JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Enabling contactless finger print matching through Deep learning

1. **Atharva Hendre , Computer dept., AISSMS IOIT , Pune**
2. **Vedant Bharvirkar , Computer dept., AISSMS IOIT , Pune**
3. **Shubham Tarate , Computer dept., AISSMS IOIT , Pune**
4. **Prof. P.S. Sadaphule , Computer dept., AISSMS IOIT , Pune**

***Abstract* — The presence of fingerprint sensors in a massive proportion of electronic devices such as mobile apps, smartphones, and laptops is, in fact, mainly likely to have contributed to the extraordinary potentials of these kinds of sensors for authentication purposes. Examples of such equipment include the smartphone as well as the E - readers. The application of biometric systems has become almost ubiquitous across a broad range of consumer electronics products that are part of the evolving technological environment. In current history, the idea of using biometric verification as a means of establishing one's identity has emerged as an important distinctive characteristics of privacy and secrecy. Personal identification is crucial due to the fact that numerous other security precautions may be easily circumvented if there is sufficient information and understanding about the individual involved. As a direct result of this, consumer electronics now frequently use fingerprints as a kind of biometric verification, which results in increased accuracy. Furthermore, since the invention of these kinds of accessibility control system, there has been a growing worry over the hygiene of certain instrumentation when it is employed in public places or other gates that are often used. In addition to lessen the risk and make it possible for fingerprint recognition to advance, there is an urgent need for an innovative and functional feature that may get biometric verification without requiring physical touch. The approach utilizes, Image Normalization, Convolutional Neural Networks and Decision Making for the purpose of achieving effective authentication of contactless fingerprints. The methodology is also examined for its effectiveness in terms of performance by means of exhaustive testing, which has produced conclusions that are quite encouraging.**

Keywords: *Image Normalization, Convolutional Neural Networks , Decision Making*

I INTRODUCTION

Substantial touch-based biometric authentication technologies are now being utilized not simply by forensic and judicial operations institutions throughout the nation, but also by the smartphone world and for operations that cover the entire nation. This is because such technologies have become available. Touch-based biometric acquisition does have its drawbacks, nevertheless, including such low resolution input variables decided to bring on by dust and debris or humidity on the transceiver surface, static fingerprints left behind because of previous customers, or interruptions managed to bring caused by the finger's energy absorbing deformation as a consequence of compaction adhered to the transceiver surface. These problems can be avoided by keeping the sensor surface clean and avoiding stains and dirt and condensation altogether. Touch-based biometric authentication may potentially have a lower level of customer acceptability owing to a difficult technique for getting the fingerprint data as well as sanitation concerns, that would also limit its ability to be widely used.

A fingerprint is characterized by a pattern of peaks and valleys, which are more colloquially known as grooves. These components begin to take shape wholly inside the uterus of the female and continue to do so for the rest of the individual's existence. Imprint characteristics on the top of a fingertips may be used to identify an individual. The fact that a fingerprint is unique and that it can't changed are two of the most important characteristics of a fingerprint. Injuries and wounds may briefly weaken the consistency of fingerprints; but, once they have fully healed, the fingerprint patterns will revert to baseline. Burning and scrapes can also make fingerprints more difficult to read. The fingerprint design is composed of features, and each fingertip has an unique composition of these contours, therefore no two fingerprints are ever the same.

The process of recognizing an individual is connected to recognizing someone as a person, and the contemporary society places a premium on uniqueness. The identity of the subject already constitutes a worry; for example, it is necessary to determine whether or not this individual is permitted to be using your gadget. Concerns of this like are voiced, on an almost daily basis, by thousands of organizations working in industries as diverse as transportation, education, the media industry, and commerce. Because of the rapid development of communication infrastructure, people are becoming considerably more electronically committed to advancements in technology; thus, accurate automated person identification is required. Because of this, fingerprint recognition is possible to take place, which is both the most common option and a biometric method that is often used.

Ridge completion and ridge splitting, together with the depths that occur between adjacent peaks, are indeed the two essential ridge characteristics or complexities of the fingerprint. Depressions that appear inside sharp peaks are also an important component of the fingerprint. Ridge completion refers to the point that occurs when the ridge on a fingerprint comes to an end, whereas ridge diversification refers to the point that occurs when a ridge splits off into many minor peaks in response to a certain path. Fingerprints, which consist of ridge as well as valley shapes upon that fingertip of a human hand, are among several of the most important biometric traits because of their well-known uniqueness and tenacious attributes. Authentication of fingerprints via a touchless, hands-free system has been the topic of intensive research for a number of years.

