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Review

The Applications of Deep Learning in ECG Classification for Disease Diagnosis: A Systematic Review and Meta-Data Analysis

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Abstract. The supremacy of deep learning in artificial intelligence (AI) contexts, including image and speech recognition, computer vision, and medical imaging, among others, has established it as AI's dominant approach. Several studies have been conducted on the use of deep learning in physiological signals, especially in ECG signals, in recent years, but there has been a lack of comprehensive review on the use of deep learning in ECG for biometric systems. This review is divided into two main sections: it provides a comprehensive bibliographic review of deep learning for ECG classification towards assisting in disease diagnosis in the first part while presenting an overview of the field, pioneers, and landmark studies. The second part offers comprehensive information on the subject, starting with the mathematical background of deep learning algorithms, the ECG signal processing, and the function of the heart. Using a PRISMA framework, 309 research papers were initially identified through specified keywords. After applying inclusion criteria, 90 articles were retained for detailed analysis, excluding 24 documents based on exclusion criteria EC1 and the remainder due to EC2. Key findings reveal that deep learning models achieve an average accuracy improvement of 10-15% over traditional methods, with convolutional neural networks (CNNs) and recurrent neural networks (RNNs) demonstrating superior performance in capturing complex ECG patterns. Through ECG databases, deep learning algorithms, assessment frameworks, metrics, and code availability, this review designs a systematic view from different perspectives to highlight the trends, challenges, and opportunities of deep learning for ECG arrhythmia classification. This paper's goal is to contribute to the knowledge of both new and experienced researchers and practitioners in the field so that they can learn and understand the various processes involved in ECG signal processing using deep learning.

Keywords: Deep learning, machine learning, ECG classification, arrhythmia.

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1. Introduction

Background: Cardiovascular diseases (CVDs) represent one of the most prevalent and challenging chronic health issues globally, posing significant threats to human health and well-being [1]. These conditions encompass a spectrum of disorders affecting the heart and blood vessels, including coronary artery disease, heart failure, arrhythmias, and hypertension, often leading to severe complications if not addressed timely. The World Health Organization (WHO) estimates that CVDs are responsible for approximately 17.9 million deaths each year, accounting for 31% of all global deaths. Given this substantial impact, there is a critical need for effective diagnostic and management strategies to combat the burden of CVDs.[2]. At its core, an ECG functions as a noninvasive technique that records the heart's electrical activity over time. Through a series of electrodes attached to the skin, this method captures the rhythmic pattern of contractions and relaxations within the heart, providing insights into its performance. By observing the distinctive waves such as the P wave, T wave, and QRS complex, medical professionals can decipher vital information about heart functionality [3]. This interconnected relationship between the cardiovascular system and ECG signals makes them critical in identifying potential health concerns. Irregularities in these signals can point to various heart-related issues, such as arrhythmia, which in turn prompt the need for accurate classification and diagnosis [2]. In the rapidly evolving landscape of healthcare, the convergence of deep learning and medical diagnostics has brought forth groundbreaking advancements. One particularly compelling application is in the realm of electrocardiogram (ECG) classification [4].

The Problem: Despite the critical role of ECGs in diagnosing cardiac conditions, traditional methods of ECG analysis often required meticulous manual examination by trained cardiologists. This process could be subjective, time-consuming, and prone to human error, leading to inconsistencies in diagnosis and potential delays in treatment. The manual analysis involves the visual inspection of ECG waveforms to identify irregularities, which may vary in appearance and complexity. This reliance on manual processes not only hampers efficiency but also poses challenges in handling large volumes of ECG data, which is increasingly common with the advent of digital health records and wearable health monitoring devices [5]. The complexity of ECG signals necessitates accurate classification to identify irregularities and ensure timely medical intervention. Various types of arrhythmias, ischemic events, and other cardiac anomalies present unique challenges for accurate detection and classification. The traditional rule-based algorithms, while useful, often lack the ability to generalize well across diverse patient populations and varying signal qualities. Consequently, there is a growing need for more advanced, automated, and reliable methods to enhance the diagnostic accuracy and efficiency of ECG interpretation. [6].

The Proposed Solution: Deep learning, which falls under the umbrella of machine learning, has become a revolutionary force in the realm of ECG classification. By utilizing convolutional neural networks (CNNs) and recurrent neural networks (RNNs), deep learning models possess the ability to autonomously acquire and decipher complex patterns embedded within ECG waveforms [7]. This automation significantly accelerates the diagnostic process, ensuring quicker and more accurate results. Deep learning models excel in discerning complex patterns that might elude human observers [8]. By scrutinizing subtle variations in ECG signals, these models can pinpoint abnormalities with exceptional accuracy. This precision translates into more reliable diagnoses and timely interventions. Deep learning models exhibit an inherent adaptability. As they encounter more data, their performance tends to improve. This adaptability is particularly advantageous in the realm of ECG classification, where datasets [9] can vary significantly due to patient diversity and the dynamic nature of cardiac anomalies. However, while DL's potential for enhancing diagnostic accuracy is undeniable, its application within practical medical procedures remains limited. The transition from research settings to real clinical scenarios poses several hurdles, including the need for standardized protocols, robust models, and validated results.

Objective of the Review: To address the intersection of these factors, this systematic review aims to provide a comprehensive overview of the landscape surrounding DL-based ECG classification. The review delves into multiple perspectives, including the composition of ECG databases, pre-processing techniques, DL methodologies, evaluation paradigms, performance metrics, and the availability of code for re-producibility. This review aims to consolidate findings from various research efforts to discern patterns, obstacles, and prospects within the field of deep learning (DL)-focused ECG categorization. It endeavors to highlight the progress achieved, identify ongoing challenges, and suggest avenues for future investigation. By conducting this comprehensive analysis, we aspire to enrich the discourse in medical technology and foster additional advancements in diagnosing and managing cardiac ailments.

2. Part A: Bibliometric Analysis

The bibliometric analysis carried out in this study was primarily done to address the following research questions (RQ):

- What is the present-day inclination in scholarly publications regarding the utilization of deep learning for diagnosing illnesses through ECG classification?
- What potential avenues for further research could be explored in this particular domain of science?

In this study, an analysis of bibliographic databases was conducted, leading to the selection of three databases deemed the relevant most for the topic of research. These were the PubMed, IEE explore (accessed on 10

September 2023)) and Scopus (https://www.scopus.com/ (accessed on 10 September 2023)) databases [10][11]. The search strategy and criteria were identical for these databases, resulting in 309 documents from Scopus, PubMed contributed 75 and 296 documents from IEEE Explore. Subsequently, the bibliographic data from Scopus was utilized for further analysis. The Scopus Content Coverage Guide [12] indicates that as of January 2020, it encompasses over 5,000 publishers and boasts more than 25,000 titles those are active with a staggering 77 million publications. The archives of Scopus trace their origins to the year of 1788, boasting a wealth of knowledge with more than 6.6 million publications predating the 1970s [12]. The SCOPUS database is primarily dedicated to four distinct categories [12], namely health sciences (accounting for 30.4\% of content), physical sciences (constituting 28.0\%), social sciences (comprising 26.2\%), and life sciences (making up 15.4\%).

In order to identify pertinent publications on ECG classification for disease diagnosis through the use of deep learning, we followed the methodology of PRISMA [13] for systematical reviews. Our search strategy was conceptualized around three essential keywords: ECG Classification, Electrocardiogram classification, and deep learning, which were interlinked with the conjunction OR, AND. The exact keyword string is ("ECG Classification" OR “Electrocardiogram classification”, AND "deep learning"). We then conducted a thorough search for these terms in the titles of publication, abstracts, or authors’ keywords, resulting in a vast compilation of documents. Our research was conducted in September 2023, and hence, publications published until the end of 2022 were considered. An exclusion criterion (EC) was established for the designated research period (2016-2023), as the primary aim of RQ 1 was to ascertain the progression of research throughout the years. To begin with, it is of utmost importance to highlight and underscore the fact that the process of selecting the manuscript was commenced with a meticulous and judicious consideration of not just one, but two criteria of inclusion (IC):

- **IC1** The string of search is (TITLE-ABS-KEY("ECG Classification" OR "Electrocardiogram Classification" AND "Deep Learning")).
- **IC2** The language of research articles should be written in English.

The parameters of exclusion (EC) serve to establish which publications ought to be dismissed from the research assemblage. In this endeavor, we have stipulated two distinct ECs:

- **EC1** Reviews and conference reviews, books and book chapters, letters and notes.
- **EC2** The research articles with less than 3 citations per annum.

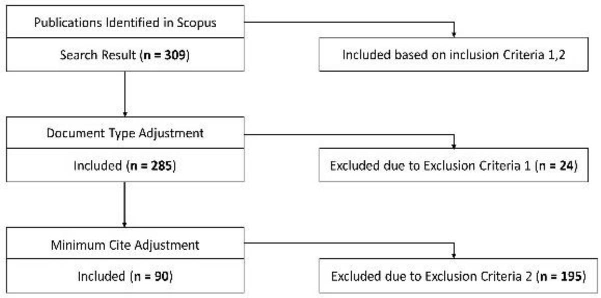

Fig. 1. PRISMA framework for the selection of appropriate articles.

Table 1. Summary bibliometric-statistics of the relevant publications on ECG Classification for the application of disease diagnosis acquired by the discussed strategy of search.

Results & Main Information	
Time_Span	2016-2023
Sources	63
Total no.of Documents	90
Average-years from publication	2.5
Average-citations per document	50.34
Average-citations per year per doc	17.72
References	122
Document types	
Article	83
Conference Paper	7
Authors and collaboration	
Authors	411
Authors of single-authored documents	1
Co-Authors per Doc	5.11
International co-authorships percentage	32.22

The initial exclusion criteria (EC) led to the elimination of articles and conference papers potentially deemed as central to scientific contributions. Documents not encompassed may have lacked sufficient novelty concerning the research topic. The second EC acted as a measure of significance, selecting only publications with a high citation count for detailed bibliometric analysis. This entire process is depicted in Fig. 1.

The bibliometric study was carried out with the R programming language, utilizing the bibliometrix package. As an open-source tool for R, bibliometrics enables detailed analyses of scientific mapping.[14].

2.1. Descriptive Bibliometric Analysis

Table 1 displays a summary of the descriptive-bibliometric-statistics for the data set (Fig. 1). The search approach produced 90 pertinent papers on the categorization of ECGs or electrocardiograms for the diagnosis of diseases using deep learning, which were found in 63 sources (Table 1). In general, there were 50.34 citations per document or 17.72 citations per document every year. There were a total of 122 documents cited in the chosen articles. Journal articles made up the majority of the publications that matched the search method (83), and conference papers made up a very small portion (7). There were only 5 articles written by a single author, and each document had an average of 4.21 co-authors.

According to Bradford's law [15], the main sources of relevant documents were *IEEE Access*, *IEEE Journal of Biomedical and Health Informatics* and *Computers in Biology and Medicine*, which published major part of the articles as given in Table 2.

2.2. Analysis of Authors

The highly significant scribes, ranked in order of their total citations and respective bibliometric data, can be found in Table 3. Hammad M emerged as the preeminent author, having garnered a remarkable 156 citations through his profound contributions in 4 distinct publications. In hot pursuit, Normainia S claimed the second spot with an impressive count of 103 citations, while simultaneously proving his productivity with 3 notable publications. The most prolific wordsmith of them all, Acharya UR, effortlessly claimed the title by authoring a staggering 3 publications with 66 citations.

The research elucidates the scientific output throughout the duration of the study, as illustrated in Table 1, focusing on the top 10 writers in terms of article quantity and total citation count per annum. The graphical representation in Fig. 2 showcases this information. Notably, the author with the highest number of citations also demonstrates an unwavering dedication to the field, evident through the longevity of their contributions, beginning in 2018 and culminating with their most recent publication in 2022. It is intriguing to observe that the author who is cited second most frequently is also the second most persistent, as evidenced by their publication of articles from 2018 to 2022. It is notable that certain authors featured in Fig. 2 are absent from Table 3, and this discrepancy is attributable to the sorting process utilized in Fig. 2 which involved the standardization of citations per annum. Consequently, some authors have recently produced valuable articles with commendable citation rates, yet their cumulative citation count has not yet reached a sufficiently high threshold to warrant inclusion in Table 3.

Table 4 encompasses the foremost documents ascertained through worldwide citations. Table 4 pertains to the publications that were chosen based on the search approach, organized according to global citations.

The research conducted by HANNUN AY et al [16] garnered the highest number of citations on a global scale. Within the examined listing of documents (Fig. 1), the study carried out by XIA Y, et al [17] was held in high regard, attracting significant attention from the broader scientific community, with a total of 221 global citations. Notably, the more recent investigation by FAN X [18] on collaborative representation for ECG recording should be emphasized, as it received considerable acclaim internationally.

Table 2. The most relevant sources according to Bradford's Law [15] are presented in descending order with number of documents.

Rank	Name of Source	Documents	Zone
1	IEEE_ACCESS	5	1
2	IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS	5	1
3	COMPUTERS_IN BIOLOGY_AND MEDICINE	4	1
4	BIOMEDICAL SIGNAL PROCESSING AND CONTROL	3	1
5	EXPERT SYSTEMS WITH APPLICATIONS	3	1
6	PHYSIOLOGICAL MEASUREMENT	3	1
7	ARTIFICIAL_ _INTELLIGENCE IN MEDICINE	2	1
8	BIOCYBERNETICS AND BIOMEDICAL ENGINEERING	2	1
9	COMPUTER METHODS AND PROGRAMS IN BIOMEDICINE	2	1
10	COMPUTERS, MATERIALS AND CONTINUA	2	1

Table 3. The most-relevant-sources according to Bradford's Law [15] are presented in descending order with no.of documents.

