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Deep Learning-Based Biometric Finger Vein Authentication System for Enhanced Security

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Abstract
Biometrics, which uses human physiological characteristics, is a method for protecting personal information. Recently, finger vein authentication has become one of the most popular biometric techniques. This method offers high security and accuracy, making it a reliable form of biometric authentication. The system compares a person's vascular structure in their finger to previously collected data. Finger vein authentication works by identifying vein patterns beneath the skin's surface. The proposed system aims to enhance user authentication security by leveraging the uniqueness of finger vein patterns. The finger vein image is obtained from a database, and preprocessing is done using a Gaussian median filter in both spatial and frequency domains to remove noise. Image segmentation is performed through a line tracking method, which enhances image contrast. For feature extraction, the system utilizes Convolutional Neural Networks (CNN), and these features are matched with the stored finger vein database. A deep learning approach is then applied to classify users as genuine or imposters. In real-time, a scanner captures the finger vein image, which is sent to an Arduino board for storage and subsequently processed in MATLAB for classification. The result is transmitted through a GSM module as an alert or message, and the information is also stored in an IoT system for future reference. A GSM module is integrated with the user for communication. The proposed system achieves an accuracy of 96%, making it highly beneficial for security applications like access control, identity verification, banking, and financial transactions.

Keywords: Biometric Recognition, Finger Vein, Line Tracking, Convolution neural network, Gaussian Filter

I. INTRODUCTION

The need to recognize specific attributes in the realm of smart recognition presents a significant global security challenge. [1]. Despite the development of various algorithms in recent years to tackle security concerns, there is still a demand for fast and efficient biometric identification systems. Biometric recognition refers to the automatic identification of individuals based on their physical and behavioral traits. Many biometric techniques have been developed using these characteristics, including hand and palm prints, iris scans, fingerprints, hand and finger veins, palm and foot veins, DNA, gait, voice, facial expressions, heartbeat, signatures, body language, and facial structure. [2]. Biometric methods can be classified into two types: intrinsic features, such as palm veins, hand veins, and finger veins, and extrinsic features, including fingerprints, iris scans, palm prints, and facial recognition. [3]. While extrinsic features are more visible, they come with certain limitations. [4]. For instance, bright light can affect the retinal surface during iris recognition, and factors like lighting, facial expressions, blood vessel obstructions, and positioning can reduce the accuracy of facial recognition. [5]. Finger vein recognition, also known as vascular biometrics, relies on the unique patterns of veins located beneath the skin of each person's finger. These blood vessel patterns, hidden under the skin where red blood cells circulate, offer identifiable information. Compared to other biometric methods such as fingerprints, finger vein identification offers several benefits, including higher accuracy and greater resistance to spoofing.

