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Study of Deep Learning Methods for Fingerprint Recognition

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Abstract: ***Biometric systems aim to reliably identify and authenticate an individual using physiological or behavioral characteristics. Traditional systems such as the use of access cards, passwords have shown limitations such as forgotten passwords, stolen cards, etc. As an alternative, biometric systems present themselves as efficient systems with a high reliability due to the physiological characteristics of each individual. This paper focuses on a deep learning method for fingerprint recognition. The described architecture uses a pre-processing phase in which grayscale images are represented on the RGB bands and then merged to obtain color images. On the obtained color images will be extracted the characteristics of the fingerprints textures.The fingerprint images after preprocessing are used in a deep convolution network system for decision making. The method is robust with an accuracy of over 99.43% and 99.53% with the respective variants densenet-201 and ResNet-50.***

Keywords: Deep learning; fingerprint authentification; Biometrics system; CNN; DenseNet-201; ResNet-50.

I. INTRODUCTION

Biometric systems are a major security issue in modern societies. The use of biometric tools is transversal because they are present in many sectors of activity that increasingly integrate dematerialization. The major success of biometrics is the use of distinct physiological, biological and behavioral characteristics for each individual. This asset allows to identify and authenticate individuals in a discriminating and reliable way. Biometric systems involve the use of image acquisition devices that are either cameras or scanners. These devices in the mode of acquisition of images of fingerprints, faces, laughter, signature, voice can be constraining or not for the users. This often guides the choice of biometric methods by decision makers. Today, the most reliable systems are fingerprint and iris recognition. These two types of biometrics have the particularity of the rarity of identical subjects. The probability that two sets of fingerprints are identical is one in 64 billion according to the studies of Francis Galton in 1982 [1]. Concerning the iris, the probability that two individuals have the same irises is more than 10-52 [2]. For its operation, the features are extracted and coded in a reference model and then stored in an image base on a medium for identification or authentication purposes. The present paper makes a study on the implementation of a biometric fingerprint system. The motivation is that it is much known, less restrictive and the fingerprints contain many reasons but specific to each individual. In addition, the legal and forensic context is highly developed, especially in the field of crimes, robberies, etc. The complex texture that a fingerprint presents gives it my specificity of representation of reliable biometric data. A fingerprint image contains overlapping ridges and valleys. The uniqueness of fingerprints is explained by the multiplicity of several descriptive elements which are ridges, grooves and line orientation while the ridges are represented as arc, ball and spiral. This complex representation of the footprint presents image analysis elements which are texture and bridges of interest obtained bifurcations, ridge terminations and spots.This article has a double objective:

- Study two methods two deep convolution networks which are the DenseNet-201 and the ResNet50;
- Using the two deep convolution networks to build a robust fingerprint recognition system

For the adopted approach, a study is made on works in the field of fingerprint recognition. After study deep convolution network methods, a methodology is described for the proposed biometric system. Finally, the results obtained in the experimental part are presented and allow to conclude on the robustness of the proposed system.

II. RELATED WORK

Biometrics measures the uniqueness of an individual based on the physiological, biological and behavioral properties of their body. This tool presents itself as a reliable scientific method to identify and authenticate an individual, which are fundamental security principles. The present work makes a contribution on the fingerprint recognition which is a robust method and has the advantage of being easily accepted by the users. Faced with the major challenge of security, many attacks are emerging. In field of fingerprinting, there are fake fingerprints are made by using printed fingerprints, silicone, wood glue or other products [3]. As an alternative to classical fingerprint biometrics, research is being done on finger veins [4]. This technology uses infrared to observe vein features [5]. The use of infrared has the advantage of extracting characteristics from the skin of the finger and from the veins of the finger to avoid forgery, because veins cannot be forged. More and more studies are made on multimodal biometrics.

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In these studies, at least two modalities are used. Faced with the complexity and precision of the textures of the sweetbread and the fingerprint, several studies are interested in the dual modality of iris prints [6].