AUTHOR	SCOPUS ID	H-INDEX	TOTAL CITATIONS	NO.OF PUBLICATION	FIRST PUBLICATION (YEAR)
HAMMAD M	57194656523	18	156	4	2017
NORMAINIA S	26639610000	17	103	3	2008
ACHARYA UR	7004510847	115	66	3	1978
LI Q	57221613252	25	42	2	2008
ZHANG Y	16177024400	46	17	1	1990
AFGHAH F	25928232700	22	44	2	2008
BAALMAN SWE	57198490021	8	44	2	2017
BLEIJENDAAL H	57217050003	6	44	2	2020
CHEN X	57192255114	29	24	1	2001
CLIFFORD GD	7004468844	59	42	2	2001
DARMAWAHYUNI A	57212509655	12	83	2	2019
BAALMAN SWE	57198490021	8	44	2	2017
ELEGENDY IA	56545658900	15	20	2	2015
FIRDAUS F	56582818700	11	83	2	2016
KHAN MA	57215096761	8	12	1	2018
LI H	55707705400	13	12	1	2000
LI Z	57212027319	5	17	1	2019
LIU C	25724384300	23	35	1	2005
LOPES RR	57191221093	5	44	2	2016
MOUSAVI S	56378061800	15	44	2	2014

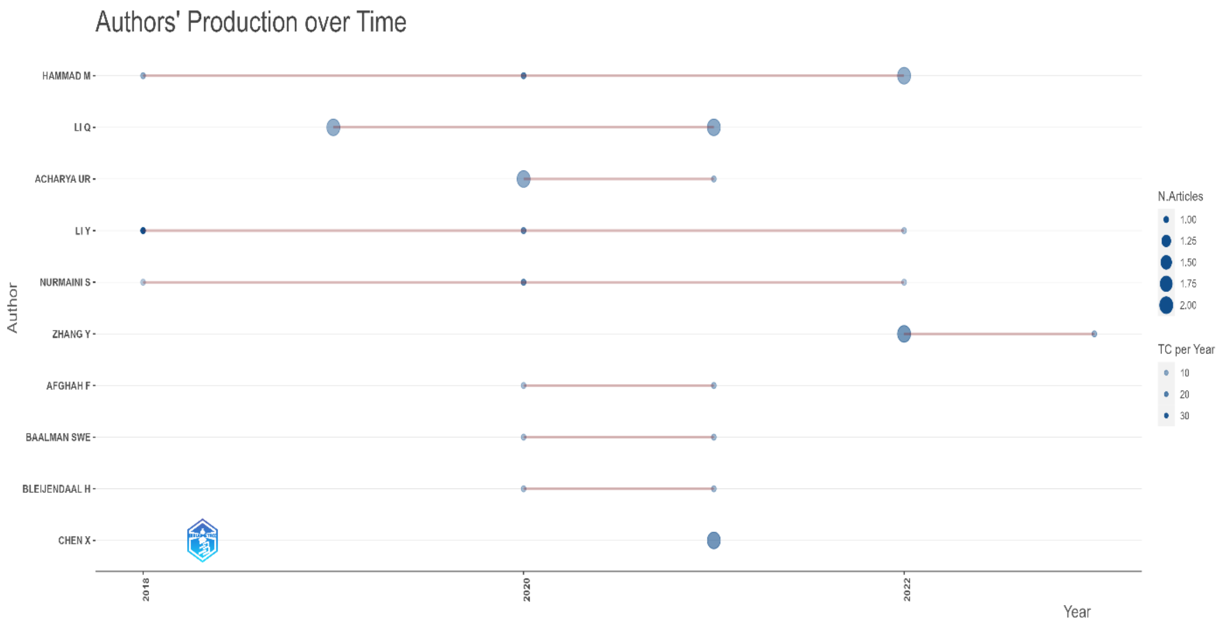

Fig. 2. According to the no.of articles (N. articles) and the total no.of citations per annum (TC per year), the top 10 writers in the area have produced the most scientific work during the course of the research. The bibliometrix R-package was used to construct the figure [14].

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Table 4. The top 10 documents with the highest number of global citations.

Paper DOI	Ref	Global Citations	TC per Year
10.1038/s41591-018-0268-3	[16]	1383	276.60
10.1016/j.compbiomed.2017.12.007	[17]	221	36.83
10.1109/JBHI.2018.2858789	[18]	199	33.18
10.1109/JBHI.2018.2871510	[19]	145	29
10.1088/1361-6579/aad9ed	[20]	99	16.5
10.7717/peerj.7731	[21]	84	16.80
10.1016/j.knosys.2021.107187	[9]	83	27.67
10.1007/s11042-020-08769-x	[22]	82	20.50
10.1109/ICIRCA48905.2020.9183244	[23]	80	20
10.1155/2018/7354081	[24]	80	13.33

Figures 3 and 4 exhibit the temporal evolution of research on ECG classification using deep learning for disease diagonosis. Figure 4 is constructed based on the author's choice of keywords, while Fig. 3 is based on the keywords found in the document titles. For Fig. 3, the most frequent trend topics per annum are presented. It is worth noting that no trivial keywords were excluded, and no manual filtering was performed.

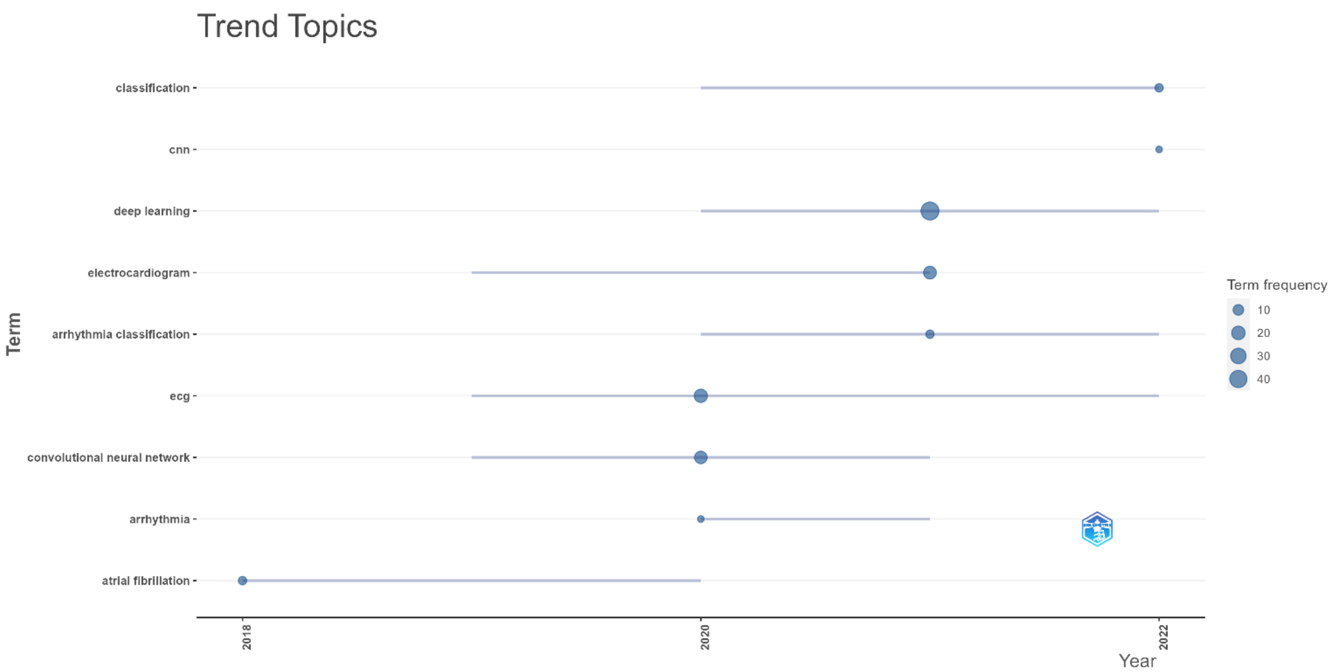

Fig. 3. The emergence of the theme as provided by the subjects of interest. The most popular trend topics' usage over time is depicted in the graph. Utilising the bibliometrix R-pack, the figure was produced.

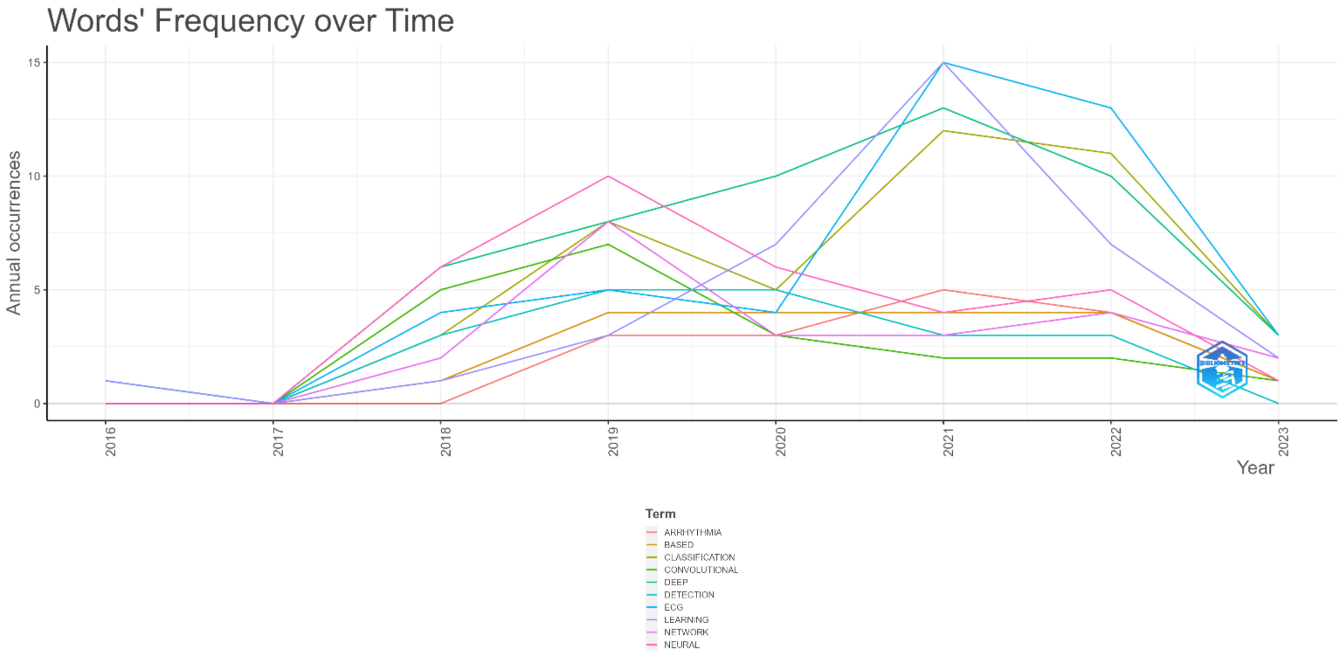

Fig. 4. The topic indicated by the title keywords is elaborated upon with a graph that tracks the occurrence frequency of these keywords over time, developed through the bibliometrix R-package. [14].

The tree map depicted in Fig. 5 provides a lucid understanding of the patterns and forthcoming scientific studies in the realm of ECG classification using deep learning for disease diagnosis. The figure was derived by employing the document title keywords, in a similar manner as displayed in Fig. 4, however, in this case, the cumulative frequency across the analyzed time period was taken into account. The relative size of the words in the map was determined by their respective frequencies, thereby ensuring that the most frequently occurring keywords were represented with more prominent characters.

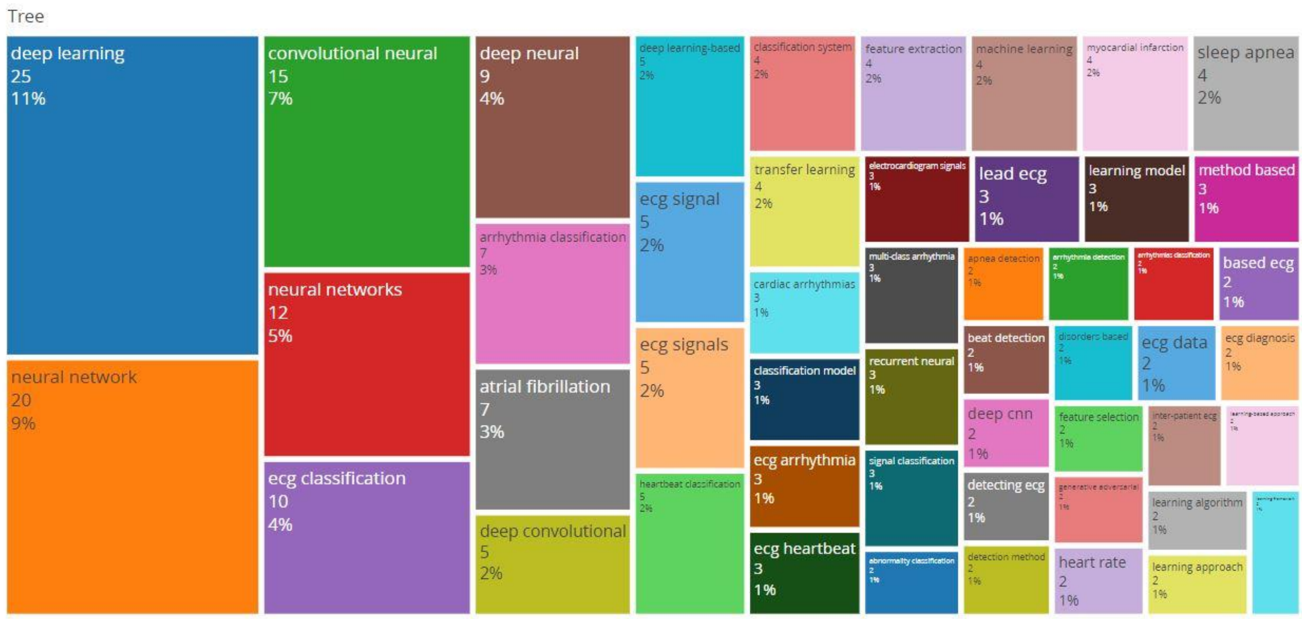

Fig. 5. A TreeMap was generated through the bibliometrix package in R, illustrating the most commonly occurring keywords in the titles of the examined papers, where the dimension of each term corresponds to its occurrence rate.

