

**A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF ÇANKIRI KARATEKİN UNIVERSITY**

**CLOUD BASED VEINS RECOGNITION AND AUTHENTICATION
USING CNN**



**IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
ELECTRONIS AND COMPUTER ENGINEERING**

BY

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ÇANKIRI

2023

CLOUD BASED VEINS RECOGNITION AND AUTHENTICATION USING CNN

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August 2023

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ABSTRACT

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Master of Science in Electronics and Computer Engineering

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August 2023

In the current digital landscape, numerous systems require a reliable recognition method to verify the identity of individuals accessing their services. As technology continues to evolve, there's an escalating demand for robust and secure biometric identification. With increasing advancements in the interface between humans and computers, new biometric modalities have emerged and gained traction. Among these, the finger vein has emerged as a particularly compelling area of research. The underlying rationale for this heightened interest is the unique characteristic of the human finger vein, its intricate structure and the inherent difficulty in counterfeiting or stealing this information. This thesis delves deep into proposing a finger vein-based recognition system tailored for individual identification. The finger vein stands out primarily because of its distinctiveness. Each individual's finger vein pattern is intricate and different, almost akin to the uniqueness of a fingerprint but concealed within the body, making it a challenging target for malicious intents. Unlike external features like facial structures, fingerprints or iris patterns which can be potentially copied, mimicked or stolen, the finger vein remains protected inside the finger, making it an optimal choice for biometric identification. The methodology of the proposed recognition system is built on a series of sequential processes. First, the acquired finger vein image undergoes a preprocessing stage. This initial step is essential to refine the image by removing any superfluous details and enhancing its core features. The color image is transitioned into a grayscale format, streamlining the data and eliminating any color-based anomalies. To accentuate the details and improve clarity, histogram equalization is employed. This technique amplifies the contrast, ensuring that the vital vein patterns stand out prominently. Once the image is preprocessed and

enhanced, the system shifts focus towards feature extraction. The choice of feature extraction method is pivotal as it directly impacts the subsequent identification accuracy. This research leverages the acclaimed Linear Discriminant Analysis (LDA) for this purpose. LDA, being one of the most prominent feature extraction techniques, ensures that the extracted features are not only distinct but also optimal for classification. The heart of the recognition system lies in its classification model. This research proposes a deep Convolutional Neural Network (CNN), renowned for its capacity to discern patterns and classify with astounding precision. The advantage of employing a deep CNN in this context is its capability to deliver high accuracy without necessitating extensive datasets. A notable outcome of this research is the exemplary recognition performance yielded by the deep CNN model. When tested on the SDUMLA-HMT finger vein dataset, the model achieved an accuracy of 99.65%. Meanwhile, on the UTFVP finger vein dataset, it further exceeded expectations with an accuracy rate of 99.72%. These results are a testament to the efficacy of the proposed model, underscoring the potency of using a 1-dimensional convolutional network combined with dense layers. Another significant contribution of this thesis is the amalgamation of LDA with the deep model. This method has demonstrated superior prowess, not just in terms of recognition accuracy, but also in training speed, ensuring a swift and efficient system. Lastly, to bridge the recognition system with the cloud database, the TCP/IP protocol is employed. This ensures that once an individual is recognized, their pertinent information can be swiftly retrieved from the cloud database. This integration not only augments the recognition system's functionality but also elevates its application potential in real-world scenarios.

2023, 77 pages

Keywords: Biometric identification, Convolutional neural network, Deep learning, Finger vein recognition, Machine learning, Linear discriminant analysis, TCP/IP

ÖZET

CNN KULLANARAK BULUT TABANLI DAMAR TANIMA VE DOĞRULAMA

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Günümüz dijital manzarasında, birçok sistem, hizmetlerine erişen bireylerin kimliğini doğrulamak için güvenilir bir tanıma yöntemine ihtiyaç duymaktadır. Teknoloji evrimleştikçe, sağlam ve güvenli biyometrik tanımlama için artan bir talep bulunmaktadır. İnsanlar ile bilgisayarlar arasındaki arayüzdeki ilerlemelerle, yeni biyometrik modlar ortaya çıkmış ve ilgi görmüştür. Bu araştırma teknikleri arasında, parmak damarı özellikle dikkat çekici bir araştırma alanı olarak öne çıkmıştır. Bu artan ilginin altında yatan temel sebep, insan parmak damarının benzersiz özelliği, karmaşık yapısı ve bu bilginin taklit edilmesinin veya çalınmasının zorluğudur. Bu tez, bireysel tanımlama için önerilen parmak damarına dayalı bir tanıma sistemini derinlemesine incelemektedir. Parmak damarı, öncelikle özgünlüğü nedeniyle öne çıkar. Her bireyin parmak damar deseni karmaşık ve farklıdır, neredeyse bir parmak izinin benzersizliğine benzer bir şekilde, ancak vücudun içinde gizlidir, bu da kötü niyetli amaçlar için zorlayıcı bir hedef haline getirir. Yüz yapıları, parmak izleri veya iris desenleri gibi dış özelliklerin aksine, potansiyel olarak kopyalanabilir, taklit edilebilir veya çalınabilirken, parmak damarı parmak içinde korunmaktadır, bu da biyometrik tanımlama için ideal bir seçenek haline getirir. Önerilen tanıma sisteminin metodolojisi, sıralı bir dizi işlem üzerine kurulmuştur. İlk olarak, elde edilen parmak damar görüntüsü bir ön işleme aşamasından geçer. Bu başlangıç adımı, gereksiz detayları kaldırarak ve temel özelliklerini artırarak görüntüyü rafine etmek için kullanılır ve renk tabanlı anomalileri ortadan kaldırmak için renkli görüntü gri tonlamalı bir formata geçirilir. Detayları vurgulamak ve netliği artırmak için histogram eşitleme kullanılır. Bu teknik, kontrastı artırarak, esas damar desenlerinin belirgin bir şekilde öne çıkmasını sağlar. Görüntü ön işlendikten ve geliştirildikten sonra,

sistem özellik çıkarımına odaklanır. Özellik çıkarımı yöntemi seçimi, sonraki tanımlama doğruluğunu doğrudan etkiler, bu nedenle kritiktir. Bu araştırma, bu amaç için ünlü Doğrusal Ayırt Edici Analiz (LDA) yöntemini kullanmaktadır. LDA, en bilinen özellik çıkarım tekniklerinden biri olduğu için, çıkarılan özelliklerin sadece belirgin olmadığını, aynı zamanda sınıflandırma için de optimal olduğunu garanti eder. Tanıma sisteminin merkezi sınıflandırma modelindedir. Bu araştırma, desenleri ayırt edebilme ve inanılmaz bir hassasiyetle sınıflandırabilme kapasitesiyle tanınan derin bir Evrişimli Sinir Ağı (CNN) önermektedir. Derin bir CNN'nin bu bağlamda kullanılmasının avantajı, geniş veri setlerine ihtiyaç duymadan yüksek doğruluk sağlama yeteneğidir. Bu araştırmanın dikkate değer bir sonucu, derin CNN modeli tarafından elde edilen örnek tanıma performansıdır. SDUMLA-HMT parmak damar veri kümesinde test edildiğinde, model için %99,65 doğruluk elde edildi. Öte yandan, UTFVP parmak damar veri kümesinde, beklentileri daha da aşarak %99,72 doğruluk oranıyla sonuçlandı. Bu sonuçlar, önerilen modelin etkinliğinin bir göstergesi olup, yoğun katmanlarla birlikte 1 boyutlu bir evrişimli ağı kullanılmasının gücünü vurgulamaktadır. Bu tezin bir diğer önemli katkısı, LDA'nın derin öğrenme modeli ile birleştirilmesidir. Bu yöntem, sadece tanıma doğruluğu açısından değil, aynı zamanda eğitim hızı açısından da üstün yetenek göstermiştir, böylece hızlı ve verimli bir sistem sağlamıştır. Son olarak, tanıma sistemini bulut veritabanıyla bağlamak için TCP/IP protokolü kullanılır. Bu, bir bireyin tanındığında, ilgili bilgilerinin bulut veritabanından hızla alınabileceğini garanti eder. Bu entegrasyon, tanıma sisteminin işlevselliğini sadece artırmakla kalmaz, aynı zamanda gerçek dünya senaryolarında uygulama potansiyelini de yükseltir.

2023, 77 sayfa

Anahtar Kelimeler: Biyometrik tanımlama, Konvansiyonel sinir ağı, Derin öğrenme, Parmak damarı tanıma, Makine öğrenmesi, Doğrusal diskriminant analizi, TCP/IP

PREFACE AND ACKNOWLEDGEMENTS

I would like to thank my thesis advisor, Asst. Prof. Dr. Seda ŞAHİN for her patience, guidance and understanding.

Natek Mohammed Sakran SAKRAN

Çankırı-2023



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LIST OF ABBREVIATIONS

ADAM	Adaptive moment estimation
CNN	Convolutional neural network
KNN	K-nearest neighbors
LDA	Linear discriminant analysis
ML	Machine learning
PCA	Principal component analysis
RF	Random forest
SVM	Support vector machine
TCP/IP	Transmission control protocol/internet protocol



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1. INTRODUCTION

To assign permissions for the use of facilities and services, it's imperative to identify users accurately. In the realms of user authentication, application speed enhancement and security fortification, biometric solutions stand out as the most reliable and efficient choice. Not only are these systems dependable, but they are also user-friendly. Among the various biometrics, finger vein recognition is particularly noteworthy for its reliability. Owing to the uniqueness and consistency of human veins, this method often surpasses others in effectiveness. Deep artificial neural networks, capable of processing vast amounts of data and ensuring precise identification and detection, have become a staple in pattern recognition and machine learning. This thesis introduces a technique for accurately recognizing and verifying individuals by analyzing infrared camera images of finger veins, employing deep learning convolutional neural networks as classifiers (Ullah *et al.* 2012, Fairuz *et al.* 2018).

Accurate, automated personal identification is essential for numerous applications in today's information-driven era, including driver's licenses, passports, citizen's cards, mobile phones and voter ID cards. Traditional solutions, such as PINs and passwords, are becoming unreliable due to the risk of fraud. A viable solution to this challenge is biometric authentication, which relies on an individual's distinct physical or behavioral characteristics to confirm their identity. Because biometric methods only need to be authenticated once initially, they are more secure than key-based cryptographic approaches.

Biometric identification systems use real-time measurements of unique observable features or behaviors to verify a person's claimed identity. Biometric information from an iris scan can be used to construct a digital identity. By applying algorithms to compare collected data to existing biometric records in a database, these systems can positively identify or verify a person. The two most common ways they do this are through identification and verification. In the identification mode, the data you provide is compared to the stored patterns to determine if they match. To prevent people from

sharing identities the verification mode of biometric security compares incoming data to an individual's unique fingerprint or iris pattern (Sahar *et al.* 2022).

A multimodal biometric authentication system that provides secure access to public and civilian data is the primary focus of this research. using CNN technology, the suggested system combines the high fidelit, non-invasive, foolproof qualities of finger vein and facial features. The model was built and trained using a GPU-enabled cloud-based service platform, with hyperparameters fine-tuned and minimal preprocessing performed. After normalizing the ensembles, They are input into a CNN model equipped with a softmax classifier. With an Equal Error Rate (EER) of 0.46 or lower, the model outperforms current state-of-the-art authentication methods (Sudhamani *et al.* 2021)

To reduce the inference time required for finger vein detection, some studies introduces a lightweight, low-complexity CNN. Using the user's finger vein picture captured by a near-infrared (NIR) camera, the system can operate autonomously in client mode. Vein characteristics are rapidly extracted with the assistance of vein curving algorithms. By combining several preprocessing methods with the adapted CNN, the system can offer improved picture quality and higher recognition accuracy. The proposed finger vein identification system underwent extensive testing using laboratory-developed picture capturing equipment, demonstrating its viability and robustness (Robert *et al.* 2023).

Humans inherit physiological traits from their early developmental stages, such as fingerprints, facial features, retina, iris and hand structure. On the other hand, behavioral traits like voice patterns, handwriting and keyboard dynamics are acquired over time. The term "biometric" originates from the Greek words "bios" (life) and "metron" (measure), denoting this scientific field. Traders and potters in ancient Egypt and East Asia were already employing primitive forms of biometrics thousands of years ago. However, it wasn't until the 1970s that biometrics became a fully automated technique. The inherent nature of biometrics, which cannot be loaned, stolen, or forgotten, makes impersonation exceedingly challenging, elevating the appeal of identification based on these traits for future tech applications. Various physiological or behavioral biometric methods can be employed to identify or verify individuals.

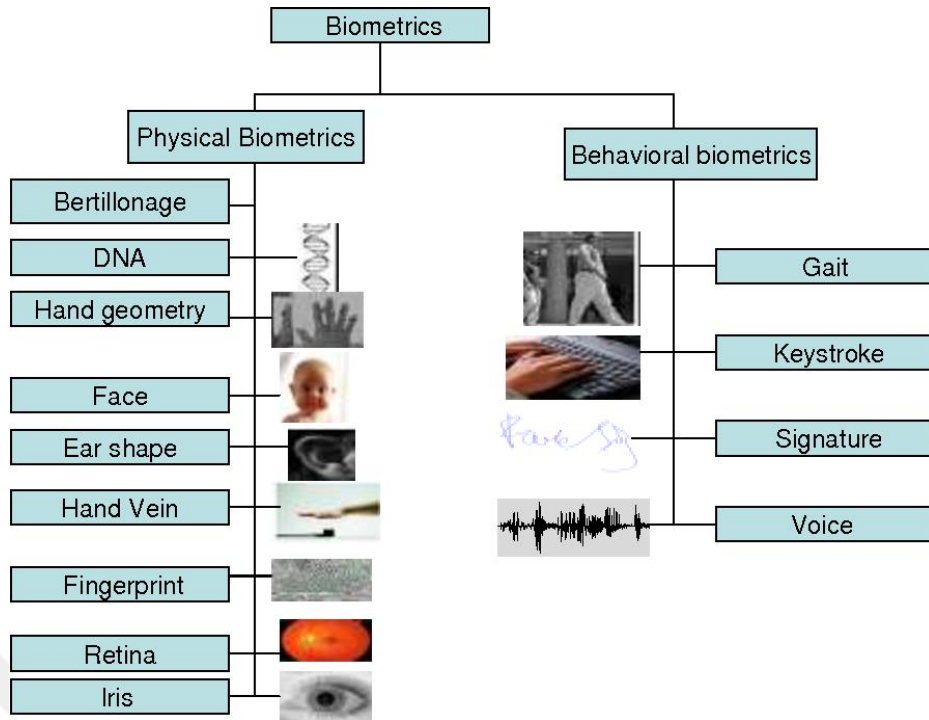


Figure 1.1 Biometrics methods (Walia and Hoshiarpur 2014)

The need for establishing identity in a dependable manner has stimulated active research in the field of biometrics, since the biometric system is a pattern recognition system that operates by acquiring biometric data from a human, extracting a feature set from the acquired data and comparing this feature set against the template set in the database.

Any human physiological or behavioral property may function as a biometric characteristic as long as it fits the following criteria (Delac and Grgic 2004):

- **Universality:** The utilized biometric either physical or behavioral must exist in all the authorized individuals of the system.
- **Distinctiveness:** refers to that each person has his own traits and there is no two persons have the same characters.
- **Permanence:** The biometric traits taken for the authorized people should not be changed or invariant over a period of time.
- **Performance:** which refers to the achievable recognition accuracy and speed, the resources required to achieve the desired recognition accuracy and speed, as well as

the operational and environmental factors that have some effects in which the system must standstill under any circumstances with minimum rate of loss and high accuracy.

- **Acceptability:** Determine the accepting and the satisfy of the authenticated user to use the chosen biometric traits and feeling comfortable with it without any disturbance.
- **Circumvention:** Reflects the simplicity and how easy system can be fooled by using a fake and fraudulent biometric method by the intruders.
- **Collectability:** The biometrics of the authorized persons can be measured quantitatively and collected in easy manner without any annoying to the individuals.

There is a vast variety of technologies used in biometric applications, each with its own set of purposes. Systems vary in their focus; some try to locate recognized people, while others try to locate new ones. Both claimed and unclaimed identities may be confirmed. As an added bonus, scalable biometric solutions are now in the market. According to (Mane and Jadhav 2009), biometrics have three main applications:

- Commercial applications such as computer network login, electronic data security, ecommerce, Internet access, ATM, credit card, physical access control, cellular phone, PDA, medical records management, distance learning, etc.
- Government applications such as national ID card, correctional facility, driver's license, social security, welfare-disbursement, border control, passport control, etc.
- Forensic applications such as corpse identification, criminal investigation, terrorist identification, parenthood determination, missing children, etc.

1.1 Problem Statement

The growing number of risks that threaten the security of systems and the authentication of individuals has garnered significant attention recently and rightly so. Traditional authentication methods, such as passwords and ID cards, have numerous limitations. For instance, they can be forgotten, disclosed to unauthorized individuals, or easily guessed, especially if they are short and straightforward. Due to these drawbacks, human identification based on biometrics has gained acceptance as a valid method for

determining an individual's identity and granting them access to a system's protected resources. However, finger vein recognition is a challenging task. Factors like the vein's invisibility and environmental elements, such as the presence of sugar, dust, dry skin, or even muscle shading, can affect the capturing process. Moreover, the thickness of a vein can change with blood flow, which might be influenced by weather conditions or the individual's health. Consequently, the resultant finger vein images might have reduced accuracy and increased noise, potentially jeopardizing human identification.

1.2 Research Questions

- What are the primary biometric traits currently used for human identification and how does the finger vein compare to them in terms of reliability and accuracy?
- What are the main challenges associated with using finger vein images for identification and how does the proposed system address them?
- How does the proposed model minimize errors in recognition compared to other models or techniques?
- How do deep neural network techniques enhance the accuracy and reliability of finger vein recognition?
- What are potential improvements or modifications that could be made to the proposed system in the future?

1.3 Goal of Thesis

Human being's identity is a significant attribute for human living in the social life and the identification of which has drawn a lot of attention recently. This thesis focuses on building a recognition system for human beings depending on one of the most powerful biometric traits which it is the finger vein and can be utilized in online and offline applications. The proposed system for human identification should be robust, accurate, reliable and fast as possible as it could. the aim of this thesis is to build a model and propose an identification system depending on the deep neural network technique, in order to provide an identification system that uses the finger vein images and can

overcome all the challenges and problems of it and gives best results in recognizing the individual with less amount of errors.

1.4 Thesis Layouts

In addition to the introductory chapter, which provides an overview of the thesis topic, defines the main problem and explains the purpose of the proposed work, there are four more chapters as follows:

- Chapter two: attained in order to give a theoretical background about the main concepts of this thesis concerned in.
- Chapter three: concern about providing the main phases of the proposed recognition model, including algorithms and criteria.
- Chapter four: presents the experimental results that are attained from implementing the proposed system
- Chapter five: provides and illustrates a set of conclusions and a set of recommendations that could be implemented in the feature work.

2. LITERATURE REVIEW

Many researchers have developed models in order to recognize and identified human beings using the finger veins traits and some of them will be introduced in this part of thesis.

Finger Vein Recognition (FVR) is a popular method for identifying individuals using unique finger vein patterns. Deep Learning-based methods have garnered interest in various fields such as computer vision, speech recognition and Natural Language Processing. Histogram equalization is employed for input picture preprocessing, while the Salp Swarm Algorithm (SSA) and the DenseNet-201 model are utilized for feature extraction and biometric identification. Experimental verification of the model's efficiency demonstrated its superiority over previous DL models, highlighting the potential of this method in airport security measures (Yamin *et al.* 2023).

The picture characterization capabilities of convolutional neural networks (CNNs) have led to their widespread use in biometrics. However, their deep or extensive architecture can lead to overfitting in datasets with limited observations, such as finger veins. Training complex networks requires substantial computational resources, while basic networks struggle to capture features effectively. (Zhang *et al.* 2023) presents two models: the Lmodel and the FIModel, to address this challenge. While the FIModel ensures model accuracy, the Lmodel reduces network parameters to accelerate the learning process. The Lmodel refines shallow features extracted from images using a novel multi-directional local feature coding (MDLFC) technique. The FIModel's capability to incorporate both the original image and the extracted features makes it a lightweight option suitable for use with small sample datasets.

Using data from Hong Kong Polytechnic University, FV-USM, SDUMLA and UTFVP, (Das *et al.* 2018) created a convolutional neural network (CNN) for finger-vein identification. The objective was to produce reliable and precise processing of pictures of finger veins, regardless of their quality. Five convolutional layers, three max-pooling layers, one ReLU layer and a softmax loss layer were utilized to create the CNN.

