Fingerprint Biometrics for Age Estimation: A Survey of Methods

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ABSTRACT

Estimating age from fingerprints is crucial in forensic science and biometrics due to the increasing use of fingerprints in various applications. This survey reviews existing age estimation methods based on fingerprints, including traditional approaches, machine learning-based methods, and deep learning techniques, highlighting their strengths, weaknesses, and limitations. Despite significant progress, there is still room for improvement in accuracy, robustness, and generalizability. Key challenges and future research directions are identified, providing a roadmap for advancing fingerprint-based age estimation. This survey serves as a valuable resource for researchers, practitioners, and forensic experts.

Keywords: Fingerprint analysis, Age estimation, Biometrics, Forensic science, Survey paper.

INTRODUCTION

Estimating age from fingerprints aids forensic investigations [1]. Traditional methods are time-consuming and subjective, whereas machine learning approaches, despite limitations, offer improved accuracy and robustness. This review synthesizes findings from 13 key studies on various methodologies for age and gender classification from fingerprints.

LITERATURE REVIEW

Age Estimation Techniques

Neural Networks and Machine Learning:

1. Amusan et al. (2024): Developed a CPNN-based system for ages 15-23, achieving 96% accuracy.
2. Basavaraj Patil & Rafi (2015): Used DWT and PCA with SVM for crime investigations, enhancing accuracy.
3. Jayakala & Sudha (2022): Utilized ResNet50 and VGG-16 for classifying fingerprints into age groups with 93% accuracy.
4. Falohun et al. (2016): Combined BPNN for gender and DWT+PCA for age classification, achieving 82.14% accuracy.

Wavelet Transforms and Statistical Methods:

1. Tom & Arulkumaran (2013): Combined DWT and PCA for 70% success in gender classification.
2. Gnanasivam & Muttan (2012): Used DWT and SVD with KNN for high accuracy in younger age groups.
3. Atiku, Adamu, & Isyaku (2023): Used fingerprint ridge density for age estimation among Hausa ethnic group, developing specific formulae.
4. Ceyhan et al. (2014): Used KNN for age estimation from fingerprints of Turkish population.

Innovative Approaches and Mixed Methods:

1. Bury et al. (2022): Used MALDI MS and machine learning to determine age from fingermarks.

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2. Olorunsola & Olorunshola (2023): Proposed DHVE approach using CNN and LSTM networks for over 91% accuracy in age group prediction (Olorunsola & Olorunshola, 2023).
3. Wadhwa, Kaur, & Singh (2013): Introduced RVA and DCT coefficients for age and gender classification.

Fingerprint Quality and Stability

1. Galbally et al. (2019): Analyzed fingerprint quality's impact on biometric systems, mapping NFIQ2 to NFIQ1.
2. Kessler, Henniger, & Busch (2021): Concluded that fingerprint characteristics remain stable over an adult's life span (Kessler et al., 2021).

Critical Evaluation

The studies reviewed demonstrate a variety of methodologies for age and gender classification, with neural networks and machine learning techniques showing high potential for accuracy and application. However, several studies highlighted the need for larger and more diverse datasets to improve model robustness and generalization. The innovative use of molecular content and dynamic ensemble methods represents significant advancements, though challenges such as computational resources and data imbalance remain.

Strengths and Limitations

Advanced neural networks demonstrate high accuracy in age and gender classification with methods like MALDI MS and DHVE offering new insights into fingerprint analysis, benefiting forensic science and biometric identification. However, limited dataset sizes and diversity impact model robustness. Significant computational resources and training time are required, limiting real-time application feasibility. Individual variations and aging effects also pose classification challenges.

Traditional Methods

Traditional methods for estimating age based on fingerprints rely on manual examination of fingerprint patterns. These methods include:

Fingerprint Patterns

Fingerprints consist of ridges, which appear as dark lines, and valleys, the lighter areas, located on the skin of your fingertips. Generally, these ridges run in parallel lines, but sometimes they split or end abruptly[1]. Fingerprints can be categorized into three main patterns: Arch, where ridges enter from one side, rise into a curved arc, and exit on the opposite side; Loop, where ridges curve and exit on the same side they enter; and Whorl, where ridges create circular patterns around a central point.

