Machine Learning based finger print Analysis for Gender Detection: A Review

Abstract

Gender detection using fingerprint biometrics has emerged as a promising area of research due to its non-intrusive nature and potential applications in biometric identification systems. The procedure can involve multiple steps are the size of finger print and their ridge pattern, minutiae point , machine learning and image processing and accuracy and limitations. This review explores the effectiveness of machine learning techniques for gender classification based on fingerprint patterns, emphasizing the role of advanced classification algorithms and feature extraction methods. Machine learning is crucial for gender detection since it classifies fingerprint patterns and biometric information using models like Convolutional Neural Networks (CNN) and Support Vector Machines (SVM). To identify traits unique to a gender, such as ridge density and minutiae points, these algorithms are trained using labelled datasets. Compared to manual procedures, these models are more effective at handling high-dimensional data and identifying subtle gender-related patterns. Although hybrid models like CNN-DNN and AlexNet further increase classification precision, Convolutional Neural Networks (CNNs) are especially effective due to their automatic feature extraction capabilities. Despite their effectiveness, factors like as picture resolution, demographic balance, and dataset heterogeneity might affect performance, highlighting the need for carefully selected datasets and improved model designs. A structured comparative analysis of multiple studies reveals the impact of various datasets, feature types, and model architectures on classification accuracy and reliability. The findings suggest that deep learning models often outperform traditional classifiers, while dimensionality reduction and hybrid approaches can further enhance performance. However, challenges such as dataset imbalances, limited diversity, and susceptibility to low-quality fingerprint data remain prominent barriers to achieving consistent results. This review also outlines key limitations observed across the studies and provides recommendations for future research, including the need for more diverse datasets and optimized classification frameworks. This study aims to improve fingerprint feature extraction for gender detection, reduce processing costs, fix dataset imbalances, and increase classification accuracy. By stating the objective, the scope and objectives of each investigation are made clear. The generalizability of machine learning models is significantly impacted by the amount, variety, and quality of the dataset. The analysis aims to support the development of more accurate, inclusive, and scalable fingerprint-based gender detection systems.

Keywords: Fingerprint Biometrics, Gender Classification, Machine Learning, Convolutional Neural Networks (CNN), Feature Extraction Techniques.

1. Introduction

Every human has their own name, a fundamental aspect of their identity and cultural heritage. The name often conveys a wealth of information, including details about an individual's background, ethnicity, and, especially, their gender [1]. Electronic equipment and digital gadgets in use today widely utilize biometric features of users to assure the security of their devices. The very purpose of biometric is to check the authenticity of the user using the device. Advancement in technology proposes various methods of validation of authenticity. Biometric features used for user validation include face, iris, palm, fingerprints and hybrid systems with usage of face and fingerprint both [2]. Every person in the world has unique biometrics characteristics such as iris, face, voice, palm or finger-vein patterns, and fingerprints [3]. Recently, the user's gender and age range are very important for organizations to understand their customers 'needs and develop their strategies to provide more enhanced services to them. These organizations mostly rely on their enterprise systems to collect data from users, which forms play an important role in it [4]. Biometric information refers to an individual's measurable, unique features, which include physical characteristics like fingerprints, iris, faces, and veins, as well as behavioural characteristics like voice, signature, and writing. Biometric information is garnering tremendous attention, primarily as a security tool, because of its high reliability and security, as it is unique for each individual.[5] An intensive research investigation by forensic scientists uncovered a unique pattern embedded in the fingerprint and determined that a deeper look at the details of the fingerprint can provide a clue to a person's gender and other rich information about that individual[6]. Fingerprints have been recognised as one of the most widely known and utilised biometric solutions for authenticating individuals in biometric systems[7] . It has been found that additional identifying information (such as gender, age, and race) can be deduced from fingerprint patterns[8] . This additional information is referred to as soft biometrics. They are soft because they are insufficient to individually identify individuals, but they can be used to supplement the identity data provided by major biometric identifiers. An intensive research investigation by forensic scientists uncovered a unique pattern contained in the fingerprint and determined that a closer look at the details of the fingerprint can provide a clue to a person's gender as well as other rich information about an individual[9] . Fingerprints' distinctive traits can be utilised to distinguish individuals based on their gender. The first mention of soft biometrics, such as gender, was for filtering massive biometric databases and limiting the number of searches. Detecting a specific fingerprint in a vast database during the fingerprint recognition process typically requires significant computational complexity in terms of time and hardware resources [10]. However, knowing the gender of the person involved in the search can help. The topic of soft biometrics is progressively garnering attention over traditional biometrics, and current studies are tilting towards it as a potential substitute for traditional biometrics[11]. Fingerprints were acquired from 125 males and 125 females aged 18 to 60. The average value of the ridges in the fingerprints obtained was computed. The findings showed that there are substantial differences in epidermal ridge density between males and females, and they also support the hypothesis that the ridge density of women's fingerprints is statistically significantly greater than men's. The results of the investigation reveal that fingerprints with 14 ridges/25 mm2 are more likely to be female. A novel method to classify gender from fingerprints was given by[12] Consequently, gender inequality and related issues represent significant challenges in our society. International donor agencies, including the World Bank, European Union, and African Development Bank (AfDB), recognise the gender identity system as a crucial foundation for women, serving as a means of empowerment and providing access to specific services and privileges as citizens [13]

The goal of this review is to give you a full picture of how to use machine learning to figure out someone's gender by looking at their fingerprints[14]. The study shows how machine learning can improve the accuracy and speed of biometric classification by looking at how fingerprint-based gender detection has changed over time[15]. The review goes into more detail about important fingerprint traits, datasets, and the different machine learning models that are used in this field[16]. There is a comparison of past research projects to find trends, problems, and holes in the way research is done now. The goal of this structured review is to provide useful information for improving fingerprint-based systems that identify gender and directing future biometric classification research[17].

