



Deep Learning for Enhancing IoT Security using Multimodal Biometric Authentication

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Abstract

Today, the Internet of Things (IoT) connects billions of electronic devices into multilateral computer networks to provide advanced and intelligent services. These networks enable numerous devices to communicate with each other for exchanging data and information with minimal human-to-machine interaction. This phenomenon increases the security issues and triggers the risks at a higher level in IoT systems compared with other computing systems. In order to maintain the security necessity when attacking the physical surface of the IoT system and its devices is a crucial and challenging task. On the other hand, implementing security mechanisms such as user authentication and access control for the IoT enabled ecosystems is essential to ensure the desired security of the IoT system devices. Usually, the security key may be stolen, forgotten, forged or duplicated by someone for misuse. The keys can be easily regenerated by intruders or men in the middle in traditional security environments. Today, biometric security is also becoming a more advanced and sophisticated alternative with technological advancements and is used widely in authentication systems. Technologically, only one biometric characteristic can be used in unimodal biometrics, which cannot be applied to ensure the high end security of IoT systems. In this research paper, we used biometric authentication to ensure the security of edge devices in the IoT environmental ecosystems. We also used the face images and fingerprint images as multimodal biometrics systems for authenticating users to secure IoT devices in an IoT environment. In the experimentation phase, we used a Pi-Camera module and a fingerprint sensor to capture biometric images. Then we used CNN algorithms for feature extraction and model development. As an activation function, the RELU function was used in model development, such as softmax for image classification, and Max-pooling for image dimensional reduction. This aided the model in speeding up the training process of the model. Finally, the experimental results demonstrate that the accuracy of the face image is 92% and the fingerprint image is 89%, which is a highly promising result to ensure the achievement of the desired objective of the research.

Keywords: Authentication, CNN, Deep Learning, Internet of Things, Multimodal Biometrics, Fingerprint

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I. Introduction

Technology is advancing at a fast rate. Technologies like IoTs are trying to integrate millions and billions of electronic devices and networks to facilitate typically enhanced, advanced and intelligent user services. These systems usually help in minimising the human-machine interactions significantly. Usually, IoT architectures are complex and contain integrative component arrangements. Thus, ensuring the security needs while attacking the physical surface of the IoT system devices becomes a challenging task. This makes the security issue a higher risk in IoT environments than in other computing system environments. In such situations, the traditionally made solutions may be ineffective in handling the security issues. The desired solutions must be holistic considerations to meet the changing needs of the security systems in the environments. However, IoT devices are usually set in unattended environmental surroundings. Consequently, an intruder may additionally physically gain access to those gadgets. Usually, the IoT gadgets are typically connected over public or private Wi-Fi networks, in which an outsider might also have access to private facts from a communication channel with the aid of eavesdropping. Thus, IoT devices cannot support such complex security structures, given their limited computation and power resources [1].

Biometric authentication is a security process that relies on the unique biological characteristics of individuals to verify who they are [2]. Biometric authentication and recognition have become the new branch of exploration in the adoption of newer techniques in terms of security, higher accuracy, and high speed [3]. Unimodal biometric authentication structures got more interest from sensible programs [4] consisting of the Internet of Things (IoT), Automated Teller Machines (ATM), and cellular packages. Thus, one feature is neither completely green nor completely adequate to expect the proper subject, particularly for the accumulated photos in diverse conditions such as rotation, illumination, and occlusion conditions. Therefore, most of the researchers focus more attention on multimodal biometric recognition to improve identity performance and provide better protection. As stated in a study, most of the latest human-popularity works [5] utilized function-degree fusion to overcome the challenges of confined assets and to boost device security and device overall performance.

Artificial intelligence is the way of creating an intelligent system that thinks and acts like a human being. It is a way of using computer machines as a power of humans [6]. A system to be an intelligent system should have six disciplines of AI (NLP, computer vision, machine learning, knowledge representation, robotics, and logical reasoning). In the current era, AI is used in different areas like healthy cars, agriculture, education, and industry. In industry IoT and AI systems are commonly used to improve services and produce more products for customers.

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In the IoT ecosystem, complex structures and heterogeneous components are interconnected. In the current era of globalization, most of the systems in industrial companies are migrating to IoT technology. Edge devices in IoT can exchange data with less human interaction. Ensuring security for the IoT ecosystem is necessarily needed to avoid unauthorized access to IoT systems.

