

Developing IRIS segmentation by using U-Net Model



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A Thesis Submitted to the Department of Computer Science and Engineering,

School of Electrical Engineering and Computing

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Declaration

I declare that this thesis proposal entitled “**Developing IRIS segmentation by using U-Net Model**”.is my own work and has not been submitted to any university for a similar purpose. The references used in this proposal are duly recognized by proper citations.

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Recommendation of Advisors

I, the major advisor of this research proposal, hereby certify that I have closely advised the student while developing this proposal and read the draft thesis entitled “**Developing IRIS segmentation by using U-Net Model**” prepared under my guidance by **Samrawit Alemayehu**. Therefore, I recommend the submission of the thesis to the department for further review and evaluation.

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Approval Page for Thesis Proposal

I hereby certify that the recommendation and suggestion given by the proposal review committee are appropriately incorporated into the final thesis proposal entitled “**Developing IRIS segmentation by using U-Net Model**” by **Samrawit Alemayehu**.

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We, the undersigned, members of the Board of Reviewers of the proposal open defence by **Samrawit Alemayehu** have read and evaluated his thesis proposal entitled “**Developing IRIS segmentation by using U-Net Model**” and assessed the understanding of the candidate about the proposed research. This is, therefore, to certify that the thesis proposal is accepted and we recommend the implementation of the proposal.

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List of Abbreviations and Acronyms

ATM	Automated Teller Machine
CED	Conventional Encoder-Decoder
CHT	Circular Hough Transform
CNN	Conventional Neural Network
ECG	Electrocardiogram
EEG	Electroencephalogram
FAR	False Acceptance Rate
FC	Fully Connected
FRR	False Rejection Rate
HCNNs	Hierarchical Conventional Neural Networks
HT	Hough transform
MFCNs	Multi-scale Fully Conventional Networks
NIR	Near-infrared
R-CNN	Region-based Conventional Neural Network
ROI	Region Of Interest
SSD	Single-shot Detector

Abstract

Abstract

Biometric authentication stands out as a superior method compared to traditional identification techniques due to the inherent uniqueness of various physiological and behavioral traits in individuals. Additionally, biometric markers such as fingerprints, facial patterns, hand geometry, retinal scans, palm prints, voice, gait, signatures, and keystroke dynamics are commonly employed for authentication.

On the other hand, conventional security measures like token-based systems, encoded cards, passwords, and PINs suffer from numerous limitations. Hence, the primary goal of this study is to employ deep learning techniques for Iris segmentation, aiming to enhance image quality and overall biometric system performance. The study's scope is specifically focused on iris segmentation using machine learning models due to the complexity of iris recognition systems.

The proposed iris segmentation system comprises several key components including image acquisition, iris segmentation, feature extraction, and matching for recognition. Datasets from repositories like CASIA were utilized, supplemented by locally collected images from volunteers for testing purposes. Limitations in image quality due to factors like light reflection, camera orientation, and uniformity of eye shape were identified. Testing data underwent pre-processing and feature extraction following the same methodology as model training.

Experimental research approaches were adopted to address the research questions, with the proposed iris segmentation system consisting of localization, normalization, feature extraction, and matching components. The importance of relevant feature extraction in building an efficient iris recognition model is highlighted, utilizing techniques such as HOG for structure description and vector support machines for classification.

The Unet model has been used to segment iris datasets obtained from the Cassia repository, utilizing specific parameters. Results indicated that efficient iris segmentation presents challenges dependent on dataset specificity and feature extraction techniques. Thus, researchers and stakeholders are encouraged to prioritize feature extraction and ROI identification to develop efficient iris recognition models.

Challenges in iris segmentation, particularly related to complex eye structures, were observed, with potential solutions including the use of standard cameras for clear image acquisition and mitigating

the impact of light on pupil visibility. In conclusion, further exploration in biometric security techniques is warranted to design robust and generalized iris recognition systems. Young researchers are encouraged to innovate in this domain to safeguard organizational and personal resources effectively using iris recognition methods.

Keywords: Biometrics identification, Iris recognition, iris segmentation, deep learning

Chapter One

1. Introduction

1.1. Background of the Study

For many applications utilized in different types of companies, there is a clear need for more security measures. Simple passwords and pins are examples of traditional security techniques that are getting ever more fragile and unsafe to use. Keys and other possession-based security measures have always been vulnerable to theft by hostile individuals. Because of this, using biometrics is a security alternative that is becoming more and more common and efficient. Biometrics offers a more competent and dependable authentication system than previous identification methods since numerous physiological and behavioral traits are unique to every human being. The following traits of human physiology or behavior can be utilized as biometric features: universality, uniqueness, permanence, and collectability. In essence, a biometric system is a pattern recognition system that works by collecting biometric data from a person, using that data to extract a feature set, and then comparing that feature set to a template set stored in the database.

The previous form of biometrics incorporated distinct proof of persons through special bodily characteristics, certain unique features that separate them from other individuals, such as skin color or texture, retina, voice, and height. Fingerprint, face patterns, hand geometry, retina, palm print, voice, gait, signature, and keystroke dynamics are some of the biometric markers that are often utilized for person authentication. Behavioural traits are associated with patterns of behavior and natural qualities of the human person such as signature, voice, keystroke, ear, giant, and so forth. Whereas physiological features are concerned with the physical appearance of the human body, such as the face, fingers, and iris.

Although the fingerprint and face are valuable characteristics for biometric identification, they come with limitations due to possible alterations over time, lookalikes, and bodily modifications like burns or wounds. An iris is not easily altered or damaged, unlike a finger or thumb print, which varies significantly over the course of a person's life and is universally different, even amongst identical twins. Therefore, if a finger is unclean, scratched, etc., iris scanners do not suffer from the same problems as fingerprint scanners. Iris scanners are a great biometric identifier because of these factors. One of the most promising technologies of the twenty-first century is iris recognition. Iris recognition has numerous superior properties over other biometric techniques, including high uniqueness and stability, non-invasiveness, and anti-falsification. The practical application of iris recognition systems will have an immense amount of potential because of the

rising needs for access control, remote monitoring, attendance tracking, and other person authentication situations.

There are many uses for iris image-based biometric systems nowadays, nevertheless the processing flow of any typical iris image-based biometric system is similar and here presented in fig 1.

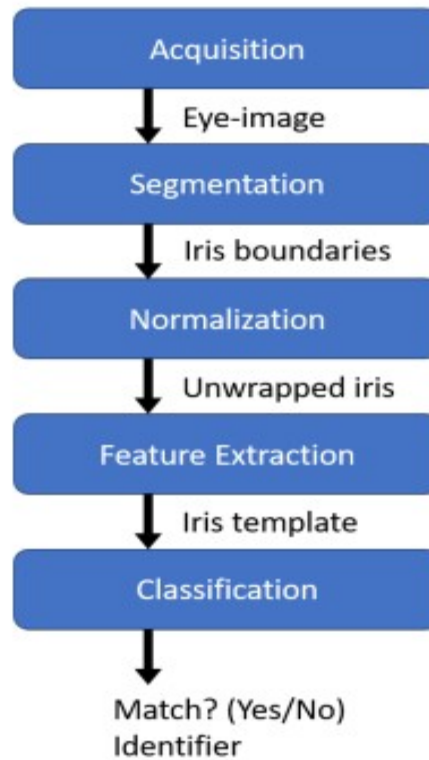


Figure 1: A basic flow of the iris recognition systems

The acquisition stage entails taking an image of an eye using a camera. Most iris identification systems nowadays use a regulated setup and an NIR imaging sensor. Following capture, pictures were pre-processed using methods for enhancing or filtering the image in order to help in segmentation or feature extraction. During the segmentation stage, the iris' borders are identified. These limits define the region containing the iris in the shape of an annulus.

During the normalization stage, the image is processed to remove undesired information and noise, such as polar coordinates, light reflections, and occlusions of the eyelashes or lids. The process of feature extraction involves identifying a feature vector that might be used to identify the candidate iris uniquely. Feature vectors are bit-string representations of what are commonly referred to as iris templates. Finding a match between the local iris template and one or more (Minaee & Abdolrashidi, 2019) iris templates that have already been recorded in a database is the goal of the classification stage, which comes after feature extraction.

The main operation in the iris identification method is iris segmentation. An essential component of the overall iris identification system, according to Xiaoyan, is the iris border segmentation phase. Iris textures are localized in the iris area around the pupillary border in an iris image. In the process of feature extraction, many iris textures will be overlooked if the pupillary region's border is not precisely detected. If the limbus boundary is not precisely identified in the iris segmentation stage, many noisy features will be retrieved in the feature extraction step because the limbus border is typically hidden by eyelashes, eyelids, and specular reflections. The overall iris recognition system's performance will suffer as a result of these characteristics.

Several studies have used various iris segmentation techniques to increase the identification accuracy. Conventional techniques frequently provide subpar results when dealing with iris pictures obtained under these circumstances. According to recent research, deep learning techniques may perform very well on tasks involving the segmentation of iris images (Abdullakutty et al., 2022). In this work, we suggested a transfer learning-based iris identification system. U-Net architecture-based models, VGG and R-CNN architecture-based models, and other CNN architecture-based models are a few of the well-known deep learning architectures in use.

1.2. Statement of the problem

Traditional security methods, which include token-based authentication, encoded cards, secret passwords, and personal identification numbers to verify an individual's identity, have a wide range of shortcomings. Tokens, for instance, might be misplaced, lost, stolen, or forgotten, and a legitimate user's PIN could become lost or guessable by a fraudster. Because techniques that rely on knowledge or tokens cannot distinguish between an authorized individual and a fraudster who obtains the token or information about an authorized individual through deception. These methods are vulnerable to mistakes and inadequate for meeting the security demands of a digitally connected information-driven society.

Given that they essentially solve the majority of the issues associated with traditional identification, biometric approaches for human identification have garnered a lot of interest lately. The biometric modality with the best performance, in terms of false acceptance rate (FAR) and false rejection rate (FRR), is iris recognition since it is globally unique. One of the most reliable biometric identifying methods is the iris, which has many intricate, one-of-a-kind traits that may be used for identification.

Notwithstanding these benefits, the implementation of an iris identification system is regarded as a difficult task since the iris acquisition process could bring up irrelevant components; for example, when the iris is photographed from a distance, certain sections of it are often obscured

by the eyelid and lash. A circle is not usually the pupil's limit. There will be portions of the pupil that are visible in the localized iris region when the iris boundary is roughly represented by circles. All of these variables will affect the processing that comes after since a poorly depicted iris pattern will always lead to subpar recognition results..

Six fundamental phases make up a typical iris recognition system: iris image acquisition, image preprocessing, segmenting the iris boundaries, normalizing the iris image, extracting features, and matching features. An essential component of the overall iris identification system is the iris border segmentation stage. The iris area around the pupillary border is where the majority of iris textures are located in an iris image. In the process of feature extraction, many iris textures will be neglected if the pupillary region's border is not precisely detected. The limbus boundary is typically hidden by eyelashes, eyelids, and specular reflections. As a result, if the limbus boundary is not precisely identified during the iris segmentation step, many noisy features will be extracted during the feature extraction stage. The effectiveness of the iris recognition system as a whole will be impacted from these characteristics.

In order to determine the part of the iris image that will be used for iris recognition, extracting the iris component from the acquired eye image, or more broadly, segmenting the iris portion in an eye image, is a crucial operation for any iris recognition system. Given the varied character of the iris images, as demonstrated by the example image in Figure 1.1, this approach can be quite difficult. Additionally, because of the richness and complexity of the iris texture, it is quite difficult to extract the key iris features that are used to represent the iris sample. Since deep learning techniques are more suitable for enhancing segmentation techniques than standard approaches, this study focuses on them.

1.3. Research Questions

In this study, the researcher attempts to answer the following research question.

RQ1: How can the system eliminate different noise types in segmentation phase which influences of the iris recognition system?

RQ2: What are the most effective deep learning techniques to improve iris segmentation?

RQ3: How to develop a better iris segmentation method for iris recognition system?

1.4. Research Objective

1.4.1. General Objective

The main objective of this study is to develop Iris segmentation using deep learning techniques to enhance the iris image quality and performance of the biometric system

1.4.2. Specific Objectives

- To review literature methods and techniques used on segmentation phase of iris recognition system
- To identify the major problem of iris image noise that influence the process of image segmentation.
- To develop an iris segmentation method using deep learning techniques and to collect dataset for training and testing.
- To test and evaluate the performance of developed techniques.

1.5. Significance of the Study

Identity fraud in welfare disbursements, credit card transactions, cell phone calls, and ATM withdrawals totals over \$6 billion annually, so organizations are seeking ways to automate personal identity authentication mechanisms in order in order to boost their client satisfaction along with operational effectiveness as well as to save critical resources (Jain et al., 1998). In addition, the development of a highly accurate automatic personal identification system is becoming increasingly important as people become more electronically connected. On top of that, biometric Iris identification is strongly advised; nevertheless, due to problems with Iris image noise, Iris segmentation can identify fake images. Furthermore, the accuracy of the iris system will be improved due to the deep learning-based image segmentation enhancement.

This research primarily benefits organizations that require high security for their data and resources for customers and authorized users. The results of this study generally have an impact on providing high-quality services and managing misconduct committed by both customers and employees, which costs the nation a significant amount of money annually. Furthermore, biometric security can be applied to a variety of organizations. The results of this research can serve as benchmarks for other governmental and private sector entities that intend to deploy highly secure systems.

1.6. Delimitation Scope

1.6.1 Scope of the study

The Scope of the study focuses on developing iris segmentation using deep learning techniques. In this study because of it is complex in nature of iris recognition system we only focus on iris segmentation using machine learning models.

Limitation of the study

Even though there are various traditional and other iris segmentation techniques available. But the limitations of this study are related with only deep learning techniques only.

1.7. Operational Definitions

It is divided into six chapters, each of which focuses on a different component of the research and provides a reason.

Chapter One: - describes the background of the study, the statement of the problem and the research question to be answered, the methodology to achieve the objective of the study, the scope and limitations, and the expected outcomes of this study.

Chapter Two: - gives an overview Literature Review and Related work

Chapter Three: - have a methodology that includes a tool for development

Chapter Four: - Implementation of the proposed system

Chapter Five: - This chapter deal with results and discussion on the experiment output

Chapter Six: - The last chapter focus on the conclusion and recommendation

Chapter Two

2. Literature Review and Related work

2.1. Biometrics Identifications

We need to be able to differentiate a person from everyone else in order to customise an experience or make an application more secure and less accessible to unwanted persons (Minaee & Abdolrashidi, 2019). Notably, such traditional security methods might be purposefully deleted, exchanged, or recreated. To deal with these flaws, scholars have been working hard to develop more durable human recognition systems, such as biometric security systems. Humans are recognized by physiological and/or behavioral features such as gait, scent, fingerprint, DNA, iris, ear, palm, and others. These methods, unlike traditional systems, do not require a person to always remember (e.g., PIN) or take something (e.g., passport) to the identification location. Without a doubt, this technology has recently become critical in surveillance and security services. It is now operational in a number of nations, including Australia, Afghanistan, the United Arab Emirates, Canada, Gambia, Germany, and the United States. It has a wide range of usage, including health and care, citizen registration, forensics and criminal investigation, law enforcement agencies, passport and immigration, border crossing control, and so on (Jan, 2017).

Because of significant developments in computer and processing technology, automated biometric systems have only recently emerged as available. despite the fact biometric technology appears to be of the twenty-first century, its history dates back thousands of years. The ancient Egyptians and Chinese played important roles in the history of biometrics. Biometrics are physical or behavioral human characteristics that have sped up and simplified life. This system is based on something that an individual possesses, so the individual does not need to remember anything. The advantage of biometric authentication over traditional methods is that it can perform an individually tailored compatibility test between the individual and the data fed into it. Numerous improvements have been accomplished in recognition systems based on physiological characteristics but this is not the case when it comes to recognition systems based on behavior (Rai et al., 2020).

The emphasis today is on utilizing biometric face recognition, iris recognition, retina recognition, and identifying traits to combat terrorism and increase security measures. A biometric system is defined as a system that collects biometric data, extracts and stores the necessary sets of characteristics, and then compares and matches it with a preset permitted dataset. The application can be seen in Access control, border security, law enforcement, surveillance systems, and financial devices are only a few examples (Abdullakutty et al., 2022).

Fingerprints have shown to be the most trustworthy individual identification method at a reasonable price, however recent worldwide pandemics have served as a stimulus for face biometrics, since they may make it simpler to regulate viral propagation rates and adhere to social distancing norms. As a result, since then, the majority of research has been devoted to the field of study of face recognition, and numerous algorithms have been presented to improve the precision and reliability of this biometric in a wide variety of applications. Other biometrics consist of: iris, hand geometrics, palmprint, voice, signature, ear shape, knuckle crease, DNA, gait, electroencephalogram (EEG), and electrocardiogram (ECG); among which the last four are still in the early stages of study and are not fully relevant., yet. Universality, uniqueness, permanency, collectability, and acceptability can best describe required characteristics of an ideal biometric trait (El-Abed et al., 2012).

