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PRISMA Approach for Assessing Fingerprint Classification Models Based on Artificial Super-Intelligence Techniques

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Abstract. The aim of this research paper focused on using PRISMA to reveal most artificial intelligence techniques that were used for fingerprint classification. Biometric technology such as fingerprints plays a key role in authenticating and identifying people's identities. Therefore, with the increasing number of population and the usage of biometrics for authentication, fingerprint classification systems are becoming important and indispensable for recognizing and authenticating individuals. Therefore, Artificial Super-Intelligence (ASI) techniques such as bioinspired algorithm, deep learning and machine learning were used to improve fingerprint classification accuracy. The proposed method aimed to assess fingerprint classification models based on ASI. The researchers employed PRISMA approach, which is based on systematic analysis and is used to select, evaluate and analyze journals. Although IEEEXplore and Web of Science were utilized to extract journal articles from 2019 to 2023. As a result, 1350 articles were found in both databases. Furthermore, a total of 35 publications were assessed to determine their eligibility and 19 articles were eliminated with reasons and 16 matched the requirements for a meta-analysis. Our findings demonstrate and highlight the need for developing a new approach to improve fingerprint classification accuracy.

Introduction

Fingerprint biometrics is a method for verifying and authenticating individuals identities [1]. For instance, biometric recognition technologies like fingerprints, palmprints, iris and face are used to identify and authenticate individuals [2]. Generally, fingerprint is the most used biometric identification method because of its permanence, singularity, ergonomics, throughput, affordability and lifetime usability. Genuinely, even identical twins have different fingerprints since each person has unique fingerprint characteristics that cannot be changed [3]. Fingerprints play a vital role among other biometric features or traits. Therefore, fingerprints have been used for recognizing individuals in several instances such as identity management, border access control and forensic investigation [4]. Fingerprint biometrics offers a greater authentication method than the traditional method of person recognition which is based on identification documents, pins and password [1]. Fingerprint biometric is an important system that detects a person based on a feature vector that is derived from a particular physiological or behavioral attribute that the individual possesses [5]. Collectively, fingerprint features are useful, when identifying fingerprint classes based on their global pattern of ridges and valleys which relies on fingerprint classification [6].

Fingerprint classification has evolved since the 1890s due to the uniqueness of fingerprint characteristics and the authentication of individual identities [7]. As a fingerprint classification method, Henry's classification approach is the most widely used in fingerprint categorization technique [8]. The Henry's classification system, then developed into eight classifications of prints particularly plain arch, right loop, tented arch, plain whorl, left loop, double loop whorl, central-pocket whorl and accidental whorl [8]. The classification of fingerprint images is shaped by it is pattern and fingerprint characterization [9]. Historically, fingerprints were similar to a picture which contains sufficient qualitative information but lacks any intrinsic traits that would allow it to be classified. Therefore, Bertillon found the solution by reducing the body to a set of numbers [7, 10].

This means that information about individuals can be retrieved from a fingerprint image. Besides, some studies did not propose that these ridges can be used for identification but the first attempt was made to categorize the pattern types, grouping them into nine categories. This today would correspond to the arch, tented arch, radial loop, ulnar loop, double loop, central loop and plain whorl such as circular and spiral and accidental [7, 11].

Additionally, the hybridization of fingerprint classification models has served as the foundation for all fingerprint classification methods that were used globally between 1890 and 1930 [7, 12]. The heuristic approach of fingerprint classification was proposed in 1900. One method for automated fingerprint classification is to codify the knowledge of human experts using a system of heuristic rules such as a combination of singularity and ridge features. Moreover, based on heuristics fingerprint classification has developed a six-class of fingerprint classification scheme. The major drawback of the system was its only reliance on singularity features for fingerprint classification which resulted in an inaccurate distinction of core and delta points [13]. Research has continued to explore the applicability and usability of neural networks in fingerprint classification [14]. The digitalization of fingerprint classification continues to add value to fingerprint classification development such as by using neural networks [14]. For instance, neural network approach was used in fingerprint classification and 100 fingerprints were classified which consisted of a total of 500 fingerprints. The findings indicated that for 500 unknown samples was an average of 86% classification rate for the first candidate and 99% classification rate for the second candidate [14].