Figures 4 and 5 analysis reveals a current pattern in the evolution of representation-based approaches. Terms like dictionary, low-rank, spare, cooperation, joint, and joint can be used to describe these strategies. As a result, Part B of this study includes a unique section devoted to these techniques.

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3. Part B: The Expansion of Deep Learning

Deep learning (DL), a new version of artificial neural networks (ANNs), falls under the broader categories of machine learning (ML) and artificial intelligence (AI).[25]. AI is firstly defined back in 1950s, during which researchers believed that computers had the potential to perform tasks comparable to human intelligence. Of particular significance, in 1950, Alan Turing posed the thought-provoking query, "Can machines exhibit thinking capabilities?" This inquiry set forth a trajectory that create a best way to the development of algorithms, progressing from knowledge-based systems to ML algorithms [26]. Claude Shannon and IBM's John McCarthy hosted a symposium on artificial intelligence (AI) at Dartmouth College in the United States in 1956. This event marked the origin and introduction of the term "Artificial Intelligence", which was subsequently employed in the 2nd conference. AI refers to the emulation of human intelligence on computer systems, aimed at replicating human cognitive abilities [25], [27],[28]. This entails the creation of computer systems capable of executing tasks at a level comparable to, or even surpassing, human capabilities. Consequently, Artificial Intelligence (AI) concerns itself with the mechanization of human intellect in order to enable machines to perform tasks with a level of intelligence akin to that of humans [26],[29][30].

The machine learning paradigm proved to be advantageous in mitigating the limitations of symbolic artificial intelligence, It was unable to manage specific rules needed to solve more complex and ambiguous issues, such computer vision, text classification, pattern recognition, image processing, audio recognition, and natural language processing. By feeding data with labelled responses into the system, the machine learning system is "trained" to gain knowledge (much like people learn by experience), in contrast to the symbolic AI, which mapped input data to output data according to a predetermined set of rules. Without explicit programming, computers may learn new things thanks to machine learning (ML) [26], [31]. The procedure of learning involves adapting the parameters of the model so that it can perform a specific task. With this skill, an artificial intelligence (AI) system may improve its capacity to make precise predictions on fresh data by extracting pertinent insights from raw data and producing insights rely on input-output linkages [32]. Widely used machine learning (ML) methods encompass decision trees (DT), multi-layer perceptron (MLP), k-nearest neighbours (KNN), support vector machines (SVM), among others. Consequently, ML presents a pathway towards realizing the ultimate aim of artificial intelligence (AI), which is to automate cognitive human functions explicitly. The connection among artificial neural networks (ANN), deep learning (DL), machine learning (ML), and AI is illustrated in Fig. 6.

When it pertains to the execution of tasks, the primary distinction between humans and machines lies in their level of intellect. Humans possess the ability to acquire knowledge through experience in order to make informed choices, whereas machines lack this capability and are designed to carry out predetermined and specific sets of tasks. The field of machine learning endeavors to narrow this disparity. The progression in bridging this gap has been facilitated by the intro of artificial neural networks (ANN).

An Artificial Neural Network (ANN) replicates the operations of the human brain in a computerized model, albeit in a highly abstracted form of animal neural structures. The evolution of ANNs is marked by three significant periods. The journey began with the creation of the perceptron in the 1950s, evolved with the development of backpropagation in the 1970s, and reached a pivotal moment with the introduction of Deep Learning (DL) in the 1990s. The concept of the ANN was first introduced in 1943 by neurophysiologist Warren McCulloch and mathematician Walter Pitts. This foundational work was later expanded upon by researchers such as Frank Rosenblatt, who developed the first perceptron in 1957. The perceptron acts as a foundational element of the ANN, mimicking the function of a biological neuron.[31].

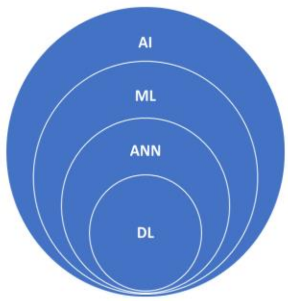

Fig. 6. This Venn indicates the link among DL, ANN, ML and AI.

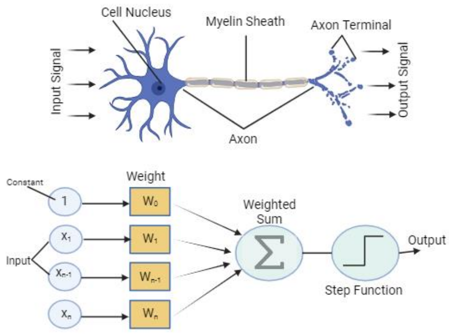

Fig. 7. Perceptron vs Neuron.

Figure 7 depicts a conventional portrayal of a perceptron, denoted as the below side of the image, alongside a biological neuron, illustrated as the upper side of the image. The dendrites, denoted as (x_1, x_2, x_3, ... x_n)

serve as the carriers of input data. These input data are then subjected to multiplication with weights produced randomly, denoted as (w_1, w_2, w_3, ... w_n), corresponding to each input-data. The dot product of matrix of (x_1, x_2, x_3, ... x_n) and (w_1, w_2, w_3, ... w_n) is subsequently aggregated, and a probable value, commonly referred to as bias, is incorporated. This bias symbolises a biological neuron's centre. Following this, the function of activation, denoted as f, which symbolizes the axon, is calculated through the utilization of a function known as the step function. However, the aforementioned function is limited to approximating linear relationships within the dataset. Nevertheless, recent developments in the functions of activation, namely sigmoid, Rectified Linear Unit (ReLU), and hyperbolic tangent (tanh), have enabled the estimation of intricate and nonlinear relationships within the input data. Moreover, these functions have the added advantage of normalizing the output data. Specifically, the output, denoted as y, assumes a value of one (1) when the result exceeds a predefined threshold, whereas it assumes a value of zero (0) otherwise. The computation of the outcome y is achieved with Eq. (1).

$$y = f\,(\sum_{k=0}^{n} w_k . x_k) + bias \qquad (1)$$

In the year 1969, an authored publication by Marvin's and Papert, entitled "Perceptrons," highlighted the restrictions of the perceptron. It was found that the perceptron was inadequate in its ability to deal with more intricate characteristics such as the logic of XOR. Additionally, it struggled to address the non-linear characteristics of input information in artificial neural networks (ANN). The argument advanced by the authors advances that the singular perceptron approach to artificial neural networks was not easily adaptable for multi-layered artificial neural networks, resulting in financial difficulties for projects involving artificial neural networks due to restrictions imposed by different organizations. However, in 1981, P-Werbos introduced the initial proficient artificial neural network (ANN) that incorporated the back-propagation method. The back-propagation method operates by delicately adjusting the ANN's weights based on the previous iteration's calculation of the mistake rate, with the objective of minimizing the discrepancy among the actual outcome and the expected outcome (error). This iterative process subsequently enhances the ANN's capacity to generalize and make predictions. In 1986, Rumelhart conducted influential work that popularized the use of back-propagation and defined the concept of hidden layers in artificial neural networks [31],[33]. A visual representation in Fig. 8 illustrates a simplified depiction of an artificial neural network employing back-propagation. A network of neurons can consist of a multitude of cells, varying in number from tens to hundreds. These cells are managed in separate layers, with every layer interconnected with the layers adjacent to it. The network itself is divided into three primary components: the input unit, positioned on the left-hand side; the hidden layer(s), located in the middle; and the output layer, situated on the right. The output layer is responsible for producing the final results.

Figure 8 illustrates the operational process of back-propagation, beginning with the initial data input, denoted as X, into the input layer. Subsequently, weights, designated as W and randomly selected, are applied to each input X and combined with a bias in the hidden layers. The output layer evaluates the training model's effectiveness. Then, the loss function is determined, and the back-propagation method is utilized to modify the weights in the hidden layers, aiming to decrease the loss function. This cycle continues repeatedly until the model has been sufficiently trained or achieves the set number of epochs.

Deep Learning (DL) technique is built upon the Artificial Neural Network (ANN), which employs both linear and nonlinear transformations to process the input data. These transformations occur across various hidden layers, ultimately leading to the output layer [34]. This method reflects the operation of the human brain by representing data across various layers of abstraction. As a result, the network gains the ability to understand diverse types of information, thereby inherently identifying important patterns within large datasets. [35]. Hinton [36] were credited as the first to introduce the notion and methodology of Deep Learning (DL). DL, a variant of Machine Learning (ML), empowers machines to acquire knowledge through experiential and progressive comprehension of worldly concepts [37],[38]. Conversely, the type of ML that utilizes only 3 layers of data representation (hidden, input and output layers) is occasionally referred to as "shallow" learning or a shallow model [39].The utilization of the term "deep" in the context of Deep Learning accentuates the concept of hierarchical strata of representations. In modern Deep Learning systems, there exists a multitude of layers, frequently encompassing tens or even hundreds of layers [26]. The primary distinction between deep learning (DL) and conventional artificial neural networks (ANNs) lies in the quantity of hidden layers (as shown in Fig. 9, their interconnections, and the ability to acquire expressive abstractions of the input information [40]. Nevertheless, the performance of DL is highly reliant on the characteristics of the data presentation provided to the technique [37]. Since the 1990s, DL has been successfully utilized in various applications, making it arguably the most renowned domain within the field of artificial intelligence [41]. For a more comprehensive historical timeline and evolution of DL, readers are referred to [42], as the details are beyond the scope of this study. DL is occasionally referred to as the universal learning approach due to its applicability in nearly all domains. Consequently, DL is considered to be task-independent [9]. Nonetheless, the potentials and possibilities of DL architectures continue to be explored.

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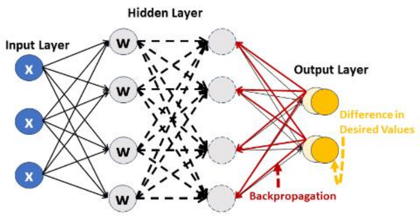

Fig. 8. A conventional ANN network with back-propagation process.

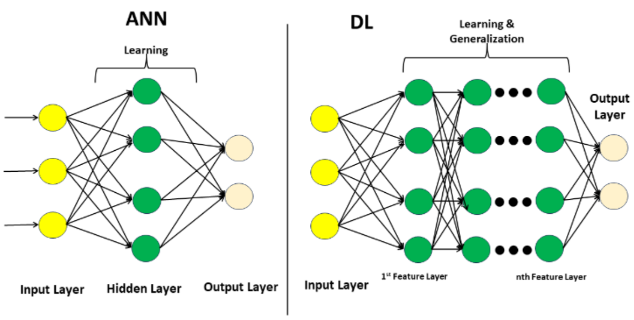

Fig. 9. This illustrates a comparison between Artificial Neural Networks (ANN) and Deep Learning (DL).

Figure 9 presents a comparison between artificial neural networks (ANNs) and deep learning (DL). ANNs are usually structured with three layers, with learning directed towards the output layer. In contrast, DL features many hidden layers, anywhere from dozens to thousands, enabling it to extract significant features and patterns from the input data. This is achieved through the back-propagation algorithm, which helps DL models to learn and correct errors, resulting in models that are more adaptable. Additionally, the learning approaches in machine learning (ML) and deep learning (DL) are categorized into several types, including supervised, unsupervised, semi-supervised, and reinforcement learning [31].

3.1. Architectures of Deep Learning

In this particular section, we shall deliberate upon the deep learning architecture that is frequently utilizing in the processing of electrocardiogram (ECG) signals.

3.1.1. Deep neural networks

Deep Neural Networks (DNNs) are a specialized category within machine learning, distinguished by their more complex network architectures relative to conventional neural networks. While Deep Learning (DL) and DNNs are often mentioned as synonymous, here we specify a DNN as a classic Artificial Neural Network (ANN) equipped with a minimum of two hidden layers. Thus, a DNN is defined as a particular form of Artificial Neural Network (ANN) that includes a minimum configuration of four layers: an input layer, several hidden layers, and an output layer.[43]. The application of DNNs faces obstacles due to the vanishing gradient issue, which complicates the training process. To address these challenges, researchers have developed diverse DL architectures. [39]. Figure 10 illustrates the structure of the DNN.

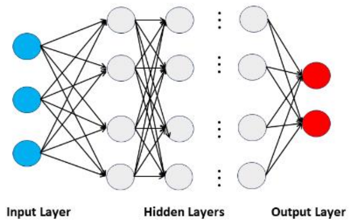

Fig. 10. Classical DNN architecture.