Considering the biometric process is often a pattern-recognition approach, data collecting, pre-processing, data representation, and decision-making are all essential. This demonstrates the extraction of people's physiological or behavioral characteristics traits. Previously, biometrics utilized it as a template database to be used for recognition later on.

Biometric methods research has received a greater emphasis in recent years as security concerns have become more prevalent. Both people and governments are acting and becoming more pro-active in security matters as a result of the rising crime rate. This desire for security includes the need for people to safeguard their living arrangements, residences, personal belongings, and investments, among other things. The most effective biometric methods have been created and are being refined, and they are used in regular law enforcement and security applications. Modern approaches are used in a number of biometric technologies. Iris recognition is one of them, and it is currently thought to be the most effective security authentication method (Tann et al., 2019)

2.2. Iris image biometrics

It has been proven to be an extremely effective authentication method because the human iris is as unique as a fingerprint. The human iris does not change as much as a fingerprint or thumbprint throughout a person's lifetime, nor is it easy to damage or modify. Consequently, iris scanners do not suffer from dirt, scrapes, etc., as fingerprint scanners do, allowing them to function as excellent biometric identifiers. A typical IRS consists of seven phases in either a traditional or deep learning approach: the acquisition of the iris image, the preprocessing phase, the segmentation phase, the normalization phase, the extraction of features, the selection phase, and finally the classification or matching of the iris image (Malgheet et al., 2021).

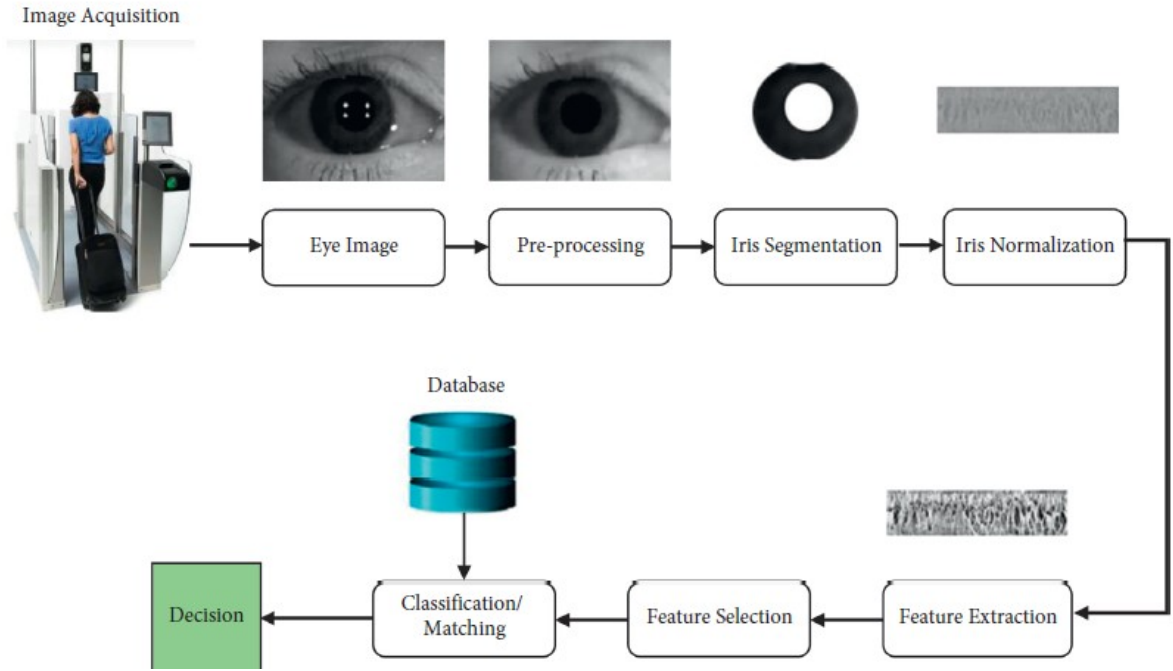


Figure 2: A fundamental structure of the iris recognition system (IRS)

2.2.1. Iris image Acquisition

The most difficult aspect in in iris recognition system are imagine acquisition and processing phases. This sub-process's completion is heavily dependent on user collaborating. The user's eye must be quite close to the lens during scanning. Furthermore, spectacles must be removed to prevent signal interference. When the user looks into the camera, he or she sees a green light on a white background. When the camera is turned on, the green light travels throughout a 360-degree circle. During this procedure, the blood vessel pattern of the retina is collected. At this point, three to five images are captured. The capture process might take up to one minute depending on the extent of user participation. The retina images must be clean and firm during image acquisition (Sadikoglu, 2016).

An iris imagine is often captured utilizing the visible spectrums or near-infrared (NIR) wavelength spectrum types. Lighting, lens, sensor, and console are the four parts responsible for iris image acquisition. Images captured in the NIR spectrum tend to interact with the iris region's complex texture rather than its pigmentation (Malgheet et al., 2021). Furthermore, using NIR iris image captured are less susceptible to different forms of noise than visible wavelength spectrum captured iris images. The majority of iris image databases of the iris image are obtained using the NIR spectrum, but some are captured using the visible wavelength (VIS) spectrum.

The iris image has so many degrees of freedom that it might be considered a sophisticated texture in contrast to the random textures provided by the human iris. To obtain the highest level of

identification accuracy, several factors in the iris recognition system should be taken into account and given the ideal threshold values. These variables comprise the input image's size as well as the normalized rectangular image's radial and angular resolutions, r and θ respectively. The number of retrieved coefficients will be determined using that. Daugman's proposal uses 2,048 bit iris template to calculate the hamming distance under different dissimilarity threshold values to calculate the recognition system accuracy (Alrifae et al., 2017) were compared 13 free available iris databases according to five criteria's (database size, light source, imaging distance and the noise factors) by categorized in two types, and the first category contains the noise free iris databases that have been captured under NIR light source (CASIA, BATH, MMU, ICE and WVU). While the noisy iris databases that have been captured under visible wavelength light source (UPOL, UBIRISv.1 and UBIRISv.2) fall in the second category.

Apart from iris capture devices there are a number of databases of iris images worldwide to assist researchers to test their techniques or algorithms and validate their performance accuracy.

2.3. Iris image prepossessing and segmentation

To implement any of the recommended approaches or algorithms of the recognition system, a preprocessing method is advised to be developed in the initial step. In order to increase the quality of the iris image and make it easier for the subsequent analysis to be performed so that it may achieve a higher identification rate, image pre-processing is necessary to eliminate and regulate any undesired types, colors, and lights that may be present in the dataset (Sallam et al., 2019). Generally speaking, iris segmentation, normalization, highlights removal, and image enhancement are some of the pre-processing techniques that are frequently utilized in the iris identification system. (Yin et al., 2023).

After preprocessing phase, the region of interest (ROI) is instantly extracted. Image capture, iris segmentation, feature extraction, matching, and identification make up a standard iris recognition system. Without a doubt, each of these modules is essential to the operation of the entire system performance, but the iris segmentation module is more important. It is because that it isolates the valid iris part, which is then used by others subsequent modules. It has two objectives: Iris localization and noise reduction. In the first task, the iris' inner (pupillary) and outer (limbic) borders are localized at the pupil and sclera, respectively, while in the second job, any overlaid noise—such as reflections or eyelids—is found and eliminated from the localized iris. The accuracy of iris localization has a significant impact on the precision of an iris segmentation module. It does this by defining the true iris outlines in the presence of distracting features like eyelashes, spectacles, hair, and eyebrows. Additionally, it takes longer than the modules that come after it.

According to the literature, the majority of iris localization algorithms were created for NIR eye pictures, hence when used straight to VW eye images, these methods do not work well. This reasoning suggests that iris localisation in VW data is still an unsolved research problem (Wei, et al., 2022).

Both Daugman's integro-differential operator-based approaches and Wilde's circular Hough transform-based methods can be used for traditional iris localization. However, The center coordinates of the iris area must be estimated via the integro-differential operator approach for iris localization, which is problematic in a non-cooperative setting. Due to noise in non-cooperative situations including reflection points, motion blur, and the occlusion of eyelashes and spectacles, circular Hough transforms have poor accuracy for outside borders. They created a circular Hough transform to solve these problems and utilized it to pinpoint the inner limits of the iris area. They then utilized the center of the inner boundary as the center coordinate to determine the outer boundary using the integro-differential operator since the center of the pupil usually lies near to the center of the iris (Farouk et al., 2022).

The Hough transform model has become a more commonly used method in iris segmentation in recent years. In addition to the Hough transform, Gaussian filters, a linear smoothing filter suitable for removing Gaussian noise, are also commonly used for iris segmentation (Omran & AlShemmary, 2020) (Haindl & Krupička, 2015).

In recent years, the Hough transform model has seen an increase in popularity as a technique for iris segmentation. For iris segmentation, Gaussian filters, a linear smoothing filter effective for eliminating Gaussian noise, are frequently employed in addition to the Hough transform (Haindl & Krupička, 2015).

The iris/sclera boundary is first determined from the whole eye, and then the pupil/iris border is determined from the iris region, both times using the Circular Hough transform. A circle with different radii will be created in Hough space by the circular Hough transform for each edge point. The radius and center coordinates of the circle that are best defined by the edge points correspond to the highest point in Hough space. Since circle parameters may be instantly transferred to the parameter space, circles can be represented in parameter space more easily than lines. As mentioned in the section above, the Hough transform was used to identify the image's boundaries and to aid in the identification of objects, which were often circles. By accounting for the intensity variation between one or more parts of an image, edge detection was made possible (Arsalan et al., 2017).

A large number of these approaches undertake segmentation by using established image processing techniques as Daugman's method, clustering, and the semantic segmentation algorithm. Even though all of these methods exhibit high levels of segmentation accuracy for iris images, their performances are still influenced by various environmental factors, such as a large standoff

distance, an off-angle, blurring, reflections, occlusion, the small size of the iris, and the ghost effect under unrestricted (non-ideal) circumstances (Alom et al., 2018).

Traditional iris segmentation techniques have difficulties since their algorithms frequently rely on manually produced feature extractions and rigorous parameter adjustments, such as using pre-calculated radii ranges for limbic and pupil boundaries. Additionally, for them to work properly, specific picture intensity profiles and pre-processing techniques may be quite important. On top of that, distinct models are frequently used to identify the iris and eyelid regions (Nguyen et al., 2018). A lot of attention has been paid in recent years to creating models that combine prediction with concurrently learning the characteristics. Convolutional neural networks have achieved great success in this direction primarily because of three important factors: the availability of sizable datasets that have been manually labeled, strong processing tools (like Nvidia's GPUs), and effective regularization techniques (like dropout, etc.) that can prevent overfitting issues. Deep learning has been utilized to solve a number of computer vision-related issues, including image classification, image segmentation, super-resolution, image captioning, emotion analysis, face recognition, and object identification, and has shown to perform much better than conventional methods (Hafner et al., 2021).

Convolutional neural network (CNN)-based iris segmentation is presented to address the issues with existing approaches and lower the computational load of pre-and post-processing. CNN offers a powerful platform for segmentation operations like segmenting a brain tumor utilizing several kernels. In contrast to its widespread usage for iris detection, iris segmentation has only sometimes been studied using CNN up to this point (Arsalan et al., 2018). A densely connected fully convolutional network (IrisDenseNet)-based technique is presented in the paper to identify an accurate iris border with improved information gradient flow. Recurrent Convolutional Neural Network (RCNN) and Recurrent Residual Convolutional Neural Network (RRCNN) models based on U-Net, referred to as RU-Net and R2U-Net, respectively, are proposed by (Wei et al., 2022). The suggested models make use of the capabilities of RCNN, Residual Network, and U-Net. These recommended structures for segmentation problems provide a number of benefits. A residual unit first aids deep architecture training. Second, more effective feature representation for segmentation tasks is ensured by feature accumulation using recurrent residual convolutional layers. Thirdly, it enables us to create better U-Net architecture for medical image segmentation while using the same amount of network parameters.

Recent research on iris segmentation using fully convolutional networks (FCNs) has demonstrated potential enhancements in accuracy and resilience. Although segmentation accuracy with FCNs has improved, current research exclusively examines segmentation accuracy without taking into account how the models affect end-to-end iris recognition systems. The assessment of

model deployments on actual HW/SW systems, such as embedded systems, which are common targets for iris recognition applications, is notably lacking in existing research on FCN-based segmentation. As a result, the computational overheads associated with deployment on systems with resource constraints are not taken into account while designing the FCN designs. Instead, the restricted focus on segmentation accuracy also results in FCN-based systems that need a significant amount of processing power. These models are not ideal for embedded systems since they might include a lot of layers and parameters and need billions of floating-point operations for each input (Arsalan et al., 2017).

2.3.1. Normalization

The process of changing the segmented iris region's circular shape into a rectangular pattern is known as normalization. Due to the pupil's expansion and contraction, the region bounded by an iris' inner and outer limits might vary. Before comparing several iris images, the impact of these variances must be reduced. To do this, a section of fixed dimension is often assigned to the segmented iris region (Yan et al., 2018).

The Daugman rubber sheet model is used in several iris normalization procedures. The iris image may be converted from Cartesian coordinates to polar coordinates using the Daugman rubber sheet model. Specifically, Daugman's model takes each point (x, y) within the iris region to a pair of normalized non-concentric polar coordinates (r, θ) where r is on the gap $[0, 1]$ and θ is the angle on the interval $[0, 2\pi]$. The mathematical definition of the iris region mapping is shown in Eq.(1):

$$\begin{aligned} I(x(r, \theta), y(r, \theta)) &\rightarrow I(r, \theta), \\ x(r, \theta) &= (1 - r)x_p(\theta) + rx_s(\theta), \\ y(r, \theta) &= (1 - r)y_p(\theta) + ry_s(\theta). \end{aligned}$$

Where $I(x, y)$ is the intensity value of (x, y) in the image of the iris region. The parameters x_p , x_l , y_p , and y_l are the coordinates of the pupil and iris boundaries along the θ direction (Rai et al., 2020).

Some of the pixels are repeated throughout the normalization process to fill in the empty area of the iris image since the pupil and iris have different radius. In order to conquer over this restriction, many scholars in the past and present have worked to constantly enhance normalization techniques, such as Hilal devised an adaptable technique for capturing non-circular pictures of the pupil area. The curved shape of the iris area was traced using flexible disks rather than a rigid circular pattern. The difficulty with this method is figuring out where the pupil's center is. It would be challenging to extract the feature since any mistakes made in identifying the center might affect the elastic curves (Alrifae, 2020).

2.3.2. Feature extraction

After determining the iris' boundaries and mapping this area, feature extraction techniques should be used to identify the unique characteristics of the region's texture, which vary from person to person. The feature extraction phase is a crucial step in the process of achieving high accuracy in a person's identification since it requires the extraction of each individual's distinctive traits. In addition to its appealing physical features, the success of iris identification is anchored in the creation of effective feature descriptors, particularly the Gabor phase-quadrant feature descriptor presented in Daugman's groundbreaking work. With very low false match rates and excellent matching efficiency, this Gabor phase-quadrant feature descriptor (commonly called the iriscode) has dominated the iris recognition industry. Numerous other iris descriptors have been proposed by researchers and used for iris recognition, including those based on discrete cosine transforms (DCT), discrete fourier transforms (DFT), ordinal measures, class-specific weight maps, compressive sensing and sparse coding, hierarchical visual codebooks, and multi-scale Taylor expansion (Abdullakutty et al., 2022).

extraction and categorization of iris features. The proposed model's structure consists of 2 fully connected layers, 3 pooling layers, 6 activation Relu layers, 4 Convolution layers, and 6 activation layers to automatically identify and extract characteristics from images without the need for domain expertise. Figure 3 depicts the 18 layers that make up IRISNet. Convolution is the first layer, then Rule, Pooling, fully-connected (FC), and Softmax is the final layer. Two dropout layers are employed at the bottom of each fully connected layer to remove overfitting in the fully connected (FC) layers. It stops all neurons from updating weights at once. The neurons in this layer are kept from aiming at the same thing. The database was divided into two distinct sections: the tested (T set) and the designed (D set). In order to extract features from a segmented iris image, CNN is employed. The design component has also been divided into two parts: training and validation (El-Abed et al., 2012). A matching metric is required to assess how similar two iris templates are to one another. The two templates are compared to see if they are from the same or different persons using this matching metric. In this instance, the feature extraction and classification steps employ either CNN or HD. The edge-detected and segmented iris image is the input to CNN or HD. The CNN model is built using two sub-datasets, one for training and the other for testing. Each sub-folder in the training dataset comprises some iris images for a single person, and the CNN model looks for distinctive properties in each of them. To establish whether the two templates were produced by a heterogeneous iris or the same iris, a second approach for feature extraction and classification called the hamming distance is applied.