Fingerprint classification continues to have a variety of approaches that are proposed either to improve performance or accuracy [15, 16]. In this regard, fingerprint classification based on learned features using genetic programming that learns to discover composite operators and features [17]. Moreover, Bayesian classifier was utilized to classify the fingerprints from NIST-4 dataset which has 4000 fingerprints. Therefore, fingerprint was classified into 4 and 5 classes and the experimental results indicated that the accuracy rate for the 4 and 5 class classifications were 93.3% and 91.6% respectively [17]. On the other hand, Poincare Index method is proposed for the classification of fingerprints, the results illustrated that the Poincare method is limited to only providing the type and position of minutiae. Therefore, the Adaboost learning algorithm was utilized for the classification of fingerprints and the results show that Adaboost methods can provide the type and positions of minutiae but also this approach can compute the directions and certainty of fingerprint minutiae [18]. The main drawback of the Adaboost was the misclassification which was caused by heavy noise in the poor quality of fingerprint and also when a pair of core and delta are too close to detect. Further, the experiment findings show that using NIST-4 fingerprint dataset, the Adaboost method can automatically select the discriminatory features for fingerprint classes [18].

Related Work

Artificial Super-Intelligence (ASI) Utilized in Fingerprint Classification. The term Artificial Super-Intelligence (ASI) is used to describe the categories of AI techniques such as bioinspired algorithm, deep learning, neural networks and machine learning approaches that are used to improve fingerprint classification accuracy (see Fig.1). The term artificial super-intelligence, first used in 1970 which has been used to describe computer skills that surpass or even beyond the capacities of the human intellect. The goal of artificial super-intelligence is to enhance machine cognition. Alternatively, the benefits of developing artificial super-intelligence include increased efficiency and automation, improved problem-solving and less chance of error. Artificial super-intelligence is also recognized as super AI. For instance, learning algorithms of bioinspired optimization, machine learning, deep learning and neural networks have become artificial super-intelligence in improving fingerprint classification accuracy. Artificial super-intelligence is meant to ensure that the AI is mature and to accelerate the development and advancement of fingerprint classification [19]. In that sense, Artificial super-intelligence revolutionizes development and seeks to establish an optimization function [20]. Overall, ASI would be powerful and effective at achieving outcomes, faster tasks, mimicking human intelligence, and also becoming fully self-aware [20, 21].

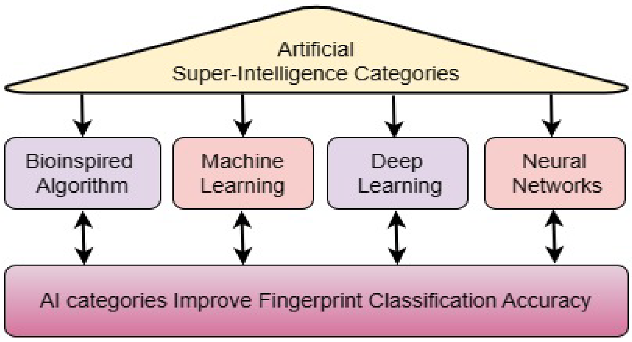

Fig. 1. Artificial super-intelligence approach used on improving fingerprint classification accuracy.

Fingerprint Classification Based on Artificial Super-Intelligence. Deep learning methods are deep neural networks that have been known as one of the most potent technologies during the past few decades. Deeper hidden layers started to outperform traditional approaches in a variety of applications including fingerprint classification. CNNs are among the most often used deep neural networks in fingerprint classification [22]. This accomplishment has inspired both researchers and developers to use larger models to tackle challenging problems that could not be solved with traditional Artificial Neural Networks (ANNs) [22]. Furthermore, ANN is similar to CNN because it's made up of layers and artificial neurons with weight and biases. ANN is limited in its ability to handle large datasets, in contrast to CNN which can process large image datasets and enable the collection of more complex and abstract features in images [23]. Another crucial component of CNN is getting abstract features when input propagates toward the deeper layers [22]. The main difference between ANN and CNN is that CNNs are tuned to work with images like 2D and 3D. CNNs are a subset of deep learning that are very adept at classifying images. A typical architecture of CNN consists of convolution layer, pooling layer and fully connected layer.

