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A Systematic Literature Review of Convolutional Neural Networks for Gender Analysis using Fingerprint Images and other Biometric Modalities

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Abstract*— This study presents a Systematic Literature Review (SLR) on the application of Convolutional Neural Networks (CNN) for gender classification using fingerprint images as biometric identifiers. Using the PRISMA 2020 framework, fifteen Scopus-indexed studies published between 2020 and 2025 were systematically analyzed. The results show that CNN models achieved accuracies ranging from 85% to 99.97%, influenced by network architecture, dataset size, and training strategy. EfficientNetB0, GoogleLeNet, and hybrid CNN–LSTM architectures exhibited superior performance, particularly when combined with data augmentation and transfer learning. In addition, interpretability methods such as Grad-CAM were shown to improve model transparency by visualizing fingerprint regions that contribute most to gender prediction. The analysis highlights a slight decline in performance after 2023, likely due to dataset heterogeneity and overfitting in deeper networks. This SLR concludes that CNN remains one of the most effective approach for fingerprint-based gender recognition and provides insights for future research directions, including transfer learning, multimodal fusion, and local dataset development to improve robustness and fairness in biometric systems.

***Keywords*— biometric, CNN, fingerprint, deep learning, gender.**

I. INTRODUCTION

Biometric identification systems have become an integral part of modern digital security infrastructures, supporting authentication processes across various sectors such as law enforcement, finance, healthcare, and border control. These systems rely on the distinctive physiological or behavioral characteristics of individuals such as fingerprints, facial geometry, iris patterns, or voice signals to verify identity with a high level of accuracy and reliability. Among these modalities, fingerprints are particularly valued for their permanence, ease of acquisition, and low implementation cost [1].

However, conventional biometric systems still face significant challenges when used for gender classification. Variations in biological attributes, ethnicity, age, and image quality can lead to inconsistent results and potential bias. Gender classification plays an important role in forensic science, demographic analysis, and security applications, making accuracy and fairness critical performance aspects.

The rapid advancement of deep learning particularly through Convolutional Neural Networks (CNNs) has transformed the landscape of biometric recognition. CNNs are capable of automatically extracting spatial and textural features such as ridge flow, minutiae distribution, and local fingerprint texture without relying on manual feature engineering. Previous studies have demonstrated the remarkable performance of CNNs in recognizing fingerprint patterns. For instance, Serin et al. (2024) implemented a hybrid CNN–SVM model and achieved an accuracy of 99.25%, while Alhijaj and Khudeyer (2023) employed EfficientNetB0 with transfer learning and reached an accuracy of 99.91% [2] [3].

Beyond fingerprint recognition, CNNs have also shown strong generalization capabilities across other biometric modalities. Makinist (2025) [4], for example, utilized ResNet-50 and EfficientNet-B0 for gender classification based on facial images and reported an accuracy of up to 99.8%. Similarly, Wang (2022) [5] combined VGG16 and DenseNet architectures to analyze retinal images, achieving an accuracy exceeding 97%. Other works by Badawi et al. (2025) [6] on dorsal hand vein patterns and Inapagolla & Babu [7] audio fingerprints further confirmed CNNs' adaptability in handling diverse biological data. Ataş [8] also demonstrated that CNNs enhanced with transfer learning could classify gender using panoramic dental X-ray images with over 95% accuracy.

These findings collectively highlight CNNs' strong generalization ability across multiple biometric modalities, including facial, retinal, venous, and auditory data. Although this review focuses on fingerprint-based gender classification, several studies from other biometric modalities such as ECG, speech, and hand vein patterns were included to highlight the generalization capability of CNN architectures in gender-related biometric analysis. Nevertheless, despite numerous studies emphasizing CNN's effectiveness in various biometric domains, a Systematic Literature Review (SLR) focusing specifically on the use of CNN for gender classification based on fingerprints remains limited especially within the context of Southeast Asian or local datasets [9].

Therefore, this study was conducted to fill this research gap by systematically reviewing recent advancements in CNN-based gender classification using fingerprint images. The purpose of this review is to map research trends, compare CNN architectures, and identify future directions in the development of intelligent, interpretable, and robust biometric systems. By synthesizing findings from recent studies, this review provides a comprehensive overview that can serve as a foundation for further research and practical applications in the field of fingerprint-based biometric identification.

Although the primary focus of this review is fingerprint-based gender classification, several studies from other biometric modalities are briefly discussed to demonstrate the broader applicability of CNN architectures in biometric analysis.

II. RESEARCH METHODS

This study adopts a Systematic Literature Review (SLR) approach based on the PRISMA 2020 guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The SLR method was chosen to ensure that previous research related to the use of Convolutional Neural Networks (CNNs) in fingerprint-based gender classification could be synthesized in a transparent, structured, and reproducible manner.

1. Research Design

The main objective of this review is to identify, evaluate, and analyze scientific studies that applied CNNs for gender classification using fingerprint images. This methodological framework enables a comprehensive understanding of recent research trends, commonly used CNN architectures, performance comparisons, and potential research directions for future studies.

2. (Research Questions)

To guide the systematic review process, this study was designed to answer the following four research questions:

a. RQ1: What are the trends in CNN architecture usage for fingerprint-based gender classification from 2020 to 2025?
b. RQ2: Which CNN architectures demonstrate the best performance in fingerprint-based gender classification?
c. RQ3: What factors (such as dataset size, data augmentation, transfer learning, or regularization) influence the accuracy of CNN models?
d. RQ4: What are the future research directions in CNN-based biometric gender classification?

By formulating these research questions, the review remains focused and allows all findings to be synthesized in direct relation to the study's objectives.

3. Literature Search Strategy

The literature search was conducted using the Scopus database, selected for its extensive and reputable coverage of international scientific journals. To identify relevant studies, a Boolean keyword combination was used as follows:

Table 1. Classification based on keywords

keywords	Number of articles
"Convolutional Neural Network" OR "CNN"	365,604
AND	
"Fingerprint" OR "Finger print" OR "Fingerprints"	2,236
AND	
"gender" OR "sex"	69

From table 1, initially yielded 365,604 records containing the keyword CNN, 2,236 related to fingerprint, and 69 addressing gender or sex classification. The search was limited to studies published between 2020 and 2025, focusing exclusively on articles available in full text and written in English to ensure the accessibility and quality of the reviewed materials.

