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DEEP LEARNING BASED FINGER VEIN AUTHENTICATION

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***ABSTRACT**: Finger vein pattern has been an effective biometric for human identification in recent years as each and every individual have an unique pattern of veins in the finger concealed under the skin surface. Finger vein biometric is a new technology, it has received much attention in recent years by providing the high level of security in data transfer. Finger vein identification method based on the self-learned features is adopted in this article. The Convolutional Neural Network (CNN) algorithm relies on the weights and biases of the biometric features which can offer an accurate matching. The deep learning approach based on the CNN algorithm is used in this system, achieved very good results. we use layers of CNN which include convolution layers.. It performs better than traditional algorithm.*

***Index Terms* - biometrics, finger vein recognition, deep learning, convolutional neural network, GSM module, Zigbee transmitter, Zigbee receiver , Arduino , LED , Buzzer .**

II. Introduction

Biometric technology is playing an important role in modern society. In Traditional authentication systems, it identifies individuals by using passwords that may be unsafe because these passwords can be stolen or forgotten, however, this new authentication technology can be used to improve the identification methods, which includes face recognition, fingerprint recognition, iris recognition, voice recognition etc. In recent years, research on finger vein recognition has increased. Since veins are located underneath the skin, they are less susceptible to damage by external factors, thus the finger-vein authentication system gives high stability and security in research. The finger veins for different people are not the same and it differs for each and every human. Finger veins vary among different fingers. One general procedure for finger-vein authentication involves finger vein image acquisition, image pre-processing, feature extraction and image matching recognition for every human. Deep convolution neural network (ConvNet/CNN) that perform more quickly and accurately than traditional algorithm, because it consists of several layers. The Convolution Neural Network was effectively used in finger vein recognition.

II. Literature survey

In biometric authentication using palm dorsal vein patterns, it focuses on the palm-dorsal vein pattern of each person. Radius distance methods are used to find position of finger from hand contour. The robust reference point at the middle of the palm is mapped in the binary hand image. The reference vein image is compared with the query palm vein image [1]. A method based on Gravitational Search Algorithm(GSA) in human identification using finger vein patterns, was discussed in this paper, a new multi-biometric system has proposed for human authentication. The proposed method used patters of different finger veins and fused them using score level fusion strategy. I this strategy combining scores from multiple bios metric using triangular norms[2] . A new multi-biometric system has proposed for human authentication. The proposed method used patterns of three different finger veins and it fused using score level fusion strategy. Experimental results show that using a heuristic method will provide a more accurate identification accuracy. The performance of the heuristic score level fusion may improve using more advanced heuristic and metaheuristic optimization techniques [3].

III. PROPOSED SYSTEM

In this system, the vein pattern prototype is used as an input image. The obtained input image is passed to the decision-making device where the data set of images are available. The data set comprises of set certain vein patterns. **Deep learning** based algorithm is used to identify the input image. The algorithm used here is **Convolutional Neural Network (CNN) Algorithm.** The CNN algorithm compares the input image with the reference image to find whether the vein pattern are the same, based on the results the vein is recognized as a vein of an authorized or unauthorized person. The computed result is passed through the USB to TTL convertor and it is transmitted with the help of Zigbee transmitter and receiver to the Arduino. If the input image matches with the dataset image, then the authorization is indicated by the glowing of LED light, whereas if any unauthorized vein image is identified, the buzzer sound indicates it. In addition to this, the identification of an unauthorized person is informed through a GSM module via an alert message.

