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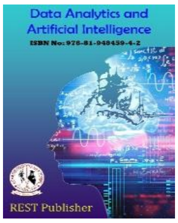

Comparison of Fingerprints using Enhanced Convolutional Neural Network

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Abstract: *The comparison of contactless and contact-based biometrics is a crucial subject in biometrics investigation. Contact-based fingerprint scanner has been used in the industry for several years, but contactless fingerprint identification is a relatively new area of research with several benefits. Yet, considerations like as image quality and sharpness might have an impact on the operation of contactless devices. Different technologies, such as feature extraction and deep learning algorithms are explored to evaluate contactless and contact-based fingerprints and enhance the precision of contactless fingerprint identification. The advancement of such technologies has the potential to broaden the usage of contactless fingerprint identification in a wide range of uses, such as network access and mobile device identification. The methodology of the proposed system is to improve the image and produce a more precise evaluation.*

1. INTRODUCTION

Fingerprint identification is a prominent identity verification process that is popularized because of its remarkable reliability and simplicity of use. This technique is employed to recognizeone's personal distinctiveness, as proof in a criminal and forensic investigation. Also it has a significant function in police departments, forensic examination, and banking transactions. It is an important means of determining the identity of human beings[9]. Conventional fingerprint verification technologies need a firm connection between all fingerprint scanner and the participant's fingertips. Contactless fingerprint scanner technologies are lately been developed as a substitute to classic contact-based techniques. Contactless systems have various benefits compared to conventional methods, like improved cleanliness, efficiency, and use.
The biometric authentication system verifies an individual's identity by using fingerprint patterns [10]. The technology scans and analyses the individuals fingerprint's ridges patterns, whorls, as well as other unique features to build a digital model [15]. In general there are two kinds of fingerprint recognition systems are available in the market. The optical fingerprint identification system employs a film camera or scanning machine to capture the fingerprint. The collected image is looked over to identify the distinct ridge patterns as well as other fingerprinting characteristics. The capacitive fingerprint identification technique works by sensing the electrical impulses created by the ridges and troughs.The device employs a network of small sensors to detect fluctuations in the electrical power and build a digital copy of the fingerprint[11]. In certain circumstances, live fingerprints are observed and distinguished from those of the deceased [12].
There are several techniques are employed to perform the fingerprint recognition. CNN compares the functionality of several systems for recognizing fingerprints and identify the one which is preferred for a particular application [14]. Patterns based finger print identification system employs an enhanced CNN network-based technique to examine the similarity among contactless and contact-based fingerprint systems. The content of this document has the following structure: Part 2 offers a brief description of contactless and contact-based fingerprint recognition systems, and then covers the subject of CNN-based fingerprint

identification in Section 3. The section 4 outlines the experimental setup and datasets considered in the proposed method's investigation. Section 5 presents and analyses the research findings.

2. Related works

The authors concentrated their efforts in this study on Machine Learning (ML) approaches for fingerprint recognition. The authors clearly stated that the finger print is the biometric property with the highest degree of safety when related to certain biometric authentication methods. This also has the advantage from being affordable to implement across real-world environment. It is quite challenging to come up with a good technique that possesses all of the properties required for finger print identification and categorization. Utilizing emerging technologies, machine learning algorithms emphasize the problem and provide a remedy for the key challenges with finger print identification [2]. The authors of this study concentrated particularly on the importance of finger print identification compared to alternative types of authentication schemes. The authors stated that fingerprint authentication is preferable than a variety of other authentication techniques, so their primary goal was to investigate CNN's finger-print identification functionalities. Researchers aim to investigate the importance of contact-free finger print authentication with simple machine learning approaches [1].The authors discussed about the finger print authentication used as a growing tool in forensic evidence and information security, along with other fields [3]. The proposed approach is susceptible to a variety of issues, including misaligned digits from badly captured hands, as well as usage patterns, that is critical in finger print registration. These are the key reasons why many users seek to circumvent finger print identification, and the authors concentrated on all of these problems in their study and sought to propose an acceptable answer to each of them.