Researchers explored different security mechanisms to ensure security in IoT systems. In the last decades, traditional security mechanisms were applied to secure edge devices in an IoT ecosystem. Traditional security mechanism has a drawback because the key used for the security method may get stolen, forgotten, or forged key may be created by intruders or a man in the middle, but in biometric security mechanism the character or the key can't be stolen by theft, forgotten, and fake character cannot be generated by the intruders. The biometric character may be physiological (face, fingerprint, iris, hand geometry, hand gesture) or behavioral (walking, typing, touchpad). Most researchers applied either of these biometrics to improve security issues in IoT.

Researchers were applying biometrics in two ways. The first one is a unimodal biometrics system in which only one biometric characteristic can be applied, which cannot be applied to ensure security in IoT systems. The second one is multimodal biometrics systems that can be applied to more than one biometrics characteristic.

II. Literature Review

Research by Mohammed Ali Al-Garadi, Amr Mohamed, and Abdulla Al-Ali [7] proposed a review of the machine learning and deep learning methods and algorithms applied to the Internet of Things IoT security which is titled "Survey of security issues Machine and deep learning knowledge of techniques for Internet of Things". In this paper, the researchers tried to address all the methods and algorithms of machine learning and deep learning and how they are applied for ensuring the security of IoT.

Another study by Jasmeen Sharma, and Dharam Veer Sharma [8] proposed a multimodal biometrics authentication using face and fingerprint. They tried to address the drawback of unimodal biometrics and how the multimodal biometric system was very advanced than the unimodal biometrics. The researchers used principal component analysis (PCA), Bacterial Foraging Optimization algorithms (BFOA), Minute Extraction, and multilayer (MLNN).

In another paper, Sudip Vhaduri and Christian Poellabauer [9] proposed "Multimodal biometric-based implicit authentication of wearable devices users". They applied authentication mechanisms using combinations of three types of coarse-grain minute-level biometrics: behavioral (step counts), physiological (heart rate), and hybrid (calorie burn and metabolic equivalent of task). Their findings show that hybrid

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biometrics perform better than other biometrics and behavioral biometrics do not have a significant impact, even during non-sedentary periods.

Very important research by Mohamed Hammad, Yashu Liu, And Kuanquan Wang [10] proposed a “Multimodal biometric authentication system using CNN based on a different level fusion of ECG and fingerprint”. These authors developed two distinct authentication systems having different level 2 fusion algorithms, i.e., 1) feature level fusion and 2) decision level fusion. Further, the feature level extraction for users’ numerous modalities was done using a CNN.

III. Research Design and Methodology

A comprehensive overview of multimodal biometric authentication for enhancing IoT security systems with face recognition and fingerprint biometric data was discussed. For the experimental investigation, images were collected through the pi-camera and fingerprint sensor.

A. Proposed Model Architecture

The proposed model contains two phases, the enrollment phase, and the authentication phase. Both phases have the same image-processing tasks. First digital face image and fingerprint images are acquired by using the Pi camera module and fingerprint sensor devices respectively. Then the image preprocessing technique is applied. The segmentation process was applied to the image which is then ready for the feature extraction process. The following Fig.1 shows the proposed model architecture.