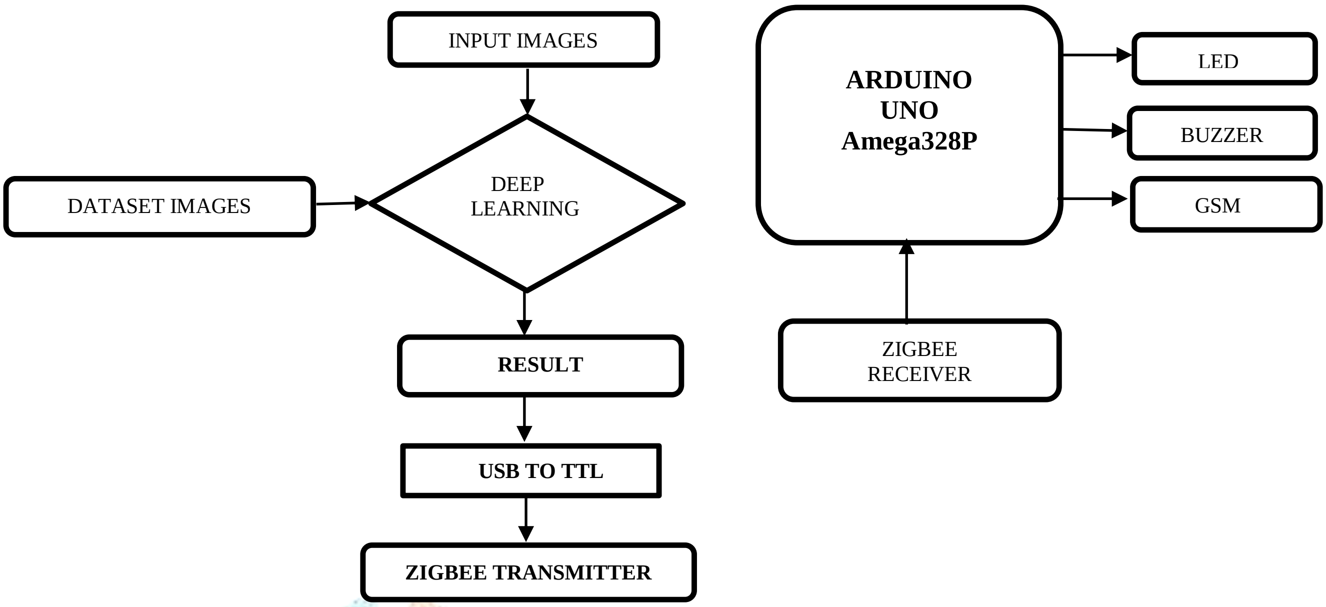

Fig.1 Block Diagram of Proposed System

IV. ALGORTHIM

In this project, the CNN (Convolution neural network) algorithm was used to implement the authentication of a person using a finger vein. The Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication where the convolutional kernels are defined by a width and height, the number of input channels and output channels. The Convolution filter slide over the input image to determine the depth of the image , considered to be the first layer. The first layer of the convolutional filter is called as a Kernel filter which has depth same as the input image. The Convolutional networks consist of local or global pooling layers. Pooling layers reduce the dimensions of the data by combining the outputs in the next layer. Local pooling combines small clusters. Global pooling acts upon all the neurons of the convolutional layer. In addition to this, pooling may compute a max or an average pooling. Max pooling extracts the maximum value from the image of a kernel used for denoising and for reduction in the dimension. Average pooling uses the average value from each of a cluster of neurons at the previous layer.

V. DEVICE REQIREMENTS

A. ARDUINO UNO

The 14 digital input/output pins can be used as input or output pins by using pin Mode (), digital Read () and digital Write () functions in Arduino programming. Each pin is operating at 5V and can get or receive a maximum of 40mA current, and has an internal pull-up resistor of 20-50 Ohms which are disconnected by default. Some pins have specific functions as listed below:

1. **Serial Pins 0 (Rx) and 1 (Tx)**: Rx and Tx pins are used for receiving and transmitting TTL serial data. They are connected with the corresponding ATmega328P using USB to TTL serial chip.

2. **External Interrupt Pins 2 and 3**: These pins are designed to trigger an interrupt on a low value, a rising edge or falling edge, or a change in value.

3. **PWM Pins 3, 5, 6, 9 and 11**: These pins provide an 8-bit PWM output by using analog Write () function.

4. **SPI Pins 10 (SS), 11 (MOSI), 12 (MISO) and 13 (SCK):** These pins are used for Serial Peripheral Interface communication.

5. **In-built LED Pin 13:** This pin is connected with a built-in LED, when pin 13 is HIGH – LED is on and when pin 13 is LOW.

B. ZIGBEE TRANSMITTER AND RECEIVER

It is used for two-way communication and It is a short range communication standard like bluetooth and wi-fi. Their Signal Coverage ranges from 10m to 100m.

- RS-232 direct interface
- TTL support
- Separate LED for RX,TX and power
- 4 bit channel selection
- Programmable output power
- Variable payload length from 1 to 32bytes
- Automatic packet processing
- 6 data pipes for 1:6 star networks

C . USB TO TTL

- Plug-and-Play (hot-pluggable)
- USB 1.1 and 2.0 compatible
- Port powered - no external power needed
- Supports 300 baud to 115,200 baud rates
- 3 feet (1m) cable for convenience
- Transmit/Receive LED indicators
- Easy to install included drivers
- Built-in surge and static protection

D . GSM MODULE

- Establish a communication between the two devices and its like a mobile phone. Which is used to send and receive a data through network
- Dual-Band 900/ 1800 MHz
- GPRS multi-slot class 10/8
- GPRS mobile station class B
- Compliant to GSM phase 2/2+
- Class 4 (2 W @900 MHz)
- Class 1 (1 W @ 1800MHz)
- Dimensions: 24*24*3 mm
- Supply voltage range: 3.1- 4.8V
- Low power consumption: 1.5mA(sleep mode)

E. USB TO TTL

- Plug-and-Play (hot-pluggable)
- USB 1.1 and 2.0 compatible
- Port powered - no external power needed
- Supports 300 baud to 115,200 baud rates
- 3 feet (1m) cable for convenience

VI. METHODOLOGY

The method of using convolution neural network will provide a high accuracy. Authenticated person find out with the help of the LED glows, and unauthenticated person will be find out with the help of buzzer and the GSM alerting system.