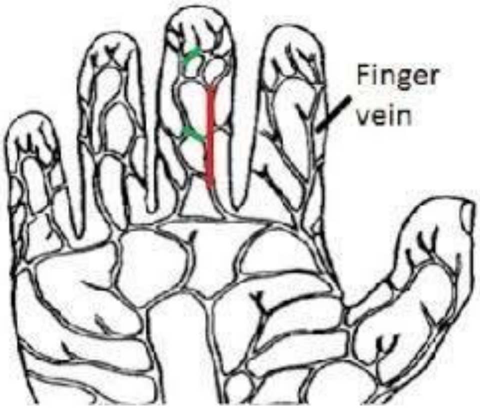


Fig.1. Finger vein structure

II. RELATED WORKS

A new technique for extracting finger vein patterns utilizing the Frangi filter and maximum curvature has been proposed. The authors introduced an innovative method to enhance the contrast and clarity of finger vein images by applying the Frangi filter to the input images. They also suggested a novel approach for detecting finger vein patterns by calculating the maximum curvature in the enhanced images. [6]. The study by George K. Kumi, Mohamed Abdul-Al, and Nabeel Abdul Jabbar offers an in-depth review of the latest developments in finger vein identification methods. The authors examine various techniques for capturing, extracting, and classifying finger vein images. They also emphasize the challenges and limitations of current methods, such as poor image quality, differences in finger size and positioning, and the diversity of finger vein image databases. [7]. In their paper, T. Sathish Kumar, Pachaivannan Parthiban, and S. Rajesh Kannan propose an innovative approach for finger vein-based identity and recognition using Gabor filters. The authors introduce a new method for segmenting vein patterns and improving finger vein images through the application of Gabor filters and thresholding. Additionally, they suggest a novel feature extraction technique by calculating the mean and standard deviation of the vein patterns. [8]. Kashif Shaheed, Ahiua Mao, and Imran Qureshi present an overview of the methodology used in finger vein recognition systems, covering key stages like image acquisition, preprocessing, feature extraction, and classification. They also address challenges faced by these systems, including variations in finger positioning and image quality. The paper offers a thorough review of the current state of finger vein recognition and discusses its potential for future advancements [9]. A new method for finger vein recognition utilizing artificial neural networks (ANNs) is proposed. This approach consists of three primary stages: preprocessing, feature extraction, and classification. During preprocessing, the input images are enhanced and filtered to eliminate noise and artifacts. In the feature extraction stage, a Convolutional Neural Network (CNN) is employed to identify distinctive features from the processed images. Finally, in the classification stage, a multi-layer perceptron (MLP) neural network is used to categorize these features. [10]. In the publication "Finger Vein Recognition Using Deep Convolutional Neural Networks" by N. Elhaddad, M. E. Elhamdadi, and A. E. Hassanien, a distinctive method for identifying finger veins using deep convolutional neural networks (CNNs) is introduced. The authors propose a new approach for segmenting vein patterns through a thresholding technique and enhancing the quality of finger vein images using histogram equalization. They also present an innovative design for the CNN-based model, which incorporates multiple convolutional and pooling layers to extract features from the finger vein patterns. [11]. A multimodal biometric authentication system that integrates fingerprints from multiple fingers at the score level has been proposed. This system creates a composite score for authentication by combining data from several fingers using a fingerprint template database. The authors show that their approach enhances accuracy and reliability by comparing its performance with that of previous multimodal biometric identification systems. [12]. A novel approach to finger vein authentication has been introduced. This study presents an advanced line detector algorithm designed to identify and enhance finger vein patterns, along with a pattern normalization technique aimed at reducing variability in vein patterns caused by differences in finger size and positioning.[13]. Wencheng Yang, Song Wang, and Jiankun Hu proposed a security mechanism for finger vein authentication that combines deep learning with binary decision diagrams. The system initially uses deep learning to extract features from finger vein images and then creates a Binary Decision Diagram to represent the decision-making process. This approach reduces the system's memory requirements and improves security by limiting the exposure of sensitive information. [14]. The paper offers a detailed review of different methods employed in finger vein recognition, a biometric authentication technique. The authors provide a comparative analysis of various finger vein recognition systems. Overall, the paper delivers valuable insights for researchers and practitioners who are developing or utilizing finger vein recognition systems for authentication. [15].

A. Motivation and Objectives

To address the aforementioned limitations, the proposed model is designed to achieve superior results compared to existing systems. The development of the Finger Vein Recognition system involves three distinct steps:

1. To preprocess the gathered images of the finger vein in order to determine the underlying structure of the vein. The preprocessing stage consists of the following steps: normalisation, feature extraction, segmentation, and image enhancement. By isolating the vein patterns, extracting significant features that depict the vein structure, and standardising these features to guarantee uniformity across various finger vein patterns, these techniques help to improve image quality.
2. To categorise vein patterns in fingers as authentic or non-authentic. Using supervised learning techniques, the model will be trained on a labelled dataset of finger vein patterns in order to carry out this classification process. Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), will be used to evaluate the performance of the classification algorithm. Evaluation metrics that will be used include precision, recall, and F1-score.

III. PROPOSED SYSTEM

Finger vein data collection is more comfortable, non-intrusive, and contactless, enhancing both user convenience and hygiene. Biometric finger vein technology shows promise for ease of use and security. Because the vein structure is hidden beneath the skin and nearly invisible to the naked eye, it is challenging to replicate or forge. The finger vein pattern, which can only be captured from a living person's finger, serves as a reliable and natural indicator of the individual's presence. The finger vein biometric pattern provides numerous advantages in terms of convenience and security. The stages of proposed system are

1. Image Acquisiton
2. Pre-Processing
   a. Filtering
   b. Edge Detection
   c. Equalization Histogram
   d. Image Segmentation
3. Feature Extraction
   a. ROI Location
   b. Feature Matching
4. Classification
5. Data storage