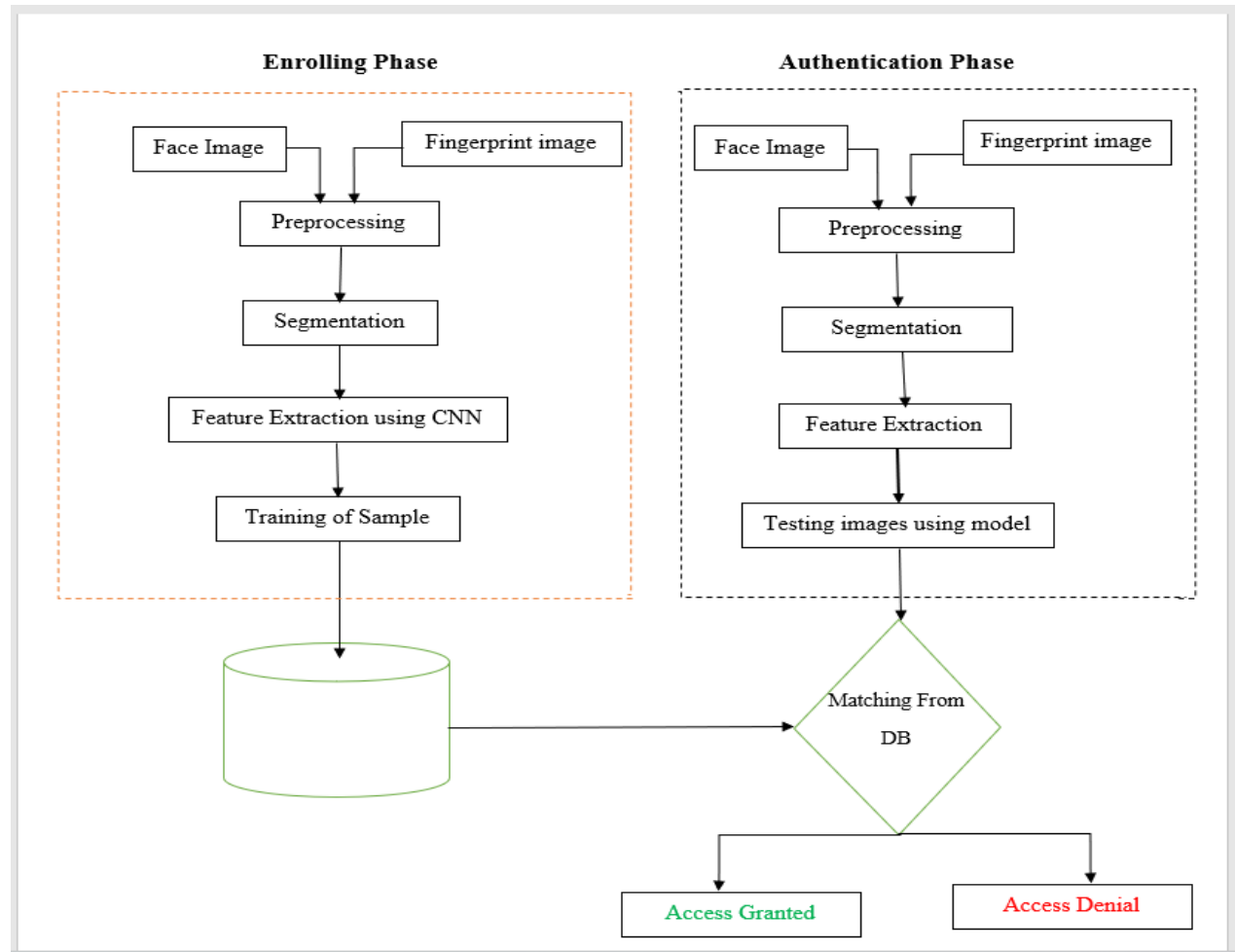


Fig. 1: Proposed Model Architecture

IV. Experimental Setup, Result and Discussion

A. The Tool Used for the Study

In this research study software and hardware tool was used for conducting an experimental activity. Software tools like Anaconda navigation and Jupiter notebook for the code editor, open-cv library for capturing images and then image processing tasks, Tensor flow, and CNN algorithms for creating the proposed model.

Different hardware tools are also used for experiments. Raspberry Pi is for implementing and controlling the research result, a Pi camera for capturing the user's facial image, fingerprint sensor devices for capturing fingerprint images, and jumper cables for assembling edge devices with a raspberry pi controller. The following Fig.2 shows a highlight of the hardware tools used.