2.3.3. Matching

The recognition system's (RS) final phase is classification. The principal objective of classification is to evaluate how closely the test samples and samples found in databases of iris images resemble one another. Usually, the complete matching of these samples is frequently impossible. In order to assist the recognition system in identifying people, the estimated rate of each sample is used.

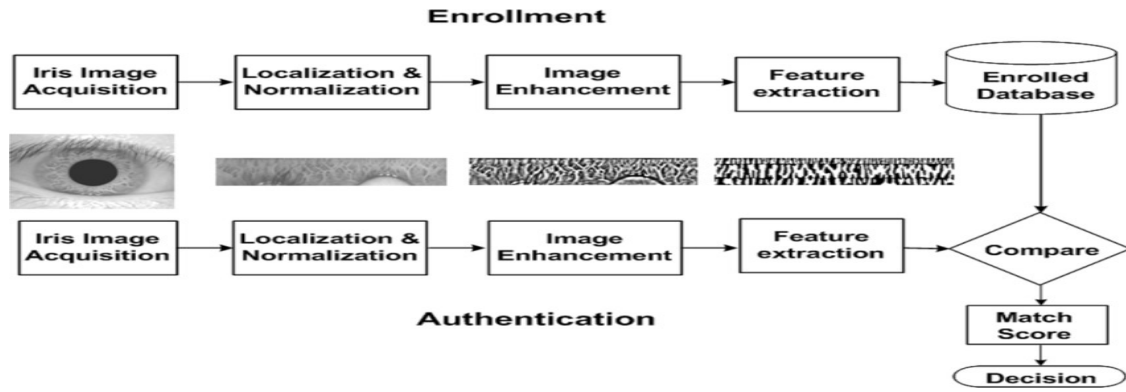


Figure 3: Performing Iris matching

The above figure 1 illustrate the process comparing the matching of new Iris image with existing database. Based on the comparison result, the final decision will be drawn matching is true or false.

IRISNet, a system that uses deep learning methods for feature extraction and classification, has been proposed as an iris identification system. IrisNet's design included Convolutional Neural Network layers for performing feature extraction and a Softmax layer for implying classification tasks. The IITD-V1 iris dataset was used to assess this system's performance. The accuracy for the original and normalized images was determined to be 97.32 and 96.43%, respectively (Haindl & Krupička, 2015).

Notable machine learning algorithms for matching in iris recognition include the support vector machine (SVM). Its fundamental model is a linear classifier with a maximum interval set on the feature space, which distinguishes it from conventional models. When performing iris recognition tasks, SVM is typically integrated with a number of different models for feature extraction (Malgheet et al., 2021).

SVM classifiers are trained using a one-against-all method using feature vectors. A distinct binary classifier is trained for each identity, resulting in the same number of classifiers as the enrolled identities. The class with the biggest margin is given the test case. On a portion of the original dataset, we sharpen their models before using them as feature extractors. This technique allows us to classify data using a straightforward similarity metric, which expedites the identification phase and makes enrolling candidates easier because no further training is required.

Using the CASIA-Iris-Thousand dataset, their models are trained and assessed (Mathisen et al., 2019).

A multi-classification framework based on CNN and the Hadamard-ECOC error correction output code (Hadamard-ECOC) was created to increase classification accuracy. Without having to retrain all the parameters, new classes of iris images were introduced to the iris identification framework. The proposed architecture combines the capacity for mistake correction with that for feature learning from the iris image characteristics. In comparison to previous methods of multi-classification, it incorporated the Hadamard-ECOC qualities of simple design and arbitrary category adaptability in addition to the CNN's strong image processing performance (Kim & Kim, 2023).

2.3.4. Summary of related work

The following table illustrate previous works of some iris segmentation methods using deep learning techniques.

Source	Database	Method	Issues focused on	Accuracy	Gaps
Unconstrained iris segmentation using convolutional neural networks, S. Ahmad and B. Fuller, 2018	UBIRIS-v2	MR-CNN algorithms based on a CNN technique	Eyelid, eyelashes, eyeglasses , and reflection	94.8%	the algorithm used to perform segmentation to Datasets where the iris is of similar scale demonstrate high accuracy in cross dataset experiments. To create a “universal” algorithm they need to correct for differing scale of the iris within dataset
An end to end deep neural network for iris segmentation in unconstrained scenarios, Bazrafkan, 2018	Bath800 UBIRIS MobBio	Fully convolutional deep neural network (FCDNN)	Shadows, socket, resolution, contrast, and blurring	98.55%	databases with very unspecific distributions which will decrease the performance after tuning. And also the designing model is for a specific task. But if there are not pre-defined situations where the network is implemented, the tuning is not advised.
IrisDenseNet: robust iris segmentation using densely connected fully	CASIA-v4 IITDelhi v1	IrisDenseNet : densely connected convolutional network	Off-angle, glasses, rotated eyes, and specular reflection	97.58	The method was innovatively powered by dense features but still has a deep network. Therefore, it is difficult to be

convolutional networks in the images by visible light and near-infrared light camera sensors, Arsalan, 2018		(DenseNet) with SegNet based on encoder-decoder convolutional network			trained with a GPU with low memory and larger mini-batch size.
An efficient and robust iris segmentation algorithm using deep learning, Huang, 2019	CASIA	Faster region-based convolutional neural network (R-CNN) with only six layers	Specular reflections , eyelashes, and eyelids	95.49	It needs to improve the speed of the algorithm by creating heterogeneous models that combining the power of CNN and the speed of traditional computer vision methods

Table 1: summery of related works

Chapter Three

3. Materials and Methods

3.1. Proposed iris segmentation system architecture

The proposed iris segmentation system comprises different major components such as Image acquisition, Iris segmentation, Features extraction, and Matching and recognition work. From the architecture, each of these modules plays a vital role in the overall system's performance, but iris segmentation module is more crucial. It is because that it isolates the valid iris part, which is then used by others subsequent modules. The precision of an iris segmentation module greatly depends on the precision of iris localization. The following figure x illustrated the proposed system architecture.

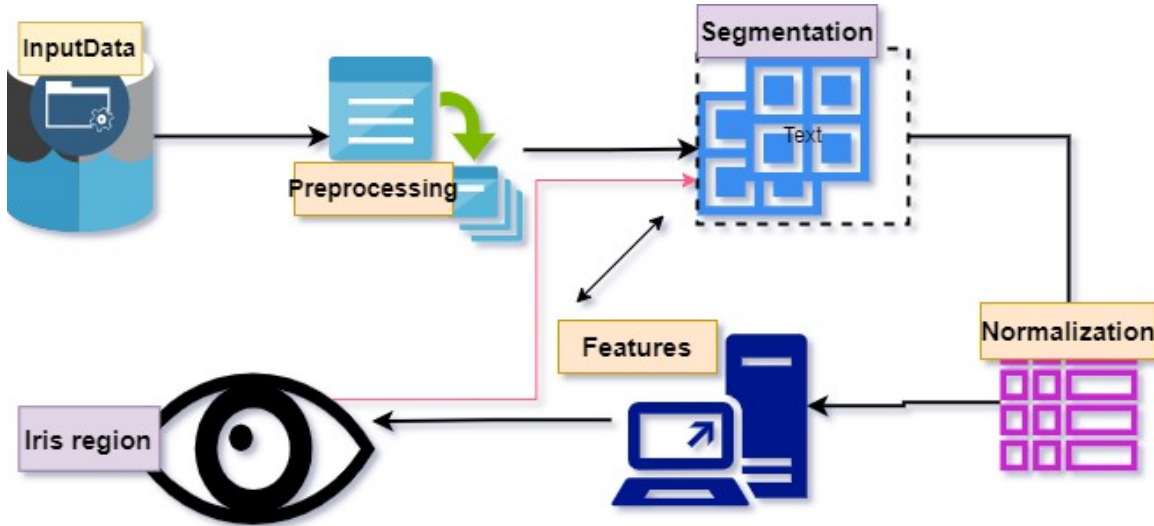


Figure 4: Proposed system architecture

Figure 4 above, illustrate the process of segmenting Iris region from eyelids. Based on the scope of proposed research, our research works mainly focus on the segmentation part. Automatic iris recognition is a challenging and complex tasks due to unpredictable variations of iris during feature extraction. Therefore, efficient iris identification mainly focus on the performance of segmentation and feature extraction techniques.

3.2. Data Collection

For the purposes this study, open sources database repository has been utilized to conduct the experiment works.

3.2.1. Brief Descriptions and Statistics of the Database

CASIA-IrisV4 is an extension of CASIA-IrisV3 and contains six subsets. The three subsets from CASIA-IrisV3 are CASIA-Iris-Interval, CASIA-Iris-Lamp, and CASIA-Iris-Twins respectively. The three new subsets are CASIA-Iris-Distance, CASIA-Iris-Thousand, and CASIA-Iris-Syn.

54,607 iris images from over 1,800 real subjects and 1,000 virtual subjects are included in CASIA-IrisV4. Every iris image is a synthesized or 8 bit gray-level JPEG file that was taken under near infrared light. Table 1 provides some statistics and characteristics of each subset. There may be a slight inter-subset overlap in subjects between CASIA-Iris-Interval, CASIA-Iris-Lamp, CASIA-Iris-Distance, and CASIA-Iris-Thousand because the six data sets were gathered or synthesized at different times.

The CASIA-V4-Interval dataset comprises 2639 near-infrared iris images obtained indoors from 249 subjects. The images have a resolution of 320 x 280 pixels and remarkably clear iris texture details. The iris camera used to take these pictures was created by the user. The developers of this dataset set up a circular array of cameras to capture the iris images in order to ensure that the images have the appropriate luminous flux. Benefiting from this method, the iris texture details are crystal clear in these superbly captured images.

There are 2,567 images from 142 subjects in CASIA-V4-Distance. Techniques for near-infrared imaging were used to capture these images. Three meters separated the subjects from the camera. The iris images have a resolution of $2,352 \times 1,728$ pixels. The upper portion of each sample in the dataset, including the irises and other facial features, is included. Skin lines are among the details that can be utilized for multi-modal biometric information fusion. This is a high-quality, long-range iris and facial dataset that is open to the public.

The CASIA-V4-Thousand dataset comprises 20,000 near-infrared images (NIR) with a resolution of 640 x 480 pixels, gathered from 1,000 subjects in an indoor setting with varying lighting conditions. The glasses' specular reflection is the primary cause of variation in this dataset. The IrisKing IKEMB-100 camera was utilized to gather the dataset.

There are 16,212 images from 411 subjects in CASIA-Iris-Lamp. The iris images have a resolution of 640 x 480 pixels. An OKI portable iris sensor was used to collect the images for this dataset. One light in the room served as the acquisition environment, which resulted in a nonlinear distortion from variations in visible illumination. In IR, one of the most prevalent and difficult issues is the elastic deformation of the iris texture due to pupil dilation and contraction in various

lighting conditions. Thus, the problem of nonlinear normalization and robust iris feature representation of the iris can be studied using CASIAIris-Lamp.

An LG Iris Access EOU2200 camera is used at Clarkson University to gather the irises for the LivDet-Iris 2017 Clarkson Dataset. 2,469 real images from 25 subjects, 1,122 images from five individuals wearing 15 different types of patterned contact lenses, and 1,346 printed images from 13 subjects made up Clarkson's training set. Every picture has 640 x 480 pixels. The testing set comprised 765 images from seven individuals wearing patterned contact lenses, 908 printed images, and 1,485 real images from 25 subjects.

3.2.2. Local Dataset

More than 300 right and left eye datasets from 18 subjects have been gathered for the proposed model test in order to assess the model's performance. In a similar vein, the testing data carry out pre-processing and feature extraction tasks using the same methodology as model training.

3.3. Ethical consideration

The Chinese Academy of Sciences (CASIA) dataset is made available for research and educational purposes with respect to the ethical consideration of our datasets. Due to the fact that all data, including the CASIA dataset that was used for this study, will be used to protect unethical and improper behavior in a way that adheres to professional ethics. For the local dataset, various volunteers participate in order to obtain the necessary image data. As a result, the study adhered to the protocol of using information obtained from the chosen subjects solely for the purpose of this research project.

3.4. Hardware tools

The hardware needed for the actual Iris recognition system implementation will be costly, starting with the iris image scanner camera for the iris acquisition step and completing with a sizable server that stores the final phase's iris template database. We suggested hardware that is required for the image segmentation phase of this study, which will gather iris images from datasets. The most advanced and precise techniques for iris segmentation use different convolutional neural network architectures. All of them, though, call for more RAM and processing power than a Raspberry Pi could provide. In addition, we've listed the high-processing-power hardware that we used for this study.

No.	Device name	Used in the study
1.	Jetson Nano 4GB	Image based machine learning need high speed computing that cannot perform using PC,

		so that we will used NIVIDIA embedded device.
2.	Hard Disk	Keeping the large number of datasets that were used to train, test the model and store its progress.
3.	GPU	We will used 128-core NIVIDIA Maxwell GPU to speed up the training and computing. In addition, Tesla 84 GPU infrastructure has been used to train the proposed deep learning model and to resolve computational limitation.

Table 2: Hardware tool used for this study implementation

3.5. Deep Learning Environment and tools

Python: - Similarly, Python programming has been utilized for implementation purpose. It mean that all proposed system implementation are written on python script following the Pytorch modular approaches.

Jupyter Notebook: - Among AI and deep learning researchers, build open-source tools, open standards, and services for interactive computing using Python, as well as develop python code. In addition, we have utilized colabs environment and T-GPU infrastructure to training our model.

3.6. Feature understanding

The most trustworthy and efficient means of identifying people are biological traits like the face, voice, fingerprint, iris, and finger vein, which have taken the place of more conventional techniques like keys, passwords, and access cards. Many biological traits are used for personal identification, such as face, voice, fingerprint, iris, and finger vein. Because iris recognition systems have an extensive set of features and remain unchanged much over time, they are frequently employed in security-related applications. They are also very difficult to forge. Due to its competitive advantages, research has demonstrated that of the biological patterns mentioned above for personal identification, the iris pattern is the most secure and reliable form:

1. **Unique:** there are not any iris having the same physical characteristic as others, even if they come from the same person or identical twins;
2. **Stability:** the iris is formed during childhood, and it generally maintains unchangeable physical characteristics throughout life;
3. **Informative:** the iris has rich texture information such as spots, stripes, filaments and coronas.
4. **Safety:** Since the iris is located in a circular area under the surface of the eye between the black pupil and the white sclera, it is rarely disturbed by external factors. As a result, it is difficult to forge the iris pattern;

5. **Contactless:** *Iris Recognition* (IR) is more hygienic than biometrics that requires contact, such as fingerprint recognition.

3.6.1 Features Extraction

The procedure of iris segment work demands the following important aspects to extract relevant features to build the proposed model.

- ✓ Highly accurate and fast iris recognition boost precision among different types of biometric authentication technologies.
- ✓ Eye Iris section remains unchanged throughout life.
- ✓ Since the iris is different between the left and right eye, recognition can be performed separately by each eye.
- ✓ Possible to distinguish even twins.
- ✓ As long as the eyes are exposed, iris recognition can be used even when the subject is wearing a hat, mask, eyeglasses or gloves.
- ✓ Because of using an infrared camera, recognition is available even at night or in the dark.
- ✓ Without the need to touch the device, contactless authentication is possible, making it hygienic to use.

A procedure of iris recognition process

- ✓ First, the location of the pupil is detected, followed by detection of the iris and the eyelids.
- ✓ Unnecessary parts (noise), such as eyelids and eyelashes, are excluded to clip out only the iris part, which is then divided into blocks and converted into feature values to quantify the image.
- ✓ Matching is then performed with feature data previously extracted in the same methods.

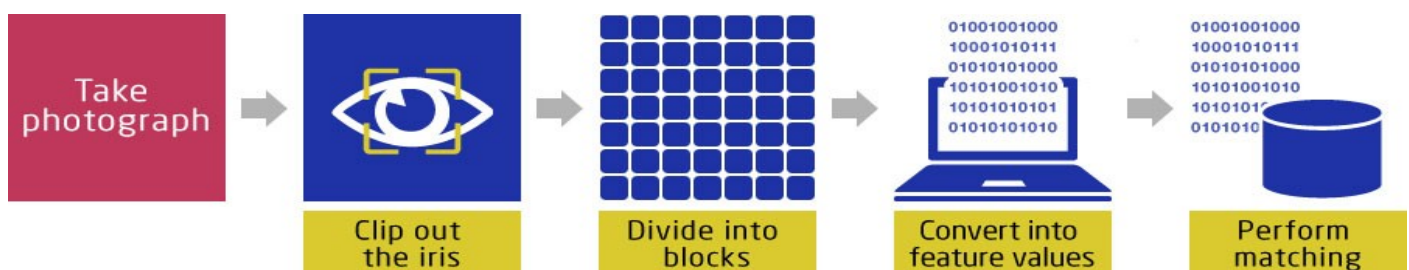


Figure 5: Data transformation process

The colorful portion of the eye that we can quickly notice. Similar to a camera aperture that regulates the quantity of light that passes through the lens, the iris regulates the amount of light that enters the eye. Pupil refers to the black hole located at the middle of the iris. Fine muscles that either inflate or constrict the iris are linked to the iris. Each person's iris has a unique color, texture, and pattern; this is comparable to, say, fingerprints. Nevertheless, compared to fingerprints, the chances of discovering two identical irises are far lower.