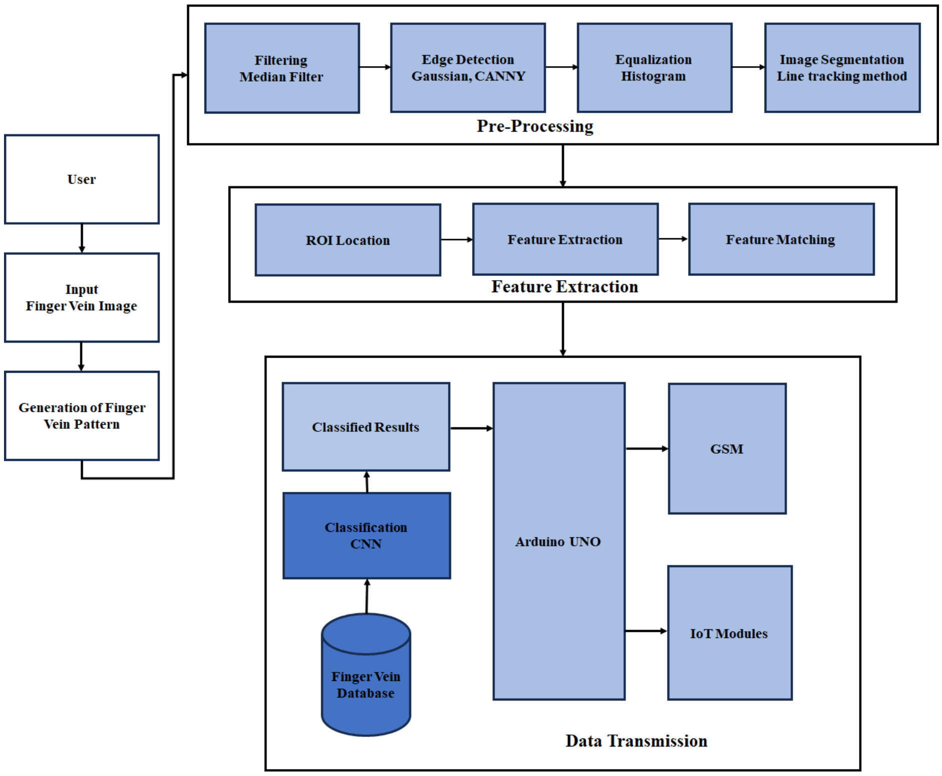


Fig.2. Flow diagram of the proposed model

The proposed system utilizes a Convolutional Neural Network to analyze images and extract the necessary features. The process involves first uploading the finger vein patterns from collected datasets. These datasets, sourced from open platforms like Kaggle, are used for training the model. After the training is complete, the next step is to test the trained model. The data processing is carried out in three stages: preprocessing, segmentation, and classification, as illustrated in Figure 2.

A. Image Acquisition

The initial step in finger vein recognition (FVR) involves capturing the finger vein image using near infrared (NIR) light through an illumination process. A charge-coupled device (CCD) camera is used to record the image of the finger vein after the finger is properly positioned with the help of an NIR assembly component of the acquisition device. [16,17]. While NIR light can penetrate a finger, blood hemoglobin absorbs it more effectively than other tissues like bones and muscles. [18]. When infrared light is absorbed by the vein, it appears as a dark line in the finger. Figure 2 illustrates the functioning of the finger vein scanner, and Figure 3 displays the device itself. Since NIR imaging involves capturing images through the finger, it ensures a high level of security. [19]. Images of finger veins are typically captured using three methods: light transmission, light reflection, and two-way radiating. [20,21]. Most finger vein imaging devices utilize the light transmission method, as it provides the highest contrast images compared to other techniques. [22]. Nonetheless, certain challenges, such as low contrast, translational and rotational variations, and noise, often hinder the optimization of the image acquisition device. Consequently, the next step—image preprocessing—is employed to address these issues.

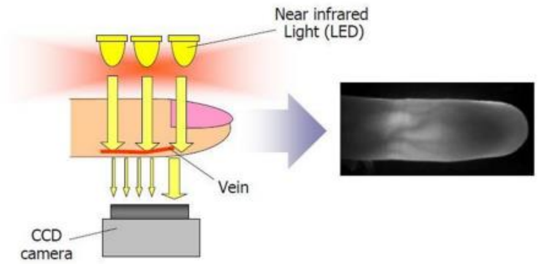


Fig.2. How a finger vein scanner works [16].

Fig.3. A finger vein scanner [17].

B. Pre-Processing

Pre-processing refers to the initial actions taken on images to reduce distortions or enhance features crucial for subsequent processing. In this model, finger vein images often contain significant noise and grain, necessitating pre-processing. This phase involves two steps: spatial domain and frequency domain processing. In the spatial domain, the image contrast is adjusted and grain size is reduced. Following this, the image is processed in the frequency domain where noise is removed using techniques such as Gaussian or Median filters.

C. Segmentation

Segmentation involves dividing an image into distinct regions that belong to the same class. In the proposed model, segmentation is used to identify edges based on contrast, color, and saturation. The finger vein features are tracked and assessed through a five-step process: confusion matrix, network estimation, softmax layer, feature layer, and label layer. Additionally, the brightness of the image will be increased.

D. Confusion Matrix

In classification tasks, a confusion matrix is utilized to visualize the results by presenting a table that shows the various outcomes of predictions and actual findings. This table displays both the predicted and actual values of a classifier, providing a clearer understanding of its performance.

E. Network Estimation

In network estimation, a histogram is generated to summarize either discrete or continuous data. A histogram graph illustrates the frequency of data points for a specific variable by showing how often each data point occurs. The data is divided into "bins" or "range groups," and the histogram counts the number of data points within each bin. This provides a visual representation of the data's frequency distribution.

F. SoftMax Layer

The SoftMax layer is an essential element of CNNs and deep learning models. It acts as the activation function in neural networks, especially when dealing with multi-class classification problems involving more than two class labels. Essentially, the SoftMax layer serves both as an activation function and a means of determining class membership.

H. Line Tracking Method

The Line Tracking Method is a technique employed to trace the lines in the finger vein, which is then used to extract features and analyze the vein's structure. This method plays a crucial role in accurately identifying and understanding vein patterns.