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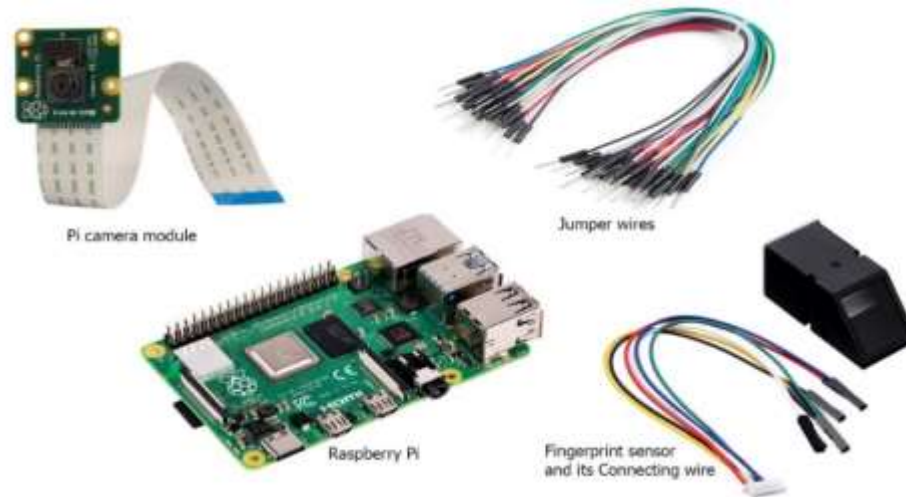


Fig. 2: Hardware tool used for the experiment

B. Experimental Setup

In the previous section tools used for experimenting were discussed in detail. In this section, experimental activities were discussed in the following subsections.

1) Assembling hardware tools: As presented in Fig. 3, Jumper wires were used to connect edge devices with Raspberry Pi, the fingerprint sensor has four/six-pin wire (ground, voltage, transmitter, and receiver) was connected to the corresponding pin of Raspberry Pi, camera module were connected to the camera port of raspberry Pi, HDMI cable to connect Raspberry Pi to displaying desktop screen and the USB cable connects raspberry Pi with direct current to provide power.

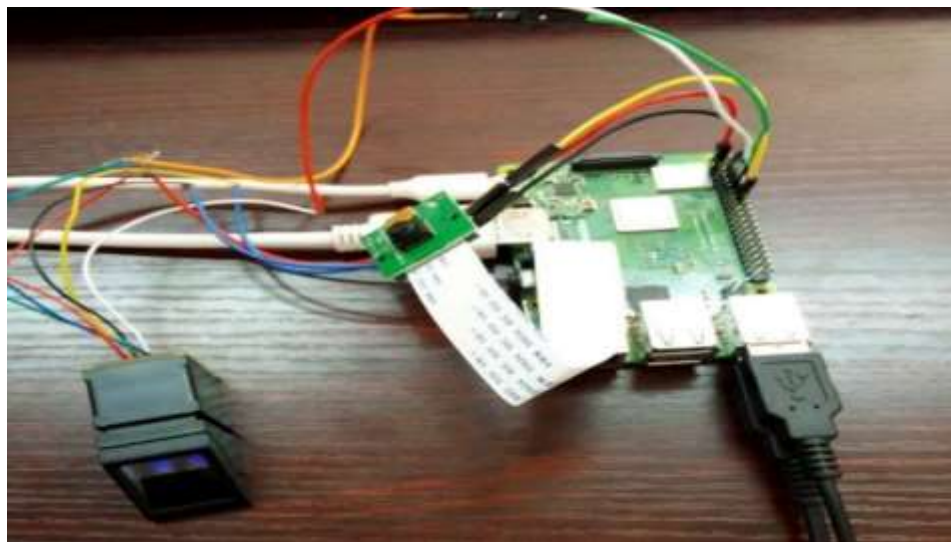


Fig. 3: Assembled hardware tools

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C. Enrollment Phase

The main aims of the study were addressed in this enrollment phase. In this phase, how users' image was collected as a dataset of the study, image processing steps, and CNN layer were discussed in detail: -

1) *Datasets (image acquiring)*: Datasets used in this research study were the image of the user's facial image and fingerprint image as presented in Fig. 4 and 5. Those images are captured by the Pi camera module and fingerprint sensor devices which means all the data sets used for the experiment were primary data. To get high accuracy in the proposed model prediction during the enrollment phase 50 users' face image with different (20) angle position was captured by the Pi camera module and two fingerprint images were captured by fingerprint sensor devices. The sample size of data is $50 \times 20 = 1000$ face images and $2 \times 50 = 100$ fingerprint images. The following Fig. 4 shows the collected data set of users.



