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A Novel Fingerprint Recognition and Verification System Using Swish Activation Based Gated Recurrent Unit and Optimal Feature Selection Mechanism

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Abstract: Using fingerprints in biometric systems is a rapidly expanding and pervasive field. The advancement of fingerprint identification as a computer technology for applications is directly linked to the latest developments in computer science. A kind of fingerprint identification algorithm has been made possible by artificial intelligence technology; particularly imaging technology based on deep learning. This paper proposes a novel fingerprint recognition and verification system using a Swish activation-based gated recurrent unit (SWAGRU) with an efficient feature selection mechanism. The system mainly includes four phases: preprocessing, feature extraction, feature selection, and fingerprint recognition. To begin, the fingerprint samples are collected from the publicly available FVC2004 database. After that, Gaussian filtering is applied to the collected dataset to suppress the noise. Then, the feature extraction is carried out with the help of Self-Attention-Based Visual Geometry Group-16 (SAVGG16), and from that, the optimal features are selected based on Cuckoo Search Optimization (CSO). Finally, the fingerprint recognition and verification are done using SWAGRU. The experimental results showed that the system outperformed existing methods in recognition performance.

Keywords: *Fingerprint Recognition, Verification, Preprocessing, Feature Extraction, Feature Selection, Deep Learning, and FVC2004 database.*

1. INTRODUCTION

Employing the distinctive qualities and characteristics of the fingerprint, fingerprint recognition technology serves as an identification and authentication tool to verify the similarity of two human fingerprints [1, 2]. One of the most commonly used biometric recognition methods is fingerprint recognition. It is sometimes referred to as the oldest human distinctive trait and has been utilized for identification for more than a century. The advantages of using fingerprints include their distinctiveness, stability, and individuality [3]. Dactyloscopy, or the analysis of fingerprints for identifying people, has been performed for many years. One of the most durable biological features, fingerprints, are used for everything from border control to smartphones. Due to the significant matching precision provided by fingerprints compared to other current biometric features, it has been and is today the most booming sector of biometric authentication [4]. Verification and identification are the two primary stages of fingerprint-based recognition systems. The systems use a 1:1 comparison between the person's fingerprints and those on file to confirm their identity during the verification step. The verification step confirms whether the fingerprint belongs to the right person. The method utilized in fingerprint identification systems is more complex than the process used in verification, particularly for large databases, as fingerprint identification calls for a comparison of the input fingerprints with every fingerprint in the database for matching [5].

Machine learning (ML) techniques provide a practical option for identifying fingerprints. Support vector machines (SVM), decision trees (DT), and random forests (RF) are some of the basis algorithms for some of the well-known traditional ML techniques [6, 7]. It displays outstanding performance in recognizing fingerprints or authentication problems, but complicated preprocessing and additional processing ability is required if the data set is too huge. Deep learning (DL) recently demonstrated superior results in the recognition domain [8]. Convolutional neural networks (CNN), in particular, have achieved great success in the field of artificial intelligence (AI) for recognizing patterns using deep learning (DL). It has been possible to restore fingerprint images using a variety of methods. However, these techniques faced overlapping patterns and low-quality images [9, 10]. When DL is used together with pre-trained models like EfficientNet, InceptionNet, Residual Network (ResNet), etc., fingerprint identification performance is outstanding. This motivates us to propose a novel fingerprint recognition and verification system using DL with pre-trained CNN models. The main contributions of the paper are outlined as follows:

- The system uses Gaussian filtering to suppress the noise in the fingerprint data, improving the image quality.
- The system proposes the SAVGG16 model to extract the most discriminant features in the dataset. Incorporating the SA mechanism in VGG16 extracts deeper features from the dataset, improving the classification rate and decreasing the computational complexity.
- The proposed system uses a CSO algorithm to optimally select the features from the extracted feature set, which makes the process more accurate. It also increases the prediction power of the algorithms by selecting the best features and eliminating the redundant and irrelevant ones.
- The proposed system uses the SWAGRU model for fingerprint recognition, in which the SWA is used to solve the gradient vanishing problem of the GRU model.

The following portions of the paper are described as follows. The survey of recent models in fingerprint recognition and their limitations are given in section 2. The overview of the proposed system is provided in section 3. Section 4 shows the outcomes and discussions of the proposed and existing fingerprint recognition systems; finally, section 5 outlines the study's conclusion.

