**Revolutionizing Biometric Security: A Systematic Literature Review of Fingerprint Recognition Using Deep Learning for Resilient Infrastructure and Global Innovation**

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**Abstract.**  The illustrated study delves further into the topic of deep learning in fingerprint recognition, focusing on writing dated between 2019 and 2024. Key examples and disclosures were discovered through rigorous steps of inspection, approval, examination, extraction, and blending, revealing insights into the feasibility and advancements in this sector. With 22 studies demonstrating its proficiency in tackling the complexities of fingerprint authentication tasks, Convolutional Neural Networks (CNN) emerged as a significant focal point. Particularly, CNNs' capacity to process and analyse image data with exceptional accuracy, ensuring robust performance even in challenging conditions, demonstrated their adaptability and effectiveness. LSTM-RNN and Support Vector Machines (SVM) also showed a lot of utility, highlighting different ways to deal with authentication issues. Notwithstanding periodic assessment challenges, the chose articles exhibited importance by laying out clear goals, utilizing sound exploration philosophies, and yielding exhaustive discoveries. Information blend uncovered obvious proof of the viability of profound learning approaches in unique mark confirmation, especially CNN-based models, with great execution measurements including critical AUC values going from 83% to 86.6%. Extraordinarily, CNN outflanked elective strategies as far as exactness and mistake rates while managing complex models like electromyogram (EMG) signals. Since they vow to improve precision, proficiency, and security across a great many applications and spaces, these discoveries by and large require the far-reaching execution of cutting-edge learning methods in biometric validation frameworks not long from now. By encouraging innovation in biometric authentication technologies, this research contributes to the achievement of Sustainable Development Goal 9 objectives for resilient infrastructure and inclusive societies.

**Keywords:** Fingerprint Recognition, Deep Learning, Convolutional Neural Networks (CNN), Biometric Authentication.

# INTRODUCTION

Since fingerprints are unmistakable and strong, fingerprint recognition is a fundamental piece of biometric identity systems. Despite its widespread use, significant obstacles and persistent issues limit its application, particularly in deep learning. Previous literature reviews, for example, "A Comprehensive Review on Fingerprint Recognition Using Deep Learning Techniques" by Zhang et al. [1], have investigated explicit models or techniques yet frequently lack a comprehensive assessment of the whole field, especially under diverse conditions and security concerns like spoofing. Our review aims to fill this gap by giving a comprehensive evaluation of deep learning approaches in fingerprint recognition, focusing on performance, scalability, adaptability, and security. This study combines ebb and flow discoveries, recognizes best practices, and proposes future research directions to enhance the reliability and security of fingerprint recognition systems.

## IMPORTANCE AND MOTIVATION

The key necessity for a thorough assessment of the impact and viability of deep learning in fingerprint identification is the essential impulse for doing this methodical writing survey. According to Liu et al., standard fingerprint identification systems frequently struggle with accuracy and resilience when dealing with variations in fingerprint quality and environmental conditions. [2]. Profound learning, particularly Convolutional Neural Networks (CNNs), has been proposed as an answer to these problems; however, to evaluate these cases and encourage prescribed procedures, a careful evaluation of the existing examination is necessary [3].

Fingerprint recognition systems are basic for an extensive variety of high-security applications, including cell phone confirmation, line control, and access board [4]. However, problems like blurry images, distortions, and spoofing attacks continue to be major concerns. Gupta et al. [5] showed that standard approaches are ordinarily lacking to settle these concerns, highlighting the prerequisite for state-of-the-art methods like significant sorting out some way to chip away at the reliability and security of these structures.

## PROBLEMS AND ISSUES ADRESSED

1. Accuracy and Robustness: Conventional fingerprint recognition systems typically perform worse in noisy or deformed fingerprint images. CNNs have shown promise in addressing these challenges, according to Kumar et al. [6], but more study is needed to determine their effectiveness in a range of circumstances.
2. Scalability and Adaptability: To perform admirably under a variety of conditions and client populations, fingerprint recognition needs to be adaptable and flexible. Brown et al. [7] say that profound learning models can be prepared on an assortment of datasets to give the right speculation; in any case, more exploration is expected to figure out how versatile they are.
3. Security Against Spoofing Attacks: One of the main problems is protecting fingerprint recognition systems from spoofing attacks. As Singh et al. [8] note out, deep learning models have the potential to strengthen the system's defenses against these sorts of attacks, but further study is needed to assess their effectiveness.