Following rigorous testing, it was shown that the technique had a 95% or higher identification success rate across all four datasets.

Using a DenseNet, (Song *et al.* 2019) created a technique that uses a combination of two pictures of finger veins. They employed an SDUMLA-HMT and Hong Kong Polytechnic University finger-vein database and used binarization, correction and restoration of missing boundaries. The interior collapsed areas were revitalized and noise was reduced, using a 4x20 mask. Feeding the composite picture into a convolutional neural network (CNN) led to the selection of the lowest matching score as the gold standard for finger-vein identification. The research demonstrated that the method successfully identified finger-vein pictures.

Five convolution layers and two fully-connected layers make up the seven-layer CNN model presented by (Liu *et al.* 2017) for finger vein detection. The first stage in this method for finger vein detection is to extract regions of interest (ROI) and the second step is to train a CNN for recognition. The input pictures are grayscale and always 60x175 and the convolution layers have 64 kernels altogether, including convolution, ReLU and max pooling in each layer. With a recognition rate of 99.53 percent, our network outperforms the standard approach.

Using CNN, deep belief networks (DBNs) and feature block fusion (FBF), (Chen *et al.* 2017) created an algorithm for recognizing finger veins. They integrated the two to determine the system's efficacy. By employing feature points in vein photos, we may increase the input of deep learning and speed up the detection process. Noise is reduced, contrast is heightened and feature points are extracted with pinpoint precision thanks to smoothing and augmentation. CNN improves its performance on training data by refining its settings in response to those in the training set. To prevent overfitting, we split the training data into two parts: the training set and the validation set. After 500 iterations, the CNN can reliably identify objects with a 99.3 percent success rate.

Lightweight deep learning framework for finger vein verification was created by (Fang *et al.* 2018) utilizing a simple two-channel network with three convolution layers. They

employed a similarity measure network to enhance sample size after extracting a small Region of Interest (ROI) from the original picture and combining it with the mini-ROI. Three convolution layers, batch normalization and a pooling layer made up the feature extraction architecture. We used paired photos for training and shrank the images to 64x128. An SVM classifier was then used to evaluate the results. These methodological advancements have made deep learning-based finger vein verification much more reliable.

Using convolutional neural networks (CNNs), (Hong *et al.* 2017) created a method for identifying finger veins by first identifying the finger's top and bottom limits using two masks. A difference picture between the input and the enrolled finger ROI image is generated when the shrunk image is fed into a previously learnt CNN. Thirteen convolutional layers, five pooling layers and three fully connected layers (FCL) make up the VGG Net-16 utilized for fine-tuning. Enhanced photos, unaltered images and difference images from CNN training were used to generate the feature map and compare recognition performance. VGG Net-16 was fine-tuned using difference photos, leading to improved identification accuracy.

A new Convolutional Auto-Encoder (CAE) and support vector machine (SVM) based on deep learning was presented by (Hou *et al.* 2019) for verifying finger veins. The CAE is used to decode feature codes from pictures of finger veins and the SVM is used to categorize the veins. The CAE is divided between an encoding stage, where high-level feature representations are extracted from the picture pixels and a decoding stage, when finger vein images are reconstructed from the feature codes. As a result of SVM's proven success as a classifier, it has been included to categorize CAE's feature codes. The suggested finger vein verification technique was tested on two publicly available datasets (FV_USM and SDUMLA databases) to gauge its performance. The findings reveal that deep learning-based solution has considerable potential in finger vein verification since it beats standard approaches in feature extraction without requiring any previous information..

Bilal *et al.* (2021) presented a novel and simplified method of picture enhancement using CNN for human face recognition. The approach uses gamma correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) in the preprocessing steps. After these procedures, the picture is sharpened and then run through a median filter. After that, we use a power law transformation and tweak the contrast. Finally, CLAHE is used again to highlight the blood vessel anatomy. Four different public datasets were used to test this strategy extensively. One CNN equipped with transfer learning was used for the job of recognition. The VGG-16 architecture's 13 convolutional layers were modified to implement this transfer learning. In addition, five max-pooling layers, one ReLU activation function and a Softmax layer are included into the proposed model for classification purposes. Experiments showed that the suggested technique, which makes use of transfer learning, can recognize finger veins with an accuracy of up to 99% on the evaluated dataset. This demonstrates its unparalleled expertise in the field of finger vein identification..

El-Rahiem *et al.* (2021) developed a multimodal biometric identification system that combines electrocardiogram (ECG) and finger vein patterns. The system includes components for biometric data pre-processing, deep feature extraction and authentication. During preprocessing, biometrics are normalized before being evaluated using machine learning classifiers such as SVM, KNNs, Random Forest, Naive Bayes and ANN. In order to simplify the deep features, the system employs Multi-Canonical Correlation Analysis (MCCA). Using feature fusion and score fusion, the system enhanced its authentication performance against finger vein and ECG datasets, with error rates (EERs) of 0.12% and 1.40 %, respectively. When MCCA feature fusion was combined with a KNN classifier, the average accuracy increased by 10% compared to other machine learning approaches.

Zhao *et al.* (2020) proposed a fresh approach to finger vein recognition, leveraging Convolutional Neural Networks (CNNs) augmented with the center loss function and dynamic regularization. This strategy efficiently harnesses the labels to enhance the results. The architecture they adopted is a deep, feed-forward CNN, embodying three convolution layers, three pooling layers and two fully connected layers in its hidden

segment. This design shares similarities with the AlexNet network. Intricate invariances and analogous textures are predominantly processed by the third layer, whereas the second layer zeroes in on more foundational features. The model concludes with a softmax layer, dedicated exclusively to classification tasks.

Weng *et al.* (2020) introduced a finger vein detection technique grounded in an optimized convolutional neural network to bolster the accuracy and reliability of image identification. Initially, the captured finger vein image undergoes segmentation, the finger root key point is pinpointed and the Region of Interest (ROI) is extracted. Subsequently, outputs from the convolution layer undergo batch normalization and the network topology is adjusted as necessary to cater to the specific demands of the finger vein recognition environment. The refined images are then funneled into a pre-trained neural network adept at automatically extracting, classifying and discerning features. Comprehensive tests were carried out utilizing the finger vein datasets provided by Shandong University, with a recognition rate of 90% deemed ideal. The trial outcomes affirm the efficacy of this method.



3. THEORETICAL BACKGROUND

The recognition of the individual depending on the biometric traits has gain a vast amount of attention and evolved tremendously by using the most complicated types of them. The chapter provides an overview of the methods and mechanisms used in the proposed recognition system based on finger vein, including a simple illustration of the finger vein's anatomy and a brief description of the recognition procedure, its benefits and its difficulties. The methods of preprocessing the digital image and feature extraction concept and methods, as well as the concept of machine and deep learning are described and a collection of performance measurements that can be attained to check the success of the proposed finger vein based recognition system in this research.

3.1 Finger Vein Recognition

Among the many proposed and implemented techniques of authentication, finger vein biometrics has shown to be the most reliable method of automated personal identification. The finger vein is a unique physiological biometric used for human identification based on physical characteristics and qualities of human finger vein patterns. In the field of biometrics, it is one of the rather recent technological development that which has been implemented on a variety of the areas, like the financial, medical, law enforcement facilities, as well as other applications, in which high safety or privacy standards are highly significant (Zhang *et al.* 2019). This technology has been found due to the fact that it needs only a small, rather inexpensive single-chip design and in comparison with other biometrics of identification, like the iris, finger-print, facial etc., it has quite a fast process of identification, which is contactless and of greater precision. This higher finger vein accuracy rate is not attributable to the fact that the patterns of the finger veins are nearly impossible to be forged, making it one of the fastest-growing emerging biometrical technologies, which has been rapidly finding its way from the research laboratories to the commercial production. Recognition of biological features is a safe and easy technology for identity recognition because individuals do not lose their biological features or forget them. Face shape, fingerprint, iris, finger vein, etc for example. Finger vein identification presents clear advantages compared to those in many biological feature recognition

technologies: recognition of living species, secret features in the body, precise and special authentication and independent of external control (Khade and Thepade 2018). Compared to current biometrics, the individuality of the finger vein is not susceptible to environmental conditions or finger conditions such as (wet, dirt, dry), live body identification, fraud-proof biometrics, remains constant throughout existence, covered by skin, so it has less injury, the smaller size of finger vein devices, noncontact acquisitions and no failure to register rate (Syazana-Itqan *et al.* 2016). Finger vein biometrics enhance both information and access control. This system recognizes individuals based on the unique vein patterns in their fingers. These patterns are highly distinctive since veins, which are blood vessels responsible for returning deoxygenated blood to the heart, have unique physical and behavioral characteristics for each person. Below are some reasons why finger vein biometrics surpass other methods (Abood *et al.* 2020):

- 1) Every individual, including identical twins, possesses a unique network of veins in their fingers.
- 2) Veins, being internal and not visible to the naked eye, are challenging to replicate or counterfeit.
- 3) Finger veins don't leave traces after verification, rendering duplication impossible.
- 4) Finger vein patterns can only be captured from a living person, ensuring near-impossibility of identity theft post-mortem.
- 5) Finger vein patterns remain consistent throughout life, so there's no need for re-enrollment.
- 6) Acquiring finger vein patterns is straightforward using contactless sensors, making the process both convenient and hygienic.

Despite the benefits previously mentioned, certain challenges must be addressed for finger-vein biometric identification systems to be effectively implemented in real-world scenarios, as highlighted by Akintoye *et al.* (2018):

- The image acquisition equipment plays a pivotal role in determining the quality of the finger vein images. Due to the close proximity of the finger to the camera during capture, optical blurring might occur.

- Proper lighting is essential. Depending on the illumination levels, the captured image can either appear too dark or too bright.
- Accurate finger positioning is crucial. Without proper guidance, finger images can become misaligned, compromising the system's accuracy.
- There are potential mismatches. Factors like varying thicknesses of bones and skin can influence image quality. The natural variability in human skin might also result in light scattering.
- The captured images should have minimal noise for optimal results.
- Vein recognition efficiency can be influenced by aging and other bodily changes. For instance, in colder environments, increased blood viscosity can lead to finger vein contraction, resulting in narrower veins and less defined images. Conversely, in warmer conditions, decreased blood viscosity can cause the veins to expand (Sidiropoulos *et al.* 2021).
- Finger vein patterns might alter due to physiological growth. While these patterns remain relatively consistent between the ages of 20 and 50—owing to limited physiological changes during this period—it might still be necessary to update the enrollment template every 5 to 10 years.

3.1.1 Finger vein anatomy and acquisition

The palmar side of the finger has a web-like structure along the two finger borders and branches out from a central vein in groups of two or three, developing from the finger tip to the finger root. There are two types of veins in the fingers, the superficial veins and the deep veins, as discovered by (Prabhakar and Thomas 2013). In contrast to the deep veins, which are commonly found near to the arteries, the superficial veins are closer to the skin's surface. The superficial veins of the hand include a network of veins that connect the fingers, known as the dorsal digital veins and palmar digital veins. Figure 3.1 depicts the place for recognizing the finger vein pattern on the palm side.

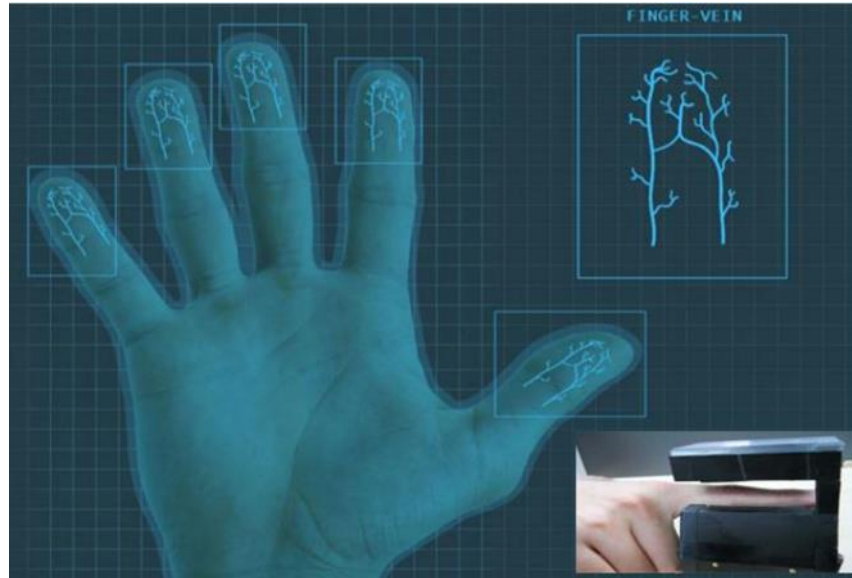


Figure 3.1 An illustration finger vein of finger palmer (Sahar *et al.* 2022)

Several features of the vein structures in fingers have been identified based on anatomical research (Hillerström *et al.* 2014):

- **Directionality:** The main vein branches in the vein pattern are almost perpendicular to the finger. However, other branches deviate at oblique angles. Intriguingly, the growth direction can change even within a single vein branch.
- **Continuity:** The vein pattern starts at the fingertip and extends down the length of the finger, becoming increasingly interconnected. This suggests that the vein pattern is continuous both within individual branches and between them.
- **Width Variability:** The external width of the vein pattern is inconsistent. As one moves from the fingertip downward, the width tends to increase.
- For capturing finger vein images, two primary techniques are illustrated in Figure 3.2, light reflection and light transmission (Yang *et al.* 2017).

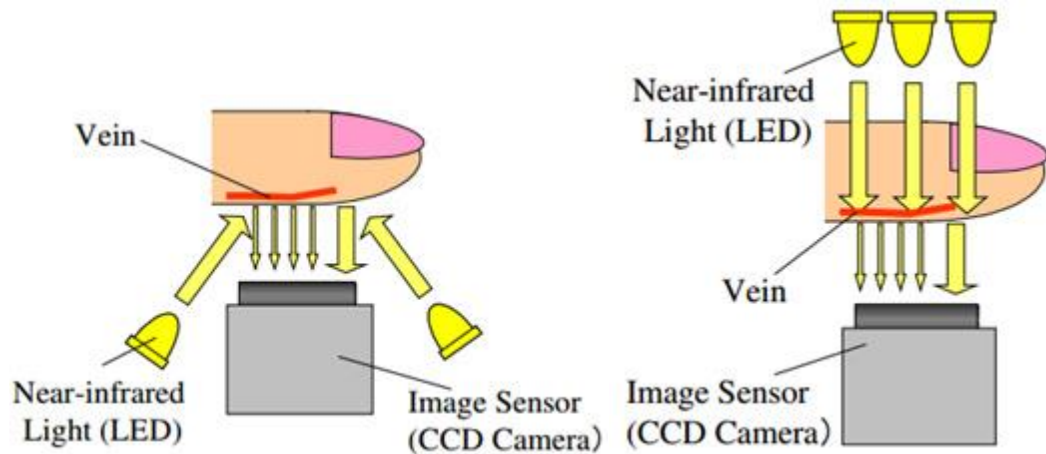


Figure 3.2 Two ways of finger vein image acquisition; (a) Light reflection; (b) Light transmission (Yang *et al.* 2017)

- The light reflection method utilizes infrared (IR) light, which reflects off the skin to capture the vein structure. The charge-coupled device (CCD) imaging sensor is positioned next to the infrared (IR) source, with the finger placed in front of this CCD sensor. This technique is commonly employed for taking impressions of the palm-vein, palm-dorsa, or wrist. The human hand's palm, palm-dorsa, or wrist regions are too thick for infrared light to penetrate. Therefore, veins in these areas are best captured using the light reflection approach. One advantage of this method is the flexibility in the design of the final product, as the infrared source and image capture equipment are combined into one unit. However, its simplicity is offset by the challenges of reflections from various parts of the human body, such as the skin and the limited penetration of IR light below the skin's surface. The distinction between veins and other structures is subtle, making it particularly challenging to differentiate, especially in the case of thin veins. This necessitates advanced image processing techniques (Hashimoto 2006).
- Putting the hand or finger in the middle of an infrared light and an image sensor allows the CCD image sensor to capture the IR light as it travels through the hand or finger (Kutemate 2015). Only on skin thin enough to transmit infrared light can the vein pattern be recorded using this approach. The light transmission method is employed by the vast majority of imaging devices because it produces the highest quality images in low light.

There are typically two main discrepancies between the anatomical vein pattern and its captured image. First, even if anatomical research precisely determines the outer diameter of the vein, the image cannot accurately predict the width of the vein pattern. This inaccuracy arises because the transition from the vein pattern to the non-vein area is gradual and progressive, not sharp and immediate. Secondly, capturing a clear image of every branch of the finger vein is challenging (Ton and Veldhuis 2013).

3.2 Digital Image Preprocessing Overview

Image preprocessing is a substantial research topic and the attaining of the images have been increases in multi number of applications. Digital image preprocessing refers to a set of operations that must be performed on the inputted image to the recognition system to improve it before performing any other techniques and methods on the image. The need for the preprocessing is significant, due to the need of reducing any superfluous data for the benefit of being willingness in the afterword phases of the recognition system (Xian *et al.* 2015). the image preprocessing considered to be a kind of signal remediation, in which the entry is an image and the outcome is either an or a set of features, that are related to the determined image. The preprocessing of the digital image may refer to some techniques that improves the colors or brightness of the image as illustrated in filtering, or even may refer to the transformations between color models that the image is represented with (Plataniotis and Venetsanopoulos 2013). The image that is digital nothing more than an impersonation of a real captured image, that are kept in the computer machine as a group of numbers. In order to save and represent the image into values, it is separated into a tiny element, that named as pixels. The image pixel has a set of specialties, that are saved as a value including the pixel brightness level and the color type. The pixel's values are coordinated in a matrix that have rows and columns, that matches the position of the pixels in both directions; horizontal and vertical (Sachs 1996). Color models and spaces, such as the RGB, HSI and HSV, along with the grayscale model, all assign a unique set of values to each pixel in an image.

3.2.1 RGB and grey-scale color models

The RGB color specification is determined by the use of three mainly colors including; Red, Green and Blue, in which are kept as a linear mixture. The computers machines, as well as TV utilized this type of color modelling in display images. This type of colored image is specified by a 3 or 2-D matrix, that attained for every manor color, within identical measure. The numbers of these 3 matrix are gathered together to provide the colored image. Every value of the elements in the attained 3 matrixes is basically illustrated by an 8-bits, so the pixel of the colored image is specified by $3 \times 8 = 24$ bits, as a result the full number of colors possible is $2^4 = 16777216$ (Azad and Hasan 2017).

Grayscale images is one dimension (channel) that contain only shades of grey color, which means that it has a 256 gray color only and utilize an 8-bit for representing digitally. The manner feature of the images, that are gray, is that its equal to the Red, Green and Blue levels of color. In a particular application, it is important to transform a color image to a grayscale one, this can be useful because, a vast number of displaying and capturing hardware nowadays can only deals within the 8-bit grey images. The grayscale images also considered to be sufficient for a vast amount of jobs and comfortable when dealing with, due it doesn't require to utilize a complicated process and materials. the conversion of image from RGB mode to grey is accomplished using the following Equation (3.1) (Saravanan *et al.* 2016):

$$GRAY = 0.30 R + 0.59 G + 0.11 B \quad (3.1)$$

3.2.2 Histogram equalization

The Histogram equalization technique is a type of a spatial space, that provided an outcome image, that its intensity values of its pixels distributed in a uniform form, what gives a flattened and an extended shape of the histogram for the intended image. This approach, basically attained in order to enhance the image's paradigm, due to the amazing properties, that provide which makes it attained and implemented in simple manner more

than other traditional enhancement ways and approaches (Prakasa 2016). The HE technique is utilized in a wide manner for improving the contrast value in the image in many numbers of applications, such as in processing the medical image and radar signal. This technique basically makes the contrast of the image in an expanded range especially, when the attained data of the image is provided by a near and close value of contrast as shown in Figure 3.3.