2. LITERATURE SURVEY

Andreea-Monica Dincă Lăzărescu ***et al.*** **[11]** recommended a convolution neural network (CNN) for fingerprint recognition. Firstly, Gaussian filters' Prewitt and Laplacian were utilized to enhance the contrast of the fingerprint images. The enhanced fingerprint data was given to CNN for identifying features and performing classification. The system was experimented on the FVC2004, DB1, DB2, DB3, and DB4 databases and attained a validation accuracy between 67.6% to 98.7% and testing accuracy between 70.2% and 75.6%. **N.K. Sreeja [12]** suggested a fingerprint recognition system using ant colony optimization. Firstly, the edges of fingerprint ridges were extracted, and the bit-wise XOR operation was utilized to determine the similarity between the stored and input ridge patterns. The ant optimization algorithm was utilized to identify whether the fingerprint data is authorized by comparing the similarity with the chosen threshold. The fingerprint is identified as unauthorized or imposter if the similarity exceeds the threshold. The system attained an equal error rate of 0.00002725% for the FVC2004 dataset. **Long The Nguyen** ***et al.*** **[13]** presented an artificial neural network system for fingerprint recognition and verification. At first, the Weiner filter was used to remove the noise from the fingerprint data, and then histogram equalization was adopted to enhance the quality of the filtered data. Then, morphological operations were employed to extract the region of interest from the pre-processed data. Then, move-expansion was utilized for image segmentation, and finally, ANN was used for fingerprint identification. The system achieved a maximum accuracy of 97.75% when tested on both low- and high-quality fingerprint data.

Halil Ibrahim Ozturk ***et al.*** **[14]** presented an automated latent fingerprint identification system using a minutia patch embedding network. The system used matching minutia pairs from the slap and rolled fingerprints of the same finger to extract the patches around the minutiae. Then, minutia cylinder coding was utilized to generate minutia pairs and to improve the system's performance, additive angular margin loss was estimated. The system reached a maximum accuracy of 98.46% on Tsinghua Distorted Fingerprint and FVC 2000-2004 datasets. **Fahman Saeed** ***et al.*** **[15]** proffered a deep learning technology called DeepFKTNet for automatic fingerprint recognition. The system learned features from the input data using CNN, in

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which the number of filters in CNN's convolution layer was determined using Fukunaga–Koontz Transform (FKT). The tuning of CNN was carried out using Adam optimizer. The system utilized FVC2004 and Finger Pass datasets to evaluate the system's performance and achieved a maximum kappa and accuracy of 96.82% and 98.89%.

2.1 Problem Statement

- For the recognition of fingerprints, some works use ML-based approaches. It offers efficient results. However, they use handcrafted features, which do not provide an optimal set of features for classification.
- Some paper skips preprocessing, but noise in the fingerprint images affects the recognition system's performance.
- The papers mentioned above do not focus on any feature selection mechanism. However, the optimal feature selection is essential to boost the classifier's performance and reduce the computational cost.
- Some works use CNN-based models for recognition, which performs better than the ML framework. However, there is a need to represent rich fingerprint features for classification and reduce the overfitting issues the CNN model faces.

With the emergence of DL, we can achieve better performance in computer vision. We can improve computer vision performance with the emergence of DL. The issue of predetermined features can be resolved by automatically extracting task-specific features using two-dimensional convolutional filters. So, this paper proposes a novel attention-included CNN model with an optimal feature selection mechanism for presenting the rich feature representation of the fingerprint data and optimal classification results for fingerprint identification.

3. PROPOSED METHODOLOGY

Figure 1 shows the proposed system's structural design, which mainly comprises four phases: preprocessing, feature extraction, feature selection, and fingerprint recognition. First, noise removal is performed on the collected images as a preprocessing step using Gaussian filtering. Then, the feature extraction is done by SAVGG16, and the CSO algorithm selects the optimal feature. Lastly, fingerprint recognition and verification are performed using the SWAGRU model.

