Comparative Evaluation of Fingerprint-Based Gender Classification (CNN)

This project is submitted to the Department of Computer Science & Engineering, Dhaka International University, in Partial fulfillment to the requirements of Bachelor of Science (B.Sc.) in Computer Science & Engineering (CSE).

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Knowledge is Power

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Estd. 7th April, 1995

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
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SUPERVISOR’S STATEMENT

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DECLARATION

We, hereby, declare that the project work which is presented by us is the outcomes of the investigations under the supervision of **Prof. Md. Abdul Based**, Additional Director of Research & Publications Cell, Dept. of Computer Science & Engineering .Dhaka International University, Bangladesh. We also declare that no part of this project and thereof has been or is being submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Gender classification is important across various domains, including biometrics, criminology, surveillance, human-computer interaction, and commercial profiling. While previous studies have primarily focused on utilizing biometric traits such as facial features, gait, iris, and hand shape for gender classification, the face has received the most attention due to its distinctive characteristics. However, this research aims to explore the potential of fingerprints as a viable avenue for gender classification. In this study, we comprehensively evaluated fingerprint-based gender classification by employing a three-convolutional layer Convolutional Neural Network (CNN) on the SOCOFing dataset, which comprised 55,273 fingerprint images. Notably, our system achieved an exceptional accuracy rate of 99.23%. This remarkable performance underscores the significant role that fingerprints can play in accurately determining an individual's gender by leveraging critical features inherent in the fingerprint data. This research highlights the promise of fingerprints as a robust biometric trait for gender classification. It provides insights into the potential benefits and implications of incorporating fingerprint-based approaches into various applications, such as biometric systems, law enforcement, surveillance technologies, interactive interfaces, and targeted marketing strategies. Further exploration of fingerprint-based gender classification could contribute to advancing gender-related research and enhance the overall efficacy of gender classification methodologies.

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Finally, we would like to dedicate this project to our teachers for their love, encouragement and professional guidance throughout the project.

Dedicated To

Our Parents

&

Teachers

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CHAPTER - 01: INTRODUCTION

1.1 INTRODUCTION

Every time someone's fingers touch a surface, whether it's while holding a coffee cup, gripping a vehicle door handle, typing on a computer keyboard, using a mobile phone, or writing with a pen, a distinctive imprint is left behind, known as a "fingerprint." It's fascinating to note that each individual has unique fingerprints, even when comparing identical siblings who share the same DNA. The distinctiveness of fingerprint patterns has proven invaluable in applications like biometric security, identifying individuals in mass disasters, and pinpointing persons of interest at crime scenes. Fingerprint-based gender classification refers to determining an individual's gender based on fingerprints. Fingerprint analysis has traditionally been used for forensic identification purposes, primarily for identifying individuals and matching fingerprints found at crime scenes to potential suspects. However, it is essential to note that fingerprints alone cannot definitively determine a person's gender. Fingerprints are unique to each individual and primarily used for personal identification rather than indicating biological characteristics such as gender. Gender identification is a complex process that involves various biological, physiological, and sociocultural factors. While there might be specific patterns or statistical trends that could potentially differentiate fingerprints between males and females, these differences are not significant enough to reliably determine gender solely based on fingerprints. Additionally, the concept of gender itself is multifaceted and extends beyond biological sex, encompassing personal identity and expression. It is worth mentioning that relying on fingerprint-based gender classification could have profound ethical implications, as it may perpetuate gender stereotypes and potentially infringe upon an individual's privacy and autonomy. While fingerprints can be used for personal identification, attempting to determine someone's gender solely based on their fingerprints is not a scientifically valid or ethically sound approach. Gender identification should be approached with respect for an individual's self-identification and considering the complex and diverse nature of gender identity. One practical application of fingerprint analysis involves classifying biometric samples based on the gender of the individual, which significantly expedites the process of eliminating suspects in criminal investigations. Additionally, fingerprints are an integral component of biometrics, and they find application in a field known as soft biometrics. Soft biometrics utilize biometric data within specific contexts. It serves various purposes, including forensics, gender- or age-based access control, video retrieval, personalized gender- or age-related services, and reducing search space in extensive biometric databases.[1-3,7,8]databases. Biometrics is the study of identifying people based on their physical, behavioral, and physiological traits.[1, 2] Fingerprints, face, eye, gait, and voice. Biometrics could be used for more than just recognizing people. It could also determine age, gender, and race [3].Several distinguishing characteristics have been discovered in fingerprint images .A fingerprint pattern is a ridge and valley pattern, with ridges as black lines and lowlands as weak spaces between the ridges. Its uniqueness is better suited for biometric authentication systems than other biometric identification methods because fingerprints have advantages such as being feasible, distinct, permanent, accurate, dependable, and acceptable. Anthropologists can use this to classify gender based on fingerprints obtained from objects and by crime investigators to narrow down the pool of suspects.[4-6] Although fingerprints are one of the most developed biometric technologies and are accepted as valid evidence in courts around the globe, relatively few machine vision methods for gender identification have been proposed. In the majority of gender determination studies, ridge-related parameters such as fingerprint ridge count, ridge density, ridge thickness to valley thickness ratio, ridge breadth, as well as fingerprint patterns and pattern types have been utilized. Several application areas, such as image recognition, have embraced the fusion of features and synthesis to create classifiers. The most available research on gender classification using fingerprints relies on patterns such as whorl, loop, and arch. These methods have provided insight into the ridge parameters but cannot provide accurate measurements of the parameter. According to studies comparing the two, female fingerprints have more loops than male fingerprints. In contrast to females, men exhibit whorls more frequently [2]. Other research has shown that ridge thickness and valley thickness ratios are often higher in female fingerprints than in male fingerprints [3]. This study investigates if gender can be determined from fingerprint photos using various classification and convolutional neural network algorithms. In the paper, a study using male and female fingerprint pictures that are publicly available is described. The objective of the project was to create a technique for frequency domain analysis-based feature extraction from fingerprint photographs. These include patterns of ridges and valleys of lines and diverse shapes, including circles, whorls, and arches. Each finger's fingerprint has a different pattern depending on how these characteristics are combined. Studies have revealed that the properties of male and female fingerprints vary. Images of selected fingerprints containing different loop, whorl, and arch patterns are shown in Figure 1.