IV. RESULTS AND DISCUSSION

Figure 4 illustrates the operational block diagram of the proposed system. The process begins with scanning the user's finger vein using an Arduino microcontroller. After scanning, the images are processed in MATLAB. The extracted features are then compared to the registered finger vein data in the database. If the features match, the system sends a notification via text/SMS through the GSM module. For precise results, the dataset can be validated using a line tracking method for image segmentation. Additionally, the system is integrated with an IoT platform, allowing for remote monitoring and control. Real-time updates are sent to the IoT platform, which can be accessed from any location via a web browser or mobile application.

The IoT platform also enables monitoring of the system's performance and status. The proposed system utilizes a technique known as Region of Interest (ROI) within the input image to generate quality scores based on information entropy and image contrast measures. Information entropy reflects variability in grey values, while contrast indicates fluctuations in image brightness. The gradient measures the sharpness of the vein structure and texture. The line tracking method has shown promising results for finger vein authentication. This method, which starts with a randomly generated seed and uses predetermined probabilities, determines paths in both horizontal and vertical directions to trace the veins in the image, repeating the process a set number of times. Consistent results have been observed with line tracking for detecting finger veins.

GSM (Global System for Mobile communication) is a digital, publicly accessible cellular technology that facilitates high-quality voice and data transmission at low cost. In this model, GSM is used to send SMS notifications to the authenticated user's mobile phone. The Internet of Things (IoT) is a network of interconnected real-world devices that can share data through integrated sensors, software, and other technologies. In the proposed model, IoT allows remote access to login data. Additionally, the system employs a Deep Learning (DL) approach using Convolutional Neural Networks (CNNs) implemented in MATLAB for finger vein authentication.

