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Deep Learning Approaches for Classification and Gender Prediction from Fingerprint Imagery: A Review

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ABSTRACT - Fingerprint biometrics is recognized as one among the most reliable modalities for identification of humans due to their uniqueness. Predicting Gender from biometric traits is emerging as a critical task in forensic science, human computer interaction, security, criminology and demographic analytics. Classification and Gender Prediction based on Fingerprints has earned increasing attention in biometric research for its potential applications in forensic profiling and identity verification. With the advancement in Deep learning which is a potential paradigm in computer vision is recently extended to soft biometric analysis, particularly prediction of gender from fingerprint images. This review of literature blends the recent advancements in deep learning models and techniques applied in fingerprint-based classification and gender prediction, highlighting the datasets, preconditioning pipelines, model architectures, metrics for assessing the performance of the models and future directions. This main focus of this survey is on deep learning models with fingerprint images as inputs for the task of binary or multi-class classification excluding methods which considers only graph-based or symbolic minutiae representations. This review paper aims to infuse practical insights for the researchers to understand the current and future directions of research in fingerprint-based gender identification and verification systems using deep learning.

Keywords: **Biometrics, Computer Vision, CNN, Fingerprint, Minutiae**

I. INTRODUCTION

Among the various Biometric traits, fingerprints play a vital role in the field of forensic science where other Biometric identifications like voice, iris, gait, face may be absent in a crime scene. Earlier work on classification of fingerprints relied on hand-crafted features which are extracted from global and local ridge characteristics. Those approaches extract minutiae details, ridge density and width, core and delta configurations, and texture descriptors such as Gabor-based features, local binary patterns, or wavelet coefficients [43], [44], [45]. These extracted features are given as inputs to conventional classifiers such as k-nearest neighbors, support vector machines or ensemble methods reporting encouraging results on specific datasets. But they exhibit limitations such as sensitivity to preprocessing, quality of the image, difficulty in capturing complex local and global structures.

The significant improvement of recognition accuracy in classification of fingerprints and prediction of Gender due to the recent advancements in Deep Learning approaches enables faster and more reliable biometric systems. Approaches such as multilayer extreme learning machines [1] and convolutional neural network (CNN) architectures including AlexNet, LeNet, VGG-16, and specialized Fingerprint-Net models [3] have established strong baselines for feature learning. While transfer learning and ensemble-based solutions have further enhanced the performance of multi-class fingerprint classification [9], attention mechanisms enhanced lightweight models demonstrate the feasibility in deploying fingerprint classification on constrained environments. [12]

Despite the advancements in the field, fingerprint classification remains highly sensitive to low quality images and real-world distortions. While many studies have explored image reconstruction and minutiae extraction techniques to improve downstream performance [10] [7], Hybrid feature extraction methods mitigate quality degradation [4]. However, such solutions struggle with partial and distorted fingerprints which are common in practical deployments. When deep learning–based methodologies achieve high accuracy, they remain computationally expensive that limits their suitability for real-time decision-making. Current literature also shows that assessing image quality, extracting features and classification being addressed in isolation rather than using unified multi-task architectures [5][8]. Such challenges highlight the need for a classification framework using fingerprint within a single pipeline that is capable of multi-attribute analysis, robust to image degradation in the real world and lightweight for deploying in the real time scenarios.

II. ANATOMY OF FINGERPRINTS

An impression made by the friction ridges, known as Fingerprints, are dominated by central features, such as whorls, loops and arches. Further analysis reveals other imperfections such as ridge endings, ridge bifurcations, island ridges etc [46]. In the fingerprint, ridges are the raised lines whereas valleys are the spaces between those ridges. Ridge endings are the point where the ridge ends, whereas the meeting point of two ridges is ridge bifurcation [32]. These two details are called minutiae. A turnabout in the ridge pattern is a core point and delta point are where ridges diverge.

Fingerprint structure consists of a rich set of global, local, and micro-level features which are essential for biometric feature extraction. By leveraging the ridge flow details which is the global feature contributing to the structure of the fingerprint, minutiae specifications arising from local discontinuity of the ridges, micro features like ridge width, ridge spacing, edge contours and texture descriptors, fingerprint recognition systems achieve impressive accuracy

even with limitations in imaging conditions. The types of fingerprint patterns are given in Table 1 and its relevant images in Table 2. On average, compared to males' females have finer ridge [46]. This study is relevant to the current research as the classifying fingerprint serves to reduce the response time in a biometric fingerprint system, when used as a preprocessing step.

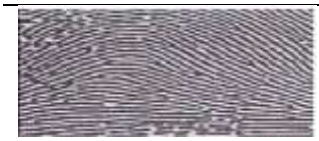
TABLE 1. FINGERPRINT PATTERN TYPES

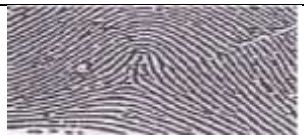
Pattern	Description	Population Frequency
Arch	Ridges make an entry from one side of the finger and exit the other side	5% - 6% [5]
Tented Arch	Same as arch but with a pointed peak at the center.	1%
Ulnar Loop	Ridges enter from one side, loop back, and exit on the same side	Most common 60% – 65% [5]
Radial Loop	Entry of ridges is from one side, Loops and opens toward the thumb side	5%
Plain Whorl	Ridges form circular or spiral patterns	24% – 26% [5]
Central Pocket Whorl	A loop pattern with a whorl at the end	Not common
Double Loop Whorl	Two separate loops intertwined.	4%
Accidental Whorl	Combination of different patterns not fitting other classification.	Rare

TABLE 2. FINGERPRINT PATTERN DETAILS [32] (Mridula et al 2014)