Figure 1. Sample of fingerprint images showing Loops, Whorls, and Arches.

CHAPTER - 02:

BACKGROUND OF THE RESEARCH

2.1HISTORY

The history of gender classification is a complex and multifaceted subject that has evolved and varies across different cultures and societies. The understanding and categorization of gender have been shaped by various factors, including social, cultural, religious, and scientific influences. Let's explore a brief overview of the history of gender classification. Ancient Societies (3000 BCE - 500 CE): Gender classification in ancient societies was often based on biological characteristics such as reproductive organs. This binary classification system categorized individuals as male or female. Examples can be found in ancient Mesopotamia, ancient Egypt, and ancient Greece.[9] Islamic Jurisprudence (7th - 19th century):Islamic jurists developed a legal framework for gender classification based on religious texts, including the Quran and Hadith. They recognized two primary genders, male (Arabic: ʾudhun) and female (Arabic: inthār), accordingly defined legal rights and responsibilities.[10]Medieval Europe (5th - 15th century): In medieval Europe, gender classification was closely linked to societal roles and expectations. It followed a binary model, where individuals were classified as male or female based on physical characteristics and reproductive capacities.[11] Rise of Modern Science (17th - 19th century): With the development of modern science, including biology and anatomy, there was a growing emphasis on biological determinants of gender. This period saw the emergence of the sex/gender distinction, where sex referred to biological characteristics and gender to social and cultural roles.[12] Psychiatric Classification (20th century): In the 20th century, psychiatric and psychological theories influenced gender classification. Concepts like gender identity and gender dysphoria were introduced, acknowledging that an individual's gender identity may not align with their assigned sex at birth.[13]Feminist Movements (20th century): Feminist movements challenged the traditional gender classification system and advocated for gender equality. They highlighted the social and cultural aspects of gender, arguing that it is a social construct rather than solely based on biological factors.LGBTQ+ Rights Movements (20th century - present): LGBTQ+ rights movements have significantly challenged and expanded the understanding of gender classification. These movements have advocated for the recognition and rights of individuals with diverse gender identities, including transgender and non-binary people.