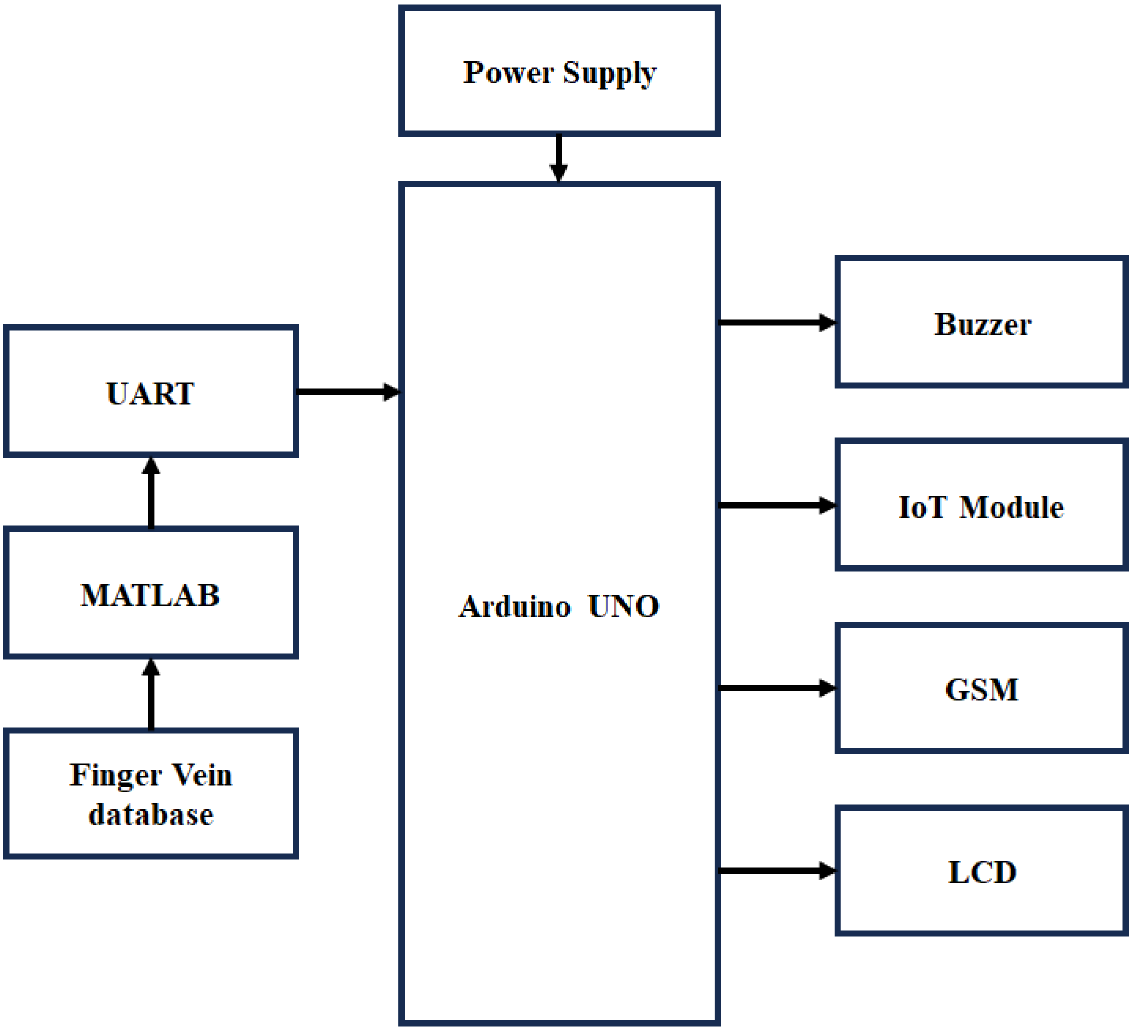


Fig.4. Block diagram of the Hardware System

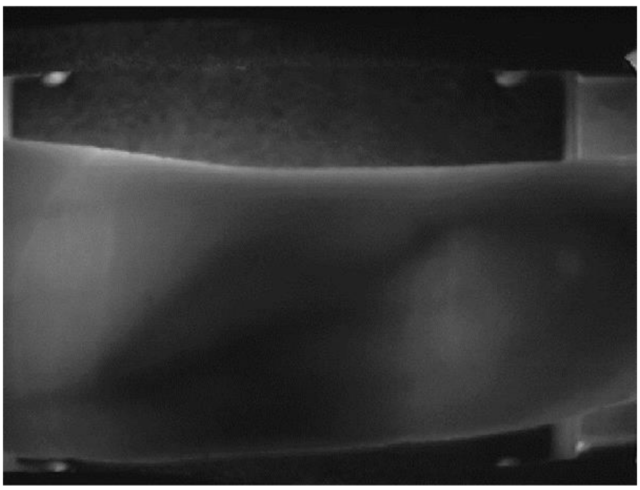


Fig.5. Grayscale image of the finger

Fig.6. Grayscale image after applying Gaussian filter

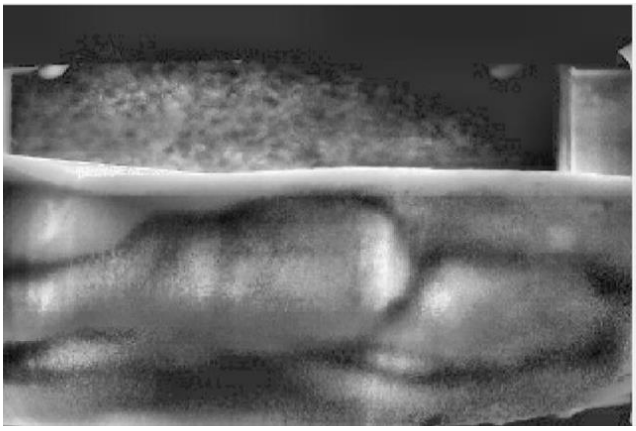
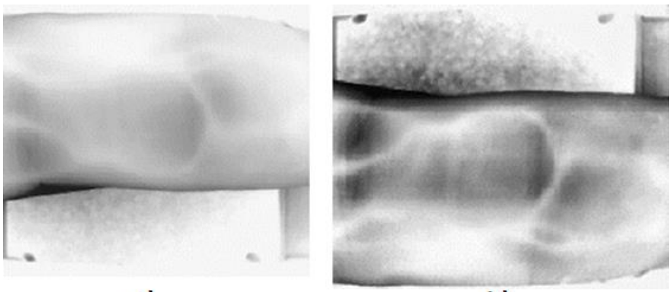


Fig.7. Amplified image of the vein structure

a) b)

Fig.8. Finding edges of vein pattern



a) b)