Ridge Characteristics

Fingerprints contain various unique features known as minutiae within their ridges. Some key ridge characteristics include ridge endings, where a ridge abruptly terminates; bifurcations, where a ridge splits into two separate ridges; dots, which are very short ridges appearing as dots; islands, which are small ridges unconnected to other ridges; lakes, which are enclosed spaces between ridges, often circular or elliptical; bridges, which are short ridges connecting two longer ridges; and spurs, which are small, short ridges branching off from a main ridge. These ridge characteristics and fingerprint patterns are unique to each individual, making fingerprints an excellent tool for identification and verification [1].

Minutiae-Based Methods:

Minutiae-based methods, which rely on specific points in fingerprint patterns called minutiae, are highly accurate and widely used in fingerprint recognition and analysis [7]. These methods involve capturing a fingerprint, enhancing and cleaning the image, identifying and extracting minutiae points, and comparing them

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with stored data. The process ensures high accuracy, reliability, and scalability, making it suitable for various applications like forensic analysis and access control. However, challenges such as noise, distortions, partial fingerprints, and elastic distortions can impact the accuracy of minutiae extraction and matching [1].

Machine Learning-Based Methods

Machine learning-based methods for estimating age from fingerprints use advanced algorithms to analyze fingerprint data and predict an individual's age [9]. These methods involve collecting a comprehensive dataset of fingerprints with age information, extracting features like minutiae points and ridge patterns, preprocessing the data to enhance quality, and training various machine learning models. The trained models are then evaluated for accuracy and used to predict the age of new individuals. These methods offer high accuracy, scalability, and automation, making them suitable for applications in forensics, access control, and demographic studies [1]. However, challenges such as data quality, ethical concerns, and computational resource requirements must be addressed. Despite these challenges, the field holds promise for more accurate and reliable age estimation as technology advances.

Deep Learning – Based Methods

Deep learning-based methods for estimating age from fingerprints utilize advanced neural network architectures to analyze and predict age. These methods include Convolutional Neural Networks (CNNs), which are specialized for image analysis and automatically learn spatial hierarchies of features from fingerprint images. Popular CNN architectures such as ResNet50 and VGG-16 [5] can directly analyze fingerprint images and extract age-related features. Long Short-Term Memory Networks (LSTMs), a type of recurrent neural network (RNN), are designed to handle sequential data and capture long-term dependencies, making them suitable for analyzing sequential patterns in fingerprint data to estimate age. Recurrent Neural Networks (RNNs) are also used for this purpose.

Overall, deep learning-based methods leverage the power of neural networks to provide accurate and reliable age estimation based on fingerprint data.

Comprehensive Survey

Fingerprint based Age Estimation via Neural Networks and Machine Learning:

The study of OO Amusan, AM Udefi, SI Eludiora developed an age estimation system based on fingerprint of individuals aged 15-23 years. They used a USB-connected scanner to capture fingerprint data, preprocesses the data, and employs a Counter-Propagation Neural Network (CPNN) trained with Grossberg's learning rule for classification [1].

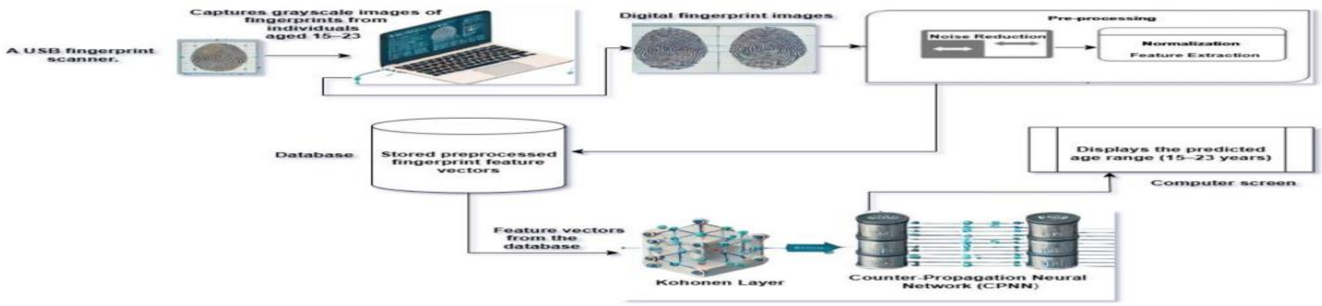

Fig 1. Workflow of Amusan et al.'s [1] System [1]

The system was evaluated using a dataset of 500 fingerprint samples and achieved a maximum accuracy of 96%, sensitivity of 94%, and specificity of 95% at a threshold of 0.7 [1]. Challenges in borderline cases indicate the need for further refinement. The research showcases the practicality of utilizing biometric information for estimating age, with promising applications in forensic science, access management, and population studies.