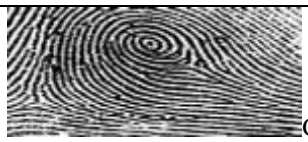

Ulnar loop


Radial loop


Plain arch


Tented arch


Plain whorl


Central pocket whorl


Double loop whorl


Accidental whorl

III. ROLE OF DEEP LEARNING IN FINGERPRINT CLASSIFICATION

[1] This paper addresses computational cost and training efficiency in Fingerprint classification. The authors propose Multilayer Extreme Learning Machines (ELMs) for efficiently classifying Images of fingerprints. This method uses a three-layer ELM with brute-force heuristic optimization technique to determine hyperparameters which improves classification accuracy while maintaining low

computational cost, avoiding excessive training time. Experiments are conducted on synthetic fingerprint databases generated by SFINGE software, that simulates realistic fingerprint distribution. Notably, the work contributes in maximizing the accuracy in classification across different M-ELM configurations while avoiding excessive training times. However, the main drawback is the samples are limited with less than 800 per group reducing the robustness of experiments, and also this method does not address a five-class classification problem, which is an important aspect that has to be considered while developing complex verification models in order to reduce the penetration rate. The authors future research will focus on optimizing M-ELM models using heuristic techniques and numerical methods for improving the performance and reducing computational costs

[2] In this paper the authors propose a "Robust Deformed Convolutional Neural Network for 5G network secure smart cities (FCD-RDCNN)" for optimized Fingerprint Crime Detection which involves a pre-processing phase to standardize the size of the image and tensor conversion using Sliding Innovation Filter (SIF). In the feature extraction step Random Quantum Circuits Transform (RQCT) is used. The features that are extracted are fed into RDCNN for classifying original images from the forged images. To further enhance the RDCNN to classify finger print crime detection, a Sand Cat Swarm Optimization (SCSO) is used. Experiments are conducted on SokotoConventry dataset showing better accuracy, precision and F1-score when compared to existing models.

[3] This paper addresses how to minimize the number of comparisons performed in biometric recognition systems when working with massive databases by classifying fingerprints into several groups. The authors compare the proposed model Fingerprint-Net, with three deep learning models, namely AlexNet, LetNet, and VGG-16 in terms of efficiency and accuracy. Experiments are conducted on the SOCOfing database, showing better performance because of the sample's superior quality. Notably, an impressive accuracy of 99.28 percent is obtained by the suggested model Fingerprint-Net, compared to the other models used in this study.

[4] This paper addresses the significant issue of low-quality fingerprints which decrease the performance of fingerprint authentication systems. The authors propose two hybrid approaches for enhancing the accuracy. The first approach, SIFT-Descriptor-SCNN, combines the proposed Siamese CNN model with scale-invariant feature transform (SIFT) by first computing the SIFT feature descriptors, then passing them to the SCNN for further feature extraction and matching that resulted in an increase of system's ability in distinguishing various patterns for accurate identification. The second approach which is novel and named as oriented FAST-Dense-SIFT-Descriptor-SCNN, uses the oriented FAST with a dense method for the detection of keypoints which are then fed into the SIFT algorithm to compute the descriptors. Experiments are conducted on the SOCOFing dataset, which includes 6000 real fingerprints and synthetically altered versions of 49,270 fingerprints that are grouped into easy, medium and hard. Notably, the second model had a faster prediction time and a higher training accuracy of 98.37, 98.08, and 97.86 and validation accuracy of 98.55, 97.40, and 98.31for all three sets.

[5] This paper addresses the issue of the performance of recognition systems which are affected by the quality of fingerprint images. The primary objective of this study is to classify the input images based on the quality, with a scale ranging from 1 to 5, where a higher score indicating the quality of the image is better. The authors propose an enhanced machine learning based approach for fingerprint image quality assessment (FIQA) with a seven-phase structure, encompassing dataset loading from the Sokoto Coventry Fingerprint dataset, preprocessing, image enhancement using Gabor filtering to enhance the texture feature and minutiae extraction for extracting distinctive features to improve image quality before feature extraction. Then features are extracted using the histogram of oriented gradients (HOG) descriptors. To classify fingerprint image quality effectively, machine learning techniques, including Support Vector Machine, Convolutional Neural Network, and Multilayer Perceptron are used. To enhance the recognition performance of the biometric system, the proposed ensemble model combines the predictions from each model using an averaging method. The ensemble method outperformed the individual classifiers thus achieving a precision of 0.91 and recall of 1.00 while maintaining minimal processing time. The study outlines a method for predicting fingerprint image quality by calculating a matching percentage based on the predictions of classifiers which are then mapped to predefined thresholds for determining the quality of the image. A matching score above 95% is corresponding to a quality level of 1, which represents the highest image quality with higher matching percentages correlating with better predicted image quality.

[6] This paper highlights the superiority of hybrid deep learning methodologies in biometric security by providing a quantifiable enhancement in both efficiency and accuracy. The authors propose a hybrid deep learning model that improves accuracy and robustness by integrating Convolutional Neural Networks for extracting intricate fingerprint patterns and Long Short-Term Memory networks for capturing sequential dependencies to refine feature representations. Experiments are conducted on Sokoto Coventry Fingerprint Dataset (SOCOFing) with synthetic alterations to create challenging test conditions. Additionally, the model was assessed for robustness and generalization capabilities using datasets FVC2000 and L3-SF-V2 to ensure the model's performance on new and unseen data. Notably, the proposed model demonstrates an efficient execution time of 1.85 seconds achieving an accuracy of 99.42% for classifying, reduces the false acceptance rate (FAR) to 0.31% and the false rejection rate (FRR) to 0.27%, thus demonstrating a 12% improvement over traditional CNN-based models which makes it suitable for real-time applications. The work contributes a faster processing optimized architecture suitable for real-time authentication by reducing computational overheads. This study is relevant to the current research as it contributes to the advancement of adaptive, secure and high-performance fingerprint authentication systems with a potential for further improvement with diverse datasets and techniques like attention-based mechanisms and transfer learning.