The iris is drawn in a greater light by the clamping muscle, which is located along its edge. The iris is stretched by the transversely positioned stretching muscle, which resembles a bicycle string under dimmed light. The front and rear of the eye are separated by the flat iris.

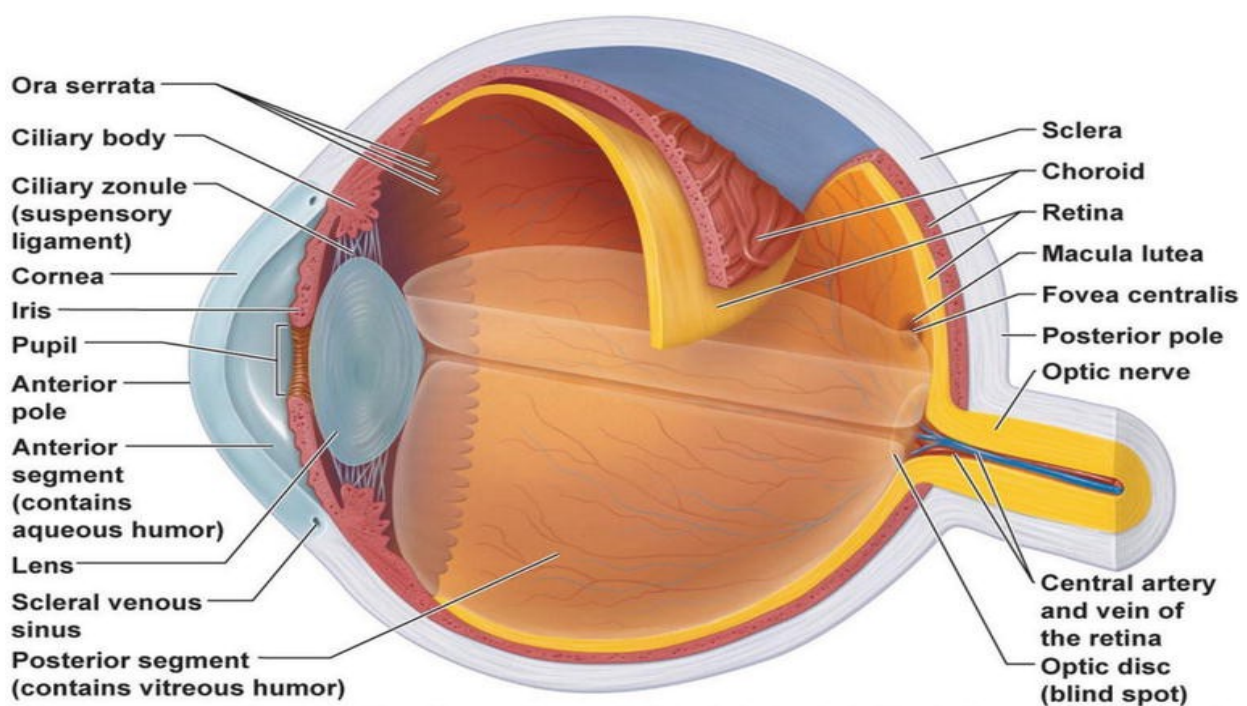


Figure 6: The general structure of human eye

Melanin is the pigment responsible for the color of the iris. It can be found between the sclera of the eye and the pupil. The iris is around 11 mm in size. Throughout life, the fundamental composition is pervasive and the iris is distinguished in twins as well. Figure 7 depicts the iris's structural makeup.

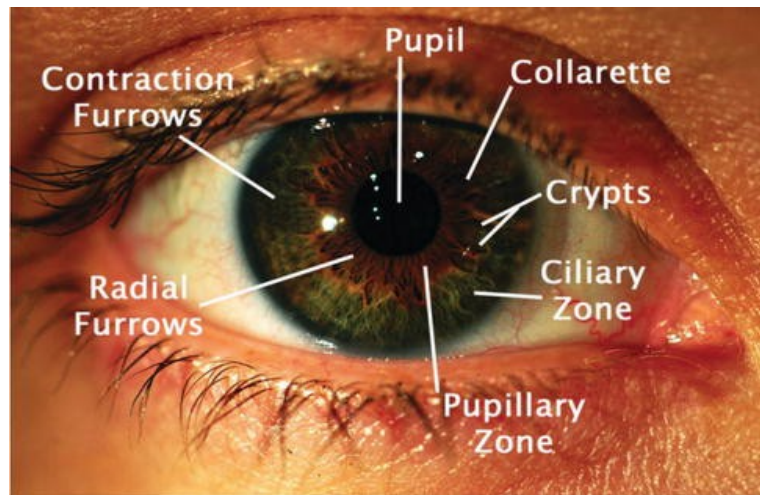


Figure 7: The location of Iris and Pupil

The process of separating the iris region from the surrounding areas is known as iris segmentation. An internal muscle in the eye called the iris controls the pupil's size, which in turn affects how much light can enter the eye. It is the colored area of the eye that is determined by the quantity of pigment in the muscle that contains melatonin, a hormone your brain releases in reaction to darkness.

3.7. Localization

Image capture, iris segmentation, features extraction, matching, and identification are the usual components of an iris recognition system. While all of these modules are undoubtedly essential to the functioning of the system as a whole. The reason for this is that, it separates the legitimate portion of the iris, which is then utilized by other modules. It consists of two tasks: (i) localizing the iris and (ii) eliminating noise.

In the first task, the iris's inner (pupillary) and outer (limbic) borders are localized at the pupil and sclera, respectively. In the second task, any overlaid noise, such as reflections or eyelids, is detected and eliminated from the localized iris. The accuracy of iris localization has a significant impact on the precision of an iris segmentation module. The reason for this is because it helps distinguish the true iris outlines when there are distracting areas nearby such as eyebrows, eyelashes, hair, and eyeglasses.

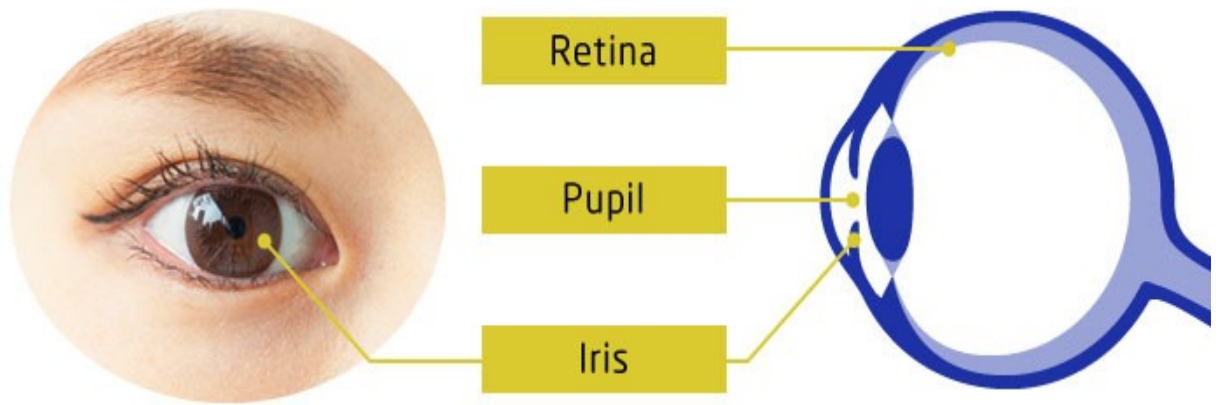


Figure 8: Iris Localization and Extraction

3.8. Segmentation

Iris segmentation is the first and most important phase in the overall iris recognition process. Its goal is to isolate the useable iris pattern from the rest of the eye, as well as the noise. It is evident that the accuracy of iris segmentation will have a significant influence on the outcome of subsequent processing. It is the technique of identifying the pupillary and limbi borders of an iris in a picture. This would aid in retrieving iris-specific characteristics while ignoring the pupil's surroundings.

The image segmentation in the iris identification task is designed to properly segment the iris area of people's eyes. Traditionally, this work has been performed using conventional threshold-based segmentation, with the goal of finding an appropriate threshold to split the picture based on the pupil's lower grey value. However, using a single threshold value reduces the segmentation method's generalization capacity.

Hough transfer

The Hough transform is a standard computer vision algorithm that can be used to determine the parameters of simple geometric objects, such as lines and circles, present in an image. The circular Hough transform can be employed to deduce the radius and the centre coordinates of the pupil. Firstly, an edge map is generated. From the edge map, votes are cast for the parameters of circles passing through each edge point. These parameters of the centre coordinates x_c and y_c , and the radius r , which are able to define any circle according to the equation:

$$x_c^2 + y_c^2 - r^2 = 0 \text{ and iris regions}$$

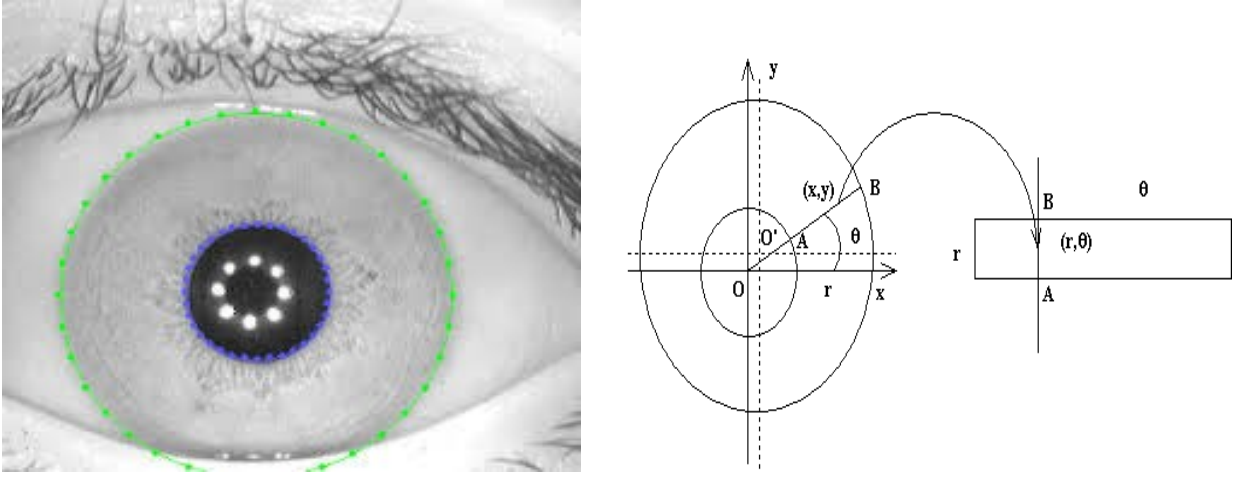


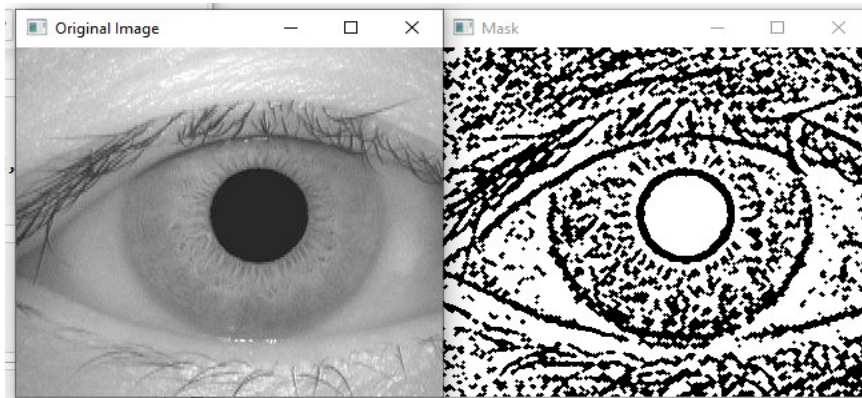
Figure 9: Iris segmentation sample Image

The Hough transform model has gained popularity as a technique for iris segmentation in recent years due to its ability to produce well-segmented iris images taken in various settings. We have utilized many established iris segmentation methods to annotate self-collected iris images. Many conventional techniques follow the two-step machine learning methodology, where in the first stage a collection of hand-crafted characteristics are obtained from iris photos, and in the second step a classifier is used for recognizing the iris images.

Morphology Operation

Morphology procedures has been used to iris segmentation, which is the process of separating the iris area from the rest of the eye in an image. This is a crucial phase in iris recognition systems used for biometric authentication.

To segment the iris using morphological operations, first establish a structuring element that corresponds to the irises overall form and size. This structuring element is then dragged across the image, and dilation and erosion processes are used in order to enhance the iris' edges while removing any noise or undesirable areas.



Opening and closing procedures can also be utilized to fine-tune the segmentation and guarantee that the iris area is completely isolated from the rest of the eye. upon completing segmentation, the iris may be further processed and examined to obtain properties including texture, color, and form for use in recognition algorithms.

3.9. Normalization

Normalization is a process that converts data from several measuring scales into a single scale, allowing for meaningful comparison and analysis. This procedure has the extra benefit of reducing the impact of outliers by deflating their magnitude, which can have a significant impact on the data's distribution and statistical features. Normalization is a popular pre-processing step in iris recognition that uses end-to-end modeling to increase the accuracy and stability of the findings.

After successfully localizing the iris image, the next step is to convert the iris area of the eye image into fixed dimensions, as shown in Figure 10. The fixed dimension iris image permits the feature extraction procedure to compare two iris images. Dimensional discrepancies may occur as a result of pupil dilatation when the level of light changes. Other sources of dimensional inconsistency include differences in image distance, camera rotation, head tilt, and ocular rotation inside the eye socket. As a result, a normalizing technique is required to obtain the same constant dimensions, ensuring that two images of the same iris taken under different conditions have the same properties at the same spatial locations.

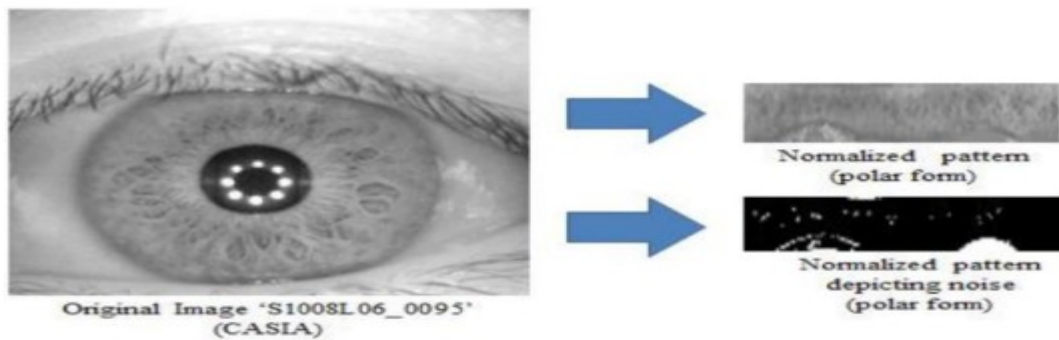


Figure 10: Iris Normalization Process [adopted from CASIA]

3.10 Feature extraction

Feature is a measurable piece of data in your image that is unique to that specific object. It may be a distinct color or a specific shape such as a line, edge, or image segment. A good feature is used to distinguish objects from one another. The iris recognition has become one of the most used methods in biometric recognition systems due to the unique characteristics of the iris and also for its steady behavior throughout the life of the human being. The fundamental objective of the segmentation process is to extract the iris texture from the structures that surround it, for example, the pupil,

the eyelids, the sclera and to eliminate or reduce reflections of light in the iris. In recent years, segmentation methods have been presented with the aim of increasing the percentages of success in the identification.

Different approaches have been implemented for iris recognition and segmentation. This task can be facilitated if its circular morphology is considered and images are prepared properly before moving on to the processing phase. The purpose of this article is to facilitate the detection process using the morphology of the circular objects contemplating different conditions in the acquisition, as well as the possible obstruction with objects surrounding the iris. Digital image processing techniques are used such as: gray scale transformation, negative and binarization. The Canny's method and the Hough transform are applied for the detection of edges and circumferences, respectively.