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The paper also describes the mechanism of obtaining fingerprints, feature extraction, classification, and match score calculation. The process involves enrollment, threshold calibration, and verification/testing using fingerprint sensors. The system records minutiae points' coordinates, ridge orientation, and type for precise extraction, essential for fingerprint recognition. Classification techniques must overcome noise and elastic distortions for reliable results.

This study provides a foundation for future work on improving system performance and scalability through advanced feature extraction techniques and larger, more diverse datasets[1].

GV Basavaraj Patil, M Rafi, in their paper presented a method for estimating human age using fingerprint images. Unlike traditional uses of fingerprints for identification, age estimation is an emerging field. The study combines 2D Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) to extract fingerprint features, which are then classified using Support Vector Machines (SVM).

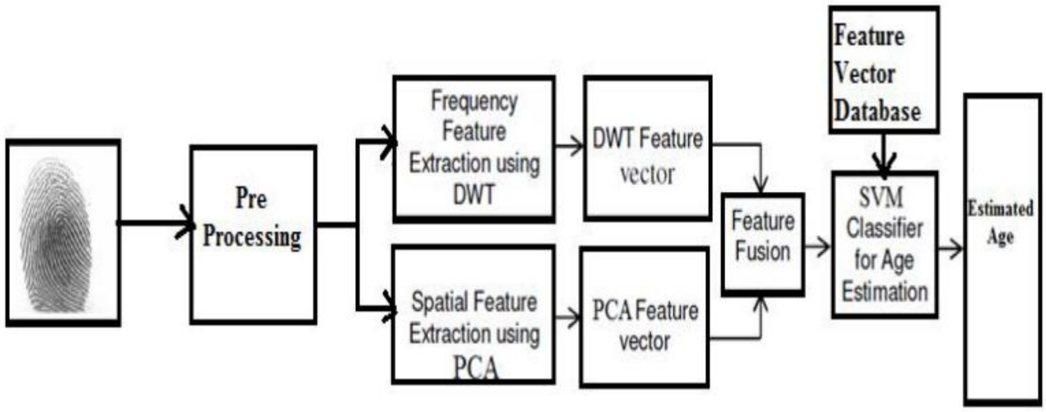

Fig 2. Basavaraj & Rafi – Feature Extraction Block Diagram [4]

The process involves preprocessing the fingerprint image, extracting features using DWT and PCA, and combining these features into a final vector. The SVM classifier then assigns the fingerprint to an age class by comparing the final vector with the database. This technique can be useful in crime investigations to narrow down the search space of suspects. Experimental results show that combining DWT and PCA enhances age estimation accuracy and good success rate [4]. The study concludes that this method provides improved performance in estimating age through fingerprint images, with potential applications in various fields.

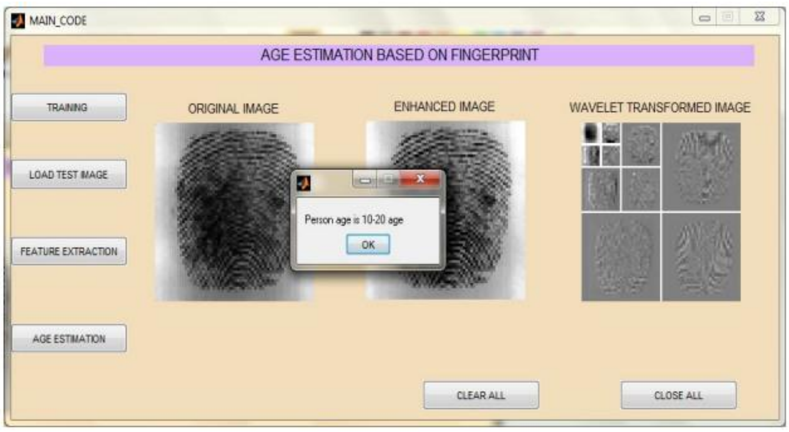

Fig 3. Result of the age estimation process [4]

The study by G Jayakala, LR Sudha explores automatic age detection from fingerprints using deep learning models, specifically ResNet50 and VGG-16. Age estimation from fingerprints is complex due to the difficulty of extracting distinguishable features. The study utilizes a fingerprint database containing 1000 images, with 900 used for training and 400 for testing. The ResNet50 model classifies fingerprints into four age groups: 1-8, 9-15, 16-25, and 25-60, achieving an accuracy of 93% [5].