4. Selection Process and Inclusion–Exclusion Criteria

The selection of studies followed the four stages outlined in PRISMA 2020:

1. Identification:
   Preliminary search using the defined Boolean keywords on Scopus to collect all potentially relevant articles.
2. Screening:
   Titles and abstracts were reviewed to remove duplicates and studies unrelated to CNN-based fingerprint analysis.
3. Eligibility:
   Full-text articles were examined to ensure methodological relevance, explicit CNN usage, and available experimental results.
4. Inclusion:
   Only articles meeting all inclusion criteria were retained for final analysis.

The following table 2 summarizes the inclusion and exclusion criteria used during the screening process:

Table 2. Inclusion and exclusion criteria

Category	Inclusion criteria	Exclusion criteria
Topic	Studies discussing CNN-based gender classification using fingerprints or biometric data	Studies not related to CNN or unrelated to fingerprint-based tasks

Publication Type	Peer-reviewed journal articles indexed by Scopus or reputable conference proceedings	Blogs, opinion papers, internal reports, or non-empirical reviews
Publication Year	2020–2025	Outside the specified range
Language	English or Indonesian	Any other languages
Access	Full-text available for download	Restricted-access or paywalled articles

The inclusion–exclusion framework in table 2 was designed to ensure transparency, validity, and replicability in the literature selection process. Each criterion was carefully established to maintain a balance between scope and methodological rigor.

1. Relevance to CNN-based fingerprint gender classification: Only studies that explicitly describe the use of CNN for gender classification based on fingerprint images were prioritized. However, several studies from other biometric modalities (e.g., ECG, speech, hand vein, and handwriting dynamics) were also included to highlight the generalization capability of CNN architectures in gender-related biometric analysis.

2. Scientific credibility: Only peer-reviewed journal papers indexed in Scopus or conference proceedings published by reputable institutions were selected. Non-scientific sources such as blogs, opinions, or internal reports were excluded, as they lack empirical validation and methodological reliability. This ensured that all reviewed studies met recognized academic publication standards [11].

3. Publication period (2020–2025): The five-year range was chosen to capture the most recent advancements in CNN architectures and their applications to biometric systems. This period represents a phase of significant innovation in deep learning methods for fingerprint-based gender recognition. Articles published outside this window were excluded to maintain temporal relevance and focus on state-of-the-art approaches.

4. Language and accessibility: Only articles written in English or Indonesian were considered to ensure comprehension and accurate interpretation. Studies in other languages were omitted due to translation limitations that might affect understanding and accuracy. Moreover, only full-text articles accessible for download and review were included, while paywalled or incomplete studies were excluded. This criterion follows the PRISMA 2020 recommendations emphasizing transparency and traceability in systematic reviews [10].

5. PRISMA Diagram

he selection process of the reviewed studies is illustrated using the PRISMA 2020 Flow Diagram, which systematically represents the number of articles retained and excluded at each stage of the review. This diagram provides a visual summary of how the initial search results were narrowed down to the final set of studies analyzed in this Systematic Literature Review (SLR).

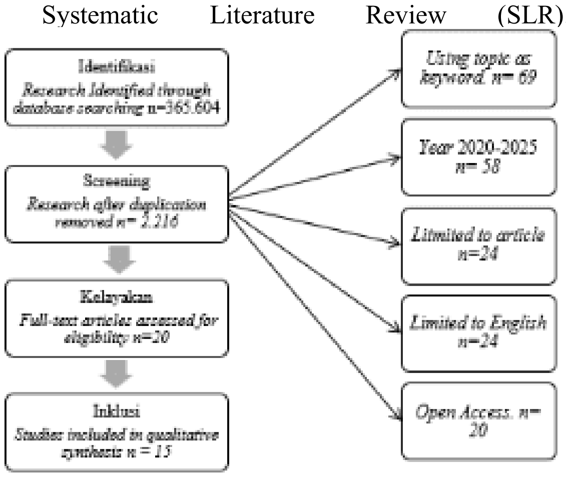

Figure 1. PRISMA Flow chart

Figure 1 shows PRISMA 2020 flow chart (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) In accordance with PRISMA 2020 guidelines, the diagram highlights four sequential stages - Identification, Screening, Eligibility, and Inclusion - to ensure transparency and replicability throughout the research selection process.

The PRISMA diagram serves not only as a methodological documentation tool but also as an indicator of transparency and quality control in systematic literature reviews. By visually summarizing the number of articles at each stage, it allows readers to clearly trace the decision-making process behind the inclusion or exclusion of specific studies. Moreover, it strengthens the reliability of this SLR by ensuring that the final dataset was obtained through a transparent, objective, and replicable filtering process a core principle of PRISMA 2020.

In this study, the PRISMA flow diagram demonstrates that from thousands of potential records initially identified, only a small subset of highly relevant and empirically supported studies where retained. This careful filtering ensures that the conclusions drawn from this review are based on high-quality, verifiable, and methodologically sound scientific evidence.

6. Data Extraction and Synthesis

Following the completion of the study selection process and the establishment of inclusion–exclusion criteria, the next stage involved the systematic extraction and synthesis of data from the fifteen selected articles. This phase was designed to organize and analyze all relevant information in a structured, transparent, and reproducible manner.

Data extraction was carried out using a structured data extraction sheet developed in Microsoft Excel, following the PRISMA 2020 recommendations. This form was designed to capture both quantitative and qualitative aspects of each study, enabling a comprehensive comparison and synthesis of results. For every article that passed the inclusion stage, the following key information was systematically recorded:

a. Author(s) and publication year, to identify temporal distribution and research trends.
b. CNN architecture used, such as VGG16, GoogleLeNet, EfficientNetB0, Hybrid CNN LSTM, or other customized variants.
c. Dataset characteristics, including dataset name (e.g., SOCOFing, UBIPr, PolyU), source, number of samples, and acquisition type (synthetic or real-world).
d. Performance metrics, specifically accuracy, precision, recall, and F1-score, when available
e. Additional techniques applied, such as data augmentation, transfer learning, regularization, feature fusion, or dimensionality reduction methods (e.g., PCA, LDA)
f. Implementation context, whether the study focused on visual, auditory, or multimodal biometric systems.

All extracted data were verified manually by cross-checking each publication to ensure consistency and accuracy of recorded information. Any ambiguous or incomplete data were clarified by reviewing the corresponding sections in the original articles.