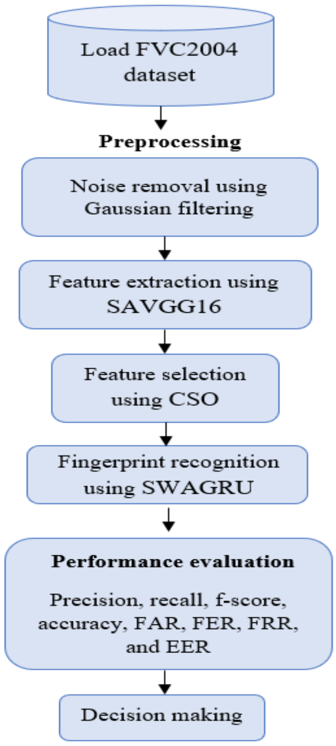

Figure 1: Workflow of the proposed methodology

Preprocessing

The system uses the sample fingerprint data from the FVC2004 database, publicly available online. The gathered dataset is next subjected to preprocessing because the fingerprints might have noise. If the fingerprint data contains noisy pixels, the fingerprint identification algorithm may identify several false minutiae while missing some actual minutiae. Therefore, the suggested method employs Gaussian filtering to enhance the quality of noisy fingerprint data and achieve good detection accuracy. The Gaussian filter uses the neighboring or surrounding pixels' average value to replace the input image's noisy pixel. The process is achieved by computing an image's weighted mean of the adjacent points (pixels). It is mathematically defined as follows:

$$\overline{GF}_I = \frac{1}{2\pi\sigma^2} e^{\left(\frac{a^2+b^2}{2\sigma^2}\right)} \tag{1}$$

The fingerprint data is rotated, shifted, flipped, cropped, and sheered once the noise has been removed from the fingerprint data. After that, the augmented images are converted into grayscale images and reduced to a 224x224 uniform dimension suitable for extracting features from CNN.

3.1 Feature Extraction

We must first extract some features from the image to categorize an object in the image. The traits of human faces are either based on geometry or statistics. The most discriminating qualities for recognizing features are robust to random environmental variations, including changes in position, scale, illumination, and emotions associated with the face. The proposed system uses SAVGG16 to extract the most discriminant features from the preprocessed dataset. A pre-trained CNN with 16 layers is called VGG16, comprising 13 convolutions, five max-pooling, and three fully connected layers. The result is one of the most incredible vision model architectures with 16 layers and configurable parameters. The most discriminating features from the data are extracted. However, it is challenging to extract the deeper features. So, to extract deeper features and enhance feature learning capabilities, the suggested system uses the SA mechanism in the general structure of VGG-16. This SA incorporation in conventional VGG16 is termed SAVGG16. The process included in the SAVGG16 is explained as follows:

A 224x224 input image is initially assigned to VGG16, which then sends it to the convolutional layer to extract local information. The VGG16 convolutional filters use a 1x1-convolution filter as the input's linear transform and have the lowest 3x3 receptive field. The SA mechanism receives the characteristics obtained from the convolutional layer. The input feature map will go through three 1x1 convolution kernels when it enters the SA module to produce various deeper feature maps. The SA weights of various channels in the fusion feature map are obtained using the SoftMax function. The SA weights of various channels in the combined feature map are obtained using the SoftMax function. From a mathematical perspective, SA extracts higher-quality feature maps using a mapping function consisting of the feature map's Query $\left(\overline{Q}\right)$, Key $\left(\overline{K}\right)$, and value $\left(\overline{V}\right)$. The attention weight is initially determined by combining the Query and each Key. It is expressed as follows:

$$F\left(\overline{Q},\overline{K}\right)=\overline{K}^{T}\,\overline{Q} \tag{2}$$

The attention weight produced in equation (2) is then normalized using the SoftMax function, as indicated in equation (3).

$$\varpi_N = soft\max\left(F\left(\overline{Q},\overline{K}\right)\right) \tag{3}$$

Where, ϖ_N refers to the normalized weight. The weighted sum of the normalized weights with associated values represents the final attention-deep feature vector $\left(\overline{SA}_{fm}\right)$, and it is shown as follows:

$$\overline{SA}_{fm}\left(\overline{Q},\overline{K},\overline{V}\right)=\Sigma\,\varpi_N\,\overline{V} \tag{4}$$

Following that, the pooling layer receives the features obtained from the SA layer to reduce the size of the feature maps. It typically employs 2 x 2 tile spacing. The two most popular types of pooling are maximum and average pooling. Each local cluster of neuron's maximum value in the feature map is employed for max pooling and average pooling. Both the computational cost and the size of the features are reduced. The fully connected layer is then given the final feature maps obtained from the MA layer. VGG16 comprises three fully connected layers, in which the first two layers contain 4096 channels, and the third layer consists of 1000 channels. This layer creates the feature set by flattening the features using these channels.

