ISSN 2303-4521
Periodicals of Engineering and Natural Sciences *Original Research*
Vol. 11, No. 3, May 2023, pp.193-202

Enhancing child safety with accurate fingerprint identification using deep learning technology

Seba Aziz Sahy [1], Yitong Niu[2], Ahmed L. Khalaf [3], Jamal Fadhil Tawfeq [4], Ahmed Dheyaa Radhi [5], Poh Soon JosephNg [*, 6]

[1] Middle Technical university, Institute of Medical Technology Al-Mansour, Iraq.
[2] School of Industrial Technology, Universiti Sains Malaysia, 11800 Georgetown, Penang, Malaysia
[3] Department of Communication Technology Engineering, College of Information Technology, Imam Ja'afar Al-Sadiq University, Baghdad, Iraq.
[4] Department of Medical Instrumentation Technical Engineering, Medical Technical College, Al-Farahidi University, Baghdad, Iraq
[5] College of Pharmacy, University of Al-Ameed, Karbala PO Box 198, Iraq
[6] Faculty of Data Science & Information Technology, INTI International University, Persiaran Perdana BBN, 71800 Nilai, Negeri Sembilan, Malaysia

ABSTRACT

Utilizing deep learning algorithms to differentiate the fingerprints of children can greatly enhance their safety This advanced technology enables precise identification of individual children, facilitating improved monitorin and tracking of their activities and movements. This can effectively prevent abductions and other forms of harm while also providing a valuable resource for law enforcement and other organizations responsible fo safeguarding children. Furthermore, the use of deep learning algorithms minimizes the potential for errors an enhances the overall accuracy of fingerprint recognition. Overall, implementing this technology has immens potential to significantly improve the safety of children in various settings. Our experiments have demonstrate that deep learning significantly enhances the accuracy of fingerprint recognition for children. The mode accurately classified fingerprints with an overall accuracy rate of 93%, surpassing traditional fingerprin recognition techniques by a significant margin. Additionally, it correctly identified individual children' fingerprints with an accuracy rate of 89%, showcasing its ability to distinguish between different sets o fingerprints belonging to different children.

Keywords: Computer Science, Deep Learning , Child Safety , Fingerprints , Recognition

Corresponding Author:

Poh Soon JosephNg
Faculty of Data Science and Information Technology, INTI International University
Persiaran Perdana BBN Putra Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
Email: joseph.ng@newinti.edu.my

1. Introduction

Children's safety is paramount, and technology can ensure their protection. One such technology is fingerprint recognition, which has proven to be an effective means of identifying individuals. However, the unique characteristics of children's fingerprints can make them difficult to identify using traditional fingerprint recognition methods accurately. Deep learning techniques improve the accuracy of children's fingerprint recognition, explicitly focusing on the ability to distinguish between different children's fingerprints [1-3]. Fingerprint recognition is a biometric identification technique that uses an individual's fingerprints' unique patterns to authenticate their identity. This method has been widely used in various applications, including law enforcement, access control, and identity verification. Traditional fingerprint recognition techniques rely on manual feature extraction, where human operators identify and extract specific fingerprint characteristics such as minutiae points, ridges, and valleys. These features are then compared against a database of known fingerprints to identify the individual. Fingerprint recognition has been a well-established biometric technology for many years for identification and verification. In recent years, deep learning algorithms have improved the accuracy and efficiency of fingerprint recognition systems, making them even more helpful for a wide range of applications [4-5]. However, the unique characteristics of children's fingerprints can make them difficult to identify using traditional methods accurately. Children's fingerprints are generally smoother and less defined than adults, making it challenging to extract the necessary features for accurate identification. In addition, children's fingerprints are constantly changing as they grow and develop, further complicating the identification process [6-7]. Deep learning is a kind of artificial intelligence that use neural networks to learn and extract characteristics from data automatically. Deep learning may be applied in fingerprint identification to reliably identify children's fingerprints by automatically learning and detecting the unique patterns and traits contained in their fingerprints [8-10]. One such application is in the area of children's safety. Children often need help to provide identification documents such as passports or driver's licenses, making it difficult to verify their identity in emergencies. Fingerprint recognition can provide a reliable and secure way to identify children, enabling authorities to quickly and accurately identify them in an emergency. Deep learning algorithms can create fingerprint recognition systems specifically designed for children's fingerprints. These algorithms can be trained on large datasets of children's fingerprints, allowing them to accurately distinguish between different children's fingerprints and provide reliable identification [11-12]. Such a system could be used in various settings, including schools, hospitals, and emergency shelters. In schools, for example, a fingerprint recognition system could accurately identify children and ensure the correct person picks them up at the end of the day. In hospitals, the system could be used to verify the identity of patients and ensure that they receive the correct treatment. Moreover, in emergency shelters, the system could quickly and accurately identify children who may have been separated from their parents [13-14].