2. Overview of Fingerprint-Based Gender Detection

Fingerprint is a significant biological characteristic of the human body, encompassing a wealth of biometric information. The current academic investigation into fingerprint gender characteristics is primarily at a foundational level, with limited research on standardisation. [18]. The tiny ridges on the tips of the fingers, which are basically folds of the epidermis, the outermost layer of skin, are known as fingerprints. Our fingerprints started to form before we were even born. Fingerprints are made up of a series of interconnected ridges and valleys that depict the epidermal layer of a finger. All fingerprints fall into one of three distinct classes: whorls, loops, or arches [3]. The distinct patterns and ridge patterns seen in fingerprints are used in fingerprint-based gender detection to categorise people according to their gender. Machine learning models may detect tiny gender variations by looking at variables like ridge density, minutiae points, and ridge flow patterns. While deep learning models like Convolutional Neural Networks (CNN) have demonstrated higher performance because of their capacity to automatically learn complicated spatial patterns, traditional classifiers like Support Vector Machines (SVM) and k-Nearest Neighbours (k-NN) have proven to be successful. Preprocessing procedures including picture improvement, feature extraction, and classification are typically included in the process[19]. Notwithstanding advancements, issues including unequal datasets, a lack of demographic representation, and disparities in image quality still have an impact on model accuracy. Diverse datasets, hybrid models, and enhanced feature extraction methods are needed to address these problems and get better results.[4] Fingerprint-based gender detection classifies people by gender using distinctive fingerprint patterns, such as minutiae points and ridge structures. Following feature extraction, machine learning models such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) are used for classification[20]. To detect minute variations between male and female fingerprints, these models are trained on fingerprint datasets. Accuracy may be impacted by issues including uneven datasets, a lack of demographic variety, and variances in image quality[21]. By creating increasingly complex models and growing datasets for greater representation and dependability, current research seeks to enhance categorisation performance.[22][23]

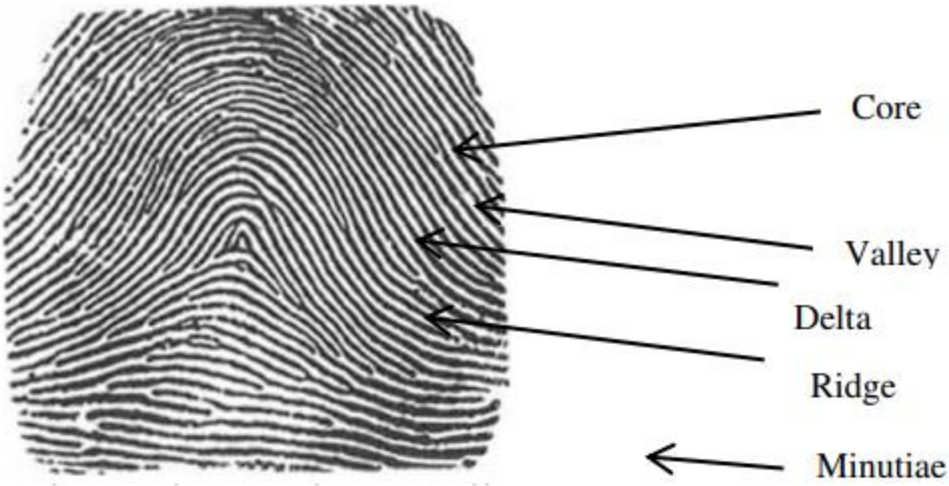

Figure1: Fingerprint details [3]

Core: is the center of fingerprint located found by analyzing the ridge orientation field's curvature.

The core location (x,y)= arg max area (the orientation field's curvature or divergence)

Delta: identified through examination of sudden shifts in the gradient of direction.

The delta point (x,y)=peak in the discontinuity of ridge flow.

Bridge: determined by calculating the separation between two ridges that run parallel to one other.

Bridge width = min distance separation between two ridges [16]

3. Role of Machine Learning in Gender Detection

Automatic gender detection has garnered interest from various academic domains, including forensic linguistics and marketing. In these domains, gender detection has been treated as a classification problem, leading to the utilisation of supervised Machine Learning techniques, including Naïve Bayes, Logistic Regression, and Support Vector Machines, among others. The aforementioned algorithm has demonstrated superior performance in gender detection [24]. A machine learning workflow for detecting gender from fingerprint pictures. It begins with pre-processing, which includes median filtering, Otsu thresholding, and image scaling.

In the feature extraction phase, data is normalised using a Box-Cox transformation before being saved in a database. Finally, a logistic regression classifier predicts the gender as female or male[25]. Machine learning is important in gender recognition because it uses models such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) to classify fingerprint patterns and biometric features[26]. These models are trained on labelled datasets to recognise gender-specific characteristics like minutiae points and ridge density. CNNs are very useful because of their automated feature extraction capabilities, and hybrid models that combine CNN with other classifiers have demonstrated increased accuracy . Performance is commonly tested using criteria like as accuracy, precision, and recall[10]. Despite its success, difficulties like as dataset imbalance and image noise still exist, emphasising the necessity for different datasets and optimised methodologies for broader applicability[27] Machine learning, particularly deep learning models such as Convolutional Neural Networks (CNN) and YOLO, helps to automate gender detection by recognising patterns in high-dimensional data. These algorithms are trained using massive datasets, allowing for precise gender classification based on morphological traits. YOLO's blend of speed and precision makes it particularly effective for real-time detection. Despite their efficiency, the performance of machine learning models can be influenced by dataset quality, feature variety, and environmental unpredictability.[28] Machine learning, especially deep learning models such as CNNs and SVMs, is essential for gender recognition through the analysis of biometric patterns and structural characteristics for automated classification. These models are proficient in managing high-dimensional data and detecting nuanced gender-related patterns more efficiently than manual techniques. Convolutional Neural Networks (CNNs) are particularly proficient owing to their automatic feature extraction abilities, although hybrid models such as CNN-DNN and AlexNet further improve classification precision. Notwithstanding their efficacy, elements like as dataset heterogeneity, picture resolution, and demographic equilibrium can influence performance, underscoring the necessity for meticulously curated datasets and refined model architectures.[29]

