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Transfer learning for improved electrocardiogram diagnosis of cardiac disease: exploring the potential of pre-trained models

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ABSTRACT

Predicting the onset of cardiovascular disease (CVD) has been a hot topic for researchers for years, and recently, the concept of transfer learning has been gaining traction in this field. Transfer learning (TL) is a process that involves transferring information gained from one task or domain to another related task or domain. This paper comprehensively reviews recent advancements in pre-trained TL models for CVD, focusing on electrocardiogram (ECG) signals. Forty-three articles were chosen from Scopus and Google Scholar sources and reviewed, focusing on the type of CVD detected, the database used, the ECG input format, and the pre-training model used for transfer learning. The results show that more than 80% of the studies utilize 2-dimensional (2D) ECG input from the two most utilized available ECG datasets: MIT-BIH arrhythmia (ARR) and MIT-BIH normal sinus rhythm. alexnet, visual geometry group (VGG), and residual network (ResNet) are among the pre-trained TL models with the highest number used among reviewed articles. Additionally, the development of pre-trained TL models over time has made it possible to detect CVD with ECG signals. It can also address limited data problems, promote the development of more dependable and resilient detection systems, and aid medical professionals in diagnosing CVD and other diseases.

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1. INTRODUCTION

Cardiovascular disease (CVD) continues to be the leading cause of death worldwide, causing the loss of up to 17.9 million lives [1]. The disease encompasses a range of conditions that impact the heart and blood vessels such as coronary artery disease, heart failure, and hypertension. These illnesses collectively result in a considerable worldwide health burden, leading to a significant number of fatalities and negatively impacting the quality of life for numerous individuals. CVD can arise from a range of risk factors, including smoking, unhealthy food, lack of physical exercise, and genetic predisposition. CVD's effect on the cardiovascular system can result in symptoms such as angina, dyspnoea, and in extreme instances, myocardial infarctions (MI) and cerebrovascular accidents. Therefore, it is vital to prioritise prevention and management strategies for maintaining optimal health and providing innovative approaches to improve detection and early diagnosis [2]. In recent years, the growing field of artificial intelligence has shown tremendous potential in CVD detection systems. CVD can be detected using several methods, such as electrocardiogram (ECG) [3], [4], phonocardiogram (PCG) [5], [6], echocardiography [7], and magnetic resonance imaging of the heart

(MRI) [8], [9]. Among these diagnostic modalities, ECG is available in the wearable form making it a low-cost, non-invasive, and easily obtainable option.

ECG device allows measurement of electrical activities in the heart and any abnormalities of the ECG pattern may reflect the occurrence of CVD condition of the heart. However, manual interpretation of these signals is time-consuming and prone to human error. Previous studies have shown that automation of interpreting these signals using machine learning (ML) and deep learning (DL) approaches will help to cope with the problems mentioned. Even though ML has the potential to automate and improve the accuracy of CVD diagnosis, it requires feature extraction to be performed before the classification process, which can be time-consuming, demanding expertise, and financially overburdened. Conversely, DL enables the integration of feature extraction and classification within the same constructed model. But it is data-hungry, requiring larger datasets for optimal performance which leads to longer training times and incurring substantial computational expenses. Hence, researchers in the field of CVD adopted transfer learning (TL) approaches to address the issues derived from ML and DL approaches [10]. TL is a method that utilises knowledge gained from one task to improve performance in another task. The method does not only eliminate the need for repetitive feature extraction and the time-consuming training procedure from scratch, but also performs exceptionally well with limited data, which sets it apart from the requirements of classical ML and DL.

Related review studies on CVD detection mostly focused on ECG in cardiovascular disease detection applications but do not discuss the transfer learning approach [11]. Other related review studies that touched on transfer learning focused only on medical imaging, such as echocardiography, X-rays, CT scans, MRI, and endoscopy [12]. Another study on transfer learning focused only on non-medical images such as time series data, audio, or text [13]. Compared with previous review studies, the main significance of this paper is to explore the potential of pre-trained models for improving CVD using ECG. Additionally, the focus of this paper is to look broadly at recent advances in the field of heart disease detection systems, with a focus on the wide variety of pre-trained models that have been used for CVD diagnosis, as well as datasets and tools commonly used with transfer learning in this domain.

The rest of this paper is structured as follows: section 2 explains the strategy of article searching used in this paper. Section 3 includes an overview of cardiovascular diseases, electrocardiograms, ECG datasets available, transfer learning and its existing pre-trained models. A review of the state-of-the-art researchers on transfer learning for CVD diagnosis is also presented in this section. Section 4 discusses the challenges and opportunities of using transfer learning for CVD diagnosis. Finally, the review is concluded in section 5.