3.1.2. Convolutional neural networks

Convolutional Neural Networks (CNNs), which are based on the neurophysiological principles of the human visual field, were initially defined in the year 1962 by Hubel and Wiesel [43]. This particular type of neural network has emerged as the most widely employed technique for computer vision and video recognition tasks [44] CNNs are designed as deep learning-based algorithms that possess the ability to autonomously and elastically learn distinctive parameters from intake images or data, subsequently facilitating the classification of said data into predefined categories. The structure of a CNN entails three fundamental components: the layers of convolution, pooling, and fully connected. The layers of Convolution & pooling are typically utilized to fetch relevant parameters, while the layers those are fully connected are responsible for the categorization process [35]. The initial proposition of CNN was introduced by Fukushima [45]; however, its utilization remained limited until Lecum et al. designed CNN in 1998 specifically for the critical analysis of a document. This design yielded favorable outcomes in the classification of handwritten digits [46]. Consequently, it took approximately 14 years for CNN to gain popularity when Krizhevsky et al. significantly enhanced their model, known as AlexNet, resulting in a remarkable performance improvement. Notably, AlexNet emerged triumphant in the ILSVRC-2012 competition [47]. The subsequent year, in 2013, ZF-Net was evolved as an improvement upon Alex-Net [48]. Later on, researchers from Google Inc. crafted GoogLeNet, a network with a remarkable depth of 22 layers [49].

The GoogLeNet emerged victorious in the ILSVRC 2014 fuss. Simonyan & Zisserman [50] introduced

VGGNet, also known as VGG, and claimed the 2nd and 1st positions in the ILSVRC 2014 for classification and localization tasks, respectively. He et al. [51] proposed ResNet, another robust CNN architecture, which is considered as the framework of residual learning. This technique achieved the top spot in the ILSVRC 2015 task of classification. There exist other variations of ResNet, namely ResNet34 & ResNet50, & ResNeXt structures. SqueezeNet [52] is a model that is built upon ResNet and boasts memory requirements that are 510 times lower, thanks to the implementation of deep compression techniques. Huang et al. [53] defined DenseNet, a CNN technique which is densely connected, which parameters each layer connected to every other layer in a network of feed-forward. This unique design provides several advantages over previous CNNs, including the reduction of the vanishing-gradient issue, enhanced parameter casting, promotion of feature reuse, and a reasonable decrease in the No.of required values. The convolutions neural network (CNN) is widely regarded as uttermost frequently employed deep learning (DL) technique for classification jobs [54][55]. Its application extends to different domains like computer vision [56], language translation [57], image segmentation [58], and object recognition [59], among others. The CNN's architectural composition, as depicted in Fig. 11, effectively illustrates the distinct components that constitute its structure.

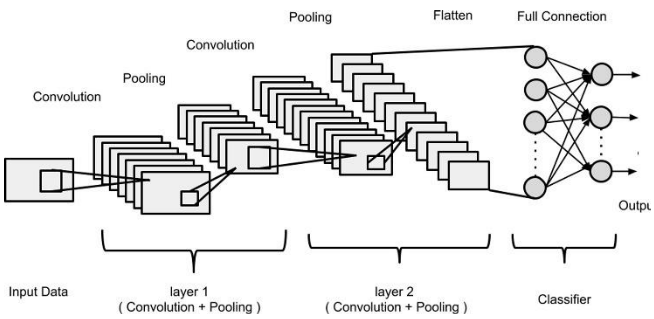

Fig. 11. The CNN's Architecture [60].

GoogLeNet clinched the top position in the ILSVRC 2014 competition. Simonyan and Zisserman[50] introduced VGGNet, or simply VGG, securing both the first and second spots in the ILSVRC 2014 for localization and classification tasks, respectively. Following this, He and colleagues [51] unveiled ResNet, a powerful CNN framework known for its residual learning capability, which took first place in the ILSVRC 2015 classification challenge. ResNet has been developed into various forms, including ResNet34, ResNet50, and ResNeXt. Built on the ResNet architecture, SqueezeNet [52] significantly reduces memory usage by 510 times through advanced deep compression methods. Huang and his team [53] developed DenseNet, a CNN with a unique architecture where each layer is directly connected to every other layer in a feed-forward manner. This design offers multiple benefits, such as alleviating the vanishing-gradient issue, improving feature propagation, encouraging feature reuse, and substantially lowering the number of parameters needed. Convolutional neural networks (CNNs) [54], [55] are recognized as the predominant deep learning method for classification, with applications in fields like computer vision [56],, language translation [57], image segmentation [58],, and object recognition [59]. The structure of CNNs, as shown in Fig. 11 [60] clearly demonstrates the various components that make up its architecture.

Data input, for example, an image with dimensions n × n × r, with n representing both the width and height of the image and r denoting the channel count, undergoes processing via convolution and pooling layers. Throughout this phase, the input image's attributes, depicted as the input tensor, are extracted. Subsequently, image classification takes place in the fully connected layer, utilizing the Softmax function to ascertain the classification of the object based on probabilities that vary from 0 to 1 [60].

The Convolutional Layer: The first layer that accepts the input information is called as the convolution layer. The Kernel, referred to as k, is an m-by-m-by-p matrix, where m is lesser than the dimensions of the input data(image), n, & p could be equal to r. The array of numbers, r is equal to tensor. To calculate the dimensions of k we can use n - m + 1. At each location of the tensor, a matrix multiplication is performed among input tensor & each element of k. This computation is executed as the kernel hovers above the input tensor with a specified length of stride, denoting the separation between two consecutive kernels. The resultant values are subsequently aggregated to acquire the output value at the corresponding location of the output tensor, widely recognized as the map of feature. The tensor proceeds to move using the identical stride value and repeats this sequence until the entirety of the image has been traversed. This process can be visualized in Fig. 12 ([61]). The convolution operation possesses the capability to be executed across many layers of convolutional, thereby effectively fetching high-level parameters to enhance performance. A fundamental characteristic of the convolution operation is its employment of sharing the weight, whereby kernels are distributed around all positions within the image. In cases wherever the kernels do not align flawlessly with the input, one may choose to employ either valid padding or zero padding. Valid padding entails a reduction in dimensionality of the convolved feature in contrast to the intake data, as it excludes the portion wherever the kernel does not suitable. On the other hand, zero padding involves the insertion of zeros in order to accommodate the filter. Prior to training, the magnitude of the kernels (typically 3 × 3), the No.of kernels, padding, & stride value are predetermined. These parameters are subsequently retained for the layer of pooling. The convolution process can be mathematically written as shown in Eq. (2) [61].

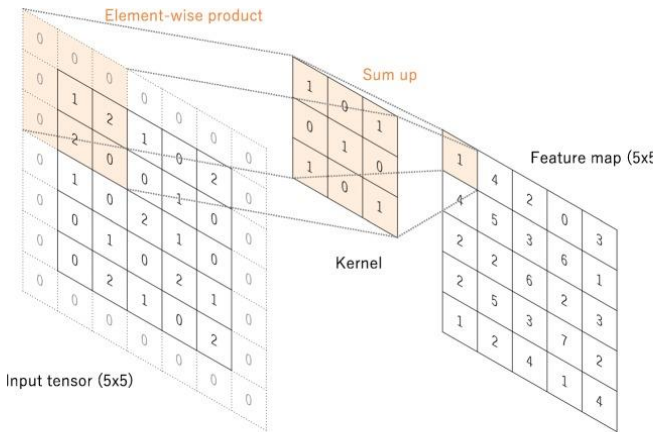

Fig. 12. A demonstration of the convolution process, specifically with a stride of 1, a kernel size of 3-by-3, and without any padding [61].

$$x_j^l = f\left(\sum_{i \in M_j} x_i^{l-1} * k_{ij}^l + b_j^l\right) \qquad (2)$$

In the given context, x_j^l represents the resultant of the present layer, x_i^{l-1} denotes the results of the precedent layer, k_{ij}^l signifies the kernel utilized by the current layer, and b_j^l embodies the biases associated with the present layer. The letter M_j symbolizes the selection of the maps of input. Each output map receives an additional bias. The input maps undergo convolution with unique kernels to produce corresponding output maps. Following this, an activation function is applied to the output maps, which may be linear or non-linear, including options like sigmoid, Softmax, rectified linear unit (ReLU), hyperbolic tangent, or identity functions.

The pooling layer, in essence, executes a sub-sampling procedure on the convolved features (also called as the feature-map) in preparation for the subsequent convolutional layer. This serves the purpose of reducing the computational power required for data processing through dimensionality reduction, while also mitigating the risk of overfitting. Nevertheless, it still retains crucial information. Various pooling operations exist, including average, max, and sum pooling. Among aforementioned techniques, average & max pooling are the most widely utilized techniques [35]. The sub-sampling procedure is mathematically written as Eq. (3).

$$x_j^l = down(x_j^{l-1}) \qquad (3)$$

Fully Connected Layer (FC): The fully connected (FC) layer serves to transform the feature maps attained from either the pooling or convolutional_layers into a flattened form. This process converts 2-dimensional (2D) feature maps into a 1-dimensional (1D) vector. After flattening, this vector is forwarded to a fully connected (FC) layer tasked with classification. A key characteristic of this layer is its ability to connect every input to each output through adjustable weights, which are fine-tuned during the learning process. Subsequent to the fully connected layer, a nonlinear_function is applied. Finally, an activation function, such as sigmoid or softmax, is utilized to classify the input image. [61].

3.1.3. Deep recurrent neural networks

One kind of recurrent neural networks (RNNs) that has at least two hidden layers is the deep recurrent neural network. The word "recurrent" comes from the fact that its current output is reliant on earlier calculations [62]. Unlike neural networks those are feed forward and solely train in the forward direction, RNNs retain information from the previous step to facilitate training. As a result, these methods are insufficient when applied to sequential data that possess interdependencies, such as making forecasts for time series, identifying speech patterns, and recognizing the meaning behind vocal cues. RNNs possess a "memory" element that retains the previous computation, providing contextual information to the current state. Recurrent Neural Networks (RNNs) have the benefit of utilizing shared parameters across all layers, from the input to the hidden layers and finally to the output layer. This feature significantly lowers the complexity of parameters in comparison to other types of artificial neural networks. The optimal method for training an RNN is to use data with inherent dependencies, which helps in retaining information from previous sequences. [40]. However, the advantages associated with the RNN are accompanied by the drawback of the vanishing gradient issue [63]. Consequently, the long short-term memory unit (LSTM) was proposed as an effective solution to address this challenge [64]. Another RNN-based architecture that exists is the gated recurrent unit (GRU), which can be considered a specialized version of LSTM. GRU exhibits comparable performance to LSTM but possesses a higher speed [65]. In the context of this work, we solely present the structure of LSTM as it is the most commonly employed variant of RNN [66]. The depiction of LSTM's architecture can be found in Fig. 13 [40].

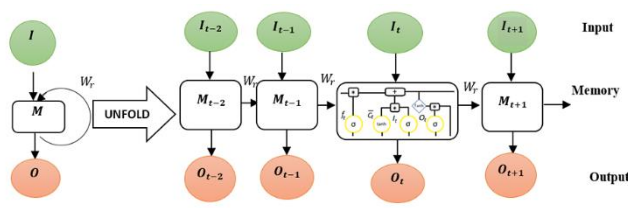

Fig. 13. Illustrates LSTM's Architecture [40].

The Long Short-Term Memory (LSTM) model enhances the capability of Recurrent Neural Networks (RNNs) to maintain information over time, even with delays in the input data. The LSTM framework is structured around three key gates: the input, forget, and output gates. These gates regulate the information transfer from the past state to the current state and between memory cells. The input gate specifically manages when new data is incorporated into the memory cell[67]. The forget gate regulates the duration for which stored information is maintained, thereby creating space for new data. Lastly, the output gate determines when the information stored in the cell is utilized in the output [68]. Figure 13 illustrates the visual representation of the Long Short-Term Memory (LSTM) architecture. The variables M_t, O_t, and I_t denote the memory, output, and current input states of the LSTM cell. Similarly, I_{t-2}, I_{t-1}, O_{t-2}, O_{t-1}, M_{t-1} and M_{t-2} represent the memory, outputs, and input states from previous time steps. On the other hand, O_{t+1} and M_{t+1} correspond to the posterior output and memory state for the posterior time step input I_{t+1}. In the operation of a simplified LSTM cell, the recurrent output, intput, and memory state are represented by the variables O, I, and M, respectively. Additionally, the weight for the computation within the cell is denoted by W_r. The LSTM model's ability to process temporal information has contributed to its popularity and widespread usage [40]. The memory cell ct is updated, while simultaneously generating an output vector ht in accordance with the prescribed equations [69].

$$f_t = s_g(W_{fx_t} + U_f h_{t-1} + b_f) \tag{4}$$

$$i_t = s_g(W_{ix_t} + U_i h_{t-1} + b_i) \tag{5}$$

$$o_t = s_g(W_{ox_t} + U_o h_{t-1} + b_o) \tag{6}$$

$$c_t = \sigma_c(W_{cx_t} + U_c h_{t-1} + b_c) \cdot i_t + f_t \cdot c_{t-1} \tag{7}$$

$$h_t = o_t \cdot \sigma_{h(C_t)} \tag{8}$$

In the context of this study, the variable x_t represents the input vector, whereas f_t, i_t, and o_t represent the activation vectors of the input, forget, and output gates, respectively. The weight matrices of the respective gates are denoted by W. The symbol · is utilized to denote the Hadamard product. The activation function σ_g, σ_c, and σ_h are employed, with σ_g representing the sigmoid function and σ_c and σ_h representing hyperbolic tangent functions, in a typical implementation.

