Artificial Neural Networks for Classification Tasks: A Systematic Literature Review

Eduardo Molina Menéndez[1], and Jorge Parraga-Alava[2]

***Abstract* — Artificial neural networks (ANNs) have become indispensable tools for solving classification tasks across various domains. This systematic literature review explores the landscape of ANN utilization in classification, addressing three key research questions: the types of architectures employed, their accuracy, and the data utilized. The review encompasses 30 studies published between 2019 and 2024, revealing Convolutional Neural Networks (CNNs) as the predominant architecture in image-related tasks, followed by Multilayer Perceptron (MLP) architectures for general classification tasks. Feed Forward Neural Networks (FFNN) exhibited the highest average accuracy with a 97.12%, with specific studies achieving exceptional results across diverse classification tasks. Moreover, the review identifies digitized images as a commonly utilized data source, reflecting the broad applicability of ANNs in tasks such as medical diagnosis and remote sensing. The findings underscore the importance of machine learning approaches, highlight the robustness of ANNs in achieving high accuracy, and suggest avenues for future research to enhance interpretability, efficiency, and generalization capabilities, as well as address challenges related to data quality.**

***Keyword:* artificial neural networks; classification; machine learning, neural networks architecture, data mining.**

***Resumen* — Las redes neuronales artificiales (ANNs) se han convertido en herramientas indispensables para resolver tareas de clasificación en diversos dominios. Esta revisión sistemática de la literatura explora el panorama de la utilización de ANN en la clasificación, abordando tres preguntas clave de investigación: los tipos de arquitecturas empleadas, su precisión y los datos utilizados. La revisión abarca 30 estudios publicados entre 2019 y 2024, revelando las Redes Neuronales Convolucionales (CNNs) como la arquitectura predominante en tareas relacionadas con imágenes, seguidas por las arquitecturas de Perceptrón Multicapa (MLP) para tareas de clasificación en general. Las Redes Neuronales de Propagación Hacia Adelante (FFNN) exhibieron la mayor precisión promedio con un 97.12 %, con estudios específicos logrando resultados excepcionales en diversas tareas de clasificación. Además, la revisión identifica las imágenes digitalizadas como una fuente de datos comúnmente utilizada, reflejando la amplia aplicabilidad de las ANN en tareas como el diagnóstico médico y la teledetección. Los hallazgos subrayan la importancia de los enfoques de aprendizaje automático, destacan la robustez de las ANN en lograr una alta precisión y sugieren caminos para investigaciones futuras para mejorar la interpretabilidad, eficiencia y capacidades de generalización, así como abordar desafíos relacionados con la calidad de los datos.**

***Palabras Clave:* redes neuronales artificiales, clasificación, aprendizaje automático, arquitectura redes neuronales, minería de datos.**

I. INTRODUCTION

THE fourth industrial revolution has reestablished every aspect of daily life across the globe, through the integration of new digital technologies such as Artificial Intelligence(AI) and Internet of Things (IoT) [1].

The emerge of this technologies have facilitated the generation of vast volumes of data known as Big Data, which presents challenges in extracting knowledge from it, needing to be processed and classified [2].

Classification is a technique for determining the class of a new observation using training data with a known class label [3], it is a common technique used in data mining to identify patterns and relationships in data [4]. It serves diverse purposes, from diagnosing diseases to predicting future events and identifying data patterns [5]. This technique encompasses two primary types: binary and multiclass classification. In binary classification, the task is to predict one of two possible outcomes, whereas multiclass classification involves predicting from several possible outcomes [6]. There are several alternatives to solve classification tasks.

Some of the commonly used methods are Machine Learning based models including Decision Trees, Random Forest, Support Vector Machines and like Artificial Neural Networks [7].

Machine learning (ML) is a field of artificial intelligence that focuses on the development of computer programs that can change when exposed to new data. It uses computer models and information obtained from past and previous data to aid classification, prediction, and detection processes [8]. Within ML Artificial Neural networks (ANN) are computational models that mimic the human brain and its information processing capabilities. They are composed of highly interconnected processing elements called neurons, which are capable of self-organization and acquisition of information [9].There are various types of ANNs, including feed-forward-based architectures such as Convolutional Neural Networks (CNN), Autoencoder and Recurrent Neural Networks (RNN) [10]. These networks are used for various applications such as pattern recognition, data mining, bioinformatics data classification, and medical diagnosis [11].

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The choice of which ANN architecture to use for a specific classification task will depend on the characteristics of the data being classified, such as the number of features, the complexity of the relationships between the features and the target variable, and the amount of available training data [12]. It is important to note that the effectiveness of an ANN also depends on the training, validation, and generalization process, as well as the choice of hyperparameters such as the number of nodes in the hidden layer and the learning rate [13].