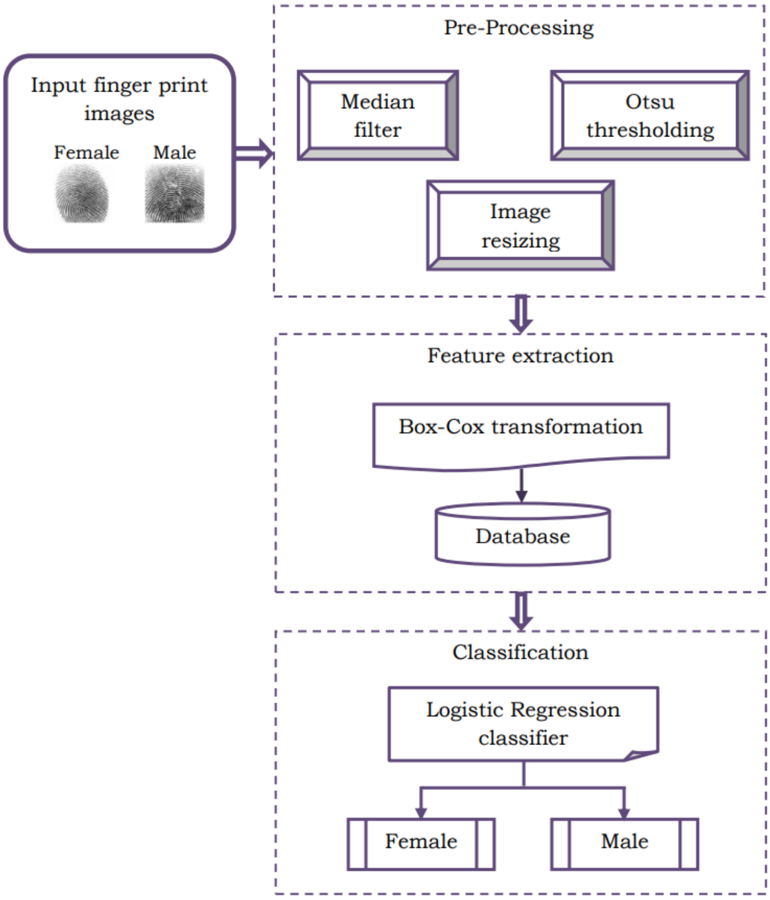

Figure 2: Workflow for Gender Detection Using Fingerprint Images with Machine Learning [24]

4- Comparative Analysis of Existing Studies

The Comparative Analysis of Existing Studies section offers a systematic assessment of diverse research initiatives centred on gender identification through fingerprint biometrics and machine learning methodologies. This section is a table that offers a detailed comparison by summarising essential elements of each study, including the objective, dataset utilised, features retrieved, machine learning methods applied, performance measures, significant findings, limitations, and recommendations for future research. This comparative methodology facilitates the identification of the most efficacious tactics for gender classification, emphasising frequently utilised datasets and feature extraction techniques, while also addressing difficulties such as dataset imbalance and restricted generalisability. This analysis provides useful insights into current trends, effective approaches, and areas needing future investigation in fingerprint-based gender classification by systematically comparing different studies.

Table 1: Comparative Analysis of Gender Detection Studies Using Machine Learning Techniques on Fingerprint Biometrics"