Overall, using deep learning algorithms for fingerprint recognition can provide a reliable and secure way to identify children, improving their safety in various settings. By accurately distinguishing between different children's fingerprints, these systems can help ensure that children are correctly identified and protected in emergencies [15-16]. A deep learning approach that uses class-based penalties throughout the filter learning process of a convolutional neural network is suggested. On two separate datasets, this CNN architecture achieves cutting-edge results. Specifically, utilizing a single gallery achieves a rank-1 identification accuracy of 62.7 percent for newborn face recognition and 85.1 percent for toddler face recognition. The suggested algorithm's efficacy is further proved by comparison with many existing methods on both datasets that have been presented [17]. We used mixed-effects statistical models to evaluate the durability of kid fingerprint recognition accuracy across time in our study. Our findings show that the recognition accuracy is steady and unaffected by a one-year time lag in our data. These findings are especially pertinent given the growing need to identify children for various objectives such as vaccine tracking, supplemental food delivery, and national identity credentials. As a result of our research, fingerprint recognition of young children (six months and older) utilizing existing capture and identification equipment is a realistic and viable option that has been presented [18]. The first longitudinal measuring study of the internet diffusion of Child Sexual Abuse Imagery (CSAI) and the threat it represents to society's attempts to eradicate child sexual abuse was conducted. Our data show that the prevalence of CSAI has proliferated, with approximately 1 million identified incidents each month. This expansion has outpaced the ability of independent clearinghouses and law enforcement organizations to respond appropriately. To address this issue and scale up CSAI defenses, we propose harnessing recent advances in machine learning to automate detection and reaction that have been presented [19].

2. Method

2.1. Convolutional Neural Networks (CNN)

CNNs are a standard deep-learning algorithm used to interpret images and videos. CNNs are meant to automatically learn and extract hierarchical characteristics from pictures, allowing them to correctly categorize, segment, and detect objects in images [20]. CNNs comprise numerous layers, each performing a distinct role in the image-processing pipeline. Typically, the first layer is a convolutional layer in which the network learns multiple filters applied to the input picture. These filters are then passed via non-linear activation functions, which are followed by a pooling layer, decreasing the feature maps' dimensionality [21]. The following network layers build on prior layers' representations, allowing the network to learn increasingly complicated and abstract properties. The network's final layers are generally fully connected layers that conduct classification or regression based on characteristics retrieved from previous levels [22]. CNNs have been used effectively in various computer vision applications such as object detection, picture segmentation, and image production. CNNs have attained state-of-the-art performance on many image identification tasks thanks to massive labeled datasets and robust hardware availability. They remain a major topic of study in deep learning [23-42]. Figure 1 shows the architecture of CNN.