Some literature reviews have examined the utilization of ANNs in classification tasks. The study in [14] conducted a review specifically focused on classification techniques in Breast Cancer diagnosis, including SVM, Decision Trees, and of course ANN. Another review study in Breast Cancer diagnosis compares the use of different ANN architectures like CNN,SNN, DBN [15]. The work in [16] highlights Machine Learning supervised algorithms to Gene classification tasks. Another review focused on Machine learning and Deep Learning methods for skin lesion classification [17]. A review discussed the opportunities and challenges of AI and ML addressing different problems, classification included [18].

While literature reviews on ML methods in classification tasks do exist, they often lack comprehensive comparisons of different ANN architectures. This omission restricts understanding and decision-making processes when selecting a specific neural network model. Absolutely, conducting a literature review is crucial to supplement the actual science knowledge in this topic.

This paper follows the subsequent structure: Section Introduction furnishes a review of the theoretical foundations and pertinent literature. Section Materials and Methods delineates the methodology utilized in this study. The findings are presented in Section Results, where the outcomes of the review process, inclusive of the analysis of the ANN architectures, their accuracies, and the dataset, are scrutinized and deliberated upon. Section Discussion provides an exhaustive discussion of the results, contextualizing the findings and drawing comparisons with existing research. Finally, Section Conclusions summarizes the main findings and their implications, while offering recommendations for future research aimed at further exploring the applications of ANN for resolving classification tasks.

II. MATERIALS AND METHODS

This study employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology to conduct a systematic literature review, ensuring a structured and transparent approach to minimize bias and enhance the reproducibility of results [19].

The choice of a systematic literature review as the study design was motivated by its rigorous and objective methodology, allowing for the comprehensive synthesis of all pertinent evidence regarding a particular topic. Specifically, this approach is well-suited for discerning and analyzing trends in the applications of artificial neural networks (ANNs) in classification problems. By adopting this methodology, the study aims to uncover current trends in ANNs, offering insights into the solutions applied to these problems. Moreover, it anticipates identifying potential gaps in existing knowledge and areas warranting further research within this domain.

The PRISMA process was conducted in three phases:
1. Identification: Initial search in databases and other sources.
2. Screening: Review of titles and abstracts for initial eligibility assessment which implies full-text evaluation of selected articles.
3. Inclusion: Final selection of studies to be included in the review.

Fig.1 diagram illustrates the process of the systematic literature review conducted in this research:

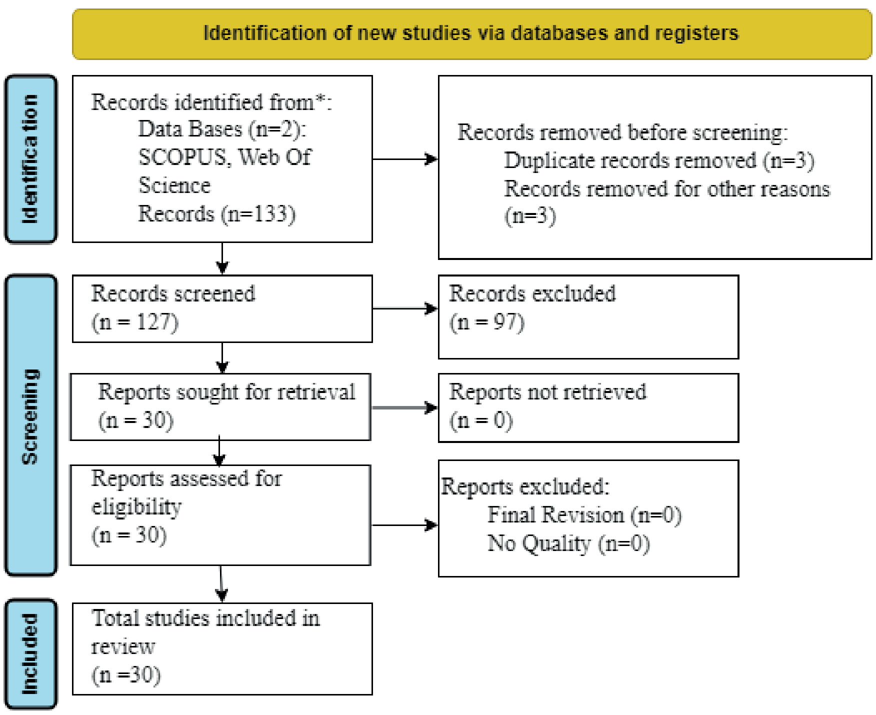

Fig. 1. Study Flow Chart.

The PARSIFAL tool was utilized to aid in organizing and selecting pertinent studies [20] and Zotero for bibliographic management [21].