During the data preprocessing phase, the Hough transform was used to detect the center of the pupil and from it to project the iris. Using different techniques for the elimination of noise on the images, in the elimination of noise was made by applying a Gaussian filter. It is important to note that, in the investigations described above, the iris detection tests were carried out on images belonging to the same database, for which, in this research, it was decided to use a database more to homogenize them in the same environment, applying techniques of pre-processing images such as conversion to gray scale and negative.

In the past, iris recognition required the extraction of various handcrafted features to complete the recognition process. The design of these handcrafted features usually relied on biological and computer experts. Since recent years, with the booming of deep learning in various visual tasks, the application of Deep Neural Networks (DNN) for feature extraction has received much attention in iris recognition. However, according to our survey, many research efforts still use handcrafted methods based on the domain's prior experiences to extract iris features. Therefore, this section summarizes not only the feature extraction methods based on deep learning but also sorts out the handcrafted methods for extracting iris features.

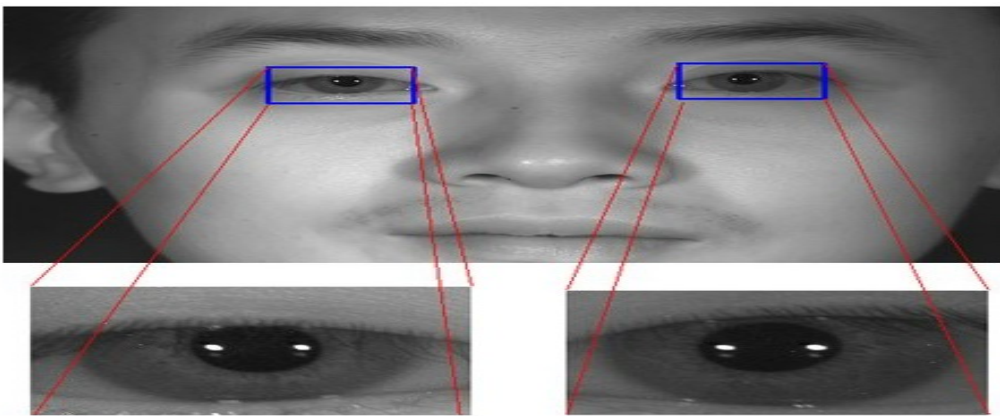


Figure 11: Eye Segmentation from face ROI

Handcrafted features

The laborious tasks involved in conventional manually operated feature extraction approaches are common. For example, extracts iris characteristics using a fusion approach that combines the Tetrolet transform, local gradient pattern, local ideal orientation pattern, and scattering transform. After that, categorization is done using Deep Belief Network (DBN). While this technique finally achieves 97.9% accuracy, the processes involved in inferring the model are rigorous. For extracting characteristics such as these, conventional methods for machine learning are costly. From enormous quantities of data, deep learning techniques may automatically extract high-level semantic characteristics. Compares a few common manual feature extraction techniques with CNN feature extraction techniques to show the differences. Local gradient autocorrelation, Contourlet transform, and Log-Gabor are some of the handmade techniques. The experimental findings demonstrate that the CNN feature extraction techniques work better than the previously indicated manual techniques.

3.11 Matching

For the purpose of to match the characteristics collected from iris images with the associated registered user, matching is the last stage of iris recognition. Matching in non-end-to-end techniques is typically handled by classifiers separate from the feature extractor.

Selection and regularization of variables are necessary for identification. Sparse linear regression techniques are employed by the model to derive matching probabilities. Using a multi-layer comparable convolutional structure to decrease computing complexity, the technique is resilient to outlier match scores, a key contributor to mistake in biometrics. By using this structure, the fundamental texture information of the iris is obtained while the dimensionality of the iris texture information is reduced. Eventually, the iris textures are extracted and categorized using a collaborative representation.

Some designed metrics that are available from matching templates

- ✓ Hamming distance metrics
- ✓ Weighted Euclidean distances
- ✓ Canberra distance metrics

Image processing techniques are employed to extract the unique iris pattern from a digitized image of the eye, and encode it into a biometric template, which is stored in a database. The steps in processing is shown in Figure 12 below.

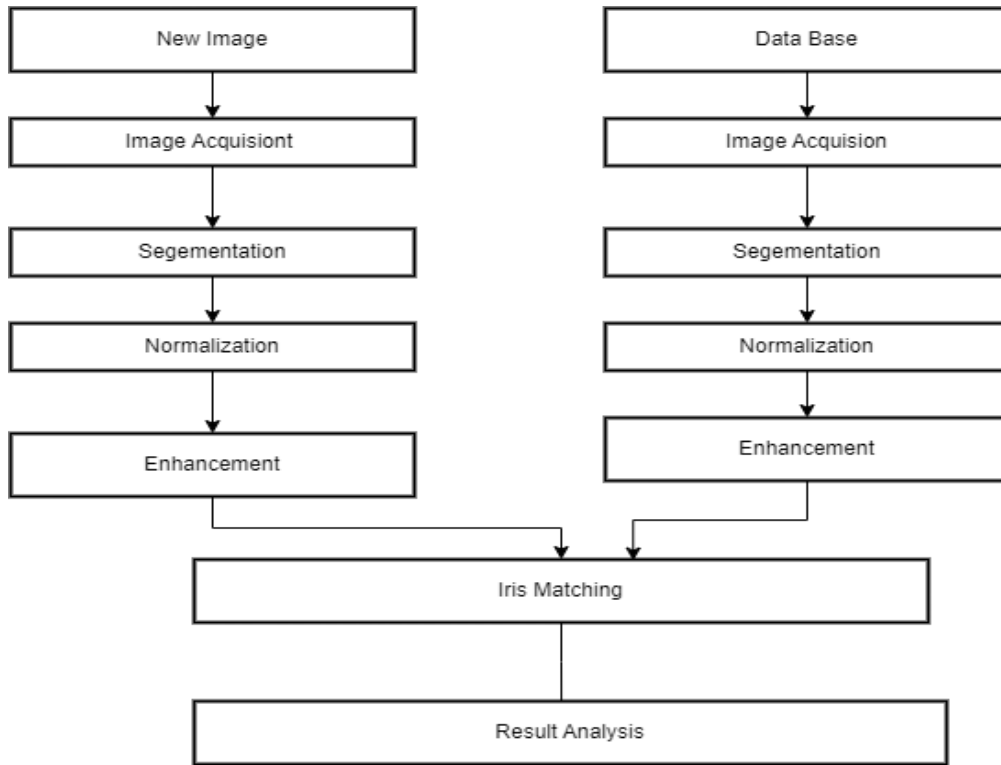


Figure 12: Iris recognition Matching Processing

3.11. Machine learning models used employed

In this study, we have used iris dataset to training different classical and deep learning models. The main object is to justify and testify which model is best fit with the problem domain. The trend in iris identification has been the use of DNNs to extract features, particularly to the ongoing advancements in deep learning techniques. Compared, for example, the feature extraction powers of many well-known deep CNNs, such as AlexNet, VGGNet, GoogLeNet, Unet, ResNet, and DenseNet. These deep CNNs are adopt at extracting and encoding intricate characteristics from iris images since they include tens or even hundreds of layers and millions of parameters. Each layer of a CNN models the visual information of an image at a different level throughout the feature extraction process. While the latter layers encode finer and more abstract properties, the older ones hold onto coarser information. Using each layer's output as a feature descriptor, this method returns the recognition accuracy. Comparably, the maximum classification accuracy was obtained by certain classical models, such as SVM, RBF, and even KNN. It is likely that machine learning models will reach their maximum accuracy if the data processing aspect is handled correctly.

Chapter Four

4.0. Iris Segmentation Implementation

In this study, we have followed experimental research approaches to address our research questions. The proposed Iris segmentation system composed of various sub-systems which are localization, normalization, feature extraction and matching of characteristics template. We have made a lot trial and error methods to utilized unique patterns within a ring-shaped region surrounding the pupil of each eye. This identification approach is incredibly precise and dependable in this location, with very low false match rates.

4.1. Experiment setting

Before we get into the results of the proposed model, let's talk about the hyper-parameters we used in our training procedure. We train the proposed model for 100 epochs on an Nvidia Tesla GPU. The batch size is set to 24, and the loss function is optimized using the Adam optimizer at a learning rate of 0.0002. All images are down-sampled to 224x224 before being fed into the neural network. All of our implementations are done with PyTorch (Malgheet et al., 2021). The following section contains information about the datasets used in our research, as well as quantitative and visual experimental results.

Dataset

To training our model, we have used the well know and well annotated cassia iris database. CASIA-V4-Thousand contains 20,000 NIR images from 1,000 subjects, collected in an indoor environment with different illumination settings and a resolution of 640× 480 pixels. The main source of variation in this dataset is the specular reflection of the glasses. The dataset was collected using the IKEMB-100 camera manufactured by IrisKing.

Similarly, we have collected 288 eye image from 18 different peoples to test the proposed model. The resolution of these images is 1280 * 804 pixels. During the data processing stage, the original resolution was standardized and normalized as training datasets. As we can see the iris images in this dataset have slightly different color distribution, as well as different sizes.

One-hot encoding is the process by which categorical data are converted into numerical data for use in machine learning. Categorical features are turned into binary features that are “one-hot” encoded, meaning that if a feature is represented by that column, it receives a 1. Otherwise, it receives a 0.

The primary steps in iris segmentation, started with understanding the overall face landmarks. We have used face_detector and eye_detector metadata generated from CASIA-iris image data using haarcascade method. We employed CascadeClassifier, first to identify face region of interest from face landmark, then from segment eye's region of interest (roi). **Haar-feature selection:** A Haar-like feature consists of dark regions and light regions. It produces a single value by taking the difference of the sum of the intensities of the dark regions and the sum of the intensities of light regions. It is done to extract useful elements necessary for identifying an object. The following figure illustrated how to perform the first step of iris segmentation works.

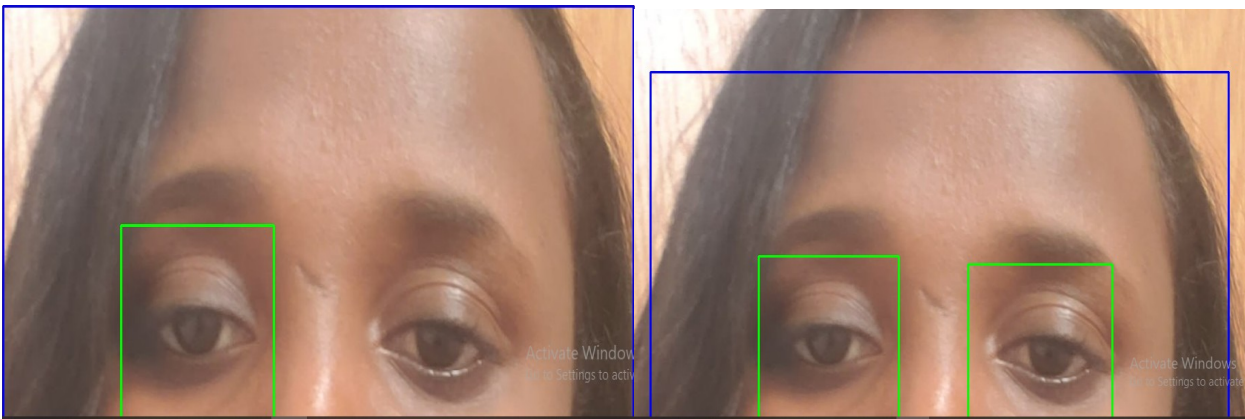


Figure 13: Haar Algorithms to segment eyes ROI

CascadeClassifier method in cv. module supports the loading of haar-cascade XML files. Here, we need “haarcascade_frontalface_default.xml” for face detection.

```
Sample scrip to detect eye using ...
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
faces = face_detector.detectMultiScale(gray, 1.2, 3)
for (x,y,w,h) in faces:
    img = cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2)
    roi_gray = gray[y:y+h, x:x+w]
```

The cascade classifier is a technique that combines progressively more complex classifiers, such as AdaBoost, in a way that expedites the discarding of negative input (non-face) and devotes more processing power to positive or promising face-like regions. It greatly speeds up the process and cuts down on computation time.

Determining the two parameters, scaleFactor and minNeighbors, is also crucial. The factor of increase in window size is determined by the scale factor, which starts at size "minSize". Once all windows of that size have been tested, we set scaleFactor=1.1 and minNeighbors=9, respectively.

Faster detection will result from fewer steps if the "scaleFactor" is large, but we run the risk of missing objects whose sizes fall between the two tested scales.

Understanding dataset

After learning how to use the haarcascade method to manipulate our facial landmark. Then, using the training dataset that we obtained from public repositories, we deal with the iris segmentation process. Prior to starting the next task, it was necessary to comprehend our dataset. Therefore, certain statistical information from a data frame or set of numerical values from the training dataset, such as the percentile, mean, standard deviation, etc. The examples below illustrate how this method produces a different result when it is applied to a sequence of strings.

Table 3: summary of iris segmentation training dataset

index	Image name	label	Statistical descriptions	
0	D:/study/iris/data\030\1\030_1_2.bmp		count	324.0000
1	D:/study/iris/data\066\1\066_1_3.bmp		mean	54.5000
2	D:/study/iris/data\011\1\011_1_2.bmp		std	31.2238
3	D:/study/iris/data\002\1\002_1_3.bmp		min	1.0000
4	D:/study/iris/data\059\1\059_1_2.bmp		25%	27.7500
...			50%	54.5000
319	D:/study/iris/data\074\1\074_1_3.bmp		75%	81.2500
320	D:/study/iris/data\091\1\091_1_3.bmp		max	108.0000
321	D:/study/iris/data\104\1\104_1_2.bmp			
322	D:/study/iris/data\038\1\038_1_2.bmp			
323	D:/study/iris/data\005\1\005_1_3.bmp			

From the input dataset, we understood that training dataset has symmetric distribution with each categories. Data creators have done important in data annotation (labeling) of individual iris with respective image. The next step further explore the process of processing and feature extraction to enhance efficient segmentation.

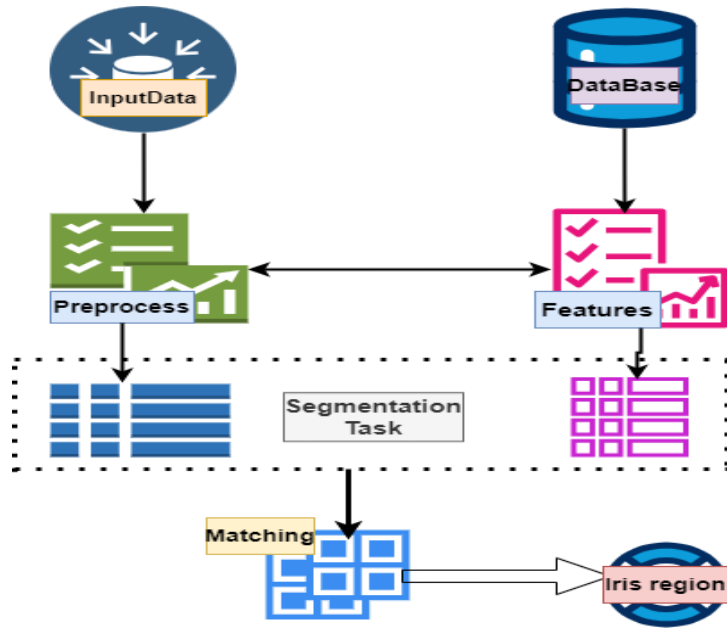


Figure 14: Iris segment work flow

Figure 14: illustrated the core process of the proposed approach to identify the iris region from the rest of eyes part. The main function of the work flow show the measuring the similarity of pixel values at each steps with the corresponding steps on the other side.

4.2 Deep learning model

4.2.1 Preprocessing and feature extraction

Immediately following segmenting the iris using the Hough transform and perceptual edge detection, we unfold the ring between the inner and outer circles to create a 64×512 rectangle. As per Li Ma's paper, we performed local image equalization following normalization. Lastly, we extract the feature vector from the ROI using the Gabor filter.

We used models to carry out facial landmark analysis in order to pinpoint the key areas of the face when completing an iris recognition task. A popular convolutional neural network (CNN) architecture for semantic segmentation tasks, such as medical image segmentation, is the U-Net model. Its U-shaped architecture, which consists of an expanding path (decoder) after a contracting path (encoder), gives it its name. Although U-Net was initially created for biomedical image segmentation, it has since been modified for use in a variety of computer vision applications.

Encoder

The input image's hierarchical features must be captured by the encoder. It is made up of several max-pooling and convolutional layers that increase the number of feature channels while gradually decreasing the input's spatial dimensions. Setting the input size in U-Net, or any other neural network, is essential to guarantee network architecture compatibility. The dimensions of the

input data that the model can accept are determined by the input size. The input size for U-Net must be compatible with both the down sampling and up sampling processes due to its symmetric architecture. In the regard, we have transformed the raw (224x224) iris image dataset to 256 * 256 *3 dimension to maintain the compatibility of the model. In this case 3 indicates number of channels (RGB) in the image source.