3.2 Feature Selection

Choosing the optimal feature subset from the extracted feature dataset is known as optimized feature selection and lowers the computational complexity while categorizing high dimensional data. The proposed system uses the Cuckoo Search Optimization (CSO) method to choose the features in the most effective manner possible. The cuckoo bird's reproductive method inspired the swarm intelligence known as CSO. In order to enhance the likelihood that their eggs will hatch, cuckoo birds will occasionally remove other people's eggs from communal nests. CSO primarily works based on three essential rules: Only one egg is laid by each cuckoo at a time and deposited into any available nest. The next generation will inherit the best nest with the best eggs. The host bird has a chance [0, 1] of discovering the cuckoo egg, and the readily available host nest is fixed. The algorithmic procedures are briefly explained as follows:

Initialize the population size N of the algorithm and other parameters such as a maximum number of iterations Max_{IR}, probability $\breve{P}_R \in [0,1]$, and initial iteration counter η. Then, each individual's fitness in the

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population is determined according to classifier accuracy, which is computed as follows.

$$Fitness = Max\left(\bar{A}_{ay}\right) \tag{5}$$

Where, $\bar{A}_{ay}$ refers to the accuracy computed by dividing the number of accurate predictions by the total number of predictions as follows.

$$\bar{A}_{ay} = \frac{\bar{P}\bar{T} + \bar{N}\bar{T}}{\bar{T}_{ToT}} \tag{6}$$

Where, $\bar{T}_{ToT}$ indicates the number of samples in the dataset, $\bar{P}\bar{T}$ and $\bar{N}\bar{T}$ indicates true positive and true negative, respectively. Equation (7) shows the new position (nest) of the individuals in the population.

$$\bar{\Upsilon}_c^{\eta+1} = \begin{cases} \bar{\Upsilon}_c^{\eta} + \beta\,\gamma\left(\bar{\Upsilon}_a^{\eta} - \bar{\Upsilon}_b^{\eta}\right), & if\ \Re \le \breve{P}_R \\ \bar{\Upsilon}_c^{\eta} + \beta\,\bar{L}\left(\gamma, \bar{I}\right), & Otherwise \end{cases} \tag{7}$$

$$\bar{L}\left(\gamma, \bar{I}\right) = \frac{\bar{I}\,\Gamma\left(\bar{I}\right)\sin\left(\pi\,\bar{I}/2\right)}{\pi\,\gamma^{1+\bar{I}}} \tag{8}$$

Where, $\gamma > 0$ indicates the step size, $\beta > 0$ refers to the scaling factor, $\bar{\Upsilon}_a^{\eta}$ and $\bar{\Upsilon}_b^{\eta}$ indicates the randomly selected positions among the existing ones, $\breve{P}_R$ represents a user-defined switching probability to perform random walk from local to global positions, and $\Gamma(.)$ refers to the Gamma function. An existing position $\bar{\Upsilon}_c^{\eta}$ is chosen at random to compete with the new position $\bar{\Upsilon}_c^{\eta+1}$ after it has been evaluated. The selected position is replaced in the group of nests if the new position has a higher value. Until the termination criteria are met, the operation is repeated. The final output of the method is the best-found solution (i.e., current optimal feature set).

3.3 Fingerprint Recognition

The recognition process is performed using the optimally selected features set with the help of SWAGRU. GRU analyzes sequential data one element at a time, changing its hidden state based on the input and the hidden state from the previous iteration. The GRU creates a candidate activation vector for every time step by fusing data from the input and the prior hidden state. The concealed state is then updated using this candidate vector for the following time step. The reset gate and the update gate are the two gates that are most frequently used. The update gate decides how much candidate activation vector should be incorporated into the new hidden state. In contrast, the reset gate defines how much of the prior hidden state should be forgotten. With fewer gating units, continuous information discarding, and the use of the hidden state to hold information dependencies, the GRU model can preserve important information over long distances. However, the vanishing gradient during backpropagation is a difficulty that the GRU faces. These problems can be resolved by introducing practical activation functions; as a result, the suggested system uses the Swish activation function, which offers improved learning accuracy compared to other activation functions and effectively addresses the gradient vanishing problem. Thus, the Swish activation function included in the original GRU is renamed SWAGRU. Figure 2 shows the structure diagram of the GRU model.