The purpose of this study is to conduct a thorough and organized examination of artificial neural networks used to classify data. Moreover, the study proposes the following three research questions:

RQ1: What are the most commonly artificial neural networks employed in classification tasks?

RQ2: What is the accuracy of the architectures utilized in the conducted studies?

RQ3: What are the most frequently used data in classification tasks?

A. Identification

For the information search, keywords related to the research topic were used. These keywords were selected based on the importance of the respective study topic, according to a preliminary review of the literature and were refined as the search progressed.

Keywords related to the research topic were carefully selected based on a preliminary literature review and refined as the search progressed. The primary keywords used were:

- "Classification"
- "Machine Learning"
- "Artificial Neural Network"
- "Neural Network"
- "Prediction"

These keywords were combined using Boolean operators (AND, OR) and truncation (*) to expand or restrict the search according to the inclusion and exclusion criteria. The search strings were tailored for each database to ensure optimal results.

To conduct the literature search, two databases deemed pertinent to the study's subject matter were chosen: Scopus and Web of Science. These databases were selected due to their extensive coverage of computer science and emerging technologies literature, robust search functionalities, and capacity to identify influential publications. The use of multiple databases ensured a comprehensive search and minimized the risk of missing relevant studies.

To establish the search criteria, limitations were set on publication dates and languages. Specifically, articles published between January 2019 and February 2024 in English were included, by this means concentrating the review on the latest and most pertinent literature pertaining to the topic. Furthermore, only articles obtained from the chosen databases were taken into account. It's important to highlight that numerous preliminary search iterations were performed to precisely define the criteria and guarantee a comprehensive and precise search. The search criteria and keywords were customized for each database, and the outcomes were meticulously assessed for relevance and consistency.

Table 1 provides a detailed breakdown of the search strings utilized during the search process

TABLE I
SEARCH STRATEGY AND INFORMATION SOURCE

Database	Search String
Scopus	("Artificial Neural Networks" OR "Neural Networks" OR "Machine Learning") AND ("Classification ")
Web of Science	("Artificial Neural Networks" OR "Neural Networks" OR "Machine Learning") AND ("Classification " OR "prediction")

B. Screening

To obtain screened records in this phase, both inclusion and exclusion criteria were established to ensure the systematic review's relevance and quality. Inclusion criteria focus on machine learning for classification, particularly ANNs, published in peer-reviewed sources from January 2019 to February 2024, ensuring the review covers current, credible, and detailed studies. Exclusion criteria remove studies without detailed methods/results, non-English publications, pre-2019 studies, review articles, theoretical papers, non-classification ANN tasks, and non-peer-reviewed works, to maintain quality, avoid language bias, focus on recent advancements, and concentrate on empirical applications. These criteria ensure that included studies directly address the research questions on ANN accuracy and applications in classification tasks. Table 2 outlines some of the relevant selection criteria that were included in the review, which led to the exclusion of certain records.

TABLE II
SELECTION CRITERIA

Inclusion Criteria	Exclusion Criteria
• Documents where classification tasks use machine learning techniques. • Documents related to Artificial Neural Networks (ANN) • Document related to Classification Tasks	• Articles that do not include the methods used or detailed results. • Articles in a different language than English. • Research below 2019.

The full text of the articles that passed the filter of the selection criteria was assessed by two independent reviewers using a standardized. The checklist included items such as:

- Relevance to the research questions
- Clarity of methodology
- Quality of data analysis
- Significance of findings

C. Included

Articles that met all eligibility criteria were included in the final review. Relevant information was extracted from these articles using a standardized data extraction form, which included fields such as:

- Type of artificial neural network used
- Specific classification task
- Dataset used
- Performance metrics
- Experimental setup and parameters
- Key findings and conclusions

III. RESULTS

A. Identification

During this phase, a total of 133 articles were obtained from the databases searched. Afterward, duplicate entries were eliminated, leading to the removal of 3 records. Additionally, 3 records were excluded as they had been withdrawn from their respective journals.

B. Screening

Following the previous phase, a total of 127 records underwent screening, leading to the exclusion of 97 records. Consequently, 30 articles were deemed eligible for retrieval and further assessment. A graphical representation of this process is illustrated in Fig. 2.

C. Included

In the final phase, 30 new studies were included in the review. Fig. 2 provides a graphical representation of the article selection process.