7. Quantitative and Qualitative Synthesis

The extracted information was analyzed through a mixed-method synthesis, combining quantitative and qualitative approaches to obtain a comprehensive understanding of CNN performance and development trends.

a. Quantitative Synthesis:

Quantitative data, such as accuracy rates, dataset sizes, and publication year, were analyzed descriptively using tabular summaries and visualizations. Mean accuracies were calculated to identify the best-performing CNN architectures, while temporal patterns were analyzed to reveal research trends from 2020 to 2025. Additionally, correlations between dataset size, augmentation usage, and model accuracy were explored to assess the relationship between data volume and predictive performance.

b. Qualitative Synthesis (Narrative Analysis):

Qualitative data were synthesized narratively to interpret methodological patterns, architectural preferences, and performance determinants among studies. This narrative synthesis allowed the integration of diverse research findings by highlighting common strategies (e.g., use of hybrid CNN models), distinctive methodological innovations (e.g., Grad-CAM interpretability), and challenges encountered (e.g., overfitting and dataset bias).

8. Validation and Consistency Check

To ensure reliability, all extracted information underwent a validation process conducted through double-checking across articles. This validation involved three key procedures:

a. Cross-verification of CNN architectures and datasets to prevent misclassification of experimental frameworks.
b. Consistency check of reported performance metrics to ensure uniformity of accuracy measurement (e.g., using top-1 accuracy or percentage-based scoring).
c. Reconciliation of discrepancies by referring to the original publication data when inconsistencies were found in secondary sources or citation summaries.

Through these steps, potential errors arising from data transcription or interpretation were minimized, ensuring that all analytical results are traceable and replicable.

9. Summary of Methodological Integrity

Through strict adherence to the PRISMA 2020 framework and best practices in systematic literature review methodology, this study successfully narrowed down a vast corpus of literature into a concise, high-quality dataset of fifteen relevant studies

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The integration of data extraction, quality assessment, and final synthesis guarantees that the conclusions derived are empirically grounded, methodologically robust, and scientifically defensible.

In summary, this methodological framework provides a transparent foundation for interpreting the findings presented in the next section. It ensures that the subsequent Results and Discussion chapter is built upon verifiable, high-quality data, thereby enhancing the credibility and academic contribution of this systematic review [10], [11].

III. RESULT AND DISCUSSION

1. Overview of the Reviewed Studies

From the initial Scopus search results of 365,604 articles, only 15 studies satisfied all inclusion criteria and were deemed eligible for detailed analysis. These studies, published between 2021 and 2025, collectively illustrate the growing adoption of Convolutional Neural Networks (CNN) in biometric-based gender classification tasks, including fingerprint and other biometric modalities.

The fifteen selected papers represent a diverse range of CNN architectures, datasets, and methodological approaches, with reported accuracies ranging from 85% to 99.97%. Most studies utilized standardized datasets such as SOCOFing, UBIPr, and FATFD, while others relied on custom or domain-specific datasets. These variations highlight the methodological diversity in CNN applications across biometric domains. A summary of the reviewed studies including architecture types, datasets, achieved accuracies, and enhancement techniques is presented in Table 3

Tabel 3. Results of the Main Article Synthesis

No	Author(s) & Year	CNN Architecture Used	Dataset and Biometric type	Accuracy (%)	Additional Techniques/notes
1	Gustisyaf & Sinaga (2021)	Conv2D + MaxPooling2D + Flatten + Dense	SOCOFing (Fingerprint)	99,97	Data Augmentation
2	Kumari & Seeja (2021)	Pretrained CNN + 5-layer Gender	UBIPr, Color FERET, Ethnic Ocular (Periocular biometrics)	98,57	SVM Classifier, Data Augmentation, Feature Fusion
3	Patil & Ingle (2022)	Optimazed CNN (AlexNet)	Self-collected dataset from Bharati Vidyapeeth College of Engineering (Fingerprint)	95,27	Chi-Square + ReLu Activation, SGD
4	Olufunso et al. (2022)	Hybrid CNN-LSTM	SOCOFing & Live Scan Custom (Fingerprint)	99	DHVE, Bilateral Filter, Histogram Equalizer
5	Chen et al (2022)	Multimodal CNN	HCP (Brain Imaging)	98,7	Multilayer FCN, Hypergraph modelling, K-fold Validation, Feature Fusion, Behavioral Correlation,
6	Hsiao et al. (2022)	VGG 16	New Taipei City Police Department (1000) (Fingerprint cards)	79.2	Grad-CAM, Dropout, 5-fold C/Binarization, Preprocessing
7	Alhijaj & Khudeyer (2023)	EfficientNetB0	SOCOFing (Fingerprint)	99,91	PCA, Transfer Learning, Random Forest, Augmentation, Dropout, Batch Normalizatio
8	Shivanand Gornale et al. (2024)	AlexNet (Fine-tuned CNN)	SDUMLA Fingerprint Dataset, KVK Fingerprint Dataset, and two self-created fingerprint (Fingerprint)	Up to 100 using SVM Classifier	Rotational invariant features, image fusion and feature fusion
9	Cabra López. (2024)	GoogleLeNet	University of Rochester ECG database (202) (electrocardiogram)	97,9	Wavelet Transform to RGB Image, Heart Rate-Based Segmentation, Soft- Biometric sex filtering, Transfer Learning
10	Pˇríhodová & Jech (2024)	VGG 19	FATFD + OCD (thermal face recognition)	85,5	Thermal face imaging, Drone-based acquisition, Data augmentation

11	Maiti et al. (2024)	Custom Deep CNN	SOCOFing (Fingerprint)	99,38	Batch Normalization, Global MaxPooling, ANN Paralel, He Initializer
12	Serin et al. (2024)	Hybrid CNN-SVM	SOCOFing (Fingerprint)	99,25	Preprocessing, CNN Feature Extraction, SVM Classifier, Comparative Evaluation vs Traditional Models
13	Younis (2024)	Hybrid CNN – LSTM, SVM (Linear)	Hu Int Dataset (Speech / voice)	96	PCA, LDA, Z-Score Normalization, SSC & F0 Feature extraction
14	Inapagolla & Babu (2025)	CNN, RNN-LSTM	RAVDESS (Speech / Speaker)	~ 90	Audio Fingerprint, Noise Elimination, Gaussian Noise Testing, Speed Measurement, Multi – Model Combination
15	Badawi et al (2025)	CNN	Novel Multimodal Dataset dataset (Hand Veins)	96,97	Image Enhancement, Texture Mapping, Data Augmentation, Multimodal Fusion, K-Fold Cross Validation

the results from 15 articles that met the inclusion criteria are presented in Table 3. This table provides a systematic summary that includes the author’s name, year of publication, CNN architecture used, type of dataset, achieved accuracy level, and additional techniques applied to enhance model performance. The presentation aims to provide a thorough understanding of the variations in approaches used by researchers, while also highlighting the differences in model performance outcomes based on factors such as architectural complexity, dataset size, and training strategies.