Ref#	Aim of the study	Dataset Used	Features Extracted	Machine Learning Techniques	Performance Metrics	Key Findings	Limitations	Future suggestions
[30]	To propose a deep learning strategy for classifying fingerprint gender (male or female) using EfficientNetB0 and machine learning techniques. To improve classification accuracy and reduce computational cost compared to previous methods.	• SOCOFing dataset obtained from Kaggle. • Consists of 6,000 fingerprint scans from 600 individuals. • Various variations were generated through augmentation and preprocessing.	Principal Component Analysis (PCA) is implemented to reduce dimensionality.	• Using EfficientNetB0 for transfer learning to extract features. PCA is used to reduce dimensionality. A classifier for classification called Random Forest (RF).	• Accuracy: 99.91% (EfficientNetB0 + PCA + RF). • Precision: 99.89%. • Recall: 100%. • F1-score: 99.94%.	• The proposed EfficientNetB0-PCA-RF model outperforms earlier techniques. • Enhanced accuracy and reduced training time over EfficientNetB0. • Enhanced classifier performance using PCA-efficient feature reduction. .	One dataset (SOCOFing) may limit generalisability. Noisy or poor fingerprint images may affect performance.	• Exploration of supplementary optimisation techniques and pre-trained convolutional neural network designs. Incorporation of varied biometric datasets to enhance model resilience. • Improving network architecture to augment speed and manage noisy images data.
[31]	• To create and evaluate fingerprint-based gender categorisation models utilising different classifiers and feature extraction approaches. • To address gender categorisation dataset imbalances and assess data balancing techniques.	• NIST Special Database 4: 2,000 greyscale fingerprint pictures from male and female samples.	• Fast Fourier Transform (FFT): Extracts features in the frequency domain. Principal Component Analysis (PCA) reduces dimensionality by identifying key eigenvalues. • Integration of FFT and PCA features to improve performance.	• K-Nearest Neighbour (KNN). • Support Vector Machine (SVM) utilising different kernel functions. • Decision Tree Analysis. • Feedforward Neural Networks (NN).	Precision and Scope The Area Under the Curve (AUC) of Receiver Operating Characteristic (ROC) curves was employed to assess the performance of classifiers.	Using SVM with hybrid sampling yielded the best results: Identification of males: 75.55 percent. The percentage of females identified is 91.62 percent.	• The dataset had few samples per class, especially for females. • Noise and uneven class distributions hindered classification performance.	Investigate supplementary dataset balancing methodologies to augment performance. Incorporate the classification system with high-performance computing (HPC) to enhance search space efficiency and reduce processing duration.
[32]	• To suggest a new method for the enhancement and	• Fingerprint Verification Competition datasets FVC2002 and	ridge termini and bifurcations are examples of minutiae points. • The components of the	• Minuties are utilised for matching and verification, but not expressly stated. A reconstruction approach	• Recognition Rate (Type I Attack): • FVC2002: 97.95% • FVC2004: 94.09% •	• Reconstructed fingerprint images are much better thanks to the suggested	• Lower recognition rates for Type II attacks owing to partial	Reconstruct fingerprints more realistically. • Study global orientation and unique points to improve ridge

	reconstruction of fingerprint images by utilising minutiae density and orientation field directions. • To resolve issues with the quality of fingerprint images, particularly those that are latent or of low quality.	FVC2004. • The DB1 and DB2 subsets, which combine a 500 DPI resolution with a number of sensors (including optical and thermal ones).	orientation field and the ridge frequency.	uses advanced modelling techniques including continuous phase and AM-FM.	Type II Attack Recognition Rate: 49.25% (FVC2002). o FVC2004: 50.02%. •	technique. • Less spurious minutiae than with previous approaches. • Better image clarity and ridge structure, particularly for latent and low-quality fingerprints.	fingerprints and low visibility. • Assuming constant ridge frequency may sometimes result in mistakes.	reconstruction. Explore frequency field reconstruction from minutiae positions.
[33]	• To develop a resilient gender prediction system utilising fingerprints through the integration of the Fuzzy C-Means (FCM) clustering method and Artificial Neural Network (ANN). • Enhance precision in gender prediction by amalgamating intricate microscopic details with sophisticated machine learning methodologies.	High-quality fingerprint pictures were collected from 100 subjects (50 male and 50 female). • Data was collected in a controlled environment to assure quality and reduce noise.	Ridge Information: Total ridge count, minimum/maximum, average, bifurcation, and ridge end counts. Minutiae count, bifurcation count, ridge end count, minimum/maximum angles. • DWT: Six decomposition stages, multi-resolution features.	Fuzzy C-Means (FCM) clustering for refined feature classification. Artificial Neural Network (ANN) for classification and forecasting .	Accuracy: 94.2% (FCM-ANN), in contrast to 86.7% for the baseline ANN. Accuracy: 92.5%. Recall: 93.9%. F1-Score: 94.8%. AUC-ROC: 0.931.	FCM-ANN integration beats independent ANN models. Ridge information and minutiae traits help differentiate gender. DWT captures multi-resolution details to strengthen models. .	Small dataset size may hinder generalization. Controlled data collection settings may not accurately imitate real-world issues like noise or incomplete prints.	• Include more participants and conditions in the dataset. • Determine how noise and low-quality fingerprints affect model performance. • Use hybrid clustering and feature selection to improve accuracy.
[34]	Using a capacitive sensor floor, create a system for gender and	• Walking data was collected from 23 participants, with each participant	Spatial features (shoe size, step length, pronation/supination, heading).	• Networks of neurones: CNN, MLP, LSTM, BLSTM, and GRU (Gateway Recurrent Units-	• In terms of gender recognition, CNN was the most accurate with a score of 93.3%.	• CNN used geographical features better than other gender recognition	• The 23-person sample reduces generalisability. • Only classified	Expand the dataset and include varied genders. Integrate more sensing modalities to improve