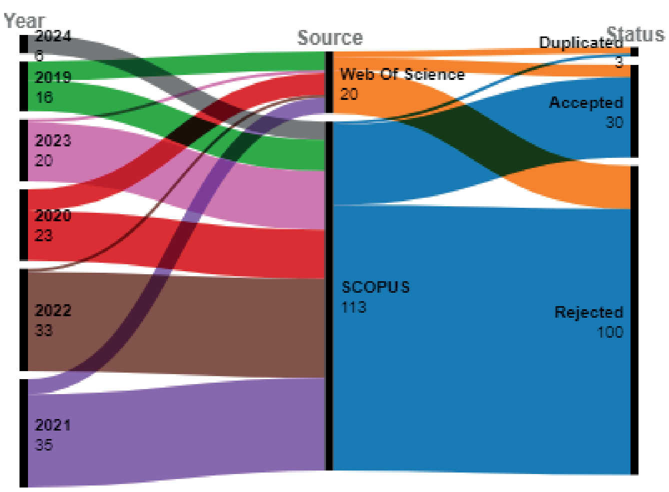

Fig. 2. Results of Article Analysis.

Fig. 2 illustrates the publication year of the studies on the left side, while the middle section displays the source repository of the articles. The number of selected articles is depicted on the right side of the diagram.

Fig. 3 emphasizes the most common words found in the selected studies, notably featuring terms like neural network, model, data, train, accuracy and machine learning. On the other hand, less prevalent terms include predict, analysis and processing.

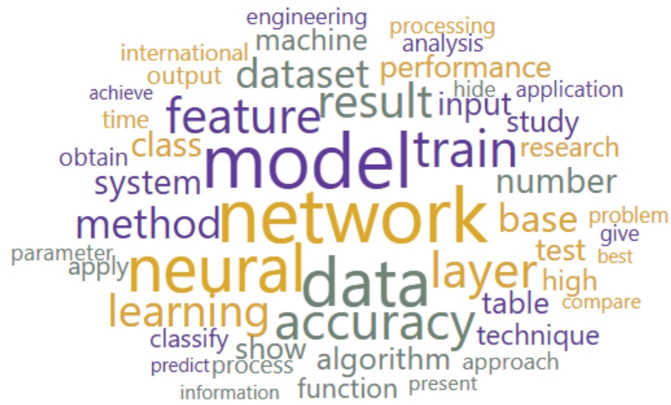

Fig. 3. Word count of the 30 selected studies

Table 3 displays the eligible records, providing details such as the year of publication, authors, study title and responses to RQ1(ANN Architecture), RQ2(ANN Accuracy) and RQ3(Data).

After ensuring that each selected study pertained to the proposed topic and addressed the research questions, the eligible documents underwent meticulous review. The information extracted from these documents was systematically organized and categorized to address the research questions, as outlined below:

> RQ1: What are the most commonly artificial neural networks employed in classification tasks?

In examining the literature, it becomes evident that various types of ANNs are favored for classification tasks. We observed a prevalent use of Convolutional Neural Networks (CNNs) across various classification tasks. CNNs are particularly popular in tasks involving image data due to their ability to effectively capture spatial dependencies. Among the reviewed studies, CNNs were utilized in 14 out of 30 cases (46.66%), indicating their dominance in the field of image classification and analysis. Multilayer Perceptron (MLP) architectures were also frequently employed, appearing in 5 out of 30 studies. MLPs are versatile and well-suited for general classification tasks. Their widespread usage suggests their effectiveness in a broad range of classification scenarios. Backpropagation Neural Networks (BPNN) and their variations, such as Bayesian regularized artificial neural networks (BRANN) and Backpropagation Neural Networks (BPNN), were employed in fewer studies compared to CNNs and MLPs. However, they still played a significant role in specific tasks, such as EEG signal analysis and wood classification.