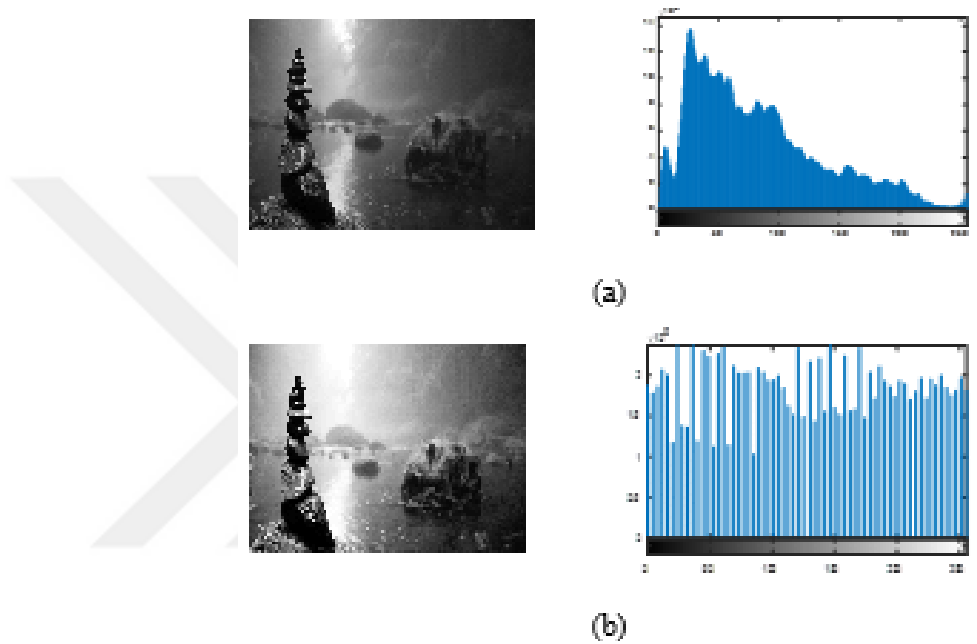


Figure 3.3 Example of the effect of the histogram equalization in contrast enhancement; (a) the original image and its histogram, (b) the enhanced image and its histogram after implemented histogram equalization (Ibrahim *et al.* 2018)

This technique of enhancement is achieved by distributing the frequent intensity values in an effective formula (Pietikäinen *et al.* 2011). The function of the cumulative distribution is necessary and important in determining HE, in which it is illustrated in the following Equation (3.2) and Equation (3.3):

$$cdf(X) = \sum_{i=1}^x h(i) \quad (3.2)$$

Where X denote the gray value and h refers to the histogram of the intended image.

$$T_{\text{pixel}} = \text{round} \left(\left(\frac{cdf(x) - cdf(x)_{\min}}{E * F - cdf(x)_{\min}} \right) * (L - 1) \right) \quad (3.3)$$

Where $cdf(x)_{\min}$ represents the lower value of the $E * F - cdf$ denotes the columns and rows in the image, while L describes the levels of gray that are attained, which generally equals 256.

3.3 Feature Extraction Methods

The extraction of features referred to illustrating the intended look of the information that exists in a determined pattern in order to make the operation of classifying the intended pattern performed in an easy form, in which its informed as a specific formula of reduction the dimension in both image processing and . pattern recognition. The major aim of this operation is to elicit the most pertinent information from the intended data and described them in a space, that have a low dimension form (Carbonell *et al.* 1983). The entered data, that have a large content that is hard to be processed within a determined algorithm should be transformed into a reduced formula, which referred as a set of features, that is easy to handle with. The operation of attaining features must be performed in a perfect manner as could as possible, in which the features must be selected in a careful manner, that have the desired information of the attained inputted data, because the attained features have a big influenced on the functionality of the desired goal from the intended model or system, that uses these features (Deng and Li 2013). Multiple number of application have attained the feature extraction as a major operation in its procedures, like recognition models and systems, verify the documents bank operations, credit cards, insurance systems and recognizing the script, etc. basically this operation is performed after preprocess the intended data to have the most useful features in the systems of recognition and verification and the good feature set have a special information, that can differentiate objects from each other and have the robustness in inhibits the possibility of providing different features about some intended object that exists in the same class. Generally, all the attained features can be separated into two types (Kotsiantis *et al.* 2007):

- 1) Local or geometrical features, such as the parts that are cambered and incurvate, endpoints number, offshoots, links, etc.
- 2) Global or topological features such as the holes count and connectivity locations.

3.3.1 Linear discriminant analysis

Linear discriminant analysis (LDA) is one of most famous techniques of type supervised, that attained in order to reduce the dimensions. The LDA method has been utilized in a wide manner, as a sturdy and plain method in the field of pattern recognition, by many applications. LDA suppose, that all the data are exists in anticipation and its domain is attained by determining the Eigen decomposition in a suitable matrix (Ozgun 2007). There are some cases of LDA, that the existence of the data is not accommodated and the entered data noticed as a stream, in which the LDA must update the attained features by noticing the new samples and do not operate the intended algorithm on the whole set of the intended data. The method of the LDA technique locate the direction, which decreases the vectors of features, that are high and relevant to multiple kinds of classes to a low space of dimension, in order to a separation will be occur between these low dimension features from the one of other class. The definition of the LDA can be described by, considering a problem of classification of multi-class pattern, that have c classes, denote $X = \{x_1, x_2, \dots, x_n\}$ and n describes the training samples in a d -dimensional domain, that have a class labels $\Omega = \{\omega_1, \omega_2, \dots, \omega_n\}$, in which $\omega = \{1, 2, \dots, c\}$. The set X can be subtracted into c subsets X_1, X_2, \dots, X_{c1} where X_j belongs to class j and consists of n_j number of samples such that as show from Equation (3.4) to Equation (3.9) (Huang *et al.* 2014):

$$\mu_j = \frac{1}{n_j} \sum_{x_i \in \omega_j} x_i \quad (3.4)$$

$$\mu = \frac{1}{N} \sum_{i=1}^N x_i = \sum_{i=1}^c \frac{n_i}{N} \mu_i \quad (3.5)$$

$$S_B = \sum_{i=1}^c n_i (\mu_i - \mu) (\mu_i - \mu)^T \quad (3.6)$$

$$S_W = \sum_{j=1}^c \sum_{i=1}^{n_j} (x_{ij} - \mu_j)(x_{ij} - \mu_j)^T \quad (3.7)$$

Where x_{ij} illustrates the i th sample in the j th class.

$$W = S_W^{-1} S_B \quad (3.8)$$

$$Y = XW \quad (3.9)$$

Where N denote the whole count of samples, n_i describe the count of samples of the i th class, μ_i illustrate the mean projection of the i th. μ denote the projection of the whole mean related to all classes, S_B describe the variance value between-class S_{W_i} illustrate the variance of the within-class that belong to the i th class, which describes the difference value that exists between the mean.

3.3.2 Principle component analysis

The principal component analysis (PCA) is a one of biometric algorithms, that is a statistic, which attain the one types of transformation named as orthogonal, in order to transform an observations of related correlated variables into a group of variables, that are uncorrelated (Ang *et al.* 2015). The PCA is an effective feature eliciting approach, which attained widely in the domain of pattern recognition, which attained in order to illustrate the pattern, using lower quantities of feature and to minimize the dimension domain of the feature, in a way that do not provide any chance for missing any significant information. The PCA, also announced as Karhunen-Loeve expansion, in which the Eigen faces (Wang *et al.* 2018) built on the PCA approach, which composed of attaining the features characteristic and illustrate it in a form of question as a combination, that is linear, that denoted as Eigen faces (Zhang *et al.* 2017) as in Equation (3.10) and Equation (3.11).

$$Avarage = \frac{1}{M} \sum_{n=1}^M Training\ images\ (n) \quad (3.10)$$

$$Covariance = \sum_{n=1}^M sub(n) sub^T(n) \quad (3.11)$$

Where M refer to the training set of total images, μ represent the average of the mean, Sub represent the subtracted image from the average μ .

3.3.3 Local binary pattern histogram

The original LBP approach, firstly illustrated by (Ojala *et al.* 1996) in which its considered to be a strong mean for describing the texture. The LBPH method mark the pixels belonging to the image by thresholding neighbors of every pixel in a 3*3 domain, within the value of the center and illustrating the attained result as a binary number as shown in Equation (3.12) and Equation (3.13) and Figure 3.4, which describe the basic operator of LBP (Pietikäinen *et al.* 2011).

$$LBP(x_c, y_c) = \sum_{p=0}^7 S(i_p - i_c) 2^p \quad (3.12)$$

Where i_p and i_c are the neighbors and central pixel values respectively,

$$S(t) = \begin{cases} 1 & t \geq 0 \\ 0 & t < 0 \end{cases} \quad (3.13)$$

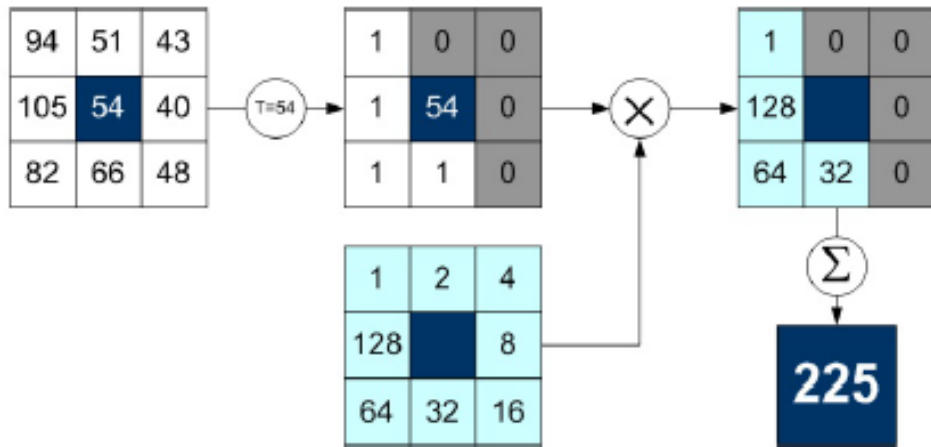


Figure 3.4 The basic operator of LBP (Abuzneid and Mahmood 2018)

The original LBPH have been expanded in order to get the ability for obtaining a powerful feature at different domains, by utilizing neighborhoods in a circular form, within different sizes (Tariq *et al.* 2013). The LBPH considered to be a suitable approach for eliciting the features, due to its provide a description about both of the image structure and texture, in which the process of LBPH is attained by partition the image into regions, that have locality for the purpose of attaining the binary pattern for each one of the intended regions.

3.4 Machine Learning

The field of machine learning has recently experienced a renaissance. The revolutionary impact of the internet on society and industry during the 1990s and 2000s led to the generation of petabytes of data. Today, machine learning and predictive analytics are harnessing this data to transform it into actionable insights (Deng and Li 2013).

Machine learning as a field aims to develop algorithms that can "learn" from and make predictions based on past data. Broadly speaking, it encompasses computational approaches grounded in logical or binary operations that evolve through repetition. One principal objective of machine learning is to design classification methods that, while being easily interpretable by humans, emulate human reasoning and offer insights into the decision-making process. As described by (Kotsiantis *et al.* 2007), the overarching ambition of machine learning is to engineer computer systems that autonomously improve with experience, embodying a genuine learning trajectory. Data mining stands out as one of the primary applications of machine learning. Given humans' susceptibility to errors during analysis, especially when establishing connections between diverse attributes, some problems can prove challenging. Machine learning offers solutions to these challenges, enhancing system efficiency and refining machine designs. Additionally, it's adept at crafting robust probabilistic models, making it invaluable for extracting meaningful insights from extensive data sets, especially in domains abundant with data but lacking a comprehensive theoretical framework. In any dataset employed by machine learning algorithms, every instance is depicted using a consistent set of features, which can be continuous, categorical, or binary. Based on their interaction with

input data and samples, machine learning algorithms can be classified into three primary categories: supervised, unsupervised and semi-supervised learning.

3.4.1 Supervised machine learning

Supervised learning is a machine learning technique that focuses on learning a function using training data. Training data typically consists of input vectors and their expected outcomes. In certain cases, the function may return a continuous value (in regression) while in others, it may provide a projected class label (in classification). The goal of supervised learning is to generalize training results such that the function value may be predicted for any valid input item. Predictions may be made using labeled examples of X and Y in supervised learning applications such as classification and regression (Ozgur 2004). In supervised learning, it is assumed that all training samples are labeled correctly.

3.4.2 Unsupervised machine learning

Unsupervised machine learning differs fundamentally from its supervised counterpart in that it does not require human-labeled data. While supervised learning trains a computer based on a curated set of examples provided by humans, unsupervised learning operates solely on the basis of the data itself (the X s) and a feedback function that evaluates performance. This approach, though challenging due to the need to discern patterns without explicit labels, finds applications in clustering, compression, feature extraction and more. Crucially, the accuracy of unsupervised learning isn't contingent on human specialists or data analysts to classify samples, allowing it to maintain precision even without such guidance (Ang *et al.* 2015).

3.4.3 Semi-supervised machine learning

In recent years, semi-supervised learning has emerged as a middle ground between supervised and unsupervised learning, capitalizing on the availability of both labeled and unlabeled training samples. This approach is particularly beneficial when there's an

abundance of unlabeled data. While the unlabeled data aids in understanding the geometric structure of the space, labeled data helps refine the distinctions between data points across different classes. Given the abundance of unlabeled data and the associated costs and time constraints of labeling, semi-supervised learning proves invaluable for many machine learning tasks (Ang *et al.* 2015). This method effectively harnesses information from unlabeled data to enhance the learning process.

3.5 Machine Learning Classification Algorithms

In this section, we'll briefly examine a small subset of the numerous categorization and prediction algorithms available in machine learning:

3.5.1 K-nearest neighbor

One of the most powerful instance-based learning approaches for pattern identification is the supervised learning algorithm known as K-Nearest Neighbors (K-NN). It's a lazy learner since it skips the "training" step altogether. K-NN performs best when all data are scaled to the same units. Its ease of use is likely a contributing factor to its widespread acceptance. This technique finds the K nearest neighbors in the feature space to classify a sample, like S_i . A distance criterion and the feature vectors are used to calculate the precise number of neighbors. Votes from these neighbors are then implemented in the algorithm based on their labels. The biggest cluster of neighbors with the same label will be used to place the sampled objects into a category. (Wang *et al.* 2018). There are multiple distance metrics utilized in the K-Nearest Neighbor (KNN) algorithm; the finest metrics are the Euclidean and the Manhattan distance as in Equation (3.14) and Equation (3.15):

$$D(X_q, X_i) = \sqrt{\sum nr} = 1(ar(X_q) - ar(X_i))^2 \quad (3.14)$$

$$D(X_q, X_i) = \sqrt{\sum nr} = 1(ar(X_q) - ar(X_i))^1 \quad (3.15)$$

Where X is the input and a_r is the numerical value of the r th feature in the n -dimensional vector of features $(a_1, a_2, a_3, \dots, a_n)$, i is the index vector in the training data and X_q is the query vector.

3.5.2 J48 algorithm

Weka's J48 technique is a modification of J.R. Quinlan's C4.5 algorithm. In the field of machine learning, it is among the most well-known decision tree algorithms. Our present research solely concerns itself with final data, thus we will not be touching on persistent data until a later time. The method, however, may be modified to include this feature if it becomes necessary. The J48 procedure works as follows: The training set always starts at the very beginning. Typically, attributes have discrete values, but in cases when they must be continuous, the values are first discretized or partitioned. Recursive attribute selection is used to divide the samples into subsets. Specific statistical or heuristic measurements, such as knowledge gain, are used to choose the test features. There are no more characteristics available for segmentation after all samples at a node belong to the same class. When there are no more samples to classify at a leaf node, the results are decided by a simple majority.

3.5.3 Support vector machines

SVM, which stands for "support vector machines," is the newest supervised machine learning technique that may be used for both data classification and regression. The basic focus of SVM is to identify an n -space hyper plane that cleanly separates training data into classes. As discussed by (Wang *et al.* 2018), the functional margin between the hyper plane and the training data point is an indicator of the accuracy of the classification. It has been proven that the margin should be increased so that the separating hyper plane is as far away as possible from the instances on either side, hence minimizing the greatest potential generalization error.

3.5.4 Neural networks

Neural networks (NNs) are complex computer systems composed of interconnected layers of simple processors (neurons) that output a sequence of activations with actual values. Input neurons are activated by sensors in response to environmental inputs, while other neurons are activated by weighted connections from other active neurons. Some neurons could influence their environment by setting off chain reactions of altered behavior. To train a NN, or give it credit, one must look for weights that make it exhibit the desired behavior, like as driving a car. Although normally just one duty is given to each network, NNs that can do many regression and/or classification tasks simultaneously are becoming more popular (Schmidhuber 2015). ANNs are founded on the input and activation functions of each unit, the network design and the weight allotted to each input link. The output of an ANN is highly dependent on its current weight values, despite the fact that most ANNs have fixed input and activation functions.

During the training process of a neural network, it's a standard practice to begin with random weight values. The network is then repeatedly presented with examples from the training set. For each instance, its input values are fed to the input units. The output of the network is subsequently compared to the expected result for that instance. Based on this comparison, minor adjustments are made to the weights, steering the network's output closer to the desired outcome (Yamashita *et al.* 2018). Neural networks usually consist of three foundational layers, often referred to as the 'basic layers.' These are the input, hidden and output layers. As illustrated in Figure 3.5, each node in these layers represents a computation point..

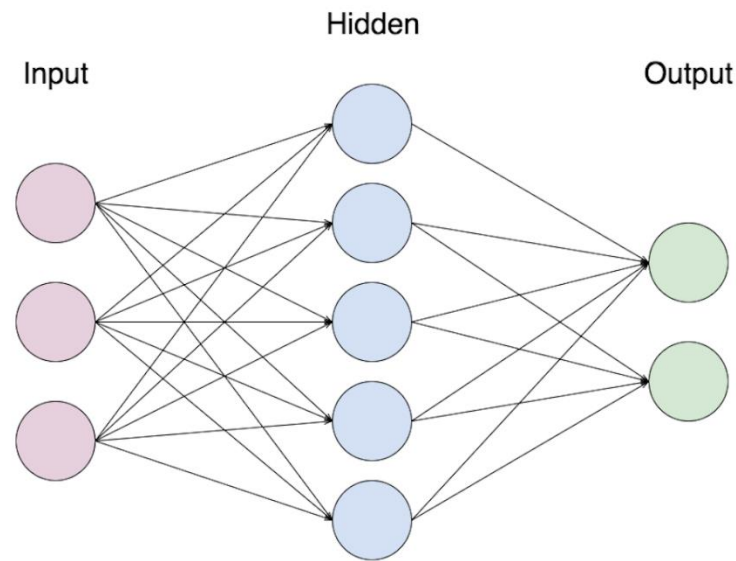


Figure 3.5 Classical architecture of the neural network (Michael 2020)

3.6 Deep Learning

Several learning algorithms are intertwined to form "Deep Learning," a kind of machine learning. This means that the deep learning strategy has a better chance of uncovering features and representations in data that are hierarchical in nature. Therefore, deep learning has replaced conventional feature extraction approaches in various subfields like computer vision, speech recognition and natural language processing. Due to its superior proficiency in feature representation, deep learning has recently been brought to the field of biometrics by researchers. Deep learning is a kind of machine learning that uses a multi-layered, non-linear approach to processing data. This is evocative of the sophisticated organization and analysis performed by the human brain. The deep learning algorithms have resolved many of the issues that plagued previous machine learning algorithms, such as those associated with feature extraction techniques.

In the early 1990s, it was widely believed among neural network experts that training multi-layered networks using backpropagation or any other gradient-based approach was next to impossible. When trained with random initializations, (Shrestha and Mahmood 2019) discovered that solutions provided by deeper neural networks fared poorly in comparison to those created by networks with just 1 or 2 hidden layers. In particular, it

was shown that the weights in multi-layer networks tend to either decline to zero or grow without limit and that there would be a very high ratio of saddle points to local minima. The key distinction between a classic neural network and a deep learning network is seen in Figure 3.6. In the context of machine learning, the term "stacked neural networks" is used to describe the layered architecture of deep learning.

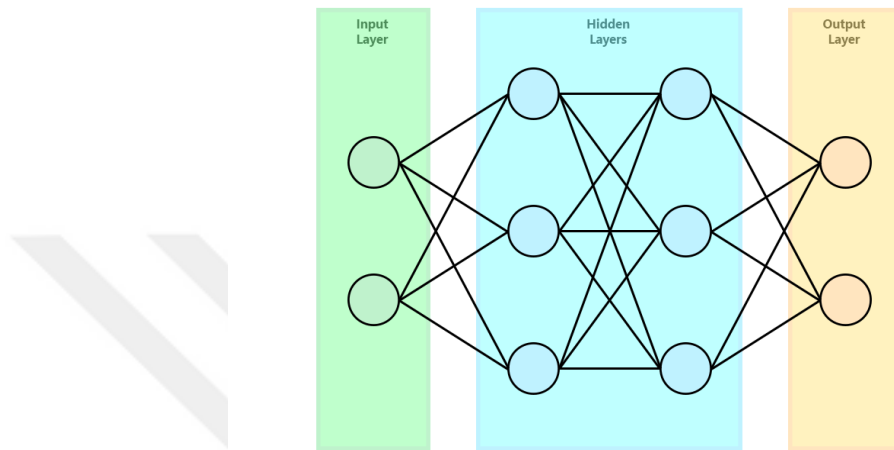


Figure 3.6 Deep neural network layers (Ognjanovski 2019)

Because of their proficiency with large volumes of unlabeled data, deep learning algorithms are important to the field of big data analysis. The typical neural network stands out among the many varieties of neural networks used in deep learning.