	identity recognition based on machine learning. • To compare and contrast the performance of several neural network designs tailored to this task.	completing 10 walking trials on a capacitive sensing floor. • Data recorded in greyscale images (200 pixels per frame) at a sampling rate of 10 Hz.	Temporal characteristics (cadence, stride length, foot planting angle).	Neural Architecture). • A baseline classifier that makes use of Support Vector Machines (SVM).	85.0% is the baseline for SVM. • For identification purposes: • BLSTM had a peak accuracy of 98.12%.	algorithms. • BLSTM extracted fine-grained temporal characteristics best for identification recognition. • Neural networks outperformed SVM in all metrics.	gender as cisgender male and female. Capacitive sensing floors may struggle in real-world applications because to deployment and maintenance issues.	performance. Real-world deployments may validate and localise several targets.
[35]	• To create a hybrid CNN-SVM machine learning strategy for accurate fingerprint-based gender classification. • Improve classification accuracy above solo CNN and other approaches.	• 55,273 fingerprint images from 600 people from SOCOFing. The STRANGE toolkit-augmented dataset includes gender and artificially changed photos.	• CNN model with two convolutional layers, max pooling layers, and dense layers automatically extracts features. High-dimensional feature vectors as SVM inputs.	Hybrid CNN-SVM model: CNN for feature extraction. SVM for classification.	Precision: 90.25%. Female: 0.98 F1-Score: 1.00 (male). Accuracy and Recall: Both categories exhibit nearly ideal levels.	• The hybrid model integrating CNN and SVM demonstrated a marked improvement over the standalone CNN, attaining superior precision and recall. • The automatic feature extraction capabilities of CNN, when paired with SVM classification, provide a reliable and efficient approach to gender determination.	Because SOCOFing dataset lacks diversity, focussing on African individuals. • Generalisability into other demographic groups or noisy real-world data is challenging.	• Expand research to demographically diverse datasets. Explore advanced data augmentation methods with Generative Adversarial Networks (GANs). • Explore geometric and histogram-based classification robustness improvements.
[36]	• Use CNN models (VGG16, Inception-v3, and ResNet50) to predict gender, finger position, and height range from fingerprints. • To give faster and more accurate automated forecasts than manual approaches	The New Taipei City Police Department contributed a dataset of 1,000 fingerprint photos, 500 of which were male and 500 of which were female, and which were digitised from paper fingerprint cards. The images had a resolution of 600 × 600 dpi.	Automated feature extraction utilising convolutional neural networks (CNNs). Ridge density and orientation patterns illustrated by Grad-CAM for enhanced interpretability.	Inception-v3, ResNet50, and VGG16 CNNs. Five-fold cross-validation ensures impartiality. Grad-CAM for model interpretability.	• Gender Prediction: Achieved an impressive accuracy of 79.2% with VGG16. • Finger Position Prediction: VGG16 stands out with an impressive accuracy of 84.8%, leading the pack of tested models. • Height Range Prediction: VGG16 reached an accuracy of 63.9%, yet the overall accuracy for height range prediction	• Ridge density predicted gender. • VGG16 beat gender categorisation specialists in speed and accuracy. • Thumbs and small fingers were accurately predicted, but other fingers were not. • Fingerprints did not predict height well, suggesting little link.	• Small dataset may limit model generalisability. • Height prediction accuracy is low, requiring larger, more diverse information. • Controlled fingerprint collection may not reflect real-world issues.	• Add more samples and heights to the dataset. • Try new deep learning architectures and methods to boost performance. • For accuracy, investigate biometric factors like ridge orientation flow.

					remained modest across all models.			
[37]	• To create a deep learning-based fingerprint classification system for left and right hands. • To improve AFIS fingerprint identification performance by adding classification.	• 10,080 fingerprint images: 9,080 for training (4,540 left-hand and 4,540 right-hand) and 1,000 for validation (500 each). • Images were scanned at 224 × 224 pixels using a customised preprocessing pipeline.	• Convolutional layers in neural network architectures automatically extract features. • Image preprocessing includes noise removal and scaling for model input dimensions.	Several CNN designs were used, such as VGG-16, AlexNet, Classic CNN, ResNet50, and YOLO (You Only Look Once).	ResNet50's best classification accuracy: 96.80% (300 epochs). • Other models had slightly lower validation accuracy: • VGG-16: 96.00% • AlexNet: 95.10 percent • Classic CNN: 84.50% • YOLO v3: 86.25% (9,000 iterations).	ResNet50 surpassed other designs in terms of validation accuracy, making it the best model for left- and right-hand classification. VGG-16 and AlexNet both performed admirably, proving the utility of deep learning models for fingerprint categorisation.	• The dataset was proprietary, restricting external researchers' reproducibility. • No testing was done on real-world applications using noisy or low-quality fingerprint data.	Expand the study to include the classification of other traits, including fingerprint type (e.g., arch, whorl, loop), or the identification of specific fingers. Test the system on diverse and noisy real-world fingerprint datasets for broader validation.
[38]	To present a deep learning-based fingerprint categorisation system for left/right hand, sweat-pore, scratch, and finger type. To increase Automated Fingerprint Identification System accuracy and efficiency.	The proprietary collection includes 10,690 fingerprint images from 1,069 people (1,008 Cambodian and 61 Korean). Images were divided: Training dataset: 10,080 Cambodian pictures. Testing dataset: 610 Korean pictures. Image scanned at 800 × 750 pixels and reduced to 224 × 224 pixels during preprocessing.	Deep learning models extract automatically. Data upgrades focused on fingerprint patterns by cropping, rotating, and scaling photos.	• Models used: VGG-16, AlexNet, Classic CNN, Yolo-v2, and ResNet-50 • Stochastic gradient descent with regularisation (dropout 0.5) was used to train and evaluate each model.	Left/Right Hand Classification: YOLO-v2 scored 90.98% accuracy (best). In Sweat-Pore Classification, ResNet-50 achieved 91.29% accuracy (best). Scratch Classification: YOLO-v2 achieved 78.68% accuracy (best). Finger Type Classification: YOLO-v2 scored 66.55% accuracy (best).	YOLO-v2 and ResNet-50 worked best for classification tasks, with good accuracy and low computing time. Narrowing AFIS search space enhanced processing efficiency and identification speed.	• Korean participants had a small dataset size, resulting in low finger type categorisation performance (66.55%).	• Add more varied participants for greater generalisation. • Create one deep learning model for all classification categories. • Explore innovative and robust deep learning architectures to boost performance.
[39]	To thoroughly evaluate fingerprint categorisation algorithms and their use in criminal investigations.	An overview of numerous investigations, not a single dataset. • Discusses mentioned works' NIST and FVC datasets.	Ridgeflow patterns. Ridge ends, bifurcations, and dots are minutiae. Level-3: Sweat pore sites, ridge route deviations, and scars (forensic).	• Backpropagation, MLP, and RNN neural networks. • K-means clustering, SVMs. • Rule-based classifiers, graph theory, and DFT.	This survey uses performance indicators from numerous research, which differ per algorithm and dataset.	• Due to its reliability and efficiency, minutiae-based matching dominates. • Neural network-rule-based classifier hybrids boost accuracy.	• Controlled datasets limit real-world applicability in most studies. Handling low-quality and noisy prints remains	Develop next-generation recognition systems that handle varied data kinds. Improved spoof detection and