A lightweight CNN model was developed for fingerprint classification as a solution to reduce computational and network complexity while maintaining impressive accuracy. Lightweight CNN models with fewer parameters can therefore train more quickly and at a lower cost, allowing them to be used in infrastructure with insufficient computer resources [24]. Similarly, the experiment results showed that the lightweight CNN model structure had better accuracy and outperformed the non-neural network classifiers like the random forest, K-Nearest-Neighbor (KNN) and linear SVM [24]. In addition, the truncation of the model is to reduce the complexity and quantity of parameters used in fingerprint image training without impacting the image performance [25]. The high processing complexity of fingerprint classification systems is one of their main drawbacks due to limitations. Deep learning algorithm is effective and reliable for the classification of fingerprints. For instance, Fukunaga-Koontz Transform was introduced for automatically determining the architecture of the CNN model which was adaptive to fingerprint classification. The DeepFKTNet model was hyperparameter tuned using the Optuna optimization algorithm which has been tested on the optimizers like learning rate, patch size and activation function. Therefore, since CNN models contain a large number of parameters, the FKT approach was built as a low-cost and high-speed CNN model for the classification of fingerprints [26].

The CNN architectures particularly AlexNet, GoogLeNet and ResNet have been used in fingerprint image classification. These models compare favorably in terms of training performance for fingerprint image classification and have a faster rate of convergence. From a computational standpoint, AlexNet needs the least amount of training time compared to GoogLeNet and ResNet. In utilizing two different databases PolyU and NIST, the three used CNNs performed well with average precision values higher than 98% on the PolyU database. Moreover, the disadvantage of GoogLeNet and ResNet is that data processing takes longer and some of their layers were frozen to improve the processing speed and performance [27]. In GoogLeNet and ResNet if the training setting is adjusted with a few parameters it can train faster with less computational cost [27]. Although the weight-sharing feature of CNNs is the primary factor to take into account because it lowers the number of trainable network parameters which in turn aids the network in enhancing generalization and preventing overfitting [28]. Nevertheless, AlexNet's architecture is more straightforward which reduces the training time and it does not limit the output image data [27]. AlexNet was coined by Alex Krizhevsky and also AlexNet presents a deeper neural structure, composed of a higher number of pooling and convolutional layers [27, 29].

The application of a hybrid approach using swarm intelligence algorithm in fingerprint classification has been explored. There are a few studies that have implemented bioinspired algorithm or metaheuristic approaches in fingerprint classification [30]. For instance, hybrid approach based on a combination of Particle Swarm Optimization (PSO) and Support Vector Machine (SVM) was implemented to improve fingerprint classification accuracy [31]. The proposed methodology is divided into three stages: preprocessing, feature extraction and classification using PSO-SVM model. In the preprocessing stage, fingerprint images were converted into binary images which is called binarization to improve the intensity of the fingerprint images for the preparation of edge detection and feature extraction phase [31]. The PSO-SVM fingerprint classification model is tested in the experiments using the CASIA V5 fingerprint dataset for the assessment of the fingerprint classification model. The experimental findings demonstrated that the PSO-SVM classification model outperforms the traditional SVM method in terms of accuracy, sensitivity and precision [31].

Mishra (2019) introduced fingerprint classification using three different hybrid techniques consisting of Biogeography Based Optimizer (BBO), PSO and Genetic Algorithm (GA) combined with a Functional Link Artificial Neural Network (FLANN). The classification approach involves adaptation and tuning of classifier parameters for better classification accuracy [32]. The dataset utilized is a sample of 50 fingerprint images of 10 students from the Silicon Institute of Technology. The extracted fingerprint image features of 50 students were set in Excel sheet and used for training and testing of the network [32]. The BBO, PSO, GA are optimizers to update the weight parameters of FLANN classifier for testing classification accuracy. Furthermore, the tuning of FLANN with hybrid techniques is done randomly and manually by hit and trial to improve fingerprint classification accuracy. The implementation and experimentation of PSO-FLANN, GA-FLANN and BBO-FLANN are designed and tested for fingerprint classification accuracy. In comparison to all, the findings showed that the PSO-FLANN technique exhibits superior performance with a high rate of accuracy. The main drawback of PSO-FLANN is the execution time was considered high [32].