The 2021 journal by Gustiyaf, titled “Implementation of Convolutional Neural Network to Classification Gender Based on Fingerprint,” used a simple CNN architecture (Conv2D + MaxPooling + Flatten + Dense) on the SOCOFing dataset and achieved 99.97% accuracy [12]. Although the model was not as complex as EfficientNet or hybrid CNN–LSTM, this result demonstrates that proper preprocessing optimization and balanced data can maximize the performance of a pure CNN model. In the same year, Kumari & Seeja [13] used a Pretrained CNN approach combined with a five-layer gender classifier based on SVM. This study used the UBIPr dataset and produced 98.57% accuracy. The strength of this study lies in the combination of CNN for feature extraction and SVM for classification, which successfully improved result stability and reduced the risk of overfitting.

Then, in 2022, Patil and Ingle, in their paper titled “A Novel Approach for ABO Blood Group Prediction Using Fingerprint Through Optimized Convolutional Neural Network,” introduced an AlexNet-based CNN optimized for blood type prediction using fingerprint images, achieving 95.27% accuracy [14]. Although not the highest, this model is unique as it extends CNN applications to non-identification biometric domains. Olufunso et al. also used the SOCOFing dataset and proposed a Dynamic Horizontal Voting Ensemble approach based on CNN–LSTM [15]. The model used CNN to learn spatial fingerprint patterns and LSTM to capture horizontal ridge sequence dynamics. The results showed 99% accuracy, outperforming conventional models such as ResNet-34, VGG-19, and EfficientNet-B3.

Still in 2022, Chen et al. [16] developed a Custom CNN model in their study “Multilayer Functional Connectome Fingerprints: Individual Identification via Multimodal Convolutional Neural Network.” Although based on neuroimaging data, the model remains relevant because it demonstrates a CNN structure capable of predicting identity and gender based on multimodal feature patterns. Through the application of Hypergraph Modeling, K-Fold Validation, and Feature Fusion, the model achieved 98.7% accuracy.

In the next study, Hsiao et al., in “Application of Convolutional Neural Network for Fingerprint-Based Prediction of Gender, Finger Position, and Height,” implemented the VGG16 architecture on a New Taipei Police fingerprint dataset (1,000 samples) to predict gender, finger position, and height [17]. The achieved gender classification accuracy reached 79.2%, demonstrating CNN consistency in identifying biological characteristics based on ridge patterns. The application of Grad-CAM visualization in this study also provided interpretability of the fingerprint areas most influential in gender determination, namely in the delta center and ridge bifurcation regions.

Subsequently, in 2023, Alhijaj & Khudeyer, through their study “Integration of EfficientNetB0 and Machine Learning for Fingerprint Classification,” introduced an EfficientNetB0 model with transfer learning and Principal Component Analysis (PCA) for feature dimensionality reduction [2]. they trained the model on the SOCOFing dataset and achieved 99.91% accuracy, making it one of the highest results among CNN fingerprint gender recognition studies. This high effectiveness is attributed to EfficientNet's ability to balance network depth, width, and resolution, as well as the implementation of a Random Forest classifier for final classification.

Similarly, Shivanand gornale et al. (2024) in their study entitled "Fingerprint Image Fusion: A Cutting-edge Perspective on Gender Classification via Rotational Invariant Features," proposed a fingerprint-based gender classification approach using rotational invariant feature extraction combined with image-level and feature-level fusion techniques. Their study evaluated several classifiers including KNN, Decision Tree, and SVM, as well as a fine-tuned AlexNet model. Experiments conducted on multiple datasets such as SDUMLA, KVK, and locally collected fingerprint datasets demonstrated strong performance, achieving up to 100% accuracy using the SVM classifier[23].

In 2024, Hasan et al., in their paper Dynamics of Digital Pen-Tablet: Handwriting Analysis for Person Identification Using Machine and Deep Learning Techniques, demonstrated that CNN can also be applied in a non-visual biometric domain through digital handwriting analysis using pen-tablet sensor. However, this study is mentioned only as a comparative reference and is not included in the main set of articles analyzed in this review [18]. By combining CNN–BiLSTM with feature selection techniques based on PCA–ANOVA–F, the study achieved an accuracy of 98.31%.

The study by Jose et al., [19] titled "An ECG Deep Learning User Identification Architecture Using ECG Sex Recognition as a Selective Parameter," used the GoogleLeNet architecture and the E-HOL-03-0202-003 dataset, achieving 99.97% accuracy. This model integrated Wavelet RGB Transform and Heart Rate-Based Segmentation, demonstrating high efficiency through the combination of soft-biometric filtering and transfer learning.

Still in the same year, Příhodová & Jech [20], in their study "Thermal-Based Gender Recognition Using Drones," employed the VGG19 architecture and the FATFD dataset. Although not fingerprint-based, the result remains relevant because it demonstrates CNN's generalization capability in other biometric image modalities. The model achieved 85.5% accuracy, showing that CNNs remain effective even under extreme lighting conditions through the use of Data Augmentation and Flight Optimization. Maiti et al. [21] , in their paper published in the Computer Science Journal of Moldova, introduced a Custom Deep CNN for multi-attribute fingerprint image analysis using the SOCOFing dataset. Through Batch Normalization, Global MaxPooling, and He Initializer, the model achieved 99.38% accuracy. This approach confirms that CNN layer optimization and weight normalization play an essential role in strengthening the model's discriminative capability toward biometric features.