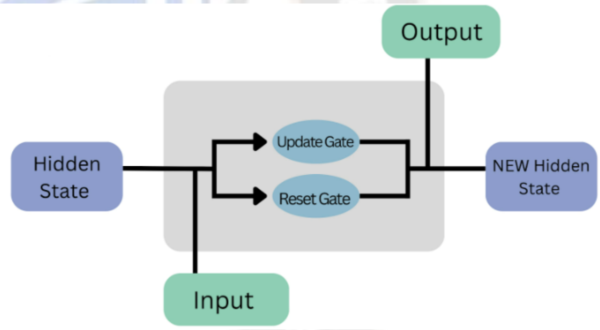

Figure 2: Structure of GRU

Consider the input sequence (optimally selected feature set) as $\bar{O}\bar{S}\_1, \bar{O}\bar{S}\_2, ... \bar{O}\bar{S}\_t$. The estimations of update gate, reset gate, and the standard GRU unit at time t is estimated as follows:

$$\overline{UG}_t = \mu^*\left(\bar{W}_{\overline{UG}}\left[\bar{h}_{t-1}, \bar{O}\bar{S}_t\right]\right) \tag{9}$$

$$\overline{RG}_t = \mu^*\left(\bar{W}_{\overline{RG}}\left[\bar{h}_{t-1}, \bar{O}\bar{S}_t\right]\right) \tag{10}$$

$$\overline{NC}_t = \mu^*\left(\bar{W}_{\bar{O}\bar{S}_t}\left[\overline{RG}_t, \bar{h}_{t-1}, \bar{O}\bar{S}_t\right]\right) \tag{11}$$

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$$\bar{h}_t = \left(1 - \overline{UG}_t\right) \bar{h}_{t-1} + \overline{UG}_t \ \overline{NC}_t \quad (12)$$

Where, $\overline{UG}$ indicates the update gate, $\overline{RG}$ refers to the reset gate, $\overline{NC}$ signifies the new candidate value, $\overline{W}_{\overline{UG}}, \overline{W}_{\overline{RG}}, and\ \overline{W}_{\overline{OS}_t}$ refers to the weight matrices of update gate, reset gate, and input, which are optimally selected by CSO algorithm. The working process of CSO algorithm is given in section 3.3, $\bar{h}_{t-1}$ represents the previous state, $\bar{h}_t$ indicates the hidden state output, which classifies the input into fake or real, and μ^* refers the Swish activation (SWA) function. SWA is a smooth, non-monotonic function that consistently matches or outperforms other activation function and it handles the gradient vanishing problem efficiently. It is defined as follows:

$$\mu^* = \overline{OS}.sigmoid\left(\varphi \overline{OS}\right) \quad (13)$$

Where, φ refers to the learnable parameter. Finally, the similarity between the identified fingerprint and the database stored fingerprint data is computed using the Euclidean distance metric. The user is identified as an authenticated one if the distance is smaller than a pre-defined threshold, otherwise the user is considered as fake or imposter.

4. RESULTS AND DISCUSSION

Here, the outcomes of the proposed fingerprint recognition and verification system with an efficient feature selection mechanism are investigated against the existing models regarding some evaluation indicators. A Windows 10 Professional 64-bit PC with an i5-4570 3.20 GHz processor and 8 GB of RAM executes the system. The evaluations are done on the Fingerprint Verification Competition's 2004 (FVC 2004) database, accessible through http://bias.csr.unibo.it/fvc2004/download.asp. The selected dataset usually comes in four formats: DB1, DB2, DB3, and DB4. Each format has 110 unique fingerprint images with eight imprints per finger for 880 fingerprints. Each database part is divided into two disjoint subsets (A and B). Set B only contains the last ten fingers (80 impressions), which is made available to allow parameter tuning before the algorithms are submitted. Set A contains the first 100 fingers and eight impressions per finger (i.e., 800 impressions total), which is commonly used for the performance evaluation of fingerprint verification systems.