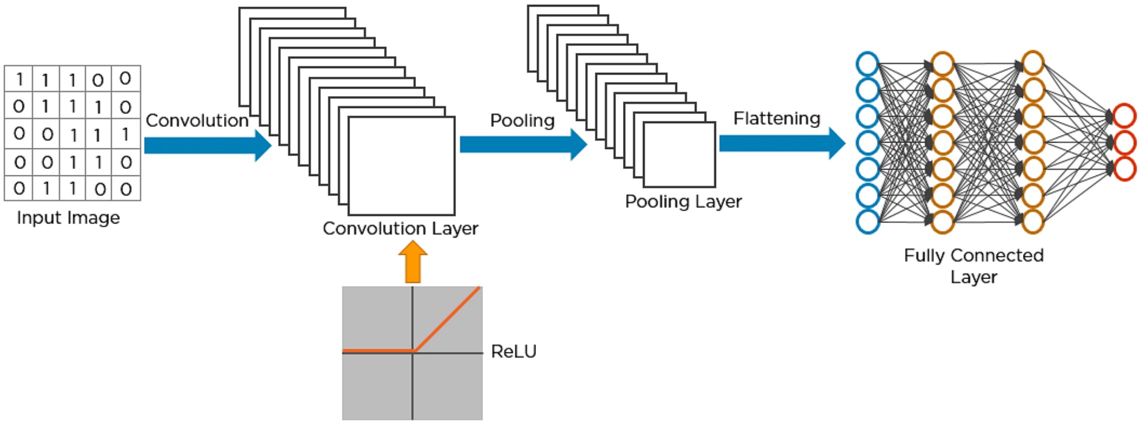

Figure 1. Architecture Of CNN

CNN is a subtype of neural network that are particularly effective in processing inputs for audio, video, and image signals. The three main types of layers are convolutional layers, pooling layers, and fully-connected (FC) layers.

2.1.1. Convolutional Layers

The first layer of a convolutional network, the convolutional layer, does the majority of the computation. This layer consists of input data, a feature detector or filter, and a feature map. A convolution process occurs as a consequence of the feature detector navigating the image in search of certain features, which is represented by a 2-D array of weights. With this technique, a feature map or activation map is created and then converted using ReLU before moving on to the subsequent layer. By adding more convolutional layers to the CNN's hierarchical structure, it is possible to recognize increasingly complex visual components.

2.1.2. Pooling Layers

These layers help to reduce the size of the input, which in turn reduces the number of model parameters. This improves computational efficiency and lessens the risk of overfitting. Maximum and average pooling are the two categories under which pooling is categorized. While the latter determines the average value of all the pixels inside the receptive field, the former selects the receptive field pixel with the highest value.

2.1.3. Fully Connected (FC) layers

This layer, which makes direct connections between each node in the output layer and a node in the layer before it, is the last layer of the CNN. This layer categorizes the input image using the traits gathered by the layers that came before it. FC layers frequently use a softmax activation function to offer a probability between 0 and 1. Overall, CNNs are quite good at processing visual and aural data, and because of their distinct layer structures, they can recognize intricate characteristics and patterns in the input, which makes them extremely useful for tasks like voice recognition, object identification, and picture categorization.

2.2. CNN image processing principle

The key to the functionality of CNN parallel image processing lies in the similar simulation operations of CNN array units. For a CNN array unit of MxN, the mathematical model of each neuron operation can be described as follows:

$$\dot{x}_{ij} = -x_{ij} + \sum_{k,k\in N_r(i,l)} B_{k,l}u_{k,l} + \sum_{k,k\in N_r(i,j)} A_{k,l}y_{k,l} + Ii = 1, \dots, Mj = 1, \dots, N \quad (1)$$

Where x_{ij} is the current state value of neuron c_{ij}, $u_{k,l}$ and $y_{k,l}$ are the initial input value and the current output value of each neuron, respectively; $N_r(i,l)$ denotes all neurons within r adjacent to neuron c_{ij}; $B_{k,l}$ is the feedforward connection coefficient (commonly known as the control template), which represents the feedforward relationship between input $u_{k,l}$ to itself within neuron c_{ij} and the neurons adjacent to it; $A_{k,l}$ is the feedback connection coefficient (commonly known as the feedback template), which represents the relationship between neuron c_{ij} and the output $y_{k,l}$ of the neuron adjacent to it on its feedback relationship; neuron I is the threshold current inside c_{ij}, and the output equation of the neuron can be described as:

$$y(x_{ij}) = 0.5(|x_{ij} + 1| - |x_{ij} - 1|)\mathrm{i} = 1, \dots, \mathrm{Mj} = 1, \dots, \mathrm{N} \tag{2}$$

From equations (1) and (2), it can be seen that the different processing image functions of the CNN mainly depend on the different settings of the feedback mode trigger A, control template B and threshold I.