3.1.4. Restricted Boltzmann machines

Boltzmann Machines (BMs) function as bidirectional networks featuring symmetric links between visible units, which are stochastic, and hidden units. Visible units form the foundational layer of the network, symbolizing various components of data, whereas hidden units are designed to discern the connections among these components. Both visible and hidden units undergo updates in their probabilistic states over time, influenced by adjacent units' states, a factor that escalates the computational demands for training Boltzmann Machines. On the other hand, Restricted Boltzmann Machines (RBMs) offer a streamlined variant of generative stochastic artificial neural networks by implementing a more defined network architecture, thus diminishing the complexity of learning parameters. RBMs facilitate undirected interactions between hidden and visible unit pairs while constraining the network's structure to enhance the efficiency of the learning mechanism [70]. Consequently, RBMs represent an evolution of BMs by imposing limitations on the interconnections within layers, notably between hidden and visible units, to simplify and optimize the learning trajectory.

This modification leads to the creation of a bipartite graph structure, which is why it is referred to as an RBM [60].

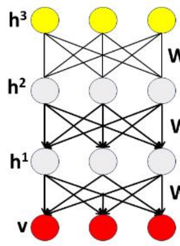

Fig. 14. The architecture of Deep Belief Network.

The Restricted Boltzmann Machine (RBM) possesses the capacity to acquire knowledge regarding the input probability distribution through both supervised and unsupervised approaches. Consequently, it has gained popularity as a framework for Deep Learning [60]. Within the realm of Deep Learning, there exist two primary architectures that incorporate the RBM as a learning module. These architectures are known as Deep Boltzmann Machines (DBM) & Deep Belief Networks (DBN). Both DBN and DBM are classified as members of the "Boltzmann family" [35]. However, this study places particular emphasis on DBN. DBN is a model that combines two distinct types of Artificial Neural Networks (ANN).The input unit of DBNs incorporates RBMs, while the output unit is composed of Deep Feedforward Neural Networks (D-FFNN) [42]. The architecture of the DBN is shown in Fig. 14.

The Deep Belief Network (DBN) exhibits undirected relationship among its top 2 layers and directional links among all prior layers [35] (refer to Fig. 14). The DBN is initialized through the application of a greedy layer-wise training approach for the Restricted Boltzmann Machine (RBM) [35], [39], [40] . The initial proposal and introduction of the DBN was made by Hinton and Salakhutdinov [36], An unsupervised learning algorithm, which functions through a greedy, layer-by-layer approach, enables the Deep Belief Network (DBN) to train hierarchical deep models effectively. This method facilitates the development of a deep hierarchical understanding of the training data. It accomplishes this by establishing a joint distribution between the observed vector x and the hidden layer, as shown in Eq. (9).

$$p(a, H^1, \ldots, H^l) = \left(\prod_{k=0}^{l-2} P(H^k | H^{k+1}) \right) p(H^{l-1}, H^l) \quad (9)$$

where $a = H^0, p(H^k | H^{k+1})$ is a conditional distribution for the visible units at level k conditioned on the hidden units of the RBM at level k+1 and $p(H^{l-1} | H^l)$ is the visible hidden joint distribution in the top level RBM [35].

3.1.5. Autoencoders

An Autoencoder (AE) is an unsupervised deep learning (DL) technique that was primarily introduced by LeCun et al. in 1987 [46]. The main objective of an AE is to decrease the dimensionality of the input information and reconstruct it in the last layer [63]. An AE consists of three layers and can be transformed into a vast AE by incorporating many hidden-layers. The output and input layers possess an equal number of units, which are denoted with identical dimensionality. Conversely, the hidden layers often possess a lesser number of units, leading to a more condensed portrayal of the input data [40], [60]. The architecture of AE is illustrated in Fig. 15 [60]. AE training conforms of two stages: the encoder & the decoder. Back propagation is employed to train the network. During the encoding stage, the inputs undergo a transformation process where they are converted into concealed representations through the utilization of weight metrics derived from the lower half layer. Subsequently, in the decoding stage, the objective of the network is to reconstruct the initial input by employing the metrics derived from the upper half layer. The encoding and decoding stages can be accurately described using mathematical language, as shown in Eq. (10) and (11), respectively.

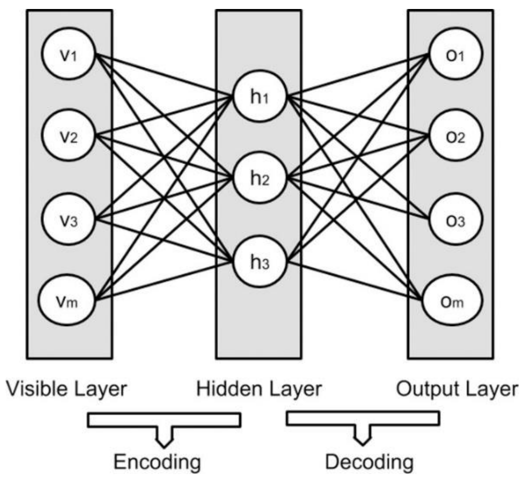

Fig. 15. The architecture of ANN [60].

$$y' = f(wx + b) \quad (10)$$

$$x' = f(w'y' + c) \quad (11)$$

The parameters w & b are subject to adjustment, while f represents the function of activation. The input vector x and the hidden representation y complete the set of variables. Moreover, the transpose of x is referred to as w', while the bias to the output layer is denoted as c. The regenerated input at the output layer is denoted as x'. To update the autoencoder's parameters, the following equations can be utilized:

$$w_{new} = w - \eta \frac{\partial E}{\partial w} \quad (12)$$

$$b_{new} = b - \eta \frac{\partial E}{\partial b} \quad (13)$$

where w_{new} and b_{new} represent the regenerated values for w & b correspondingly at the conclusion of the present iteration, while E denotes the regeneration error of the input at the layer of output [60].

3.1.6. Generative adversarial networks (GAN)

First introduced by Goodfellow et al. in 2014 [71], the Generative Adversarial Network (GAN) is a deep learning topology that uses an unsupervised learning technique. This network conforms of two competing topologies, namely the generative & the discriminator network, engaged in a zero-sum game. The discriminative model aims to determine the likelihood that a specific sample originates from the training data, or the distribution depicted by the generative model. On the other hand, the purpose of the generative model is to grasp and mimic the basic distribution underlying the data. This interaction can be interpreted as a game of min-max between the two algorithms, where the discriminative model aims to accurately recognize adversarial instances generated by the generative model. Until the adversarial instances can no longer be distinguished from the initial ones, both algorithms' performance is consistently improved [60]. A graphic representation of data flow inside the GAN deep network can be found in Fig. 16 [60].

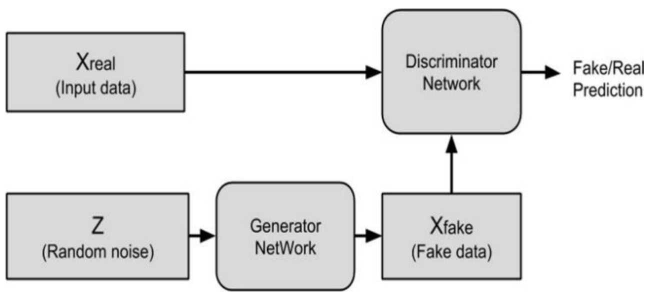

Fig. 16. The architecture of GAN [60].

For a panoramic discussion contrasting RNN & CNN, DBN & DBM, RBM & AE structures, readers are directed to consult the work of Tobore et al [40] as the scope of this present work does not encompass such an extensive analysis.

4. The Electrocardiogram (ECG)

An electrocardiogram, often referred to as an "ECG" or "EKG," is a diagnostic test that measures the electrical activity of the heart. This test helps identify different cardiovascular diseases (CVDs) and offers insightful information on the condition of the heart. With continuous monitoring, The ECG is a cost-effective, non-invasive tool for diagnosing cardiac issues like arrhythmias. Through ECG analysis, crucial information about an individual's heart rate, rhythm, and structure can be obtained [72], [73]. The ECG examination, as a customary procedure, furnishes pertinent information regarding the temporal extent of electrical wave transmission within the cardiac organ. By analyzing time intervals, healthcare professionals are able to ascertain the regularity, velocity, or irregularity of the aforementioned electrical signal as it progresses through the heart. Moreover, the quantification of the intensity of electrical wave propagation across the myocardial tissue aids cardiologists in the detection of potential concerns, including excessive exertion or hypertrophy of specific cardiac areas. Electrocardiography, a technique with a century-long history, holds a well-established position in the management of patients with diagnosed or potential cardiovascular conditions [74]. Research also delves into a range of other biosignals such as Photoplethysmography (PPG), Phonocardiography (PCG), Electroencephalography (EEG), Electrooculography (EOG), Electromyography (EMG), and the monitoring of blood pressure.The Electrocardiogram (ECG) is just one among many biosignals or physiological signals studied.

Other relevant biosignals include EMG, associated with changes in skeletal muscle movements; EEG, for recording brain activity via the scalp; and EOG, monitoring variations in the eye's corneo-retinal potential [75]. Additional measures such as PPG, which assesses organ volume changes over time through light absorption, blood pressure readings, and more, are also of significant interest.

The electrocardiogram (ECG), created in 1895 by Willem Einthoven, emerged as the pioneering diagnostic tool [34]. Its utility extended to encompass medical diagnosis, particularly in relation to cardiovascular diseases (CVDs) [76]. ECG-based biometric systems, utilizing both single and multimodal approaches, have been proposed for the purpose of human validation and authentication, relying on ECG as the physical attribute. Furthermore, scholarly literature has presented ECG-based systems for detecting driver drowsiness and stress levels, aiming to mitigate the occurrence of accidents. The ECG has additionally demonstrated its value in predicting the heart's size and location, locating cardiac wounds, and assessing the efficacy of pharmaceutical interventions [77].

4.1. The morphology of ECG wave

Measurement is conducted in the standard ECG machine of 12-lead by positioning the leads on the body, which serve as the channels for recording. These leads include lead I to III, aVR, aVF, aVL, V1 to V6. Among these leads, lead II is predominantly utilized for assessing the behavior of the five waves due to its distinct signal compared to the others [78], [79]. Typically, these leads are positioned on the chest of the individual, with six electrodes in total. Each electrode records the activity from various angles. The 12-lead resting ECG is widely acknowledged as the most precise tool for capturing cardiac rhythm [80]. However, the system of ECG's framework utilized to fetch signals depends on the specific application [81]. Some procedures require the patient to lie down in a supine position, as is the case with the 12-lead resting ECG, while others require continuous monitoring over several hours or days, like the use of a Holter monitor. ECG measurement techniques have been categorized into on-body, in-body, and no-contact methods. On-body ECG recording involves attaching electrodes directly to the patient's skin to record the heart's electrical activity. In-body measurement involves placing a device inside the patient's body. No-contact methods, on the other hand, allow for ECG recording without direct skin contact, such as through capacitive sensing [82].

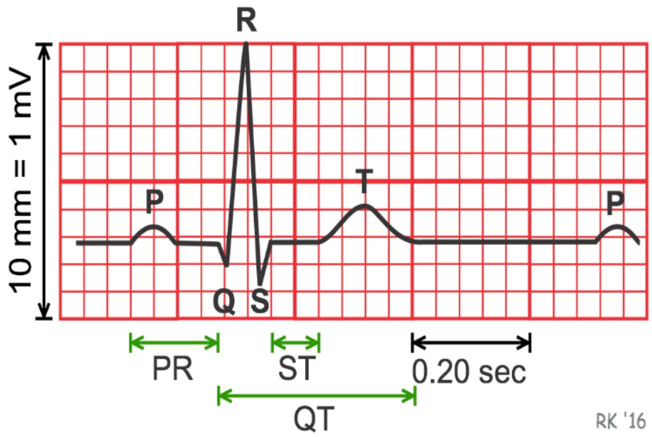

Fig. 17. The ECG Signal[1].

Figure 17 demonstrates the elements of ECG waveforms as recorded by an ECG device. The ECG is composed of five waves, known as the PQRST sequence, which shed light on the heart's electrical functions. These waves play a crucial role in diagnosing heart irregularities. The initiation of the heart's cycle is marked by an electrical

[1] https://cvphysiology.com/arrhythmias/a009

DOI:10.4186/ej.2024.28.8.45

signal from the sinoatrial (SA) node in the heart's right atrium, causing the atria to contract and send blood to the ventricles. The P wave in the ECG indicates the atrial depolarization, illustrating the electrical signal's distribution across the atria. The QRS complex, encompassing the R, Q, and S waves, depicts a single cardiac beat and the ventricular depolarization that occurs in sync with atrial contraction, facilitating the movement of blood into the ventricles, then their subsequent relaxation. The electrical impulse then progresses from the SA node to the atrioventricular (AV) node, serving as the electrical link from the atria to the ventricles, leading to ventricular contraction. Finally, the T wave represents the ventricular repolarization, signaling the end of electrical activity and the ventricles returning to a relaxed state. [69].

4.2. ECG Waveforms Measuring and Diagnoses

The analysis of the standard electrocardiogram (ECG) waveform necessitates the examination of the time intervals separating different waves. More precisely, the ECG waveform incorporates the P-Q-R-S-T intervals, with the P wave occurring before and finishing prior to the QRS complex, lasting anywhere from 0.06sec to 0.12sec. The PR time span extends from 0.12sec to 0.20sec. An elongated time span of PR may serve as an indicator of cardiac blockage. Subsequently, the QRS complex ensues the PR time span, lasting from 0.06sec to 0.10sec. The ST part persists from the S wave until the onset of the T wave. The duration of the QT time span typically ranges from 0.36sec to 0.44sec [83]. Extended intervals might signal the presence of specific cardiac disorders, like arrhythmias. According to the American Heart Association, arrhythmias are deviations from the regular pattern of heart's electrical impulses. This can manifest as bradycardia, where the heart beats more slowly than normal, covering conditions like supraventricular tachycardia, atrial tachycardia including fibrillation and flutter, and ventricular tachycardia. On the flip side, tachycardia, or an accelerated heart rate, might include AV heart blocks, bundle branch blocks, and tachybrady syndrome. Additional manifestations of arrhythmia include irregular contractions of the upper cardiac chamber called atrial fibrillation, abnormal heart rhythms known as conduction disorders, and premature heart contractions, among others. Other accompanying symptoms may include syncope, vertigo, debility, and typically anginal pain. In some cases, individuals may remain asymptomatic [80], [84].