Decoder:

The decoder is responsible for generating the segmented output based on the features extracted by the encoder. It consists of multiple up sampling (transpose convolution) and concatenation layers to progressively increase the spatial dimensions of the input. The goal is to recover the spatial information and generate a high-resolution output.

Skip Connections:

In order to connect the corresponding encoder and decoder layers, U-Net introduces skip connections. The model can capture fine details during segmentation thanks to these connections, which also aid in the preservation of spatial information. During training, skip connections help to improve gradient flow and lessen the issue of vanishing gradients.

Final Layer:

Typically, a 1x1 convolutional layer with a sigmoid activation function makes up the decoder's final layer. This layer's output is the segmentation mask, where the value of each pixel represents the likelihood that it belongs to the target class. The Unet model was demonstrated in the following for iris segmentation work.

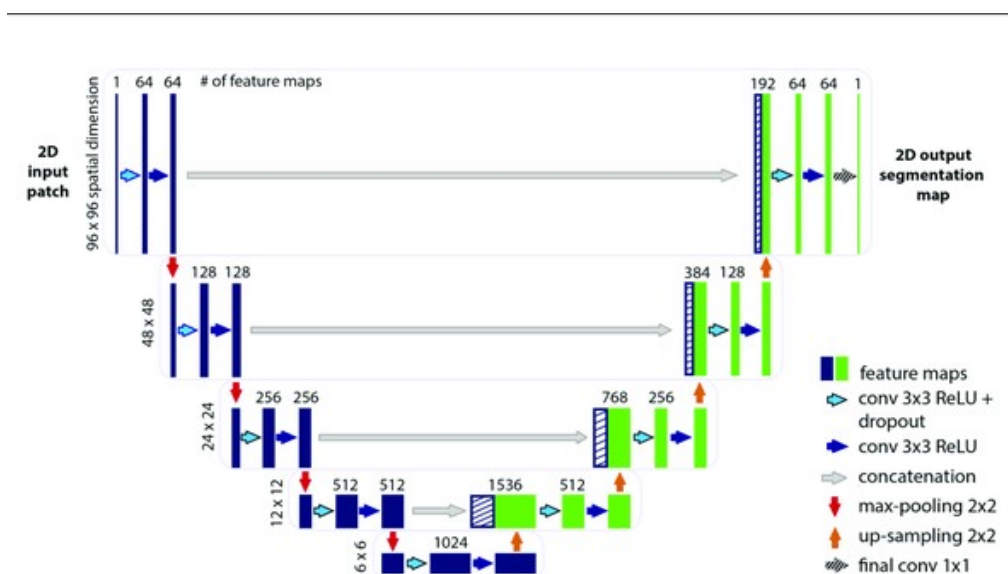


Figure 15: Unet model Architecture

Similarity measurement using Hamming Distance

Hamming distance is a metric used to measure the difference between two strings of equal length. It is calculated as the number of positions at which the corresponding symbols (characters or bits) are different.

The following steps show the general explanation of how Hamming distance could be applied in iris segmentation work.

Feature Extraction: Initially, various features are extracted from the iris image, forming a template or code. These features could include texture patterns, crypts, furrows, etc.

Encoding: The extracted features are then encoded into a binary string or code. Each feature or characteristic may be represented by a set of bits.

Template Matching: During recognition or verification, the new iris image's features are similarly encoded into a binary string.

Hamming Distance Calculation: The Hamming distance is then computed between the encoded template from the database and the newly acquired template. A lower Hamming distance suggests a closer match.

To use various feature extraction techniques to perform iris segmentation and visualize the most significant region of interest (roi). Starting from the upper-left corner of an image, we successively zero out a square region of $N \times N$ inside the image, and then we use the trained model on the obscured image to make a prediction. It would be deemed an important region if blocking that area caused the model to incorrectly identify the iris image. However, we deduce that region is not as significant if eliminating it has no effect on the model's prediction. Now if we repeat this procedure for different sliding windows of $N \times N$, each time shifting them with a stride of S , we can get a saliency map for the most important regions in recognizing fingerprints. As it can be seen, most regions inside the iris area seem to be important while doing iris recognition.

To justify this approach, we took two eyes as input dataset, then conduct similarity measurement based each roi pixel values. The model compute the difference values of RGB between image1 and image2. If the difference between the two images are 0, then it conclude that the two are perfectly matching.

Hamming Distance: 0.0

Iris images match.

This is one of the possible procedure to check the similarity and dissimilarity of two eyes. The algorithm try to measure the difference between r,g,b values of the two images.

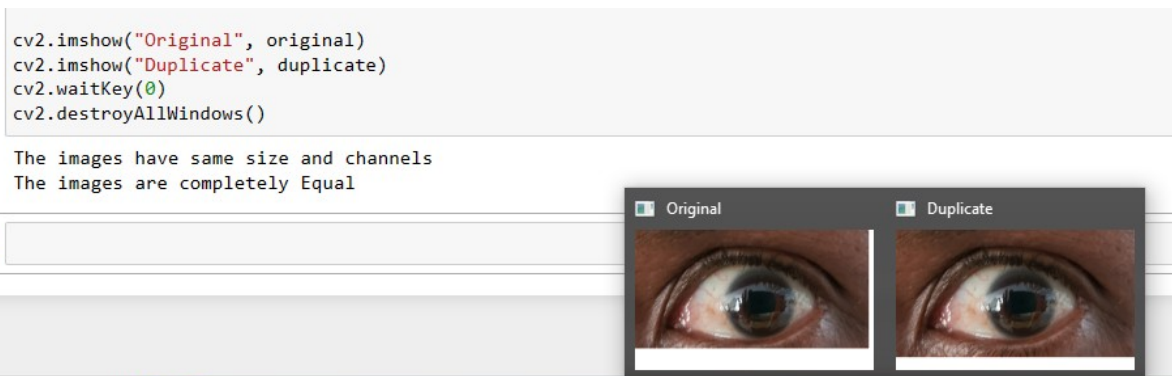


Figure 16: The images have same size and perfect matching

From the above figure Q, during feature extraction If two eye image have the same pixel value or feature, then it displayed the second eye image as duplication of the first one. The potential search area where the eye center can be found is calculated as one-ninth ($1/9$) of the image dimensions.

Iris segmentation is one of the image processing tasks where morphological operations are essential. Isolating the iris area from the remainder of the eye image is the process of iris segmentation. It is customary to apply morphological operations to improve and strengthen the segmentation outcomes.

#Morphological operation to perform extraction /iris masking using morphological operation

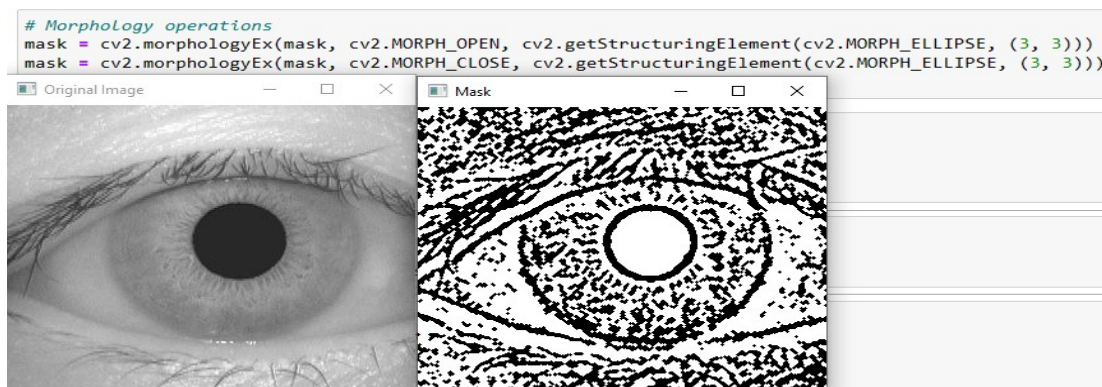


Figure 17: Masking using morphological operation

There a lot of techniques employed with morphological operation depending on your objectives and types of problems you are dealing with such as Erosion, Dilation, Opening, Closing, and Morphological Gradient.

The application of iris recognition improved dramatically with the advancement of computer vision technology. The state-of-the-art feature extraction and robust recognition algorithm are mainly depends on efficiently segmentation techniques. In this regard, we have used Haar cascading

algorithms to segment the face and eye components. The main objective was to understand the problem domain of iris segmentation. Once we are able to segment relevant Region of interest, then we further explore how to segment only the iris part to extract its unique feature.

The next step was to start segmenting the iris region from the eyelids. This is the major work in iris segmentation task. Then implementing Daugman's algorithm to segment iris and pupil from eye section. The algorithm analyzes the pixel data in the image to determine the iris and pupil regions, based on the principle of enclosing the iris pattern with a circular boundary, where $I(x,y)$ is the eye image, r is the radius to searches over the image (x,y) , $G(r)$ is a Gaussian smoothing function. The algorithm starts to search from the pupil, in order to detect the changing of maximum pixel values.

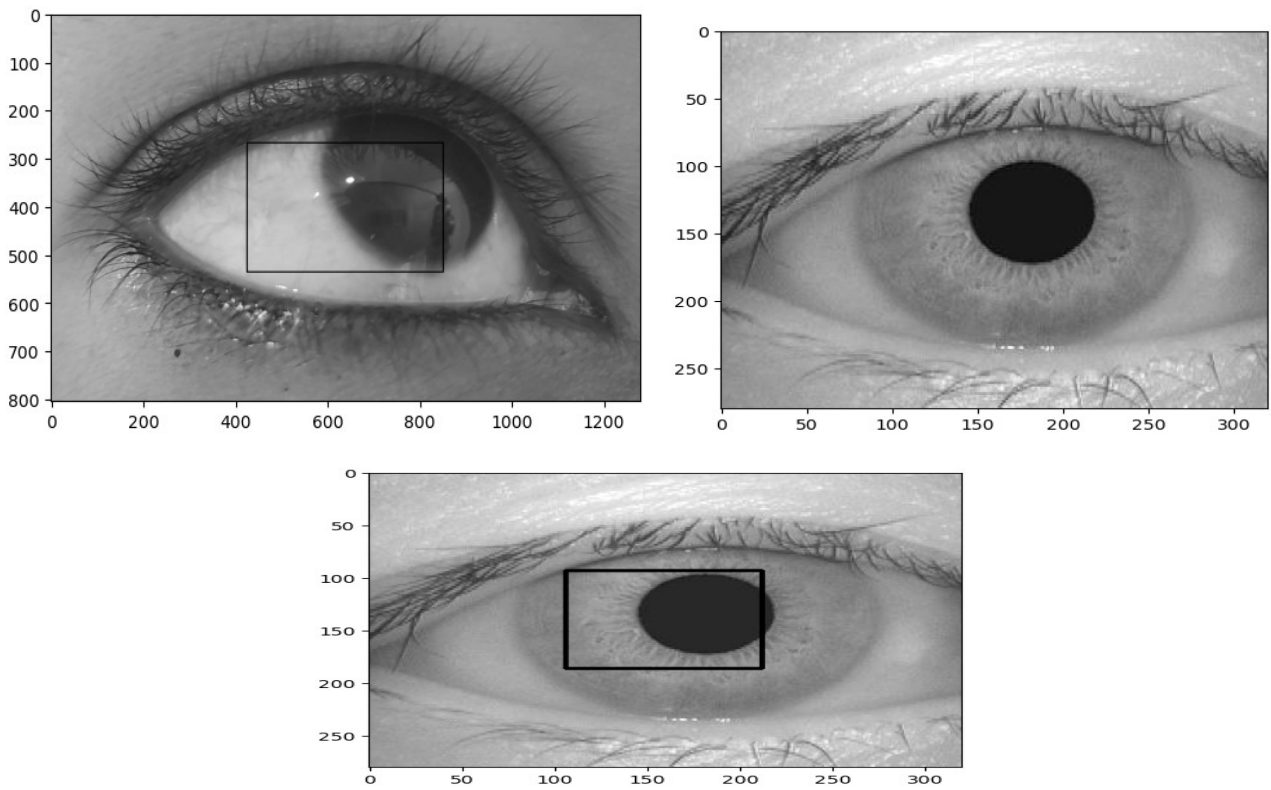


Figure 18: Top-left Eye unlabeled and Top-right Eye labeled Iris image and B labeled iris image

One of the major concern in iris segmentation task is to double check the orientation or focuses of eye during data acquisition. From the above figure, we can clearly see how the orientation of iris deviate from its center. Well labeled iris dataset would improve the challenge related with orientation issue to enhanced recognition performance of proposed model.

#image denoising task

In iris recognition systems, where precise and trustworthy identification of individuals is critical, iris denoising is a necessary step. Systems for recognizing iris images depend on capturing distinctive characteristics of the iris, like patterns and texture. Errors in recognition may arise from noise in the iris image interfering with the proper extraction of these features. Denoising increases the signal-to-noise ratio and consequently the recognition process' accuracy. The process of denoising helps to extract pertinent features from the iris texture. The system can concentrate on finding real patterns and structures in the iris by lowering unwanted noise, which improves the effectiveness of the feature extraction procedure.

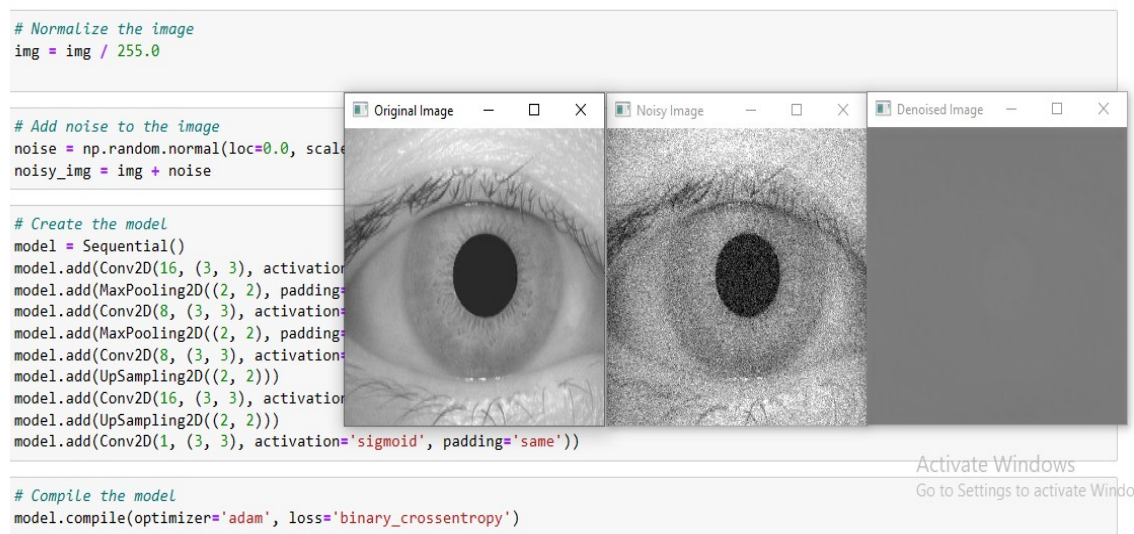


Figure 19: Iris image denoising

We build small unet model to perform the denoising tasks; first we upload in the input image, the image rescale activities has been done then normalization task is followed. Then we feed the normalized input to the unet model to perform the denoising task. By reducing noise in iris images, denoising contributes to the overall robustness and trustworthiness of the system, making it more resistant to spoofing attempts or fraudulent activities.

Not that if you may get a total black or void output due to loss of important features or total ignorance feature from source dataset.

In the case CASIA irs dataset; mention the amount of time required to read the files from directory. The iris segmentation using Daugman operation function.

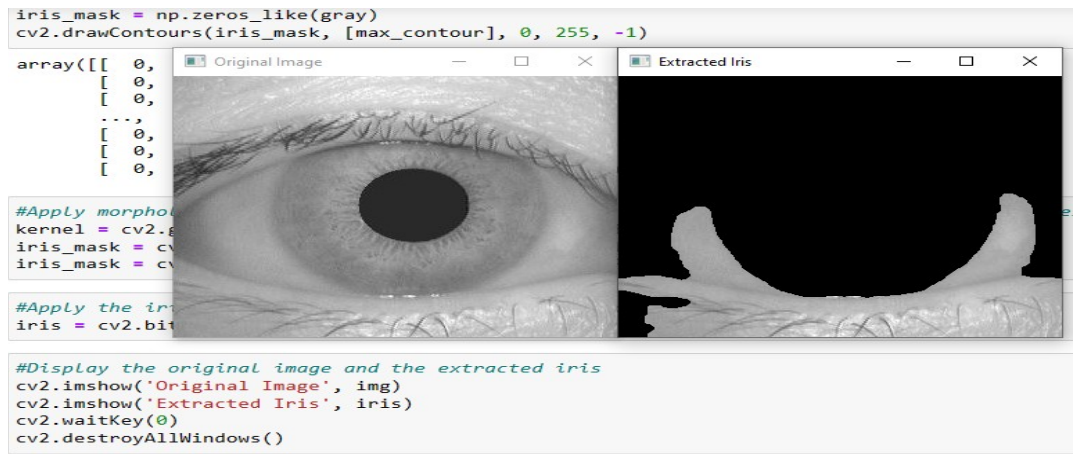


Figure 20: Iris Segmentation using Daugman

Then, we further explore the feature extraction and segmentation task by employing Gaussian blur, and canny edge detection techniques to find the contour with the largest area. Then we draw the largest contour on a black background. In this case, morphological transformations has been used to remove noise and fill in gaps to find the center and radius of the iris.