2. METHOD

This study adheres to the preferred reporting items for systematic reviews and meta-analyses (PRISMA). The selection of publications in this study is primarily drawn from two scholarly databases i.e., Scopus and Google Scholar. These two sources provide access to a wide range of scholarly literature, including research articles and conference proceedings. The search focuses on the publications from the year 2018 to March 2023 that were written in English. For the early screening, the title or abstract should at least contain the keywords "electrocardiogram", "ECG", "pre-trained", and "transfer learning." Any publications that do not include any of these keywords were not considered. The search strategy resulted in more than 200 papers meeting these criteria. After an initial screening involving titles and abstracts, we refined the list to 73 articles eligible for further evaluation. The selected publications should focus on detecting cardiovascular diseases using transfer learning approaches. If not, it will be eliminated from the list. The full text for the selected articles was acquired and further assessments were carried out. Finally, 43 papers are selected after evaluating the complete text, and the critical information for this review is recorded. The information includes the type of CVD detected, the database used, the ECG input format used, and the pre-trained model used for transfer learning. Each piece of information is presented and discussed in the following section. Figure 1 shows the process flow in the preferred reporting items for systematic reviews and meta-analyses (PRISMA) diagram.

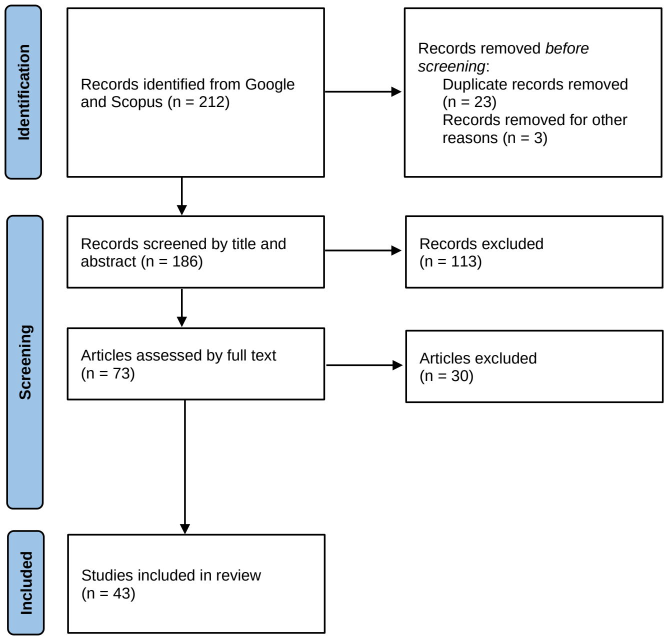

Figure 1. The PRISMA diagram

3. RESULT

All selected papers are reviewed, focusing on the type of CVD detected, the database used, the ECG input format, and the pre-training model used for transfer learning. These key points are important in developing CVD detection systems, especially in determining the appropriate database of the solution, the signal pre-processing process, designing, and building transfer learning models while improving system performance, and considering the cost of CVD detection using transfer learning. A summary of the information extracted from the selected paper is presented in the next section.

3.1. Cardiovascular disease

The following is a list of some of the most well-known types of CVDs:

a. Coronary heart disease (CHD): CHD is a problem that occurs when the blood supply to the heart muscle is interrupted by a cholesterol deposit known as plaque. Plaque is a build-up of cholesterol that happens naturally and causes blood vessels to get narrower over time. If the blood vessels are totally clogged, this may result in chest discomfort or a heart attack.

b. MI: a MI, more often referred to as a "heart attack," is defined by the obstruction of blood flow to the heart muscle caused by the presence of a blood clot or plaque. A heart attack may be fatal. The early diagnosis of this illness is very necessary in order to prevent unexpected deaths and an increasing mortality rate [14].

c. Arrhythmia (ARR): when there is a disturbance in the heart's electrical conduction system, it can lead to an irregular heartbeat or abnormal cardiac rhythms, a condition known as ARR. This condition is characterized by an irregularity in the heart's electrical activity. In most cases, ARRs are accompanied by additional symptoms such as exhaustion, chest discomfort, shortness of breath, or unconsciousness [15]. These symptoms need prompt medical care since, if left untreated, they may advance to the point where they cause permanent paralysis or a stroke.