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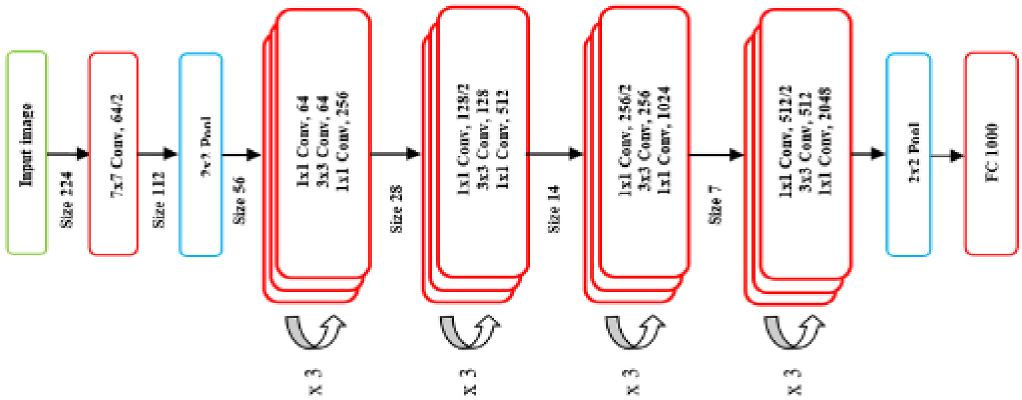

Fig 4. ResNet50 Architecture [5]

VGG-16 (Visual Geometry Groups Networks), a deep convolutional neural network, is also employed for classification. Both models use confusion matrices to summarize performance. The approach is beneficial for forensic applications by narrowing down the search space of suspects and aiding anthropologists in estimating the age of fingerprints from excavated articles. The experimental results demonstrate the efficiency of these deep learning models in age estimation based on fingerprints. While deep CNNs showed superior accuracy, they require substantial computational resources and time for training, which may not be feasible for real-time or low-resource applications.

AS Falohun, OD Fenwa, FA Ajala developed a fingerprint-based system to determine human age-range and gender using fingerprint pattern analysis. The system leverages Back Propagation Neural Network (BPNN) for gender classification and Discrete Wavelet Transform combined with Principal Component Analysis (DWT+PCA) for age classification. A total of 280 fingerprint samples from various age groups (1-70 years) and genders were collected, with half used for training and the rest for testing. The Ridge Thickness to Valley Thickness Ratio (RTVTR) was used for gender determination, achieving a classification accuracy of 80.00% for females and 72.86% for males, while 82.14% of subjects were correctly classified by age [6]. The study emphasizes the importance of biometric technology for identification and verification, particularly in voting systems. It highlights the unique and unchanging nature of fingerprints, making them a reliable biometric identifier. Despite challenges such as misclassifications due to variations in body size, the system showed satisfactory performance. The authors recommend further research combining DNA analysis with fingerprint ridge information for improved accuracy in gender and age classification, and suggest age classification systems for verifying voter eligibility in elections.

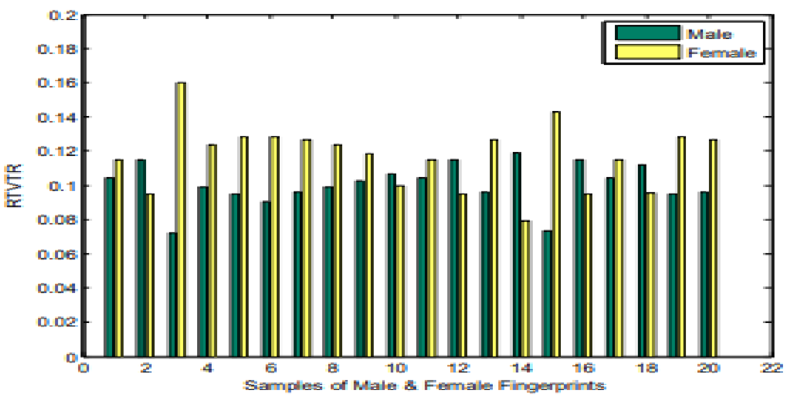

Fig 5. RTVTR Male/Female Graph by Falohun et al. [6]