TABLE III
RESULTS OF RESEARCH

Year	Authors	Study	ANN Architecture (RQ1)	Model Accuracy (RQ2)	Data used (RQ3)
2019	Omondiagbe, David A. and Veeramani, Shanmugam and Sidhu, Amandeep S.	Machine Learning Classification Techniques for Breast Cancer Diagnosis [22]	Multilayer Feed Forward Neural Network (MFFNN)	97.06 %	Digitized images of fine needle aspirates (FNA)
	Rivera Sánchez, F A and González Cervera, J A	ECG Classification Using Artificial Neural Networks [23]	Convolutional Neural Network (CNN)	97.6 %	ECG signals
	Haider Bin Abu Yazid, Mohamad and Shukor Talib, Mohamad and Haikal Satria, Muhammad	Flower Pollination Neural Network For Heart Disease Classification [24]	Flower Pollination Neural Network	91.42 %	Patient Records
	E. Rehn, A. Rehnc, A.Possemiers	Fossil charcoal particle identification and classification by two convolutional neural networks [25]	Convolutional neural network (CNN)	85.6 %	Sediment Samples Images
2020	Iqbal, Mudasser and Ali, Syed and Abid, Muhammad and Majeed, Furqan and Ali, Ans	Artificial Neural Network based Emotion Classification and Recognition from Speech [26]	Bayesian Regularized Artificial Neural Network (BRANN)	95 %	Speech Samples
	Li, Ying and Di, Jianglei and Wang, Kaiqiang and Wang, Sufang and Zhao, Jianlin	Classification of cell morphology with quantitative phase microscopy and machine learning [27]	Convolutional Neural Network (CNN)	93.5 %	Cell morphology
	Mohammad Vahedi Torshizi, Ali Asghari, Farhad Tabarsa, Payam Danesh, Ali Akbarzadeh	Classification by artificial neural network for mushroom color changing under effect uv-a irradiation [28]	Multilayer Perceptron (MLP)	100%	Mushroom Color
	Zaloga, Alexander N. and Stanovov, Vladimir V. and Bezrukova, Oksana E. and Dubinin, Petr S. and Yakimov, Igor S.	Crystal symmetry classification from powder X-ray diffraction patterns using a convolutional neural network [29]	Convolutional Neural Network (CNN)	90.02 %	Crystal structures
	Berto, Tamires Messias and Santos, Mônica Cardoso and Pereira, Fabíola Manhas Verbi and Filletti, Érica Regina	Artificial neural networks applied to the classification of hair samples according to pigment and sex using non-invasive analytical techniques [13]	Multilayer Perceptron (MLP)	92.1 %	wavelength dispersive X-ray fluorescence (WDXRF) aser-induced breakdown spectroscopy (LIBS)
2021	Hu, Xudong and Zhang, Penglin and Zhang, Qi and Wang, Junqiang	Improving wetland cover classification using artificial neural networks with ensemble techniques [30]	Rotation Artificial Neural Network (RANN)	96.1 %	Landsat 8 OLI images.
	Koklu, Murat and Cinar, Ilkay and Taspinar, Yavuz Selim	Classification of rice varieties with deep learning methods [31]	Convolutional Neural Network (CNN)	100 %	Rice Images
	Hartpence, Bruce and Kwasinski, Andres	CNN and MLP neural network ensembles for packet classification and adversary defense [32]	Multilayer Perceptron (MLP) and Convolutional neural network (CNN)	99 %	Network Packet
	Vives-Boix, Víctor and Ruiz-Fernández, Daniel	Fundamentals of artificial metaplasticity in radial basis function networks for breast cancer classification [33]	Artificial Metaplasticity Radial Basis Function Network (AMRBFN)	98.82 %	Digitized images of fine needle aspirates (FNA)
	Majidzadeh Gorjani, Ojan and Byrtus, Radek and Dohnal, Jakub and Bilik, Petr and Koziorek, Jiri and Martinek, Radek	Human Activity Classification Using Multilayer Perceptron [34]	Multilayer Perceptron (MLP)	98 %	Environmental parameters and Mechanical quantities
	Rwigema, James and Mfitumukiza, Joseph and Tae-Yong, Kim	A hybrid approach of neural networks for age and gender classification through decision fusion [35]	Convolutional Neural Network (CNN)	80.5 %	Facial Images Samples
	Totakura, Varun and Madhusudhana Reddy, E. and Vuribindi, Bhargava Reddy	Symptomatically Brain Tumor Detection Using Convolutional Neural Networks [36]	Convolutional Neural Network (CNN)	99.89 %	Magnetic Resonance Images (MRI)
	Maria Camila Guerrero, Juan Sebastián Parada, Helbert Eduardo Espitia	EEG signal analysis using classification techniques: Logistic regression, artificial neural networks, support vector machines, and convolutional neural networks [37]	Convolutional neural network (CNN)	59,90 %	Electroencephalogram (EEG) signals
2022	Anupama, Bollampally and Narayana, Somayajulu Laxmi and Rao, K S	Artificial neural network model for detection and classification of alcoholic patterns in EEG [38]	Back propagation neural network (BPNN)	92 %	Electroencephalogram (EEG) signals
	Das, Subrata and Wahi, Amitabh and Kumar, S. Madhan and Mishra, Ravi Shankar and Sundaramurthy, S.	Moment-Based Features of Knitted Cotton Fabric Defect Classification by Artificial Neural Networks [39]	Back propagation neural network (BPNN)	77.78 %	Cotton Fabric Images
	Kostrzewa, Łukasz and Nowak, Robert	Polish Court Ruling Classification Using Deep Neural Networks [40]	Convolutional Neural Networks (CNNs)	98.8 %	Court Ruling

