Developing an algorithm for Fingerprint Recognition of Newborns and Toddlers based on Deep Neural Networks and Transfer Learning

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Abstract: In the late 19th century, Sir Galton started the use of fingerprint recognition as a method for baby identification. However, even after the extent two centuries, fingerprint identification for newborns and toddlers has not advanced to the same level as that for adults. According to research from the International Centre for Missing and Exploited Children, there is a growing request for fingerprint identification of babies because more than a million of them go missing each year. So, we want to ensure that newborns and toddlers have access to their rights, including vaccinations, healthcare, and nutritional supplements until they reach school age. This paper develops an algorithm that has been used in previous research to recognize newborns and toddlers to produce remarkable and promising results by Pre-trained model deep neural networks and transfer learning to extract the deep features and to get the identification score, aiming to enhance accuracy and validate. The proposed model is validated on the fingerprint dataset of babies named as NITG dataset. The fingerprint recognition model proposed in the research showcases excellent results, where achieved 100% accuracy in training and 90.35% in validation.

Keywords: Fingerprint recognition, Newborns and Toddlers, Pre- trained mode, deep neural networks, transfer learning

1. Introduction

According to Sir Galton's hypothesis, the likelihood of two adults having the same fingerprints is 1 in 64 billion [1], making fingerprints the most used biometric for adult identification globally. The universality, performance, resistance, collectability, uniqueness, acceptability, and permanence to circumvention are the seven criteria for the desirable qualities of biometric features that this fingerprint identification method is based on [2]. Researchers investigated various biometrics, including palmprint [3, 4], headprint [5], face [6-9], footprint, and ear [5, 10], to identify children. However, children's fingerprints exhibit distinguishing characteristics that can distinguish them from others, even though they are still in the developing stage. For newborns and toddlers, the rate of mishaps happening to them is increasing day by day, representing kidnapping and not receiving full vaccinations and health care due to the non-availability of an authentic system for recognition them. The issue with minutia recognition for newborns and toddlers is biometric aging. According to research on age and aging in fingerprints, the most difficult age range was 0–4 years [11]. The accuracy of standard equipment, the poor picture quality of the fingerprints, and a pronounced aging effect impact were all problems in fingerprint analysis [12, 13]. Small features in the fingerprints of babies, such as Ridge, Valley, Ridge Ending, and bifurcation, as shown in Fig. 1, can be recognized to aid in fingerprint recognition. Different minutiae are compared to one another in minutiae recognition, and the match with the highest recognition probability is deemed to be right.

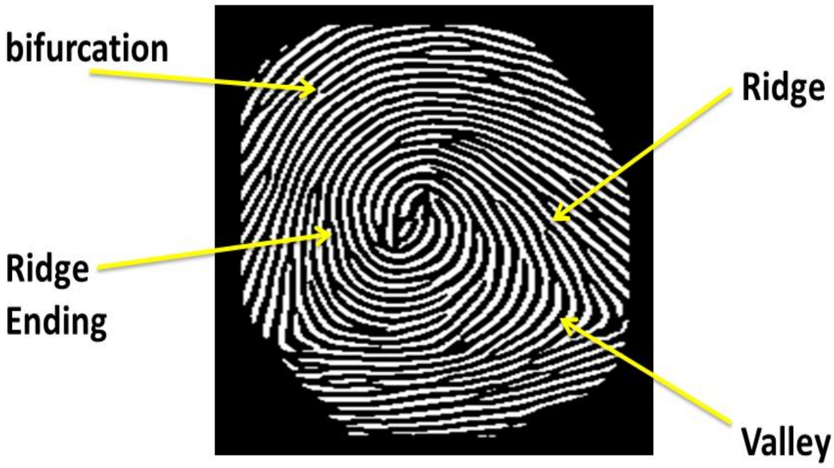

Fig 1: Some Small features in fingerprints of babies

At birth, the distance between ridges on a newborn's fingerprint is 100-150 microns [14]. For an adult is 450-500 microns. Since the ridge distance is up to 5 times smaller for newborns compared to adults, we need a resolution 5 times greater than is needed in adults to resolve the ridges for newborns and toddlers.