	To discuss classification, feature extraction, and matching machine learning methods.					• Reliability requires spoof detection and improvement methods like Gabor filters.	challenging.	postmortem fingerprinting. Fingerprinting with other biometrics (e.g., vein recognition).
[6]	Examine biometric technologies' design and use in identity verification to better understand how they interact with human body differences.	The text makes generic references to biometric technologies used in European borders, Asian airports, and the Netherlands' immigration processes.	Fingerprints, iris patterns, and facial features. Contains ethnicity, gender, and age metadata for classification and analysis.	Iris, face, and demographic classification algorithms (e.g., Doddington's Zoo classification model for biometric accuracy evaluation).	Fehlerrate (false acceptance, false rejection), picture quality criteria, and demographic cohort matching accuracy (e.g., ethnicity, gender) are metrics.	to design biases like bration to whiteness" etric systems have er mistake rates for ific groups. algorithms struggle with er-race effects," rming better on faces those in training sets. rational tweaking is alent.	Dependence on design assumptions like body homogeneity. - Variability issues like sleepiness impacting iris scans. - Biases from opaque algorithms and training sets.	Design algorithms and systems for various demographics. Add reflexivity to system design to reduce bias. Enhance datasets with real-world diversity. Focus on biometrics' identity-building role.
[40]	To evaluate minutiae-based and deep learning fingerprint reconstruction methods to improve fingerprint matching and validation.	Fingerprint reconstruction evaluation datasets include NIST SD4, FVC2002 DB1, FVC2004, and IIITD-MOLF.	Ridge patterns, minutiae, and latent characteristics.	Minutiae-based reconstruction using orientation fields, CNNs for fingerprint autoencoding, and GANs for data synthesis and reconstruction.	TAR, FAR, EER, and matching scores for reconstructed fingerprints are metrics.	Deep learning improves fingerprint reconstruction, especially for low-quality pictures. Deep learning techniques have TARs from 20% to 98.1%, whereas minutiae-based models reach 99.9%.	The computational cost of deep learning is high. - Deep learning reconstruction accuracy is lower than minutiae-based models. Extraneous details in some models diminish accuracy.	Address irrelevant details with powerful deep learning approaches. Improve fingerprint databases to reflect real-world differences. Enhance models' spoofing and Type-I/II resistance.
[3]	Review fingerprint gender identification methods, highlighting methods, and algorithms.	CASIA, NIST SD4, and proprietary study datasets.	Regional Binary Patterns (LBP), ridge density, size of fingertip, minutiae points, and ridge patterns.	Various approaches are available, such as Support Vector Machines (SVM), Convolutional Neural Networks (CNNs), k-NNs, Naïve Bayes, Artificial Neural Networks (ANNs), Decision Trees, and Fusion methods that combine Local Binary Patterns (LBP) and Local Phase	Some examples of metrics include success rate, classification efficiency, and accuracy (e.g., 99% accuracy for CNN-based approaches, 97% accuracy for SVM with LBP and LPQ fusion).	Fingerprint analysis enables highly accurate gender classification. The best performance, up to 99%, is achieved by CNN. - A Gender plays a significant role in determining ridge density.	The capacity to generalise results from smaller, less diverse datasets is severely limited. - Methods like feature extraction and noise removal necessitate substantial preprocessing.	Use larger, more diversified datasets. - Improved noisy and latent fingerprint preprocessing. - Improve real-time model scalability.