Year	Authors	Study	ANN Architecture (RQ1)	Model Accuraccy (RQ2)	Data used (RQ3)
	Nasien, Dewi and Enjeslina, Veren and Hasmil Adiya, M. and Baharum, Zirawani	Breast Cancer Prediction Using Artificial Neural Networks Back Propagation Method [41]	Back propagation neural network (BPNN)	96.929 %	Digitized images of fine needle aspirates (FNA)
	Alkhamees, Bader Fahad	An Optimized Single Layer Perceptron-based Approach for Cardiotocography Data Classification [42]	Single Layer Perceptron (SLP)	99.20 %	Cardiotocography (CTG) patterns
	Cao, Shubo and Zhou, Shiyu and Liu, Jiying and Liu, Xiaoping and Zhou, Yucheng	Wood Classification Study based on Thermal Physical Parameters with Intelligent Method of Artificial Neural Networks [43]	Back Propagation Neural Network (BPNN)	98.95 %	Wood samples
2023	Leško, Jakub and Andoga, Rudolf and Bréda, Róbert and Hlinková, Miriam and Főző, Ladislav	Flight Phase Classification For Small Unmanned Aerial Vehicles [44]	Feedforward Neural Network (FFNN)	97.18 %	Fuzzy inference
	Ahmed, Mumtaz and Afreen, Neda and Ahmed, Muneeb and Sameer, Mustafa and Ahamed, Jameel	An inception V3 approach for malware classification using machine learning and transfer learning [45]	Convolutional Neural Network (CNN)	98.76 %	Malware Samples
	Nurulain Nusrah Mohd Azam, Mohd Arfian Ismail, Mohd Saberi Mohamad, Ashraf Osman Ibrahim, Shermina Jeba	Classification of COVID-19 Symptoms Using Multilayer Perceptron [46]	Multilayer Perceptron (MLP)	77.10 %	Patient symptom
	Tran-Thi-Kim,Tuan Pham-Viet,Insoo Koo,Vladimir Mariano,Tuan Do-Hong	Enhancing the Classification Accuracy of Rice Varieties by Using Convolutional Neural Networks [47]	Convolutional neural network (CNN)	97.88 %	Rice Images and Features
	Muhammad Hasanat, Waleed Khan, Nasru Minallah, Najam Aziz, Awab-Ur-Rashid Durrani	Performance evaluation of transfer learning based deep convolutional neural network with limited fused spectrotemporal data for land cover classification [48]	Deep Convolutional Neural Network (DCNN)	93 %	Land Cover Images
2024	Chavan, Rupali and Pete, Dnyandeo	Automatic multi-disease classification on retinal images using multilevel glowworm swarm convolutional neural network [49]	Multilevel Glowworm Swarm Optimization Convolutional Neural network (MGSCNN)	95.09 %	Retinal Images
	Susanto, Susanto and Nanda, Deri Sis	Predicting the classification of high vowel sound by using artificial neural network: a study in forensic linguistics [50]	Backpropagation Artificial Neural Network (BPNN)	92.26 %	Vowel Sounds

Table 4 provides an overview of the prevalence of different artificial neural network (ANN) architectures used in the studies reviewed, first column lists the types of ANN architectures used in the reviewed studies, next column indicates the number of studies that utilized each type of ANN, last column shows the percentage of the total 30 studies that employed each ANN architecture

TABLE IV
ANN ARCHITECTURES EMPLOYED

Architecture	Number of Studies	Percentage
CNN	14	46.66 %
MLP	5	16.67 %
BPNN	5	16.67 %
FFNN	2	6.67 %
Others	4	13.33 %

RQ2: What is the accuracy of the architectures utilized in the conducted studies?

Analyzing the accuracy of the architectures utilized in the reviewed studies provides insights into their performance across different classification tasks. FFNNs demonstrated the highest average accuracy among the architectures, with an average accuracy of 97.12%. CNNs exhibited a great accuracy of 90.7% This high accuracy can be attributed to CNNs' ability to automatically learn hierarchical features from raw input data, making them particularly effective in tasks such as image classification and pattern recognition. MLPs also showcased strong performance, with an average accuracy of 93.87%. MLPs are known for their simplicity and flexibility, making them suitable for a wide range of classification tasks. Specific studies reported exceptional accuracies, such as Multilevel Perceptron achieving 100 % accuracy in mushroom color classification [28] and CNNs achieving 100 % accuracy in symptomatically brain tumor detection [36]. While BPNNs and their variations exhibited slightly lower average accuracies compared to MLPs, they still demonstrated great performance. These architectures are often employed in tasks requiring sequential processing, such as time series analysis or signal processing.

Table 5 showcases the averages and highest accuracies obtained by the different ANN architectures.

TABLE V
ANN ARCHITECTURES ACCURACY

Architecture	Average Accuracy	Highest Reported Accuracy
FFNN	97.12%	97.18%
CNN	90.7%	100.00%
MLP	93.87%	100.00%
BPNN	91.58%	98.95%
Others	88.45%	99.20%

RQ3: What are the most frequently used data in classification tasks?