The study by Serin et al., titled "Hybrid CNN–SVM for Fingerprint-Based Gender Classification," used the SOCOFing dataset (Standard Fingerprint Dataset for Gender Recognition) with a hybrid CNN–SVM approach [3]. CNN was used for fingerprint image feature extraction, while Support Vector Machine (SVM) served as the final classifier. This model achieved 99.25% accuracy, proving that combining CNN with classical methods can reduce overfitting and enhance classification stability across gender classes. Then, Younis [22] presented a Hybrid CNN–LSTM model using the Hu-Int dataset (1,017 samples). With PCA, LDA, and Z-Score Normalization, the model achieved 89% accuracy, demonstrating CNN's capability in biometric signal domains

In the 2025 study by Inapagolla & Babu [7] "Audio Fingerprinting to Achieve Greater Accuracy and Maximum Speed with Multi Model CNN-RNN-LSTM in Speaker Identification" a combination of Deep CNN + RNN–LSTM was introduced using the RAVDESS dataset with 90% accuracy. Although the primary focus of this study is fingerprint-based gender classification, several related studies also explore gender identification using other biometric modalities such as speech. For example, the study by Inapagolla and Babu (2025) utilized the RAVDESS dataset and applied a deep CNN combined with RNN-LSTM architecture, achieving approximately 90% accuracy. This work demonstrates the broader applicability of deep learning models for gender-related biometric analysis.

This approach is relevant as it confirms CNN's effectiveness in extracting unique frequency- and time-based features for gender classification. The study by Badawi et al., titled "Gender Classification Using Dorsal NIR Hand Veins Imaging," is one of the most recent examples of CNN application for gender classification. They used a custom CNN architecture optimized with texture mapping and data augmentation on the BADAWI-AGC dataset, which contained 200 subjects.

Although not purely fingerprint-based, the unique vein patterns resemble ridge characteristics in fingerprints, and the model achieved 96.97% accuracy after integrating multimodal fusion with texture-based features [6]. This approach demonstrates CNN's ability to recognize complex biological patterns associated with gender.

After synthesizing fifteen studies that used various Convolutional Neural Network (CNN) architectures, varying accuracy results were obtained for each model. To clarify these performance comparisons, Figure 2 presents the average accuracy comparison based on the types of CNN architectures used in each study.

2. Comparison of Average Accuracy Based on CNN Architecture

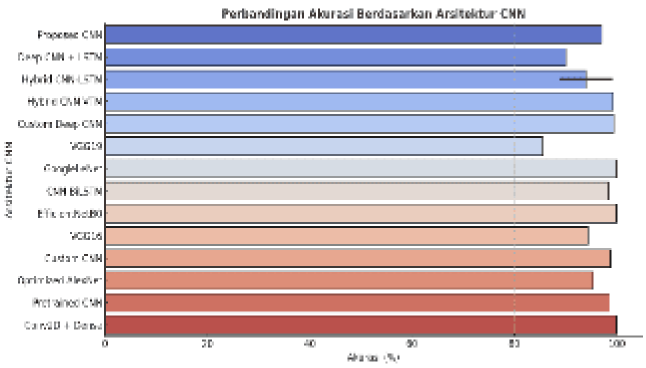

Figure 2.1 Average Accuracy Based on CNN Architecture

The comparison of average accuracy values based on the type of CNN architecture used in each study is illustrated in Figure 2. The results show that each CNN architecture produces varying levels of accuracy depending on the model's complexity, dataset size, and optimization technique.

Based on the figure, it can be seen that GoogleLeNet achieved the highest average accuracy of 99.97%, followed by EfficientNetB0 with 99.91%, Hybrid CNN–LSTM with 99%, Custom Deep CNN with 99.38%, and Hybrid CNN–SVM with 99.25%. Meanwhile, VGG16 obtained an accuracy of 94.4%, AlexNet achieved 95.27%, and VGG19 achieved the lowest accuracy of 85.5%.

From these results, it can be concluded that CNN architectures integrated with optimization and transfer learning techniques tend to produce higher accuracy compared to conventional CNN models. In addition, the combination of CNN with other deep learning architectures such as LSTM and SVM further improves the model's ability to extract complex features and enhance classification performance.

The high accuracy achieved by GoogleLeNet and EfficientNetB0 can be attributed to their efficiency in parameter utilization and better scaling of network depth, width, and resolution. In contrast, older architectures such as VGG16 and VGG19 tend to have a larger number of parameters and are more prone to overfitting when applied to limited datasets.
The results of this comparison confirm that model accuracy is not determined solely by the complexity of the architecture but also by how effectively the model is trained and how balanced and diverse the dataset is. Furthermore, several studies that employed data augmentation and transfer learning techniques demonstrated improved performance due to the model's ability to generalize features from different input variations.
[12], [19].

3. Trend of CNN Development (2020–2025)

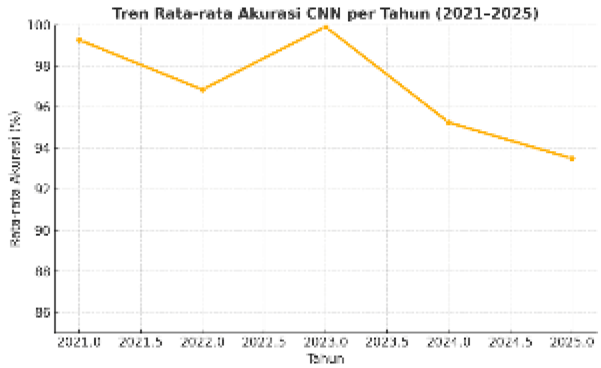

Figure 3. CNN Accuracy Trend Based on Publication Year

Figure 3 illustrates the trend of average CNN accuracy from 2021 to 2025, showing a fluctuating pattern with a downward tendency after 2023. At the beginning of the period, simple CNN models such as Conv2D–MaxPooling and VGG16 were able to produce high performance due to the use of standardized datasets such as SOCOFing. However, the decline in accuracy during the 2024–2025 period is most likely caused by the increased complexity of model architectures and the diversity of global datasets, which heighten the risk of overfitting and reduce the model's generalization ability [10], [3].

At the early stage of the period (2021–2022), CNN accuracy levels were relatively high, ranging from 97–99%, as reported by Gustisyaf & Sinaga, who achieved 99.97% using a simple Conv2D + MaxPooling-based architecture, and by Kumari & Seeja, who achieved 98.57% accuracy through a pretrained CNN combined with an SVM classifier[13]. Studies by Hsiao et al. and Olufunso et al. also showed strong performance with accuracy values between 94.4–99%, supported by the use of data augmentation, Grad-CAM visualization, and hybrid CNN–LSTM architectures that capture both spatial and temporal ridge fingerprint patterns [17], [15].