Methodology

In this section, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) have been utilized to provide evidence on fingerprint classification models based on ASI approaches. PRISMA includes the use of meta-analysis which integrate study findings from several PRISMA checklists and aggregate the outcomes of multiple research publications through a systematic review procedure. The PRISMA checklist is a crucial resource for reporting the results of a systematic review and meta-analysis for providing a comprehensive report on the literature review and the progress made in fingerprint classification research and development. In this regard, using the IEEE and Web of Science databases which include scholarly literature from many domains, a thorough analysis and methodical literature search were carried out. Similarly, the screening procedure is graphically summarized in the PRISMA flow diagram as shown in Fig. 2. Moreover, PRISMA approach was used for the study selection and the keywords are (Fingerprint Classification AND Deep Learning AND Machine Learning AND Neural Network AND Bioinspired OR Metaheuristic Algorithm). The search for the articles was acquired between the years 2019 and 2023. This led to the publication of research that solely used fingerprint classification based on ASI approaches for analysis. Although in terms of quality standards to assess the reliability of the selected journal articles. As a result, the articles that were taken from the databases are relevant to this study and sufficient. Initially, 1350 research papers were found from both IEEE-Xplore and Web of Science databases, then screened accordingly. Moreover, 1187 articles were excluded, and 16 research articles were eligible to be included in the meta-analysis with the following attributes: article title, publication year, author name, classifier, dataset and overall accuracy as described in Table 1.

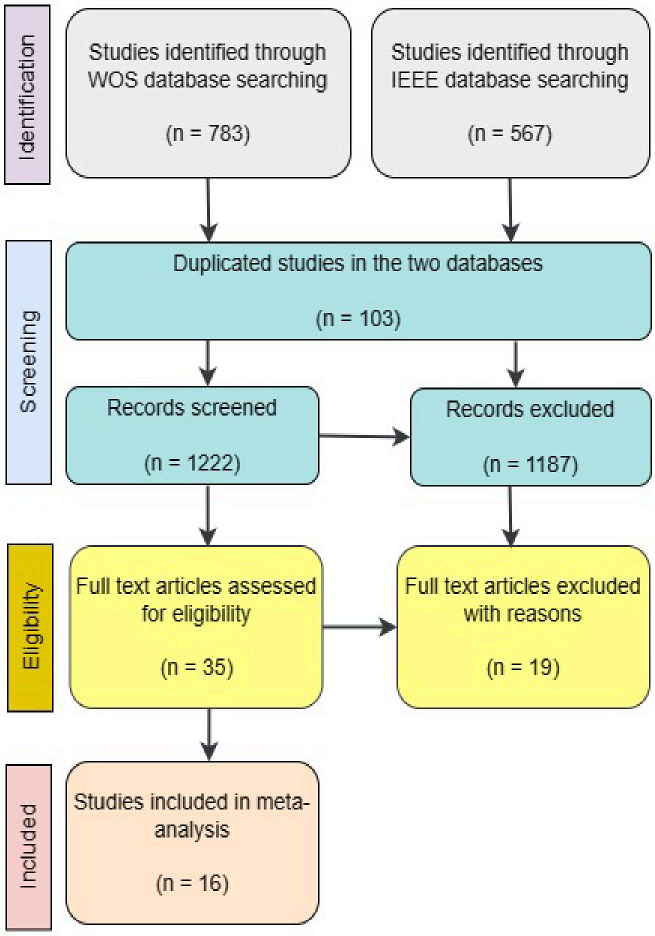

Fig. 2. PRISMA flowchart elucidating the selection of studies.