[7] This paper proposes a fingerprint analysis and matching system based on deep learning and machine learning techniques. Edge detection and adaptive thresholding is implemented for feature extraction to identify unique ridge and edge patterns in a fingerprint image. Templates are generated using pattern recognition of fingerprint features and minutiae for preventing spoofing attacks. For matching the fingerprints, the authors compare and analyses Convolutional Neural Network, Random Forest, K Nearest Neighbor and Support Vector Machine and concludes CNN's performance is better compared to others with an accuracy of 97.6%.

[8] The study presents a deep learning framework for

simultaneously predicting gender, age group, and quality of fingerprint images in a single pipeline rather than as a separate task using a unified CNN-based architecture that branches into three output heads, each for one attribute. The authors propose a 5-layer convolution with a Maxpooling and batch normalization followed by a global Maxpooling operation at the end to extract features. The obtained fine-tuned feature sets are subsequently fed into 3 parallel artificial neural network classifiers dedicated for detecting gender, hand, and finger respectively. Experiments are conducted on the publicly available SOCOFIG dataset achieving a validation accuracy of 99.38% on gender, 99.46% on hand, and 97.36% on finger prediction respectively. The proposed model reveals an impressive accuracy of 96% when tested on the NIST Special Database 4. However, the limitations include declining in accuracy when faced with incomplete or heavily distorted fingerprint images highlighting the importance of further research to address the challenges with fingerprint images having substantial background noise or partial image content, in order to enhance the accuracy and reliability of fingerprint identification systems.

[9] This study proposes a framework for fingerprints classification combining deep transfer learning and a majority voting system which is a multi-classifier system that is capable of classifying six types of fingerprints. The authors fine-tuned 16 deep transfer learning models for classifying fingerprints. Predictions from the models are combined using a soft majority voting approach to identify the optimal combination of classifiers. Experiments are conducted on six different fingerprint databases consisting of both synthetic and real images. The study finds the majority voting approach of the three deep transfer-learning models, namely DenseNet 121, ResNet152V1, and EfficientNetB7 outperforms the individual transfer learning model in terms of precision for fingerprint classification.

[10] This paper addresses the issue of failing to validate the identity because of the poor fingerprint image that appears damaged due to poor skin condition/large cuts on the fingers/wet fingers/poor scanning of images by reconstructing such images. The authors discuss about two fingerprint reconstruction methods, one using minutiae features for reconstruction from stored minutiae templates using orientation maps, ridge patterns, and phase models and the other method using deep learning approach like CNNs, autoencoders, and GANs to reconstruct the fingerprint images. The paper concludes that Minutiae-based methods are highly accurate with a matching score ranging between 82 and 99.99% but pose security risks whereas Deep learning methods have matching scores ranging between 23-94% which are secure against Type-I and Type-II attacks and better suited for reconstructing poor-quality fingerprints.

[11] This paper addresses the issue of limited size training samples availability for extracting fingerprint features. The authors propose two approaches, inversion by creating two inverted images to get deep features and multi augmentation by applying data augmentation technique and splitting methods on each input image resulting in getting eight distinct images. Features extracted from each method are combined together through a concatenate layer which are passed through Deep neural network architectures VGG16, VGG19, ResNet50, InceptionV3 models to classify the samples of fingerprints. Experiments are conducted on FVC2000-DB4 dataset with accuracy, precision, recall and F1-score as performance metrics parameters achieving the best results with VGG16 model exhibiting an accuracy of 93 % with inversion approach and 97 % with multi augmentation approach. This study is relevant to the current research as it suggests that this approach can be extended to extract deep features from multiple biometrics which can combine to improve the performance of a multimodal biometric recognition.

[12] This paper discusses using lightweight deep learning models integrated with attention modules that focus on distinctive features for fingerprint patterns classification to achieve optimal performance and reduce computational complexity. The author proposes an approach that integrates four attention modules namely Squeeze and excitation, Dual, Self, Convolutional block attention module for fingerprint pattern classification into two lightweight deep learning models MobileNet and EfficientNet-B0 to form the MobileNet+ and EfficientNet-B0+. Experiments are conducted on NIST special database 301 dataset and the LivDet dataset showing a classification accuracy of 97% with only 854,086 training parameters on EfficientNet-B0+ model which uses a swish activation function further reducing information loss, and increases its discriminative capacity that makes it suitable for deployment on low-resource devices. Also, the author observed that the dual attention module outperformed the other module in all the metrics on EfficientNet-B0+ model.

IV. ROLE OF DEEP LEARNING IN FINGERPRINT BASED GENDER PREDICTION

[13] This paper discusses the use of Convolutional Neural Network with Support Vector Machine in improving the accuracy in predicting gender using fingerprint images. The authors propose CNN and SVM to extract features and train models on a dataset of 500 thumb prints. The study mentions that though SVM is a trustworthy performer in gender classification, CNN outperforms other models. This study suggests the use of Convolutional Neural Networks and Support Vector Machines for developing novel technologies which can boost the performance of biometric systems specifically built for gender prediction using fingerprints.

[14] This paper addresses the issue of CNNs slow and premature convergence and getting trapped in local minima by presenting an optimized Convolutional Neural Network (CNN) enhanced by the Whale Optimization Algorithm (WOA) to optimize CNN parameters for Gender detection using fingerprints. Experiments are conducted on 2200 gender labelled fingerprint images acquired from Kaggle. The images are enhanced by histogram equalization and noise is eliminated by using edge detection filtering. While CNN achieved an accuracy of 95.86% and 99.90s recognition time, WOA-CNN outperformed in all metrics demonstrating an accuracy of 97.23% and faster training time, decreasing from 99.20 to 87.40 seconds showing improvement in computational efficiency.