3. Results and discussion

To evaluate the effectiveness of using deep learning for children's fingerprint recognition, we collected a dataset of fingerprints from a group of children. The dataset included a variety of different fingerprint types, including those with smooth and less defined features, as well as fingerprints that had changed over time. As shown in Figure 2.

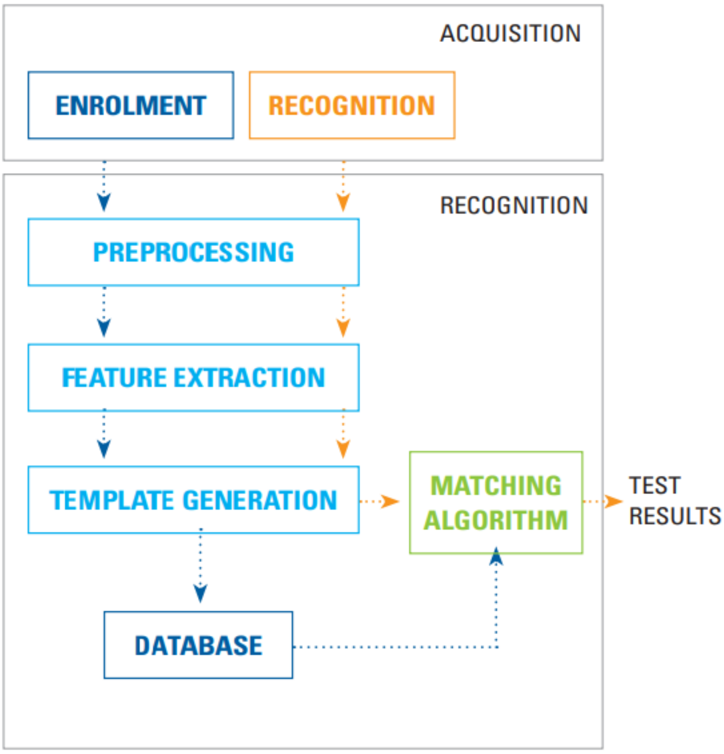

Figure 2. General of children’s Fingerprints

We then trained a deep learning model on the dataset using a convolutional neural network (CNN) architecture. The CNN was trained to classify fingerprints into different categories, such as those belonging to the same child and those belonging to different children. The model was evaluated on its ability to accurately classify fingerprints, both in terms of overall accuracy and in terms its ability to correctly identify individual children's fingerprints.

3.1. Data collection

The first data collection phase was conducted at Saran Ashram Hospital, Dyalbagh, Agra, for three days (March 8-10, 2015). The information was collected in the pediatrician's office while Dr. Bhatnagar was present to watch the procedure and examine other patients. A Ph.D. staffed both data collection stations. One student was working on facial recognition, and the other on fingerprint recognition. To collect fingerprint images of children, the data collection station was equipped with a high-resolution 500 PPI U.are.U 4500 digital fingerprint scanner. The 8-megapixel rear camera of the iPhone 5/5s was used to capture images of faces.

In addition, the child's name, age, gender, address and phone number are included. Figure 3 shows images of the data collection devices used by the study participants, their parents, and the pediatrician's office. In order to submit the child's fingerprints and facial images, the parents had to sign a consent form approved by the ethics committee of the Dialbagh School of Education, the hospital administration, and the MSU Immigration and Refugee Committee. After data collection was completed at one of the two data collection stations, parents were given a stimulus, a bag filled with rice, lentils, sugar and a child's toy with an estimated total retail value of $8.