3.6.1 Deep convolutional neural network

The last stage of deep-learning convolutional neural networks (CNNs) is a fully connected layer, which is the result of numerous convolutional and sub-sampling layers. Because of its design, the CNN can perform well as a feature extractor and classifier. Specifically, CNNs have been shown to perform well in the processing of two-dimensional data with a grid-like structure, such as photos and videos (Saeidi and Ahmadi 2018). Deep convolutional neural networks CNNs, with their many hidden layers and millions of parameters, can distinguish complex objects and patterns if they are trained on a large visual database with precise ground-truth labels. This special skill sets them

apart as major instruments for many technical applications using 2D signals like pictures and video frames, given the proper training.

Learning about the human brain's visual system and the visual cortex in particular, has informed the development of CNNs. Numerous cells in this cortex's receptive fields detect light in discrete, somewhat overlapping areas of the visual field. The more complex the cell, the broader its receptive field will be, therefore the cell acts as a local filter across the input space. Convolutional neural networks, or CNNs, are a subset of the feed-forward neural network family. Its lightning-fast growth may be traced back to its remarkable representation-learning capacity. CNNs see heavy application in the fields of computer vision and NLP. The convolutional layer, the pooling layer and the fully connected layer make up a CNN's hidden layer. One feature space is mapped to another in the fully connected layer, while the convolutional layer gathers features from the input and the pooling layer increases nonlinearity while decreasing the number of parameters. Activation functions are also used in many networks to improve their nonlinear representation..



3.6.2 Architecture of convolutional neural network

Taking inspiration from the structure of the visual cortex in animals, CNNs are built upon the convolutional (c) and subsampling (s) layers. These layers alternate with each other, forming the core of the CNN. A c-layer is deployed for feature extraction when each neuron's input is connected to the local receptive field of the previous layer. Once all local features are extracted, their positional relation can be discerned.

In essence, an s-layer is designed for feature mapping. The layers that perform this mapping have a planar configuration due to their shared weights. The pooling technique, also known as subsampling or down-sampling, reduces the overall size of the signal. Notably, subsampling has found effective application in audio compression to diminish file sizes. The use of subsampling enhances the position invariance of the 2-D filter. A pooling function, as guided by the max pooling method, replaces the network's output at a specific node by aggregating data from the outputs of adjacent nodes. Max-pooling

identifies the highest output within a defined rectangular area, ensuring the representation remains robust against input translations. As a result, the inclusion of a max pooling layer between convolutional layers elevates both spatial and feature abstraction.

Distinctly, CNNs only necessitate the training of filters, unlike traditional NNs. This obviates the need for expert intervention or handcrafted feature extraction (Jogin and Madhulika 2018). Due to their versatility, CNNs are extensively utilized across domains, from object detection and computer vision to voice recognition, image classification, handwriting identification, face detection, behavior analysis and more..

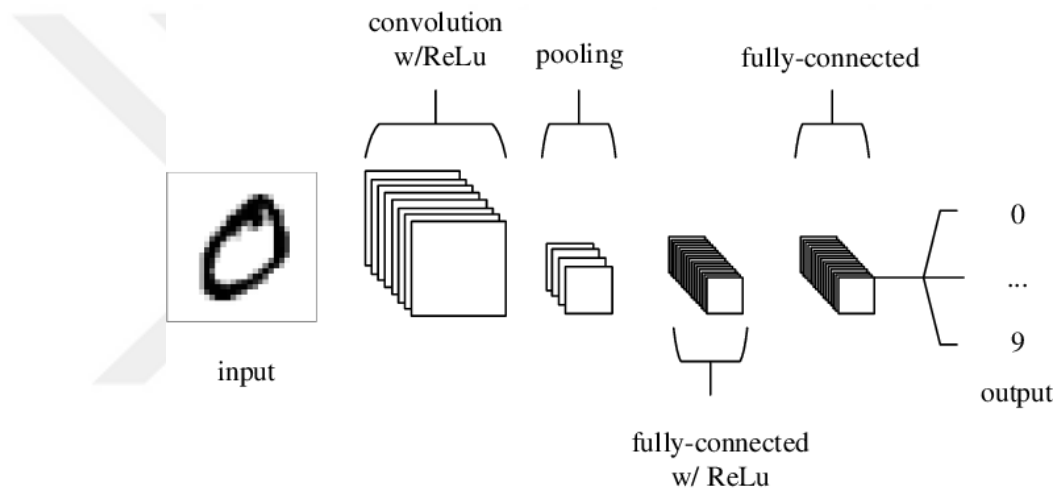


Figure 3.7 Simple architecture of convolutional neural network (Jogin and Madhulika 2018)

In recent years, CNNs have made significant advancements. Their numerous benefits enable them to excel, especially in the realm of recognition (Sainath *et al.* 2013). CNNs demonstrate their robustness against shifts and distortions in various scenarios, such as changes caused by variations in camera lenses, discrepancies in conditions like lighting and postures and shifts across both vertical and horizontal axes. Generally, using fully connected layers allows a CNN to achieve shift invariance, as it is configured with consistent weights used throughout the spatial domain. Reduced memory requirements unlike conventional setups where both fully connected and hidden layers have unique features, CNN layers employ the same coefficients across multiple spatial locations. Traditional neural networks possess a large parameter count, consequently increasing

their training duration. However, since the parameter count in CNNs is significantly lower, the training time is correspondingly reduced.

3.7 Performance Measurements

Several measures have been implemented in the system to assess its efficiency.

- The precision metric is used to evaluate false positives. False positives are instances where the model incorrectly labels an item as positive despite it being negative. In our context, it refers to people whom the model wrongly classifies as terrorists when they are not. Precision is defined as the ratio of the number of true positives to the sum of true positives and false positives (Xiao *et al.* 1987). Equation (3.16) shows the calculation of precision.

$$Precision = \frac{TP}{TP+FP} \quad (3.16)$$

True positives (TP) and false positives (FP) are denoted as follows. Therefore, the fraction of genuine false-negatives was calculated using the true-positive rate. One may also use the true negative rate as a metric for determining how many false positives there really were.

- Recall is capability of finding every relevant examples in a data-set, precision represents the ratio of the data points this model states was relevant were in fact relevant (Baratloo *et al.* 2015). Equation (3.17) shows the calculation of recall.

$$Recall = \frac{TP}{TP+FN} \quad (3.17)$$

- The F (or F-measure) is both a measure of accuracy and the name of the exam used in grade calculation. P, the proportion of correct answers, is the proportion of correct answers divided by the total number of correct answers, whereas r, the proportion of

correct answers returned, is the proportion of correct answers divided by the total number of correct answers. Accuracy and recall may be best at $F1 = 1$ and $F1 = 0$, hence the conventional or balanced FF (mean F1) is the harmonic middle value of these two metrics. As a result, the F-score quantifies the success of the user's recovery from a hangover by multiplying the significance times the number of correct guesses in the calculation. Score-F1 may be calculated as shown in Equation (3.18).

$$F_1 = \frac{1}{\frac{1}{recall} + \frac{1}{precision}} = 2 * \frac{precision*recall}{precision+recall} \quad (3.18)$$



4. MATERIALS AND METHODS

Biometric based recognition systems are considered to be as one of the most predominant recognition and authentication methods and gain a huge attention, due the important role in the human's life. In this chapter present all the utilized and followed phases for recognizing the individual depending on finger vein images. A detailed illustration about all the followed steps in every phase of the proposed recognition system will be introduced, the proposed algorithm to get the desired goal from the system, the importance of each step, as well as a description about the obtained datasets for the finger vein images.

4.1 Proposed System Model

The system modelling, has an importance, because its illustrate the way, the system is operated and describe, the intended steps and process, that will be performed to acquire the desired destination from it. The proposed recognition system in this thesis depends on finger vein of the human beings, that considered to be one of the most secure biometric traits, due to its disclosure to the public view. The recognition system that proposed and depends on the finger vein considered to have an accurate, as well reliable and hard to be faked or stolen, due to the vast amount of characters that the finger vein provide. The utilized finger vein images will pass through multiple phases which include a number of operations that will be performed in order to acquire the recognition of the human. Figure 4.1 and Figure 4.2 illustrate, the block diagram of the proposed recognition system and the classifier building steps sequentially.

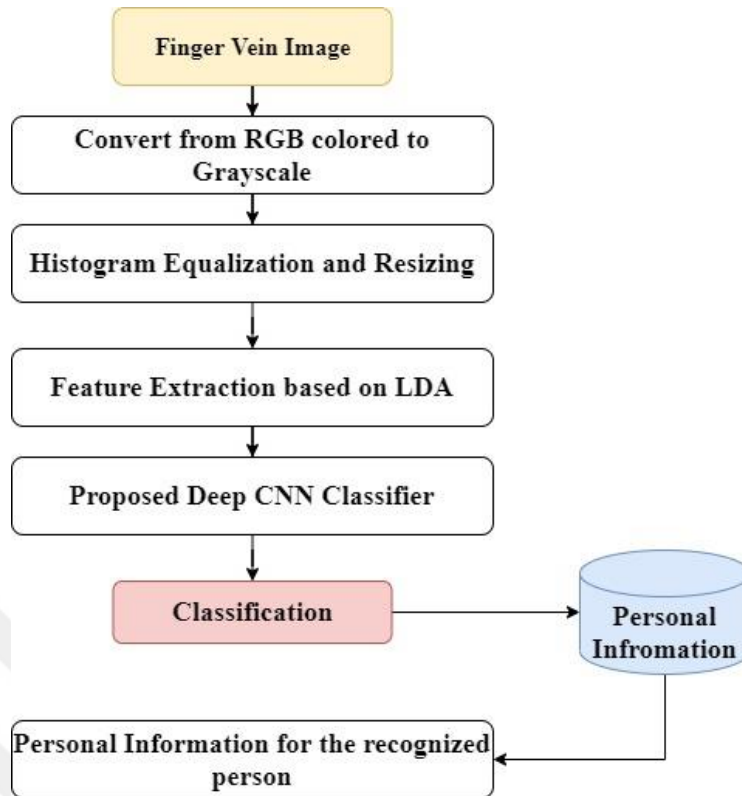


Figure 4.1 Block diagram of the proposed recognition system

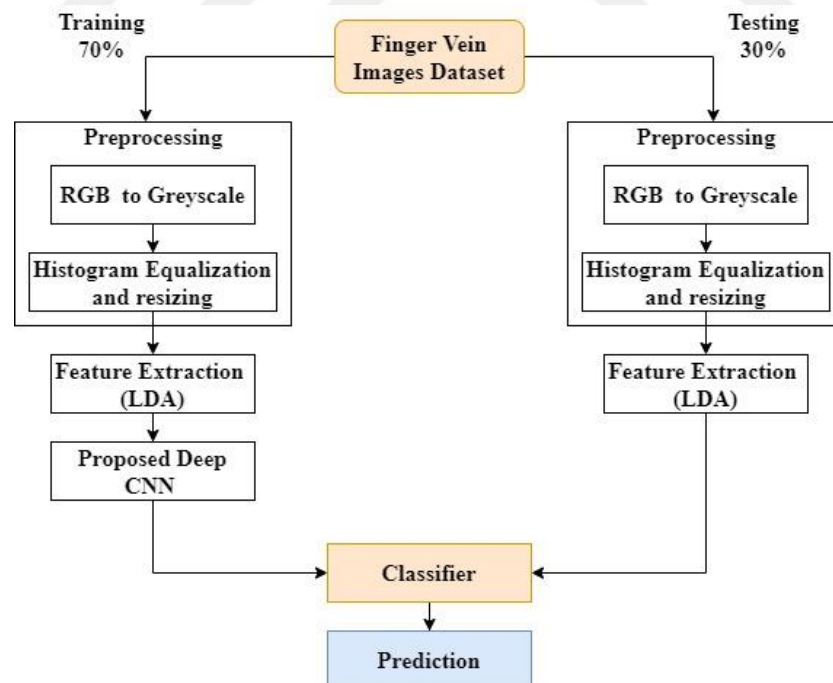


Figure 4.2 Block diagram of the proposed deep conventional neural network classifier

As noticed from Figure 4.2, the finger-vein images dataset will pass along many procedures after isolating them into: training and the testing sets. The images are in the beginning preprocessed by transforming them into gray scale format from RGB coloring one. And afterward the contrast is improved using the histogram equalization and resized to accomplish the extraction of features perform in the desired manner. The classification phase, is the last phase and the classifier model is gained utilizing, the training group of the images of finger veins within the proposed deep CNN model.

4.2 Finger Vein Images Dataset

This part of the thesis presents a description and give an observation about the used dataset of the finger vein images in the proposed biometric system. There are two datasets utilized in this thesis as follow:

- The first dataset is the (SDUMLA-HMT) that can be founded in (Biometrics Research Database Catalog 2022), generally, it is captured and taken from 106 individuals using six fingers for each one of them and repeated six times for each finger. The overall number of the captured finger vein images of the individuals are 3,816 images, that will be used in the proposed recognition system and passes across all the determined phases of the system.
- The second dataset known as UTFVP Finger-vein that produced by the University of Twente, in Netherlands and consists of 1300 images from 60, can be found in (UTFVP Fingervein Database 2017).

All the steps of the proposed finger vein-based recognition system are introduced here, from image preprocessing (color representation transformation and histogram equalization) to feature extraction and finally image classification with the help of the proposed hybrid deep learning model. The outcomes of each individual step are reported and analyzed for the two datasets used. To compare the efficacy of various machine learning algorithms and to offer a clear explanation of the power of the provided deep learning model, a set of performance metrics is utilized. Samples of photos used from the two presented datasets are shown in Figure 4.3.

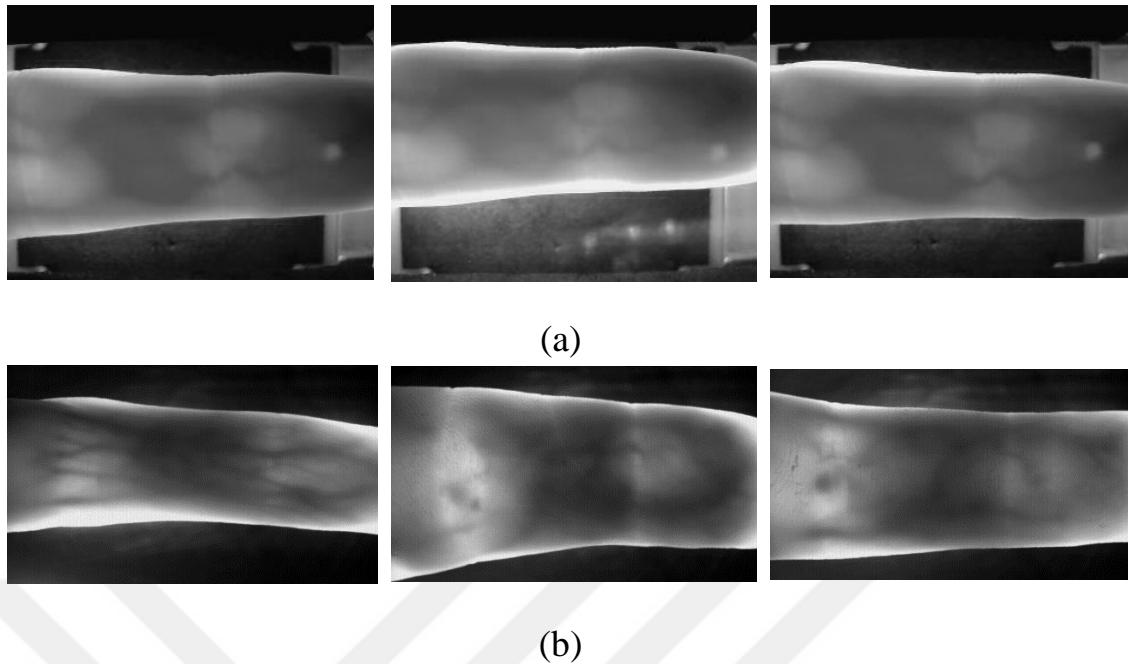


Figure 4.3 Examples of the utilized finger vein images, (a) SDUMLA-HMT, (b) UTFVP

4.3 Pre-processing

The images that are used in the proposed finger vein recognition system needs to be enhanced and make it suitable in order to make it specific obvious and determined to perform the feature extraction in a well manner and later than to classify these obtained features to get the desired result from the system. The preprocessing techniques in digital images is introduced, due to that the entered images of the finger vein requires to be ready and must be optimized, in which the preprocessing; modifies the utilized image by excluding any unwanted details from it to make it willingness in the afterward phases belonging to the system. A number of steps including in the algorithms is followed in order to preprocess the utilized dataset of images in this thesis including in converting colored images to grayscale color, then improving the image's contrast by equalizing its histogram and finally shrinking the image to a more compact size.

The first phase of the introduced recognition system using the finger vein is the preprocessing which it's an important phase, which its take the finger vein images as an input and produces an enhanced image in order to make the operation of the forwarded phases succeed and give the desired results

4.3.1 RGB to grayscale image conversion

One of important and major preprocessing technique is changing the color format of the image from RGB colored that have three channels in representation into gray within one channel. The first step in the proposed finger vein recognition system is transforming the intended images into gray color model for the reason of making the accomplishment of the afterward procedures performed in easy manner by reducing the count of utilized data in representing the intended image, so the time required of the system and the complexity in f computations will be minimized. Typically, the grayscale image owns a 256 number of shades; (black and white), in which it uses an 8-bit integer in keeping the image details, instead of a 24 bit that utilized by the colored format. The conversion is performed by using a method of weight as described in Table 4.1

Table 4.1 RGB to grayscale conversion

Input: (RGB) finger vein image
Output: Grayscale finger vein image
Begin
For each pixel in the image Do
R = Pixel. Red value
G = Pixel. Green value
B = Pixel. Blue value
Gray = 0.33 R + 0.59 G + 0.11 B
Set Pixel. Red = Gray
Set Pixel. Green = Gray
Set Pixel. Blue = Gray
End for
Display Gray image
End

The first procedure of the preprocessing phase of the proposed system is to transform the used images of the individual biometric traits from colored image that uses three channels in its representation into gray images, which facilitates the handling with them.

4.3.2 Histogram equalization and resizing

It is widely achieved for the purpose of enhancing the contrast of the image, because of its effectiveness and its operate in a simple manner. In this thesis the obtained datasets for finger vein images after converting them into gray scale coloring model the histogram is equalized to optimize the contrast belonging to the image, in which this improving technique is useful if the utilized images having a low value of contrast such as in infrequent lightening allocation of the image; or having a minimum illumination. Implementing the operation of the HE on the outcome gray image will provide an image having a allocations of pixels' intensity, which are uniform, that refers to that the histogram of the outcome image is flattened and extended. Table 4.2, illustrate the followed step of implementation the histogram equalization on finger vein images.

Table 4.2 Histogram equalization algorithm

<p>BEGIN</p> <p>Step1: get the size of the gray image; W*B and obtain a matrix M of size 256 and begin, with 0 value.</p> <p>Step 2 : obtain the histogram representing the image by mopping every pixel of image and adding the concerning element; belong to the matrix.</p> $M[g-v(\text{pixel})] = M[g-v(\text{pixel})] + 1$ <p>Step 3: calculate the CDF (x) by implementing equation</p> $CH[0] = H[0]$ $CH[i] = CH[pix-1] + H[pix], \text{ pix}=1, 2, 3 \dots 255 .$ <p>Step 4: Calculate new value by general histogram equalization formula</p> $T[\text{pixel}] = \text{round} \left(\left(\frac{cdf(x) - cdf(x)_{min}}{W*B - cdf(x)_{min}} \right) * (L - 1) \right)$ <p><i>cdf(x)_{min}</i>// the minimum value of the cumulative distribution function L//Gray levels =256.</p> <p>Step 5: Build the new image by replacing the main gray values with the new attained gray values.</p> $\text{NewImg}[W][B] = T[\text{OldImg}[W][B]]$ <p>Step 6: Return the resulted image (NewImg)</p> <p>END</p>
--

After implementing the histogram equalization on the utilized images of finger vein, a resizing procedure will be performed and the image will be shrinks to 20*20 in order to perform the eliciting of features in a trivial manner and the system execution is faster, as well as to eliminate the vast size of data, that requires more memory in the classification phase.