2.2 HARDWARE REQUIREMENTS:

Computer System: Intel Core i7 processor, 16 GB RAM, GPU, Operating system Windows 10.

2.2.1 FINGERPRINT SCANNER

A high-quality fingerprint scanner capable of capturing clear and detailed fingerprint images. It is recommended to use scanners with a resolution of at least 500 DPI (dots per inch) to ensure accurate feature extraction

2.2.2 CONNECTIVITY (USB Port)

Connect the fingerprint scanner to the computer system.

2.3 SOFTWARE REQUIREMENTS:

Python 3.8.0 64 bit, PyCharm IDE, is needed to run the required libraries and frameworks. Install deep learning libraries such as TensorFlow, Keras, or PyTorch. Image Processing Libraries: Libraries like OpenCV or Pillow are necessary for image preprocessing and feature extraction from fingerprint images.

2.4 RELATED WORK

Gnanasivam and Muttan [14] proposed a system that uses 6-level DWT and SVD and a database of 3,570 fingerprints to determine a person's gender based on their fingerprint. For classification, they used the KNN algorithm to compare the fingerprint's feature vector to the feature vector in the database. For a 6-level DWT, the average accuracy is 89.32% for men and 81.59% for women. The left little finger was the best way to tell for females, and for men, the right thumb was best. On the other hand, the average accuracy when using SVD as a feature extraction method is 91.74% for males, with the right index giving the best result and 83.30% for females, with the left little finger giving the best result. When 6-level DWT and SVD are used together, the average accuracy rate for men is 91.67%, and for females, it is 84.89%. Overall, the chance of success goes down from the pinky to the thumb. In [15], the writers suggested using the haar wavelet in the frequency domain and canny edge detection to use fingerprints to tell a person's gender. The recommended method is based on a database of 275 male and 275 female fingerprints. The KNN algorithm was used to figure out who was who. The proposed system will lead to a result of 98%. In [16], the authors suggested a system that uses fingerprints (DWT and SVD) to determine a person's gender. The system would use a set of 1000 fingerprints, 500 from men and 500 from women, to determine a person's gender. With a DWT of level 6, the success rate of determining a person's gender is 82.90% for men and 82.60% for females. Abdullah et al. [17] made a new algorithm that uses the global traits of a fingerprint to figure out a person's gender. A Fuji Xerox printer was used to take pictures of the fingerprints. The algorithm is based on counting the linked black and white pixels in the image to determine how many ridges there are. Then they figure out how many ridges there are about 74.5% of the time, and the suggested method works. In [18], a system for figuring out a person's gender based on DWT and an artificial neural network (ANN) is suggested. After the fingerprint picture was cropped, resized, and threshold, the discrete wavelet transform (DWT) was used at six decomposition levels to extract features. The back propagation method trained an ANN with the parts taken out. Images of fingerprints were taken from computer databases that were open to the public. They used a set of 300 pictures of left thumbprints, of which 200 were used for training and 100 for testing. They were right 78% of the time for men and 82% for women. Iloanusi and Ejiogu have a convolutional neural network (CNN) design for figuring out a person's gender from each of their five fingerprints [19]. They used their dataset, which had 8025 pictures from 239 people, and the Sokoto Coventry Fingerprint dataset. They used data enhancement based on idea processing. They showed that sure fingers were the best way to determine a person's gender. For the thumb and finger, they got an average confirmation accuracy of 80% for their dataset and 83% for the Sokoto dataset. They showed that the performance could be improved by determining a person's gender based on how the five fingers on their right hand are fused. They found that the thumb-index-pinky combination was the best way to tell if a person was a woman. This combination has a 94.7% success rate. With the thumb, middle, and ring methods, the average accuracy for determining a man's gender was the same. With their dataset and the 84% accuracy of the Sokoto dataset, the same fusion gives the best overall accuracy of 91%. In [20], ReLu and Tanh activation functions were used with CNN. They used the DB4 dataset from the National Institute of Standards and Technology (NIST) to teach their neural models how to work. With ReLu turned on and 20 epochs, they got to a 99% success rate. In [21], the authors suggested looking at AdaBoost, SVM with a linear, radial basis function (RBF), and polynomial kernel, KNN, J48, the Iterative Dichotomizer (ID3), linear discriminant analysis (LDA), and a CNN. They pulled out features using FFT, DWT, SVD, ResNet, VGG, and DDC-ResNet. They used a set of 6,000 fingers in their tests. They showed that the most accurate results come from SVM with a polynomial kernel and CNN. Their SVM algorithm identified males at a rate of

97.43% and females at a rate of 93.24%. Their CNN classifier could tell the difference between men and women 97.52% and 95.48% of the time, respectively. Then, they used CNN with DDC-ResNet to determine which finger was best for sexism. They found that the average accuracy of the right ring finger is 92.45%.