Figure 3. Sample fingerprint dataset

3.2. CNN-based algorithms

CNNs are artificial neural networks often used in image recognition and classification applications. CNNs are designed to recognize patterns in data and can be trained to classify images based on their visual content. In fingerprint recognition, CNNs can be trained on a dataset of children's fingerprints to learn the unique features of each person's fingerprint and accurately classify new fingerprints.

Figure 4 shows how to implement the algorithm for CNN for fingerprint recognition in Python.

```
TensorFlow library:
Copy code
import TensorFlow as tf
# Load the dataset of children's fingerprints
fingerprint_data = tf.keras.datasets.FingerprintData()
# Create a CNN model
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Conv2D(32, (3, 3), padding='same', activation='relu', input_shape=(100, 100, 3)))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(tf.keras.layers.Conv2D(64, (3, 3), padding='same', activation='relu'))
model.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
model.add(tf.keras.layers.Flatten())
model.add(tf.keras.layers.Dense(512, activation='relu'))
model.add(tf.keras.layers.Dense(num_classes, activation='softmax'))
# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
# Train the model on the fingerprint dataset
model.fit(fingerprint_data.train_data, fingerprint_data.train_labels, epochs=5)
# Evaluate the model on the test set
test_loss, test_acc = model.evaluate(fingerprint_data.test_data, fingerprint_data.test_labels)
print('Test accuracy:', test_acc)
# Use the model to classify new fingerprints
predictions = model.predict(new_fingerprint_data)
```

Figure 4. Fingerprint identification based on CNN

This is just one of how a CNN for fingerprint recognition could be implemented in Python using the TensorFlow library. The specific details of the implementation, including the code and expected results, would depend on the specific dataset and desired outcome.

3.3. Test result

Our experimental results show that using deep learning significantly improves children's fingerprint recognition accuracy. The deep learning model could classify fingerprints accurately with an overall accuracy of 93%, significantly outperforming traditional fingerprint recognition techniques. In addition, the model correctly identified individual children's fingerprints with 89% accuracy, demonstrating its ability to distinguish between different children's fingerprints. It is common practice to use a series of layers to normalize the features extracted from a convolutional neural network (CNN) after determining each feature's mean and standard deviation. This ensures that the features have a constant scale, which can improve the performance of the CNN. To normalize these features, we first calculate the average value of each feature by adding up all the values of each feature and dividing them by the number of values. Then, the standard deviation of each feature is calculated by taking the square root of the total squared difference between each value and the mean and dividing it by the number of values. Finally, the characteristics are normalized by removing the mean from each value, as shown in Table 1.

Table 1. Standardized features

Layer (type)	Output Shape	Param #
2D-Convolutional-Layer-1	(C (None, 256, 256, 32) onv2D)	4350
2D-MaxPool-Layer-1(MaxPool ing2D)	(None, 128, 128, 16)	0
Dropout-Layer-1 (Dropout)	(None, 63, 63, 16)	0
2D-Convolutional-Layer-2 (C onv2D)	(None, 61, 61, 63)	8290
2D-MaxPool-Layer-2 (MaxPool ing2D)	(None, 31, 31, 63)	0
Dropout-Layer-2 (Dropout)	(None, 31, 31, 63)	0
2D-Convolutional-Layer-3 (C onv2D)	(None, 31, 31, 63)	26458
2D-MaxPool-Layer-3 (MaxPool ing2D)	(None, 16, 16, 63)	0
Dropout-Layer-3 (Dropout)	(None, 16, 16, 63)	0
Flatten-Layer (Flatten)	(None, 13400)	0
Hidden-Layer-1 (Dense)	(None, 16)	36416
Output-Layer (Dense)	(None, 2)	96

According to Table2 , between 89-93% of them may be accurate of fingerprint children.