Y. Chen [1] proposed a visible light positioning system that consolidated fingerprinting as well as the extreme learning machine algorithm for real-time placement. This framework was capable of reducing placement error and provide real-time placement after already separating the vast indoor location atmosphere in and out of normal visible light positional awareness kernels. During the trial with the simulator, the three-dimensional placement error is on averaged, and the positioning duration on average is sufficient. In the investigation performed in the actual world, both the mean placement time and the three-dimensional placement error were significantly reduced. The findings of the simulations and the experimentation indicate that the recommended visible light proposed system is capable of providing real-time three-dimensional tracking with a significantly lower mean absolute error than other systems. This demonstrates that the technology is suitable for the location of indoor robots, surveillance drones, and other autonomous drones, as well as other interior scenarios that need real-time placement.

K. Sutanto [2] created RNA secondary architecture fingerprinting relying on RNA as Graphs and popular small RNA fundamental organization characteristics. These fingerprints were used to classify nucleotides into several non-coding RNA categories by making use of machine learning features. The fundamental idea behind the configuration was to incorporate potential, albeit less desirable, protein structures conformational changes into characteristics that otherwise would have been overlooked if only a single estimated structure was employed to assemble the others. These characteristics would indeed be overlooked if only a single predicted structure was employed to create them. The fingerprints of RNA as graphs are obtained by the process of comparing as well as rating sequences across graph protein structures reconstructions. The fingerprints that are derived from common patterns are created by first comparing every chosen motif to the sequences, and then calculating the free electricity estimates of the various matches.

The research conducted by C.-W. Hung [3] employs a wide range of different techniques for artificial neural networks. In combination to convolutional neural networks, autoencoders, and variational autoencoders, the implementation of data augmentation shortens the dispersion separation here between input and output variables. This helps to limit the amount of model overfitting that occurs. The optical fingerprint identification system required those comparison procedures in order to function properly. All of the models have at long last been placed into the microcontroller unit. Consequently, during the training phase, several Bayesian optimisation strategies were used in order to achieve search optimization. After looking over the results page, the version that provided the most accurate results while using the least amount of RAM was selected for future investigation.

Section 2 of this research article presents an analysis of the relevant literature; Section 3 explains the research approach; Section 4 discusses the experimental assessments; and Section 5 closes with suggestions for further study in the future.

II RELATED WORKS

D.-H. Jeon came up with an innovative design for a tiny Led screen that does not need the inclusion of any other sensors in order to recognize fingerprints. [4] The researchers demonstrated that when regular LEDs were used, active-matrix pixel circuitry may potentially function as photodiodes. The findings of this research are the only ones in the universe to illustrate that fingerprint recognition can indeed be accomplished on a micro-LED screen that does not necessitate any supplemental illumination or sensor innovation. These findings are also the first anywhere in the globe to exemplify that fingerprint recognition can indeed be accomplished in real time. When the tiny Led screen contains multiple contacts, it opens up the possibility of being able to recognise a large number of fingers. This significantly boosts the level of biometric authentication that smart phones possess.

J. Zhang [5] presents a brand-new Sliding Window Variance Trajectory-based Posterior Probability Density Method for detecting to handle the problem of detecting the temporary thread signal's turn-on scheduling. This method is intended to be used in order to find the turn-on scheduling. When contrasted to methods of a similar nature, this strategy performs substantially better in noisy environments and has a dramatically lower computational cost. It is recommended that a one-of-a-kind radio frequency fingerprinting extraction of features strategy be used for the temporal subfragment information. Investigations have shown that this method is effective, and practical explanations have shown that the radio frequency fingerprint qualities of various devices can be differentiated based on the exponential output cosine spectra.