Examining the data sources utilized in classification tasks sheds light on the types of input data that ANNs are commonly applied to. Digitized images emerged as the most frequently utilized data type, appearing in 14 out of 30 studies (46.66 %). These images encompassed various domains, including medical imaging (MRI scans [36], ECG signals [23], retinal images [49]), microscopy (cell morphology [27]), and remote sensing (land cover [30], [48]).

Patient records, symptoms and patterns were also commonly used, appearing in 3 out of 30 studies (10 %). These records typically include demographic information, medical history, and diagnostic test results, making them valuable for tasks such as disease prediction and risk assessment, and reveals the importance of ANN models in the medicine campus.

Other data types, such as environmental parameters, mechanical quantities, and sound samples [26], [50], were utilized in a smaller proportion of studies. These data sources reflect the diverse range of applications for ANNs, spanning domains such as environmental science, engineering, and forensic linguistics.

The differences in accuracy among various ANN architectures can be attributed to the nature of the data and the specific requirements of the classification tasks. CNNs, for instance, excel in tasks involving image data due to their ability to capture spatial hierarchies through convolutional layers. This explains their dominance and high accuracy in image-related studies. FFNNs, MLPs, and BPNNs, while versatile and effective for general classification tasks, may not perform as well as CNNs in image-intensive tasks but excel in handling structured and sequential data. The high accuracy of FFNNs and BPNNs in certain studies indicates their robustness in tasks with less complex spatial relationships. BPNNs, in particular, have shown significant performance in tasks requiring sequential processing, such as sample analysis and prediction.

IV. DISCUSSION

A comprehensive analysis of 30 studies was conducted to investigate Artificial neural networks (ANNs) for solving classification tasks across diverse domains. In this systematic literature review, we addressed three research questions pertaining to the types of architectures employed, their accuracy, and the data sources utilized.

Our findings reveal a prevalent use of Convolutional Neural Networks (CNNs) in classification tasks, particularly those involving image data [25], [31], [35], [36], [47], [48]. CNNs have revolutionized the field of computer vision due to their ability to automatically learn hierarchical features from raw input data, making them highly effective in tasks such as object detection, image recognition, and medical imaging [23], [36], [37], [38]. Additionally, Multilayer Perceptron (MLP) architectures were frequently employed, showcasing their versatility and effectiveness in handling different tasks, such as sex classification from hair samples [13]. While other architectures, such as Backpropagation Neural Networks (BPNN), were employed in fewer studies, they still played significant roles in specific tasks requiring sequential processing.

Analyzing the accuracy of the architectures utilized in the reviewed studies provides insights into their performance across different classification tasks. The FFNNs demonstrated the highest average accuracy in our study, achieving a remarkable 97.12 %. This superior performance can be attributed to several factors. FFNNs are highly effective at capturing complex, non-linear relationships within the data, which is critical for accurate classification tasks. Their architecture, which consists of multiple layers of interconnected neurons, allows for the automatic learning of features without manual intervention. This adaptability makes FFNNs particularly robust in various applications [51], such as medical diagnosis [22], followed closely by MLPs, these networks are versatile and well-suited for a broad range of classification tasks. Their simplicity and ease of implementation make them a popular choice for general classification problems [52]. These findings are consistent with existing literature highlighting the superior performance of CNNs in image classification tasks. Notably, specific studies reported exceptional accuracies, underscoring the effectiveness of ANNs in achieving high accuracy across a broad spectrum of classification tasks, according to the work related in [14], high accuracy is one of the strengths of machine learning methods.

Examining the data sources utilized in classification tasks revealed a diverse range of inputs employed across the studies. Digitized images emerged as the most frequently utilized data type, reflecting the widespread application of ANNs in image-based tasks such as medical diagnosis [22], [23], [24], [33], [36], [37], [38], [41], [42], [46], matching with the review conducted in [53] that exhibits image classification as one of the most common application purposes for ANN in the maritime industry. Remote sensing, and object recognition. Patient records were also commonly used, highlighting the utility of ANNs in healthcare applications for disease prediction, risk assessment, and patient management. Other data types, such as environmental parameters and sound samples, were utilized in a smaller proportion of studies, demonstrating the versatility of ANNs in handling various types of input data for classification tasks.

The findings of this systematic literature review have several implications for both researchers and practitioners in the field of artificial intelligence and machine learning. Firstly, the prevalence of CNNs in classification tasks underscores the importance of machine learning approaches, particularly in domains where image data are prevalent, the same review mentioned before [53], reveals FFNNs and CNNs as the most commonly employed ANNs architectures in the maritime industry. Secondly, the high accuracy achieved by ANNs across a broad range of tasks highlights their effectiveness as robust and reliable classification tools. Lastly, the diverse range of data sources utilized in classification tasks suggests the potential for further exploration and integration of multimodal data in ANN-based approaches.