[15] This paper considers the variations in fingerprint image quality, giving a pioneering comparison of gender classification across diverse datasets. Authors propose an advanced AI technique that compares performance across three public datasets namely NIST-DB4, SOCOfing, NIST-302 and one private dataset named IsrPoliceDB collected from the Israeli police. The study introduces Data-Centric AI (DCAI) namely Cleanlab-OOD to filter out distribution outliers, FLIP-Easy/Hard to remove unstable predictions and Margin of Confidence-Easy/Hard that targets low-confidence samples to improve model robustness. Five models VGG16, VGG19, ResNet18/50/101 were evaluated on the four datasets and found VGG19 with DCAI filtering proved to be effective by achieving an accuracy that ranged from 70% to 95% based on fingerprint quality. Also, DCAI

methods contribute a noteworthy improvement of 1–4% in accuracy. However, the employed methodology does not consider scenarios where only a part of the fingerprint is visible.

[16] This main focus of this paper is to study and analyze fingerprints for classifying the gender of humans using in-line digital holography which is a non-contact optical technique that captures phase information for enhancing ridge-valley contrast and minutiae visibility. The authors propose a two-layer CNN with Pooling and Dense layers to train on 6000 images achieving 99% accuracy. The same model achieved an accuracy of 83% when used on fingerprint images obtained through Inline Digital Holography (IDH) technique. The study concluded that fingerprints contain vital features for effectively discriminating against human gender.

[17] This study aims to provide an optimal neural network algorithm based on an intelligent fingerprint system for classifying humans. The authors propose a Polar Bear tuned Dynamic Recurrent Neural Network (PB-DRNN) algorithm for classifying human gender using fingerprints. Experiments are conducted on fingerprint data collected from Kaggle dataset. To remove the distortion from the collected data, a Gaussian filter is used. The experiment findings include accuracy of 99.87%, recall of 99.50% and precision of 99.84% showed that the proposed model works better than other conventional methods in classifying human gender based on fingerprint.

[18] This study proposes a CNN based framework named FigNet for detecting Gender where the architecture is made up of seven layers: 3 convolution layers, 3 pooling levels followed by one fully connected layer. Experiments are conducted on SOCOFING dataset using both real and synthetically altered fingerprints. The authors use the convolutional layers with ReLu activation to ensure nonlinearity in the model. The pooling layers are used to ensure spatial invariance. FigNet architecture achieved an accuracy of 95.2% for classifying females and 97.6% for predicting males. However, there is only limited focus on computational efficiency metrics. Furthermore the effectiveness of the proposed model can be assessed against other datasets and usage of optimization techniques to improve performance.

[19] This paper discusses about a multitask Deep Learning model a Dynamic Horizontal Voting Ensemble (DHVE) with Hybrid of Convolutional Neural Network and Long Short-Term Memory (LSTM) for classifying the combined traits of ethnicity, gender and age group estimation using fingerprint pattern. CNN is used for extracting features which are reshaped into a 3D dataset for LSTM. The authors propose a novel Dynamic Horizontal Voting Ensemble (DHVE) where intermediate results are saved with a predetermined local accuracy threshold as selection criteria and the output of the models is combined using voting techniques to enhance the accuracy. The best of a single sub-classifier score or the ensemble score is dynamically considered for the final prediction. Experiments are conducted by collecting 450 subject fingerprint images representing three predominant Nigerian ethnic groupings with distinct gender and age categories. DHVE outperforms with an accuracy of 0.762 that other two models CNN-LSTM of 0.752 and HVE of 0.747 with a total precision of 0.762% making it a suitable tool for fingerprint recognition in biometric systems.

[20] This study focuses on exploring and developing a robust approach for extracting features from fingerprints for predicting Gender using Dense Dilated Convolution ResNet Autoencoder by replacing the normal convolution operations with the atrous convolution in the backbone and providing prior knowledge for keeping the edge details. The efficiency of this model is evaluated in the dataset containing 6000 images collected from 200 persons containing 98 males and 102 females with 54 combinations using 6 automatic feature extractors and 9 classifiers. The combination of DDC-ResNet and CNN classifiers achieved an accuracy of 96.5% on an average, with a classification accuracy of 95.48% for females and 97.52% for males. The study also inferred the effectiveness of the right ring finger and fingerprint epidermal texture features in gender classification

[21] This paper explores multi-attribute prediction such as Gender, hand type, Finger position and Height range from fingerprint images using convolutional neural networks. The study implements three CNNs VGG16, Inception-v3 and Resnet50 to predict the biometrics. Experiments were conducted on 1000 paper-based fingerprint cards collected from the New Taipei City police department after removing all personal identification data. The results were visualized using Grad-CAM technique and compared with experts' predictions. The CNN models outperformed the experts in terms of speed and accuracy with VGG16 achieving an accuracy of 79.2% in predicting gender, 94.4% in predicting hand types, 84.8% for finger position and 69.8% for height range.

[22] The study presents a novel method of dynamic horizontal voting ensemble model with hybrid CNN and LSTM as the base learner to predict gender based on fingerprint patterns. Experiments were conducted on four thousand Live fingerprint images collected from 450 Nigerian participants. The images were preprocessed using Histogram Equalization Technique and Bilateral Filter to improve the quality of the Images. This study resulted in above 99% accuracy in predicting gender. The authors implemented this model on SOCOFing public dataset and found that the proposed deep learning model has achieved 21% higher accuracy than the other state-of-the-art models such as VGG-19, ResNet-34, ResNet-50 and EfficientNet-B3 used in the benchmark study on SOCOFing dataset.

[23] The paper highlights the ability of Convolutional Neural Network in learning discriminative features without manual feature engineering for classifying Gender using fingerprints. The authors implemented 3 CNN models with multiple convolutional layers extracting features, Pooling layers for reducing spatial dimensions and fully connected layers for classification. The CNN model with a combination of Adam optimizer, learning rate 0.00001 and binary entropy as loss function achieved the high evaluation accuracy of 99.9667%. on the dataset of 49270 images that has been sourced from Kaggle from a gender classification competition based on fingerprints.