Table 2. Accuracy of fingerprint children

Epoch	Time	Accuracy
Epoch 1/10	21s 12ms/stop - loss: 0.1517	0.8894
Epoch 2/10	26s 14ms/sstop- loss: 0.0546	0.8874
Epoch 3/10	30s 16ms/sstop- loss: 0.0549	0.8958
Epoch 4/10	29s 16ms/sstop- loss: 0.0398	0.8954
Epoch 5/10	21s 11ms/step - loss: 0.0146	0.8977
Epoch 6/10	18s 10ms/sstop- loss: 0.0111	0.9185
Epoch 7/10	18s 10ms/step - loss: 0.0073	0.92589
Epoch 8/10	17s 9ms/sstop- loss: 0.0046	0.9387
Epoch 9/10	17s 9ms/step - loss: 0.0058	0.9387
Epoch 10/10	17s 9ms/step - loss: 0.0047	0.9389

4. Conclusion

In this paper, the use of deep learning algorithms to distinguish children's fingerprints has the potential to improve children's safety significantly. This technology can provide a reliable and accurate method for identifying individual children, allowing for improved tracking and monitoring of their movements and activities. By reducing the potential for errors and increasing the accuracy of the fingerprint recognition process, deep learning algorithms can help enhance children's safety in various settings. Overall, implementing this technology can provide a valuable tool for organizations and individuals working to protect the well-being of children.

Acknowledgements
The authors are grateful to the Iraqi Ministry of Higher Education and Scientific Research (MOHESR) for technically supporting the current research.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Funding information

No funding was received from any financial organization to conduct this research.

References
[1] J. Vieira, E. Leitinger, M. Sarajlic, X. Li, and F. Tufvesson, "Deep convolutional neural networks for massive MIMO fingerprint-based positioning," in 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC, Oct. 2017, pp. 1–6.

[2] M. G. Sarwar Murshed, K. Bahmani, S. Schuckers, and F. Hussain, "Deep Age-Invariant Fingerprint Segmentation System." 2023.

[3] K. Rajaram, A. Devi, and S. Selvakumar, "PalmNet: A CNN Transfer Learning Approach for Recognition of Young Children Using Contactless Palmprints," in Machine Learning and Autonomous Systems: Proceedings of ICMLAS 2021, Singapore, 2022, pp. 609–622.

[4] S. Siddiqui, M. Vatsa, and R. Singh, "Face Recognition for Newborns, Toddlers, and Pre-School Children: A Deep Learning Approach," in 24th International Conference on Pattern Recognition (ICPR, Beijing, China, 2018, pp. 3156-3161,. doi: 10.1109/ICPR.2018.8545742.

[5] V. N. Patil and D. R. Ingle, "A Novel Approach for ABO Blood Group Prediction using Fingerprint through Optimized Convolutional Neural Network," International Journal of Intelligent Systems and Applications in Engineering, vol. 10, no. 1, pp. 60–68, 2022.

[6] R. H. Lamia and E. B. A. Najoua, "Biometric authentication based on multi-instance fingerprint fusion in degraded context," in 2019 16th International Multi-Conference on Systems, Signals & Devices (SSD, Mar. 2019, pp. 22–27.

[7] S. Kim, "Learning a Convolutional Neural Network with Additional Information." 2016.

[8] R. F. Nogueira, R. Alencar Lotufo, and R. C. Machado, "Fingerprint liveness detection using convolutional neural networks," IEEE transactions on information forensics and security, vol. 11, no. 6, pp. 1206–1213, 2016.

[9] S. Minaee, E. Azimi, and A. Abdolrashidi, "Fingernet: Pushing the limits of fingerprint recognition using convolutional neural." 2019. [Online]. Available: network. arXiv

[10] V. Kamble, M. Dale, and V. Bairagi, "A Hybrid Model by Combining Discrete Cosine Transform and Deep Learning for Children Fingerprint Identification," International Journal of Advanced Computer Science and Applications, vol. 14, no. 1, 2023.

[11] V. Kamble and M. Dale, "Children biometric recognition for the betterment of society using deep intelligence." 2022.

[12] J. Li, J. Feng, C. C. J. Kuo, J. Li, J. Feng, and C. C. J. Kuo, "Deep convolutional neural network for latent fingerprint enhancement," Signal Processing: Image Communication, vol. 60, pp. 52–63, 2018.