2.5 EXISTING CLASSIFICATION SYSTEMS

2.5.1 Iris Based Classification System:

Iris-based classification systems refer to technologies and methods that utilize the iris patterns of individuals for identification and classification. The iris, the colored part of the eye surrounding the pupil, contains unique patterns that are highly distinctive for each individual. Iris-based classification systems leverage the unique patterns of the iris for identification and classification purposes. With their high accuracy, stability, and security, these systems have gained prominence in various domains, from access control and security to immigration and forensic investigations.

2.5.2 Face Based Classification System:

The face-recognition system takes a person's attendance using high-resolution cameras. When new individuals register, the system needs training. However, if the system's model has already been trained, there is no need to train the system. Since the system already knows which faces belong to humans. Individual facial features or the entire face may be affected. Even though a person's visage is unique, this system cannot eliminate proxies based on an image of an absent individual. Face-recognition technology compares only faces. Therefore, if someone uploads an image of an absent individual, the system can also record their attendance because the image's facial features are compared to the dataset. Another issue is that the camera may not be able to capture the employee's visage due to factors such as lighting, employee movement, or resolution.

2.5.3Radio Frequency Identification (RFID Based Classification System

RFID-based classification systems utilize radio frequency technology to categorize and identify objects or entities automatically. These systems employ RFID tags, readers, and a centralized database to classify and track items in various domains efficiently. The RFID technology allows for seamless data capture and retrieval, offering significant advantages over traditional manual classification methods. A person needs to carry an RFID Card in this RFID-based recognition system. Need to place this ID card on the card reader to store their attendance. The system is nice, but the major problem is people may put multiple ID cards in the card reader for the marks present who is absent. This is the big chance to do proxies which have been discussed in the introduction part before

2.5.4 Fingerprint-Based Classification System:

In the biometric-based recognition system, a fingerprint scanner device must be installed. To indicate the presence, the finger must be placed in the scanner. After that, the device scans the finger and compares the scan to the database. If the fingerprint matched the database, the individual was marked as present. This device is also helpful for minimizing proxies in the workplace or classroom. Every person has unique digits. Each individual's fingerprint cannot match another's. Therefore, proxies have no hope in the fingerprint-based recognition system. However, if the server goes down, the scanner will not record the person's attendance. When a digit is injured, it cannot be matched with the database, posing a second significant issue. Therefore, it is necessary to update or replace the individual's digits. Even if the finger and the scanner are filthy, the scanner will not function.

CHAPTER - 03: METHODOLOGY

3. METHODOLOGY

3.1 Dataset

In this study, we preprocess the dataset adopted from the Sokoto Coventry Fingerprint (SOCOFing) dataset [22] contains 6,000 fingerprints belonging to 600 African subjects. There are 10 fingerprints per subject; all subjects are 18 or older. SOCOFing contains unique attributes such as labels for gender and hand and finger names. Moreover, using the STRANGE toolbox, synthetically altered versions of these fingerprints are provided with three different levels of alteration for obliteration, central rotation, and z-cut. Alterations were done using easy, medium, and hard parameter settings in the STRANGE toolbox over 500dbi resolution images. Therefore, the dataset provides 17,934 altered images with accessible parameter settings, 17,067 with medium settings, and 14,272 with hard parameter settings. Note that in some cases, some images did not meet the criteria for alteration with specific settings using the STRANGE toolbox, hence the unequal number of altered images across all three alteration categories.All original images were acquired based on impressions collected with Hamster plus (HSDU03PTM) and SecuGen SDU03PTM sensor scanners. SOCOFing consists of a total of 55,273 fingerprint images combined. All file images have a resolution of 1 × 96 × 103 (gray × width × height). The dataset is divided into two subfolders containing real, i.e. original images, and altered images. The altered folder is further divided into three levels of alteration difficulty: easy, medium and hard. SOCOFing Real Altered-Easy Altered-Medium Altered-hard Altered The file format provides the labels for each individual image and has the naming convention of: “001_M_Left_little_finger_Obl.bmp” 1 2 3 4 5 6. Identifies the number of the subject: 001 to 600.Indicates the gender of the subject: M – male, F – female. Denotes the hand: Left or Right. Indicates the finger name: little, ring, middle, index, or thumb. Indicates the type of alteration type (altered images only): Obl – obliteration, CR – central rotation, or Zcut. And File extension: “.bmp” for all images. Figure 2 below shows some samples of the original fingerprints and the synthetic alternation and generation of the fingerprints images into Z-cut, obliteration and central rotation.