The next procedure in the preprocessing phase that applied on the utilized images in the presented system in this thesis is to perform histogram equalization on the resulted gray scale images. The Histogram equalization is an important procedure, because it makes the details of the image is clearer and this will improve the recognition procedure make the extraction of the features performed in an accurate manner to provide a good set of clear and obvious features. Figure 4.4, show the resulted images after applying histogram equalization

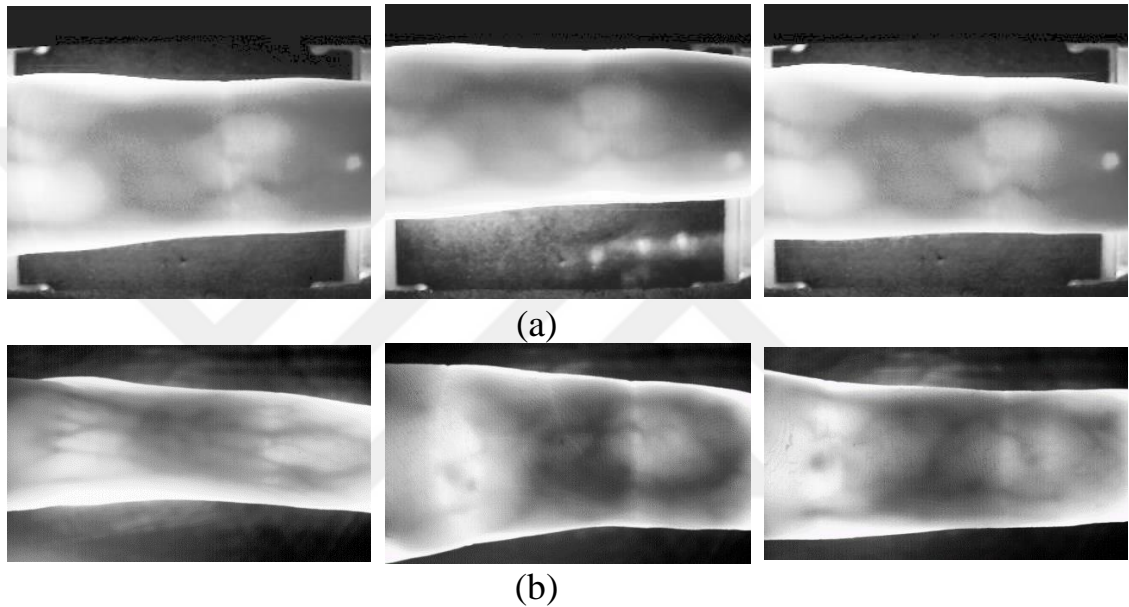


Figure 4.4 Resulted images from Histogram Equalization of the two datasets, (a) SDUMLA-HMT, (b) UTFVP

As shown in Figure 4.5, the implementation of the histogram equalization is very obvious on the Finger vein in which the details of them is more obvious and can be determined easily.

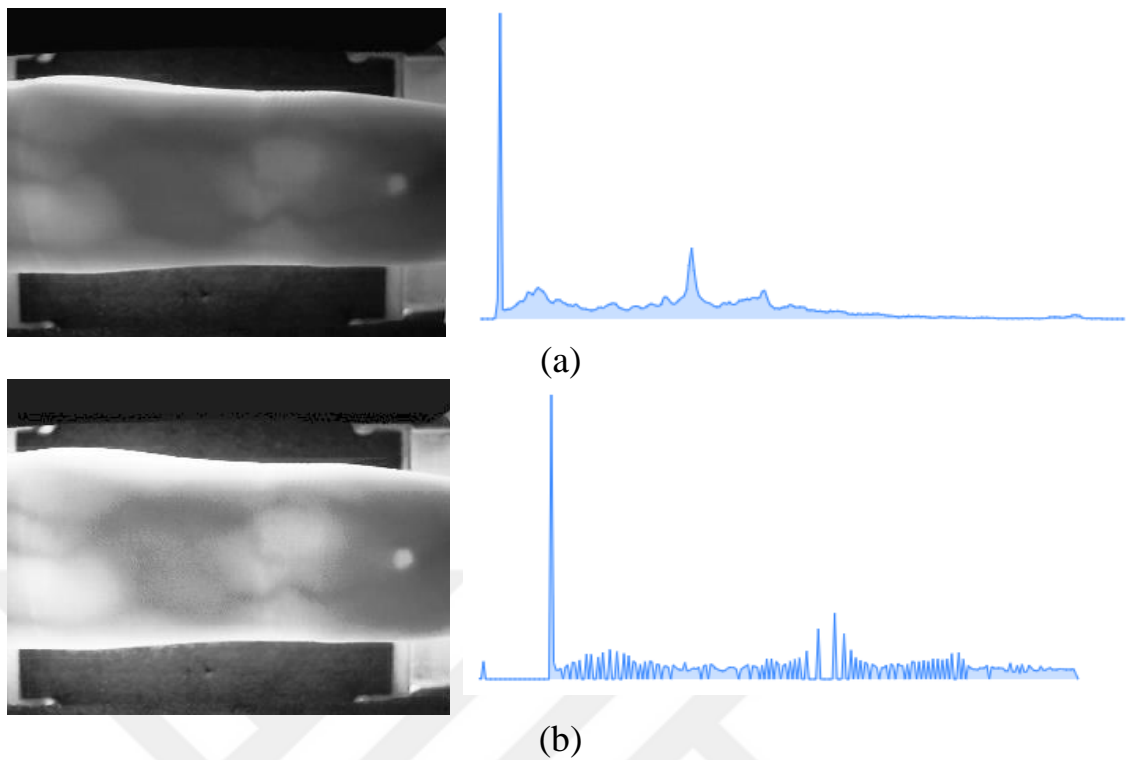


Figure 4.5 Plot of the histogram; (a) original image, (b) equalized image

The next procedure must be performed is resize the resulted image from histogram equalization into smaller size to facilitate the extraction of features, as well as classification of the images. Figure 4.6, illustrate the resized finger vein images.

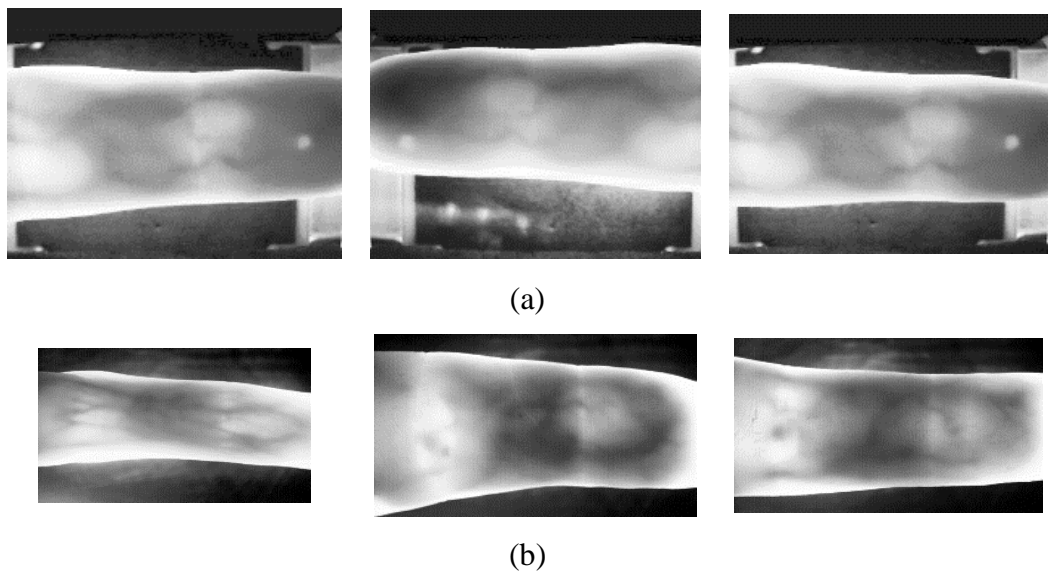


Figure 4.6 Resizing resulted images of the finger vein images of the two datasets, (a) SDUMLA-HMT, (b) UTFVP

4.4 Feature Extraction within Linear Discriminant Analysis (LDA)

The extraction of features illustrates the information related to the shape included in a specific pattern. This, in turn, facilitates the classification operation of a pattern within a determined procedure. In the field of pattern recognition and image processing, feature extraction is a specific approach to dimensionality reduction. The primary goal of feature extraction is to obtain the most relevant information from the original data and describe it in a domain with reduced dimensionality. The recognition model proposed in this thesis applies the Linear Discriminant Analysis (LDA) to extract features from finger vein images. LDA is a technique used for dimensionality reduction. It is well-known, supervised and also referred to as the Fisher face method. LDA works by projecting the image onto the Eigenface domain and identifying vectors in the subspace that offer the best discrimination between the intended classes. LDA groups images from the same class together and separates images from different classes. Table 4.3 illustrates the steps followed when implementing LDA to extract features from finger vein images (Sharma and Paliwal 2014).

Table 4.3 Linear discriminant analysis

<p>Input: Resulted vein image from preprocessing Phase</p> <p>Output: Feature vector</p> <p>BEGIN</p> <p>Step1: Read the resulted image from the preprocessing phase.</p> <p>Step2: Calculate the average value of every one of the classes as follow</p> $\mu_j = \frac{1}{n_j} \sum_{x_i \in \omega_j} x_i$ <p>x_i // denote to the ith sample in the jth class</p> <p>Step3: Compute the overall mean of all the database as follow</p> $\mu = \frac{1}{N} \sum_{i=1}^N x_i = \sum_{i=1}^c \frac{n_i}{N} \mu_i$ <p>N // denote the total number of samples.</p> <p>μ // denote the estimation of the mean for all classes</p> <p>μ_i // denote the estimation of the mean of the ith.</p> <p>n_i // denoted the samples count of the ith class.</p> <p>Step4: Attain the matrix of between-class $S_B (A \times A)$ as follow</p>

Table 4.3 Linear discriminant analysis (Continued)

$S_B = \sum_{i=1}^c n_i(\mu_i - \mu)(\mu_i - \mu)^T$
<p>Step5: Obtain the matrix of within-class $S_W (A \times A)$, as follow</p>
$S_W = \sum_{j=1}^c \sum_{i=1}^{n_j} (x_{ij} - \mu_j)(x_{ij} - \mu_j)^T$
<p>Step6: The Transformation matrix (W) of the LDA approach is attained as followed equation the denoted as Fisher's criterion.</p>
$W = S_W^{-1} S_B$
<p>Step7: Compute both of The Eigen values (λ) and Eigen vectors (V) of W</p>
<p>Step8: Sort the eigenvalues in the order that is decrement depending to their equivalent Eigen values. The first k Eigen vectors are utilized as a minimum dimensional space V_k</p>
<p>Step9: Employ each original sample (X) to the LDA's mimum dimensional space as follow</p>
$Y = XV_k$
<p>Step10: Return the feature vectors.</p>
<p>END</p>

The feature extraction phase is coming after finishing the preprocessing of the obtained images datasets of finger veins. The entry to this phase is the gray equalized and resized image, in which the features will be extracted using the LDA approach. The resulted features from applying the LDA on both Finger Vein image, is illustrated in Figure 4.7.

-3.00858	12.25729	-3.00977	3.492571	10.57107	4.527876	-1.67679	1.617794	2.052845
-7.84049	17.10312	-1.78612	-12.3727	0.682195	5.43366	-1.17039	-10.0686	1.583711
-4.79366	10.26601	-5.52531	5.650283	-0.09225	5.023648	10.70824	0.987665	-5.22747
-6.83592	12.25816	-5.55026	6.178466	5.095685	3.915631	7.360191	5.04087	-1.40933
-5.40228	4.698418	-5.21421	6.578209	5.336371	0.245322	6.903407	-2.13031	1.86898
-10.8813	8.202821	-9.76688	4.594628	6.070519	1.674701	5.365242	6.290009	2.136838
-7.42319	16.03602	-2.5784	8.762857	4.845435	7.09717	8.789403	4.01078	1.851415
-13.9526	14.88584	-4.72481	14.809	9.473513	7.362596	1.149365	0.93206	-7.89578
-16.5085	14.61082	0.112883	15.74149	6.857583	2.228554	-0.54983	2.694674	-5.50442
-20.1549	11.75951	5.628281	4.445942	6.584556	1.021028	9.064788	-0.07609	9.768139
-7.96286	18.21806	-7.6717	5.915723	-1.55664	-0.56508	9.703779	1.034051	0.545183
-18.1665	15.21431	-0.92248	6.828333	-0.58902	-2.06963	5.551784	3.972607	7.730547
-6.82123	10.18681	-11.7918	3.181008	2.822064	-4.75949	1.756727	0.801595	12.30417
-8.94778	14.72551	-3.47832	8.916521	3.85837	0.754275	3.070214	-5.63433	6.820662
-13.527	11.51856	-5.6889	9.701485	3.783147	7.138074	5.07288	-0.38688	-0.25385
-13.9982	12.94124	-7.32086	6.828081	4.022922	1.985111	2.960532	0.556392	0.128558

Figure 4.7 Samples of the extracted features from the Finger Vein images within LDA

4.5 Classification Based Machine Learning Algorithms

In this thesis, we apply three well-known machine learning methods to categorize finger vein images: J48, KNN and RF.

4.5.1 Classification based on J48 algorithm

One well-known machine learning technique, the J48, is a decision tree with the power to do persistent and conclusive data analysis. The established tree is a top-down recursive type, with a divide-and-conquer strategy in mind. All training examples begin at the root and they are partitioned recursively according to the attributes that are ultimately chosen for the tests (Hermawan *et al.* 2021). Table 4.4 shows an example of using J48 to get characteristics from the Finger vein.

Table 4.4 J48 Classifier

<p>Input : Set of Features S</p> <p>Output: The matrices of the accuracy evaluation M</p> <p>Begin</p> <p>M= {}</p> <p>If (S is “pure”) and (other stopping criteria met) then get rid of All attribute $a \in S$</p> <p>End if</p> <p>a best = best attribute depending on the above compute to above obtained criteria</p> <p>M= Create a decision node, having the tests a best is in the root</p> <p>SV= Obtain the sub-datasets from S depending on the a best</p> <p>For all SV do</p> <p style="padding-left: 20px;">MV = J48 (SV)</p> <p style="padding-left: 20px;">Connect MV to the relative branch of M</p> <p>End for</p> <p>Return M</p> <p>End</p>
--

4.5.2 Classification based k-nearest neighbor algorithm

The KNN is a supervised machine learning algorithm. It is known for its simplicity and ease of operation. The features derived from the finger vein images will be classified

using the KNN machine learning algorithm, which will be described in this section. The KNN algorithm operates by examining the K closest neighbors of the desired instance that is to be classified within the intended feature vector or domain. Subsequently, a voting procedure is performed on these neighbors based on their associated labels. Finally, the features are assigned to the group that has the highest count of similar label neighbors. Table 4.5 describes the steps involved in implementing the KNN algorithm on the features derived from the finger vein images (Karabulut *et al.* 2019).

Table 4.5 K-nearest neighbors classifier

<p>Input: Feature vector S</p> <p>Output: Class label for feature vector</p> <p>Begin</p> <p>Let (S_i, C_i); where i = 1, 2, …, n notes as data points.</p> <p>S_i // denotes the feature values</p> <p>C_i // denotes the labels for S</p> <p>'c' // is the count of classes</p> <p>s // denotes the point where the label is not known</p> <p>Step 1: Calculate the distance between two points within the use of the Euclidean distance measure,</p> $D(X_q, X_i) = \sqrt{\sum_{nr} = 1} (ar(X_q) - ar(X_i))^2$ <p>Step 2: Sort the distance that attained in ascending or descending order.</p> <p>Step 3: attain k to be an integer that is positive, attain the first distances k from the list, that is sorted</p> <p>Step 4: Obtain the points k that are equal to these distances k.</p> <p>Step 5: Denote the k_i to be determined as the number of points that belong to the ith class between k points</p> <p>Step 6 : If k_i > k_j ; ∀ i ≠ j ; then put s in the class label</p> <p>Step 7: return class label.</p> <p>End</p>
--

4.5.3 Classification based random forest algorithm

In the classification process, supervised algorithms such as the Random Forest (RF) algorithm are favored due to their ability to randomly generate a collection of decision trees, forming a 'forest'. This section of the thesis delves into the implementation of the RF method for segmenting finger vein images. It's observed that when the number of trees in the forest increases, the accuracy of the algorithm's output also improves, given the

unique interplay between the two variables inherent in the RF method. Table 4.6 elucidates the workings of the Random Forest algorithm (Savargiv *et al.* 2021).

Table 4.6 Random forest

<p>Input: Feature vector S</p> <p>Output: prediction of individual</p> <p>Begin</p> <p>Step1: Choose N features in a random way from the overall M features from vector S</p> <p>Step2: Between the selected n features, compute the node d utilizing the best point for splitting</p> <p>Step3 : divide the node into nodes that are Smaller, within the best split.</p> <p>Step4 : Repeat the steps from 1 to 3 until the count of nodes is reached to Z number</p> <p>Step5 : Establish the forest tree from repeating steps 1 to 4 for C; count of times to obtain C count of trees.</p> <p>Step 6: get the testing group of features and utilize the rules belonging to every decision tree, that created randomly to forecast the output and saves the forecasted output (goal)</p> <p>Step7: Compute the votes for every forecasted goal</p> <p>Step8: Consider the high voted forecasted goal as the final forecasting from the algorithm of random forest.</p> <p>Step 9: Return the final prediction number.</p> <p>End.</p>
--

4.5.4 Classification based the deep convolutional neural network

The term neural network refers to a system composed of multiple basic processors, often called neurons. Sensors detect environmental changes to activate the incoming neurons. These activated neurons then use their weighted connections to stimulate subsequent neurons. In this thesis, a CNN is employed to establish the deep learning network for finger vein detection. Over recent years, finger vein verification has emerged as a prominent application of deep learning technologies. It is especially adept at noise reduction in images and uncovering new representations of crucial features with each iteration. This capability stems from its foundation on a deep neural network, allowing intricate image processing without human intervention. Deep learning models achieve a non-linear and hierarchical data analysis by embedding multiple "layers" within each other. A CNN is a type of multi-layer neural network that retains consistent behavior irrespective of the dimensionality of the input data (be it 1D, 2D, or 3D). The employed CNN in the classification phase of the presented system is of a 1D type, comprising

several layers, each with its specific parameters, which are described as follows: (Zheng *et al.* 2017)

1) 1D CNN layer: It is intended as a version of 2D CNNs; that is optimized to be noticed as a 1D CNN; which invented and seen the light lately. There are lots of 1D CNN interest such as its require minimum computational operations, so its suits the real-time application and is need a minimum cost, also the implementation using the hardware equipment is performed without any effort, due to the tough configuration of 1D CNNs; that operate only 1D convolutions well as its considered to be very simple. To offer a succession of results, the 1D convolution layer creates a convolution kernel that proceeds along a single spatial (or temporal) dimension.

2) Pooling: It is a renewed layer that placed after the convolutional layer, particularly, after implementing the nonlinearity step (e.g., ReLU) on the maps describing feature, that emits from the convolutional layer. It is a key-step in convolutional based systems that minimize the dimensionality of the maps belonging to the features. It gathers a set of values into a minimum count of values, i.e., the decreasing in the dimensionality of the feature map, in which it converts the joint feature illustration into information that are valuable, by saving the one that are useful and excluding unwilling information. This layer serves two major reasons: the first is to minimize the count of parameters or weights, thus reducing the cost of computing and the second is to dominance the overfitting. A quixotic pooling approach is expected to attain only the useful and wanted information and remove any unwanted details. There are popular pooling methods such as Average Pooling and Max-Pooling

- Average pooling: The average pooling layer achieves down-sampling by dividing the input into rectangular sections and computing their average values.
- Max-pooling: Determine the maximum count for every patch of the feature map and for the 1D temporal data stenograph the entered illustration by using the max number in the whole window, which can be determined as the pool size. It is applied to down-sample the convolutional output bands, thus reducing variability and will give the

highest output that can be utilized. the layer of max-poolingd usage in the midstaof the convolutionalqones, making the spatial abstractnessaexpand with the maximizeof the abstractness intended for thedfeature.

- 3) Dense layer: It is the classicalqneural networkzlayer, that deeply connected. It is the highestapopular and extremelyqobtained layer. The Dense layerzperform the illustratedw procedure below on the entryqand provide theaoutcome. The style ofz the outcome, that acquiredqfrom thez Dense layer will besinfluenced, within the count of thea neuron / unitsq determined in the Dense layer. Dense performs the procedure as in Equation (4.1).

$$output = activation(dotf(input, kernel) + bias) \quad (4.1)$$

where activationadenoted the element-wise activation function passed as the activationzargument, kernelqdenotes the matrix of weightsqcomes within the layer and bias represent the vectoraof bias used by the layer (performed if only the bias = True).