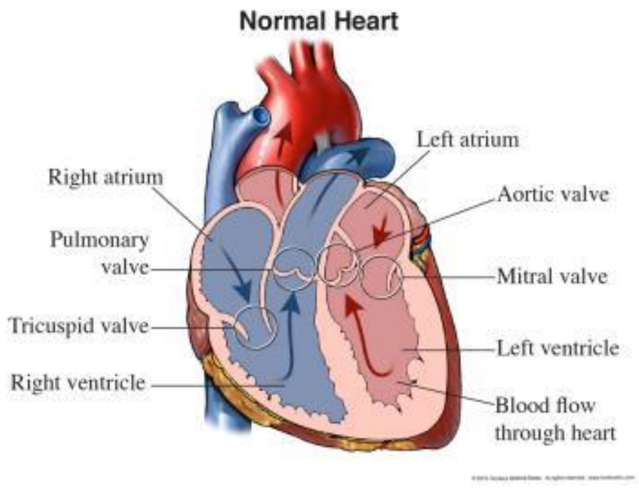

Fig. 18. Normal Human Heart Structure[2].

However, the process of manually inspecting ECG strips for diagnostic intentions is a laborious undertaking that heavily depends on the proficiency of the Physiologist or Cardiologist. Moreover, it is susceptible to human mistake caused by fatigue [72] Fig. 18 got from[3] . However, the implementation of Deep Learning techniques has demonstrated promising outcomes in automatically fetching the intricate attributes of the ECG raw information and conducting analysis [85]. This advancement significantly increase the fertility of Cardiologists by facilitating prompt and accurate decision-making. Other diagnostic methods employed in the detection of heart conditions and infections contain chest X-rays. These images of chest X-ray have proven to be effective in identifying the emergence of respiratory infectious diseases, such as the coronavirus 2019 (COVID-19), by utilizing Deep Learning techniques [86]. Although COVID-19 is primarily classified as a lung-related illness, a research has proved that 20% patients with COVID-19 exhibit indications of cardiac issue [87].

5. Discussion and Findings

The domain of Deep Learning (DL) has emerged as an active and crucial field, particularly in the context of medical and healthcare applications, where its utilization aims to enhance the quality of diagnoses. Within this domain, healthcare personnel play a pivotal role in the identification of diseases and the determination of the most suitable treatment methods. However, this responsibility comes with a set of challenges and obligations that healthcare practitioners have to face over an extended period of time. Furthermore, medical doctors are professionals who rely on symptoms and test results to make intelligent decisions. Nevertheless, the attainment of sound judgments necessitates a certain level of knowledge [88]. The electrocardiogram (ECG) is an

[2] https://www.nhlbi.nih.gov/health/heart/anatomy

essential tool used in the detection and evaluation of cardiovascular diseases (CVDs). Its utilization aids medical professionals and cardiologists in making more informed judgments. Presently, deep learning (DL) techniques are being applied to analyze physiological waves, enabling the discovery of hidden links. This assists healthcare providers and medical practitioners in making timely and knowledgeable decisions, as well as predicting a wide range of clinical events [89].

A suggestion was put forward to apply a deep densely connected neural network (DDNN) model for detecting Atrial Fibrillation (AF) [90]. Leveraging data from three sources: the Chinese PLA General Hospital, the China Physiological Signal Challenge 2018, and CardioCloud Medical Technology, the research demonstrated exceptional outcomes in accuracy, specificity, and sensitivity across 11,994 participants. In a separate study, a deep neural network (DNN) model was employed for the Prenatal Detection of Congenital Heart Disease (CHD), achieving a 76% accuracy rate using a private dataset of fetal ECG readings from both normal and CHD-affected groups [91]. To improve results, increasing the sample size or dataset might be considered necessary.

A CNN technique was proposed by Acharya and Fujita et al [34] to accurately detect arrhythmias. In this study, two CNN architectures, namely Net A & Net B, were introduced, each utilizing different input samples. The evaluation of the CNN models focused on specificity, accuracy, and sensitivity. Notably, Net B achieved an accuracy of 81.44% when utilizing specific databases. The DL architectures demonstrated favorable performance when applied to ECG segments of varying durations. However, it was observed that there existed limited data and required lengthy training time. To address the issue of limited data, data augmentation and the bagging algorithm were suggested as potential solutions. Additionally, Acharya et al [92] proposed another study involving a CNN architecture designed for the classification of life-threatening ventricular arrhythmias. This architecture successfully distinguished between shockable & non-shockable ventricular arrhythmias through the utilization of 2-sec ECG portions. Immediate treatment options for shockable arrhythmias include CPR and defibrillation. Accurate diagnosis of these arrhythmias is critical for improving the efficiency of automated external defibrillators. The CNN algorithm secure 93.18% accuracy using specific databases, but limited data and training time posed challenges. In another study by [93], a CNN model was proposed to classify heartbeats with high accuracy.

The model demonstrated a 94.03% accuracy rate using the MITDB dataset . [94]. A study introduced a 2D-CNN algorithm specifically designed for arrhythmia detection, transforming ECG signals into 2D images and achieving a notable accuracy of 96.69% on the MITDB dataset. CNN models, after being thoroughly trained on extensive datasets [95]., can be adapted for various applications with little to no adjustments, whether using the original dataset or different data types. Known as pre-trained or transfer learning models, these are advantageous in scenarios of data scarcity or when computational resources for training are limited. Alquran et al . [96]. used two such models, AlexNet and GoogleNet, for ECG signal classification, applying Higher Order Spectral estimation to extract features from ECG signals before classification. Using the MITDB dataset, the combination of third cumulants with GoogleNet achieved a 97.8% classification accuracy. In another study, Mohamad et al. leveraged the pre-trained VGG-Net [97]. CNN model for effective ECG signal classification, showing promising results in identifying supraventricular ectopic beats (SVEB) and ventricular ectopic beats (VEB). Additionally, Amrani et al. utilized a deep CNN for feature extraction, employing a fusion technique named multi-canonical correlation analysis (MCCA) for feature collection, which were then classified using a Q-Gaussian multi-class SVM (QG-MSVM) [78].

Cai et al [98]. introduced a deep densely neural network (DDNN)-based algorithm in their research to detect Atrial Fibrillation (AF), focusing specifically on the AF category due to the scarcity of data in other classes. The model demonstrated remarkable performance, achieving specificity, accuracy, and sensitivity rates all exceeding 99%. This research analyzed data from three different sources, including 11,994 unique patients from the China Physiological Signal Challenge 2018, the Chinese PLA General Hospital, and wearable ECG devices by CardioCloud Medical Technology Co. Ltd. in Beijing. In another study, Vullings utilized a Deep Neural Network (DNN) to develop an approach for the prenatal identification of congenital heart disease (CHD) [91]. This study used a proprietary dataset containing fetal ECG readings from 266 healthy individuals and 120 patients with CHD, achieving an accuracy rate of 76%. The findings suggest that the model's performance could be enhanced with a larger dataset or population.

Acharya et al. [93] introduced a convolutional neural network (CNN) approach for detecting arrhythmias. The research proposed two distinct CNN architectures, labeled as Net B and Net A, with input sizes of 500 and 1250 samples, respectively. Apart from Net B, which achieved an accuracy rate of 81.44% utilizing the MIT-BIH Atrial Fibrillation Database (AFDB), the Creighton University Ventricular Tachyarrhythmia Database (CUDB), and the MIT-BIH Arrhythmia Database (MITDB), all other CNN models surpassed 90% in specificity, accuracy, and sensitivity. These deep learning frameworks demonstrated notable effectiveness with 2-second and 5-second segments of electrocardiogram (ECG) recordings. However, the study encountered limited information availability for training, consequently leading to excessive training time. To address this issue, data augmentation and bagging algorithms were suggested as potential solutions. Furthermore, utilising 2s ECG sections and a CNN construction, which Acharya et al. [92] presented the categorization of shockable and non-shockable life-threatening ventricular arrhythmias. Defibrillation & Cardiopulmonary resuscitation (CPR) are

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often used and strongly advised for the timely treatment of shockable ventricular arrhythmias. Nevertheless, precise detection of both shockable & non-shockable ventricular arrhythmias is essential to improving the efficacy of automated external defibrillators (AEDs) for defibrillation. When the CNN model was assessed using VFDB, MITDB, and CUDB, its accuracy was found to be 93.18%. But issues that affected the model's effectiveness included the scarcity of data and the length of the training period. Another work by Acharya et al.[93] offered a CNN algorithm for heartbeat classification, which used the MITDB and produced an accuracy of 94.03% (Set B). Additionally, a research by Al-Huseiny et al. [94] introduced a 2D-CNN model for arrhythmia identification. Initially, the ECG signals were converted into two-dimensional ECG pictures, which were then used as training model inputs. On the MITDB a database, the algorithm's performance was 96.69%.

Algorithms based on Convolutional Neural Networks (CNNs) that have been trained on large-scale datasets can be redeployed with little to no adjustments, whether they are applied to the same type of data they were originally trained on or to different datasets. These are often referred to as pre-trained models or, within the context of transfer learning, as models ready for application across various tasks [95]. Such models are particularly valuable in scenarios where data or computational resources are scarce for training on new datasets [77]. In one study, pre-trained CNNs, specifically GoogleNet and AlexNet, were employed to classify electrocardiogram signals after applying higher-order spectral analysis for feature extraction [96]. This approach, using pre-trained GoogleNet combined with third cumulants on the MITDB, achieved an accuracy of 97.8% [97]. Another study introduced the use of a pre-trained VGG-Net for direct ECG signal classification, demonstrating effective detection of supraventricular and ventricular ectopic beats using the MITDB [78]. A sophisticated CNN model using a multi-canonical correlation analysis (MCCA) as a feature extraction method was proposed, with Q-Gaussian multi-class SVM (QG-MSVM) for feature classification, achieving an accuracy of 97.37% in arrhythmia detection. This indicates the fusion method's superiority over other evaluated techniques, albeit with potentially longer training times. Additionally, a study utilizing a pre-trained CNN, ResNet, optimized with adaptive moment estimation (Adam) and stochastic gradient descent (SGD), showed SGD achieving higher accuracy, at 96% compared to Adam's 83% [99]., underscoring the effectiveness of pre-trained CNNs in medical signal analysis.

However, more research is necessary to solve the data imbalance problem and enhance performance. [100] suggested using a convolutional block to enhance the performance of the three-layer baseline CNN (network A), which is a multiscale fusion CNN. Using the MITDB, the suggested model (Network B) performed on average 96.53%, 95.48%, and 87.75% for sensitivity, accuracy, and specificity, respectively. For the categorization of ECG readings, [101] proposed a model combining Extreme Learning Machine (ELM) & CNN . Even with the Physikalisch-Technische Bundesanstalt Diagnostic database (PTBDB), the performance accuracy was still higher than with more conventional models like K-NN, Decision Trees, and SVM, even if it was less than 90% (8 Algorithms based on Convolutional Neural Networks (CNNs) that have been trained on large-scale datasets can be redeployed with little to no adjustments, whether they are applied to the same type of data they were originally trained on or to different datasets. These are often referred to as pre-trained models or, within the context of transfer learning, as models ready for application across various tasks. Such models are particularly valuable in scenarios where data or computational resources are scarce for training on new datasets. In one study, pre-trained CNNs, specifically GoogleNet and AlexNet, were employed to classify electrocardiogram signals after applying higher-order spectral analysis for feature extraction. This approach, using pre-trained GoogleNet combined with third cumulants on the MITDB, achieved an accuracy of 97.8%. Another study introduced the use of a pre-trained VGG-Net for direct ECG signal classification, demonstrating effective detection of supraventricular and ventricular ectopic beats using the MITDB. A sophisticated CNN model using a multi-canonical correlation analysis (MCCA) as a feature extraction method was proposed, with Q-Gaussian multi-class SVM (QG-MSVM) for feature classification, achieving an accuracy of 97.37% in arrhythmia detection. This indicates the fusion method's superiority over other evaluated techniques, albeit with potentially longer training times. Additionally, a study utilizing a pre-trained CNN, ResNet, optimized with adaptive moment estimation (Adam) and stochastic gradient descent (SGD), showed SGD achieving higher accuracy, at 96% compared to Adam's 83%, underscoring the effectiveness of pre-trained CNNs in medical signal analysis.8.33%). A research study introduced by Dokur and Colleagues [102] introduced an algorithm for classifying heartbeats relied on Convolutional Neural Networks (CNN). However, they excluded the Fully Connected Neural Network (FCNN) component from the base level CNN model. In order to maintain performance during training, they applied Walsh functions. Additionally, they looked at the restrictions associated with translating one-dimensional (1D) ECG impulses into two-dimensional (2D) pictures. The MITDB dataset was used to evaluate this method, and the average accuracy for 1D ECG signals & 2D ECG pictures was 99.45% & 98.7%, respectively. Fujita and Cimr [103] presented a CNN-based application for ECG rhythm recognition in another study. In order to automatically classify the ECG rhythms within the CNN framework, the model used Continuous Wavelet Transformation (CWT) to extract attributes. The accuracy attained was 97.78%.