Figure 2. Images are altered into z-cut, obliteration, and central rotation.

3.2 Image Processing for model

We utilized the CNN model for image processing due to its effective feature extraction capabilities and pattern recognition abilities. This makes CNNs highly suitable for tasks like object detection, image segmentation, and classification. As a preprocessing step, we resized all data images to a size of 224x224x3. Subsequently, global average pooling was applied to the data images. Global average pooling involves taking the average of all features within an image. To mitigate over fitting issues, we used the dropout technique, specifying a dropout rate of 0.5 in the dense() function, which determines the dimensionality of the output space and fraction rate on input units.In order to determine the actual class from a given number of classes (n), we employed the softmax activation function. This function identifies the class based on the maximum probability obtained at the output, effectively ignoring the probabilities of the remaining classes.

3.3 Proposed Model

In paper employs a convolutional neural network (CNN) model to perform gender classification using fingerprint images. CNNs are widely recognized models extensively employed in various computer vision applications. In this study, we leverage the exceptional capabilities of CNNs to train a model capable of discerning the gender of individuals from the provided fingerprint dataset. The CNN used in this work uses the construction shown in Figure 3.

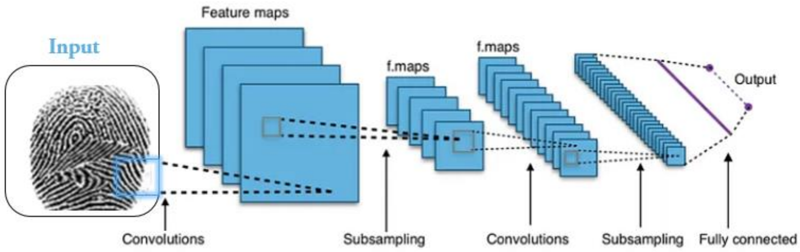

Figure 3. Convolutional neural network (CNN) Architecture.

The convolutional layer plays a vital role in the model, as it aims to reduce the image size to expedite weight calculations and increase its applicability. The CNN model consists of three convolutional layers, each containing 20, 40, 60, and 80 filter kernels with dimensions of 3x3. Each convolutional layer comprises a bank of filters (weights) that are combined with the previous layer's output or the input image in the case of the first layer, generating a response. These convolutional layers extract features from the input images. The initial layer extracts low-level features like lines and edges, while the subsequent layers extract high-level features. During the convolutional process, the network retains the important components of the image while eliminating irrelevant noise. Additionally, the output of each convolutional layer is passed through a rectifier linear unit (ReLU) formula.To reduce feature sharpness and accelerate the process, a subsampling layer is employed. This layer also decreases the number of connections between the convolutional layers. In each instance, the input image is divided into non-overlapping two-dimensional regions. The input size is 4x4, and a subsample size of 2x2 is used. A 4x4 image is partitioned into four 2x2 grids that do not overlap. The max-pooling layer performs subsampling by selecting the highest value within an MxM window from the outputs of the preceding convolutional layers. Conversely, minimum pooling selects the smallest value among the four numbers. By reducing the dimensionality, the network minimizes the number of weights to compute, preventing overfitting. Activation functions are employed to enhance CNN performance. Commonly used activation functions include sigmoid, tanh, and ReLU. In this study, the standard ReLU activation function and the Tanh activation function were compared to evaluate their effectiveness. In the fully connected layer, groups of neurons are connected to each neuron in the layer below. The flattening layer simply converts all the previous layer's outputs into vectors and connects them to the inputs of the fully connected layer.