Fingerprint based Age Estimation via Wavelet Transforms and Statistical Methods:

The study of RJ Tom, T Arulkumaran explores using fingerprints for gender classification by leveraging frequency domain techniques (2D Discrete Wavelet Transform) and pattern recognition (Principal Component Analysis) [2]. Traditional methods often relied on ridge count and thickness. This study aims to enhance

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classification accuracy by combining DWT and PCA, using a minimum distance method. Fingerprints from 200 males and 200 females (aged between 12 and 60 years) were analyzed, showing that increasing the database size improves performance [2]. The methodology involves fingerprint acquisition, preprocessing, feature extraction using DWT and PCA, and classification. Results show a 70% success rate, with better performance on optical scanned prints than ink prints [2]. Future work suggests improving the algorithm with neural networks and expanding the database to include diverse ethnic groups. The study demonstrates the feasibility and effectiveness of this combined approach for fingerprint-based gender classification.

The dataset, limited to 400 fingerprints, lacks diversity and may not represent broader populations. A larger, more diverse dataset is essential for robustness. The system performed well on the training data but showed signs of overfitting, with its generalization to unseen data unaddressed, raising concerns about its reliability.

P Gnanasivam, DS Muttan discussed a method for estimating age from fingerprints using Discrete Wavelet Transform (DWT) and Singular Value Decomposition (SVD). The system employs K Nearest Neighbor (KNN) as a classifier. The study evaluated the method using an internal database of 3570 fingerprints, with results showing varying classification accuracies across different age groups for both males and females.

The study highlights the importance of age information for forensic investigations, as existing methods for age estimation are limited. By utilizing DWT and SVD for fingerprint feature extraction, the proposed method classifies fingerprints into five age groups. The results showed high accuracy for age estimation in younger age groups, with the highest success rate for males under 12 years old (96.67%) [8]. However, the accuracy decreased for older age groups, particularly for those aged 36 and above [8].

In conclusion, the proposed method demonstrates promise in estimating age from fingerprint images, with higher accuracy observed in certain age groups. The study suggests that increasing the number of samples in each category could further improve the accuracy of age estimation [8].

The study titled "Age Estimation from Fingerprints: Examination of the Population in Turkey" by Eyüp Burak Ceyhan et al. explores a novel approach to estimate ages from fingerprints. The authors collected 500 fingerprints from 50 Turkish citizens and converted these images to binary forms [10]. Using the k-nearest neighbors (KNN) classification algorithm, they achieved an impressive average success rate of 93.3% for males aged 18-24 and 83.0% for females in the same age group [10].

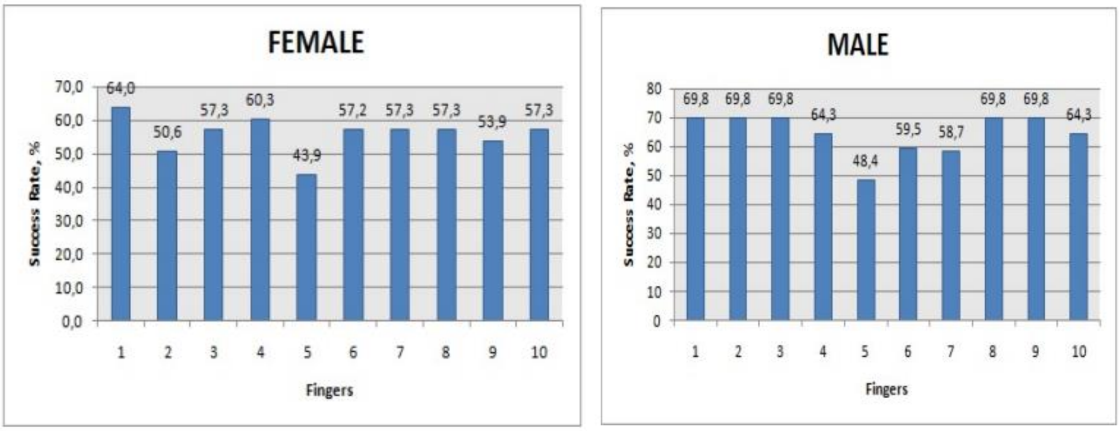

Fig 6. Ceyhan et al. – Accuracy by Gender and Age [10]

The study shows that the proposed method is effective for age estimation, particularly in younger populations. It highlights the potential applications of this technique in forensic science, aiming to narrow down suspects in criminal investigations. However, the accuracy decreases with age, attributed to the loss of fingerprint epidermis edges over time and the limited dataset size for older age groups [10]. Future research aims to expand the dataset and include diverse ethnic groups to improve model precision and reliability.