The sections of the paper include an Introduction, which elaborates on the need for fingerprint recognition of newborns and toddlers. The Related Work, on newborns' and toddlers' fingerprint identification systems is elaborated. Methodology, which gives an overall idea of the method used in the proposed algorithm. The experimental results and discussion were achieved after using the proposed algorithm with a comparison between the proposed method and previous works. Finally, concludes our research work, followed by a list of references.

2. Related Work

In this section, we review previous works on the fingerprints of babies. We mention among them, Preciusi et al [13] created a scaling factor based on the distance between bumps of adult age and baby age. The accuracy of children's fingerprint verification improves with these scaling factors. Koda et al [15] to capture the precise features of children's fingerprints and recognition, a high-resolution 1270 ppi fingerprint scanner was created. Jain et al [12] to boost immunization coverage for the age period from 0 to 4 years, employed a sampling procedure with a factor of 1.8 to match the finger edge distance for adults. Haraksim et al [16] fingerprints' tiny details are used in a computed growth model to minimize the biometric aging score when recognizing children. Additionally, fingerprint system hardware is put into use to test the precision of fingerprint identification. To identify newborns and toddlers, the majority of researchers employed commercial software identification tools (SDKs) [17, 18]. Including Jain et al [19] To further their investigation on toddlers identification, they created the toddlers longitudinal database, used CNN to enhance the quality of images, and the commercial SDK used to extract and match features. Camacho et al [20] have put out a factor interpolation approach to fingerprint sampling based on children's ridge distance. Engelsma et al [21] used the 1900 dpi RaspiReader they created to study the issue of babies recognizing immunization and dietary supplies. Two commercial off-the-shelf (COTS) texture-based CNN matches were used to extract the features. Engelsma et al [22] 0 to 3-month-old babies were investigated to lower infant mortality. They took the baby's fingerprints using a 1,900 dpi scanner and observed to show an improvement in accuracy. Patel et al [23] created a baby's fingerprint recognition system by features extracting fingers using a Gabor filter and matching them using Euclidean distance. Molla et al [24] examined the most effective method for identifying babies by their ear, iris, and fingerprint. Shabil et al [25] used Pre-trained model of Keras applications with CNN custom by transfer learning for recognition of newborns and toddlers by using multiclass. Kamble V et al [26] discrete Cosine Transform (DCT) characteristics, machine learning classifiers, and deep learning algorithms are used to identify children. The mid-and high-frequency bands of the DCT coefficient are used to derive the handmade fingerprint traits.

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3. Methodology

In this research, transfer learning by a Pre-trained model is proposed based on the Deep Learning algorithms ResNet-152 Model to quickly and precisely authenticates and identify newborns and toddlers using their fingerprints.

In a previous research, an algorithm based on deep learning through transfer learning was used with Model ResNet-50 to recognize newborns and toddlers and gave promising results, but still shortcomings, in this research, an algorithm was developed using a model deeper than it in recognition and accuracy, which is Model ResNet-152 based transfer learning and gave results Excellent, and here we will compare the two algorithms.

The proposed deep learning model involves a few steps to be fulfilled to improve the accuracy of fingerprint recognition of newborns and toddlers, as shown in Figure 2.

After the acquisition of the dataset, the pre-processing process is performed, and it includes cropping the image so that only the position of the fingerprint remains, because children's fingerprints are small, and then we perform the process of resizing the image so that all images are of one size, and then we perform the enhancement for images. The dataset was subsequently divided into training and testing. After training and testing, the proposed AI model is providing predictions (Recognition) that come. If a newborn or toddler's fingerprint is not present in the dataset, it will be considered (an unrecognition) result and must to entered into the enrollment stage for taking a fingerprint. Once the recognition) the result appears necessary actions will be taken to provide the child with their rights, as mentioned in the objectives of this study.