Fig. 4. Sample dataset user's face image



Fig. 5. Sample dataset of user's fingerprint image

2) *Pre-processing*: first activity of image processing is capturing the image as a dataset. The face region was detected and cropped then resized to 200×200 on the face image. Image enhancement and minutiae extraction was applied as a preprocessing task on the fingerprint image.

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3) *Segmentation*: segmentation task on the face image is responsible for converting a colored image (RGB) into a grayscale image and then transforming the image into a numerical data array by using the NumPy library. The segmentation process in the fingerprint image was responsible to remove unnecessary or unwanted data from the image. And then ridge flow estimation and region of interest of minutiae were considered under this task.

4) *Feature Extraction*: The feature extraction process was done by using a supervised deep learning method called CNN. The collected dataset of the user's image was split into 70% of the dataset as a training dataset and 30% used as a test dataset. To train the model CNN passes the following four layers: -

a) *Convolution layer*: In this layer, the preprocessed image with 200 X 200-pixel resolution was multiplied by 30 X 30 filter images magically generated by CNN. In this case, 1st filtered image output becomes 171 X 171.

b) *Normalization/Activation layer*: In this layer, non-linear functions called RELU were used to train the dataset and speed up the training process and reduce computational time.

c) *Pooling layer*: The main aim of this layer in CNN is to reduce the dimension of an image which highly probably reduces computational time and avoids overfitting of a proposed model. The max-pooling method was applied to a normalized image. To reduce the dimension of an image, 20 X 20 Max-pooling was applied. So, the first-round max-pooling result was 152 X 152 pixels.

d) *Fully connected layer*: The output of the pooling layer which is a 3D image was converted to a 1D image by applying the flatten method on the image. The output of this layer was used as the input layer for a neural network. The following Fig. 6 shows the summary of feature extraction.

D) Authentication Phase

The main responsibility of this phase is to check whether the captured face image and fingerprint was matching it from the created mode during the enrollment phase and then make a decision based on the output result. In this authentication process, the first three steps of the image processing task are similar to that of enrolling phase, but the difference is that there is no need to train the captured image rather it tests and then matches it from the trained model. Another difference is that in the case of enrolling phase RELU functions were used as activation functions for training the model, but in the authentication phase Regression function as optimizer and SOFT-MAX were used as the activation function for classifying images to corresponding users.