[24] This study explores Gender prediction based on fingerprints using Convolutional Neural Networks. The authors used a three convolutional layer with RELU and tanh activation functions on 4000 images of NIST DB4 dataset achieving an optimal performance of 99% accuracy for Relu activation function at 20th epoch. However, this paper does not have any mention about the training time.

[25] The study explores feature extraction and classification of Gender using Fingerprints by considering the global reception field in gender classification and replacing normal convolutions with dilated convolution in the extraction method. The authors had used 6 automatic feature extraction methods like VGG, SVD, DWT with their proposed method Dense Dilated Convolution-Resnet for extracting features coupled with 9 classifiers such as SVM

(3 kernels), KNN, Adaboost, LDA, J48, ID3 and CNN. The fingerprint dataset is obtained from 200 persons collected from 102 females and 98 males with a total of 6000 images. The results showed that the DDC-Resnet extractor with CNN classifier outperformed achieving an accuracy of 96.5% with the right ring finger contributing more in predicting gender with an accuracy of 92.455%

V. COMPARATIVE STUDY OF RELATED WORKS

The Comparative Analysis provides a systematic evaluation of the research initiatives dedicated to classification of fingerprints and Gender Prediction through fingerprints, with particular emphasis on the integration of Deep Learning methodologies.

A. Datasets used in the reviewed papers

The researchers had employed SOCOFing dataset in approximately 70% of the studies for classifying fingerprint classes and custom collected dataset in approximately 46% for predicting Gender based on fingerprint images. The datasets most frequently used in the study are as follows:

- SOCOFing Dataset: ~6,000 fingerprint images authentic + synthetically altered, relatively balanced male and female labelled dataset collected from 600 African Subjects suitable for Gender Prediction. [18]
- NIST DB4: 4,000 plain fingerprint images which are real with gender labels that makes it suitable for Gender Prediction tasks. [23]
- FVC 2000-2004: Fingerprint Verification Competition dataset having approximately 800 samples per edition with Real and Synthetic samples without Gender labels that makes it suitable for Classifying the Fingerprint samples and used to evaluate the performance of Fingerprint Recognition Algorithms. [11]
- PolyU: Approximately 1800 Images collected from collected from 300 people with no explicit Gender metadata [29]
- LivDet: Liveness Detection Competition Dataset which are restricted only to participants of the Competition. Samples are mainly used for liveness detection and not suitable for Gender Prediction as it does not contain Gender Labels. [12]

Figure 1 illustrates the total number of studies which had used the various mentioned fingerprint datasets in predicting Gender from the 23 papers reviewed. Figure 2 illustrates the total number of studies which had used the various mentioned fingerprint datasets in Classification of the Fingerprints from the 18 papers reviewed.

B. Deep Learning models used in the reviewed papers

The researchers had employed Convolutional Neural Networks in approximately 39% of the studies for classifying fingerprint classes and approximately 30% for predicting Gender based on fingerprint images. The Models most frequently used in the study are as follows:

- Convolutional Neural Networks: A Convolutional Neural Network (CNN) is a deep learning model which is designed to learn and extract features automatically from data with spatial structure, such as pixels in an image. CNN is useful for computer vision tasks like classification, segmentation and object detection. Early layers apply filters or kernels to detect local patterns like edges, corners, shapes or textures [21] whereas the next level deeper layers combine these into complex features like objects, humans etc. The fully connected layer maps the learned features to categories.[23]
- ResNet: Introduced by He et al. (2015), revolutionized deep learning by employing residual connections that enabled the successful training of ultra-deep networks, achieving state-of-the-art performance on ImageNet and establishing itself as a foundational architecture for modern computer vision tasks [41]
- VGG16 and VGG19: VGG16 was introduced in 2014 in the paper by Simonyan et al. which has 16 weight layers (13 convolutional and 3 fully connected) using 3×3 convolution filters across all layers, employing max pooling for down sampling and ReLU activation for non-linearity [42]. VGG19 is a deeper variant of VGG16 with 19 weight layers (16 convolutional and 3 fully connected). As its pretrained weights generalize well with other computer vision tasks is is widely used in transfer learning

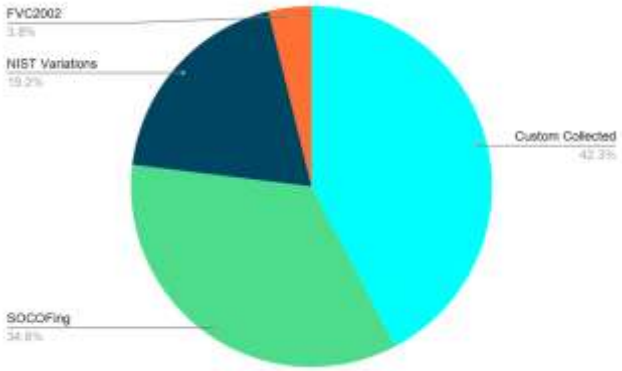


Fig 1. Datasets used in Gender Prediction.

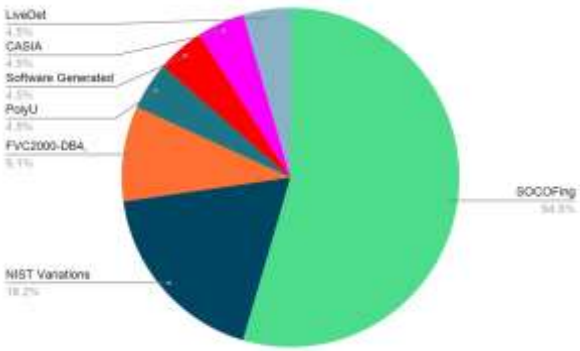


Fig 2. Datasets used in Classification.