In this research, the used methodology is not binary class, it is multiclass, and that is that we put all five fingerprints of the child taken from the thumb finger only in an independent class, meaning that we have classes with the number of all children. The operation of each stage of the proposed technique is described as follows:

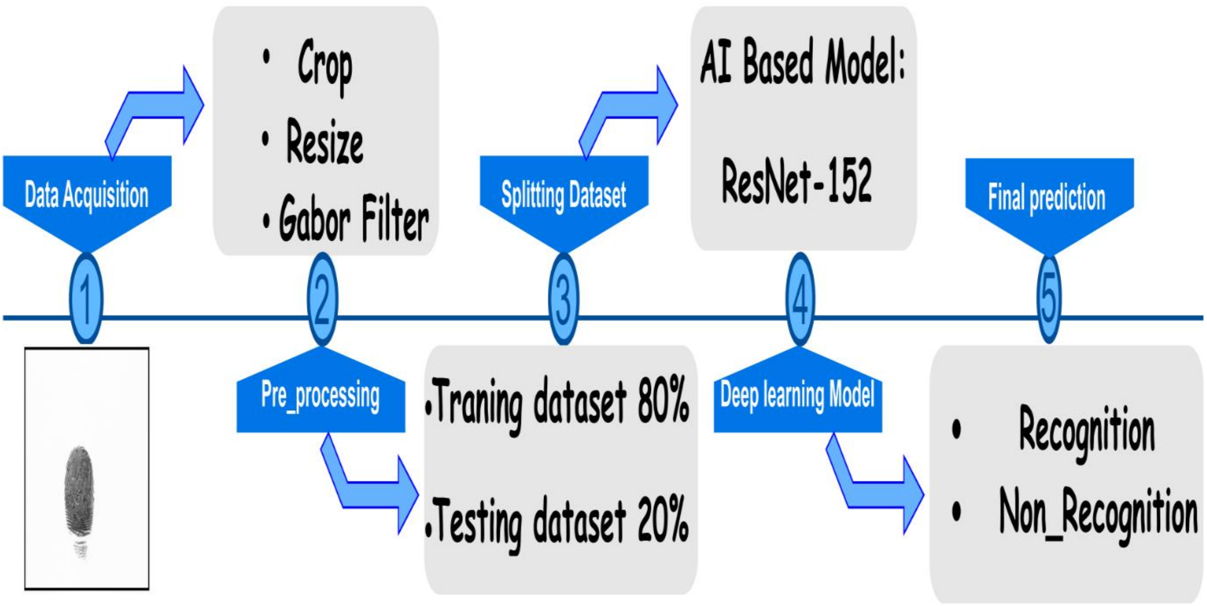


Fig 2: The proposed method

3.1 Data Acquisition Module

Most of the databases of fingerprint babies are not available due to security reasons except the database of the National Institute of Technology Goa (NITG), India 2019 for research purposes.

This research used a dataset (NITG) [23] consisting of 154 subjects a total of 770 images of the left thumb who ranged in age from 0 to 5 years, five images of each subject's left thumb print was taken for each one.

Taken fingerprints using machine Real Scan G10 Multi Fingerprint Scanner (Suprema) with 500 ppi resolution, it was in BMP type and then we converted it to PNG type because of the advantages this type has. Some sample images of this dataset are displayed in Fig. 3.

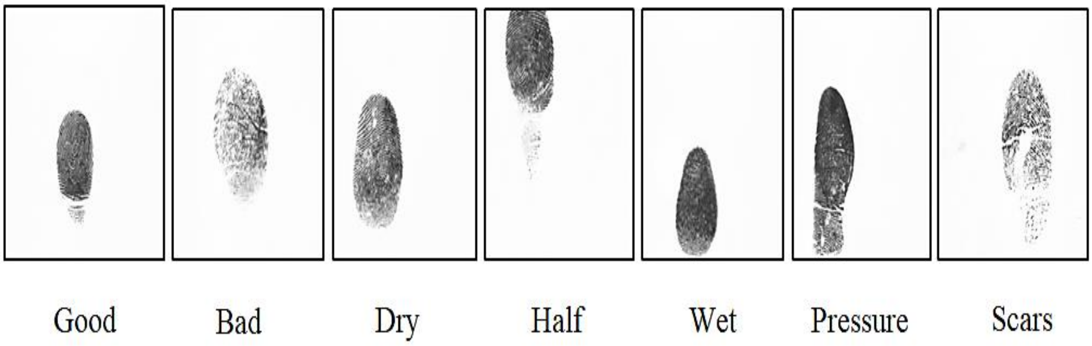


Fig 3: Some sample images of dataset (NITG)

3.2 Pre-Processing Module

In this module, for improving the recognition rate the input fingerprint image must be enhanced. In this research, there are three main steps: First, because babies' fingerprints are so small on the fingerprint scanner, we had to crop everything around the fingertip except for its position. To extract the feature of fingerprint only.