X. Gong [6] investigated fingerprint-based placement methodologies for large-scale MIMO systems. Working under the supposition that the percentage of struts can be greater than the amount of transmission schemes, the author proposed a geographically sophisticated beam-based channel prototype that is capable of attaining improved angle settlement. The beam domain channel amplitude matrix has additionally been employed by us to provide a location-related fingerprinting. This matrix includes intensity, angle of arrival, as well as delay of arrival in addition to other rich and stable multi-path characteristics. The authors propose two deep learning algorithm placement approaches that rely on regression and classification techniques using fully-connected neural network models to tackle a matching-to-placement issue. These methods are used to determine where an object should be placed. The results of the simulation reveal that the primary neural networks are able to classify the user terminal in an effective manner, and that the subsequent neural networks are able to reliably regress the position of the mobile terminal.

An accurate three-dimensional automatic fingerprint identification method based on ridge valley assisted three-dimensional restoration and topological polymer separation of parameters was proposed by X. Yin [7]. The first approach achieves real-time restoration whilst also constructing ridge valley correlations that rely heavily on the configuration of ridge valley curvatures and take into consideration the particular fingerprint characteristics of the ridge valley. This is in contrast to traditional methodologies, that also yield correlations among both points rather than ridge valley interactions. The latter method, that has been proven to be successful and effective in the characterization of three-dimensional fingerprint recognition, retrieves the topology polymer characteristic, that also encode the three-dimensional configuration, by superimposing the three-dimensional information onto multiple planes as well as acquiring the accompanying two-dimensional structures. This method has been shown to be successful and effective in the recognition of three-dimensional fingerprints. The outcomes of the in-depth research indicated that the suggested technique outclasses methodologies that are considered to be current state of the art when it comes to the rebuilding and identifiers of a three-dimensional thumbprint. In addition, the presented scheme has a greater reduction time complexity than other methodologies, making it appropriate for a broad range of applications.

Y. Moolla [8] proposed the use of fingerprints, eyeballs, and the form of an infant's eardrum as biometric identifiers for the purpose of determining the child. Each mode of transportation comes with its own unique set of advantages and disadvantages. It has been demonstrated that techniques developed for adults ears generally operate for the ears of newborns, allowing infants to understand ear characteristics easily form birth forward. Respondents as youthful as six weeks old were used to demonstrate that it can be feasible to build a hardware component that could really encapsulate fingerprint image from newborns and keep the information in a manner that is consistent with fingerprint comparative apps. The authors demonstrated that it is feasible to do this by demonstrating that it is feasible to construct a machine which could collect fingerprints from newborns. The researchers demonstrated that iris biometrics can effectively match individuals as early as six weeks old, and that as youngsters become stronger, their assimilation rate rises. The researchers also demonstrated that iris fingerprinting can completely match individuals as old as six years old.

Y. Zhang [9] came up with an innovative real-time mosaicking method specifically for wrapped fingerprints that he called the Block-based Rolled Fingerprint Synthesis. The Block premised Rolled Fingerprint Development method has the potential to analyze and correct imbalances in the presently rolled thumbprint. As either a result, the Block predicated Rolled Fingerprint Development method reduces the need for human specialists to witness as the consumer starts rolling his thumb on a live scanning. The author believes that the Mosaicking Gap Rate measure that they provided would be the one to calculate the mosaicking gaps inside the rolled fingerprint. This is based on the author's perspective. It is essential for detecting mosaicking gaps and making the most of their potential. The fingerprint block is processed using the Block-based Rolled Fingerprint Construction method as opposed to more conventional techniques being used. It completely exploits the grayscale information as well as the fingerprint foreground area of blocks rather than the traditional biological data that is present in fingerprints. The authors examine the Block based Rolled Fingerprint Construction through three different vantage points: presentation, the efficiency of fingerprint identification, and the consequences of improvement. The outcomes of the testing reveal that the method is not only better effective than earlier tactics in locating and eliminating mosaicking gaps, however it also reaches a greater level of matching precision.

C. Yuan [10] proposes a new method for detecting whether or not a fingerprint is still alive. This method relies on an improved convolutional neural network visual scale normalization in order to circumvent the image size limitation. On however one side, the difficulty of the image scale is circumvented by the resolution that has been offered, which is that pictures of any size can be employed as inputs to the model.. In contrast side, the deep convolutional neural network photograph scale normalization has been updated to incorporate an adaptive speed of learning framework. This strategy stops the weighting factors from falling into a local optimum and instead attempts to force people to congregate to the optimization algorithm while the slope back deduction is taking place. The findings of a few comparative studies demonstrate that the suggested method is better than other approaches and is suitable for fingerprint liveness recognition to avoid exhibition strikes. Additionally, the findings from the study suggest that perhaps the suggested approach is suitable for fingerprint detection and tracking.