- LSTM: Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that overcomes the vanishing gradient problem, effectively learning long-term dependencies in sequential data with the ability to selectively recollect patterns for an extensive time period. [6][35][21]

Figure 3 illustrates the total number of studies which had used the various mentioned Deep Learning Models in Predicting Gender from the 23 papers reviewed. Figure 4 illustrates the total number of studies which had used the various mentioned Deep Learning Models in Classification of the Fingerprints from the 18 papers reviewed.

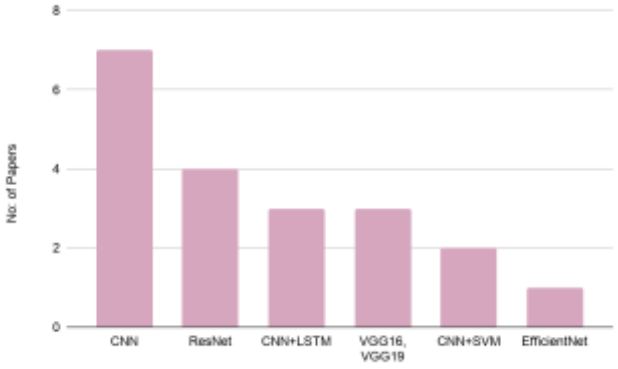


Fig 3. Models used in Gender Prediction

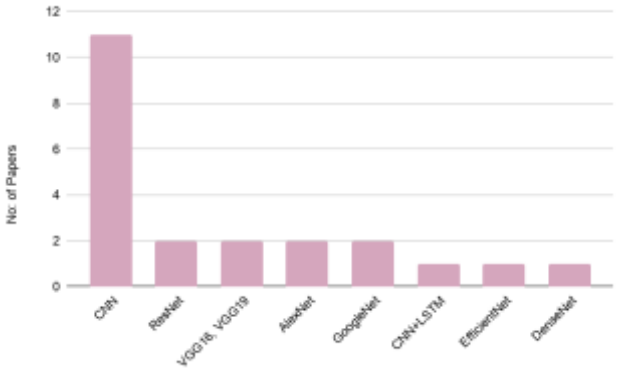


Fig 4. Models used in Classification

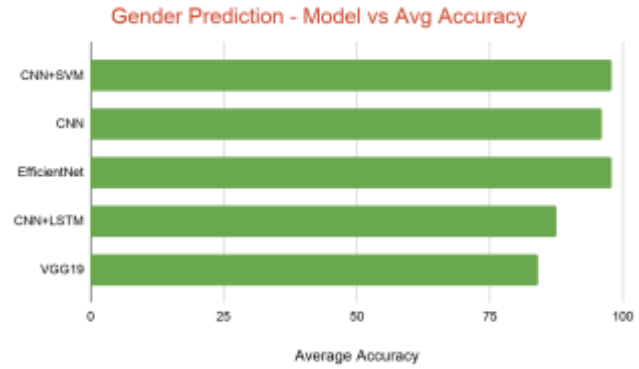


Fig 5. Average Accuracy in Gender Prediction

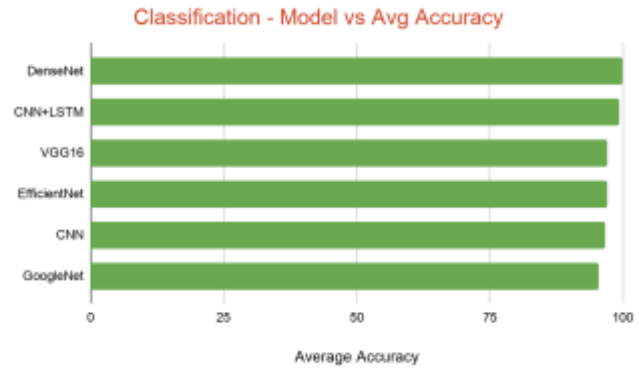


Fig 6. Average Accuracy in Classification

C. Performance Metrics used in the reviewed papers

The researchers had used Accuracy as the metric to measure the performance of the proposed models in most of the Study. Few studies have also considered Precision, Recall and F1 Score metrics. These metrics are calculated using four values "True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN)" [38]. The calculation of the performance metrics is given in Table 3.

D. Average Accuracy achieved in the reviewed papers

Figure 5 illustrates the Average Accuracy achieved in various Deep Learning Models in Predicting Gender from the 23 papers reviewed. Figure 6 illustrates the Average Accuracy achieved in various Deep Learning Models in Classification of Fingerprints from the 18 papers reviewed.

E. Comparison Tables

The systematic comparison of the reviewed literatures for Fingerprint classification is given in Table 4 and Gender Prediction in Table 5. They provide a comparison of the studies using deep learning highlighting the dataset used, preprocessing applied to the images in the dataset, approaches utilized, and metrics reported to measure the performance.

Table 4 provides a structured view of methodological diversity and performance outcomes to facilitate the identification of dominant approaches in fingerprint classification.

The Table 5 synthesizes the key methodologies spanning a range of architectures including Convolutional Neural Networks, Ensemble approaches and Autoencoders to identify common approaches and recent trends in gender prediction.

VI. CONCLUSION

This review of literature in Fingerprint classification and Gender prediction not only catalogues the methodologies but also highlights the recurring trends across studies. As an example, though datasets such as SOCOFing, NIST and custom collected fingerprints are frequently used, it suffers from limited demographic diversity and imbalanced classes. Classical approaches rely on minutiae distribution and ridge density while Deep Learning approaches leverage Convolutional Neural Networks (CNN) to learn representations from fingerprint images for extracting features. The Machine Learning methodologies used in the studies range from Support Vector Machines (SVMs) to ensemble models.