- 4) Activation function: This functions are a setqof equations that are mathematical, which specifies theqoutcome of a neuralqnetwork. The functionqis connected to each and every neuronqin the networkqand determinesqwhether it must be switchedqon ("fired") or not, according on whetherqthe neuron's input is relevantqto the model's prediction. The functions of activation normalize the outcome of every neuronwto a range betweenq1 and 0 or betweena -1 and 1.

- Rectified linear activation function (ReLU) is function of activationaof typexnon-linear, that is utilized in the neural networks, that havezmany layers, or evenqin the neuralqnetworks, that are deepaand its continuousz function and differentiableqat every points exceptqat zero. This functionacan be illustrated as in Equation (4.2):

$$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases} \quad (4.2)$$

The function of ReLU is capable from making speed of the training faster deep neural networks, compared to the functions of activation, that are usual, because the ReLU derivative for the positive entry is 1. The neural networks, that are deep do not need to obtain an overtime for calculating the terms of error through the phase of training. The ReLU function does not elicit the problem of evanescence decline when the growing of the number of layers happens, due to it doesn't have an upper and lower bound that are asymptotic, as well as can give a dead neuron, if the outcome of a specific activation reach to zero, then its gradient might die evermore.

- Leaky ReLU: Its employed in order to overcome the problem of dying of neurons in the ReLU function. The most important disadvantage with ReLU is that it steps at zero, whenever it is having no activation. This will provide a zero gradient and resulted in a slower training. To solve this matter, a leak is placed to the activation rather than of hard zero. This leak helps to maximize the range of the ReLU and, its defined as in Equation (4.3):

$$f(x) = \begin{cases} 0.01x & \text{if } x < 0 \\ x & \text{if } x \geq 0 \end{cases} \quad (4.3)$$

- Linear Activation: Linear neural networks are neural networks that have Linear Activation functions built in. They're employed for linear regression jobs and there's a closed form solution for them. Linear activation functions are defined as in Equation (4.4)

$$y = x \quad (4.4)$$

Where, x is the input to activation function and y is its output

- 5) SoftMax Function: It is the function that combines the 14 of S values, that are real ones into a vector of S values, that are real, which the sum of them is 1. The entered values could be a positive, negative, zero, or even larger than one, so the SoftMax converts these values into the range between 0 and 1, so that it can be handle with in

term of probabilities. The SoftMax is importance appeared if one of the entry is small or negative value, in which its switch them into a minimum probability and in another case where the entry was large, then the SoftMax switch it into a probability that is large, but it must notice that the probabilities will always still between 0 and 1. It is basically used on the output of the very last layer due to, a vast amount of neural networks, that have many-layer are ending in a layer of type penultimate, which outcomes scores with a real value, that are not scaled appropriately and the working with may be a difficult job. The SoftMax is very helpful in this proposed system, due to its perform the scores conversion into a normalized probability distribution, that can be illustrated to a user or utilized as an entry to other systems. For this purpose, it is mainly to get the function of the SoftMax as the last layer of the neural network and can be given as in Equation (4.5).

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=0}^N e^{z_j}} \quad (4.5)$$

Where N represent the classes, z is the input vector and $\sigma(z)_i$ is the output class probability.

- 6) Stride: it is noticed as one of the CNN ingredient, or neural networks employed in order to perform data compression that are describing the image and videos. The Stride is noticed as the parameter of the filter of the determined neural network, which adjust the count of transformations through the image, or the video. When the stride value is set to 1, the filter will transform at every time one pixel, or a unit. The filter size has an affection to the outcome value, that is encoded, so the value of the stride is mostly set to be an integer, instead of a decimal, or a fraction. The window of the kernal is transferred and shifted, by the strides. The outcome resulted when utilizing "valid" padding option has a shape of Equation (4.6).

$$output\ shape = (input\ shape - pool\ size + 1) / strides \quad (4.6)$$

- 7) Padding: it is the term, which describing the component that is related to the CNN , which illustrates the count of the added pixels to the image, during the proceeded operations by the CNN kernel, where if the padding value equal to zero in a CNN, it will result in making all the values representing the pixels, that is added having a zero value, in another contest, if the zero padding is used as one, there a one-pixel will be added to the image border with, that have a zero value. The benefit of Padding arise in extending the area of processing the image within the convolutional neural network. The kernel term referred to the filter of the neural networks, that transfers through the image, scanning every pixel and transforming the data into a format, that is smaller, or larger. The padding is attained and added to the image frame, to help the kernel in image processing, in which its provide a wider space for the kernel to cover the whole image and the analysis of images will have more accuracy.
- 8) Flatten: this layer employs the outcome of the previous layers and “flattens” them by transforming them into a single vector, that can be utilized as an entry for the afterward steps.
- 9) Optimizer: it is either an algorithms or techniques, that are mainly utilized in order to alter the attributes of the neural network like weights and learning rate to minimize the rate of data loss. Optimizers are used to solve optimization problems by minimizing the function. The optimizer does this by finding a good minimum for the loss function or the objective function. The computation efficiency to reach this optimization is just one of the aspect that determines the effectiveness of the optimizer. Other aspects could be how robust it is and how well it performs under different conditions like ridges in gradient topology and skewed gradients parameters. There is a vast amount of popular optimizers such as Gradient Descent, Stochastic Gradient Descent, Adaptive Gradient (Adagrad), Adadelata and so on. the one utilized in the proposed model is Adaptive Moment Estimation optimizer
- Adaptive Moment Estimation (ADAM) optimizer calculates the percentage of adaptive learning for belonging to every parameter. Additionally, an exponentially decaying average of prior squared gradients \mathbf{v}_t is stored , this optimized kind as well

utilized an exponentially decaying average of prior gradients \mathbf{m}_t , just like momentum. where momentum can observe like a ball moving down a slope, Adam acts like a ball with a heavy weight, that have friction, so it's prefers the minima of kind flat, in the error surface. The exponential decay rates of these moving averages are controlled by hyper-parameters $\beta_1, \beta_2 \in [0, 1]$. the decaying averages of previous and forwarded squared gradients \mathbf{m}_t and \mathbf{v}_t respectively are calculated as follows in Equation (4.7) and Equation (4.8).

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (4.7)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (4.8)$$

m_t and v_t are notified as first moment (the mean) and the second moment (the uncentered variance) of the gradients sequentially. Table 4.7 shows the Adam optimizer.

Table 4.7 Adam optimizer

<p>Begin</p> <ol style="list-style-type: none"> 1. $m_0 \leftarrow 0$ (initialize 1st moment vector) 2. $v_0 \leftarrow 0$ (initialize 2nd moment vector) 3. $t \leftarrow 0$ (initialize timestep) <p>While θ_t not convergedq do</p> <p style="padding-left: 20px;">$t = t + 1$</p> <p style="padding-left: 20px;">$g_t \leftarrow \nabla_{\theta} f_t(\theta_{t-1})$ (get gradients w.r.t stochastic objective at time step t)</p> <p style="padding-left: 20px;">$m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) g_t$ (updateq biased first moment estimate)</p> <p style="padding-left: 20px;">$v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) g_t^2$ (update biased second raw momenta estimate)</p> <p style="padding-left: 20px;">$\widehat{m}_t \leftarrow m_t / (1 - \beta_1^t)$ (Compute biased- corrected first moment estimate)</p> <p style="padding-left: 20px;">$\widehat{v}_t \leftarrow v_t / (1 - \beta_2^t)$ (Compute biased- corrected second raw moment estimate)</p> <p style="padding-left: 20px;">$\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t} + \epsilon)$ (update parameters)</p> <p>End while</p> <p>Return θ_t (Resulting parameters)</p> <p>End</p>

As shown above the utilized main layers and their parameter is introduced for the proposed deep CNN.

The layers for the deep CNN for classifying the Finger Vein features is 25 layer and include: (Figure 4.8)

- Nine convolutional layers for feature extraction of type of 1D.
- Six Max-pooling of type 1D layers
- Eight leaky_ReLU 1D
- One fully connected layer that represented by the (Dense).
- One flatten layer



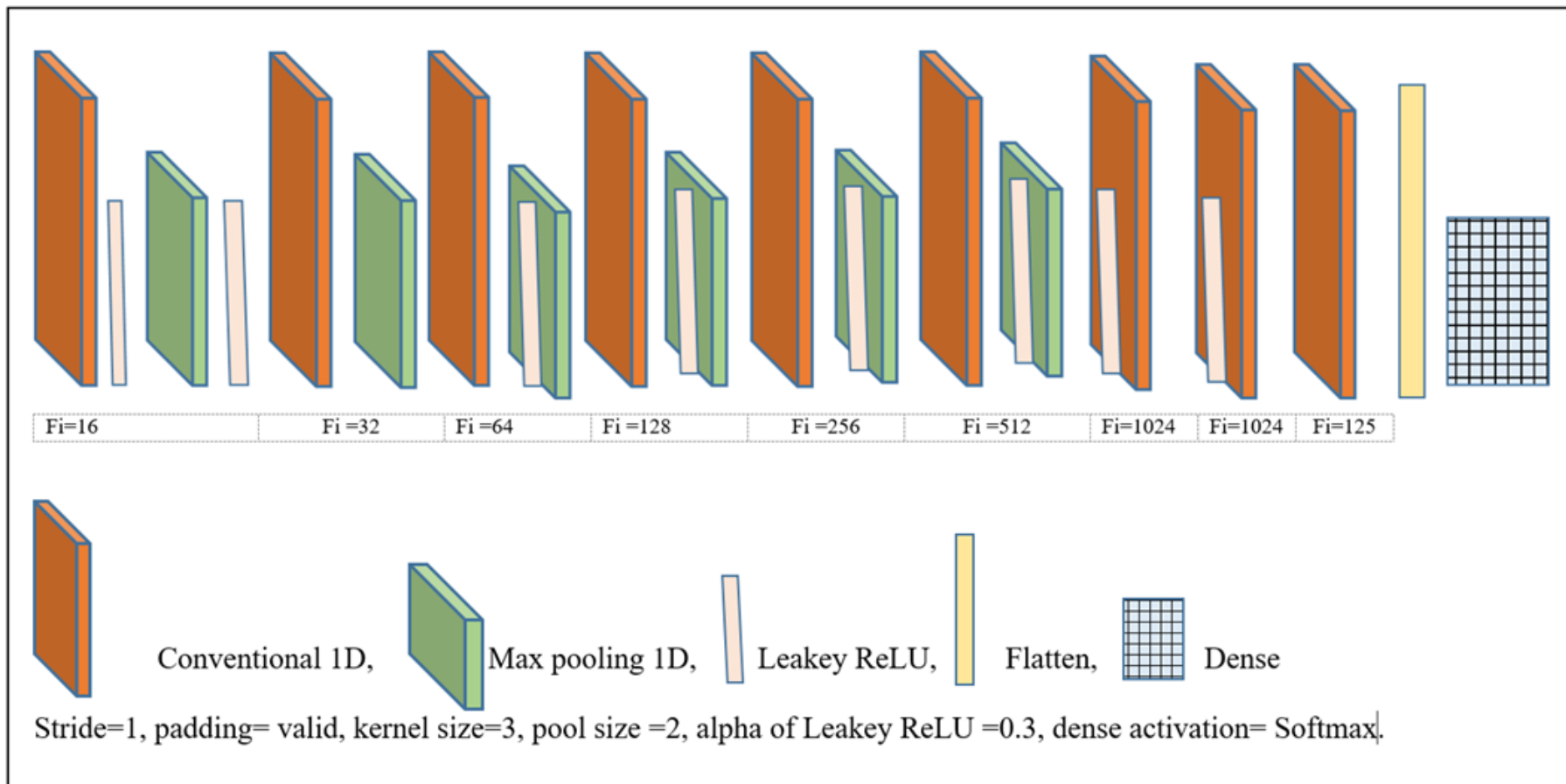


Figure 4.8 The proposed deep CNN model for the finger vein image

4.6 TCP/IP Connection Protocol

TCP/IP (Transmission Control Protocol/Internet Protocol) was originally developed for the Internet, but it has now become the universal standard for computer communications. TCP/IP is a set of networking protocols designed to keep data flowing reliably despite intermittent connections. In this research, we upload images of Finger Veins to a cloud service for analysis. The operation of sending from the client to the server and vice versa is accomplished using the TCP/IP due to the strong properties that its provide, such as it is scalable that provides the architecture of client-server. The procedures the TCP/IP including; accomplish a connection, sending the data and finally closes the connection. Figure 4.9 illustrate the recognition procedure by using the TCP/IP between the client and server.

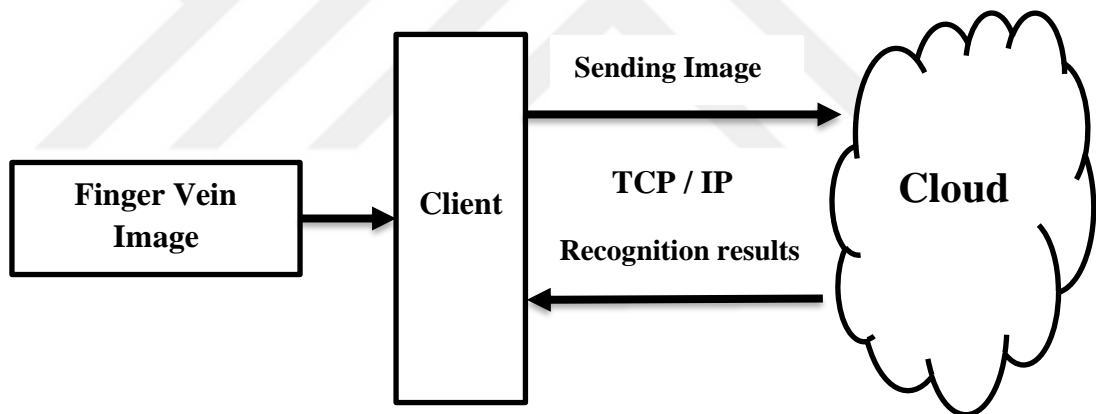


Figure 4.9 The TCP/IP in the proposed recognition model

5. RESULTS AND DISCUSSION

The purpose of this chapter is to describe and show all the outcome results obtained from implementing the proposed recognition system that depends on the finger vein biometric trait. All the proposed system phases results are introduced in this part of the thesis, also a description about the environment where the proposed system is implemented in is described and shown in details. A set of performance measurement results are used to show the degree of the proposed success is also presented including; accuracy, precision, recall and F-score.

5.1 Proposed System Implementation Environment

Provide a description about the utilized environment, where the system has been implemented is significant issue, due to it has a big influence on the success and the power of the proposed system, in which it effected on the results of the proposed system illustrated in this work. The required system functionality is realized using the latest version of Java 8 through NETBEANS IDE 8.2, C++ in Visual Studio 2013 connected to an Oracle database and Python version 3.6. All of the recommended procedures are performed on Lenovo laptops with identical hardware configurations, including seventh-generation CORE i7 CPUs, 16 GB of RAM, NVIDIA GTX 6G graphics cards, solid-state drives, Windows 10 64-bit operating systems and so on.

5.2 Classification Results and Comparison

This part of the thesis will show and illustrated the obtained results when using the features extracted from the Finger Vein images as an entry in machine learning algorithms including; J48, KNN and Random Forest and our proposed CNN. A set of measurements is used to show the results obtained from implementing the mentioned algorithms, including; Precision, Recall and F-measure. The reason of utilizing the machine learning algorithms in classification of the extracted features from the biometric images of the individual is to compare the results within the proposed deep neural network in this thesis.

Table 5.1 and Table 5.2 are illustrating the results of implementing the J48, KNN and Random Forest algorithms for both datasets of finger vein images.

Table 5.1 Experimental results of implementing machine learning algorithms on SDUMLA-HMT finger vein dataset

Algorithm	Accuracy	Precision	Recall	F-measure	Time
J48	64.924	64.924	64.570	64.392	21.12 sec
KNN	93.528	93.528	88.548	89.591	6.506 sec
Random Forest	95.139	95.139	95.073	95.014	19.254 sec
Propoed Model	99.65	99.05	99.25	99.6	5.25 sec

Table 5.2 Experimental results of implementing machine learning algorithms on UTFVP finger vein dataset

Algorithm	Accuracy	Precision	Recall	F-measure	Time
J48	64.788	64.788	63.68	63.951	20 sec
KNN	99.538	99.538	99.513	99.515	7.56 sec
Random Forest	97.75	97.75	97.708	97.681	16.214 sec
Proposed model	99.72	99.812	99.611	99.699	6.12 sec

The proposed deep neural network mainly consists from multi layers of type conventional, dense, max-pooling and its details architecture is illustrated in Table 5.3, that include a full description about each layer parameters and the output-shape.

Table 5.3 Proposed deep CNN architecture

No.	Layer Type	Parameter	Output-shape
1	Convolution 1D	64	(Non,103 ,16)
2	leaky_ReLU	-	(Non,103 ,16)
3	Max pooling 1D	-	(Non,51 ,16)
4	leaky_ReLU	-	(Non,51 ,16)
5	Convolution 1D	1568	(Non, 49, 32)
6	Max pooling 1D	-	(Non, 48, 32)
7	Convolution 1D	6208	(Non, 46, 64)
8	leaky_ReLU	-	(Non, 46, 64)
9	Max pooling 1D	-	(Non, 45, 64)
10	Convolution 1D	24704	(Non, 43, 128)
11	leaky_ReLU	-	(Non, 43, 128)
12	Max pooling 1D	-	(Non, 42, 128)
13	Convolution 1D	98560	(Non, 40, 256)
14	leaky_ReLU	-	(Non, 40, 256)
15	Max pooling 1D	-	(Non, 39, 256)
16	Convolution 1D	393728	(Non, 37, 512)
17	leaky_ReLU	-	(Non, 37, 512)
18	Max pooling 1D	-	(Non, 18, 512)
19	Convolution 1D	1573888	(Non, 16, 1024)
20	leaky_ReLU	-	(Non, 16, 1024)
21	Convolution 1D	3146752	(Non, 14, 1024)
22	leaky_ReLU	-	(Non, 14, 1024)
23	Convolution 1D	384125	(Non, 12, 125)
24	Flatten 1D	-	(Non, 1500)
25	Dense 1D	159106	(Non, 106)
Total no. of parameters		5,788,703	
Trainable parameters		5,788,703	
Non-trainable parameters		0	

As noticed from the Table 5.3, is that all the utilized 25 layers are implemented for both of the two datasets of finger vein images. The utilized deep learning model considered to hybrid due to the usage of the Dense along with the CNN, taking into account that the epoch value is equal to 100 within patch size of 64.

Results explained from Figure 5.1 to Figure 5.8.