A unique outlier immunological multipath fingerprinting framework for indoor single-site localisation was presented by L. Chen [11]. Within the context of the concept, the multipath fingerprint refers to the spatial-temporal correlation matrix of something like the multipath signals that were obtained by the specific website. In contrast to the amplitude of the signal and the Channel Impulse Reaction, which really only retrieve the geolocation data from the impulse response or the reference signal, the multipath fingerprint is able to get the position details from the original broadcast as well. The construction of the orientation feature extraction module makes advantage of the low-dimensional continuous domain of the multipath fingerprinting, that was driven by the affine hull framework. Since the Grassmann manifold may indeed keep the operability of the linear subspace, the multipath biometric data is transmitted using Binet-Cauchy kernel to a higher dimensional Reproducing Kernel Subspace. This is done because the Grassmann manifold might well preserve the invariance of the linear latent space. As a result, one pixel will be assigned to the repeating kernel on the Hilbert space to every specification. The findings indicate that the suggested multipath fingerprinting paradigm is capable of handling outliers, assuming that the quantity of exceptions somehow doesn't transcend the fraction of outliers.

T. N. Tan [12] presents a brand-new approach for identifying fingerprints that is very safe and relies on ring training with mistakes encrypting. Employing the cutting-edge method of numerical theoretic transformation multiplying and extraction of features results in a considerable rise in the amount of resources duration for the recommended system to complete its execution. It is possible to use it in real-time signature schemes, and it accomplishes minimum throughput while doing so. However, this depends on the outcomes of the simulations. In particular, the ring training with mistakes cryptographic offers a high degree of confidentiality that completely shields the users' secret fingerprint information from prying eyes. The biometric identification approach that was described may thus be employed in applications that need a significant level of security,, such as biometric identification, the transmission of diagnostic images, and the confidentiality of internet of things devices.

III PROPOSED METHODOLGY

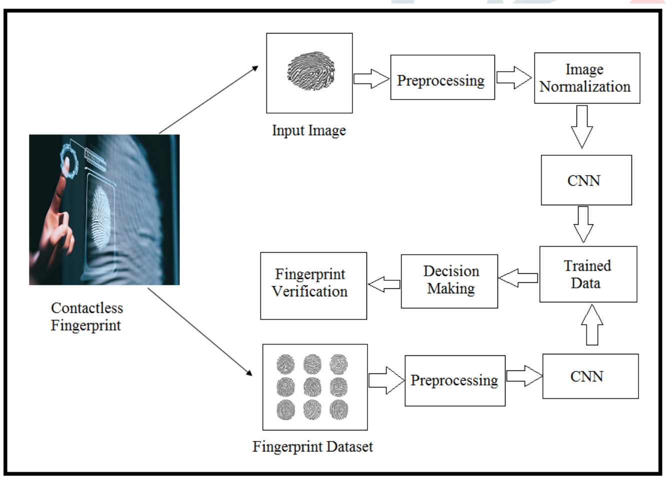

Figure 1: Proposed Methodology

The proposed methodology for the purpose of achieving the contactless fingerprint authentication using CNN has been depicted in the figure 1 above and the steps taken to achieve this system are elaborated below.

Step 1: Preprocessing – Using OpenCv to take pictures of the fingerprints is the initial step in the process, which is ultimately used to create a digital fingerprint database. The VideoCapture method included within the cv2 library is responsible for photographing the user's unique fingerprint in its entirety. The subject's finger is dipped in ink and then pressed against a white surface to leave an impression. The picture of the fingerprint that is obtained this is a task that is sharp and unmistakable.

After the image of the fingerprint was successfully resized, the next step is to do a grayscale conversion. The end result is a scaled-down version of the original picture that has been captured. After being scaled down to 150 by 150 pixels, the picture would then be stored in a specific directory that would be given the same name as either the subject's or the user. For the goal of demonstrating how to utilize this methodology, this stage is carried out in an iterative manner for a total of 5 participants. This process is repeated for every user until the objective of obtaining the input dataset is achieved, at which point each of the five unique fingerprint sets is created using around 200–300 photographs of their fingerprints.