Metrics for Performance used are Accuracy, ROC-AUC, Recall, Precision and F1 Score with Deep Learning approaches outperforming at the cost of Computational complexity. The comparison of the literature underscores the key findings as the CNNs achieves superior accuracy for both classification and Gender prediction using fingerprints. However, the limitations include the Dataset imbalance, Less sample size and restricted demographic diversity. Finally, the consolidated recommendations of the review include Dataset generalizability to include diverse population groups and balanced age, gender distributions, Data augmentation leveraging Generative AI to mitigate imbalances, Multimodal biometric exploration for improved

performance, Model generalization by benchmarking across multiple datasets.

TABLE 3. PERFORMANCE METRICS CALCULATIONS

Metrics	Description	Calculation Formula
Accuracy	It is the percentage of correct prediction to the real target class calculated using the formula	(TP+TN) / (TP+FP+TN+FN)
Precision	It is a measure of the number of positive predictions made by a model that are actually positive.	TP / TP+FP
Recall	Otherwise known as Sensitivity, that measures the number of actual positive samples a model correctly identifies.	TP / TP + FN
F1 Score	It is a balanced measure considering both Precision and Recall which is useful when the dataset is imbalanced.	2 * (Precision * Recall) / (Precision + Recall)

TABLE 4. COMPARISON OF FINGERPRINT CLASSIFICATION STUDIES

Ref	Year	Type of Classification	Dataset	Preprocessing	Methodology	Performance Metrics
[1]	2025	Five different classes	Fingerprints are generated by SFINGE software simulating realistic distributions	-	Multilayer Extreme Learning Machine (M-ELM)	Two-layer hidden ELM had achieved superior classification of both minority and majority classes of fingerprint with a remarkable computational efficiency.
[2]	2025	Original images and forged images	SOCOFing	Sliding Innovation Filter (SIF) is used to standardize image sizes	Feature Extraction: Random Quantum Circuits Transform (RQCT). Classification: Robust Deformed Convolutional Neural network (RDCNN). Optimization: Sand Cat Swarm Optimization (SCSO).	99.35 % 99.37 % precision, 98.83 % recall 98.67 % F1-score.
[3]	2025	Fingerprint into different classes	SOCOFing	Standard Normalization	AlexNet, LeNet, VGG-16 and custom-designed Fingerprint-Net	Fingerprint-Net 99.28%
[4]	2025	Real and Fake Fingerprint for verification and a reliable identification system	SOCOFing	Standard Normalization	2 Novel Approaches SIFT-Descriptor-(SCNN) Siamese convolutional neural network model Oriented FAST-Dense-SIFT Descriptor-SCNN	Second approach Training: 98.37% Validation: 98.55% with a faster prediction time
[5]	2025	Classifies Fingerprint image based on their quality, using a scale from 1 to 5	SOCOFing	Gaussian smoothing, ROI Selection, Gabor filtering	Feature Extraction: Histogram of Oriented Gradients (HOG) Ensemble: Convolutional Neural Networks Support Vector	99.8% The ensemble model outperformed with precision 0.91, recall 1.00 and minimal processing time

					Machines Multi-Layer Perceptron	
[6]	2025	Fake and Real Fingerprints for Authentication	SOCOFing and STRANGE toolbox to generate synthetically altered versions of the fingerprints	Resized and normalized	CNN+LSTM	99.42% Execution time: 1.85 seconds
[7]	2025	Identifies Subject and Finger Number for fingerprint analysis and matching system	SOCOFing	Adaptive thresholding, Roberts, Sobel, and Prewitt filters for enhancement	Minutiae points Extraction: Image thinning algorithms and ridge orientation maps Classifier: CNN, RF, KNN, SVM	CNN 97.6%
[26]	2025	Minutiae enhancement and extraction.	Not Mentioned	Improved Gabor filtering	Hybrid deep CNN with improved Gabor filtering	98.6% improved processing speed by 30% Outperformed conventional methods by ~20% margin
[8]	2024	Estimates the gender, hand, and finger from the fingerprint	SOCOFing	Standard Augmentation	CNN 5 Layer convolution	99.38% -gender, 99.46% - hand, 97.36% - finger 96% on the NIST Special Database 4
[9]	2024	Real and Fake Rolled, Plain and Latent Fingerprints	Six fingerprint databases are used, including 4 real datasets namely NIST SD27, NIST SD301, FVC2002, Anguli with synthetic datasets using IWGAN and Mask2lf models	Standard Augmentation and Normalization	Classification: 16 pre-trained CNN architectures Ensemble: Soft majority voting strategy.	DenseNet121: 99.94% precision (99.95%), recall (99.94%), F1-score (99.95%), AUC (99.99%), MCC (99.9%3)
[11]	2024	Samples of fingerprints into ten classes for personnel identification and verification.	FVC2000-DB4	Standard Normalization	VGG16, VGG19 with multi-Inversion and multi augmentation methods, ResNet50, InceptionV3	VGG16: 93 % with inversion approach 97 % with multi augmentation approach
[12]	2024	Six classes: plain arch, double loop, left loop, right loop, tented arch, and whorl.	NIST Special Database 301 (SD301), LiveDet	Standard Augmentation and Resizing	Four attention modules namely Squeeze and excitation, Dual, Self, Convolutional block attention module integrated to MobileNet and EfficientNet-B0, referred to as MobileNet+ and EfficientNet-B0+	EfficientNet-B0+ 97% with only 854,086 training parameters,
[27]	2022	Identifies gender, hand and fingers	SOCOFing Dataset	Wiener filter and multi-level	Three Convolutional Neural Network	99.96%.

