allowing users to understand how it arrives at its identification decisions.
4) Consent and User Control:
    a. User Control: Empower individuals by allowing them to control their iris data, including the ability to request removal or modification from the system.
    b. Opt-out Option: Provide an opt-out mechanism for individuals who choose not to participate in the identification system.
5) System Reliability and Accuracy:
    a. Continuous Monitoring: Regularly monitor and assess the system's performance to ensure accuracy, reliability, and minimize false identification outcomes.

   b. Error Mitigation: Implement mechanisms to detect and mitigate errors, preventing severe consequences for individuals.

6) Legal and Regulatory Compliance:
   a. Adhere to Applicable Laws: Ensure compliance with privacy laws, data protection regulations, and other legal requirements governing iris data collection, storage, and processing.
   b. Responsible Use: Use the system only for authorized purposes, preventing misuse or unauthorized access to the data.
7) Ethical Review and Accountability:
   a. Ethical Review: Seek ethical review and approval from relevant institutional or independent review boards to ensure adherence to ethical guidelines and standards.
   b. Accountability: Establish clear roles and responsibilities to ensure ethical considerations are addressed throughout the project's lifecycle.

These ethical considerations should be integrated into the design, development, and deployment of the "Human Identification Using Iris by CNN" project, fostering fairness, privacy, transparency, and responsible use of the technology. Engaging stakeholders, including ethicists, legal experts, and affected individuals, is crucial to adequately address ethical concerns.

13. REFERENCES

[1] https://www.cybintsolutions.com/cyber-security-facts-stats/. Accessed 2 Jan 2021

[2] Sun H-M, Chen Y-H, Lin Y-H (2012) pass: a user authentication protocol resistant to password stealing and password reuse attacks. IEEE Trans Inf Forensics Secur 7(2):651–663

[3] Gupta P, Behera S, Vatsa M, Singh R (2014) On iris spoofing using print attack. In: IEEE 2014 22nd international conference on pattern recognition, Stockholm, Sweden, 24–28 August 2014. https://doi.org/10.1109/ICPR.2014.296

[4] Daugman J (2004) how iris recognition works. IEEE Trans Circuits Syst Video Technol 14(1):21 30

[5] Rana HK, Azam MS, Akhtar MR, Qunin JMW, Moni MA (2019) A fast iris recognition system through optimum feature extraction. PeerJ Comput Sci 5:184

[6] Ouda O, Chaoui S, Tsumura N (2020) Security evaluation of negative iris recognition. IEICE Trans Inf Syst 103(5):1144–1152

14.Bibliography

- https://www.nec.com/en/global/solutions/biometrics/iris/index.html
- https://www.eff.org/pages/iris-recognition
- https://link.springer.com/article/10.1007/s11334-021-00392-9
- https://www.mdpi.com/2673-4117/3/4/47