Step 2: Image Segmentation – Prior to this juncture, the user lacked the means to scrutinize the input dataset; however, they are now equipped with such capability. The images were gathered exclusively for the sole purpose of the aforementioned data set. The execution of this task will be accomplished through a joint endeavor between the training generators along with the validation generator. The training generator is configured with a batch count of 64 and requires images with dimensions of 150 by 150 pixels for both height and width. Additionally, the generator employs a monochromatic color palette and is set up for classification purposes. The aforementioned parameters are utilized in the construction of the training generators.

The architecture of the proposed validation generators exhibits analogous components. The available choices comprise a batch quantity of 64, a desired image dimension of 150 by 150 pixels, and a chromatic arrangement that encompasses grayscale and classification category as the variables. Furthermore, the batch size utilized for the validation element in this procedure is 64.

Step 3: Convolution Neural Network – The most critical element of the suggested approach is its recognition and classification of diverse types of fingerprints, considering its essential responsibility. The input data for each of the elements of the Convolutional Neural Network is the the original image. The procedure involves utilizing input images that have been gathered, processed beforehand and categorized for the purpose of training the neural network.

The dataset input comprises of folders containing the two the training and testing images. Subsequently, the documents contained within every directory are segregated into distinct subfolders, wherein each subdirectory denotes the unique fingerprint of a specific user and associated images. The aforementioned visuals are subsequently transmitted into the convolutional neural network's fundamental computational framework during the course of the training regimen. Therefore, it is necessary for users to modify their images to possess a precise width and height of 150 pixels prior to moving forward, in order to maintain uniformity in input size.

In light of the presumption that the system will only be interacting with an aggregate of five distinct individuals in the above scenario, the neural network was trained employing each of these images for an entirety of 500 epochs with a batch count of 64 as well as a density of 5. The development of Convolutional Neural Networks can be facilitated through the utilization of two supplementary Python libraries, namely TensorFlow and Keras. The presence of these innovations facilitates the CNN's composition of multiple layers. The illustration presented in Figure 2 portrays the comprehensive CNN layer layout.

Layer	Activation
Conv 2D 32x3x3	ReLU
Conv 2D 32x3x3	ReLU
MaxPooling2D 2x2	
Droupout 0.25	
Conv 2D 128x3x3	ReLU
MaxPooling2D 2x2	
Conv 2D 128x3x3	ReLU
MaxPooling2D 2x2	
Droupout 0.25	
Flatten	
Dense 1024	ReLU
Droupout 0.25	
Dense 5	Softmax
Adam Optimizer	

Figure 2: CNN network Architecture

The earlier established deep convolutional neural network is subsequently subjected to a training process of 500 iterations utilizing the aforementioned architecture. Upon completion of the training process, a file denoted by the h5 extension is generated.

Step 4: Decision Making – Upon the completion of the CNN-based implementing approach, an evaluation of its capacity to identify fingerprints linked to a specific user could be conducted. The assessment can be conducted subsequent to the completion of the instructional methodology based on Convolutional Neural Network (CNN). The OpenCV platform is utilized to initiate the video camera and commence the recording procedure with the aim of obtaining fingerprints. The OpenCV approach has a particular swift feature which allows for the matching of the fingerprints.

Each human fingerprint consists of specific features that sets them apart and also allows the model to perform the matching correctly. The features are intrinsic to each of the fingerprints, such as ridges and grooves that we normally associate with fingerprints. But also there are patterns that appear with intersecting ridges and grooves, such as whorls, islands, arches and loops. These are useful markers that render the prints unique and easily identifiable. Therefore, the CNN model is trained to identify the distinctiveness of these features and apply it to match the fingerprints effectively. The testing approach initiates with the user providing the fingerprint to be identified which is given to the model as an input.

As a result, the recorded input fingerprints undergo a cropping process. The present exhibit displays an image that has undergone several modifications, including a reduction in its overall size, conversion of the color palette to grayscale, and identification of its border for integration with the trained data weights of the .h5 file. Following the conclusion of this procedure, the appropriate fingerprint, is collected simultaneously prior to being recognized as being associated with a specific user.