Results and Discussion

This section presents the results of assessing fingerprint classification based on artificial super-intelligence techniques, which aim to improve fingerprint classification accuracy. In this regard, a total of 16 articles and conference papers were identified for the study context as elucidated in section 3 and Fig. 2. Notably, journal articles that were published in scientific journals served as the main information sources as indicated in Table 1. PRISMA approach was carried out to analyze the checklist indicated in Table 1 such as authors, year of publications, classifier, dataset, sample and accuracy. Additionally, it has been shown that deep learning models perform astonishingly well in tasks involving fingerprint categorization. For instance, the classifier column elucidates deep learning techniques such as AlexNet, RestNet50, GoogLeNet, DenseNet121, LeNet and CaffeNet. Although machine learning techniques are included such as random forest, few-shot, SVM and Naïve Bayes. KNN is a non-parametric learning classifier that has been utilized in fingerprint classification as well. The dataset, sample and accuracy columns show how well fingerprint classification performs when the classifier is used to find the most optimum solution. Basically, the fingerprint dataset consists of digital images that were captured for evaluation, comparison and usefulness in the fingerprint classification process using an algorithm to show improved accuracy and performance. The distinct dataset comprises unique fingerprint features that are filtered and then stored as a mathematical representation and encrypted as biometric information. As shown in Table 1, the fingerprint image, dataset and fingerprint sample are all binary codes that are utilized for verification and authentication of fingerprint. The accuracy column shows the percentage yield during the fingerprint classification process for each research paper that were selected for meta-analysis. Although some authors used both datasets and samples. Moreover, each author has unique results that have been obtained for improving fingerprint classification accuracy. In this regard, we've used the most important PRISMA checklists that are related to the research paper context as indicated in Table 1.

Table 1. Describe the classification technique & accuracy.

Authors	Year	Classifier	Dataset	Sample	Accuracy
[33]	2023	AlexNet CNN	N/A	500	96,7%
[34]	2023	Random Forest	FVC2002	N/A	96,88%
[25]	2023	ResNet50 CNN	NIST SD4	800	93,3%
[35]	2022	CNN	SOCOfing	6000	99.98%
[36]	2021	Few-shot	NIST-4	600	92.34%
[37]	2021	Naïve Bayes-SVM AlexNet-Multiclass SVM AlexNet-Multiclass NB	PolyU 3D	N/A	98.6% 97.5% 90.2%
[36]	2021	AlexNet CNN and Calibration algorithm	HQNoPert Default VQAndPert NIST F NIST S	4000	98,4% 98,35 96,75 88,48 84,85
[38]	2021	Decision trees, Linear Discriminant Analysis Naive Bayes SVM k-NN Ensemble classifiers	1. DB1-2000 2. DB2-2000 3. DB3-2000 4. DB4-2000	960	1/ (76.3%/ 90%/ 90%/ 93.8%/ 93.8%/ 95%). 2/ (72.5%/ 95%/ 82.5%/ 92.5%/ 90 %/ 96.3%). 3/ (63.7%/ 95%/ 92.5%/ 96.3%/ 92.5%/ 98.8%). 4/ (76.3%/ 92.5%/ 85%/ 93.8%/ 82.5%/ 96.3%).
[27]	2021	AlexNet CNN GoogLeNet CNN ResNet CNN	NIST & PolyU (Eight-class)	7800	93.75/ 92.07/ 92.71 & 99.51 / 99.58/ 99.31
[39]	2020	One-Versus-All Twin-SVM / Binary Tree Quantum PSO / Twin-SVM Binary Tree SVM	NIST-4	2000	87.13%/ 93.83%/ 90.35%
[40]	2020	Extreme Learning Machine based on CaffeNet CNN	HQNoPert/ Default/ VQAndPert	30000	99%/ 98%/ 96%
[41]	2020	DenseNet 121 CNN	NIST-4	4000	97.7%
[24]	2020	CNN	NIST SD4	20000	93%
[42]	2020	Alexnet CNN LeNet CNN CaffeNet CNN	NIST: Six-class	100000	57.84%/ 17.03%/ 91.63%
[43]	2019	GoogLeNet CNN	NIST-4: five-class and four-class	4000	94.7% and 96.2%
[44]	2019	Random Forest & SVM	NIST-DB4	4000	96.75% & 95.5%

Fig. 3 indicates the total number of journal articles that were found in the databases. There are nine journal articles from IEEE and six from Web of Science. These journal articles pertain to the study of fingerprint classification based on an artificial super-intelligence approach.