Many researchers devoted time and energy to this field to improve health care by enabling more accurate diagnosis and faster treatment of heart-related diseases. For example, Abo-Zahhad and Hassan [16] has studied and detected CHD using ECG signals. Rahman *et al.* [17] applied a long-term ECG to detect ARRs. In addition, some authors narrow the focus to specific diseases grouped under ARR, such as atrial fibrillation [18]. The researchers in [19] begin to explore CVD affecting the ventricles of the heart and detect ventricular tachyARR. This irregular and rapid heart rhythm arises from inappropriate electrical impulses in the ventricles of the heart. On the contrary, James *et al.* [2], Suinesiaputra *et al.* [9], and Naz *et al.* [19] used a 12-lead ECG in their MI detection system. Another study in 2021 developed MI detection using a combined strategy of ECG data and features called DeepMI [20]. A study by Fatema *et al.* [21] and Bhosale and Patnaik [22] both classified CVD disease involving MI and abnormal heartbeats using paper-based ECG images.

3.2. Electrocardiogram

CVD correlates with the ECG pattern, which explains the need to analyse the ECG taken immediately after the onset of symptoms. Each ECG cycle consists of three phases: The P wave, the QRS complex, and the T wave. In these three phases, there is a segment called ST segments that reflect ventricular repolarization. In this segment, elevation or depression of the ST may indicate signs of a heart attack and is usually used to detect MI. In addition, the interval from peak R to another peak R may indicate the heart rhythm is either under normal conditions, too slow (i.e., bradycardia ARR), or too fast (i.e., tachycardia ARR). Figure 2 shows various patterns of ECG, including normal ECG pattern (Figure 2(a)), abnormal ST-elevation for MI (Figure 2(b)), abnormal ST depression for MI (Figure 2(c)), fast heart rhythm (Figure 2(d)), and slow heart rhythm that usually reflects the presence of CVD (Figure 2(e)).

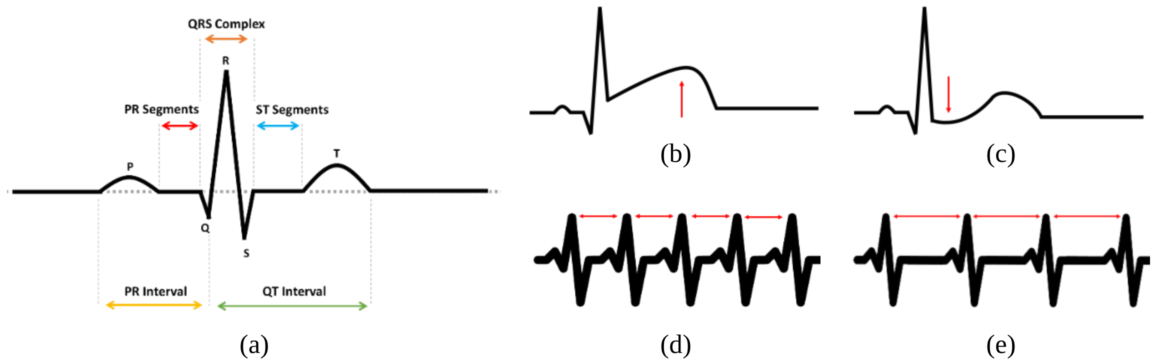

Figure 2. Various pattern of ECG; (a) normal ECG pattern; (b) abnormal ST elevation–MI; (c) abnormal ST depression–MI; (d) fast heart rhythm; and (e) slow heart rhythm

Based on the analysis of the reviewed papers, more than 80% of the studies utilize 2-dimensional (2D) ECG input comprised of beat images, spectrograms, scalograms, and printed images. ECG raw data (i.e., 1-dimensional, 1D) was used in the study by Mohebbanaaz *et al.* [23] as primary data. In the study by Kim *et al.* [24], an ECG spectrogram and an ECG scalogram were used, and the performance of the detection system between these two was compared. The ECG scalogram was found to have a more stable CVD prediction than the ECG spectrogram. The ECG scalogram and ECG raw data were compared in the study by Sabeenian and Janani [25]. The authors found that both input types perform best using different pre-trained models. Besides, Venton *et al.* [26] studies the impact of four separate methods of generating an image from a single ECG: the ECG scalogram, the ECG spectrogram, the attractor, and the Poincare plot. The finding shows that the scalogram and spectrogram perform the best, followed by the Poincare plot and the attractor.