However, it is important to note that prior information of attributes is necessary for training the model. Hao et al. [104] put forth a multi-channel CNN model for classifying ECG beats. In this study, single-beat & beat-to-beat information were utilized. Initially, ECG signals were converted into spectro-temporal pictures using wavelet transform & Short-Time Fourier Transform (STFT). These images were then utilized for model training. The model's positive predictive value (PPV) & sensitivity for detection were equivalent. In a similar vein, Huang et al. [105] suggested a 2D-CNN model for STFT-transformed ECG picture training. Employing the ID-CNN technique, the model attained an efficiency of 99.00% for the ECG classification assignment when it was tested on the MITDB dataset.

Isin and Ozdalili's [106] investigation was centred on the identification of cardiac arrhythmias. They used the AlexNet, a CNN model that has already been trained, as an attribute extractor in their study. The back-propagation approach was used for training the model, and the MITDB dataset yielded an amazing identification rate of 98.51%. Izci et al. [107] presented a 2D-CNN model for the problem of recognising arrhythmia in a different investigation. On the MITDB dataset, they obtained a performance accuracy of 97.42\%. A deep residual CNN model was presented by Kachuee et al. [108] for the categorization of arrhythmias, particularly for the prediction of myocardial infarction (MI). Using the PTBDB dataset, the model showed a 93.4% accuracy in classification for arrhythmias and a 95.9% accuracy in predicting for MI. A CNN model for ECG classification was introduced by Kaouter et al. [109]. Their model was tested against CNN complete training, Google Net-144 layers, Res Net-50, VGG Net-16, and an ensemble of optimised CNNs. Utilising ECG signals tested on the MITBIH normal sinus rhythm database (NSRDB), MITDB, and Beth Israel Deaconess Medical Centre (BIDMC) congestive heart failure database, the study indicated that the CNN model achieved the greatest performance accuracy of 93.75%. However, it is advised to incorporate additional patient factors in addition to the ECG signals in order to improve the diagnostic value of the suggested model.

Additionally, a research conducted by Li et al. [110] explored the classification of ECG using a 1D-CNN. The accuracy achieved by the model was 97.5% as evaluated using the MITDB dataset. To further enhance detection capabilities, it may be worthwhile to investigate additional ECG leads. A further contribution made by Li et al. [111] concerned the suggestion of an already trained algorithm for ECG classification, namely ResNet-31. Both single and 2-lead Electrocardiogram data sets were used to evaluate this model. The findings demonstrated that, with an efficacy of 99.38%, the 2-lead data outperformed the single-lead data, which had an efficiency of 99.06%. It is noteworthy, therefore, that the 2-leads ECG dataset required more time for the training procedure to converge than the single ECG dataset. Pandey and Janghel [112] presented a CNN-based model for identify arrhythmia in a different investigation. The Synthetic Minority Oversampling Technique (SMOTE) was utilised to rectify the imbalance present in the MITDB dataset. With a precision of 86.06%, accuracy of 98%, recall of 95.51%, and F1-score of 89.57%, the model performed admirably. A CNN model was presented by Rajkumar et al. [113] to perform the job of classifying arrhythmias. The MITDB dataset yielded an accuracy of 93.6% for this model. ResNet is a residue framework that was introduced in a recent research by Ribeiro et al. [74] for the efficient diagnosis of ECG. A private dataset of 2,322,512 ECG recordings from 1,676,383 distinct patients was used by the authors. The model was able to attain a specificity of higher than 99% and an F1-score above 80% by utilising a conventional 12-lead ECG with a short duration. The application of deep CNN and two-stage deep CNN for classifying electrocardiograms was first presented by Shaker et al.[114]. Additionally, they showed how well GANs work for heartbeat augmentation, outperforming imbalanced data in the process. Above 90.0% precision, 98.0% overall accuracy, over 97.4% specificity, and more than 97.7% sensitivity were all attained by the models. Nonetheless, pulse quality may be increased by using post-processing methods like smoothing filters, and accuracy findings can be enhanced by removing outliers. A CNN model suggested by Xu and Liu [6] demonstrated great performance, achieving an average accuracy of 99.43% for both VEB and SVEB beats when tested on the MITDB dataset. Yao and Chen (2018) introduced a Multi-Scale CNN (MCNN) which surpassed methods utilizing hand-crafted features in terms of overall accuracy, achieving 88.66% for SVEB and VEB beats. It is worth considering the utilization of landmark information to further enhance the model's performance.

In Yıldırım et al.'s study [66], a one-dimensional convolutional neural network (1D-CNN) was used to identify arrhythmias. The model classified electrocardiogram (ECG) recordings using the MITDB dataset and achieved 83.91% sensitivity, 91.33% accuracy, and 99.41% specificity. In a different study, a CNN algorithm was presented by [115] for classifying ECG, and it showed 98.37% sensitivity, 98.92% accuracy, and 99.19% specificity on the MITDB set of data. In Zhou and Tan's study [116], the CNN-based structure was utilised for extraction of features. The authors then included the extreme learning machine (ELM) for ECG signal classification, achieving 98.77% on the MITDB dataset. In a research, Li et al. [24] presented a novel method for feeding into an CNN framework for ECG categorization by combining rhythm and the morphology of heartbeats. The one-dimensional ECG data were converted into two-dimensional pictures by the authors using the one-hot encoding approach, which increased both the convergence speed and accuracy. The MITDB dataset was utilised to evaluate the efficacy of the model, and it yielded accuracy rates of above 90% for both the VEB & SVEB classes. It is important to note, nevertheless, that because V beat used raw ECG data without representation extraction, its accuracy & specificity were significantly lower than those of the other approaches under consideration. Takalo-Mattila et al. [117] proposed a 1D-CNN model for the classification of ECG signals, which was evaluated on the MITDB dataset and exhibited a competitive performance for the Normal, SVEB, & SVEB classes.

Models based on Convolutional Neural Networks (CNN) have been utilized for the automated classification of cardiovascular diseases, such as anterior myocardial infarction (AMI), myocardial infarction disease (MID), atrial fibrillation (AF), and congestive heart failure (CHF). MID, commonly referred to as a heart attack, is caused by a dysfunction in the myocardium that reduces blood flow [89].. Acharya et al , [93]. developed a CNN model for the automated detection of myocardial infarction. The research highlighted the impact of noise by processing the first set of electrocardiogram (ECG) data to eliminate baseline wander and leaving the second set with noise. The findings from the noisy dataset demonstrated efficiencies with sensitivity, accuracy, and specificity rates of 93.71%, 93.53%, and 92.83%, respectively. In contrast, when evaluated on the PTBDB, the dataset without noise showed improved performance, achieving a sensitivity of 95.49%, accuracy of 95.22%, and specificity of 94.19%. In another study, Acharya et al [118]. proposed a CNN model specifically for diagnosing CHF, showcasing the versatility of CNNs in medical diagnostics.

The datasets were combined into sets A, B, C, and D in order to evaluate the framework. BIDMC & NSRDB were in Set A; BIDMC & Fantasia were in Set B; BIDMC & NSRDB were in Set C; and BIDMC & Fantasia were in Set D. In all three instances, the CNN model's sensitivity, accuracy, and specificity scores were more than 90%. In a research by Ahmed et al. [119], MID was predicted using a model based on CNN, which the authors optimised using Ant Colony Optimisation (CNN-ACO). 95.78% accuracy was achieved on the UCI-ML Dataset. However, because of the added ACO, the CNN-ACO model used an enormous amount of storage when compared to the standard CNN design. Alghamdi et al. [22] suggested using an already trained deep CNN (VGG-Net) for automated MI identification. Two variants of VGG-Net, VGG-MI2 and VGG-MI1, were introduced, where VGG-Net served either as a static feature extractor or underwent fine-tuning. VGG-MI2 functioned as a feature extraction tool, utilizing QG-MSVM for classification, whereas VGG-MI1 employed the VGG-Net model with minimal fine-tuning adjustments. This approach led to a 2% increase in accuracy, with VGG-MI2 achieving the highest accuracy rate of 99.22% on the PTBDB. In their study on MI classification, Baloglu et al . [120]. employed a deep CNN method, achieving an accuracy of 99.78% on the PTBDB. However, this model fell short in pinpointing the exact locations of the MIs.

Chen et al [121]. proposed the Multi-Channel Lightweight CNN (MCL-CNN), which demonstrated a 96.18% accuracy rate in identifying Anterior MI (AMI) on the PTBDB database. In a study focused on AF detection, the use of pre-trained CNN models (VGG-16, AlexNet, ResNet-152, and AlexNet-scratch) as feature extractors and SVM & MLP for classification was explored , [95]. The MLP+AlexNet combination yielded the most impressive outcomes, achieving a sensitivity of 81.1% (85.7%), an accuracy of 87.6% (87.9%), and a specificity of 94.3% (92.7%), with values for more challenging classes provided in parentheses. During the 2017 PhysioNet/Computing in Cardiology (CinC) Challenge, the performance of the model was evaluated. In this challenge, Hsieh et al [122]. demonstrated a 90.7% accuracy rate using their proposed 1D-CNN model for detecting atrial fibrillation (AF). By employing a 2D-CNN trained on the Normal Sinus Rhythm Database (NSRDB) and the Atrial Fibrillation Database (AFDB), Huang and Wu recommended a method for classifying ECG data into normal sinus rhythm and AF categories. Their approach achieved a sensitivity of 99.71%, an accuracy of 99.23%, and a specificity of 98.66%, showing that the first experiment, which involved filtered ECG signals, surpassed the second one, which used unfiltered signals, in terms of performance metrics. Additionally, Kamaleswaran et al [123]. proposed a deep CNN architecture for the task of AF detection, further contributing to the research in this field. In the PhysioNet/CinC Challenge 2017, the developed algorithm reached an F1-score of 0.83 and an accuracy rate of 85.99%. Employing a Multi-Layer Perceptron (MLP) for classification and a Convolutional Neural Network (CNN) for feature extraction, Li et al [24]. managed to attain a sensitivity of 93.14%, an accuracy of 83.5%, and a specificity of 95.99%. This outcome was based on data gathered from 14 atrial fibrillation (AF) patients using the 128-Leads Body Surface Potential Mapping (BSPM) System at West China Hospital, owing to the lack of a publicly accessible database containing detailed postoperative patient information for AF at that time. Furthermore, Li et al [111]. combined CNN with Support Vector Machine (SVM) for the classification of AF, where the SVM was fed features extracted by the CNN model to categorize the ECG signals. Despite the small size of the dataset used, this model achieved a sensitivity of 88%, an accuracy of 96%, and a specificity of 96%.

Pourbabaee and colleagues [44] proposed integrating CNN with conventional classifiers (MLP, KNN, & SVM) for evaluating paroxysmal atrial fibrillation (PAF). The most effective model pairing (KNN + CNN) achieved the highest performance on the PAF prediction challenge database. In a separate study, Xia and co-authors [17]. recommended a CNN-based approach for the end-to-end classification of AF, where ECG segments transformed by stationary wavelet transform (SWT) and short-time Fourier transform (STFT) were inputted into the model. The models showcased strong performance metrics, with the STFT-CNN model achieving a specificity of 98.24%, a sensitivity of 98.34%, and an overall accuracy of 98.29% when evaluated on the AFDB database. In comparison, the SWT-CNN model reported specificity at 97.87%, sensitivity at 98.79%, and accuracy at 98.63%. Xiong et al. [20] investigated atrial fibrillation detection using a CNN model, comparing its performance against spectrogram learning and RNN methods. The CNN model outperformed the other algorithms, showing an overall accuracy improvement of 82%. However, challenges such as imbalanced ECG data and variations in signal length affected the model's performance.

The literature presents several instances where models based on recurrent neural networks (RNN) have been employed for analyzing electrocardiogram (ECG) signals. Banerjee and colleagues [124] introduced an RNN model that utilizes a dual LSTM network configuration, enhancing it with manually selected ECG wave features to accurately identify atrial fibrillation (AF). This model exhibited impressive results, achieving a specificity of 0.98, a sensitivity of 0.93, and an F1-score of 0.89, highlighting the advantage of incorporating handcrafted features. In another study by Darmawahyuni and Nurmaini [125], the use of an LSTM model for the classification of myocardial infarction (MI) showcased its potential in accurately distinguishing between binary classes. This model achieved notable performance metrics, including a sensitivity and precision both at 0.91, a Balanced Accuracy (BAcc) of 0.83, and an F1 score of 0.90, through the application of PTBDB. In a separate study, Darmawahyuni and colleagues [126] introduced models based on LSTM, RNN, and GRN for myocardial infarction classification. Among these, the LSTM model stood out, delivering the highest performance with a specificity of 97.97%, sensitivity of 98.49%, an F1 score of 96.32%, precision of 95.67%, a Matthews Correlation Coefficient (MCC) of 95.32%, and a Balanced Accuracy (BACC) of 97.56%, utilizing PTBDB.