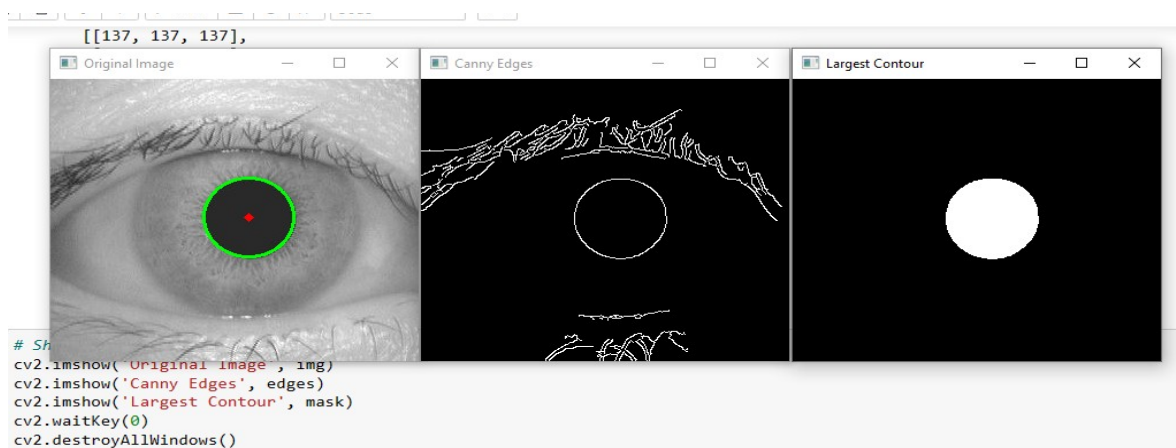


Figure 21: Combined technique to find the center and radius of iris

Experiment Implementation using Unet model

In this subsection, in-depth discussion on the implementation of Unet model for iris segmentation are presented as follows:

Model training

We training the Unet model with small size iris datasets collect from cassia repository. The following parameter has been used to train the model.

Total params: 1,883,137

Trainable params: 1,883,137

Non-trainable params: 0

Data Splitting

Splitting the data into training and test sets is a crucial step in machine learning model development to assess its generalization performance. By dividing the dataset, typically using a predefined ratio (e.g., 80% training and 20% testing), the model can learn patterns from the training data while evaluating its performance on unseen data from the test set. This approach helps in detecting overfitting, ensuring that the model can generalize well to new, unseen examples. The training set is used to optimize the model's parameters, while the test set evaluates its performance by comparing predictions against ground truth labels, enabling an accurate assessment of its effectiveness before deployment.

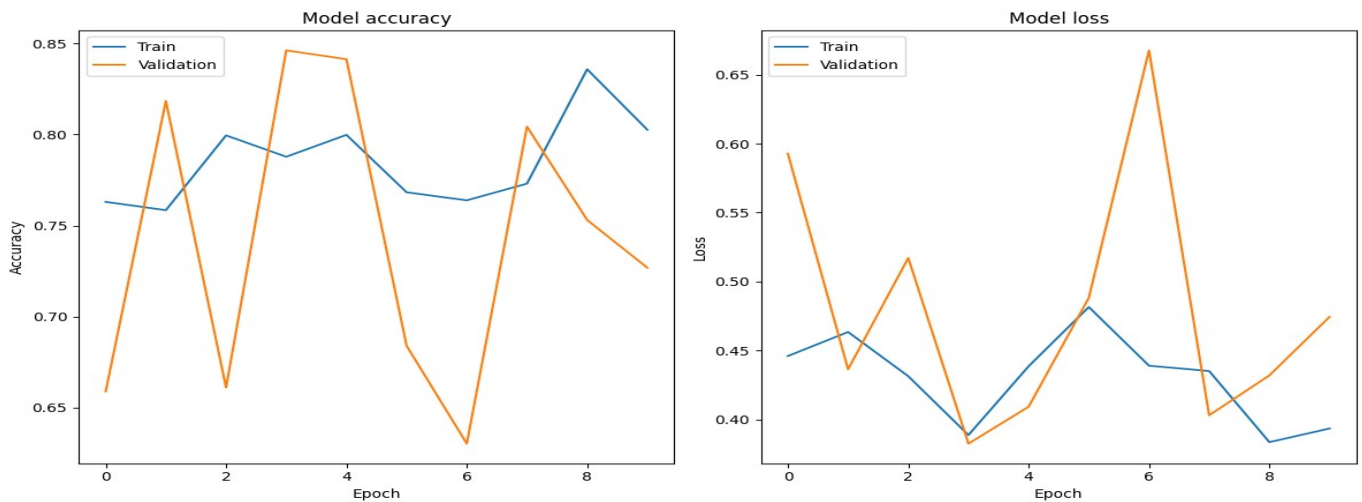


Figure 22: Unet model performance on model training

The performance of the Unet model is further improved by increasing number of iteration from 10 epoch to 20 epochs. The model gained significant training and validation accuracy on the given iris image data. The following figure illustrate the performance of Unet model segmentation training and validation accuracy with 50 and 20 epoch iteration rate respectively.

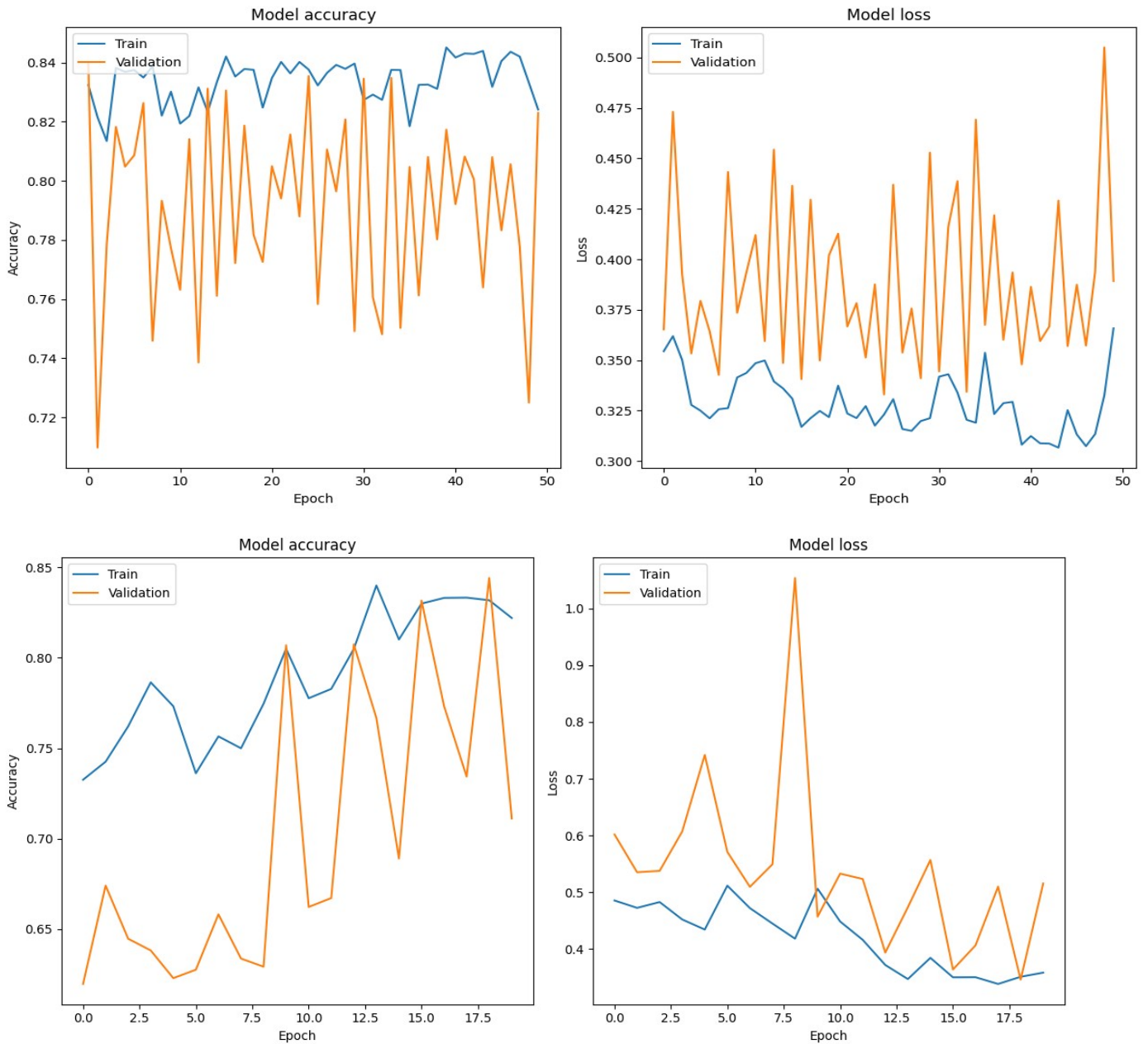


Figure 23: Unet model performance after changing iteration rate

From Figure 23 above, we can understand that, the performance of Unet model can be further optimized by experimenting for n number of times with try and errors. From our experiment results one of the big challenges the nature of iris image shape, structure of eyes, the difference of eye focus, specific instrument used to collect eye image, and other factors limit the performance of the model.

Parameters used to build Unet model

In this subsection, the parameters used to build and compile the U-Net model has been summarized as follows:

Input Shape: The shape of the input images expected by the model, specified as (height, width, channels). In the provided code snippet, the input shape is (256, 256, 3).

Number of Filters: The number of convolutional filters used in each layer of the encoder and decoder. These filters extract features from the input data at different scales, capturing both low-level and high-level features.

Kernel Size: The size of the convolutional kernels applied to the input data. In the provided code snippet, a kernel size of 3x3 is used.

Activation Function: The activation function applied after each convolutional layer to introduce non-linearity into the model. ReLU (Rectified Linear Unit) activation is commonly used in U-Net models to introduce non-linearity.

Pooling: Max pooling layers are used in the encoder to downsample feature maps and reduce spatial dimensions, aiding in capturing hierarchical features while reducing computational complexity.

Upsampling: UpSampling2D layers are used in the decoder to increase the spatial dimensions of feature maps, restoring the original image resolution.

Output Activation: The activation function applied to the output layer of the model. For binary segmentation tasks like iris segmentation, a sigmoid activation function is often used to produce pixel-wise predictions in the range [0, 1].

Loss Function: The loss function used to measure the difference between the model's predictions and the ground truth labels during training. Binary cross-entropy loss is commonly used for binary segmentation tasks.

Optimizer: The optimization algorithm used to update the model's parameters during training to minimize the loss function. Adam optimizer is a popular choice due to its adaptive learning rate capabilities and efficient convergence.

Metrics: The evaluation metrics used to monitor the model's performance during training and validation. Accuracy is commonly used to measure the proportion of correctly classified pixels, while other metrics like Intersection over Union (IoU) provide more insights into segmentation performance.

Iris image masking and challenges

From the experiment results, the primary drawback of iris image masking lies in its complexity and variability. The intricate patterns and structures within the iris region make accurate segmentation challenging, especially in low-quality images or when dealing with factors like occlusions, reflections, or iris deformation. Additionally, achieving precise segmentation requires

high-resolution images, which may not always be available or feasible to obtain in real-world scenarios.



Figure 24: Iris image masking Constraint

From Figure 24 above, Thresholding the predicted masks involves converting the probability values predicted by the model into binary values (0 or 1) based on a certain threshold. This threshold can be adjusted depending on the task requirements and dataset characteristics. A higher threshold may lead to more conservative predictions, while a lower threshold may result in more inclusive predictions. It's essential to choose a threshold that balances between sensitivity and specificity, ensuring accurate segmentation results without overly under- or over-segmenting the objects of interest. Experimenting with different thresholds and evaluating their impact on the model's performance can help determine the optimal threshold for the specific segmentation task at hand.

Computation complexity

When encountering computational complexity issues during model training on a CPU, transitioning to GPU acceleration, such as the Tesla T4 NVIDIA GPU, significantly enhances processing power and speed. GPUs excel in parallel computing tasks, making them ideal for deep learning tasks with large datasets and complex models. The Tesla T4, equipped with CUDA cores optimized for deep learning workloads, efficiently handles the heavy computations required for training neural networks.

Chapter Five

5. Results and summary

Introduction

Individual identification via biometrics has been routine practice for decades. Biometrics refers to the measurement, analysis, and categorization of personal recognition and verification or identity based on distinguishing biological (physiological) or behavioral traits, features, or characteristics of that individual. According to academics in the domain area, biometric identification is the process of connecting an identity with the input biometric data by comparing it to the enrolled identities in a database.

Some of the commonly used physical or behavioral traits are: Face, fingerprint, palm print, hand geometry, iris, keystroke, signature, voice and gait. Apart from these, there are also some traits which are used to identify a person uniquely based on odour, tongue, ear, knuckle print. Among the various biometric traits, 'Iris' is proved to be a major and popular biometric feature for authentication and identification with a high degree of accuracy and distinctiveness.

The eyes are regarded as the most prominent and stable feature in the computer vision community. Automatic eye extraction is useful in a variety of real-world applications, including face alignment, driver sleepiness detection, face recognition, and human-computer interaction. Several factors make it difficult to identify and track eyeballs, including head postures, lighting circumstances, eye form and color, iris movement, imaging quality and conditions, and so on. A lot of effort has been done to overcome the above challenges, but it is still an open subject matter of study in the computer vision community.

Iris recognition is a novel feature in personal identification that is said to be the most reliable biometric property for identification and authentication. Similarly, the structure of the iris is more closely tied to its geometric shape, making it easier to extract these elements. Iris-based recognition is a relatively new research topic that has been motivated by numerous domain-specific researchers. One of the primary tasks in designing a strong iris identification system is to separate the iris area from the eyelid. Based on the scope of the study, the primary goal of our work is to use several ways to accurately segment the iris area from the rest of the eye.

5.2 Iris segmentation

To carry out the iris segment experiment, we obtained iris images data from an open source repository and local data from participants. Data acquired from repositories is well-labeled and more than 95% ready for the feature extraction procedure. Locally collected images, on the other

hand, have poor quality due to low resolution, picture orientation, image size variation, light reflection, and distance from camera that do not meet standards. Image preprocessing is critical for extracting crucial information; otherwise, the pupil/iris border may be incorrectly detected. It is critical to eliminate any artifacts that might disrupt the feature extraction step. First, the image complement was analyzed. Areas of dark pixels surrounded by lighter pixels were replaced by the lighter pixels. The image is then smoothed using averaging filter. Then, an edge image is found using the Canny edge detector. The Canny edge detector was used as it is capable of detecting both strong and weak edges.

The iris region can be approximated by two circles, one for the pupil/iris boundary and one for the iris/sclera boundary.

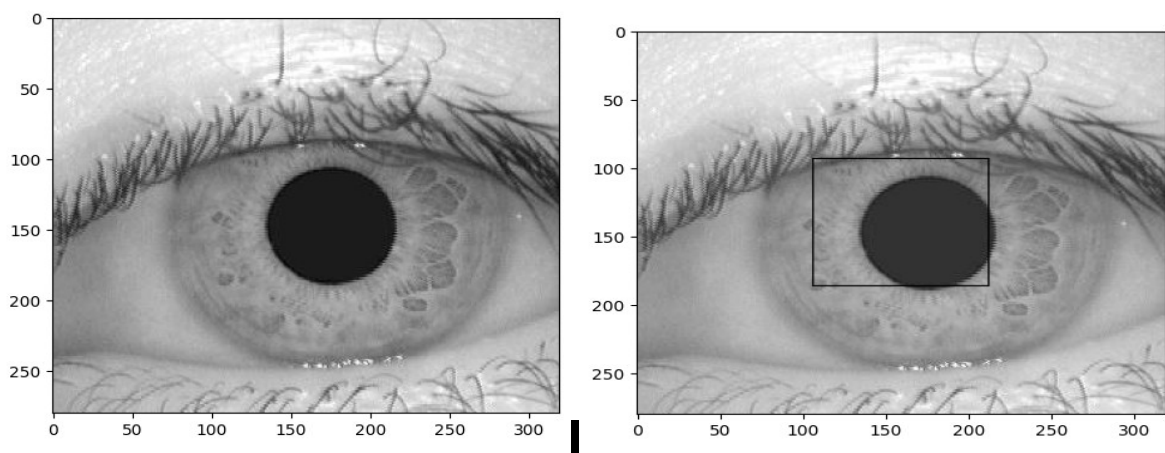


Figure 23: Input eye image left-side and detection iris region right-side

Before detection of these boundaries, the edges of the eye image must be found. From the edge image, the circular Hough transform can be used to detect the centers and radii of the two boundaries. The main objective of iris segmentation is to separate the usable iris pattern from other parts of the eye and the noise as well. It is obvious that, the accuracy of the iris segmentation will impact on the result of feature extraction. It's the process of detecting the pupillary and limbi boundaries of an iris in the image. This would help in extracting features of the iris, excluding the surrounding of the pupil.