The rectifier linear activation function (ReLU) is utilized in all convolutional layers and the first fully connected layer. Various software tools serve as frameworks for implementing neural networks. Keras, a Python library, offers user-friendly abstractions for powerful learning libraries such as Theano and TensorFlow, which were employed in the presented work. Convolutional neural networks effectively capture spatial information through filter kernels. In this work, we use CNN's unique ability to identify images to teach a model how to do this. In here, we consider the simple case when the stride is 1 and no padding is used.

Hence, we have y (or x l+1) in $R^{Hl+1 \times Wl+1 \times Dl+1}$, with $H^{l+1} = H^{l} - H + 1$, $Wl+1 = W^{l} - W + 1$, and $D^{l+1} = D$. In precise mathematics, the convolution procedure can be expressed as an equation:

$$y_{i}^{l+1}, j^{l+1}, d = \sum_{i=0}^{H} \sum_{j=0}^{W} \sum_{dl=o}^{dl} f i, j \text{ fi, j, } d^{l}, d \times x_{i}^{l} \text{ l+1+I , } j^{l+1}+j \text{ , } d^{l} \quad (1)$$

Equation is repeated for all $0 \le d \le D = D^{l+1}$, and for any spatial location (i^{l+1}, j^{l+1}) satisfying $0 \le i^{l+1} < H^{l} - H + 1 = H^{l+1}$, $0 \le j^{l+1} < W^{l} - W + 1 = W^{l+1}$. In this equation, $x^{l}{}_{i}{}^{l+1}$+i, j^{l+1}+j, d^{l} refers to the element of x l indexed by the triplet (i^{l+1} + i, j^{l+1} + j, d^{l}).

3.4 Neural Network Training

Our proposed work employed a straightforward convolutional neural network (CNN). To enhance performance, we utilized Stochastic Gradient Descent (SGD) with a rapidly decreasing learning schedule. Throughout the training process, we incorporated three callbacks to monitor progress and log it into a file. We also employed a callback to create checkpoints of the model, saving them in the hdf5 file format. Only the most learned models were preserved based on the best score obtained

CHAPTER - 04:

Experimental Result and Analysis

4. Experimental Result and Analysis

In this section, we present and discuss the findings of the gender recognition system that we developed. To evaluate the system, we conducted tests using the Sokoto Coventry Fingerprint (SOCOFing) dataset [17], a well-known public-domain fingerprint database. We will provide an overview of these databases and describe the experimental setup used. For our evaluation, we utilized the (SOCOFing) dataset, a comprehensive fingerprint dataset designed explicitly for gender classification. This dataset consists of images with dimensions of 512x512 pixels. Our experiments focused on classifying fingerprints into two categories: male and female. We employed a Convolutional Neural Network (CNN) model for this purpose. To train the CNN model, we allocated 80% of the dataset for training and used the remaining 20% for testing. The TensorFlow framework was utilized to train and test the model. The training was conducted on a core i7 CPU clocked at 2.6 GHz, a 1-TB hard disk, and 16-GB RAM. Sample training male and female fingerprint images are shown in Figure 4.