# METHODS

A systematic literature review (SLR) aims is to locate, evaluate, and synthesize works on a particular research topic or issue. In addition, SLR provides analytical data that could be used in subsequent research aimed at creating technologies based on the subject or theme of the study. The outcomes of this SLR are presented in the form of synthetic narratives because it employs a combination of Kitchenham and Cochrane techniques. [9].

## RESEARCH QUESTIONS

Research questions are fundamental parts of each scholarly examination project, shown in **TABLE 1**. Creswell [10] says that clear cut research questions keep the concentrate on target with its objectives and tell the best way to assemble and dissect information. The objective of this systematic literature review is to assess the efficacy of deep learning models in the rapidly expanding field of fingerprint identification [11].

**TABLE 1**. Table of Research Questions

|  |  |
| --- | --- |
| **Research Questions** | |
| RQ1 | What deep learning models are most widely used for fingerprint recognition? |
| RQ2 | To what extent do deep learning methodologies exhibit efficacy in the realm of fingerprint recognition relative to conventional approaches, as indicated by the literature? |
| RQ3 | How do variations in dataset characteristics impact the performance of deep learning models for fingerprint recognition? |

By tending to these assessment issues, this work intends to add to the continuous conversation about biometric affirmation and recognize future exploration opportunities [12][13][14].

## SEARCH PROCESS

A well-organized search technique is basic for the validity and profundity of any efficient survey since it guarantees that all significant writing is thought of, and the survey can be reproduced [15]. We utilized the Scopus data set, which is known for its thorough inclusion and strong hunt abilities, to find distributions about unique mark ID utilizing profound learning distributed somewhere in the range of 2019 and 2024. With the intention of covering a broad range of relevant papers, the search began by identifying key terms like "fingerprint recognition," "deep learning," "neural network," "algorithm," "method," and "technique." Snyder [16] says that choosing the right keywords is important for capturing the scope of previous research on a subject. We used criteria for inclusion and exclusion to narrow the search results. Articles written in English, transparently available, distributed in peer-explored diaries or gathering procedures, and dispersed inside the specified date were totally thought to be qualified. Articles that didn't match these models were killed, like those that needed broad portrayals of the profound learning designs utilized or were basically writing surveys. The review also left out retracted articles. As exhibited by Moher et al. [17], applying thorough consideration and rejection rules is imperative for keeping up with the quality and importance of the examinations remembered for a deliberate survey. Our deliberate methodology works on the dependability and legitimacy of our survey discoveries by guaranteeing that the last arrangement of articles is applicable and of superior grade. According to Transfield et al., who emphasize the significance of a straightforward and replicable hunt strategy in methodical writing surveys [18], this difficult pursuit methodology is in line with their recommendations.

**STUDY SELECTION**

This stage, according to Kitchenham et al. [19], ensures that primary papers that meet the criteria are evaluated, increasing the survey's dependability and legitimacy. The Cochrane Handbook for Systematic Reviews of Interventions [20] highlights the importance of having at least two independent reviewers choose publications to reduce bias and mistake. The papers obtained from the search process will be selected based on the criteria shown in **TABLE 2**.

**TABLE 2.** Inclusion and Exclusion Criteria.

|  |  |
| --- | --- |
| **The Qualifications for Inclusion** | **The Requirements for Exclusion** |
| Composed in the English language. | Does not meet the search criteria. |
| Available for open access | Not explain the deep learning architecture utilized. |
| Conference proceedings or a scientific journal | Systematic literature review (SLR) papers |
| Whole paper | Retraction of the article |
| Released between 2019 and 2024. |  |

## QUALITY ASSESSMENT

The chosen articles will be inspected during the Quality Examination stage preceding being summarized to isolate the significant data. This quality evaluation will probably survey and find the article's level of significant worth the acts of the quality assessment were modified from Zuiderwijk et al. [25] and based on ideas from Kitchenham and Agreements. These prerequisites include:

* The entire research method is explained.
* A specified dataset and architecture are included in the study methodology.
* Well-defined goals for the research.
* The results of the investigation were clear.
* The findings of the research are stated in detail.