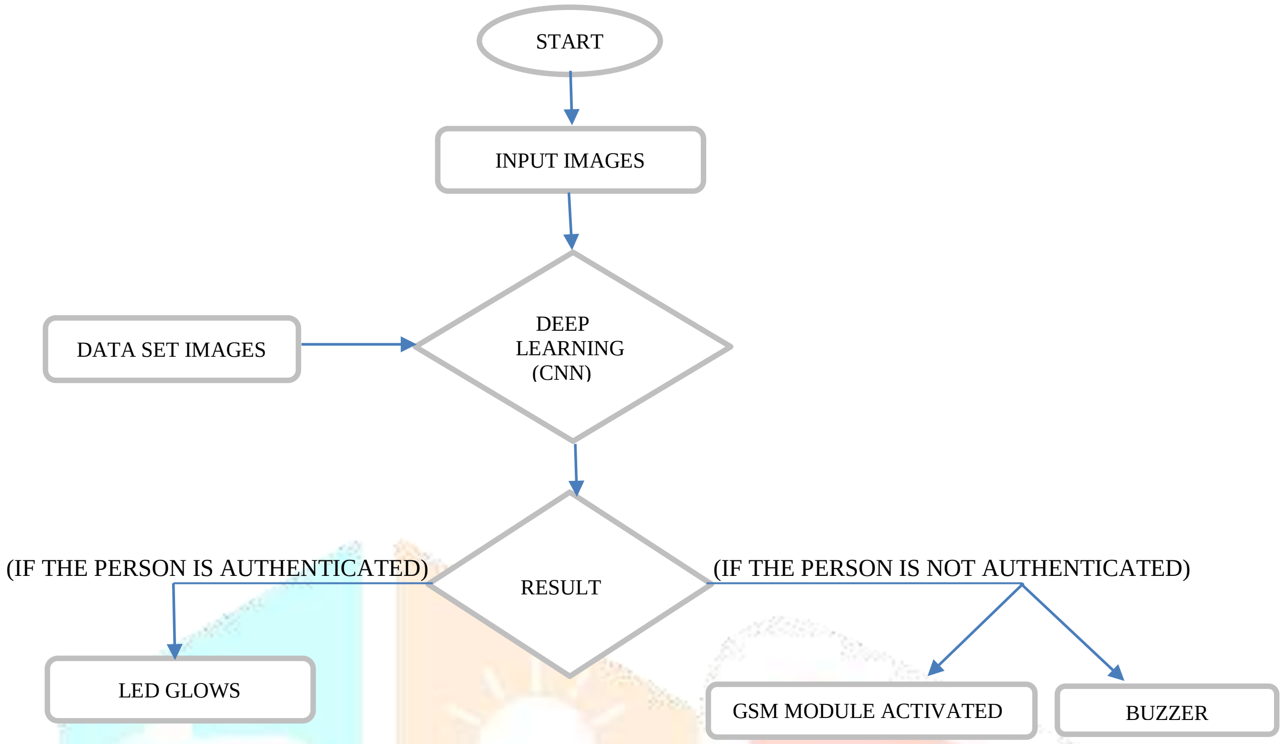

Fig.2 Flow Diagram

VII. OUTCOME

In this designed system, the expected outcome is to recognize the authentic person based on their figure vein .The vein pattern to be identified as an authorized is stored in the dataset to which the scanned finger vein is compared. If the scanned finger vein image matches with the image available in the dataset the LED glows indicating that the person is authorized person

On the other hand, if the given input vein pattern is unauthorized which does not match with the stored prototype image, then the

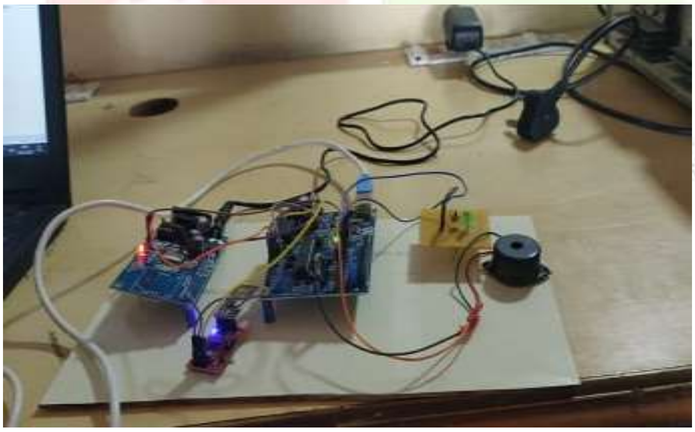

Fig.3 Hardware Implementation of the system

Fig.4 Received alert message in registered mobile

system raises a buzzer alert sound and an alert message also set by GSM module displaying "UNAUTHORIZED PERSON" to the corresponding user. This system establishes a high security and can be enabled in various fields for safety purposes.

VIII. CONCLUSION

This paper utilized a deep learning algorithm for finger vein authentication. It was evident that the deep learning based algorithm is data-driven. The data quality is a key element to achieve successful experimental results with high accuracy. Final results of the identification model and the verification model provides high-quality output when compared to all other algorithms. When compared to other model, deep learning methods are fast to implement and more straightforward to build up without diving into too much complicated feature handling.

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