Second, the blurry images make it difficult for the fingerprint recognition system to read the newborns and toddlers' fingerprints, according to NFIQ 2.0 [27]. So, we used the Gabor filter for image enhancement because it has important characteristics such being frequency- and orientation-selective [28], and is appropriate for frequency and spatial domains, which are necessary for exact feature extraction and matching. The major goal of this step is to provide clear input fingerprint images of newborns and toddlers.

Last, the fingerprints are resized into the dimension of (300*300) after doing cropping and enhancement. Figure 4, illustrates this module.

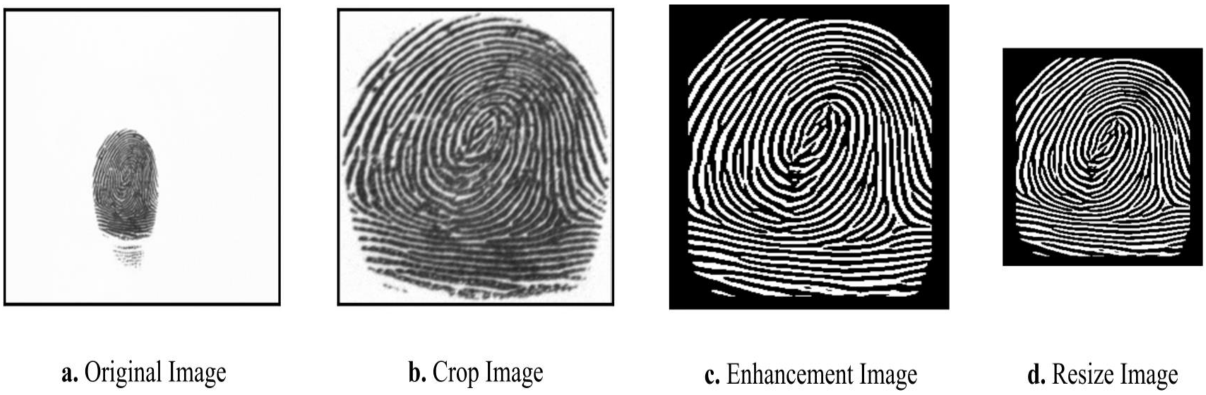


Fig 4: Fingerprint Pre-processing Module

3.3 Data Splitting Module

Our dataset comprises 154 subjects, each one of them having five image fingerprints on their left thumb, using four of each newborn's and toddler's fingerprints for training and one fingerprint for testing, the dataset was divided into training and testing groups of 80% and 20%, respectively. Table 1 displays the number of subjects acquired from the training and testing dataset.