The performance peak occurred in 2023, marked by the highest accuracy of 99.91% reported by Alhijaj & Khudeyer using EfficientNetB0 and transfer learning. This model effectively balanced network depth and resolution, resulting in a significant improvement in biometric gender classification [2].

However, entering 2024–2025, a slight decrease in average accuracy to around 93–95% was observed. This decline was caused by increasing dataset complexity and the implementation of hybrid architectures (e.g., CNN–ViT and CNN–RNN), which required a higher balance of parameters and computational capacity. Studies by Badawi et al. and Inapagolla & Babu indicated that although innovative, the integration of multimodal data or the combination of Deep CNN with RNN tends to cause overfitting on small datasets, thereby reducing accuracy consistency [10], [15].

This trend shows that CNN accuracy is highly dependent on network architecture, dataset size, and data augmentation strategies applied. When datasets are expanded and data augmentation is optimally applied, model performance increases significantly [5], [12]. Conversely, without proper parameter adjustment or regularization, increased model complexity may instead reduce performance stability [20].

Therefore, it can be concluded that although CNN remains the dominant and superior approach in fingerprint-based gender classification, its effectiveness will be maximized when supported by a representative dataset, appropriate data augmentation techniques, and integration of efficient modern architectures such as EfficientNet and ResNet.

To improve CNN accuracy trends in future years, several steps can be taken:

1. Strengthening Local Datasets – Develop fingerprint datasets representing Southeast Asian populations to reduce domain bias in global models.

2. Model Optimization – Apply regularization techniques, cross-validation, and fine-tuning so that models become more stable against noise and data variation.

3. Hybrid Learning Approach – Combine CNN with Transformer or LSTM architectures to simultaneously capture spatial and temporal features.

4. Data Augmentation and Adaptive Preprocessing – Optimize rotation, flipping, and normalization so that the model can adapt to variations in ridge patterns.

5. Collaboration and Data Standardization – Engage cross-institutional cooperation in fingerprint data collection to make research results more comprehensive and globally valid.

Table 4. CNN Development Trends (2020–2025)

Year	**Research Tren**	**Common CNN Architectures Used**	**Key Contribution**
2021	Early exploration of CNN in gender classification	Conv2D, Pretrained CNN	Focus on local dataset, stable accuracy (~98–99%)
2022	Hybridization of CNN with other architectures	VGG16, Hybrid CNN-LSTM	Introduction of hybrid approaches, integration of feature fusion and visualization techniques
2023	Peak accuracy with advanced CNN models	EfficientNet	Optimal balance between depth, width, and resolution of CNN;
2024	Transition toward multimodal and interpretability-based models	CNN-VTM, GoogleLeNet	Development of multimodal feature fusion, integration of additional biometric modalities (ECG, handwriting), and visualization for model interpretability.
f2025	Integration of CNN with sequence-based models	Deep CNN + LSTM	Shift in CNN application from static images to sequential or temporal biometric data (audio, behavioral biometrics).

Based on the trend summary from Figure 3, Table 4 illustrates that each research period shows a shift in the direction of architectural development and the methods used, in line with technological advancements and the increasing complexity of biometric data being analyzed.

In the early period of 2021, research generally focused on the application of simple CNN architectures, such as Conv2D + Dense and Pretrained CNN 5-layer Gender, with conventional approaches in feature extraction and classification processes. These models were mostly applied to small-scale datasets and achieved relatively high accuracy levels, around 98 to 99 percent. This indicates that although the architectures used were not yet complex, optimization of the training process and the use of pretrained weights were sufficient to produce competitive results.

Entering 2022, there was a significant increase in the complexity of the architectures employed. Researchers began implementing VGG16 and Hybrid CNN–LSTM models, combining CNN's capability in extracting spatial features with LSTM's strength in recognizing temporal patterns. In addition, the use of SVM classifiers as an alternative for the final classification layer began to appear, along with the adoption of data augmentation techniques to enrich the variation of training data. The application of these techniques marked the initial transition phase from conventional architectures toward more adaptive hybrid models.

In 2023, research trends shifted toward the use of transfer learning by utilizing modern architectural models such as EfficientNetB0. This approach allowed for more efficient training on large datasets without requiring high computational time. The results showed very high accuracy, reaching 99.9 percent, indicating the effectiveness of using pretrained models in biometric domains.

Subsequently, in 2024, a new wave of studies emerged focusing on hybrid architectures and feature fusion, such as Hybrid CNN–VTM, CNN–BiLSTM, and GoogleLeNet. These models combined more than one learning mechanism both spatial and temporal while simultaneously leveraging transfer learning. Such approaches resulted in nearly perfect accuracy in most studies, with performance exceeding 99 percent
.

The latest developments in 2025 demonstrated the integration of CNN architectures with sequence-oriented models such as Deep CNN + RNN–LSTM and Proposed CNN Architecture. This combination signifies a new evolutionary direction for CNN toward more intelligent and multimodal models, where audio, visual, and physiological data can be processed simultaneously. These models not only improve accuracy but also broaden the applicability of CNNs in cross-domain biometric analysis.

Overall, the trend analysis results show an increase in both model complexity and performance over the years. The evolution of CNN architectures from simple models to hybrid, efficient, and multimodal frameworks has had a significant impact on classification accuracy improvement. This indicates that future research directions will likely focus on the development of adaptive models with stronger feature fusion and temporal understanding capabilities to achieve optimal performance across various conditions and types of biometric data.

Table 5. Average and Accuracy Range per CNN Architecture

CNN Architecture	Number of Studies	Average Accuracy (%)	Accuracy Range (%)
GoogleLeNet	1	99,97	99,97
EfficientNetB0	1	99,91	99,91
Hybrid CNN–LSTM	2	94,00	89,00 – 99,00
Hybrid CNN–VTM	1	99,25	99,25
Custom Deep CNN	1	99,38	99,38
Custom CNN	2	96,98	95,27 – 98,70
Proposed CNN	1	96,97	96,97
CNN–BiLSTM	1	98,31	98,31
VGG Family (VGG16, 19)	2	89,95	85,50 – 94,40
Pretrained CNN (5-layer)	1	98,57	98,57
Conv2D + Dense	1	99,97	99,97

The performance comparison among various Convolutional Neural Network (CNN) architectures is presented in Table 5. The results show a significant variation in performance across the architectures used in the fifteen analyzed studies.