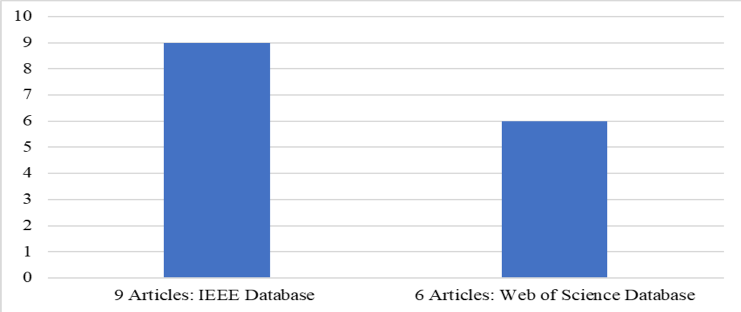

Fig. 3. The graph represents journal articles found in databases.

Fig. 4 displays the total number of selected published journal articles per year. Furthermore, there were 2 journal articles published in 2019, and 5 articles were published for each year in 2020 and 2021. Similarly, in 2022, one journal paper was published and three publications were published in 2023.

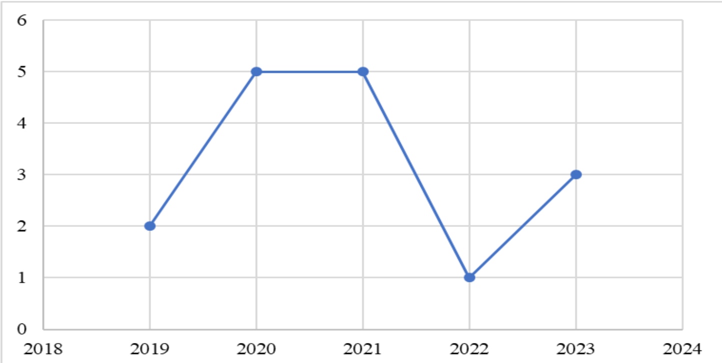

Fig. 4. Total number of articles published between 2019 and 2023.

The percentage of published articles by country and the total number of articles are displayed in Fig 5 and 6.

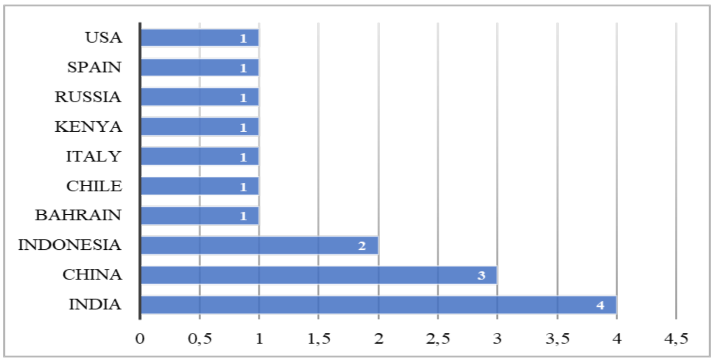

Fig. 5. Total number of published articles per country.

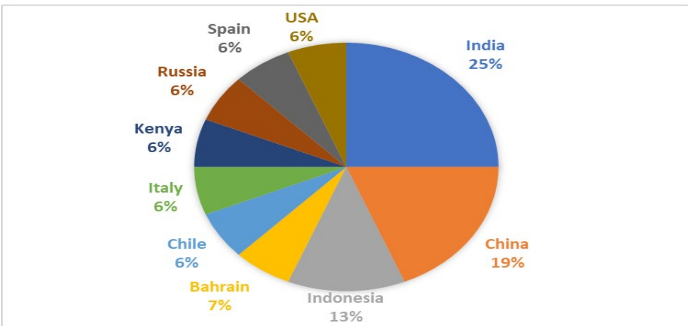

Fig. 6. Percentage of published articles per country.

Fig. 7 shows the number of published articles for each country. For instance, 4 describes the number of articles that is published, and yellow represents the country which is India and so forth for others.