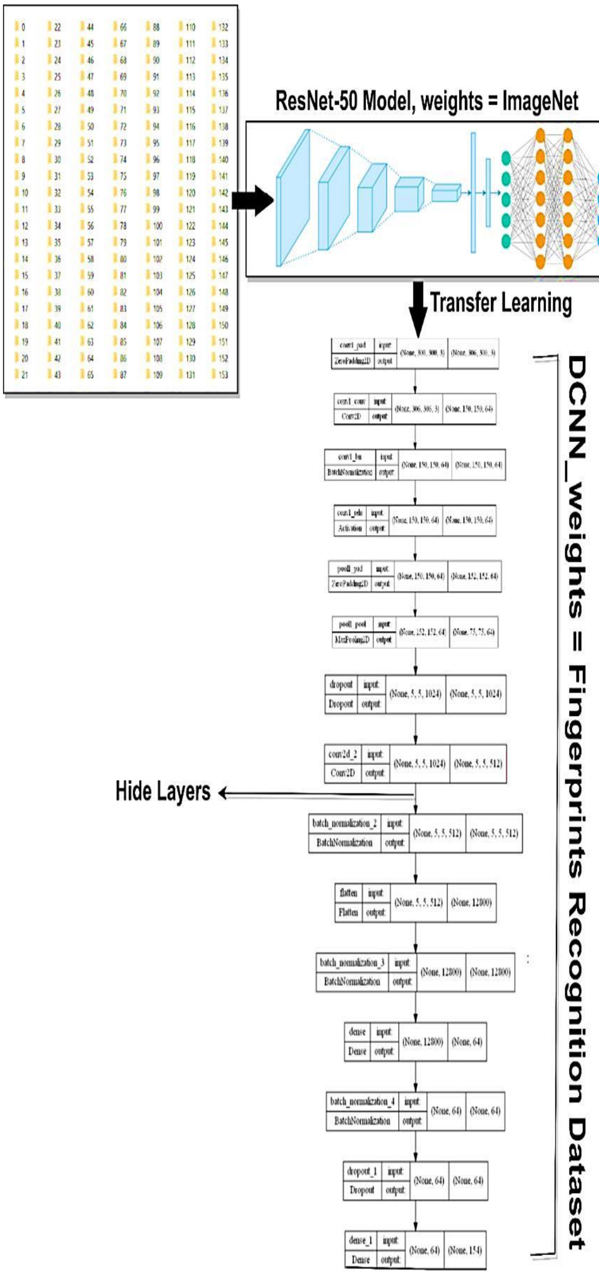
Table 1: Size of the training and testing dataset

Name of Dataset	NITG
Subjects	154
Training fingerprints (80%)	616
Testing fingerprints (20%)	154
Total fingerprints number	770

3.4 The proposed AI Model

The previous algorithm relied use a pre-trained model called ResNet-50 model-based transfer learning under convolution neural networks [25]. The ResNet-50 model provides deep layers to detect fingerprint features, as its layers contain 50 layers and use 3-layer bottleneck blocks to ensure improved accuracy and shorter training times, The ResNet-50 model consists of 5 stages each has a wrapper block and an identity block. There are three wrapper layers in each identity block and each wrapper block.

The deep learning model of ResNet50 was pre-trained using ImageNet. This pre-trained weight was used for this study based on the transfer learning strategy, and the optimizer used was Adam the highest accuracy was achieved when the number of units was 1024, the learning rate was 0.001, and the number Batch size of epochs was 64, details of this algorithm in the following:



A1: Fingerprint Recognition DCNN Proposed Algorithm

Input: Upload NITG Dataset to platform Jupyter

Output: Prediction Multi Classification (154 Classes)

Begin

Step1: Load "ResNet-50" model with weights which trained on ImageNet dataset

Step2: Freezing "ResNet-50" model layers so didn't change

Step3: Add Output layer

Step4: Add AveragePooling2D layer and set parameters:

- Pool_size = (2, 2)

Step5: Add Conv2D layer and set parameters:

- Conv2D =1024, size = (3,3)
- padding = "same"
- Activation = "relu"

Step6: Add BatchNormalization layer

Step7: Add Conv2D layer and set parameters:

- Conv2D =1024, size = (3,3)
- padding = "same"
- Activation = "relu"

Step8: Add BatchNormalization layer

Step9: Add Dropout layer (0.50)

Step10: Add Conv2D layer and set parameters:

- Conv2D = 512, size = (3,3)
- padding = "same"
- Activation = "relu"

Step11: Add BatchNormalization layer

Step12: Add Flatten layer

Step13: Add BatchNormalization layer

Step14: Add Dense layer and set parameters:

- size = 64
- Activation function = "relu"

Step15: Add BatchNormalization layer

Step16: Add Dropout layer = (0.5)

Step17: Add Dense layer and set parameters:

- No. of classes (M = 154)
- Activation function = " softmax"

Step18: Add Compile function and set parameters:

- Learning Rate = 0.001 "Adam"
- Loss Function = "categorical_crossentropy"

Step19: Evaluation the model:

If Accuracy is optimal go to ***Step20*** else go to ***Step 3***

Step20: Prediction for Multi Classification

Step21: Save Model

End

We present here the proposed method by developing the previous algorithm through which we can extract the fingerprint features more accurately to solve the problem of fingerprint recognition in Newborns and toddlers.