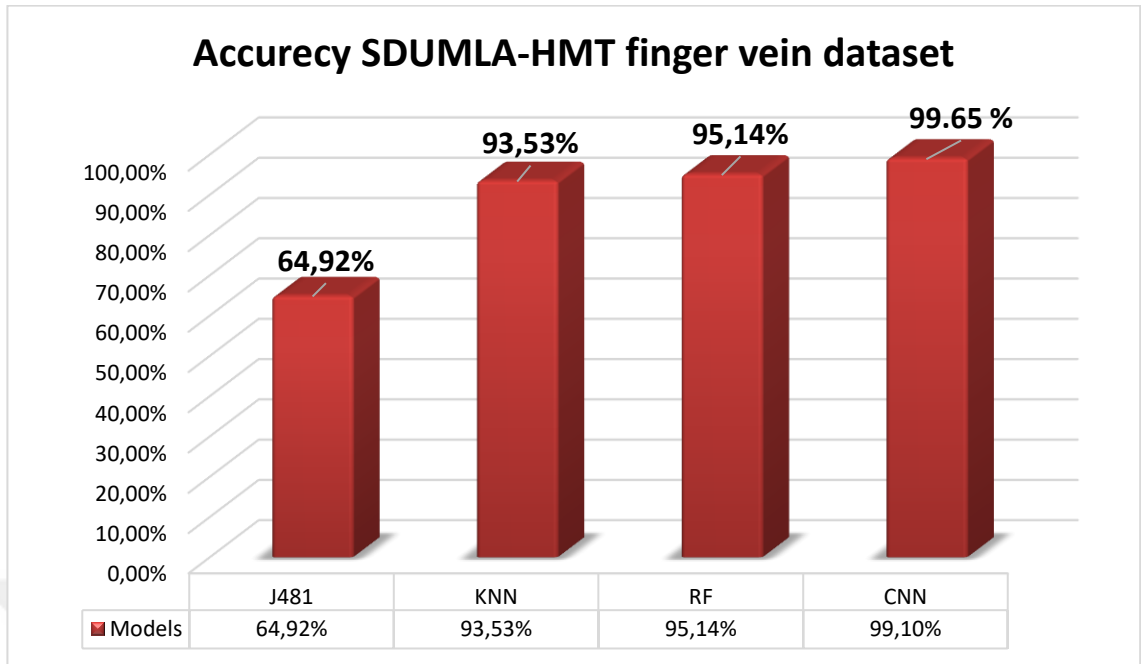


Figure 5.1 Accuracy results of the proposed deep CNN within machine learning algorithms using SDUMLA-HMT dataset

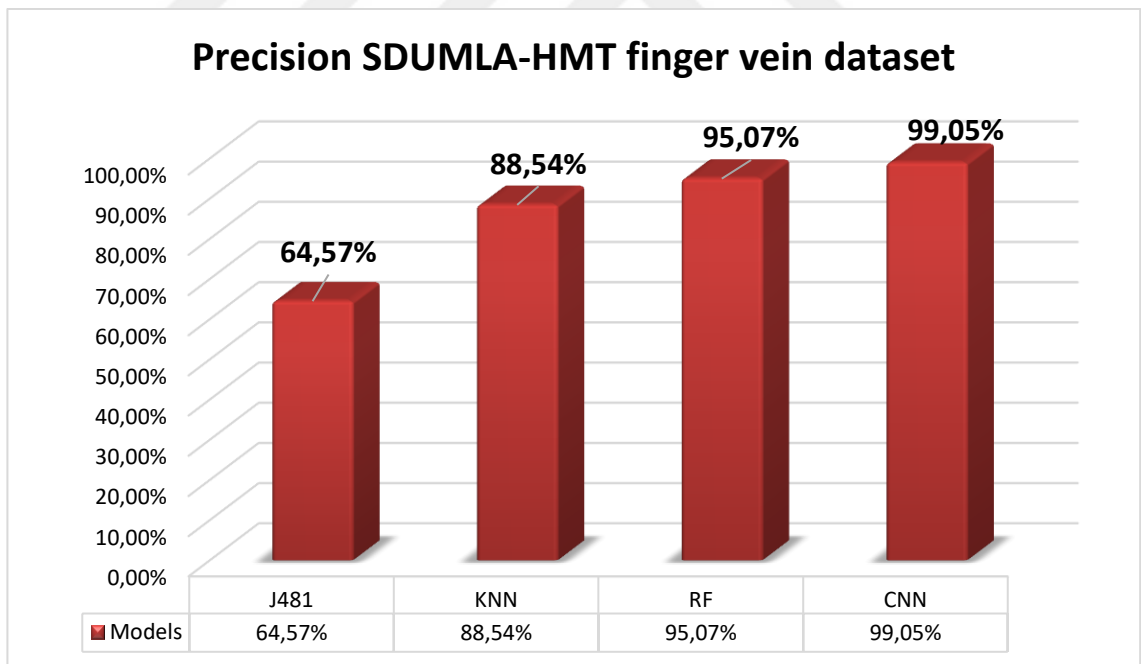


Figure 5.2 Precision results of the proposed deep CNN within machine learning algorithms using SDUMLA-HMT dataset

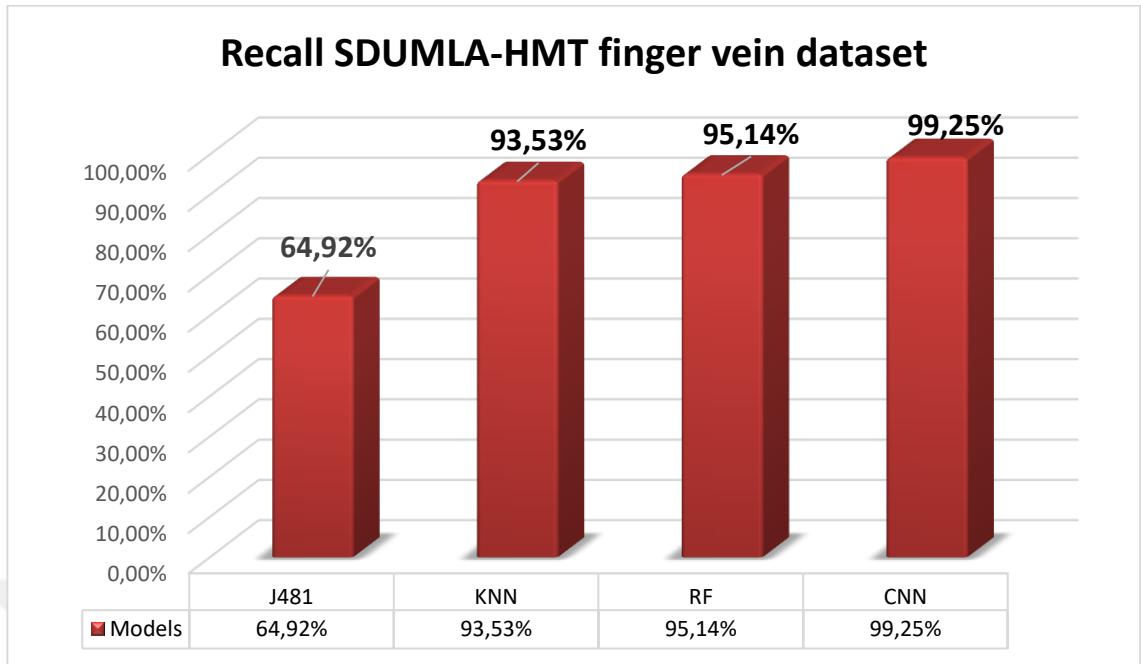


Figure 5.3 Recall results of the proposed deep CNN within machine learning algorithms using SDUMLA-HMT dataset

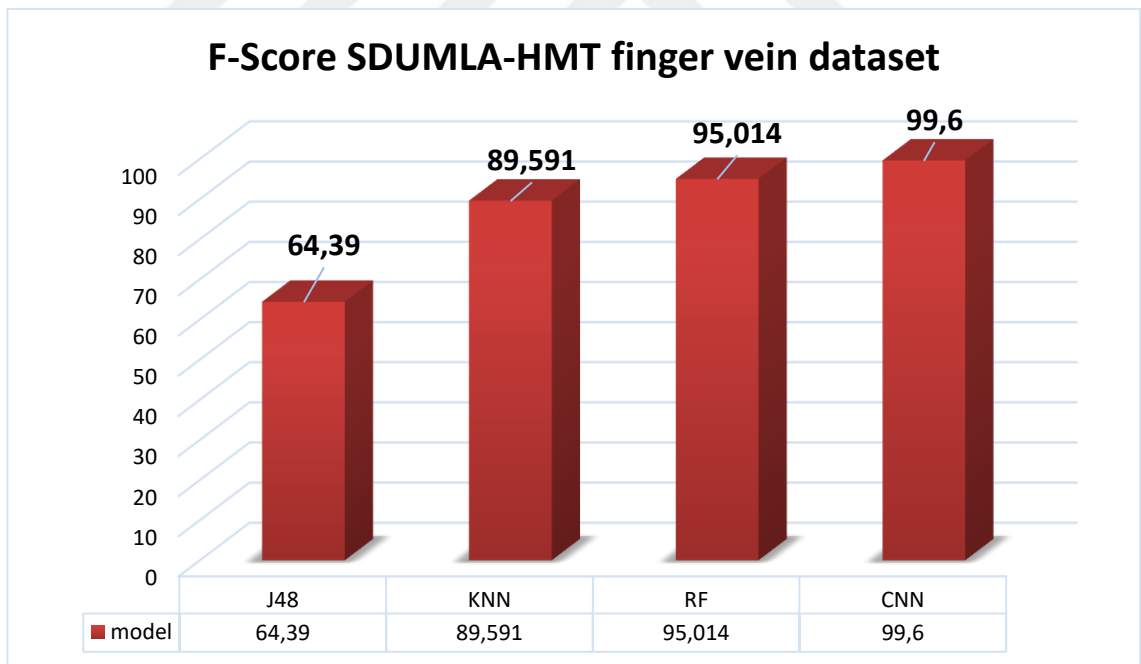


Figure 5.4 F-measure results of the proposed deep CNN within machine learning algorithms using SDUMLA-HMT dataset

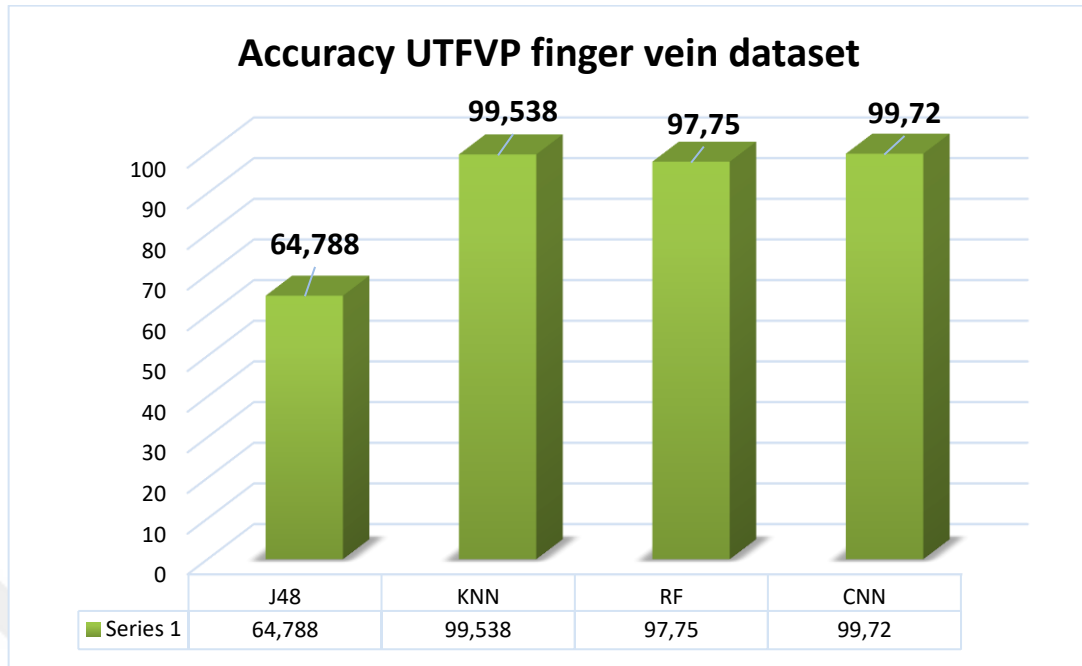


Figure 5.5 Accuracy results of the proposed deep CNN within machine learning algorithms using UTFVP dataset

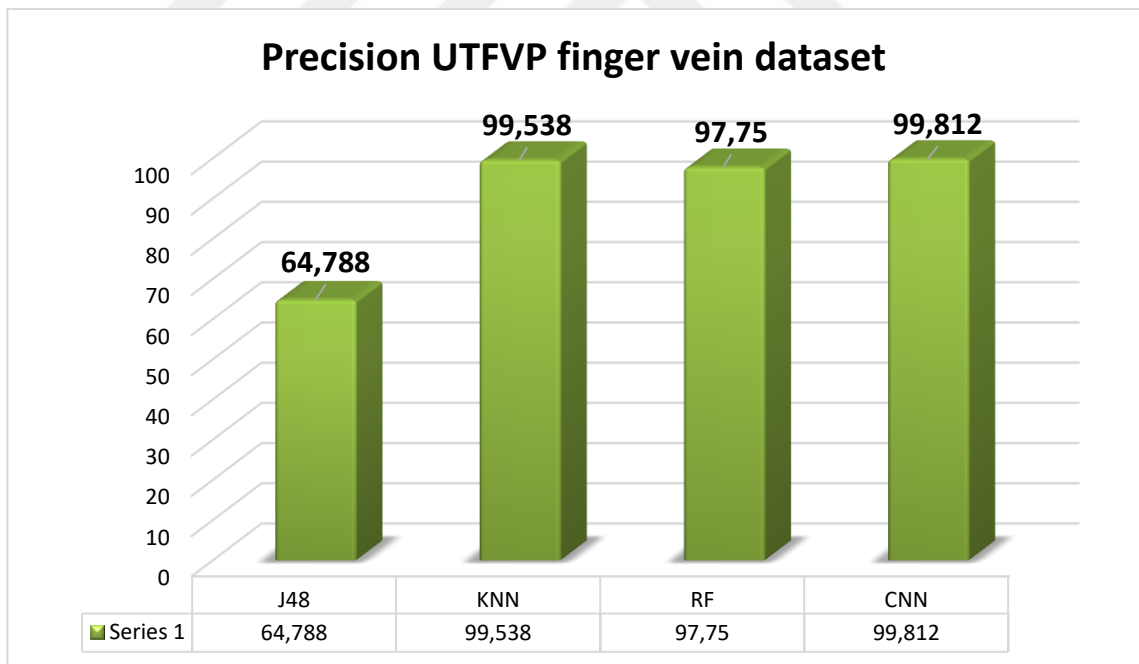


Figure 5.6 Precision results of the proposed deep CNN within machine learning algorithms using UTFVP dataset

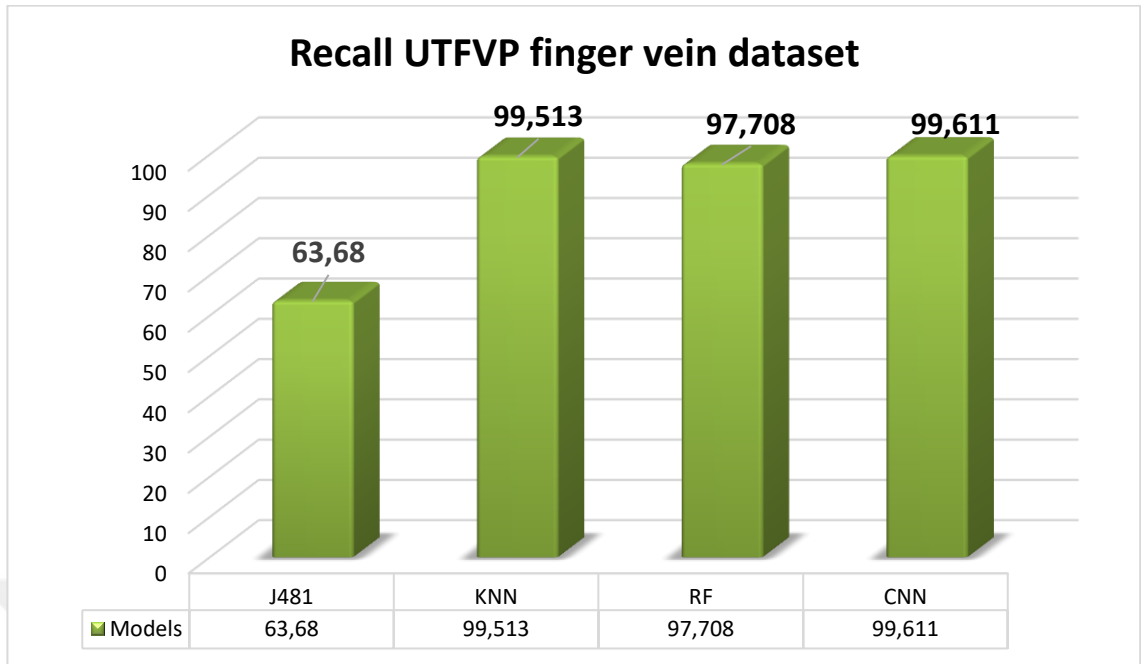


Figure 5.7 Recall results of the proposed deep CNN within machine learning algorithms using UTFVP dataset

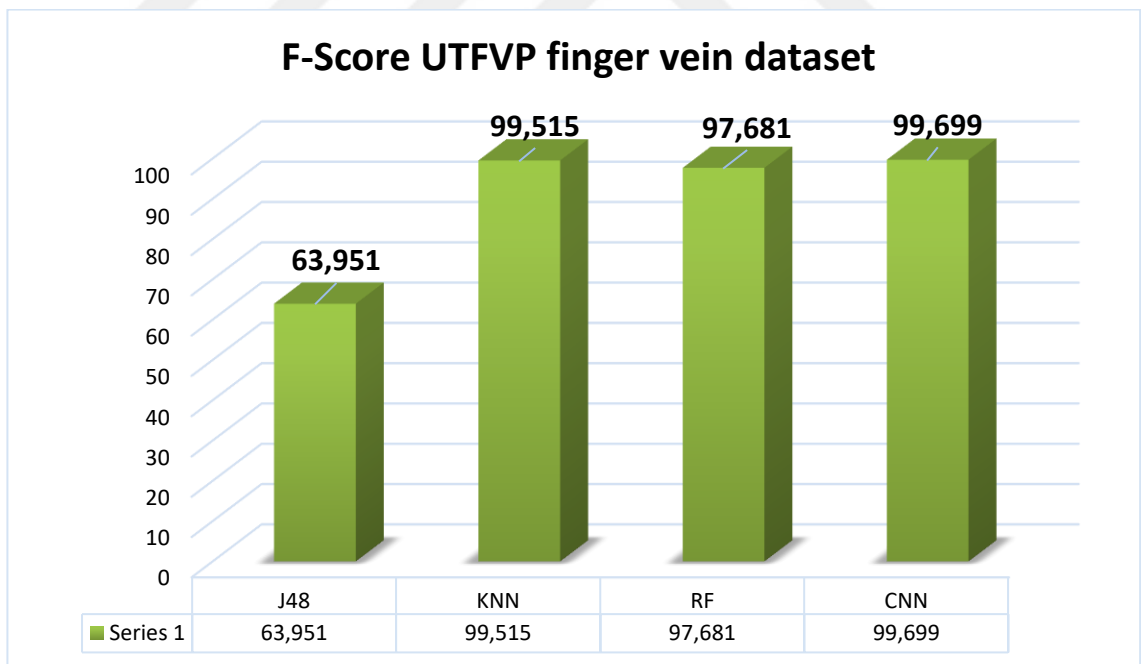


Figure 5.8 F-score results of the proposed deep CNN within machine learning algorithms using UTFVP dataset

Its noticeable that the presented deep model provide a fabulous recognition performance in both datasets which its 99.65 percent for SDUMLA-HMT finger vein dataset and 99.72 percent for UTFVP finger vein dataset, which approve the success of the proposed model and the power of using the conventional network of type 1 dimension along with Dense. The following figures provide a flow charts that describes the results comes from the presented model within the one comes from applying machine learning algorithms to explain the difference in the obtained results in more clear way an approve the power of the deep models over the machine learning algorithms.



6. CONCLUSIONS AND RECOMMENDATION

Establish individual's identity verification has gain a lot of attention in the last few years in many aspects of real life and in a vast number of applications and fields in order to get and reach the desired level of information security. The individual's biometrics traits whether its physical, or behavioral approve its power in recognition and identity authentication and the finger vein considered one of the most powerful, unique, impossible to be faked or stolen biometric trait that approved its effectiveness in recognizing individual.

In this thesis some conclusions have been get depending on a specific result via designing and implementing the proposed work. The following represent the most important ones:

- The human has been recognized using a dataset of finger vein images via deep conventional neural network
- Images are preprocessed and feature are extracted using LDA feature extraction technique
- The proposed deep network approved its power in recognizing individual and obtain a perfect recognition rate within accuracy equal to 99.65% for the SDUMLA-HMT finger vein dataset and on the UTFVP finger vein dataset, it further exceeded expectations with an accuracy rate of 99.72%.
- The implemented proposed model is a 1D that illustrates that it can give a perfect result even when the number of data in small and there is no need to use a bulk amount of data to train the model as well as its computational complexity that is considered to be low and simple in implementation.
- The proposed model compared within the machine learning algorithms that show different results and do not reach to the accuracy that achieved by the proposed deep learning network.
- Using the LDA along with Deep learning achieves high results within high speed in recognizing individuals.

Also, many suggestions can be performed and may implemented in many ways using different aspects and in this section some suggestions are illustrated as follow:

- Use another kind of vein images rather than finger such as hand veins
- Apply the proposed model on type of finger vein images with lower quality and effected by different capturing environment condition
- Develop the system to be used in order to discover if the person suffers from some kind of illness
- Use the proposed identification system to build a mobile application to get access to the mobile or perform a recognition from a distance.
- Combine the system within another kind of biometric trait in order to build a multi biometric identification system such as iris, facial, finger print, etc.