ConvNet is used to differentiate between real fingerprints. Modern benchmark datasets are produced using pre-trained CNN model, yielding insights irrespective of architectural or hyper - parameter selection. Moreover, they showed that all these algorithms had great accuracy on a limited amount of training data sets. The conventional computer vision approaches did not additionally use a task-specific hand-engineered technique. Despite the differences in the obtained images, the researchers employed a variety of sensors to train a single classifier to produce the accurate results. These datasets improved accuracy and robustness. This suggests that if several datasets are used, the labor required constructing a real - time intrusion could be significantly reduced. These sensors are integrated during the development of a single classifier [4].A fingerprint recognition technique that is fully dependent on CNN is presented in this work. The pre-processing algorithms enhance the fingerprint's quality, which would be frequently lowered throughout the acquisition procedure. The characteristics of the fingerprint image are recovered by flattening the ridge lines, which has been achieved by an unique application of the skeletonization approach. The proposed thinning method is now operating more effectively. The system's performance is also measured using two biometric variables, FAR and FRR, in to perform prospective trade-off assessments in implementations [8].

3. Methodologies

Pre-processing allows enhancing the pixel density before training the model. It entails translating, filtering, and structuring original data into a meaningful pattern. By eliminating unimportant content, lowering distortion, and addressing discrepancies in the dataset improves the quality of the data. The proposed model pre-process the input image using scaling, translation, rotation, and resizing, as well as operations including Gaussian Blur.

Gaussian Blur: Convolving the source image with Gaussian filtering kernel yields the Gaussian blur operation. Convolution is accomplished by sliding the kernel across each pixels of the picture, multiplication of each pixel value by the corresponding kernel value, and combining the results. After that, the resultant value is allocated to the relevant output neuron. Convolution is performed for each pixel in the image, producing a flattened image. The degree of smoothness performed to the image is determined by the dimension of the kernel as well as the variance of the Gaussian function..

Scaling: The intention of scaling in CNN is to modify the image size to reach a particular given threshold while preserving the original image size. This is useful in situations in which the picture size is fixed, including such object recognition or segmentation techniques. Scaling is accomplished using a variety of approaches, including bilinear interpolation and bicubic interpolation. These approaches include computing the resized object's number of pixels according to the initial image's pixels.

Translation: Translation in CNNs is used to diversify the traininginformation through a slightly modified versions of the initial pictures. This assists in avoiding over fitting and increases the network's generalization capabilities. During training, the network chooses a randomly of translations path and distance for each picture and performs the shift prior to actually sending it to the network. The amount of translation used might range from just a few pixels to a significant portion of the bounding box.

Rotation: The rotation procedure entails making a geometrical alteration to the input images by rotating it to a specified amount. This is accomplished by the use of various rotation methods, such as bilinear or closest neighbour interpolation. After that, the rotated picture is sent into the CNN for training or prediction. The CNN can improve its ability to identify these fingerprints regardless of their position by training on rotated images.The angle of rotation is a key issue while applying rotations in CNN during pre-processing. When the inclination is too great, the rotated images become distorted and lost critical details. On the reverse side, if the angle is too tiny, the rotated pictures may be too like the initial images, resulting in over fitting.

Resizing: Resizing is a crucial pre-processing step in CNNs that ensures all pictures have an identical size and lowers the computing cost of the network. The smaller images demand less storage and processing time, and reduce the computational cost while training the network. The aspect ratio of the image varies during the resizing process, resulting in distortion or stretching of the image. Padding is the process of adding additional pixels to an image in order to make it fit a specific size while keeping the aspect ratio. To prevent distortion or stretching, padding is applied to the image's edges to shrink while maintaining its aspect ratio. The extra cells are filled with zeros or values determined by the heuristics of the image.