IA Atiku, LH Adamu, MU Isyaku investigated the use of fingerprint ridge density for age estimation among the Hausa ethnic group in Nigeria. The study collected data from 530 individuals aged 12-35 years, using a fingerprint scanner to capture ridge densities from radial and ulnar areas of the thumbs [12]. Statistical analyses, including one-way ANOVA and step-wise multiple linear regression, were conducted to compare ridge density across age groups and develop age estimation models. The study found significant differences between sexes and age groups [12] and developed separate formulae for males and females. For males, the formula is [Age = Height (0.064) + URD (-0.158) + 7.133], while for females, it is [Age = RRD (-0.295) + Weight (0.040) + 16.509] [12]. The researchers observed that ridge density varies significantly across specific age groups [12] and found that the radial ridge density of the left hand was a better predictor of age for males [12]. However, the regression models showed limited predictive power when considering only fingerprint ridge density, highlighting the need for additional biometric data for more accurate age estimation. This research provides valuable insights into the potential applications of fingerprint ridge density in forensic science, particularly in regions with limited previous studies on fingerprint-based age estimation. It emphasizes the importance of incorporating biometric data to enhance the accuracy and reliability of forensic investigations.

Fingerprint based Age Estimation via Innovative Approaches and Mixed Methods:

The research by CS Bury, C Heaton, L Cole, R McColm, S Francese explores the innovative use of Matrix-Assisted Laser Desorption Ionisation Mass Spectrometry (MALDI MS) and machine learning to determine human age from fingermarks [9]. Traditionally, fingerprint analysis relies on ridge patterns for identification, but this study delves into the molecular content of peptides and small proteins for additional insights [9].

Researchers evaluated various supervised learning methods on a dataset of natural fingermarks from both male and female donors. They employed machine learning models like random forest, XGBOOST, and linear regression to predict age from spectral data.

(i). Main Findings:

Binary Classification: Models classifying donors as "young" or "old" achieved accuracy similar to sex prediction models, though practical application is limited by arbitrary age boundaries [9].

Categorical Classification: Models categorizing donors into specific age groups performed better than random baseline models, indicating a potential link between age and molecular fingerprints [9].

Age Regression: Regression models struggled with precise age prediction due to a small, imbalanced dataset and discrepancies between chronological and biological ages [9].

The study concludes that while initial results are promising, further research with larger, balanced datasets is needed to refine and validate these predictive models for practical forensic use. The approach shows potential but also highlights challenges like protein degradation and the need for more precise biological age assessments.

R Wadhwa, M Kaur, KVP Singh introduced a novel method for estimating age and gender using fingerprints. This study utilizes Ridge to Valley Area (RVA) and Discrete Cosine Transform (DCT) coefficients to classify age and gender. The fingerprints are pre-processed and binarized, followed by feature extraction to compute RVA and DCT coefficients, which are independent of finger pressure variations, ensuring robustness. Image acquisition is performed using a 300 dpi fingerprint scanner, and preprocessing includes converting grayscale images to binary using the Otsu algorithm [11]. Ridge to Valley Area (RVA) computation involves defining ridges and valleys in the fingerprint image, while entropy calculation measures the information richness of the image. The Root Mean Square (RMS) value of the DCT coefficients is calculated for 8x8 pixel blocks, enhancing feature extraction [11]. The classification results indicate promising accuracy, especially with neural network models. This research highlights the potential of using fingerprint biometrics for accurate age and gender determination, contributing valuable insights to forensic science and biometric identification [11]. It shows that the proposed method achieves high accuracy rates for age and gender classification, making it a robust solution for forensic applications.