IV RESULTS AND DISCUSSIONS

The suggested method for contactless fingerprint identification through CNN has been implemented in the Python programming language. The concept has been transformed into a reality through the utilization of the Spyder integrated development environment. The methodology necessitates the utilization of OpenCV, TensorFlow, and Keras frameworks to perform the essential functions of furnishing the foundational libraries for the Convolutional Neural Network (CNN) model. The optimal hardware configuration for implementing the presented technique was found to be a laptop equipped with an Intel Core i5 CPU, 8 GB of RAM, and 1 TB of storage capacity.

The assessment of the precision of fingerprint identification necessitates an evaluation of the effectiveness of the proposed methodology. The level of accuracy in the identification process can serve as a metric for evaluating the reliability of a given methodology. The assessment of accuracy must be conducted in an impartial way, utilizing the metrics of Precision and Recall as outlined below.

Performance Evaluation based on Precision and Recall

The utilization of precision and recall metrics is highly beneficial in evaluating the comprehensiveness of the implementation of a specific module within the paradigm. The two aforementioned measurements are being deliberated within the broader framework of this particular approach. The precision of a module determines its relative correctness, encompassing its dependability over a broad spectrum.

The level of accuracy of this methodology was assessed through a comparative analysis between the total number of assessments and the number of accurate identifications. The inclusion of recall requirements serves as a valuable supplement to the evaluation of precision when gauging the overall reliability of the CNN component. Ample precision monitoring is a contributing factor for this outcome.

The method utilized for determining the recall involves the comparison of the ratio of accurate fingerprint identifications to inaccurate ones. The subsequent equations are presented to calculate this aforementioned metrics.

Precision and Recall can be depicted as below:

- ✓ A = The number of accurate fingerprint identifications
- ✓ B = The number of inaccurate fingerprint identifications

✓ C = The number of accurate fingerprint identifications not done

So, precision can be defined as

Precision = (A / (A+ B)) *100
Recall = (B / (B+ C)) *100

The experimental results are presented in Table 1 using the aforementioned formula. By utilizing these previously mentioned statistical parameters, it is possible to produce the visual depiction depicted in figure 3.

No. of Iterations	Accurate Fingerprint identifications (X)	Inaccurate Fingerprint identifications (Y)	Accurate Fingerprint Identifications not done (Z)	Precision	Recall
10	10	0	0	100	100
20	17	2	2	89.47368	89.47368
30	27	2	2	93.10345	93.10345
40	35	3	3	92.10526	92.10526
50	44	5	2	89.79592	95.65217

Table 1: Precision and Recall Measurement Table

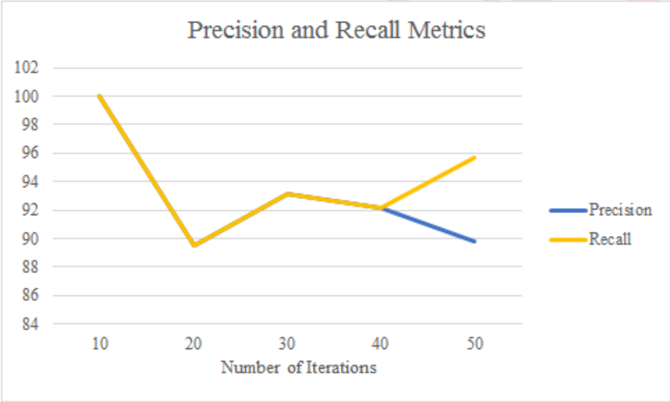

Figure 3: Comparison of Precision and Recall

The graph depicts the performance of CNN in detecting fingerprints accurately across a wide range of trial counts, based on the input data. The method's reliability is demonstrated by its high precision and recall percentages of 92.89 and 94.06 percent, correspondingly. The numerical values obtained in the initial application of this methodology are considerable, and the resulting achievements are praiseworthy.

V CONCLUSION AND FUTURE SCOPE

The proposed methodology for the purpose of achieving the contactless fingerprint authentication has been elaborated in this research article. The presented technique is effective in improving the current infrastructure in biometric authentication that can be secure and highly accessible. The problems faced by the current implementations for fingerprint authentication allow for touching the sensor by multiple individuals that can lead to transference of any pathogens and other material between users. This is highly undesirable and can lead to infections and other hygiene problems. Therefore, this approach mitigates these issues through an effective implementation. The proposed approach initiates with the contactless fingerprints being collected in the form of a dataset that is provided to the system as an input. These contactless fingerprints are then effectively preprocessed to eliminate any unnecessary or unwanted elements from the images. The preprocessed contactless fingerprints are then provided as an input to the Convolutional Neural Network that is specifically designed for the purpose of training on such images. Once the Convolutional Neural Network is trained, the output results in the trained data that is stored successfully. The user can then input the contactless fingerprint for the authentication which is captured and preprocessed. The preprocessed contactless fingerprint of the user is then subjected the process of image normalization and the normalized image is obtained. The normalized image is then provided to the trained data for the authentication that results in a probability score. This probability score is then provided to the decision making approach that verifies the fingerprint. The approach is also evaluated for its performance efficiency through rigorous testing that has resulted in highly promising outcomes.