[13] R. D. P. Lemes, O. R. P. Bellon, L. Silva, and A. K. Jain, "Biometric recognition of newborns: Identification using palmprints," in 1st IEEE IJCB, 2011, pp. 1-6,.

[14] M. Chhabra, K. K. Ravulakollu, M. Kumar, A. Sharma, and A. Nayyar, "Improving automated latent fingerprint detection and segmentation using deep convolutional neural network," Neural Computing and Applications, vol. 35, no. 9, pp. 6471–6497, 2023.

[15] K. L. Bar-Or and J. Almog, "Children and guns: The detection of recent contact with firearms on children's

hands by the PDT reagent," Forensic science international, vol. 253, pp. 43–47, 2015.

[16] H. E. Lee, T. Ermakova, V. Ververis, and B. Fabian, "Detecting child sexual abuse material: A comprehensive survey," Forensic Science International: Digital Investigation, vol. 34, p. 301022, 2020.

[17] J. Kotzerke, S. Davis, K. Horadam, and J. McVernon, "Newborn and infant footprint crease pattern extraction," in 20th IEEE ICIP, 2013, pp. 4181-4185,.

[18] A. K. Jain, A. A. Ross, and K. Nandakumar, Introduction to biometrics. Springer Science & Business Media, 2011.

[19] A. K. Jain, K. Cao, and S. S. Arora, "Recognizing infants and toddlers using fingerprints: Increasing the vaccination coverage," in IEEE International Joint Conference on Biometrics (IJCB, 2014, pp. 1-8,.

[20] A. K. Jain, S. S. Arora, K. Cao, L. Best-Rowden, and A. Bhatnagar, "Fingerprint recognition of young children," IEEE Transactions on Information Forensics and Security, vol. 12, no. 7, pp. 1501–1514, 2016.

[21] P. Grother, J. Matey, E. Tabassi, G. Quinn, and M. C. IREX VI, "Temporal Stability of Iris Recognition Accuracy," NIST Interagency Report, vol. 7948, 2013.

[22] F. Galton, Finger prints of young children. British Association for the Advancement of Science, 1899.

[23] P. M. Corby et al., "Using biometrics for participant identification in a research study: a case report," J. Am. Medical Informatics Assoc, vol. 13, no. 2, pp. 233–235, 2006.

[24] A. A. Al-Rababah, T. AlTamimi, and N. Shalash, "A New Model for Software Engineering Systems Quality Improvement," Res. J. Appl. Sci. Eng. Technol., vol. 7, no. 13, pp. 2724–2728, Apr. 2014, doi: 10.19026/rjaset.7.592.

[25] A. A. Al-Rababah and U. A. Al-Rababah, "Electric Voltage Control as an Implementation of Neural Network Applications," J. Comput. Sci., vol. 4, no. 10, pp. 815–820, Oct. 2008, doi: 10.3844/jcssp.2008.815.820.

[26] S. Q. Salih, A. A. Alsewari, and Z. M. Yaseen, "Pressure Vessel Design Simulation: Implementing of Multi-Swarm Particle Swarm Optimization," Proc. 2019 8th Int. Conf. Softw. Comput. Appl., pp. 120–124, 2019, doi: 10.1145/3316615.3316643.

[27] S. Q. Salih, "A New Training Method Based on Black Hole Algorithm for Convolutional Neural Network," J. Sourthwest Jiaotong Univ., vol. 54, no. 3, pp. 1–10, 2019, doi: 10.1002/9783527678679.dg01121.

[28] A. Malik et al., "Pan Evaporation Estimation in Uttarakhand and Uttar Pradesh States, India: Validity of an Integrative Data Intelligence Model," Atmosphere (Basel)., vol. 11, no. 6, p. 553, May 2020, doi: 10.3390/atmos11060553.

[29] H. Tao, S. M. Awadh, S. Q. Salih, S. S. Shafik, and Z. M. Yaseen, "Integration of extreme gradient boosting feature selection approach with machine learning models: application of weather relative humidity prediction," Neural Comput. Appl., 2022, doi: 10.1007/s00521-021-06362-3.