Data Augmentation: The linear translation that retains parallelism and distances between points is known as an affine transformation. CNNs tend to use affine transformations to perform operations on input images. An affine transformation can be described mathematically as a combination of a linear transformation and a translation where x is the input picture. A is the transformed image's linear matrix, b is the translation vector, and T(x) is the modified image. Backpropagation is used during training to learn the affine transformation parameters of the matrix A and vector b. This enables the CNN to acquire the best transformation for every single layer dependent on the job and dataset.An augmentation sequence consists of GaussianBlur and Affine based augmentations. The image was blurred with a Gaussian blur with a sampled at random deviation from the mean sigma between 0 and 0.5. According to the Figure 1, the affine augmentation performs a random affine modification. The scale option adjusts the image sequentially in the x and y dimensions by a random number between 0.9 and 1.1. The translate option shifts the picture by a random percentage of -10% to +10% in the x and y dimensions. The rotate option rotates the image by an arbitrary angle between -30 and +30 degrees. The order option defines the interpolated order to be used while performing the affine transformation.The cval specifies the value to be used for pixels outside of the image's borders. The acquired findings show the original fingerprint and the data pre-processing procedures that were applied to the image. The aug 01 represents the image's Gaussian blur. The image in aug 02 is scaled 90 to 110% in the x axis, while the image in aug 03 is scaled 90 to 100% in the y axis.The optimised scaled image is the aug 04 image. The image in aug 04 is translated by -10 to 10% in the x-axis, while the image in aug 05 is translated by -10 to 10% in the y-axis. The aug 06 has been rotated by -30 to 30%. The order of the image is aug 07 to have a more in-depth look at the image. The image's distant look is aug 08. The aug 09 is the result of denoise when the background is disregarded.

4. Proposed segmentation technique

Enhanced CNN Model: CNNs is viewed as the most effective solution for image processing and computer vision problems due to its ability to acquire complicated visual features, accommodate spatial features, trained and scalable. As a result, CNN performs well and it is extensively employed in a variety of fields, like autonomous vehicles, diagnostic imaging, and facial identification.

Proposed CNN architecture: CNN architecture employs a series of layers to acquire all complicated features from an input image. The first layer is a convolutional layer that extracts features from the input image by applying a set of filters. The second level is a max pooling layer that decreases the feature space dimensions of the preceding layer's outputs. The third level layer helps to smooth the preceding layer's output into a 1-D vector that transfers the data to the fully linked layer. The fourth layer is a fully linked layer that generates an output matrix. To create a probability distribution across the potential classes, the output layer, in its last step, applies a softmax or sigmoid activation function to the output of the preceding layer. The proposed system employed a CNN architecture and shown in Figure 2. This model uses two CNN models with identical weights but distinct input images for the feature models. There are two convolution layers and a pooling layer in the proposed models was compared. The convolution features a 32-filter kernel that is 3x3 in dimension that has identical padding and a relu activation function. The maximum size of the pooling layer is 2. The two feature model is the input for the subtract function.The model is then trained using two dense layers, the first of which has an activation function sigmoid and the second of which has an activation function relu.

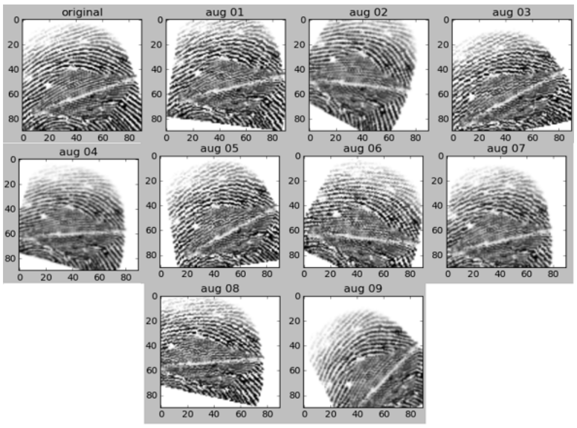

FIGURE 1. Data Pre-processing result

of carbon and silicon is analyzed based on stress, strain and other parameters and various wheel rim geometry and different loading conditions will impose. 3D model is created using various tools in CREO. For finding the variation the analytical calculations are done for some cases through finite element analysis. It's a powerful tool for numerical procedure to obtain solutions for engineering analysis. We can find a complex region for complex regions into simple geometric shapes. It's all done by finding loading and boundary condition.