				Quantisation (LPQ).				
[41]	To test foot, footprint, hand, and handprint dimensions for gender classification in Sinhalese using machine learning.	A sample of 117 University of Peradeniya, Sri Lanka, students aged 20–30 (51 males and 66 females).	Body measurements include foot, hand, palm, and finger lengths (index, middle, ring).	Supervised learning methods such as SVM, Naïve Bayes, and CART.	CART: Best foot (95.83%) and hand (91.67%) accuracy. SVM with Naïve Bayes achieve 93.75% accuracy in foot measurements.	Foot measures are most accurate for classification. Outperforming other approaches, CART is followed by SVM and Naïve Bayes. - Some measurements show gender-specific bilateral asymmetry.	A small sample size with a specific ethnic group and age range. Findings may not apply to other populations beyond the Sinhalese.	Expand the study to encompass various people and larger samples. Improve accuracy with more features and powerful machine learning.
[42]	Create a fingerprint pattern analysis gender determination system utilising CNN and SVM.	6,000 fingerprints from 600 Africans in SOCOFing. 10 fingerprints per individual, synthetically manipulated for obliteration, rotation, etc.	CNN feature extraction and PCA dimensionality reduction on minutiae, ridge patterns, and derived features.	CNN for feature extraction and classification, SVM for post-feature extraction classification.	- CNN Accuracy: 96.5%, Sensitivity: 97.3%, Precision: 97.9%. - SVM Accuracy: 94.8%, Sensitivity: 97.3%, Precision: 96.8%.	CNN outperforms SVM in classification sensitivity and accuracy. Minute details and ridge patterns distinguish genders. - Traditional approaches perform poorly compared to deep learning.	A limited dataset that concentrates on a particular demographic (African subjects). - The accuracy of the model may be compromised by noise and modified fingerprints.	Use DNA analysis to improve precision. - Incorporate more varied demographics into databases. - Create state-of-the-art methods for extracting features for accurate classification.
[43]	The goal of this study is to assess the efficacy of gender classification from fingerprints utilising state-of-the-art Data-Centric AI (DCAI) methods on various datasets, taking into account both incomplete and poor-quality fingerprints.	Four datasets: NIST-DB4 (4,000 photos), SOCOfing (6,000 images), NIST-302 (2,000 images), and IsrPoliceDB (1,271 images)	Various details, such as the density of fingerprint ridges, the interior and external cylindrical regions, and the ROI (region of interest) for fingerprints that are incomplete or of poor quality.	VGG19 and ResNet CNN architectures with DCAI techniques such as Cleanlab-OOD, FLIP (Easy and Hard), and MOC (Easy and Hard) for data optimization.	Reliability: 70–96% based on the quality of the dataset. Enhancements to F-Scores of up to 2.75 percent with FLIP-Easy. When compared to ResNet, VGG19 achieved better recall and precision.	VGG19 had the best dataset generalisation. Gender classification relies largely on fingerprint outer regions. DCAI enhances data and model accuracy.	- Dataset-specific biases limit generalization for crime scene scenarios. - Study focused on clean datasets, with limited real-world fingerprint variability.	Improve robustness by exploring real-world fingerprint settings. For better generalisation, include varied populations and environments. Further investigate partial fingerprint cases.
[44]	Use a deep learning-based CNN architecture	Custom dataset comprising 8025 fingerprints from 239	Using 128x128 pixel greyscale pictures, fingerprint patterns from	A custom CNN architecture with abstract fusion combines	Male (94.7%), Female (88.0%), Overall (91.3%) thumb-	- Classification accuracy varies by finger type.	Datasets are imbalanced (Sokoto has more	Expand to noisy, low-resolution fingerprints. Test fusion on a larger, more

	and a fusion strategy for several fingerprints of the same hand to increase gender categorisation accuracy.	people (111 men, 128 women). - 3000 Sokoto Coventry fingerprints (477 men, 123 women).	thumb, index, middle, ring, and pinkie fingers were processed.	predictions from 3 or 5 fingers.	middle-ring fusion accuracy. Fusion boosted accuracy by 31.02% for men and 18.72% overall.	- Fusion of multiple fingerprints significantly improves accuracy. - Thumb-middle-ring fusion provides the best results.	men than women). Results are limited to high-quality greyscale photos and may not apply to real-world photographs.	diversified dataset. Enhance dynamic, real-time classification fusion algorithms.
[45]	To improve gender categorisation accuracy and efficiency with a dynamic horizontal voting ensemble model with hybrid CNN-LSTM and fingerprint patterns.	450 Nigerian participants (4,500 fingerprints, balanced subset of 2,030 male and 2,030 female samples). 2,460-image SOCOFing dataset.	Greyscale minutiae and ridge patterns preprocessed using histogram equalisation and bilateral filtering for noise reduction and edge preservation.	DHVE and hybrid CNN-LSTM base learner increase prediction.	DHVE was 99% accurate on the custom dataset. On SOCOFing, accuracy increased from 75.2% (ResNet-34) to 98%. - Precision, Recall, F1-score ≈ 0.99.	Hybrid CNN-LSTM with DHVE beats ResNet-34, VGG-19, and EfficientNet-B3. - Greater accuracy with 1.7M fewer trainable parameters.	- Dataset peculiarities limit generalisability. Performance evaluation limited to noise-free, high-quality datasets.	Individual finger type performance analysis. For noisy, low-resolution fingerprint datasets, extend the model. Improve computational efficiency.
[7]	To create a gender classification system for facial photographs utilising HOG, RILBP, and PCA.	The IOG has 1344 group portraits. Scarves and cosmetics were captured in 604 Nigerian pictures.	HOG, RILBP, and PCA for dimensionality reduction.	Support Vector Machine (SVM) classifier trained on extracted features.	Accuracy: Up to 99.8% (Local Dataset, PCA on RILBP). - AUC (Area Under Curve): 99% for PCA on RILBP.	PCA on RILBP outperforms other models in accuracy and generalisability. HOG features performed better than RILBP features but had worse precision.	It's possible that the results won't apply to other demographics because they are dataset-specific. - Useful in practical settings with a modest dataset size.	- Increase the diversity of demographics and actual variation in datasets. - Investigate several approaches to feature extraction and fusion.
[8]	Create a semi-supervised deep learning technique for indoor localisation using fingerprint high-level characteristics in dynamic contexts.	Databases for RSS fingerprinting were simulated in a 40x29m laboratory and real-world data was obtained using cellphones.	Received Signal Strength (RSS) measures analysed with autoencoders for advanced feature extraction.	Semi-supervised Deep Extreme Learning Machine (SDELM) and Autoencoder-based SDELM (ASDELM) for feature extraction and classification purposes.	- Localisation success rate: 77.95% with original labelled data, enhanced to 89.42% with supplementary data. - Enhanced time and resource efficiency relative to supervised methodologies.	- Employing a combination of labelled and unlabelled data enhances accuracy while decreasing labelling expenses. - The proposed ASDELM surpasses conventional approaches (k-NN, Horus).	- The method depends on particular environmental conditions (e.g., RSS-based Wi-Fi fingerprinting). - Performance may deteriorate in extremely dynamic conditions.	Broaden the methodology to encompass larger and more intricate ecosystems. - Enhance feature extraction to accommodate noise and variability in practical data.