3.3. ECG datasets for cardiovascular disease

Typically, ECG data used in previous studies was obtained from publicly accessible databases such as PhysioNet or Kaggle. The collaboration between the Massachusetts Institute of Technology (MIT) and the Beth Israel Hospital (BIH) in Boston is the first standard public dataset available for CVD evaluation [27]. This major contributor establishes several datasets, including MIT-BIH ARR, MIT-BIH normal sinus rhythm (NSR), MIT-BIH atrial fibrillation (AFib), and the longer version of it called MIT-BIH Long-Term AF, MIT-BIH malignant ventricular arrhythmia (VT), and MIT-BIH ventricular fibrillation (VFib). Among these MIT-BIH datasets, the MIT-BIH ARR dataset and MIT-BIH NSR were the most popular datasets used in the reviewed studies. The MIT-BIH ARR was collected at Boston's Beth Israel Hospital using Holter monitors on 47 subjects, while the MIT-BIH normal sinus rhythm database contains a long-term (25-hour) recording of ECG Holter data from 18 normal subjects.

Besides the MIT-BIH dataset collection, several researchers used the physionet database purposely built for the computing in cardiology challenge 2017 [28]. This dataset consists of 8528 single-lead ECG recordings of normal, AFib, noisy, and others using an AliveCor device with 9 to 60 seconds of training and testing sets. The length of ECG recordings varies depending on the specific dataset and its intended purpose. There are several other datasets used in CVD studies, such as the China physiological signal challenge 2018 (ICBEB) dataset, the European ST-T, INCART ARR, BIDMC congestive heart failure (CHF), QT, and Creighton University Ventricular Tachyarrhythmia (CUDB).

Several datasets are built specifically for MI evaluation. For instance, Physikalisch-Technische Bundesanstalt (PTB), the National Metrology Institute of Germany, has provided this compilation of digitised

ECGs for CVD studies that contain 549 ECG recordings from 290 subjects recorded using the prototype ECG devices [29]. Like PhysioNet 2017, the PTB dataset has various lengths of ECG recording, from 10 seconds to 2 minutes long. Khan *et al.* [30] established a dataset that consists of paper-based ECG images that contain ECG from MI patients. The ECG recording was recorded using the EDAN 3-series on 1937 patients. The duration of the recording is not reported. Besides, another dataset called the European ST-T Database is built to evaluate MI by analysing ST and T-wave changes [31]. The ECG recording was taken from 79 subjects with a range of ages from 30 to 84 years old.

Besides, several studies utilise private datasets. These include the Hualien Tzu Chi database [32], the first China ECG intelligent competition dataset [33], and the provincial key laboratory of CHD, Guangdong Cardiovascular Institute (GCI) database [20], [34], [35]. In addition, since ECG patterns differ for everyone according to demographic factors, several researchers collect their dataset for CVD detection. For instance, [36] collected raw ECG recordings from PDF versions and then converted them into PNG format, resulting in over 51 thousand images of ECG. Sun *et al.* [37] obtained 12-lead resting ECG signals from 285 AFib patients categorised as mild and severe. In addition to using an MIT-BIH ARR, Asif *et al.* [38] also captures real-time ECG, known as real-time cardiac arrhythmia (RT-CarArr).

3.4. Transfer learning

In ML, despite receiving considerable attention recently, transfer learning is still a work in progress. Establishing a strategy for transfer learning mostly depends on the availability of data and the similarity between the original and new tasks. According to Pan and Yan [39], there are three strategies for setting up transfer learning. The first setting strategy is inductive transfer learning, which is used when there are data labels in the target domain regardless of whether labelled data is available in source domain or not. The second setting strategy is called transductive transfer learning. This is used when data labels are only available in the source domain and not in the target domain. The third type of setting is unattended or unsupervised transfer learning, which is used when no labelled data exists in the source or target domain. Figure 3 illustrates this transfer learning placement strategy.

Source Domain Labels	Target Domain Labels		Setting Strategies
Yes	Yes	→	Inductive
No	Yes	→	Inductive
Yes	No	→	Transductive
No	No	→	Unsupervised

Figure 3. Transfer learning setting strategies [39]

Transfer learning has seen recent trends such as utilizing pre-trained models to transfer knowledge between domains [40], [41], developing novel approaches for few-shot and one-shot learning [42], and applying transfer learning to reinforcement learning [43]. Pre-trained models, in particular, have become a common and productive tactic in transfer learning [44] and typically fall under the inductive transfer learning setting. These models are first trained on large datasets, such as imagenet, before being fine-tuned on smaller, domain-specific datasets. Many pre-trained models are now accessible to users through deep-learning frameworks like TensorFlow [45] and PyTorch [46].