REFERENCES

- Abood, A. M., Hussein, M. S. and Abbood, A. A. 2020. Finger vein techniques: Survey. In AIP Conference Proceedings, 2213(1): 020246.
- Abuzneid, M. A. and Mahmood, A. 2018. Enhanced human face recognition using LBPH descriptor, multi-KNN and back-propagation neural network. IEEE Access, 6, 20641-20651.
- Akintoye, K. A., Rahim, M. S. and Abdullah, A. H. 2018. Challenges of finger vein recognition system: a theoretical perspective. International Journal of Emerging Technology and Advanced Engineering, 8(2): 196-204.
- Ang, J. C., Mirzal, A., Haron, H. and Hamed, H. N. A. 2015. Supervised, unsupervised and semi-supervised feature selection: a review on gene selection. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 135: 971-989.
- Anguita, D., Ghelardoni, L., Ghio, A., Oneto, L. and Ridella, S. 2012. The 'K' in K-fold cross validation, In: 20th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, pp. 441-446.
- Azad, D. and Hasan, M. 2017. Color image processing on digital image. International Journal of New Technology and Research, 3(3).
- Bahi, M. and Batouche, M. 2018. Deep learning for ligand-based virtual screening in drug discovery. In 2018 3rd International Conference on Pattern Analysis and Intelligent Systems (PAIS) pp. 1-5. IEEE.
- Bala, R. and Braun, K. M. 2003. Color-to-grayscale conversion to maintain discriminability. In Color Imaging IX: Processing, Hardcopy and Applications International Society for Optics and Photonics, 5293:196-202.
- Baratloo, A., Hosseini, M., Negida, A. and El Ashal, G. 2015. Part 1: simple definition and calculation of accuracy, sensitivity and specificity. Evidence-Based Emergency Medicine, 3(2): 48-49.
- Bilal, A., Sun, G. and Mazhar, S. 2021. Finger-vein recognition using a novel enhancement method with convolutional neural network. Journal of the Chinese Institute of Engineers, 1-11.
- Boulesteix, A. L., Janitza, S., Kruppa, J. and König, I. R. 2012. Overview of random forest methodology and practical guidance with emphasis on computational biology

- and bioinformatics. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 2(6): 493-507.
- Bowyer, K. W., Chang, K. I., Yan, P., Flynn, P. J., Hansley, E. and Sarkar, S. 2006. Multi-modal biometrics: an overview, In: 12th European Signal Processing Conference, pp. 105-111, Austria.
- Cao, B., Araujo, A. and Sim, J. 2020. Unifying deep local and global features for image search, In: European Conference on Computer Vision, pp.726-743, Cham.
- Carbonell, J. G., Michalski, R. S. and Mitchell, T. M. 1983. An overview of machine learning. In *Machine learning*, pp. 3-23. Morgan Kaufmann.
- Chaurasia, V. and Pal, S. 2014. Data mining approach to detect heart diseases. *International Journal of Advanced Computer Science and Information Technology (IJACSIT)*, 2: 56-66.
- Chen, C., Wu, Z., Zhang, J., Li, P. and Azmat, F. 2017. A finger vein recognition algorithm based on deep learning. *International Journal of Embedded Systems*, 9(3): 220-228.
- Christopher, A. B. A. and Balamurugan, S. A. 2014. Prediction of warning level in aircraft accidents using data mining techniques. *The Aeronautical Journal*, 118(1206): 935-952.
- Das, R., Piciuccio, E., Maiorana, E. and Campisi, P. 2018. Convolutional neural network for finger-vein-based biometric identification. *IEEE Transactions on Information Forensics and Security*, 14(2): 360-373.
- Delac, K. and Grgic, M. 2004. A survey of biometric recognition methods. In *Proceedings. Elmar-2004. 46th International Symposium on Electronics in Marine*, pp. 184-193, Marine.
- Deng, L. and Li, X. 2013. Machine learning paradigms for speech recognition: An overview. *IEEE Transactions on Audio, Speech and Language Processing*, 21(5): 1060-1089.
- Du, S., Lee, J., Li, H., Wang, L. and Zhai, X. 2019. Gradient descent finds global minima of deep neural networks. In *International conference on machine learning*, pp. 1675-1685, PMLR.

- Ebied, H. M. 2012. Feature extraction using PCA and Kernel-PCA for face recognition. In 2012 8th International Conference on Informatics and Systems (INFOS) pp. MM-72. IEEE.
- El-Rahiem, B. A., Abd El-Samie, F. E. and Amin, M. 2021. Multimodal biometric authentication based on deep fusion of electrocardiogram (ECG) and finger vein. *Multimedia Systems*, 1-13.
- Fairuz, S., Habaebi, M. H. and Elsheikh, E. M. A. 2018. Finger vein identification based on transfer learning of AlexNet. In 2018 7th International Conference on Computer and Communication Engineering (ICCCCE), pp. 465-469. IEEE.
- Fang, Y., Wu, Q. and Kang, W. 2018. A novel finger vein verification system based on two-stream convolutional network learning. *Neurocomputing*, 290: 100-107.
- Ghannay, S., Caubriere, A., Esteve, Y., Laurent, A. and Morin, E. 2018. End-to-end named entity extraction from speech. *Computation and Language*, 1-5.
- Ghassabeh, Y. A., Rudzicz, F. and Moghaddam, H. A. 2015. Fast incremental LDA feature extraction. *Pattern Recognition*, 48(6): 1999-2012.
- Han, J., Zhang, D., Cheng, G., Liu, N. and Xu, D. 2018. Advanced deep-learning techniques for salient and category-specific object detection: a survey. *IEEE Signal Processing Magazine*, 35(1): 84-100.
- Hashimoto, J. 2006. Finger vein authentication technology and its future. In 2006 Symposium on VLSI Circuits, 2006. Digest of Technical Papers, pp. 5-8. IEEE.
- Hermawan, D. R., Fatihah, F. G., Kurniawati, L. and Helen, A. 2021. Comparative study of j48 decision tree classification algorithm, random tree and random forest on in-vehicle coupon recommendation data, In: *International Conference on Artificial Intelligence and Big Data Analytics*.
- Hernández-García, A. and König, P. 2018. Further advantages of data augmentation on convolutional neural networks. In *International Conference on Artificial Neural Networks*, Springer, pp. 95-103. Cham.
- Hillerström, F., Kumar, A. and Veldhuis, R. 2014. Generating and analyzing synthetic finger vein images. In 2014 International Conference of the Biometrics Special Interest Group (BIOSIG), pp. 1-9. IEEE.
- Hong, H. G., Lee, M. B. and Park, K. R. 2017. Convolutional neural network-based finger-vein recognition using NIR image sensors. *Sensors*, 17(6): 1297.

- Hou, B. and Yan, R. 2019. Convolutional auto encoder model for finger-vein verification. *IEEE Transactions on Instrumentation and Measurement*, 69(5): 2067-2074.
- Huang, G., Song, S., Gupta, J. N. D. and Wu, C. 2014. Semi-supervised and unsupervised extreme learning machines. *IEEE Transactions on Cybernetics*, 44(12): 2405-2417.
- Idrus, S. Z. S., Cherrier, E., Rosenberger, C. and Schwartzmann, J-J. 2013. A review on authentication methods. *Australian Journal of Basic and Applied Sciences*, 7(5): 95-107.
- Jain, A. K. and Kumar, A. 2012. Biometric recognition: an overview. In *Second Generation Biometrics: The Ethical, Legal and Social Context*, Springer, pp. 49-79, Dordrecht.
- Jain, A. K., Ross, A. and Prabhakar, S. 2004. An introduction to biometric recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1): 4-20.
- Jogin, M., Madhulika, M. S., Divya, G. D., Meghana, R. K. and Apoorva, S. 2018. Feature extraction using convolution neural networks (CNN) and deep learning. In *2018 3rd IEEE international conference on recent trends in electronics, information & communication technology*, pp. 2319-2323, IEEE.
- Karabulut, B., Arslan, G. and Ünver, H. M. 2019. A weighted similarity measure for k-nearest neighbors algorithm. *Celal Bayar Üniversitesi Fen Bilimleri Dergisi*, 15(4): 393–400.
- Karamizadeh, S., Abdullah, S. M., Manaf, A. A., Zamani, M. and Hooman, A. 2013. An overview of principal component analysis. *Journal of Signal and Information Processing*, 4(3B): 173.
- Khade, S. and Thepade, S. D. 2018. Novel fingerprint liveness detection with fractional energy of cosine transformed fingerprint images and machine learning classifiers. In *2018 IEEE Punecon*, pp. 1-7, IEEE.
- Kotsiantis, S. B., Zaharakis, I. and Pintelas, P. 2007. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160, 3-24.
- Kumar, G. and Bhatia, P. K. 2014. A detailed review of feature extraction in image processing systems. In *2014 Fourth International Conference on Advanced Computing & Communication Technologies*, pp. 5-12, India.

- Kutemate, S. B. 2015. Prof. Shekokar RU. Secure and reliable human identification based on finger-vein patterns. *International Journal of Engineering Research & Technology (IJERT)*: 4(3): 978–980.
- Lee, J. H., Shin, J. and Realff, M. J. 2018. Machine learning: Overview of the recent progresses and implications for the process systems engineering field. *Computers & Chemical Engineering*, 114, 111–121.
- Liu, W., Li, W., Sun, L., Zhang, L. and Chen, P. 2017. Finger vein recognition based on deep learning. In 2017 12th IEEE Conference on Industrial Electronics and Applications (ICIEA) pp. 205-210, Cambodia.
- Liu, W., Wang, Z., Liu, X., Zeng, N., Liu, Y. and Alsaadi, F. E. 2017. A survey of deep neural network architectures and their applications. *Neurocomputing*, 234, 11-26.
- Luque, A., Carrasco, A., Martín, A. and de Las Heras, A. 2019. The impact of class imbalance in classification performance metrics based on the binary confusion matrix. *Pattern Recognition*, 91, 216-231.
- Mane, V. M. and Jadhav, D. V. 2009. Review of multimodal biometrics: applications, challenges and research areas. *International Journal of Biometrics and Bioinformatics (IJBB)*: 3(5): 90-95.
- Marmolin, H. 1986. Subjective MSE measures. *IEEE transactions on systems, man and cybernetics*, 16(3): 486-489.
- MICHAEL, C. 2020. Website: <https://towardsdatascience.com/classical-neural-network-what-really-are-nodes-and-layers-ec51c6122e09>. Date of access: 24.02.2020
- OGNJANOVSKI, G. 2019. Website: <https://towardsdatascience.com/everything-you-need-to-know-about-neural-networks-and-backpropagation-machine-learning-made-easy-e5285bc2be3a>. Date of access : 14.01.2019
- Ojala, T., Pietikäinen, M. and Harwood, D. 1996. A comparative study of texture measures with classification based on featured distributions. *Pattern recognition*, 29(1): 51-59.
- Osisanwo, F. Y., Akinsola, J. E. T., Awodele, O., Hinmikaiye, J. O., Olakanmi, O. and Akinjobi, J. 2017. Supervised machine learning algorithms: classification and comparison. *International Journal of Computer Trends and Technology (IJCTT)*, 48(3): 128-138.

- Ozgur, A. 2004. Supervised and unsupervised machine learning techniques for text document categorization. MSc Thesis, İstanbul: Boğaziçi University, 80 page, İstanbul.
- Pietikäinen, M., Hadid, A., Zhao, G. and Ahonen, T. 2011. Local binary patterns for still images. In *Computer vision using local binary patterns*, Springer, pp. 13-47, London.
- Plagianakos, V. P., Magoulas, G. D. and Vrahatis, M. N. 2001. Learning rate adaptation in stochastic gradient descent. In *Advances in convex analysis and global optimization*, Springer, pp. 433-444, Boston.
- Plataniotis, K. N. and Venetsanopoulos, A. N. 2013. *Color image processing and applications*. Springer, 355 page, Berlin.
- Prabhakar, P. and Thomas, T. 2013. Finger vein identification based on minutiae feature extraction with spurious minutiae removal. In *2013 Third International Conference on Advances in Computing and Communications*, pp. 196-199, IEEE.
- Prakasa, E. 2016. Texture feature extraction by using local binary pattern. *INKOM Journal*, 9(2): 45-48.
- Raissi, M., Ramezani, N. and Seshaiyer, P. 2019. On parameter estimation approaches for predicting disease transmission through optimization, deep learning and statistical inference methods. *Letters in Biomathematics*, 6(2): 1-26.
- Robert Chen-Hao Chang, Wang, C.-Y., Li, Y.-H. and Chiu, C.-D. 2023. Design of low-complexity convolutional neural network accelerator for finger vein identification system. *Sensors*, 23(4), 2184–2184.
- Ross, A. and Jain, A. K. 2007. Human recognition using biometrics: an overview. In *Annales Des Télécommunications*, Springer, 621(2): 11-35.
- Sachs, J. 1996. *Digital image basics*. Digital Light & Color, 1999.
- Saeidi, M. and Ahmadi, A. 2018. Deep learning based on CNN for pedestrian detection: an overview and analysis. In *2018 9th International Symposium on Telecommunications*, pp. 108-112, IEEE.
- Sahar W. S., Hussain K. I., Ameen M. S. 2022. Finger vein recognition using deep learning technique. *Wasit Journal of Computer and Mathematic Science*, 1:(2).

- Sainath, T. N., Mohamed, A., Kingsbury, B. and Ramabhadran, B. 2013. Deep convolutional neural networks for LVCSR, In: 2013 IEEE international conference on acoustics, speech and signal processing, pp. 8614-8618, Canada.
- Saravanan, G., Yamuna, G. and Nandhini, S. 2016. Real-time implementation of RGB to HSV/HSI/HSL and its reverse color space models, In: International Conference on Communication and Signal Processing, pp. 0462-0466, India.
- Savargiv, M., Masoumi, B. and Keyvanpour, M. R. 2021. A new random forest algorithm based on learning automata. *Computational Intelligence and Neuroscience*, 2021: 1–19.
- Schmidhuber, J. 2015. Deep learning in neural networks: An overview. *Neural networks*, 61, 85-117.
- Seeger, S. and Laboureaux, X. 2002. Feature extraction and registration: An overview. *Principles of 3D image analysis and synthesis*, 153-166.
- Shanono, I. H., Sapiee, M., Aziz, K. A., Zakaria Suleiman, N. H., Gomes, A. and Gomes, C. 2018. Image processing techniques applicable to wastewater quality detection: towards a hygienic environment. *Journal of Materials and Environmental Science*, 9: 2288-2303.
- Sharma, A. and Paliwal, K. K. 2014. Linear discriminant analysis for the small sample size problem: an overview. *International Journal of Machine Learning and Cybernetics*, 6(3): 443–454.
- Sharma, A. and Paliwal, K. K. 2015. Linear discriminant analysis for the small sample size problem: an overview. *International Journal of Machine Learning and Cybernetics*, 6(3): 443-454.
- Shrestha, A. and Mahmood, A. 2019. Review of deep learning algorithms and architectures. *IEEE access*, 7: 53040-53065.
- Sidiropoulos, G. K., Kiratsa, P., Chatzipetrou, P. and Papakostas, G. A. 2021. Feature Extraction for Finger-Vein-Based Identity Recognition. *Journal of Imaging*, 7(5): 89.
- Singh, R. P. and Dixit, M. 2015. Histogram equalization: a strong technique for image enhancement. *International Journal of Signal Processing, Image Processing and Pattern Recognition*, 8(8): 345-352.

- Song, J. M., Kim, W. and Park, K. R. 2019. Finger-vein recognition based on deep DenseNet using composite image. *IEEE Access*, 7, 66845-66863.
- Sudhamani, M. J., Sanyal, I. and Venkatesha, M. K. 2021. Artificial neural network approach for multimodal biometric authentication system. *Proceedings of Data Analytics and Management*, 253–265.
- Sun, S. and Huang, R. 2010. An adaptive k-nearest neighbor algorithm, In: 2010 Seventh International Conference on Fuzzy Systems and Knowledge Discovery, pp. 91-94, China.
- Syazana-Itqan, K., Syafeeza, A. R., Saad, N. M., Hamid, N. A. and Saad, W. H. B. M. 2016. A review of finger-vein biometrics identification approaches. *Indian J. Sci. Technol*, 9(32): 1-9.
- Tariq, U. U., Ahmad, W., Abdullah Asif, M. D. and Hussain, M. 2013. Gender Perception From Faces Using Boosted LBPH (Local Binary Patten Histograms). *Carpathian Journal of Electronic & Computer Engineering*, 6(1).
- Toepfer, M. and Seifert, C. 2018. Content-based quality estimation for automatic subject indexing of short texts under precision and recall constraints. In *International Conference on Theory and Practice of Digital Libraries*, Springer, pp. 3-15, Cham.
- Ton, B. T. and Veldhuis, R. N. J. 2013. A high-quality finger vascular pattern dataset collected using a custom-designed capturing device, In: 2013 International Conference on Biometrics (ICB), pp. 1-5, Spain.
- Turk, M. and Pentland, A. 1991. Eigenfaces for recognition. *Journal of cognitive neuroscience*, 3(1): 71-86.
- Ullah, I., Hussain, M., Muhammad, G., Aboalsamh, H., Bebis, G. and Mirza, A. M. 2012. Gender recognition from face images with local wld descriptor, In: 2012 19th International Conference on Systems, Signals and Image Processing (IWSSIP), pp. 417-420, Austria.
- Vehils, J. M. D. 2011. Design and Implementation of a Finger Vein Identification System. MSc Thesis. Universitat Politècnica de Catalunya, 69 page, Barcelona.
- Vishwakarma, V. P., Pandey, S. and Gupta, M. N. 2009. Adaptive histogram equalization and logarithm transform with rescaled low-frequency DCT coefficients for illumination normalization. *International Journal of Recent Trends in Engineering*, 1(1): 318.

- Walia, M. S. and Hoshiarpur, P. 2014. Challenges in automated iris recognition system. *IOSR Journal of Engineering*, 2278-8719.
- Wang, F., Zhen, Z., Wang, B. and Mi, Z. 2018. Comparative study on KNN and SVM based weather classification models for day ahead short term solar PV power forecasting. *Applied Sciences*, 8(1): 28.
- Weng, L., Li, X. and Wang, W. 2020. Finger vein recognition based on Deep Convolutional Neural Networks. In 2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), pp. 266-269, China.
- Xian, R., Ni, L. and Li, W. 2015. The icb-2015 competition on finger vein recognition. In 2015 International Conference on Biometrics (ICB), pp. 85-89, Thailand.
- Xiao, M., Wu, L.-A. and Kimble, H. J. 1987. Precision measurement beyond the shot-noise limit. *Physical review letters*, 59(3): 278.
- Yadav, S. and Shukla, S. 2016. Analysis of k-fold cross-validation over hold-out validation on colossal datasets for quality classification. In 2016 IEEE 6th International conference on advanced computing, pp. 78-83, India.
- Yamashita, R., Nishio, M., Do, R. K. G. and Togashi, K. 2018. Convolutional neural networks: an overview and application in radiology. *Insights into imaging*, 9(4): 611-629.
- Yamin, Mohammad; Gedeon, Tom; Bajaba, Saleh; Abusurrah, Mona M. 2023. Biometric Finger Vein Recognition Using Evolutionary Algorithm with Deep Learning. *Computers, Materials & Continua*, 75(3): 5659-5674.
- Yang, L., Yang, G., Yin, Y. and Xi, X. 2017. Finger vein recognition with anatomy structure analysis. *IEEE Transactions on Circuits and Systems for Video Technology*, 28(8): 1892-1905.
- Yang, L., Yang, G., Yin, Y. and Zhou, L. 2014. A survey of finger vein recognition. In Chinese conference on biometric recognition, Springer, pp. 234-243, Cham.
- Zhang, Q., Wu, Y. N. and Zhu, S.-C. 2018. Interpretable convolutional neural networks, In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition pp. 8827-8836, USA.

- Zhang, S., Li, X., Zong, M., Zhu, X. and Wang, R. 2017. Efficient knn classification with different numbers of nearest neighbors. *IEEE Transactions on Neural Networks and Learning Systems*, 29(5): 1774-1785.
- Zhang, Y., Li, W., Zhang, L., Ning, X., Sun, L. and Lu, Y. 2019. Adaptive learning Gabor filter for finger-vein recognition. *IEEE Access*, 7, 159821-159830.
- Zhang, Z., Zhou, Z., Yang, X., Meng, H. and Wu, G. 2023. Convolutional neural network based on multi-directional local coding for finger vein recognition. *Information Sciences*, 623: 633–647.
- Zhao, D., Ma, H., Yang, Z., Li, J. and Tian, W. 2020. Finger vein recognition based on lightweight CNN combining center loss and dynamic regularization. *Infrared Physics & Technology*, 105: 103221.
- Zheng, Z., Zhang, Y., Li, L., Zhu, M., He, Y., Li, M., Guo, Z., He, Y., Yu, Z., Yang, X., Liu, X., Luo, J., Yang, T., Liu, Y. and Li, J. 2017. Classification based on deep convolutional neural networks with hyperspectral image.

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