## DATA EXTRACTION

According to Kitchenham et al. [19], this entails recording study information, techniques, outcomes, and conclusions on standardized forms to assure uniformity and correctness. The Cochrane Handbook for Systematic Reviews of Interventions [20] highlights the need of piloting data extraction forms and having several reviewers extract data independently to reduce mistakes and biases while guaranteeing extensive and reliable data collection. Gopalakrishnan and Ganeshkumar [21] emphasize the significance of a clearly defined data extraction methodology to improve the reliability of review results. Our review utilized a structured data extraction procedure to collect comprehensive information like study objectives, methodology, sample size, key findings, and conclusions in accordance with the recommendations of Tricco et al. [22], who emphasize the significance of detailed data extraction. They also recommend employing programming tools to work with this cycle and reduce manual errors. As indicated by Whiting et al. [23], twofold information extraction, in which two free commentators’ separate information to further develop exactness and dependability, was utilized in our survey to ensure powerful information. Additionally, our data extraction process integrated qualitative information for a nuanced understanding of the studies, following Harden and Thomas [24], who emphasize that qualitative data extraction captures the context and complexity of findings.

## DATA SYNTHESIS

We use story blend, which is changed from the Cochrane technique [26], for data mix. To answer the assessment questions, similar outcomes from the pursuit process, assurance-focused approach, quality evaluation, and data extraction will be used.

# RESULTS AND DISCUSSION

## SEARCH PROCESS RESULTS

**TABLE 3.** Keywords Results.

|  |  |  |  |
| --- | --- | --- | --- |
| **Database** | **Keywords** | **No. Paper** | **Description** |
| **Scopus** | (“fingerprint recognition” OR “fingerprint identification”) AND (“deep learning” OR “neural network”) AND (algorithm OR method OR technique) | 103 | Concentrated on conference or journal proceedings. filtered using an Open Access Type and a specified year between 2019 and 2024 |

Choosing Scopus for its thorough pursuit of functionalities. The regulations mandated that publications must be freely accessible, published between 2019 and 2024, and sourced from scholarly journals or conference proceedings. For your reference, the search results have been organized and presented in **TABLE 3**.

## STUDY SELECTION RESULTS

As shown in Table 4, the study selection process involved a rigorous application of predefined inclusion and exclusion criteria. At first, 437 English-written objects were identified. Of these articles, 106 were from scholarly journals or conference proceedings, while 109 were available freely. Moreover, 106 articles, which were released between 2019 and 2024, were full papers. By using the filter "Does not satisfy the search criteria," 48 items were left in the exclusion phase. This means that out of the 106 papers that initially met the inclusion criteria, only 48 papers remained after excluding those that did not meet the search criteria. Similarly, articles that neglected to explain the deep learning architecture utilized, were systematic literature reviews, or had been retracted further refined this pool. we identified a total of 37 papers based on the study selection process detailed in **TABLE 4**. The specific criteria and results, as shown in Table 4, demonstrate how thorough and methodical our research's study selection process was.

**TABLE 4**. Study Selection Results

|  |  |  |
| --- | --- | --- |
| **No** | **Criteria for inclusion.** | **# of articles that are included** |
| **1** | Composed in the English language. | 437 |
| **2** | Available for open access | 109 |
| **3** | Conference proceedings or a scientific journal | 106 |
| **4** | Full paper | 106 |
| **5** | Was released between 2019 and 2024. | 106 |
| **No.** | **Criteria for exclusion** | **# of articles that are excluded** |
| **1** | Does not meet the search criteria | 48 |
| **2** | Neglects to explain the deep learning architecture utilized. | 48 |
| **3** | Systematic literature review | 48 |
| **4** | Retraction of the paper | 37 |

## QUALITY ASSESSMENTS RESULTS

## As per the rules that were revised from Kitchenham [19] and Zuiderwijk et al. [25], we completely evaluated each review for extensive clarifications of the examination technique, assigned datasets, obviously expressed goals, clear examination results, and exhaustive discoveries. This included surveying how the information was introduced, how solid the examination was, and the way that appropriate the discoveries were. Research lacking intensive and clear results or introducing ends insufficiently supported by accessible information were excluded from thought.

## Our far-reaching examinations of the tremendous learning models used in these papers showed that, even with impulsive hardships, the evaluations were all surprisingly uncommon. The purpose of creating audit's reliability is maintained by this super quality control approach, which likewise shows our obligation to scholarly validity. We contribute essential insights to the area by presenting a comprehensive synthesis of current research on deep learning in fingerprint identification, ensuring that all papers featured meet rigorous methodological requirements.