[9]	To examine the socio-technical interactions inherent in biometric technologies and their manifestation of body diversity, encompassing gender and ethnicity, throughout the design and utilisation processes.	No particular dataset; mentions of extensive biometric systems (e.g., European border control, Indian UID system).	Fingerprints, iris patterns, and face structures are examples of features; biases in feature extraction techniques and picture quality corrections are examined.	explains how training datasets and algorithmic adjustments affect recognition accuracy for various demographic groups.	Qualitative discussion is given to metrics including erroneous acceptance/rejection rates, failure-to-enroll, and the effect of physical and environmental variations on accuracy.	In particular, gender and race are two areas where biometric systems are susceptible to unconscious bias. - Predominant demographic groupings are frequently favoured by system modifications and mistakes.	- Design flaws make it hard to generalise to the real world. - Mistakes affect non-dominant groups more than others, like people of colour and skilled labourers.	- To reduce bias, design should be more reflexive. - Incorporate more diverse populations into training datasets. Prioritise the enhancement of systems that impact underserved communities.
[11]	This study aims to examine the progress and innovations in soft biometrics, with an emphasis on datasets, annotation methodologies, performance metrics, fusion techniques, and prospective challenges.	Peta, LFW, Southampton Biometric Tunnel, MORPH, and ATVS Forensic databases are among those that cover facial, bodily, and garment characteristics.	Information about a person's gender, height, skin tone, clothes, and dimensions (such as the length of their arms and legs) that is considered a soft biometric.	Bayesian, LRT, and SVM-LRT fusion frameworks as well as Pearson and Kendall correlation algorithms are utilised in these techniques for feature analysis and recognition.	For bodily features, the accuracy can reach 99.3 percent. Other metrics include the Equal Error Rate (EER) and the efficiency of fusion across different modalities.	- Non-intrusive recognition is improved by soft biometrics technologies. Improving recognition accuracy is achieved through fusing modalities such as face, body, and clothes. One essential feature of autonomous systems is gender.	Generalisation is impacted by biases that are specific to datasets. - Difficulty in getting features out of uncontrolled settings (as in a surveillance scenario).	- Represent variety in the real world in datasets you create. - Investigate strong annotation techniques to improve trait estimate. Try out some novel hybrid and fusion methods.

This review's comparative table organises fingerprint-based machine learning gender detection experiments. It organises material to explain domain approaches, datasets, techniques, and conclusions. The table's columns indicate key research process components, allowing for cross-study comparisons. The Aim of the Study column describes each study's goals and motives. The authors' goals include improving classification accuracy, reducing computing costs, correcting dataset imbalances, and improving fingerprint feature extraction for gender detection. Stating the goal clarifies each study's scope and intent. The Dataset Used column lists model training and validation datasets. Dataset quality, size, and variety greatly affect machine learning model generalisability. SOCOFing, NIST SD4, and experimental datasets are commonly used. This section describes the dataset size, diversity, preprocessing, and augmentation methods. The Features Extracted column lists fingerprint gender classification attributes. Feature extraction uses fingerprint pictures to detect gender-specific traits. Miniature points, ridge density, ridge patterns, orientation fields, and dimensionality reduction methods like PCA and DWT are typical. Classification relies on these features, which vary by study and technique. The Machine Learning Techniques column describes gender classification algorithms. In addition to standard classifiers like SVM and k-NN, the investigations use advanced deep learning architectures like CNNs. CNN-SVM or LSTM hybrid models are also investigated to increase classification accuracy. Featuring these methods lets you compare model complexity and efficacy. The Performance measures column includes model effectiveness measures. Quantifying model accuracy, dependability, and generalisation requires these measures. Accuracy, precision, recall, F1-score, and AUC-ROC are often reported metrics. Performance metrics standardise model and dataset comparisons. Each study's key findings are in the Key Findings column. It showcases top-performing models and their key features or strategies. This section discusses the best machine learning methods and feature sets for fingerprint-based gender classification. Limitations highlights study challenges and constraints. Lack of diversity, imbalance, small sample numbers, and performance decrease in noisy or low-quality fingerprint photos are common drawbacks. Understanding model generalisability and accuracy requires identifying these limits. The authors suggest gender classification model improvements in Future Suggestions. Expanding dataset variety, researching sophisticated machine learning architectures, adding synthetic data for augmentation, and improving preprocessing are common suggestions. These recommendations guide fingerprint biometric gender classification research and development.

5. Conclusion

With a focus on machine learning methods, this review has given a thorough look at how to tell someone's gender by looking at their fingerprints. The review shows how useful machine learning methods are by looking at many studies, datasets, and classification methods. It focusses on deep learning models like CNNs and mixed models like CNN-SVM and CNN-LSTM. It was found that dimensionality reduction methods like PCA and DWT, as well as feature extraction techniques like tiny patterns and ridge density, are very important for improving model performance. Many studies have shown that classification accuracy is high, but the results are still affected by things like the size, variety, and quality of the dataset. A few of the problems that have been pointed out are uneven datasets, a lack of representation from certain groups, and poor or noisy fingerprint pictures that make the models less useful in real life. It is also emphasised in the study how important it is to use diverse and larger datasets to make models more reliable and robust across a wide range of population groups. In the future, fingerprint-based gender classification should focus on building bigger datasets, researching more advanced ways to add to existing datasets, and creating more advanced deep learning frameworks. Adding mixed models and better preprocessing methods can also make things more accurate and scalable. The goal of this study is to help the continued progress of technologies that classify people by gender by showing how they are used now, what problems they face, and where future research might go.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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