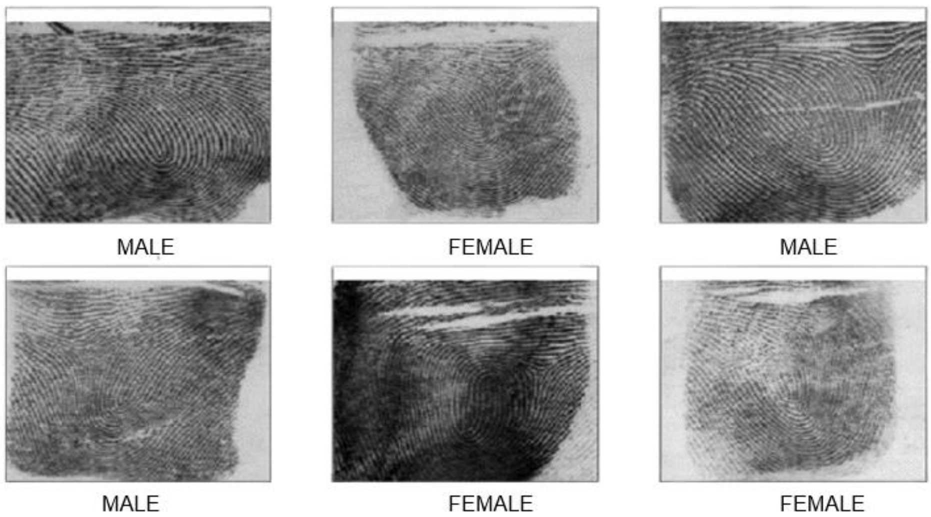

Figure 4. Sample input fingerprint images of male and female.

We assessed the effectiveness of the proposed framework by analyzing four sets of predicted and actual values: TP (true positives), FP (false positives), TN (true negatives), and FN (false negatives). TP represents instances where the system correctly identifies positive cases. TN represents instances where the system correctly identifies negative cases. FP occurs when the system incorrectly predicts a negative case as positive, while FN happens when the system incorrectly predicts a positive case as negative. We calculated the accuracy to evaluate the overall performance, which is the ratio of correctly identified genders to the total number of genders (equation 1). Additionally, we employed equations 2, 3, and 4 to provide a comprehensive view of the results by describing precision, recall, and F-measure. The F-measure serves as an evaluation metric to gauge the effectiveness of our proposed regression approach. A high F-measure indicates a high classification rate, indicating the efficacy of our method.

$$Accuracy = \frac{\text{Total no.of correct prediction}}{Total\ no.fo\ correct\ prediction} \quad (2)$$

$$\text{PRE} = \frac{\text{TPi}}{\text{TPi+FPi}} \quad (3)$$

$$REC = \frac{\text{TPi}}{\text{TPi+FNi}} \quad (4)$$

$$\text{F} = \frac{\text{PREi} \times \text{RECi}}{\text{PREi+RECi}} \quad (5)$$

The performance metrics of the suggested approach are presented in **Table 1**. The table reveals that, following Z epochs of training the network model, the proposed method employing the Relu activation function achieved a remarkable 99% accuracy in classifying the given image.

Table1. Confusion Matrix

Class Name	Male	Female
Male	99	1
Female	1	99

The accuracy and loss curve of the proposed model provides valuable insights into its performance during training and validation. It depicts the relationship between the model's accuracy and loss over epochs or iterations. In the accuracy curve, the y-axis represents the model's accuracy, which indicates the percentage of correctly predicted instances. The x-axis typically represents the number of epochs or iterations. As the model undergoes training, the accuracy curve shows how the accuracy improves or fluctuates over time. Ideally, we would like the accuracy curve to ascend steadily or plateau at a high level, indicating that the model is learning effectively and making accurate predictions. Analyzing the accuracy and loss curves of the proposed model helps us evaluate its performance, identify potential issues, and make informed decisions regarding model optimization, such as adjusting hyper parameters, modifying the architecture, or increasing the training data size.

The accuracy and loss curve of the proposed model is given in figure 5.

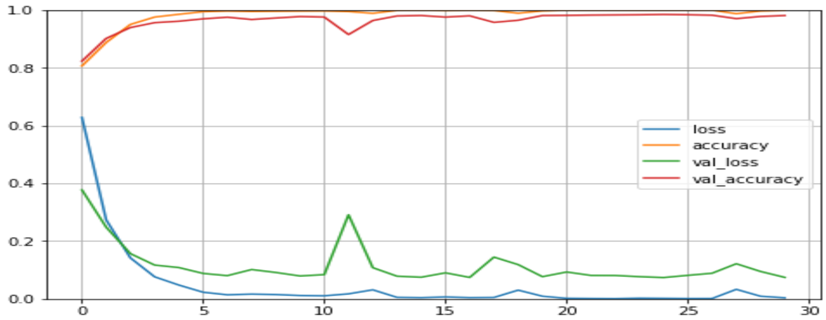

Figure 5. Accuracy and loss curve of the proposed model CNN.