The algorithm relies use a pre-trained model called the ResNet-152 model based on deep neural networks and transfer learning. The ResNet-152 model provides deep layers to detect fingerprint features, as its layers contain a depth of up to 152 layers, 8x deeper than VGG nets. The bottleneck of Torch Vision places the stride for down sampling to the second 3x3 convolution while the original paper places it to the first 1x1 convolution. This variant improves the accuracy [29].

ResNet-152 introduced the idea of residual learning, where features are subtracted from the input of that layer and learned utilizing shortcut connections (directly linking the input of the (n)th layer to some (n+x)th layer). It has been shown that residual learning may enhance the performance of model training, particularly when the model contains a deep network with more than 20 layers, and can also address the issue of deep networks' deteriorating accuracy. The architecture of ResNet-152 is shown in Figure 5.

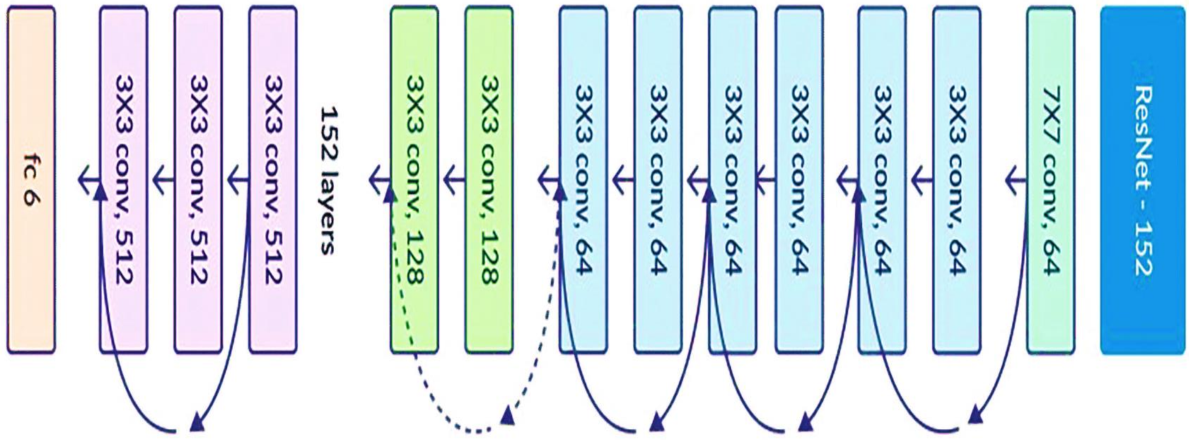
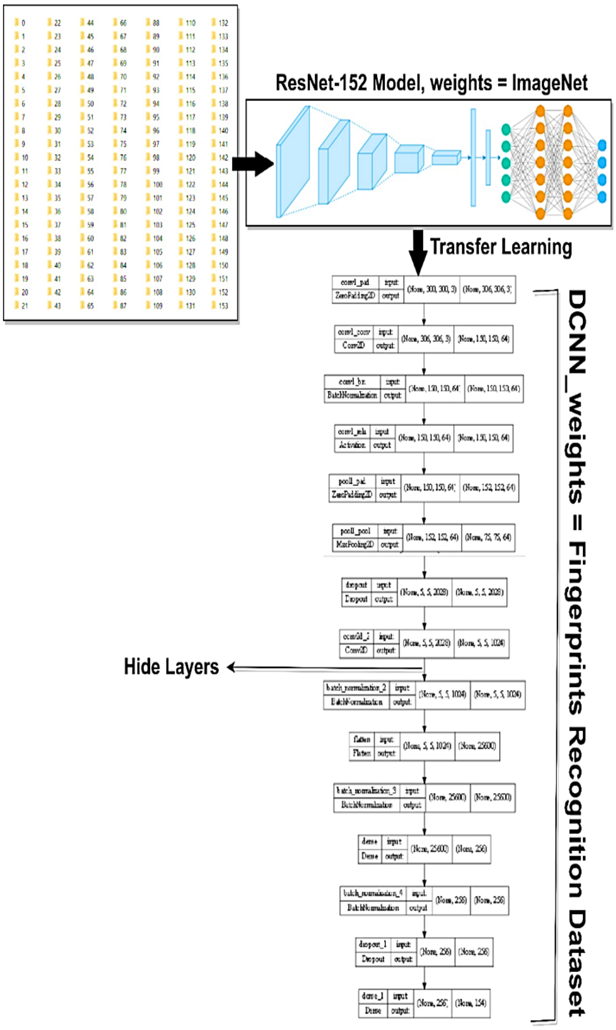