Fig.10(a) Diluted image, Fig. 10(b). Diluted image with improved contrast

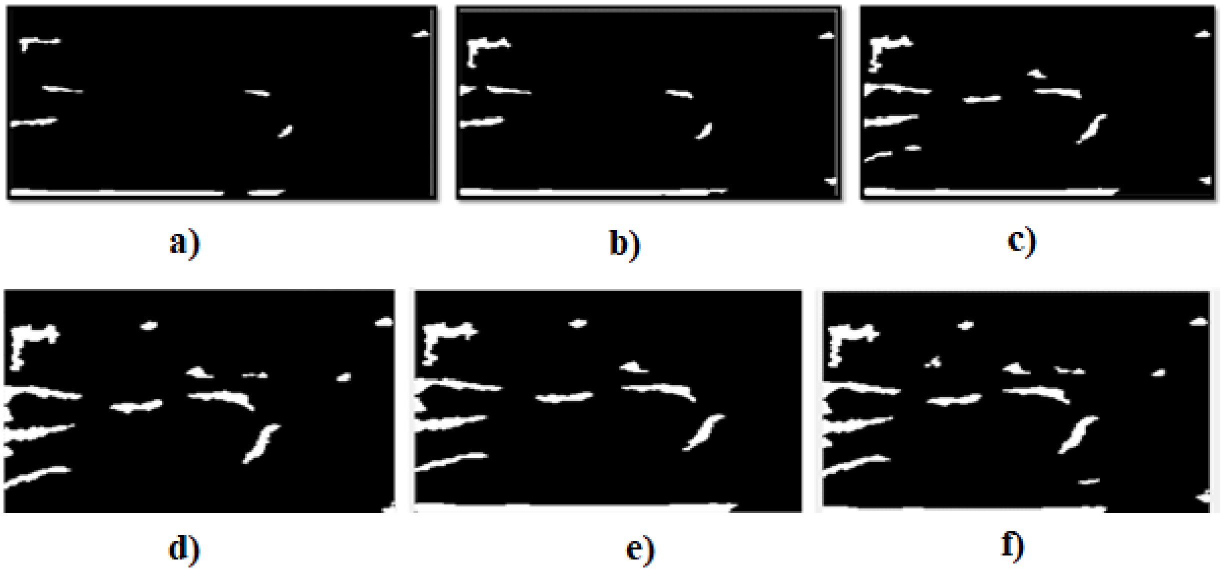


Fig.11(a) Line Tracking Segmented image, Fig. 11(b), (c), (d), (e) & (f). Improved Line Tracking

The suggested finger vein recognition system, which combines MATLAB, Arduino, GSM, and IoT technologies, achieved an accuracy rate of 96% when evaluated using a dataset of images of finger veins. It is thought that this high accuracy is exceptional for a biometric system. The greyscale images from Kaggle that make up the finger vein dataset are imported into MATLAB. The greyscale input image of the finger vein is shown in Figure 5. As seen in Figure 6, the greyscale image is filtered using a median filter during pre-processing. The spatial domain technique is then used to further process the image in order to improve contrast, as shown in Figure 7. Figure 8 displays the results of applying a Gaussian filter to the contrast-enhanced image in order to identify the edges of the vein structure.

Using the refined vein image as displayed in Figures 9(a) and 9(b), the Line Tracking method is applied in conjunction with a Convolutional Neural Network to identify the vein structure. For accurate vein structure detection, the image is segmented multiple times. Figures 11(a) through 11(f) show the improved contrast results. As seen in Figure 13, the vein edges that have been detected are further refined to produce the detailed structure required for precise line tracking. The combined processed images produce an overall vein pattern that is utilised for perimeter extraction, producing the output image that is diluted and shown in Figure 14. The vein's features and structure are fully revealed by the perimeter extraction. The model's effectiveness is evaluated using the final product, and and loss rates, with the success rate predictions shown in Figure 16, highlighting label 9 as having the highest success rate for the proposed system.

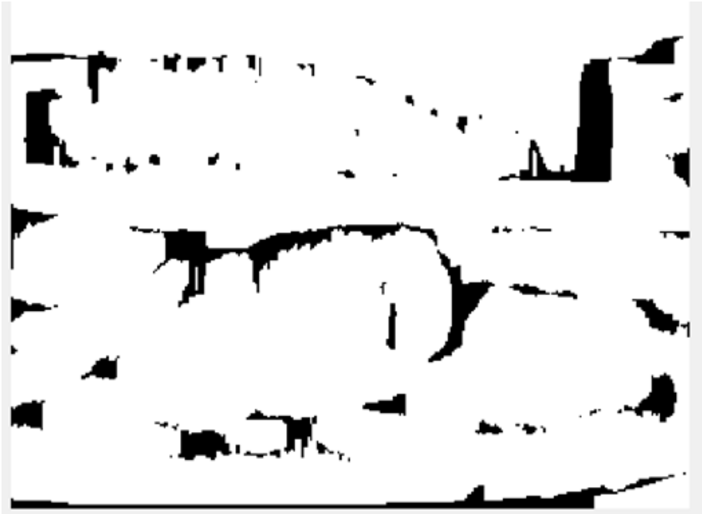


Fig.13. Diluted image of the combined vein structure

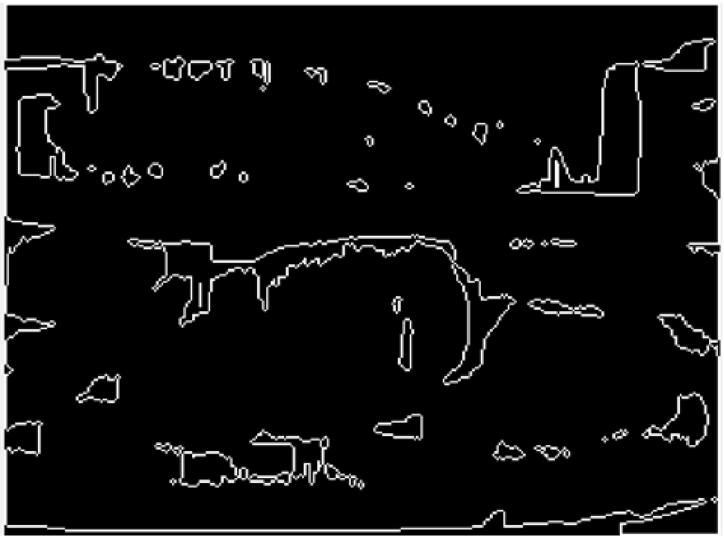


Fig.14. Perimeter extraction of the pattern

additionally to determine the model's accuracy through the confusion matrix. The uploaded image has received a matching score of 96% as indicated in figure 17, according to the confusion matrix displayed in the figure below. As a result, the model's accuracy has been determined. Using network estimation, a frequency estimation graph—also known as a histogram graph—is obtained. This graph, as illustrated in figure 18, is used to display a lot of data as well as the frequency of the data values. The suggested system includes an IoT platform to enable remote monitoring features as well. The IoT platform can be accessed from anywhere with a web browser or a mobile application, and as figure 19 illustrates, it can receive real-time updates from the system. In addition to adding or removing users from the database, the IoT platform can be used to monitor the system's performance and status.