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Their work of O Olorunsola, O Olorunshola proposed a novel method for classifying age groups using fingerprint patterns. The study introduces a Dynamic Horizontal Voting Ensemble (DHVE) approach that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks as the base learners. This method dynamically selects proficient models based on validation accuracy, constructing a horizontal voting ensemble for prediction. The researchers report an accuracy rate of over 91% for age group prediction [13], attributed to the design of the network layers and the dynamic selection approach. Fingerprint images were collected from 453 Nigerian subjects [13], with 4500 images used in the study. The images were labeled with attributes such as image ID, gender, age group, ethnicity, and finger type labels, and were enhanced using histogram equalization and bilateral filters [13]. The Deep CNN-LSTM model featured two convolutional layers, two max-pooling layers, and two fully connected layers, providing access to 3D data for effective classification [13].The dynamic selection technique improved model robustness and overall accuracy, achieving a precision, recall, and F1 score of 0.91 for age group classification, with the highest performance in the "Teen" category [13]. The study also compared the DHVE model's performance with k-Nearest Oracle (KNORA) and Dynamic Classifier Selection with Overall Local Accuracy (DCS-LA) algorithms, finding that the DHVE model outperformed these methods with an overall accuracy of 91% [13]. This research contributes to the field of biometric identification by providing a robust and accurate method for age group classification based on fingerprint patterns.

Fingerprint based Age Estimation with Fingerprint Quality and Stability:

The paper by J Galbally et.al discusses the significance of fingerprint quality on the performance of biometric recognition systems, focusing on two widely-used quality metrics developed by NIST: NFIQ1 and NFIQ2. NFIQ1, introduced in 2004, classifies fingerprints into five quality classes (1 for excellent to 5 for very poor), while NFIQ2, developed in 2011, offers improved accuracy and sensitivity with values ranging from 0 to 100. The study aims to bridge the understanding gap between these metrics by presenting a mapping function that translates NFIQ2 values to NFIQ1 classes using a classification approach based on the Bayes classifier[3]. The experiments, conducted on a database of over 421,000 fingerprint images, show that the mapping can reliably estimate conditional probabilities [3], allowing for accurate classification. The study concludes that NFIQ1 classes can be grouped into three meaningful categories and validates the consistency of the mapping across different age groups, demonstrating the utility of the mapping function for various biometric applications.

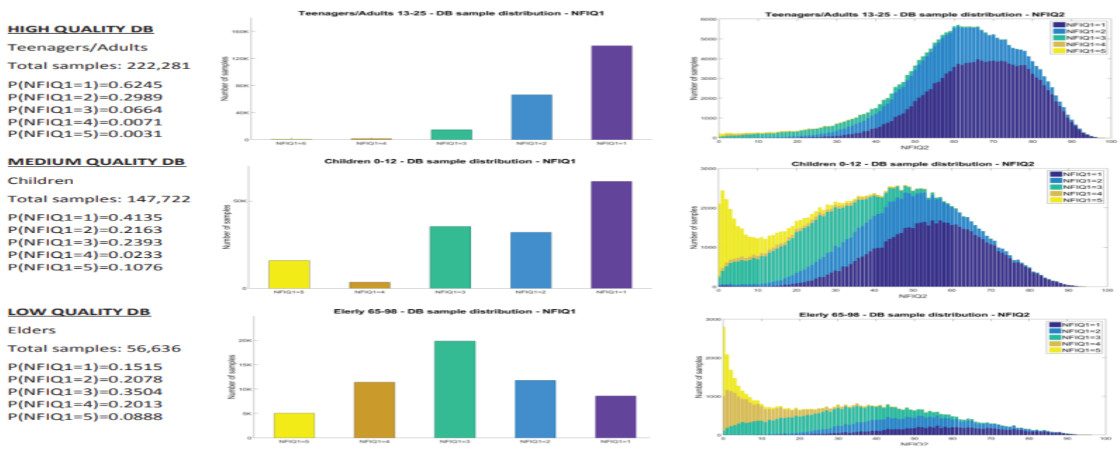

Fig 7: NFIQ Quality Mapping by Galbally et al. [3]

The study focused on analyzing the variation in genuine matching score (GMS) differences across different age groups. The goal was to determine whether the age of an individual affects the performance of a biometric system. The classification into broad age groups (children, adults, elderly) may not provide the precision needed for more detailed or fine-grained age estimation, such as estimating specific ages within these categories.

The study of R Kessler, O Henniger, C Busch analyzed longitudinal fingerprint data of 20 subjects over up to 12 years to investigate whether fingerprints and their features change over time [7]. Using hierarchical linear modeling, the researchers examined mated similarity scores based on fingerprint quality and the time interval between reference and probe images. The results showed no significant effect of time on mated similarity scores, suggesting that fingerprint characteristics remain stable over an adult's life span. However, individual differences were observed [7].