4.1 Performance Analysis

The performance of the proposed SWAGRU is weighted against the existing GRU, Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Support Vector Machine (SVM) models with respect to recognition accuracy, precision, recall, f-measure, False Acceptance Rate (FAR), Equal Error Rate (EER), False Rejection Rate (FRR), and Elapsed time, respectively.

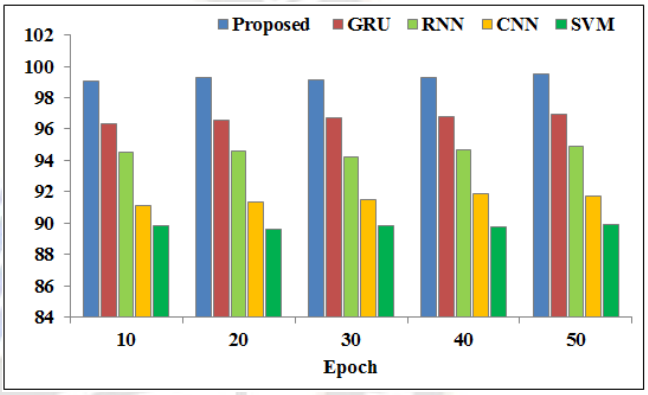

Figure 3: Training accuracy versus number of epochs

Figure 3 shows the training accuracy obtained by the proposed and existing systems when varying the number of epochs from 10 to 50. Epochs are the number of training iterations carried out across the entire network. For epoch 10, the proposed method achieves a better recognition rate than the existing methods. When increasing the epoch from 20 to 50, the proposed one slightly achieves a better accuracy rate. For example, the proposed one achieves a 99.08% recognition accuracy rate for epoch ten; increasing the epoch from 20 to 50 yields 0.46% greater than the ten epochs. Overall, it shows that the proposed method achieves superior results than the existing methods. Table 1 shows the average outcomes of the proposed method with existing methods based on the metrics mentioned earlier.

Table 1: Performance evaluation

Metrics	Proposed	GRU	RNN	CNN	SVM
Accuracy (%)	99.26	96.68	94.59	91.51	89.79
Precision (%)	99.35	96.74	94.68	91.69	89.91
Recall (%)	99.12	96.54	94.42	91.39	89.62

F-Measure (%)	99.28	96.74	94.63	91.56	89.85
FAR (%)	0	0.54	0.81	1.23	1.74
FRR (%)	0.102	0.215	0.382	0.496	0.769
EER (%)	0.432	1.167	1.269	1.275	1.363
Elapsed time (ms)	423	504	796	914	1075

The tremendous efficiency of fingerprint recognition and verification systems is displayed in the above table. As a result, the proposed method outperforms the traditional GRU, RNN, CNN, and SVM approaches regarding all metrics. Herein, first consider the accuracy metric. The proposed one achieves 99.26% accuracy, which is higher than the existing methods, because the existing GRU, RNN, CNN, and SVM methods achieve lower accuracy of 96.68%, 94.59%, 91.51%, and 89.79%, respectively. Likewise, the proposed one offers higher prediction efficiency than the existing methods for all the remaining metrics, i.e., the proposed one achieves 99.35% precision, 99.12% recall, 99.28% f-measure, 0% FAR, 0.102% FRR, and 0.432% EER, which are better outcomes than the classical approaches. Moreover, the elapsed time metric is essential to analyze the proposed work's outcomes. The proposed one takes 423ms to recognize the fingerprints, which is 81ms, 373ms, 491ms, and 652ms less than the existing GRU, RNN, CNN, and SVM methods. The results demonstrated that the suggested model succeeded in realizing its goals for categorizing and recognizing the fingerprint. As a result, the proposed system was able to complete complex computations in a short amount of time. So, the suggested system is trustworthy, efficient, and robust.