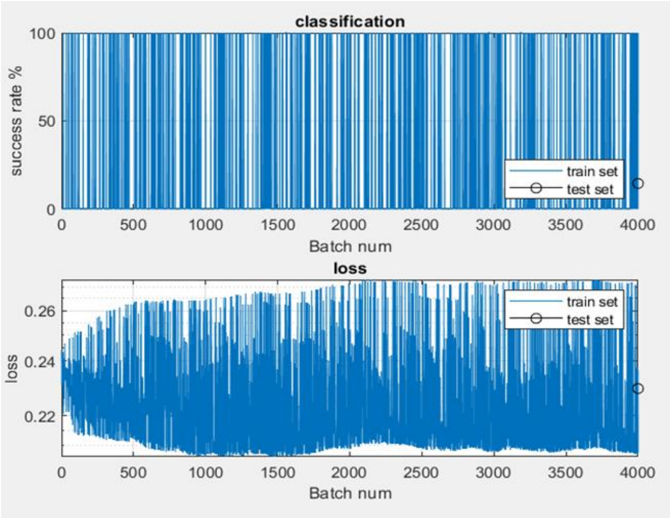


Fig.15. Loss and success rate graph

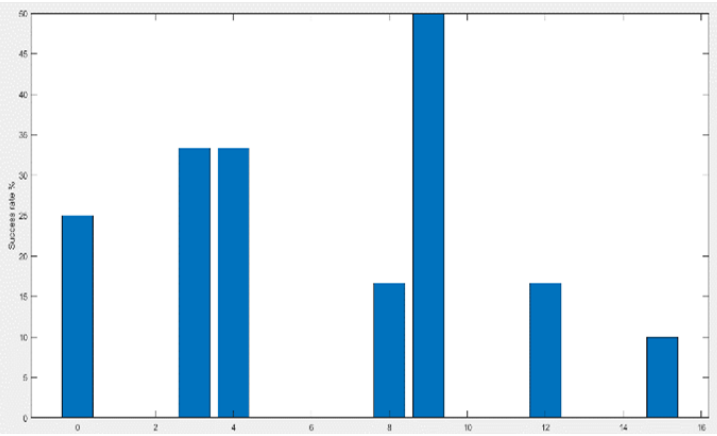


Fig.16. Success rate prediction

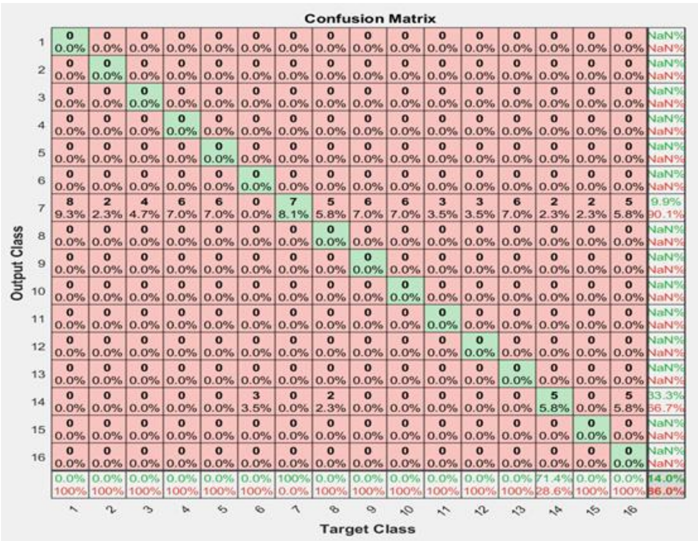


Fig.17. Output of confusion matrix

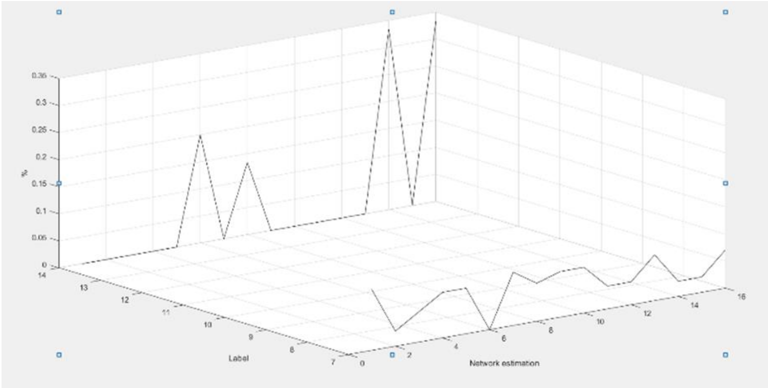


Fig.18. Network estimation graph

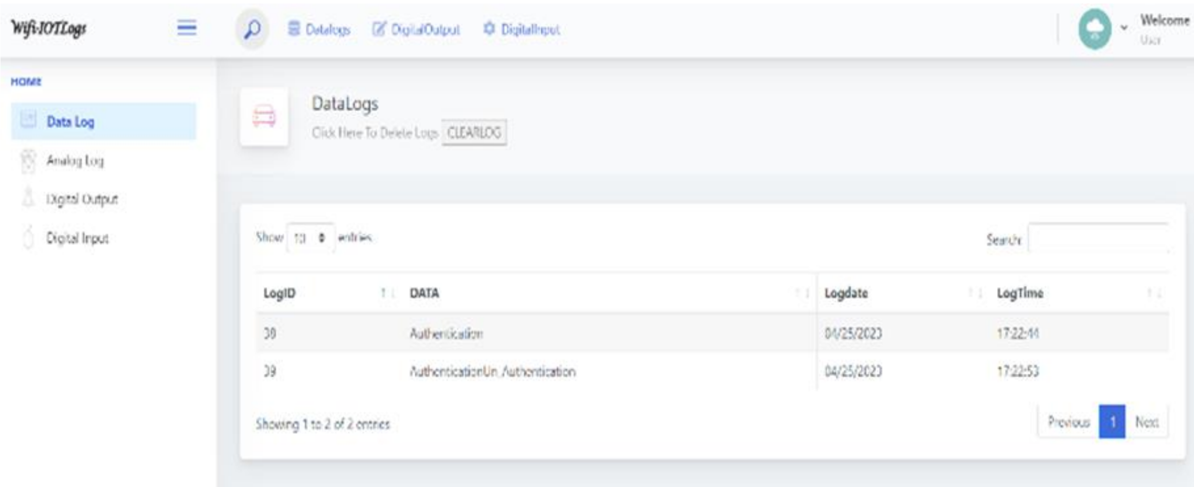


Fig.19. Entries recorded in the IoT data logs

As illustrated in figure 20, the processing time of the scanned finger vein image, feature extraction, feature comparison with the finger vein features of the registered user, and sending a confirmation message to the user's phone via the GSM module. Because the system can be remotely monitored through integration with an IoT platform, the administrators of the proposed system will have more convenience and control.

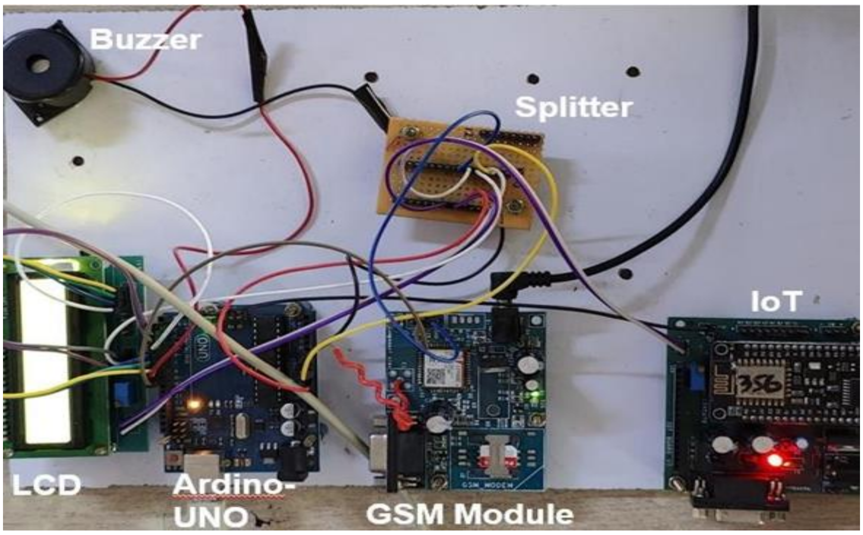


Fig.20. Prototype of the Proposed System

V. CONCLUSION

The suggested technique for finger vein recognition offers a trustworthy and safe method of biometric identification. Real-time applications such as financial transactions and access control are deemed suitable due to the high accuracy of the system. The proposed system reacts faster than current models when processing an image of a finger vein and transmitting an alarm message to the user's mobile device via the GSM module. System administrators can more easily handle the system effectively thanks to the IoT platform's real-time updates and remote access to the system's status. Remotely adding or removing users from the database is also made feasible by the system's integration with an IoT platform. Applications for the proposed system include financial transactions, access control, security, and any other area where dependable and secure biometric identification is needed. High-security applications requiring quick and precise identification can benefit from the system's accuracy and response time. Overall, the system under consideration provides a reliable, secure, and efficient means of biometric identification. Finger vein biometric systems have a bright future in terms of security applications. For real-time apps, it can be connected to a finger vein scanner. Overall, finger vein biometric systems have a bright future in terms of security applications. These systems are probably going to be very important in a lot of different industries and applications because there is a growing need for reliable and secure identification techniques.

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