Recent research focuses on deep learning, which is widely used in computer vision and mainly in biometrics [7]. Its success is due to its robustness with better recognition scores. The study done in this work shows the performance of convolutional neural networks (CNN) in fingerprint recognition. CNN algorithms were applied to the fingerprint database named SOCOFing and the experimental results obtained are compared to the results of studies in the literature to prove the performance of the adopted methodology.. The different experiments were done with the CNN variants which are DenseNet-201 and ResNet-50 [8] [9]. In addition to the quality of the results obtained, metrics were used to evaluate the scores obtained.

III. PROPOSED METHOD

Our method will be based on deep learning. Deep learning is also a multilayer artificial neural network or multilayer perceptron. There are different types of deep learning systems depending on the architecture of the neural network and its operating principles.

A multilayer artificial neural network is composed of at least three types of layers, namely the input layer, the layers and the output layer(s). A convolutional neural network (CNN) is a class of deep neural networks. These deep learning tools are used in computer vision. [10].

A. The convolutional neural network

The success of the CNN in computer vision applications is due to its processing speed, accuracy power and ability to drive a large volume of data. The structure of a CNN is as follows :

- Convolutional layer: The convolution layer is the main layer of the convolutional neural network, its function is to extract the characteristics of an image received as input. It proceeds by a filtering by convolution. The convolution consists in the multiplication operation of two matrices of different sizes to produce a new matrix called feature map. The convolution is therefore the treatment of a matrix by another small matrix called convolution matrix or kernel [11].
- Pooling layer: The pooling step aims to reduce the size of the resulting images of the convolution layer. The output and input give the same number of feature maps with smaller sizes. This leads to a reduction in the number of parameters and calculations in the network to avoid overlearning [12].
- Fully connected layers: It receives an input vector containing a flattened matrix of all filtered, corrected and pooling reduced images. In the case of image classification, feature extraction and segmentation in input sequence of RGB images is done automatically through the convolution and pooling layers of our models. Using the softmax function in the outputs of the fully connected layer, the probability of each class is obtained [13].

B. Tranfert learning

Over the years, deep convolutional neural networks have made a series of breakthroughs in the field of image recognition and classification. Training deeper neural networks has proven difficult due to problems such as the evanescent gradient problem and the degradation problem. Transfer learning solves this difficulty. Transfer learning is a machine learning technique bases a model trained on one task and is reused on an other related task.

. Transfer learning is related to problems such as multitasking and drift. Nevertheless, transfer learning is widely used in deep learning. This technique can manipulate the huge resources needed to train deep learning models or large, difficult data sets. On these data deep learning models are trained. [14] [15]. In our study we will use two pre-trained convolutional neural network algorithms namely ResNet-50 and DenseNet-201.

C. ResNet-50

ResNet-50 is a convolutional neural network architecture trained on ImageNet, a database containing over one million images. The network depth of 50 levels allows the classification of images into 1000 classifications of objects such as keyboards, mice, pencils, etc. and many species. Thus, the network has acquired a wide variety of images in a multitude of features. The network has an image input of 224 x 224. ResNet exists in several variants such as ResNet-50, ResNet-101 and ResNet-152 [9].

Table- I: ResNet Setting

Models	Input Size	Network Deepth	Train parameters
Resnet-50	224x224	50	28 449 892

D. DenseNet-201

DenseNet-201 is a convolutional neural network trained on the ImageNet database with a large volume of images. This architecture has 201 layers. Depth of 201 levels allows the classification of images into 1000 classifications of objects such as keyboards, mice, pencils, etc. and many species. It was developed specifically to overcome the declining accuracy caused by the leakage gradient in high level neural networks. DenseNet has several versions, such as DenseNet-121, DenseNet-169, and DenseNet-201[8].