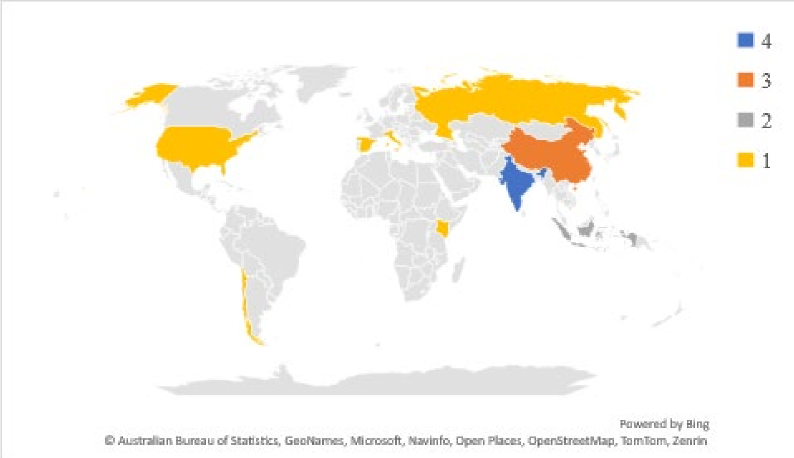

Fig. 7. The number of publications for each country.

Figs. 8 and 9 indicates the overall number of AI approaches undertaken in each study and the percentage of each used approach.

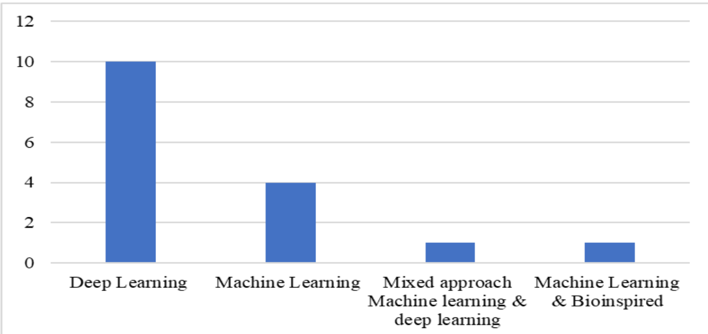

Fig. 8. Total number of approaches used in various studies.

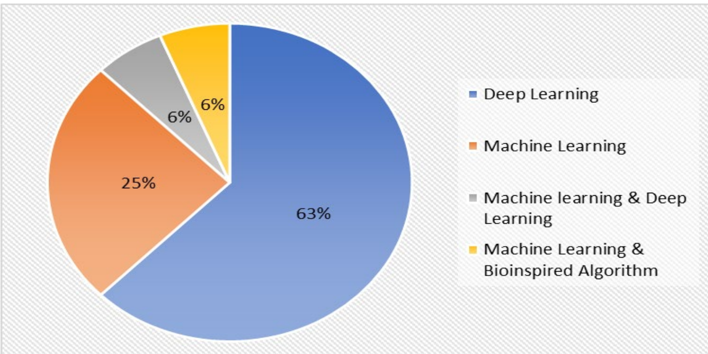

Fig. 9. Percentage of each approach utilized.

In summary, a comprehensive analysis of 16 published articles were carried out on fingerprint classification based on machine learning and deep learning for improving fingerprint classification accuracy. In general, the studies shown various classifiers were utilized as mentioned in Table 1. Although in Fig 5 and 6 indicated that India is the most country that has published journal articles in fingerprint classification and followed by China and Indonesia. These significant differences in national research focus could be attributed, in part to India having the largest national biometric identification system in the world [45]. India uses biometrics to identify and verify individuals because of its large population of 1.2 billion citizens. Therefore, Indian institutions are working to enhance their national biometric identification system through research and the application of bioinspired algorithm [45]. Nevertheless, in 2023, we conducted a systematic review on bioinspired algorithm based on fingerprint classification models. Furthermore, we found that hybrid methods that combined bioinspired optimization and deep learning are not utilized to improve fingerprint classification accuracy [30]. Lastly, there are a few studies on fingerprint classification combined with a bioinspired algorithm and classical model and the results indicated that the combined model outperforms the standard classical technique [31].

Conclusion

In this research paper, we presented state-of-the-art PRISMA analysis for assessing fingerprint classification models based on artificial super intelligence approaches. The findings shows that combined approaches like deep learning and bioinspired optimization haven't been used for improving fingerprint classification accuracy. The hybrid approach of artificial super intelligence to fingerprint classification promises to be the future endeavor. For this reason, future research will therefore focus on developing a fingerprint classification model based on the hyper-parameterization of a traditional method using a metaheuristic algorithm.

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