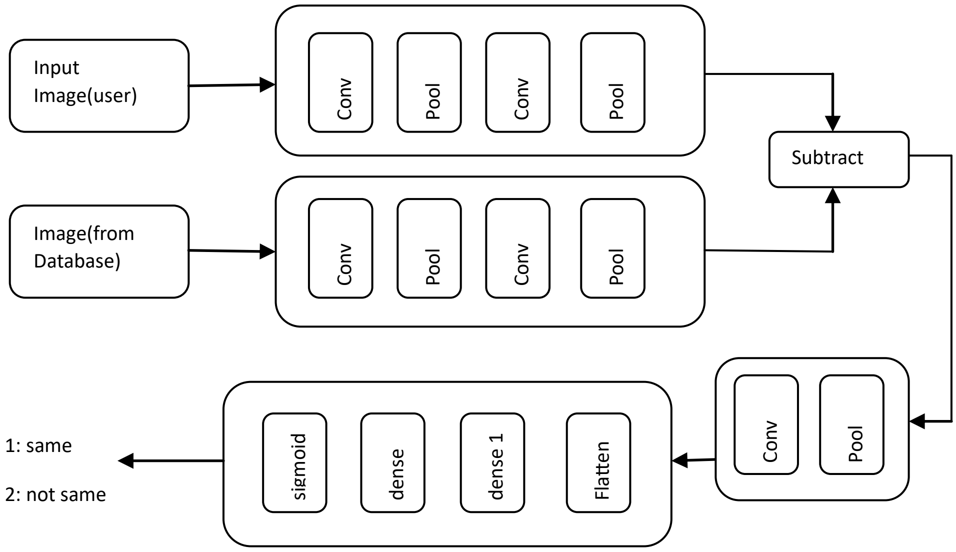

TABLE 1. Model summary Table

Layer	Type	Output Shape	Params	Connected To
input_1	Input Layer	(None,90,90,1)	0	-
input_2	Input Layer	(None,90,90,1)	0	-
model_1	Model	(None,22,22,32)	9568	input_1[0][0] input_2[0][0]
subtract_1	Subtract	(None,22,22,32)	0	model_1[0][0] model_2[2][0]
conv2d_3	Convolutional 2D	(None,22,22,32)	9248	subtract_1[0][0]
max_pooling_2d_3	Pooling Layer	(None,11,11,32)	0	conv2d_3[0][0]
flatten_1	Flatten	(None,3972)	0	max_pooling_2d_3[0][0]
dense_1	Dense	(None,64)	247872	flatten_1[0][0]
dense_2	Dense	(None,1)	65	dense_[0][0]

5. Experiments and Results

Datasets: The Sokoto Coventry Fingerprint Dataset (SOCOFing) biometric fingerprint dataset consists of 6,000 fingerprint images from 600 African individuals, as well as copies of them have been electronically changed with three various degrees of obliteration, central rotations, and z-cut at each degree of alteration. This kaggle fingerprint dataset is divided into two parts: changed and easy. The changed file is divided into three subdirectories: Altered-Easy, Altered-Medium, and Altered-Hard. These subdirectories include a maximum number of 49,300 files, with Altered-Easy including 17,900 files, Altered-Hard containing 14,300 files, and Altered-Medium containing 17,100 files. On the other hand, the Real section has around 6000 actual fingerprint images.

Modal Summary: As shown in Table 1there are two input layers with identical dimensions. The two input layers have the same structure and feature, which has two convolutional layers and two pooling layers, with the two convolutional layers having the same kernel size, padding, and activation function. The relu activation function is used in this instance. The two input layers are then supplied to a feature model to a remove feature. The two models are compared in this remove feature, and the resultant model is then sent to a convolutional neural network.

Loss Function: The binary cross-entropy is a loss function that is extensively used in machine learning, especially in binary classification issues. The target variable in binary classification has two potential values: 0 or 1. The binary cross-entropy loss function calculates the difference between anticipated and real binary labels. The formula is as follows:

$$L(y,p) = -[y \times \log(p) + (1-y) \times \log(1-p)] \qquad \text{------------------(1)}$$

where ‘p’ represents the anticipated probability of the true positive and ‘y’ represents the real binary indicator (either 0 or 1). As per eqn(1), its first term calculates the loss when the actual label is 1, whereas the second term calculates the loss when it's 0. Whenever the projected probabilities are distant from the real label, the error function penalizes the model more.