Table- II: DENSENET-201 Setting

Models	Input Size	Network Deepth	Train parameters
DenseNet-201	224x224	201	20 973 028

E. Architecture

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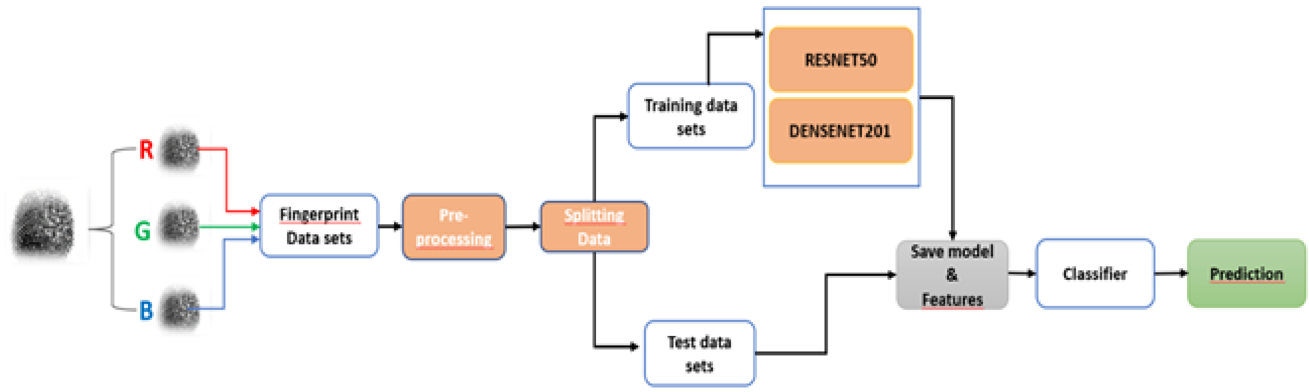

Fig. 1 : architecture of our method

Proposed Algorithm:

Input: a grey level borrowing dataset.

Ouput: Classification of the dataset

Step 1: Importing Essential Libraries

In this part, we are going to import our different libraries which will be used for the good functioning of our program.

Step 2: Loading pictures and merging of channels RGB

We load the images in gray then we duplicate them on the 3 channels to obtain an image in RGB mode.

Step 3: Making List of images and labels

Create two lists by putting in the first list the RGB images and in the second list the category to which each image belongs.

Step 4: Categorical Labels

We will use a hot coding: where each label is mapped to a binary vector.

Step 5 : Normalization

We will normalize each pixel value of images in the database. The values will be between 0 and 1.

Step 6 : Train and Test Split

Our dataset will be divided into two sets of data, namely the training set which will have 80% of data and 20% for the test set.

Step 7: Loading and parameter ResNet-50 or DenseNet-201

We load the models of our study and proceed to the training phase of the model in 20 epochs with a block size of 32..

Step 8 : Classifier and prediction.

We proceed to the recognition of each image according to its classification in a category.

IV. EXPERIMENT RESULTS

We trained the models on a Windows 10 system with an Intel(R) Core™ i7-8650U processor, 16 GB of random-access memory (RAM), and an NVIDIA GeForce MX150 graphics processing unit (GPU). The models are configured in Python using the Keras version 2.4 API with the Tensorflow version 2.4 backend and CUDA/CuDNN dependencies for GPU acceleration.

A. Dataset

To experiment and evaluate the proposed method, the study uses two of the most well-known image datasets. Sokoto Coventry Fingerprint Dataset (SOCOFing) is a biometric

The different steps for the implementation of our model are represented in the algorithm below:

fingerprint database for academic research. SOCOFing consists of 6,000 fingerprint images of 600 African subjects. [16]. SOCOFing presents unique attributes such as labels for gender, hand and finger name, and synthetic alterations.