				Histogram techniques		
[28]	2022	Finger types.	SOCOFing, NIST	Standard Normalization and Resizing	4 Layer CNN named Thumb CNN (TCNN)	90% and 89% across both datasets.
[29]	2021	Four, five, and eight classes.	PolyU and NIST Special DB 4	Standard Normalization and Resizing	AlexNet, GoogLeNet, ResNet Statistical validation using McNemar test to confirm reliability of results	AlexNet: an average precision of ~97% on both the datasets with less training time.
[30]	2021	Fingers, hands, and gender class category	SOCOFing Dataset	Standard Normalization and Resizing	Modified Capsule Network	>99%
[31]	2019	Five and four classes of fingerprints.	NIST Special Database 4	Standard Normalization and Resizing	GoogleNet	94.7% and 96.2% for the five-class and four-class classification

TABLE 5. COMPARISON OF FINGERPRINT-BASED GENDER PREDICTION STUDIES

Ref	Year	Dataset used	Preprocessing	Approaches	Performance Metrics in Accuracy
[14]	2025	SOCOFing	Cropping, grayscale conversion, histogram equalization for enhancement, and edge detection filtering to eliminate noise	Whale Optimisation Algorithm with CNN	97.23% 97.58% sensitivity, 96.70% specificity, 97.80% precision and 87.40 s recognition time
[15]	2024	3 Public datasets, NIST-DB4, SOCOFing, NIST-302, and Private Sources IsrPoliceDB	Standard Augmentation, Weighted Random Sampling	VGG16, VGG19, ResNet18,15, 101 + Data-Centric AI (DCAI) Strategies	VGG19 - 70% to 95% based on fingerprint quality. Improvement of 1 - 4% for Accuracy and 2.5% - 2.75% F Score in using DCAI
[16]	2024	Custom or institutionally curated collection 6 000 optical + 6 000 holographic	None	2-layer CNN	Optical: 99% Holographic: 83%
[17]	2024	Kaggle Probably SOCOFing	Gaussian filtering	A Dynamic Recurrent Neural Network (DRNN) optimized using a Polar Bear tuning algorithm (PB-DRNN)	99.87% recall (99.50%) precision (99.84%)
[18]	2023	SOCOFing Dataset	None	CNN Fig-Net Architecture - Three convolutional layers, three subsampling (pooling) levels, one fully connected layer, and lastly an output layer which make up its seven-layer architecture	96.47% Females: 95.2% Males: 97.6%
[33]	2023	Custom 49,270 FP Images	Standard Augmentation and Resizing	CNN	Training: 80% Testing: 93%
[34]	2023	FVC2002 for regeneration, SOCOFing for evaluation	Gabor filters for Noise Reduction and Otsu's thresholding technique, Image enhancement with	CNN	Training: exceeding 99%, Validation: 97%, 93%, 87% on 3 sets of SocoFing Dataset

			Contrast Limited Adaptive Histogram Equalization (CLAHE)		
[35]	2023	Totally 4500 Images collected using a live scan method with 450 (10 on each) subjects from three most numerous racial groups of Nigeria which are Yoruba, Igbo and Hausa	Histogram equalization, Edge Preserving Bilateral Filter	CNN-LSTM	76%
[36]	2023	NIST SD-4 000	Not needed	Feature extraction by 4-level Haar Wavelet followed by Max pooling process and classification by MLP	80.10%
[37]	2023	SOCOFing	Standard Resizing and Normalization	DCNN 4 layer	96.46%
[38]	2023	NIST Sample 200	None	No convolution layers used. Instead, the model applies three types of pooling, Min pooling, Average pooling, Max pooling. These pooling operations are stacked up to eight levels to extract hierarchical features directly from raw fingerprint images. Extracted features are then fed into a K-Nearest Neighbor classifier.	Average: 66.25%
[19]	2023	Generated	Resized 256x256 and normalized	Dense Dilated Conv-ResNet Auto-encoder + 54 classifier combos	96.5% Males: 97.52% Females: 95.48%
[20]	2022	1000 paper-based FP cards provided by new Taipei City Police Dept	Crop, Binarization, Resize	VGG16, Inception V3, Restnet 50	VGG16 - 79.2% Inception V3 - 79.1% Restnet 50 - 77.1%
[21]	2022	> Four thousand Live fingerprint images	Histogram Equalization Technique followed by Bilateral Filter	Dynamic horizontal voting ensemble model with hybrid Convolutional Neural Network and Long Short Term Memory deep learning algorithm	>99%
[22]	2022	Collected via live scan under real-world conditions from Nigeria's three major ethnic groups: Yoruba, Igbo, and Hausa.	Histogram Equalization Technique followed by Bilateral Filter	Dynamic Horizontal Voting Ensemble (DHVE) with a hybrid of Base learners Convolutional Neural Networks and Long Short-Term Memory networks.	76%
[39]	2022	SOCOFing	Standard Normalization	CNN+SVM	CNN: Threshold 0.75 96.5% Sensitivity: 97.3% Precision: 97.9%
[23]	2021	NIST DB4	Minor contrast stretch	3 Layer CNN	99%
[24]	2021	SOCOFing	Resized to 96x96 Pixels	CNN	99.97%
[25]	2021	Collected from 200 persons (102	Standard Normalization and	Dense Dilated Conv-ResNet Auto-encoder + 54 classifier combos	96.50% Male: 97.52%

		females and 98 males)	Resizing		Female: 95.48%
[40]	2020	Collected from volunteers of Cambodia and Korea	None	VGG-19, ResNet-50, EfficientNet-B3 (trained from scratch)	EfficientNet-B3: Training: 97.89% Validation: 69.86% Testing: 63.05%

This review of literature provides insights into current trends, effective methodologies and unresolved challenges in Fingerprint classification and Fingerprint based Gender Prediction which can be used as a roadmap by researchers to extend or replicate existing work and a basis to identify promising directions for research advancements in the field of biometric science.

CONFLICTS OF INTEREST

"The authors declare that there is no conflict of interest regarding the publication of this paper."

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