Fig 5: Architecture of ResNet-152

In this work, the deep learning model of ResNet-152 was pre-trained using ImageNet. This pre-trained weight was used for this study based on the transfer learning strategy, and the optimizer used was Adam the highest accuracy was achieved when the number of units was 2028, the learning rate was 0.001, and the number of Batch size of epochs was 64, details of this algorithm in the following:



A2: Development Fingerprint Recognition DCNN Proposed Algorithm

Input: Upload NITG Dataset to platform Jupyter

Output: Prediction Multi Classification (154 Classes)

Begin

Step1: Load "ResNet-152" model with weights which trained on ImageNet dataset

Step2: Freezing "ResNet-152" model layers so didn't change

Step3: Add Output layer

Step4: Add AveragePooling2D layer and set parameters:
- Pool_size = (2, 2)

Step5: Add Conv2D layer and set parameters:
- Conv2D =2028, size = (3,3)
- padding = "same"
- Activation = "relu"

Step6: Add BatchNormalization layer

Step7: Add Conv2D layer and set parameters:
- Conv2D =2028, size = (3,3)
- padding = "same"
- Activation = "relu"

Step8: Add BatchNormalization layer

Step9: Add Dropout layer (0.50)

Step10: Add Conv2D layer and set parameters:
- Conv2D = 1024, size = (3,3)
- padding = "same"
- Activation = "relu"

Step11: Add BatchNormalization layer

Step12: Add Flatten layer

Step13: Add BatchNormalization layer

Step14: Add Dense layer and set parameters:
- size = 256
- Activation function = "relu"

Step15: Add BatchNormalization layer

Step16: Add Dropout layer = (0.5)

Step17: Add Dense layer and set parameters:
- No. of classes (M = 154)
- Activation function = " softmax"

Step18: Add Compile function and set parameters:
- Learning Rate = 0.001 "Adam"
- Loss Function = "categorical_crossentropy"

Step19: Evaluation the model:
If Accuracy is optimal go to ***Step20*** else go to ***Step 3***

Step20: Prediction for Multi Classification

Step21: Save Model

End

3.5 Evaluation Metrics

According to the common assessment criteria employed by many researchers, such as accuracy and confusion matrix, the detection and classification phases were assessed based on Equation (1) to determine the accuracy of a machine learning model as a percentage.

$$\text{Accuracy(Acc.)} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (1)$$

Where TP (True-Positive) stands for predictions that were made correctly and matched as positive, while FN (False-Negative) stands for predictions that were made incorrectly and matched as negative. The term TN (True-Negative) refers to predictions that were made correctly but matched as being negative. Last, FP (False-Positive) refers to incorrect predictions that match as positive.

3.6 Execution Environment

An ASUS Company laptop was used for the experiment, and its characteristics were as follows: AMD Ryzen 9 5900 HX with Graphics Radeon (16 CPUs), 3.3 GHz, 32 GB of RAM, and a 16 GB NVIDIA GeForce RTX 3080 GPU. The experiments conducted for this study made use of Jupyter Notebook, Python 3.8.0, Windows 11, and the backend libraries Keras and TensorFlow.