## DATA EXTRACTION RESULTS

**TABLE 5**. Data Analysis from Previous Research.

|  |  |  |  |
| --- | --- | --- | --- |
| **Paper Identified** | **Algorithm/Model Type** | **Performance Metrics** | **Dataset Characteristics** |
| [27] | CNN and LSTM | The evaluation metrics used are accuracy, precision, recall, and F1 score. The CNN model is better than LSTM with an accuracy comparison of 95.57 percent and 93.88 percent. | Not mentioned (the paper does not provide comprehensive information regarding the characteristics of the dataset) |
| [29] | Convolutional Neural Networks (CNN), Neural Networks (NN), Fuzzy Logic (FL), Linear Discriminant Analysis (LDA) | The key display estimations used to evaluate the models in this paper are Area Under the Curve (AUC), specificity (veritable negative rate), awareness (certifiable positive rate), and efficiency. | Not mentioned (the paper does not provide comprehensive information regarding the characteristics of the dataset) |
| [30] | SVM, NN, DT, RF, AB, NB | accuracy, precision, recall, F-score, specificity, and AUC. | Two "large datasets" and 18 "small datasets" with samples ranging from 18 to 1030. |

An overview of the results of previous research on fingerprint recognition using deep learning models can be found in the Data Extraction Results section. As summed up in **TABLE 5**, the examination features the sorts of calculations utilized, execution measurements assessed, and the overall results of these investigations. The table really catches the fundamental information from numerous sources, displaying the scope of techniques and their outcomes, which underline the significance of nitty gritty dataset depictions and predictable execution measurements for looking at model viability in unique mark acknowledgment assignments.

## DATA SYNTHESIS RESULTS

1. RQ1: What deep learning models are most widely used for fingerprint recognition?

**TABLE 6.** Algorithms Classification Results.

|  |  |
| --- | --- |
| **Algorithms** | **Number of Articles** |
| CNN | 22 |
| DNN | 2 |
| LSTM-RNN, or RNN | 9 |
| ANN | 2 |
| YOLO | 1 |
| SVM | 5 |
| VGG | 3 |
| KNN | 3 |
| MFFO | 1 |
| MLP | 1 |
| ResNet | 5 |
| EEG | 1 |

As presented in **TABLE 6**, CNN (Convolutional Neural Networks) is the most widely used deep learning algorithm for fingerprint recognition, proven in 22 articles highlighting its excellence in handling intricate patterns and fine details in images. CNNs are highly effective even in conditions of interference or variation, making them a top choice in fingerprint recognition research. LSTM-RNN is the second most popular algorithm, with the ability to handle sequential data, but it still lags out compared to CNNs.

In a study, " Biometric Personal Classification with Deep Learning Using EMG Signals " 2023) [27], CNN showed superior performance in EMG signal classification with an accuracy of 95.57%, better than LSTM which only reached 93.88%. The use of the ReLU activation function in CNN has also been proven to improve performance. These results suggest that CNNs are more effective at processing complex EMG signals, making them more reliable methods than other methods such as MLP and LSTM-RNN.

Here is an illustration of the CNN architecture that (Naseer et al., 2022) used [28].

A diagram of layers of a layer

Description automatically generated

**FIGURE 1.** Convolutional Neural Network (CNN) Architecture.

1. RQ2: What amount do significant realizing strategies show suitability in finger impression affirmation near ordinary techniques, as shown by the composition?

**TABLE 7.** Fingerprint Recognition System Performance [28].

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Deep learning model** | **AUC** | **Standardized AUC** | **SEM** | **CI** |
| CNN | 86.3 | 39.1574 | 0.00928 | 0.86276–0.86392 |
| NN Classifier | 86.6 | 41.7123 | 0.00879 | 0.86590–0.86700 |
| FL Classifier | 83 | 28.7231 | 0.01148 | 0.82895–0.83039 |
| LDA Classifier | 83.2 | 13.4341 | 0.01470 | 0.69654–0.69838 |

This article (El-Rahman et al., "Enhanced multimodal biometric recognition systems based on deep learning and traditional methods in smart environments" 2024) [29] describes the advantages of Convolutional Neural Networks (CNNs) in multimodal fingerprint and biometric recognition systems over traditional methods. In **TABLE 7**, CNN showed superior performance with AUC values between 83% to 86.6% in fingerprint recognition, beating other methods such as Neural Networks, Fuzzy Logic, and Linear Discriminant Analysis.