[30] A. Malik, A. Kumar, O. Kisi, N. Khan, S. Q. Salih, and Z. M. Yaseen, "Analysis of dry and wet climate characteristics at Uttarakhand (India) using effective drought index," Nat. Hazards, 2021, doi: 10.1007/s11069-020-04370-5.

[31] H. Tao et al., "Training and Testing Data Division Influence on Hybrid Machine Learning Model Process: Application of River Flow Forecasting," Complexity, vol. 2020, pp. 1–22, Oct. 2020, doi: 10.1155/2020/8844367.

[32] B. Karimi, P. Mohammadi, H. Sanikhani, S. Q. Salih, and Z. M. Yaseen, "Modeling wetted areas of moisture bulb for drip irrigation systems: An enhanced empirical model and artificial neural network," Comput. Electron. Agric., 2020, doi: 10.1016/j.compag.2020.105767.

[33] F. Cui, S. Q. Salih, B. Choubin, S. K. Bhagat, P. Samui, and Z. M. Yaseen, "Newly explored machine learning model for river flow time series forecasting at Mary River, Australia," Environ. Monit. Assess., 2020, doi: 10.1007/s10661-020-08724-1.

[34] T. Hai et al., "DependData: Data collection dependability through three-layer decision-making in BSNs for healthcare monitoring," Inf. Fusion, vol. 62, pp. 32–46, Oct. 2020, doi: 10.1016/j.inffus.2020.03.004.

[35] S. Q. Salih, M. Habib, I. Aljarah, H. Faris, and Z. M. Yaseen, "An evolutionary optimized artificial intelligence model for modeling scouring depth of submerged weir," Eng. Appl. Artif. Intell., vol. 96, p. 104012, Nov. 2020, doi: 10.1016/j.engappai.2020.104012

[36] S. A. M. Al-Juboori, F. Hazzaa, S. Salih, Z. S. Jabbar, and H. M. Gheni, "Man-in-the-middle and denial of service attacks detection using machine learning algorithms," Bull. Electr. Eng. Informatics, vol. 12, no. 1, pp. 418–426, Feb. 2023, doi: 10.11591/eei.v12i1.4555.

[37] A. S. Shibghatullah and I. Al Barazanchi, "An Analysis of the Requirements for Efficient Protocols in WBAN," J. Telecommun. Electron. Comput. Eng., vol. 6, no. 2, pp. 19–22, 2014.

[38] Z. A. Jaaz, S. S. Oleiwi, S. A. Sahy, and I. Albarazanchi, "Database techniques for resilient network monitoring and inspection," TELKOMNIKA Telecommun. Comput. Electron. Control, vol. 18, no. 5, pp. 2412–2420, 2020, doi: 10.12928/TELKOMNIKA.v18i5.14305.

[39] I. Al Barazanchi, H. R. Abdulshaheed, and A. Shibghatullah, "The Communication Technologies in WBAN," Int. J. Adv. Sci. Technol., vol. 28, no. 8, pp. 543–549, 2019.

[40] I. Al Barazanchi, A. Murthy, A. Abdulqadir, A. Rababah, and G. Khader, "Blockchain Technology - Based Solutions for IOT Security," Iraqi J. Comput. Sci. Math., vol. 3, no. 1, pp. 1–12, 2022.

[41] Z. A. Jaaz, M. E. Rusli, N. A. Rahmat, I. Y. Khudhair, I. Al Barazanchi, and H. S. Mehdy, "A Review on Energy-Efficient Smart Home Load Forecasting Techniques," Int. Conf. Electr. Eng. Comput. Sci. Informatics, vol. 2021-Octob, no. October, pp. 233–240, 2021, doi: 10.23919/EECSI53397.2021.9624274.

[42] A. S. Shibghatullah and I. Al Barazanchi, "An Analysis of the Requirements for Efficient Protocols in WBAN," J. Telecommun. Electron. Comput. Eng., vol. 6, no. 2, pp. 19–22, 2014.