Daugman algorithm

The Daugman algorithm is a commonly used method for iris and pupil detection. The algorithm analyzes the pixel data in the image to determine the iris and pupil regions, based on the principle of enclosing the iris pattern with a circular boundary. The Daugman function follow the following outline to identify iris region. First it, we convert the rgb image input to gray-scale image data. The iris search region size of the circle center is defined by the top-left corner (x0,y0) and bot-

tom-right corner (x1,y1). The other parameter is the min and max value of circle radius. Then the last parameter is center step size to determine the distance between circles with the same center.

```
(x0, y0), (x1, y1) = search_region
x_axis_p = list(range(x0, x1, center_step_size))
y_axis_p = list(range(y0, y1, center_step_size))
```

Where $I(x,y)$ is the eye image, r is the radius to searches over the image (x,y) , $G(r)$ is a Gaussian smoothing function. The algorithm starts to search from the pupil, in order to detect the changing of maximum pixel values. The Gaussian Smoothing Operator performs a weighted average of surrounding pixels based on the Gaussian distribution. It is used to remove Gaussian noise and is a realistic model of defocused lens. Sigma defines the amount of blurring. The radius slider is used to control how large the template is. Large values for sigma will only give large blurring for larger template sizes. The calculation is more when the σ value becomes high.

Hough transform

We have employed Hough transform feature extraction technique to extract relevant feature used segment the iris region. The Hough took x_i and y_i value, where (x_i, y_i) are central coordinates, and r is the radius. Generally, and eye would be modeled by two circles, pupil and limbus (iris region), and two parabolas, upper and lower eyelids.

The following sample script describe how to implement the Hough transformation method to segment the iris and pupil region from eyelids. Different experiment result recommend that, we can get segmentation line using the radius boundary of the iris between 35 and 55 pixels respectively.

```
iris_c, iris_r = iris_seg(img, (start_point, end_point), 35, 55, 2)
then
#we took 0.2 and 0.5 to determine pupils radius boundaries. Check the variation with different values
pupil_r_min, pupil_r_max = int(iris_rad * 0.2), int(iris_rad * 0.5)
pupil_center, pupil_rad = iris_segmentation(result_img, (start_point, end_point),
pupil_r_min, pupil_r_max, 2)
cv.circle(result_img, iris_center, iris_rad, (0, 0, 255), 1)
cv.circle(result_img, pupil_center, pupil_rad, (255, 255, 255), 1)
```

Figure 24: Sample code to detect iris region

This is block-code is define how to apply iris min and max radius; and pupils min_max values respectively to identify the segmentation line between iris and pupils region. It detect the eyelids form the horizontal direction, then detects the pupil and iris boundary by the vertical direction.

The transform is computed by drawing circles of a given radius at every point in the edge image. For every point where the perimeter of a drawn circle passes, the coordinate was incremented by 1. This was done for every circle drawn to create an accumulation array. A circle is indicated by peaks in the accumulation array.

Detection of circles using this transformation requires knowledge of the radius. As we don't know the definite radius of the pupil or iris, the transform must be computed for a range of radii. For each radius tested, the location and value of the maximum is stored. The radius with the highest peak indicates the most likely radius and center coordinate for the boundary. Circular Hough Transform can be used to detect geometric shapes that can be written in parametric form such as lines, circles, parabolas, and hyperbolas. The circular Hough transform can be used to detect the circles of a known radius in an image. The equation of a circle can be written as $r^2 = (x - a)^2 + (y - b)^2$, where r is the radius of the circle and a and b are the center coordinates. In parametric form, the points on the equation of a circle can be written as follows: $x = a + r \cos(\theta)$, $y = b + r \sin(\theta)$ (2)

5.3 Performance evaluation

The final task is computing the iris segmentation performance on the basis of the given parameters. The following simple equation compute the number of iris correctly segmented versus number of iris wrongly segment given a total training image data.

$$SP = (pS / TII) * 100\% \text{ and } (ws / TII) * 100\%$$

$$\text{The summation of } (pS / TII) * 100\% + (ws / TII) * 100\% = 1$$

Where sp is segmentation model, ps number of iris perfectly segmented, ws is wrongly segmented, and TII is total iris image data set used as input dataset. Accordingly HT algorithm score optimal result in segmenting iris from eye image. But if we able to remove the noises and some reflection, the performance of the model can be enhanced further.

To build the segmentation model it took more than one hour using TPU infrastructure. This raised the issues of computation against the size of image datasets. For the purpose of our experiment, we have used colabs GPU facility. But to speed-up the computation, it demands to utilize high performance computing infrastructure.

Experiment output

Daugman operator: this function uses the Daugman operator to detect the boundaries of the iris and pupil. The search region size of the circle centers is defined by the top-left corner. The minimum values of the circle radius for the iteration.

Performance of the iris the model

SN	Data sources	Correctly classified	Miss-classified	Accuracy
1	Iris-thousand (1999 samples)	1853/1999	146/1999	92.5%
2	New image (25 sample)	19/25	6/25	76%

Segmentation performance

From experiment results, we have identified that efficient iris segmentation is a data specific and feature extraction challenge. Therefore, we recommend interested researcher and stakeholder to give due attention for feature extraction and identification ROI to build efficient iris recognition model. The following figures show some of the complex eye shape, structure and size.

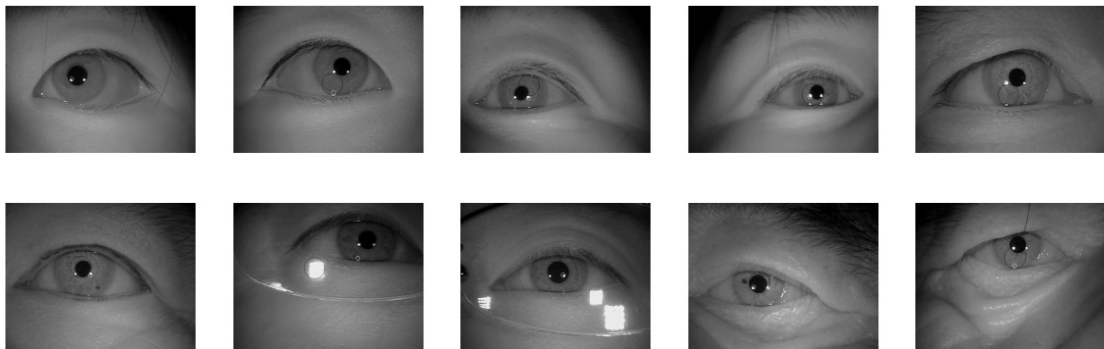


Figure 25: Some of the complex iris structure

From the experiment result, we found that there are some challenge in iris segmentation related with the complex structure of the eye. In the case, incorrect results occur in images where the eye is partially or completely closed. There are some possible solution to solve this challenge; using standard camera to acquire clear iris image and incorrect results are observed due to the impact of light on the pupil. Therefore, properly adjusting radius range for the pupil also help to handle the errors.

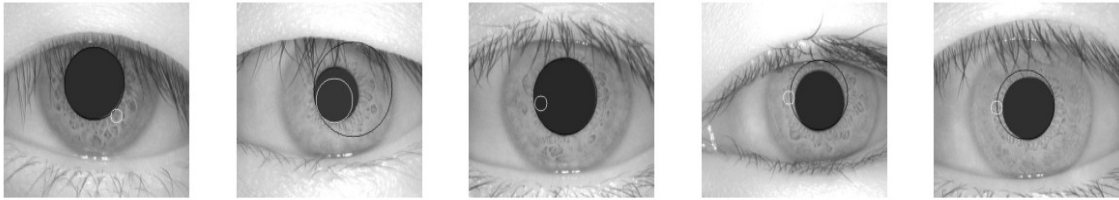


Figure 26: Segmentation output from new-dataset, to show the comparison with casia iris thousand image data. In this case we took only 25 sample data, but if we increase training data size most probably the segmentation performance will also increases.

Finally, The U-Net model demonstrates notable capabilities and performance in iris segmentation tasks compared to other deep learning models. Its architecture, featuring an encoder-decoder structure with skip connections, effectively captures both global context and fine-grained details, leading to accurate segmentation results. The model's ability to preserve spatial information through skip connections enhances its performance, particularly in tasks involving intricate structures like the iris. The use of skip connections enables the model to leverage features from multiple scales, effectively addressing the challenges associated with iris segmentation, such as occlusions and variations in illumination.

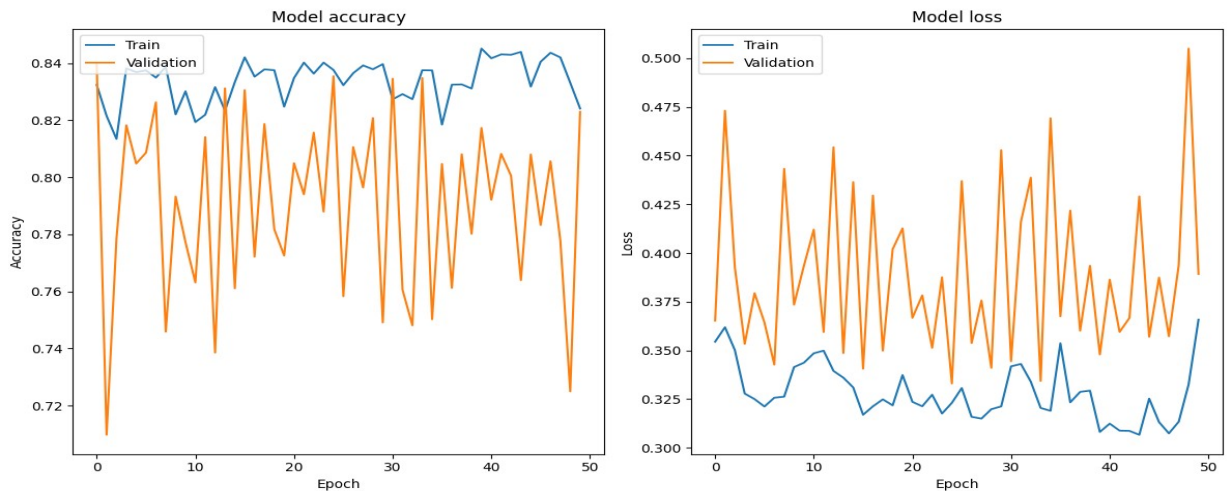


Figure : U-Net model segmentation Accuracy

In similar problems requiring precise segmentation of complex structures, considerations should be made regarding data augmentation techniques to enhance model robustness and generalization. Additionally, fine-tuning the model architecture and hyperparameters, along with incorporating domain-specific knowledge, can further improve performance. Overall, while U-Net demonstrates Training accuracy: 0.8241 val_accuracy: 0.8230 performance in iris segmentation tasks, continued research and experimentation with novel methodologies are essential for further advance-

ments in this field. This performance can be further improved based on the effort we made on data preprocessing task and quality iris image collection method we followed

Chapter Six

6. Conclusion and Recommendation

6.1 Conclusion

In this study, we have made analysis on review of related works to identify the feasibility of using biometric features to develop iris segmentation to for biometric identification system. As we all understood, biometric based authorized user identification system a common method for the last many decades. Most organization employed biometric security techniques to protect their organization. But due to relative proximity, access to organization by external or internal worker, the old technique are highly prone to organizational security challenge. In this research study, we proposed iris segmentation method to support the development of efficiently the iris recognition process.

Due to globalization, digitalization, and electronic transaction process, organizations demands advanced security system to protect their wealth from unauthorized traits. In the last many decades, organization have used different types of biometric techniques to identify authorized user. In this research, we proposed iris region segmentation using different feature engineering techniques which uses for building robust recognition model. From the experiment results, we found that iris segmentation task is a complex problem to understand the feature used to identify iris region. In the case of local situation, it very difficult to get access to researchable in the domain of iris segmentation tasks. The CASIA and other open sources repositories has been used to acquire iris datasets. Similarly, we have collect eyes image dataset locally from some volunteers for test purpose. We have seen that limitation of image quality issues due to many factors such as light reflection, orientation of camera device, distance from the focus, uniformity eye shape, and many other challenges.

Hence, to build robust iris recognition system, investing time and effort on the segmentation work will have potential competitive advantages. Because, iris segmentation is mainly depends on first identify the iris region from the rest of eye's part. Proper iris segmentation also demand good understand about the problem domain. In this regards, we have made a lot of attempts to segment iris region using different iris segmentation techniques. But the area need further study in the case of local iris dataset. We have already mentioned that, there is no well labelled and annotate iris dataset for researcher. Therefore, we would like to inspire interested research to exert his/her time to address the bottleneck in the domain area. The last but not the least, is the access to advance camera for iris image collection is remain as another challenge for research in the domain area.

6.2 Recommendation

The proposed system in this research study was able to perform promising accurate results, however there are still number of issues which need to be addressed. Reliable high performance computing facility is required to process the large size image data. Similarly, robust feature extraction technique is needed to extraction features from the complex iris image data. The other import research insight is the limitations of access to well labeled and annotated iris dataset in case of Ethiopia, hence the area demand further work to resolve these challenge. Generally, the domain biometric security techniques needs further exploration to design generalization and reliable iris recognition system. I recommend young researcher to invest their time and skill to design innovative approaches to protect the organizational and personal resources using iris recognition method.

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APPENDIXES

Appendix A: Block of Code

Sample codes for extracting iris image

```
def calculate_hamming_distance(binary_template1, binary_template2):
    # Ensure binary templates have the same length
    assert len(binary_template1) == len(binary_template2)

    # Calculate Hamming distance
    hamming_distance = np.sum(binary_template1 != binary_template2)

    # Normalize the Hamming distance (optional)
    normalized_distance = hamming_distance / len(binary_template1)

    return normalized_distance


def extract_iris_template(image_path):
    # Replace this with your iris segmentation code or use a pre-trained segmentation model
    iris_image = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)

    # Example: Use the whole iris image as the template (you may use a feature extractor instead)
    iris_template = iris_image.flatten()

    # Binarize the template (assuming it's a grayscale image)
    binary_template = (iris_template > 128).astype(np.uint8)

    return binary_template
```

sample code of U-Net model

```
# Define the U-Net model for iris segmentation
def unet_model(input_shape=(256, 256, 3)):
    inputs = tf.keras.Input(shape=input_shape)

    # Encoder
    conv1 = layers.Conv2D(64, 3, activation='relu', padding='same')(inputs)
    conv1 = layers.Conv2D(64, 3, activation='relu', padding='same')(conv1)
    pool1 = layers.MaxPooling2D(pool_size=(2, 2))(conv1)

    conv2 = layers.Conv2D(128, 3, activation='relu', padding='same')(pool1)
    conv2 = layers.Conv2D(128, 3, activation='relu', padding='same')(conv2)
    pool2 = layers.MaxPooling2D(pool_size=(2, 2))(conv2)

    # Midpoint (bottleneck)
    conv3 = layers.Conv2D(256, 3, activation='relu', padding='same')(pool2)
    conv3 = layers.Conv2D(256, 3, activation='relu', padding='same')(conv3)

    # Decoder
    up4 = layers.UpSampling2D(size=(2, 2))(conv3)
    concat4 = layers.concatenate([conv2, up4], axis=-1)
    conv4 = layers.Conv2D(128, 3, activation='relu', padding='same')(concat4)
    conv4 = layers.Conv2D(128, 3, activation='relu', padding='same')(conv4)

    up5 = layers.UpSampling2D(size=(2, 2))(conv4)
    concat5 = layers.concatenate([conv1, up5], axis=-1)
    conv5 = layers.Conv2D(64, 3, activation='relu', padding='same')(concat5)
    conv5 = layers.Conv2D(64, 3, activation='relu', padding='same')(conv5)

    # Output Layer
    outputs = layers.Conv2D(1, 1, activation='sigmoid')(conv5)

    model = models.Model(inputs=inputs, outputs=outputs)
    return model
```