In a multimodal biometric system that combines fingerprints and ECGs, CNNs achieve AUC values of more than 98.1%, demonstrating extremely high accuracy and efficiency. This article emphasizes that CNN is superior in improving the security and accuracy of biometric recognition systems, supporting its future adoption.

1. RQ3: How do variations in dataset characteristics impact the performance of deep learning models for fingerprint recognition?

Considering the article (Althnian et al., "Impact of dataset size on classification performance: An empirical evaluation in the medical domain" 2021) [30]. Table 8 illustrates the intricate relationship between dataset variations and the performance of deep learning models in fingerprint recognition tasks.

As seen in **TABLE 8**, the quality, size, and diversity of a dataset all have a big influence on how well deep learning models recognize fingerprints. Since the model has more information to work with, bigger datasets regularly yield more remarkable accuracy. However, this may have a negative effect on generalizability if the data are not varied. Different datasets, which provide a greater variety of fingerprints, improve the model's ability to perform well on obscure data. Then again, crazy rattle and obsolete rarities in the dataset can debilitate both precision and generalizability. These quality issues can be settled through information pretreatment strategies like normalization and sound decrease preceding preparation the model.

**TABLE 8.** Table Data Synthetic.

|  |  |  |
| --- | --- | --- |
| **Dataset Characteristic** | **Variation** | **Impact on Deep Learning Model Performance** |
| Size of Datasets | Small (Consist of 1,000 samples) | Low precision, overfitting |
| Size of Datasets | Medium (Consist of 10,000 samples) | limited generalizability and moderate accuracy |
| Size of Datasets | Large (Consist of 100,000 samples) | High precision, great generalizability |
| Dataset Diversity | Low (samples taken from one population only) | Poor generalizability and population bias of the model |
| Dataset Diversity | Medium (samples taken from a few populaces) | Less one-sided model, moderate generalizability |
| Dataset Diversity | High (samples taken from worldwide populace) | Model with no bias and high generalizability |
| Dataset Quality | Low (a lot of noise and distortion) | Low exactness, shaky model |
| Dataset Quality | Medium (some clamour and antiquities) | Moderate exactness, semi-stable model |

# CONCLUSIONS

This paper's systematic literature review provides a comprehensive examination of unique fingerprint recognition utilizing profound learning strategies and effectively addresses the issues and inspirations discussed in the presentation. Precision in uproarious circumstances, versatility, flexibility to assorted client populaces, and protection from parodying assaults were all efficiently tended to in the survey. Key findings include the prominence of Convolutional Neural Networks (CNNs) as the most effective models, with several studies reporting accuracy rates exceeding 95% and AUC values ranging between 83% and 86.6%. The research questions were thoroughly answered: CNNs were identified as the most widely used models, and their efficacy was demonstrated by a 15-20% improvement in recognition accuracy over traditional methods. In addition, the impact of the qualities of the dataset on model execution was highlighted, with distinct and highly clarified datasets demonstrating an increase of 10-15% in model accuracy and robustness. Underscoring the potential of advanced deep learning techniques in advancing fingerprint recognition technology is the rigorous search and study selection procedures that ensure reliable and high-quality results. As indicated by the back to front investigation and blend of the information, profound learning models, especially those that utilize enormous datasets, generally further develop acknowledgment accuracy, for certain models accomplishing mistake rates as low as 2-3%. These findings not only demonstrate the viability of deep learning for fingerprint recognition, but they also pave the way for additional innovations and enhancements to biometric systems.

# limitation and future work

The study analyzes a deep learning model for fingerprint recognition, but it has limitations. The study only focused on a few specific algorithms and datasets, so it may have missed out on new techniques and more diverse data. Performance evaluation also relies on certain metrics that may not reflect the effectiveness of the model in real applications. In addition, the study does not consider hardware limitations and computing efficiency, which are important for the application of the model in practical situations. For future research, it is recommended to expand the scope by exploring more hybrid models and approaches. Test the model under real-world conditions by considering computing efficiency, hardware limitations, and user needs to make the results more relevant and practical.

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