REFERENCES

[1] Y. Chen, W. Guan, J. Li and H. Song, "Indoor Real-Time 3-D Visible Light Positioning System Using Fingerprinting and Extreme Learning Machine," in IEEE Access, vol. 8, pp. 13875-13886, 2020, DOI: 10.1109/ACCESS.2019.2961939.

[2] K. Sutanto and M. Turcotte, "Assessing Global-Local Secondary Structure Fingerprints to Classify RNA Sequences with Deep Learning," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, DOI: 10.1109/TCBB.2021.3118358.

[3] C. -W. Hung, J. -R. Wu and C. -H. Lee, "Device Light Fingerprints Identification Using MCU-Based Deep Learning Approach," in IEEE Access, vol. 9, pp. 168134-168140, 2021, DOI: 10.1109/ACCESS.2021.3135448.

[4] D. -H. Jeon, W. -B. Jeong, H. -J. Chung and S. -W. Lee, "Novel Micro-LED Display Featuring Fingerprint Recognition Without Additional Sensors," in IEEE Access, vol. 10, pp. 74187-74197, 2022, DOI: 10.1109/ACCESS.2022.3190608.

[5] J. Zhang, Q. Wang, X. Guo, X. Zheng, and D. Liu, "Radio Frequency Fingerprint Identification Based on Logarithmic Power Cosine Spectrum," in IEEE Access, vol. 10, pp. 79165-79179, 2022, DOI: 10.1109/ACCESS.2022.3194124.

[6] X. Gong, X. Yu, X. Liu, and X. Gao, "Machine Learning-Based Fingerprint Positioning for Massive MIMO Systems," in IEEE Access, vol. 10, pp. 89320-89330, 2022, DOI: 10.1109/ACCESS.2022.3199728.

[7] X. Yin, Y. Zhu, and J. Hu, "3D Fingerprint Recognition based on Ridge-Valley-Guided 3D Reconstruction and 3D Topology Polymer Feature Extraction," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 3, pp. 1085-1091, 1 March 2021, DOI: 10.1109/TPAMI.2019.2949299.

[8] Y. Moolla, A. De Kock, G. Mabuza-Hocquet, C. S. Ntshangase, N. Nelufule, and P. Khanyile, "Biometric Recognition of Infants using Fingerprint, Iris, and Ear Biometrics," in IEEE Access, vol. 9, pp. 38269-38286, 2021, DOI: 10.1109/ACCESS.2021.3062282.

[9] Y. Zhang, Y. Wu, M. Gao, S. Pan, Z. Shao, and T. Luo, "BlockRFC: Real-Time Rolled Fingerprint Construction and Distortion Rectification," in IEEE Access, vol. 8, pp. 216948-216959, 2020, DOI: 10.1109/ACCESS.2020.3041716.

[10] C. Yuan, Z. Xia, L. Jiang, Y. Cao, Q. M. Jonathan Wu and X. Sun, "Fingerprint Liveness Detection Using an Improved CNN With Image Scale Equalization," in IEEE Access, vol. 7, pp. 26953-26966, 2019, DOI: 10.1109/ACCESS.2019.2901235.

[11] L. Chen, X. Yang, P. X. Liu, and C. Li, "A Novel Outlier Immune Multipath Fingerprinting Model for Indoor Single-Site Localization," in IEEE Access, vol. 7, pp. 21971-21980, 2019, DOI: 10.1109/ACCESS.2019.2899169.

[12] T. N. Tan and H. Lee, "High-Secure Fingerprint Authentication System Using Ring-LWE Cryptography," in IEEE Access, vol. 7, pp. 23379-23387, 2019, DOI: 10.1109/ACCESS.2019.2899359.

*****