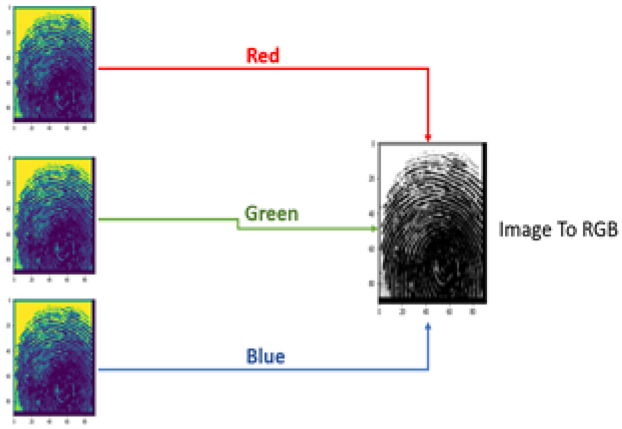

Fig. 2 : Gray to RGB image transformation

B. Experiment Setup

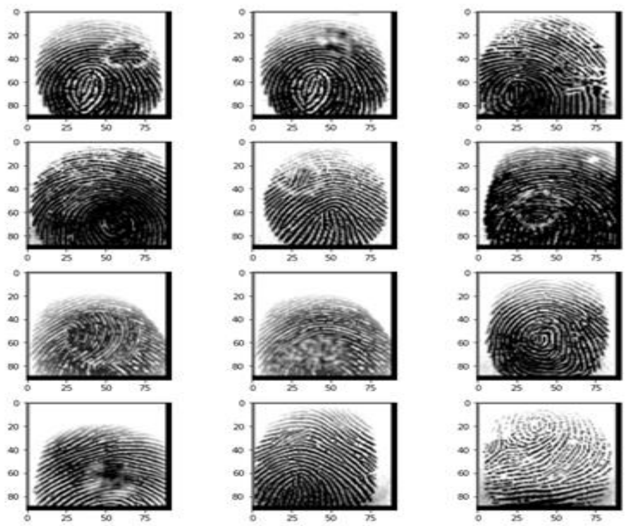

Fig. 3 : SOCOFing fingerprint images

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To maximize the weights and biases, the Stochastic Gradient Descent (SGD) optimizer was considered while performing the forward propagation. The learning rate was kept at 0.001 with a momentum of 0.9.

Table - III: Model configuration

Parameter	Value
Epoch	20
Batch size	32
Optimizer	SGD with momentum 0,9
Learning rates	0,001
Loss function	Categorical cross entropy
Input shape	92 x 92 x 3
Activation	softmax

C. Experiment Results

In our multi-category classification, the accuracy is a function that computes the subset accuracy, the set of predicted categories for a sample must exactly match the corresponding category set. Its formula is the following :