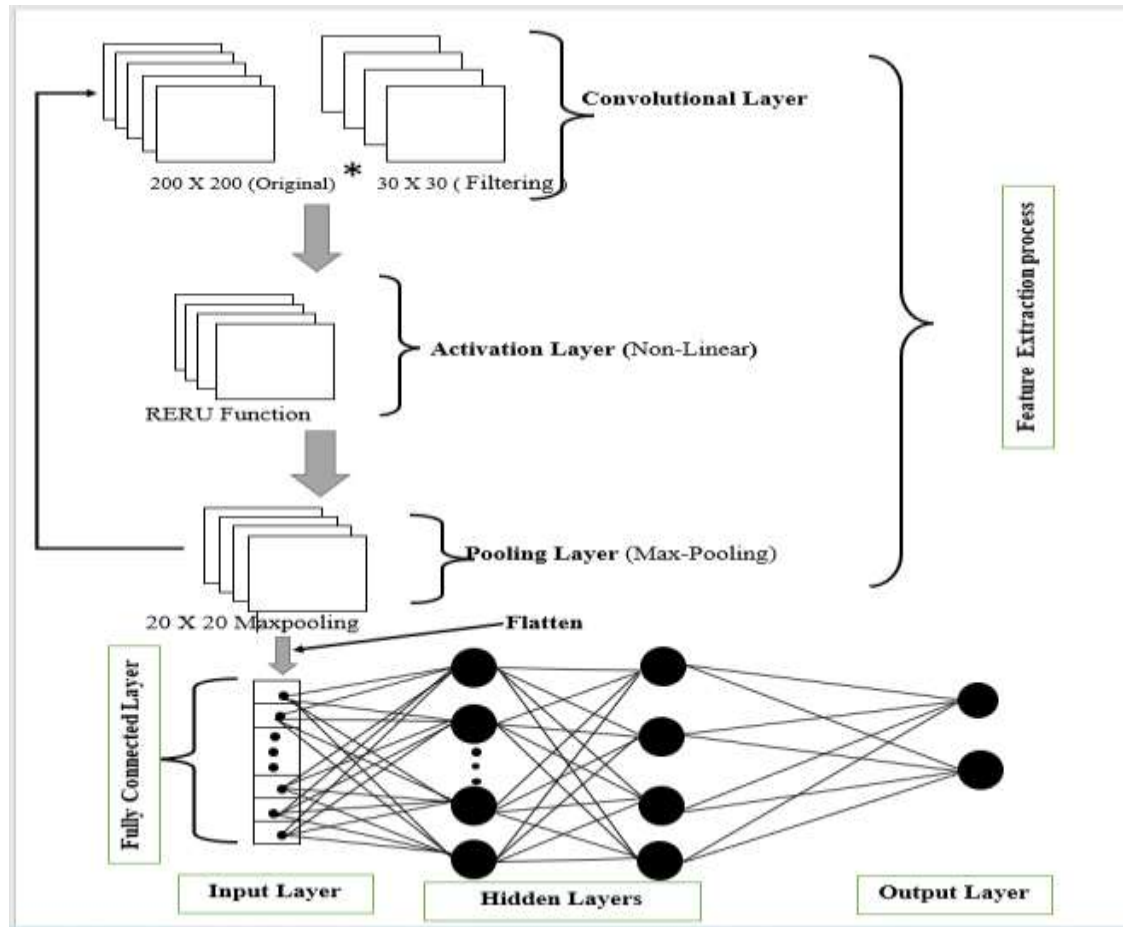


Fig. 6. Feature extraction using CNN

V. Conclusion

IoT system is a highly growing technology that improves the quality of our daily life. So, to ensure the physical security of IoT systems and their operating technology, multimodal biometric authentication systems were designed. In this research work, the unimodal and multimodal biometric system is discussed in detail after the multimodal system is implemented by using CNN algorithms on both face and fingerprint images. The Relu function was used as an activation function and a max-pooling method for dimension reduction on both images. The softMax function was applied for classification. Three parameters of performance analysis were considered (Accuracy, FAR, and FRR). The result shows that accuracy is 92% and 89% for the face and fingerprint respectively, FAR is 1.35%, and FRR is 1.5%.

Future works: From the results of the experiment, it shows that the accuracy of the fingerprint image is 89%, which still has scope to enhance. So, this research work may be extended for improving the existing accuracy of results or by adding another biometric system.

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References

1. M. Abomhara, "Cyber security and the Internet of things vulnerabilities, threats, intruder and attacks," *Journal of Cyber security and mobility*, vol. 4, no. 1, pp. 65-88, 2015.
2. "TeachTarget," [Online]. Available: <https://www.techtargt.com/searchsecurity/definition/biometric-authentication>, 2022.
3. S. Prabu, M. Lakshmanan & V. Noor Mohammed "A multimodal authentication for biometric recognition system using intelligent hybrid fusion techniques," *Journal of the medical system (Springer)*, vol.43, no. 249, p. 2, 2019.
4. A. H. S. C. Ibrahim Omara, "A Hybrid Model Combining Learning Distance Metric and DAG Support Vector Machine for Multimodal Biometric Recognition," *IEEE Access*, vol. iii, no. 43, p. 3, 2020.
5. M. T. M. B. a. N. C. M. Regoudi, "Multimodal biometric system for ECG, ear and iris recognition based on local descriptors," *Multimedia Tools Appl*, vol. 78, no. 16, 2019.
6. S. J. R. a. p. Norvig, "Artifitial Intelligent in moderen Approarch," second edition, United stat of america, 2003.
7. Y. B. Y. Lecun, "Deep Learning nature," vol. 521, p. 436, 2015.
8. A. M. A. A.-A. Mohammed Ali Al-Garadi, "Servey of Machine and Deep Learning methods for IoT security," *IEEE Communications Surveys & Tutorials*, 2020.
9. D. V. S. Jasmeen Sharma, "Multimodal biometric authentication using face and fingerprint," *IOSR Journal of Engineering*, vol. 08, no. 4, 2018.
10. S. V. a. C. Poellabauer, "Multimodal Biometric-based implicit authentication of wearable devices for the users," *IEEE Transactions on Information Forensics and Security*, 2019.