Minutiae were extracted using the FingerNet framework and converted to the Minutia Cylinder-Code (MCC) format for comparison. Image quality was assessed using NFIQ 2.0, and low-quality images were excluded from the analysis [7]. Key findings indicated no global effect of time or image quality on mated similarity scores, although individual effects were noted. Subjects had varying average mated similarity scores, but gender and age did not predict these scores [7]. The study faced limitations due to the small number of subjects and the specific setting of data collection[7].

In conclusion, the study did not support the fingerprint template aging hypothesis, indicating that fingerprint characteristics remain "forever young" over long periods of professional life[7].

Comparative Evaluation

Study	Technique	Accuracy	Dataset Size	Strengths	Limitations
Amusan et al.	CPNN	96%	500	High accuracy	Small age range
Patil & Rafi	DWT + PCA + SVM	Not Reported	8 Age Groups	Dual-domain feature fusion	No numerical accuracy reported; overlapping age classes
Jayakala & Sudha	ResNet50, VGG-16	93%	1000	Deep learning	High compute cost
Falohun et al.	BPNN, DWT+PCA	82%	280	Dual classification	Gender bias
Gnanasivam & Muttan	DWT+SVD+KNN	96.6% (young)	3570	Good for youth	Low old-age accuracy
Bury et al.	MALDI MS + ML	~85%	Small	New modality	Protein degradation
Olorunsola et al.	CNN+LSTM (DHVE)	91%	4500	High accuracy	Needs preprocessing

Critical Evaluation

While neural networks and deep learning offer high accuracy, their reliance on large datasets and resources restricts real-time use. Wavelet/statistical models perform well with smaller samples but lack scalability. Novel hybrid methods like DHVE bridge this gap but need further validation across ethnic groups. Most studies highlight limitations in dataset diversity, and very few account for aging effects explicitly.

Challenges

The challenges faced by these studies include limited dataset diversity, which impacts model robustness and generalizability, and the handling of noise and elastic distortions in fingerprint images[1]. Borderline cases where age or gender classification is not clear-cut also pose significant difficulties. Models often show high accuracy on training data but fail to generalize to unseen data, leading to reliability issues. Ensuring models can scale effectively to handle larger and more diverse datasets is another challenge. Deep learning models, such as ResNet50 and VGG-16, require substantial computational resources and time for training, which can be a significant hurdle[5]. Optimizing models for real-time processing, particularly in low-resource environments, is challenging, as is integrating fingerprint-based systems with other biometric modalities for enhanced security and accuracy. By addressing these collective challenges, future research can significantly advance the field of fingerprint-based biometric systems, enhancing their accuracy, reliability, and applicability across various domains.

Ethical and Privacy Considerations

The use of biometric data for age estimation raises several important ethical and privacy concerns. Since fingerprints are permanent identifiers, any misuse of this data can result in serious risks such as identity theft. It is essential that datasets used for training such systems are collected with proper informed consent and undergo anonymization to protect individual identities. Furthermore, if the datasets are demographically skewed, the models developed may exhibit bias, thereby affecting fairness and reliability. Therefore, strong regulatory frameworks must be established to govern the collection, storage, usage, and sharing of biometric data, ensuring that these systems are both secure and ethically sound.

Future Directions

Several promising directions can advance the field of fingerprint-based age estimation. One key area is data augmentation, where techniques such as rotation, noise injection, and generative adversarial networks (GANs) can be used to synthetically expand training datasets, thereby improving model robustness and reducing overfitting. Another important approach is federated learning, which allows models to be trained across decentralized data sources without transferring the raw data, ensuring privacy preservation and enhanced generalization. Additionally, hybrid models that integrate handcrafted features with deep neural embeddings offer a balanced solution that leverages both domain knowledge and automated feature learning. Integrating multimodal biometrics, such as combining fingerprint data with facial or iris information, can further enhance classification accuracy and system reliability. Finally, incorporating explainable artificial intelligence (XAI) techniques will be essential to ensure that these systems provide interpretable and transparent results, thereby building trust in their use for sensitive forensic applications.

CONCLUSION

Fingerprint-based age estimation continues to evolve, with traditional, machine learning, and deep learning approaches each contributing uniquely. This paper provides a consolidated view of existing methods and highlights future opportunities to enhance accuracy and fairness. Addressing dataset limitations, ethical risks, and technical trade-offs will be essential for real-world adoption.

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