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

With TP: True positive
TN: True negative
FP: False positive
FN: False negative

Table - IV: RESULTS OF THE PRECISION IN %

Model	Accuracy (%)
ResNet-50	99.5
DenseNet-201	99.4

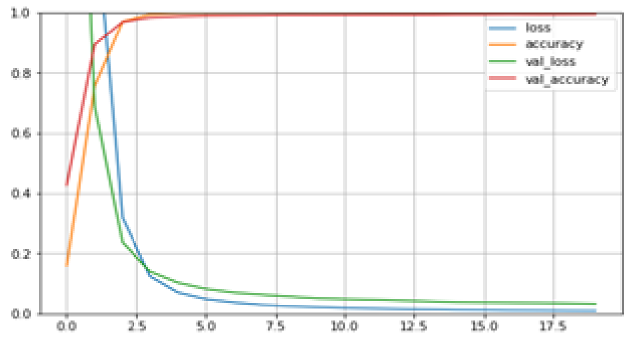

Fig 4 : DenseNet-201 learning and testing graph

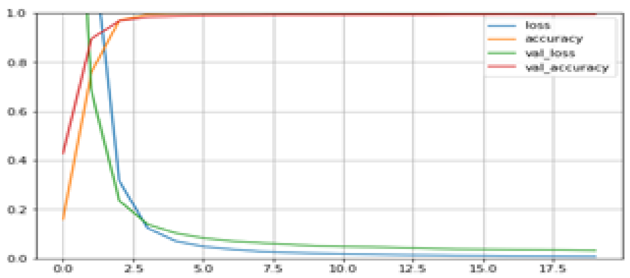

Fig. 5 : Learning and test graph of the ResNet-50

D. Parameters evalutions

For the evaluation of our experiment, we will use parametric and non-parametric metrics, which are statistical measures. These metrics were used to evaluate performance, including specificity, sensitivity, accuracy, F1 score, Matthews correlation coefficient (MCC) and mean square. error (MSE).

- Specificity

The specificity determines the proportion of true negatives out of the total number of negative observations predicted by an algorithm. It is also called the true negative rate [17]. Its formula is the following:

$$specifity = \frac{TN}{TN + FP} \quad (2)$$

- Sensitivity

Sensitivity measures the proportion of true positives among total positive observations. It is also named as the true positive rate or recall rate [17]. Its formula is given by :

$$sensibility = \frac{TP}{TP + FN} \quad (3)$$

- F1 score

F1-Score allows for a combination of precision and recall, It calculates the overall model precision with positive and negative predictions. It is a more reliable performance measure than the accuracy and precision measures, which can be erroneous when the data are highly unbalanced [18]. Its formula is as follows:

$$F1\ score = 2 \times \frac{precision \times recall}{precision + recall} \quad (4)$$

Matthews correlation coefficient (MCC)

The Matthews correlation coefficient determined a measure of the quality of binary and multi-class classifications. It exploits true and false positives and negatives and is generally considered a balanced measure that can be used even if the classes are very different in size. The MCC has a correlation coefficient value between -1 and +1. A coefficient of +1 represents a perfect prediction, 0 a mean random prediction and -1 an inverse prediction [20]. Its formula is as follows:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (5)$$

- Mean Square Error (MSE)

The MSE is a measure of accuracy, which is used to compare the errors of different predictive models for a particular data set. It measures the mean squared error, i.e., the root mean square difference between the estimated values and the true value. MSE is a risk function, corresponding to the expected value of the squared error loss

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Yi - \bar{Y}i\right)^{2} \quad (6)$$

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TABLE – V: Metric of the various models

Model	Precision (%)	MSE (%)	F-score (%)	Recall (%)	MCC (%)
ResNet-50	99,53	0,0017	99,50	99,50	99,50
DenseNet-201	99,43	0,0024	99,39	99,40	99,40

E. Self Comparaison

All these performance metrics were calculated for both deep learning models. The results thus obtained are summarized in the table above. The results show that the ResNet-50 algorithm for fingerprint recognition performs better than the DenseNet-201 algorithm. We also compare the performance of the proposed CNN models with other methods to evaluate its robustness.

F. *Stat of art comparaisons*

TABLE -VI: COMPARAISON OF THE PROPOSED METHOD WITH THE CNN METHOD

Method	Accuracy (%)
V. A. Bharadi et al. [23]	77.00
Bhavesh Pandya et al. [24]	98.21
DenseNet-201	**99.40**
ResNet-50	**99.50**

This article is focused on the work of V. A. Bharadi et al. [23] and Bhavesh Pandya et al [24] using pre-trained convolutional neural networks to improve the accuracy of fingerprint recognition from 98.21 to 99.50% on the same dataset. The proposed deep learning model achieved high accuracy in fingerprint image classification

V. CONCLUSION

This paper proposed a deep learning approach for automatic fingerprint recognition based on gray level image fusion into RGB image. The proposed CNN models in this case DenseNet-201 and ResNet-50 have shown results ranging from 99.43 to 99.53 respectively. The robustness of the proposed methods are also compared with the methods of V. A. Bharadi et al. [23] and Bhavesh Pandya et al. [24]. The experimental evaluations performed on a reference dataset show that the proposed methods perform better.

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