Classification algorithms are machine learning algorithms that categorize or predict the class labels of data instances based on their features. They are widely used in various domains classification. Metrics such as accuracy, precision, recall, and F1 score are commonly used to evaluate the performance of classification algorithms. These metrics help assess the performance of classification algorithms and guide the selection of appropriate models for specific tasks. However, depending on the problem domain, other metrics or evaluation techniques may be more suitable. **Table 2** shows the values of deep learning algorithms CNN, KNN and SVM. To evaluate the performance of gender classification algorithms, metrics such as accuracy, precision, recall, and F1 score are commonly used. These metrics allow researchers to quantify the effectiveness of their models in correctly classifying the gender of individuals based on their fingerprints.

Table2. Classifying accuracy, precision, recall, and F1 score.

Deep Learning Algorithm	Accuracy	Precision	Recall	F1-Score
Convolutional Neural Network	99.23%	98.39%	98.88%	0.978754
K-Nearest Neighbors	95.28%	94.91%	94.91%	0.889352
Support Vector Machine	93.45%	92.43%	92.94%	0.876849

CHAPTER -05: DISCUSSIONS

5.1 DISCUSSIONS

Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision and achieved remarkable success in various image-related tasks. In this discussion, we focus on a specific CNN model with an impressive accuracy of 99.23%. Along with accuracy, we will also explore other key performance metrics such as precision, recall, and F1 score to understand its effectiveness comprehensively. The accuracy of a model is a fundamental metric that measures the overall correctness of its predictions. In this case, CNN achieved an outstanding accuracy of 99.23%. This means that 99.23% of the predicted labels matched the ground truth labels in the test dataset. A high accuracy indicates that the model has successfully learned meaningful patterns and features in the images, leading to accurate classification. Precision is a metric that quantifies the proportion of accurate positive predictions among all positive predictions made by the model. For this CNN, the precision is reported at 98.39%. In image classification tasks, precision signifies how well the model avoids false positives, i.e., instances where it wrongly classifies an image as positive. The high precision score indicates that the CNN is reliable in minimizing misclassifications, providing confidence in its positive predictions. Recall, also known as sensitivity or true positive rate, measures the ability of the model to identify all positive instances correctly. The CNN achieved a recall score of 98.88%, indicating that it effectively detects nearly all positive instances in the test dataset. A high recall implies that the model captures many relevant features, resulting in fewer false negatives. In image classification, recall is crucial for minimizing the chances of missing essential objects or patterns. The F1 score is the harmonic mean of precision and recall and provides a balanced assessment of a model's performance. The reported F1 score for this CNN is 0.978754, which strongly indicates its overall effectiveness. A high F1 score suggests that the model achieves a good balance between precision and recall, indicating robust performance in capturing both positive and negative instances accurately. In summary, the discussed CNN model exhibits exceptional performance with an accuracy of 99.23%. Alongside accuracy, it demonstrates high precision (98.39%), recall (98.88%), and F1 score (0.978754). These results indicate that the CNN has effectively learned meaningful features and patterns from the input images, enabling accurate classification with a low rate of false positives and false negatives. Such high-performance CNNs have immense potential in various real-world applications, including object recognition, medical imaging, and autonomous vehicles, where accurate and reliable predictions are paramount.

CHAPTER - 06: CONCLUSION

6. CONCLUSION

In this paper, we have proposed a gender classification model, which is easy for humans but not for machines. Convolutional Neural Network (CNN), one of the widely used models to classify images, is employed to classify gender based on fingerprint images. Using the activation function, we have trained the convolutional model with images from SOCOFing. In the final analysis, the Convolutional Neural Network (CNN) accuracy was an amazing 99.23%. This level of accuracy shows that CNNs are good at dealing with complex visual data like pictures. Using the power of convolutional layers and pooling operations, CNN could find essential features and intricate patterns in the data, which led to accurate predictions. This process aids in refining existing techniques and developing new approaches that can provide more accurate and reliable gender classification results. The findings from these evaluations contribute to the advancement of biometric research and may have practical applications in various fields, such as law enforcement, border control, and forensic sciences. It's important to note that while fingerprint-based gender classification shows promise, it is not without limitations. Factors like image quality, variations in fingerprint acquisition devices, and noise can affect the accuracy of gender classification algorithms. Additionally, ethical considerations regarding privacy and potential biases must be considered when deploying such technologies in real-world applications.

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