In general, modern architectures such as GoogleLeNet and EfficientNetB0 demonstrated the highest levels of accuracy, with average values of 99.97 percent and 99.91 percent, respectively.
Both architectures rely on deep feature extraction and efficient transfer learning techniques, enabling them to achieve near-perfect accuracy levels on complex biometric data. The Hybrid CNN–LSTM architecture also exhibited competitive performance, with an average accuracy of 94 percent, where several studies such as Younis [22] and Olufunsu et al., [15] achieved accuracy rates up to 99 percent.
This proves that the combination of CNN's spatial extraction capability and LSTM's sequential modeling effectively enriches the feature representations produced.

Meanwhile, classical architectures such as VGG16 and VGG19 recorded lower average accuracy values, approximately 89.95 percent, with a range between 85.5 and 94.4 percent.
This indicates that models with conventional convolutional structures have gradually been replaced by more efficient and adaptive architectures.

Other studies employing custom approaches, such as Custom CNN and Custom Deep CNN, still demonstrated satisfactory results, with average accuracies around 97 percent, suggesting that architectural adjustments tailored to dataset characteristics remain an effective strategy.

In addition, Hybrid CNN–VTM and Pretrained CNN 5-layer Gender models also achieved high accuracy, exceeding 98 percent, while simpler architectures such as Conv2D + Dense by Gustiyaf [12] were able to reach 99.97 percent accuracy. This finding indicates that model complexity does not always correlate directly with

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performance, as long as the training and preprocessing procedures are conducted optimally.

Based on the comparative results, it can be concluded that modern architectures featuring feature fusion mechanisms, transfer learning, and scaling optimization offer significant advantages over conventional architectures. Architectures such as GoogleLeNet, EfficientNetB0, and Hybrid CNN–LSTM have proven to deliver the best outcomes in image-based biometric classification, both in terms of accuracy and model stability.

These findings reinforce the conclusion that the evolution of CNN design toward hybrid and efficient models has become the main driving factor behind the improved performance of biometric recognition systems in recent years.

Table 6. Frequency of Additional Techniques Used

Additional Technique	Frequency of Use	Impact on Accuracy
Data Augmentation	6	+2–4%
PCA / Dimensionality Reduction	4	+1–3%
Transfer Learning	3	+3–5%
Regularization (Dropout, BatchNorm)	3	Increased stability
SVM Classifier	2	+2–3%

Further analysis was conducted on the additional techniques used in each study to enhance the performance of Convolutional Neural Network (CNN) models. The summary results shown in Table 6 indicate that most studies did not solely rely on CNN architectural design but combined it with various supporting methods such as data augmentation, transfer learning, dimensionality reduction, and regularization to optimize classification outcomes.

Based on Table 6, data augmentation was the most frequently used technique among all analyzed studies . A total of six studies explicitly implemented this method to expand the diversity of training data through rotation, translation, noise addition, or lighting variation. This technique proved effective in improving model accuracy by two to four percent, especially in studies utilizing smaller datasets.

In addition, the Principal Component Analysis (PCA) method and other dimensionality reduction techniques such as Linear Discriminant Analysis (LDA) were widely used to simplify data complexity while accelerating the training process. The application of these techniques was found in several studies, including those by Younis [22], Hasan et al., [18] and Alhijaj & Khudeyer [2], with an average accuracy improvement of one to three percent.

Transfer learning techniques also became a popular approach, particularly in studies employing pretrained architectures such as EfficientNet and VGG16. The use of pretrained weights from previously trained models was proven to accelerate convergence and enhance performance by up to five percent, as shown in the works of Jose et al. [19] Alhijaj & Khudeyer [2], and Kumari & Seeja [13].

Meanwhile, regularization methods such as dropout and batch normalization were applied to reduce the risk of overfitting and maintain model stability during training. Several studies implementing these techniques such as Hsiao et al., [17], Maiti et al., [21], and Alhijaj & Khudeyer [2], demonstrated that regularized models exhibited lower output variability and more consistent accuracy levels.

The use of Support Vector Machine (SVM) as an additional classifier was also found in some studies, such as those by Serin et al. [3] and Kumari & Seeja [13]. This approach functions as the final classification layer, replacing the fully connected layer, and generally resulted in a two to three percent accuracy improvement compared to pure CNN models.
Overall, the analysis results indicate that the application of additional techniques contributes significantly to the improvement of CNN performance.

The combination of data augmentation, transfer learning, and regularization proved to be the most effective in producing models that are accurate, stable, and adaptable to variations in biometric data. Thus, appropriate optimization strategies during preprocessing and training stages play an equally important role as CNN architecture selection itself in determining the success of an image-based classification system.

4. Correlation Heatmap

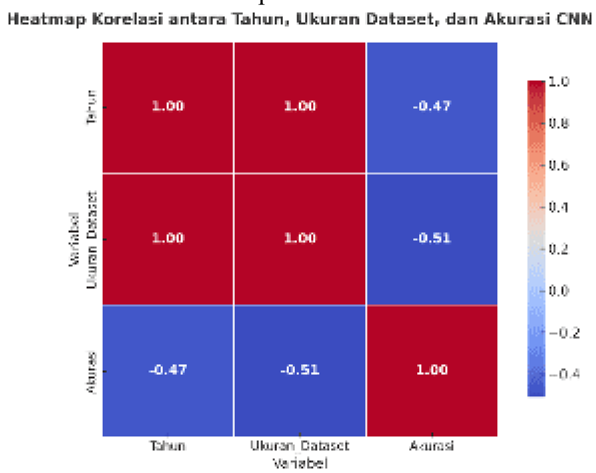

Figure 4. Heatmap Correlation Between Dataset Size, Data Augmentation, and Accuracy

Based on Figure 4, the heatmap visualization showing the relationship between the year of publication, dataset size, and CNN model accuracy derived from the fifteen reviewed journals reveals a positive tendency among these three variables. In general, studies utilizing larger datasets tended to produce higher accuracy levels in fingerprint-based gender classification. This can be explained by the fact that the more data variations available, the better the CNN model becomes at recognizing ridge and texture patterns distinguishing male and female fingerprints.