The Faust et al, [88] study introduced the utilization of a bi-LSTM for the identification of atrial fibrillation (AF). The results of their model demonstrated high levels of specificity, accuracy, & sensitivity, surpassing 98% in both blind & cross validation. In a separate study, Sujadevi et al, [127] proposed the use of LSTM, RNN, & GRU models for AF identification. These frameworks achieved accuracies of 1.000, 0.950, & 1.000, respectively, without the need for any preprocessing methods. To conduct their research, the NSRDB & AFDB datasets from MIT-BIH Physionet were utilized. Another study by Chang et al, [128] put forth an LSTM model for the classification & detection of cardiac arrhythmias. A comparative study involving emergency physicians, cardiologists, and internal medicine specialists revealed that the model performed competitively. It reached an accuracy of 90% by analyzing ECG signals gathered from the China Medical University Hospital (CMUH) using a GE Marquette MAC 5500 device. However, it failed to detect the ST-T shift, crucial for diagnosing acute myocardial infarction. Pandey and Janghel proposed the identification of arrhythmia [129]. The LSTM was trained with statistical, morphological, R-R interval, & wavelet characteristics as inputs for classifying. On the MITDB dataset, the model yielded 99.37% accuracy, 96.73% precision, 95.77% F-score, 99.14% specificity, & 94.89% sensitivity. However, the model was dependent on handmade elements. An LSTM model was suggested by Sharma et al. [130] for the categorization of arrhythmias. The RR-intervals were expanded using Fourier-Bessel extension to create intelligent sequence, which were then input into the LSTM model for classifications. On the MITDB and an exclusive dataset, the model's accuracy was 90.07% & 89.04%, respectively.

An LSTM model was suggested by Saadatnejad et al [131] for the categorization of ECG in their study. Wavelet & RR characteristics were used to train the algorithm. Using the MITDB dataset, the LSTM model's performance was evaluated, and it obtained accuracy values of 98.3% & 99.2% for SVEB and VEB, respectively. In Singh et al.'s work [85], RNN-based models (GRU, RNN, & LSTM) were examined. The accuracy achieved when tested on the MITDB dataset was 82.5% (GRU), 85.4% (RNN), & 88.1% (LSTM). However, it should be noted that hand-crafted features were utilized and the efficacy of these features for new diseases remains uncertain. A deep bidirectional LSTM-based algorithm was presented for classifying electrocardiograms in a paper by Yildirim [66]. With the use of wavelet sequences (WS), this model's wavelet-based layer improved classification performance. The best performance was achieved by the proposed DBLSTM-WS with a WS layer of 3, achieving an accuracy of 99.399% on the MITDB dataset. However, due to limited hardware, not every data-sets from the MITDB were utilized. In another study, Cheng et al. [128] conducted research on OSA detection using an LSTM model. Using 70 ECG recordings from the Apnea-ECG database, the model was evaluated and its accuracy was 97.799%.

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Table 5. Findings from different articles.

REF	MODEL	DATASET	ACC%	F1%	SEN%	PPR%	SPE%
[98]	DDNN	Dataset from the China Physiological Signal (CPS) Challenge 2018, Chinese PLA General Hospital, (11,995 unique subject)	99.34	90	99	/	99.44
[91]	DNN	Private dataset with fetal ECG measurements performed at six different medical centres in the (266 from the healthy group and 120 from the CHD group)	76	/	/	/	/
[92]	CNN	MITDB, CUDB, VFDB (105 subjects)	93.18	/	95.32	/	91.04
[94]	2D-CNN	MITDB (54 subjects)	96.67	86.62	84.53	/	99.28
[96]	CNN Architectures (GoogleNet)	AlexNet)	MITDB (48 subjects)	97.8	/	/	/
[97]	Pre-trained CNN (VGGNet)	INCART, MITDB, SVDB (201 records)	99.9	/	99.7	99.3	100
[78]	deep CNN	QG-MSVM+MCCA Fusion, deep CNN without Fusion QG-SVM	MITDB, AFDB, SVDB (111,901 ECG segments)	94.74	97.37	/	/
[99]	ResNet	MITDB (48 records)	96(SGD)	83(ADAM)	90	/	/
[100]	Multi-scale fusion CNN	MITDB (47 subjects)	92.81(A), 95.48(B)	/	95.84(A), 96.53(B)	/	93.92(A), 87.74(B)
[101]	ELM+CNN	PTBDB (294 subjects)	83.33	/	89.47	/	87.8
[102]	CNN without FCNN	MITDB (47 subjects)	99.45(1D)	98.7(2D)	/	/	/
[103]	CNN+CWT	AFDB, VFDB \	MITDB (25,459 segments)	97.78	/	99.76	/
[104]	Multi-channel dense CNNs + WT \	STFT	Biofourmis for training (more than 10,000 ECG records), MITDB for testing (44 subjects)	/	/	N(97.0) L(98.9) R(91.4) V(95.0) S(90.4)	N(97.7) L(92.2) R(90.2) V(94.5) S(91.5)
[105]	2D-CNN+STFT	MITDB(47 records)	99	/	/	/	/
[106]	BPNNs+AlexNet	MITDB (23 subjects)	92	/	/	/	/
[107]	2D-CNN	MITDB(47 records)	97.42	/	/	/	/
[108]	Deep residual CNN	MITDB (47 records), PTBDB (290 records)	93.4	/	/	/	/
[109]	CNN	MITDB (47 records), NSRDB (18 records), BIDMC congestive heart failure database (15 records)	93.75	/	/	/	/
[110]	ID-CNN	MITDB (48 subjects)	97.5	/	/	/	/

REF	MODEL	DATASET	ACC%	F1%	SEN%	PPR%	SPE%
[111]	ResNet-31	MITDB(47 records)	99.06	/	93.21	96.76	/
[112]	SMOTE+CNN	MITDB(47 records)	98.3	89.87	/	/	86.06
[132]	ID-CNN	PhysioNet\	CinC Challenge 2017	86	/	/	/
[113]	CNN	MITDB(47 records)	93.6	/	/	/	/
[74]	ResNet	Private dataset having 2,322,513 ECG subjects from 1,676,384 different patients of 811 counties in the state of Minas Gerais/ Brazil from the TNMG	/	80	/	/	99
[114]	Twostage deep-CNN	Deep-CNN	MITDB (48 subjects)	98	/	97.7	/
[6]	CNN	MITDB(48 records)	99.43	/	99.2	99.4	/
[133]	MCNN	MITDB (48 subjects), private dataset HEDB (22 subjects)	96(SVEB)	92.50(VEB)	/	/	/
[66]	1D-CNN	MITDB(45 records)	91.33	85.38	83.91	/	99.41
[116]	ELM+CNN	MITDB(47 records)	98.77	/	/	/	/
[24]	2D-CNN	MITDB(47 records)	98.2(VEB)	99.5(SVEB)	/	99.3(VEB) \	99.4(SVEB)
[117]	1D-CNN	MITDB(47 records)	/	/	89(VEB)	62(SVEB)	51(VEB)
[93]	CNN	PTBDB (200 records)	93.53(with noise)	95.22(with out noise)	/	93.71(with noise)	95.49(with out noise)
[118]	CNN	BIDMC Congestive Heart Failure Database, Fantasia Database, NSRDB (73 records)	(NSRDB, BIDMC): 95.98	(Fantasia, BIDMC): 98.97	(NSRDB, BIDMC): 94.40	(Fantasia, BIDMC): 98.33	/
[119]	CNN-ACO	UCI-ML Repository (43,401 people's records)	95.78	/	/	/	/
[22]	Pre-trained CNN (VGG-Net = VGG-MI2	VGGMI1) + VGGNet/QG-MSVM, Alex Net	PTBDB (290 records)	VGG-MI2: 99.22	VGG-MI1: 97.24	/	VGG-MI2: 99.15
[120]	Deep CNN	PTBDB (200 records)	99.78	/	99.8	/	/
[95]	AlexNet, ResNet-152 1D-CNN, VGG-16,	SVM, Alexnetscratch + MLP	PhysioNet/ CinC Challenge 2017 (40,882 dataset)	87.9	86.4	/	/
[122]	ID-CNN	PhysioNet/CinC Challenge 2017 (8528 ECG records)	79.1(AF), 90.7(Normal), 65.3(Noisy), 76(other)	78.2	/	/	/
[134]	2D-CNN	AFDB, NSRDB (41 records)	99.23(EXP1)	99.23(EXP 2)	/	99.71(EXP 1)	99.31(EXP 2)
[123]	Deep CNNs	PhysioNet/CinC Challenge 2017 (8,528 ECG records)	85.99	83	/	/	/

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REF	MODEL	DATASET	ACC%	F1%	SEN%	PPR%	SPE%
[124]	LSTM	handcrafted features	PhysioNet/CinC Challenge 2017 dataset (8528 ECG data)	/	89	93	/
[125]	LSTM	PTBDB (290 records)	/	90	91	/	/
[126]	LSTM, GRN, RNN	PTBDB (290 subjects)	/	96.32	98.49	/	97.97
[135]	bi-LSTM	AFDB (23 records)	98.51	/	98.32	98.39	98.67
[127]	LSTM, RNN, GRU	AFDB (25 signals), NSRDB (25 signals)	95(RNN), 100(LSTM), 100(GRU)	94.1(RNN), 100(LSTM),100(GRU)	/	/	/
[128]	LSTM	China Medical University Hospital (CMUH) recorded by a GE Marquette MAC 5500 (38,899 subjects)	98.2	77	/	/	/
[129]	LSTM+waveletfeatures	MITDB(48 subjects)	99.37	95.77	94.89	/	99.14
[130]	FB expansion+LSMT	MITDB (2880 segments), PhysioNet/ CinC Challenge 2017 dataset (8528 segments)and private dataset (301 segments)	90.07(MITBIH)	89.04(private datset)	89.04(MITBIH)	85.01(private datset)	/
[131]	RR features	wavelet features+LSTM	MITDB(47 subjects)	99.2(VEB)	98.3(SVE)	95.1(VEB)	78.8(SVEB)
[136]	LSTM	Apnea-ECG database (70 ECG records)	97.8	/	/	/	/
[137]	ACE-GAN	MITDB(47 subjects)	99(VEB)	99(SVEB)	95(VEB)	81(SVEB)	93(VEB)
[121]	LSTM+CNN	MITDB, Physionet/CinC Challenge 2017, NSRDB, AFDB	(MITDB,Physionet 96.2} (AFDB, NSRDB 97.15)	/	(MITDB,Physionet 95.40), (AFDB, NSRDB 97.11)	(MITDB,Physionet 95.56) (AFDB, NSRDB 97.66)	(MITDB,Physionet 96.80) (AFDB, NSRDB 97.06)
[55]	Handcrafted Features+LSTM+CNN	MITDB(48 subjects)	(Class-oriented)99.26	(subject-oriented)94.20	/	(SVEB)90.74	(VEB)92.92
[100]	Deep CNN-BLSTM	MITDB (47 subjects), AFDB	99.94	/	99.93	/	97.03
[138]	LSTM-CNN	PTBDB and Fantasia Databases, INCART Arrhythmia Database , PTBDB, BIDMC Congestive Heart Failure Databases	98.51	/	/	/	/
[139]	SincNet+CNN	PTB-XL database	90	/	/	/	/
[8]	LSTM-CNN	MIT-BIH arrhythmia	98.55	/	96.54	/	99.33

REF	MODEL	DATASET	ACC%	F1%	SEN%	PPR%	SPE%
[140]	multiple scale-dependent DCNN expert classifiers	PTBXL-2020 12-lead ECG and the CinC-training2017 single-lead ECG	/	84.5(PTBXL-2020)	88.3(CinC-training2017)	/	/
[141]	CNN	MIT-BIH	98.87	/	/	/	/
[142]	CNN	The China Physiological Signal Challenge 2018: Automatic identification of the rhythm/morphology abnormalities in 12-lead ECGs	96.2	/	96.7	/	/
[143]	SVM-CNN	PTB-XL	99.2	/	/	/	/
[144]	TCGAN	MIT-BIH	94.69	/	/	/	/
[145]	Hybrid-CNN	MIT–BIH	99.28	99.24	/	/	/
[146]	MorphGAN+Bi-LSTMs	(MIT-BIH-AR), (MIT-BIH-SUP), (INCART), (MIT-BIH-L),(Wrist-PPG)	/	N(60), S(16), V(1.8)	/	/	/
[147]	VGG16+CNN	MIT-BIH Arrhythmia	95	/	/	/	/
[148]	CardioNet, Transfer Learning	MIT-BIH Arrhythmia	98.92	/	/	/	/
[149]	DCNN	MIT-BIH Atrial Fibrillation	98.73(binary)	97.33(quinary)	/	/	/
[150]	Hybrid-CNN	CPSC2020	99.32	/	/	/	/
[151]	DCNN	MIT-BIH	95.5	/	94.5	/	96

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6. Conclusion

This study carried out a comprehensive review of literature on the application of Deep Learning (DL) techniques in analyzing Electrocardiogram (ECG) data across various fields. It underscored the enhanced efficacy of DL models over traditional Machine Learning (ML) techniques in ECG data analysis. The paper delved into the development of biometric ECG systems and scrutinized empirical research that applied DL to ECG signal processing, considering aspects such as the application domain, specific tasks, DL models used, sources of datasets, and the architectures for training. The study revealed an escalating interest in applying DL to ECG analysis in recent years, especially within the medical and healthcare sectors, a trend likely to persist as DL technologies become more widespread. The opening section of the document explored scientific research trends through bibliometric analysis, identifying key journals, prominent authors, and their contributions, as well as tracking the growth of this area through the analysis of titles and author keywords. Notably, the bulk of the sources cited in this investigation were published in the last eight years.

This study lays the foundation for the following section of the document, providing an extensive examination of the subject, beginning with the mathematical underpinnings of various deep learning algorithms. It then delves into the structure of ECG signals and the operations of the cardiac system. Following this, the study methodically presents findings from various angles, including ECG databases, deep learning algorithms, assessment frameworks, evaluation metrics, and code availability. The goal of this detailed investigation is to highlight emerging research directions, obstacles, and prospects in the realm of deep learning for ECG arrhythmia detection. This research is expected to significantly benefit both emerging and established scholars aiming to enhance the current knowledge base in ECG signal processing through deep learning techniques.

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