D. Experiment Analysis

The training loss and validation loss, as well as the training accuracy and model validation accuracy are determined based on the CNN model architecture and the loss function. The training loss vs. validation loss graph is shown in Figure 3. The graph clearly shows that as the epoch size grows, the training loss rapidly lowers until it equals the validation loss. This demonstrates that the model is effective.

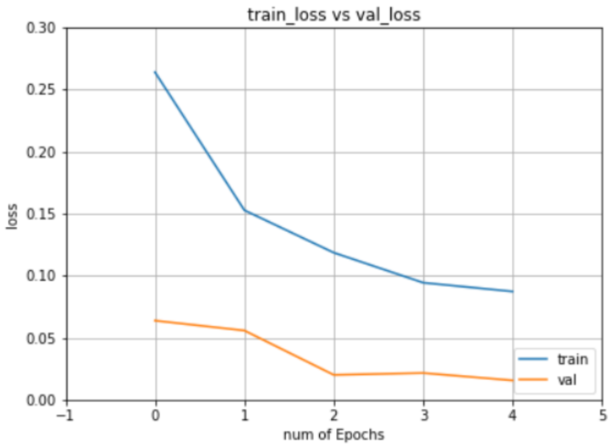

FIGURE 3. Train loss vs validation loss

Result: The associations between the resultant images are depicted in Figure 4. Where, Figure 4(a) represents the user fingerprint picture provided as input. Figure 4(b) represents the relatable fingerprint image that matches the input image, and Figure 4(c) represents the fingerprint image that does not match the input image. The Input is the fingerprint of the user, and it contains impurity as evidenced by a blurred image conditions in the middle. Zero represents a comparable fingerprint that resembles the structures of the source images and is selected depending on the binary crossentropy. The model returns '1' if the image resembles the patterns of the source images and has an accuracy of 99%, and X represents an unmatched image that has zero confidence when it resembles the structures of that same source images.

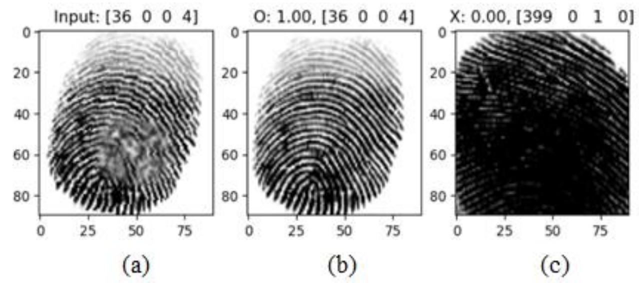

FIGURE 4. Comparison of the related & unrelated Fingerprint images. (a) Input (b)Related (c) Unrelated

TABLE 2. Comparison of the proposed CNN with competitive methods

Authors	Methods	Accuracy
Sarbadhikari et al., [16]	Two-staged fingerprint classifier	84%
Mohamed et al., [17]	Fuzzy neural network	98.35%
Kumar et al., [18]	Multi-dimensional ANN	97.37%
Kristensen et al., [27]	Multi-Layer Perceptron	88.8%
Liu et al., [20]	Support Vector Machine	96.03%
Proposed method	**Enhanced CNN**	**99%**

As shown in Table 2, the proposed CNN method outperforms the competitive methods and produced the accuracy of 99%.

6. CONCLUSION

The comparison of CNN-based methodology with the contactless and contact-based fingerprint identification offers significant knowledge into the strengths and drawbacks of various researchers' outcomes. The proposed method shows that contactless fingerprint identification systems outperform contact-based systems in various ways, including simplicity of being used, lower possibility of cross-contamination and infections, and higher accuracy and comfort. The findings of the system emphasise the need of selecting the appropriate fingerprint recognition method for the desired process. In some cases, like when great precision is needed or even when contending with low-quality fingerprints where the contact-based systems may continue to be the best option. Overall, the enhanced CNN model is an effective tool for analysing and enhancing fingerprint identification methods. It has the potential to steer future advancements.It might serve as a roadmap for future research in this area and eventually result in biometric authentication systems that are more precise, effective, and easy to use.

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