4. Experimental Results And Discussion

4.1 Experimental Results

In this work, the fingerprints of stored babies are recognized by Multiclass classification. The numbers of the tested subjects were 154 from newborns and toddlers; the left thumb fingerprint was taken from each subject five images from several directions. The baby comes and puts his/her left thumb fingerprint in the sensor, It appears automatically either (Recognition) and the number of ID cards that gave him/her when the enrollment for previse time, meaning it is in our dataset, or it appears automatically (Non_Recognition), meaning it is not in our dataset, and he/she has to go to the first stage, which is enrollment, by taking his/her left thumb fingerprint five images from Several directions and giving him/her number of ID card. The trained model will extract all the features of the fingerprints automatically that will come to it by the enrollment stage and transfer them to the dataset store so that if this baby returns it will appear automatically (Recognition) with the number of ID cards.

The accuracy of fingerprint authentication was assessed using empirical data, and the performance and efficiency findings are displayed in Table 2. The accuracy of the proposed method for the fingerprint dataset is more than (90%) as shown in Table. It has a false rejection rate under (10%). The proposed approach requires an average of 3 seconds for recognition.

Table 2: Evaluation performance of the proposed AI Model

Evaluation Testing (20%)	**154 images**
Successful Verification	139
Unsuccessful Verification	15
True Acceptance Rate/ Verification Accuracy	90.35%
False Rejection Rate	9.65%
Authentication Time (Seconds)/ Sample	3 Seconds

4.2 Discussion

The research Enhancing Newborn and Toddler Fingerprint Recognition with AI and Machine Learning Techniques" proposes a biometric tracking mechanism using fingerprints for newborns and toddlers" to address concerns such as abduction, swapping, disappearance, and unlawful adoption. The objective is to ensure that newborns and toddlers have access to their rights, including vaccinations, healthcare, and nutritional supplements until they reach school age.

The related work presented provides a comparison of different studies focusing on children's fingerprint recognition. I will focus here on two studies that used the same dataset and methodology and I will compare them with my results.

First, A. R. Patil et al. (2019) [23], used features extracting fingers based on a Gabor filter and matching them using Euclidean distance for recognition of newborns and toddlers and achieved a validation rate of 81.82%.

Second, Shabil et al (2023) [25], used Pre- a trained model of Keras applications with CNN by transfer learning for recognition of newborns and toddlers and achieved a validation rate of 82.47%.

I developed an algorithm that used Shabil et al [25] and used another Pre- trained model called ResNet-152 by transfer learning to get the best result reached to validation rate of 90.35% as mentioned in section the Results. Table 3 shows the proposed method and compares it with tow study previous works that used the same dataset and methodology:

Table 3: Compared between the proposed method and previous works

Reference	Subjects	AI Method	Time	Accuracy (%)
A. R. Patil et al. (2019), [23]	154	features extracting finger based on a Gabor filter and matching them using Euclidean distance	7 Seconds	81.82
Shabil et al. (2023), [25]	154	Pre- trained model with CNN by transfer learning	2 Seconds	82.47
Our	**154**	**The proposed Model**	**3 Seconds**	**90.35**

5. Conclusion

In conclusion, this research focused on evaluating the effectiveness of the proposed ResNet-152 Model for the Recognition of fingerprints of newborns and toddlers. The evaluation utilized the dataset NITG. The proposed model involved several steps, including preprocessing, training, and testing. Given the small size of newborns' and toddlers' fingerprints, we cropped images to remove surrounding elements and ensure analysis only of the entire fingerprint. To enhance feature extraction from fuzzy images, a Gabor filter was applied for smoothing and then doing resize for all images. The dataset was divided into training and testing sets for recognition fingerprints. In this work, the trained model ResNet-152 demonstrated its ability to obtain excellent results by obtaining 100% on the training set and 90.35% on validation compared to previous results that used the same dataset and methodology.

In general, this research contributes to the field of fingerprint recognition for newborns and toddlers, providing a reliable and efficient approach to ensure their safety. The proposed ResNet-152 Model has fantastic performance and offers promising possibilities for improving the identification and protection of newborns and toddlers in various healthcare and security settings.

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