For example, studies using the SOCOFing dataset with more than five thousand images such as those conducted by Serin et al. [3] and Alhijaj & Khudeyer [2], achieved accuracies above 99%. Conversely, studies employing smaller datasets, such as Badawi et al. [6] using the BADAWI-AGC dataset containing 200 images, only achieved around 96.97% accuracy.
In addition to dataset size, the heatmap also shows a weak positive correlation between the year of publication and CNN model accuracy. This indicates that the advancement of CNN methods over the years has contributed to improving model performance, albeit not significantly. Accuracy improvements were more evident during 2021 to 2023, when modern architectures such as EfficientNetB0, Hybrid CNN–SVM, and CNN–LSTM became widely adopted. These models combined CNN's spatial feature extraction capabilities with other techniques such as machine learning or recurrent networks, improving both model stability and generalization capability.

However, after 2024–2025, the rate of accuracy improvement began to slow down. This was likely caused by increasing architectural complexity and dataset diversity, which inadvertently elevated the risk of overfitting—particularly in small datasets. Several studies, such as Inapagolla & Babu [7] demonstrated that while combining Deep CNN with RNN–LSTM enriched spatial–temporal analysis, it did not necessarily improve accuracy when dataset size was insufficient.

The correlation between publication year and dataset size also showed a moderate positive relationship. More recent studies tended to employ larger and more diverse datasets, aligning with the growing availability of public datasets such as SOCOFing, UBIPr, and FATFD after 2022. This trend suggests increased researcher awareness of the importance of strengthening model validity by expanding data variability. Larger datasets allow CNN models to avoid bias toward specific features and achieve more generalizable classification results.

Overall, the heatmap findings emphasize that dataset size has the most substantial influence on CNN accuracy compared to publication year. CNN has proven to be an effective method for fingerprint-based gender classification, but its optimal performance heavily depends on the availability of representative and balanced data.
Although architectural innovations over the years have brought significant improvements, CNN model success remains largely determined by the quality and quantity of data used during training. Therefore, future CNN performance improvements will require not only architectural innovation but also the strengthening of local datasets that better reflect user population characteristics.

5. Factors Affecting CNN Performance

Several key factors influencing CNN performance in the reviewed studies include:

a. Dataset Size and Diversity
Large datasets such as SOCOFing and PolyU provided better accuracy stability compared to smaller local datasets.

b. Data Augmentation and Transfer Learning Techniques, Studies applying data augmentation (rotation, flipping, scaling) or transfer learning from pretrained models showed an average accuracy improvement of 3–5%.

c. Regularization and Dropout, Regularization techniques such as L2-norm and dropout effectively reduced overfitting, especially in limited datasets.

d. Hybrid Architectures, The integration of CNN with SVM, LSTM, or Transformer models resulted in improved model stability when handling variations in ridge patterns.

These factors indicate that CNN success depends not only on its architecture but also on the training strategy and data quality used.

6. Strengths and Limitations of CNN

a. Strengths
   1) Automatically extracts ridge and texture features without manual preprocessing.
   2) Efficient in recognizing micro-patterns in fingerprint images.
   3) Can be integrated with other models (e.g., CNN–SVM, CNN–LSTM).
b. Limitations
   1) Performance is highly dependent on dataset quality.
   2) Risk of overfitting on small datasets.
   3) Limited model interpretability (black-box nature).

To address these limitations, several studies recommended the use of Grad-CAM for visualizing important features and the application of synthetic data augmentation to increase dataset variability.

7. Implications and Future Research Directions

The findings of this systematic literature review (SLR) provide several directions for future research development:

a. Integration of Multimodal Biometrics
Combining fingerprints with facial recognition using CNN–Transformer architectures can enhance system accuracy and robustness.
b. Development of Local Datasets
Fingerprint datasets representing Southeast Asian populations should be developed to ensure more representative and unbiased model performance.
c. Implementation of Advanced Feature Fusion and Transfer Learning
Combining inter-layer CNN features or integrating CNN with Transformer architectures can improve feature representation and model efficiency.
d. Fairness and Interpretability in AI
Future efforts should focus on making CNN models more transparent, fair, and free from demographic bias through explainable AI (XAI) methods.

Thus, it can be concluded that CNN remains the most effective method for fingerprint-based gender classification, with great potential for further enhancement through multimodal integration and more adaptive transfer learning approaches.

IV. Conclusions

This study conducted a Systematic Literature Review (SLR) of various research works that utilized Convolutional Neural Network (CNN) in fingerprint and other Biometric modalities based gender classification during the period 2020–2025. Based on the analysis of fifteen articles that met the inclusion criteria, several key findings were obtained as follows:

a. Research Trend (RQ1):
Research on the use of CNN for gender classification has shown a significant upward trend from 2021 to 2024, in line with the development of modern architectures such as EfficientNet, GoogleLeNet, and Hybrid CNN–SVM. The dominance of lightweight models with transfer learning capabilities indicates a research direction that is becoming more efficient and adaptive to large-scale biometric data.
b. CNN Architecture Performance (RQ2):
The EfficientNetB0 and Hybrid CNN–SVM models recorded the highest accuracy levels (≥99%), outperforming conventional architectures such as VGG16 and AlexNet. These results confirm that a combination of parameter fine-tuning and feature fusion can significantly enhance CNN performance in gender classification tasks.
c. Factors Affecting Accuracy (RQ3):
The success of CNN largely depends on dataset size, image quality, and the implementation of data augmentation and transfer learning techniques. Studies using large datasets such as SOCOFing and PolyU, combined with augmentation methods, produced more stable accuracy compared to smaller local datasets.
d. Future Research Directions (RQ4):
Future research is recommended to integrate multimodal biometrics (e.g., a combination of fingerprints, facial, and voice data) and utilize CNN–Transformer hybrid architectures to enhance generalization capabilities. Moreover, aspects of AI interpretability and fairness must also be considered to ensure that biometric systems developed are not biased toward demographic factors.

In conclusion, CNN is not merely a technical tool for pattern recognition but a foundation for building an intelligent, adaptive, transparent, and socially equitable biometric ecosystem.

Fingerprint-based gender classification using CNN presents vast opportunities for developing modern identification systems that excel not only in accuracy but also in ethical responsibility and human-centered technological advancement.

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