5. CONCLUSION

This paper proposes a novel fingerprint recognition and verification system using SWAGRU with an efficient feature selection mechanism. The experimentation was done with the help of a publicly available source, the FVC 2004 database. The experimental outcomes of the proposed SWAGRU are investigated against the conventional GRU, RNN, CNN, and SVM methods. This evaluation was done based on accuracy, precision, recall, f-measure, FAR, FRR, EER, and elapsed time. From experiments, the designed model performed well with these metrics and achieved 99.26% accuracy, 99.35% precision, 99.12% recall, 99.28% f-measure, 0% FAR, 0.102% FRR, and 0.432% EER, with a minimum elapsed time of 423 ms, which was better when compared to the existing methods in all metrics. According to the findings, the suggested method is scalable and appropriate for real-time applications that require fast fingerprint identification and verification.

REFERENCES

[1] Kaur, Navdeep. "A study of biometric identification and verification system." In *2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, pp. 60-64. IEEE, 2021.

[2] Tomar, Peeyush, and Ram C. Singh. "Cascade-based Multimodal Biometric Recognition System with Fingerprint and Face." In *Macromolecular Symposia*, vol. 397, no. 1, p. 2000271. 2021.

[3] Elsadai, Ali, Saša Adamović, Marko Šarac, Muzafer Saračević, and Sudhir Kumar Sharma. "New approach for fingerprint recognition based on stylometric features with blockchain and cancellable biometric aspects." *Multimedia Tools and Applications* 81, no. 25 (2022): 36715-36733.

[4] Ali, Syed Farooq, Muhammad Aamir Khan, and Ahmed Sohail Aslam. "Fingerprint matching, spoof and liveness detection: classification and literature review." *Frontiers of Computer Science* 15 (2021): 1-18.

[5] Ametefe, Divine Senanu, Suzi Seroja Sarnin, Darmawaty Mohd Ali, and Zaigham Zaheer Muhammad. "Fingerprint pattern classification using deep transfer learning and data augmentation." *The Visual Computer* 39, no. 4 (2023): 1703-1716.

[6] Qing, Guangwei, Huifang Wang, and Tingping Zhang. "Radio frequency fingerprinting identification for Zigbee via lightweight CNN." *Physical Communication* 44 (2021): 101250.

[7] Patro, Kiran Kumar, Allam Jaya Prakash, M. Jayamanmadha Rao, and P. Rajesh Kumar. "An efficient optimized feature selection with machine learning approach for ECG biometric recognition." *IETE Journal of Research* 68, no. 4 (2022): 2743-2754.

[8] Chowdhury, AM Mahmud, and Masudul Haider Imtiaz. "Contactless fingerprint recognition using deep learning—a systematic review." *Journal of Cybersecurity and Privacy* 2, no. 3 (2022): 714-730.

[9] Saponara, Sergio, Abdussalam Elhanashi, and Qinghe Zheng. "Recreating fingerprint images by convolutional neural network autoencoder architecture." *IEEE Access* 9 (2021): 147888-147899.

[10] Lee, Samuel, Seok-Woo Jang, Dongho Kim, Hernsoo Hahn, and Gye-Young Kim. "A novel fingerprint recovery scheme using deep neural network-based learning." *Multimedia Tools and Applications* 80 (2021): 34121-34135.

[11] Dincă Lăzărescu, Andreea-Monica, Simona Moldovanu, and Luminita Moraru. "A fingerprint matching algorithm using the combination of edge features and convolution neural networks." *Inventions* 7, no. 2 (2022): 39.

[12] Sreeja, N. K. "A hierarchical heterogeneous ant colony optimization-based fingerprint recognition system." *Intelligent Systems with Applications* 17 (2023): 200180.

[13] Nguyen, Long The, Huong Thu Nguyen, Alexander Diomidovich Afanasiev, and Tao Van Nguyen. "Automatic identification fingerprint based on machine learning method." *Journal of the Operations Research Society of China* 10, no. 4 (2022): 849-860.

[14] Öztürk, Halil İbrahim, Berkay Selbes, and Yusuf Artan. "Minnet: Minutia patch embedding network for automated latent fingerprint recognition." In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1627-1635. 2022.

[15] Saeed, Fahman, Muhammad Hussain, and Hatim A. Aboalsamh. "Automatic fingerprint classification using deep learning technology (DeepFKTNet)." *Mathematics* 10, no. 8 (2022): 1285.