The present study showcases several strengths in the application of artificial neural networks (ANN) to classification problems. Firstly, the utilization of a robust dataset and advanced preprocessing techniques has ensured high-quality input data, which is critical for the accurate training of ANN models [54]. This high-quality data can serve as a benchmark for future research, enabling other studies to compare their results against a standardized dataset and ensuring consistency in the evaluation of ANN models. The implementation of various architectures and the systematic evaluation of their performance has provided a comprehensive understanding of the capabilities and limitations of different ANN configurations. This detailed evaluation is invaluable for guiding future research in selecting the most appropriate ANN architectures for specific types of classification tasks. For instance, our findings on the strengths of Convolutional Neural Networks (CNNs) in image data tasks can inform future studies focusing on medical imaging or remote sensing, while the versatility of Multilayer Perceptrons (MLPs) and Feedforward Neural Networks (FFNNs) can be leveraged for tasks involving structured data.

However, there are inherent limitations to this research that must be acknowledged. One significant limitation is the computational complexity associated with deep training neural networks [55], which may not be feasible for all research environments due to resource constraints. Addressing this issue in future research could involve developing more efficient algorithms or leveraging cloud computing resources to make deep learning more accessible. Additionally, the variability in performance metrics across different datasets suggests that further research is needed to confirm the robustness of these models in diverse real-world scenarios. Future studies could focus on testing ANN models across a wider range of datasets to enhance their generalizability and reliability. Another limitation is the potential for hyperparameter selection bias, which, despite efforts to mitigate it through systematic tuning, could still influence the outcomes. Future research should aim to develop more automated and unbiased methods for hyperparameter optimization to ensure that the performance improvements are genuine and not artifacts of overfitting.

The precision of the models is another critical aspect of this study. High precision in ANN models indicates their reliability and accuracy in making predictions [56], which is essential for applications in fields like healthcare, finance, and autonomous systems. Future research should continue to focus on improving the precision of these models through better training techniques, more diverse datasets, and advancements in ANN architectures. By addressing these strengths and limitations, this study lays the groundwork for future research to build upon, aiming to develop more robust, efficient, and precise ANN models for a variety of classification tasks.

Future research should focus on enhancing the interpretability, efficiency, and generalization capabilities of ANNs. One approach to improving interpretability is the development of visualization tools that can provide insights into the decision-making process of neural networks. Techniques such as Layer-wise Relevance Propagation (LRP) and Gradient-weighted Class Activation Mapping (Grad-CAM) can help researchers and practitioners understand which features are most influential in a model's predictions.

To improve efficiency, research can explore the optimization of neural network architectures and the use of advanced training techniques such as transfer learning and fine-tuning. These methods can reduce the computational burden and make ANN applications more accessible in various domains.

Enhancing generalization capabilities requires addressing issues related to data quality and diversity. One strategy is to employ data augmentation techniques to create more representative training datasets. Additionally, the development of hybrid models that combine different neural network architectures could leverage the strengths of each, leading to more robust and generalizable solutions.

V. CONCLUSION

Through our systematic literature review, we have provided a comprehensive analysis of the utilization of ANNs in classification tasks, addressing three key research questions pertaining to the types of architectures employed, their accuracy, and the data sources utilized.

The most commonly used ANN architectures identified in this review are Convolutional Neural Networks (CNNs), Multilayer Perceptrons (MLPs), Feedforward Neural Networks (FFNNs), and Backpropagation Neural Networks (BPNNs). CNNs dominate in image-related tasks due to their ability to capture spatial hierarchies, while MLPs and FFNNs are versatile and effective for general classification tasks involving structured and sequential data. BPNNs, although less common, have shown significant performance in tasks requiring sequential processing.

The accuracy of ANN architectures varies depending on the nature of the data and the specific requirements of the classification tasks. FFNNs demonstrated the highest average accuracy in this review, achieving a remarkable 97.12%. CNNs also exhibited high accuracy, particularly in image classification tasks, with some studies reporting accuracies as high as 100 %. MLPs and BPNNs showed strong performance across various classification scenarios, indicating their robustness and reliability in handling diverse types of data.

For Convolutional Neural Networks (CNNs), the most frequently used data type is digitized images. Multilayer Perceptrons (MLPs) commonly use structured data. Feedforward Neural Networks (FFNNs) are often used with tabular data and images. Backpropagation Neural Networks (BPNNs) frequently use data that require sequential processing, such as sample analysis and prediction.

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