AlexNet [47], visual geometry group (VGG) [48], GoogLeNet [49], residual network (ResNet) [50], and DenseNet [51] are regarded as the most popular models among the numerous pre-trained models of transfer learning because of their great performance on various benchmarks for recognition tasks. LeNet-5 is originally presented by LeCun in the late 1990s, about a decade before the establishment of AlexNet in 2012. Owing to the computing capacity restriction, it was difficult to implement LeNet until roughly 2010 [52]. On the other hand, in comparison to LeNet, AlexNet has an architecture that is more extensive and detailed, and it was successful in beating out all of the other conventional methods of recognition in the imagenet competition in 2012 [47].

At the imagenet large scale visual recognition challenge (ILSVRC) in 2014, GoogLeNet won first place [49], while VGG took second place [48]. GoogLeNet is the first to propose the idea of an "inception layer," also known as Inception-V1, which ultimately led to the successful use of dimensionality reduction. Inception-V2, Inception-V3, and Inception-V4 are a few examples of the latest updates to this design [53].

Nevertheless, VGG demonstrates that a network's depth is crucial for improving recognition accuracy, and three different VGG based models have been developed, namely, VGG-11, VGG-16, and VGG-19, where the numbers are with respect to the number of layers they have.

In 2015, a network called ResNet [50] was developed with many layers, and it ended up winning the 2015 ILSVRC. Among all the designs, the ResNet50 architecture has become the most widespread, featuring a composition of 49 convolutional layers and a single fully connected layer located at the network's end. After some time, a number of developments were made, one of which is the proposal of combining Inception with the residual network, which is referred to as inception-ResNet [53].

DenseNet was developed in 2017 by Huang *et al.* [51]. By implementing the concept of feature reuse, the number of parameters required for a network is drastically decrease. DenseNet has greater classification performance while utilizing small datasets. There are many other additional pre-trained models available today in addition to these five popular, and choosing which one to use depends on the application as well as the resources that are at your disposal. The development of a pre-trained model of transfer learning throughout the period is shown in Figure 4.

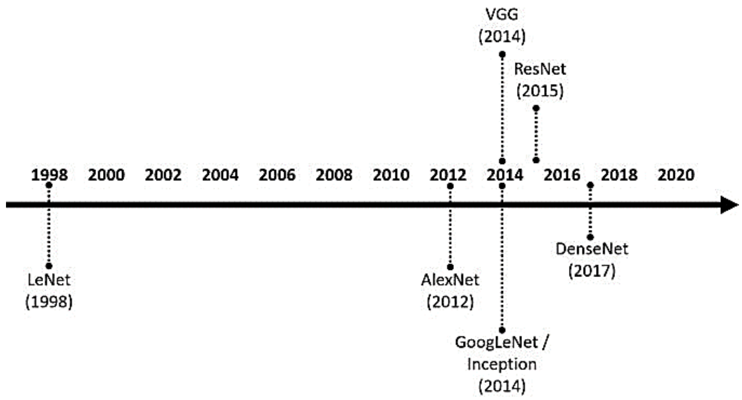

Figure 4. Evolution of pre-trained model of transfer learning

According to Salem *et al.* [54], DenseNet was proposed as a tool for extracting features from ECG recordings containing 12 different irregular heartbeats along with normal sinus rhythms to classify various ECG rhythms. In this method, ECG signals were preprocessed and converted into two-dimensional (2D) images before being fed into a DenseNet for feature extraction. The authors then used the chi-squared test to identify the most important feature maps and applied the support vector machine (SVM) to classify the data. This approach achieved an impressively high accuracy of 97.23% in the classification of ECG ARRs.

Similarly, Qayyum *et al.* [55] used ResNet, GoogleNet, AlexNet, and VGG 16 and 19 models that had already been trained to classify AF with ECG spectrogram images. These pre-trained models were applied in two different ways: as feature extractors feeding SVM or Ensemble classifiers or as AF classifiers. Overall accuracy was up to 97.89%. The authors also recommended conducting additional research using new models like recurrent neural networks (RNN) and larger datasets.

Diker *et al.* [56] used the PTB database to classify abnormal ECG that was first turned into spectrogram images and then fed as input to three different transfer learning algorithms: AlexNet, VGG16, and ResNet18. With an accuracy of 83.82%, AlexNet is the best of these three transfer learning algorithms at classifying an abnormal ECG, and ResNet18 and VGG16 come in second and third, respectively. Interestingly, the authors of this paper also recommended further investigation to gain a more comprehensive understanding of transfer learning in the future.

Mashrur *et al.* [57] proposed an automated ARR identification based on the AlexNet model in their study. Before the classification procedure, ECG data were transformed into spectrograms, which were then passed into AlexNet to identify ARRs. The proposed approach was effective in achieving 97.90% accuracy. For improved results, the author recommended tuning the AlexNet or combining it with another pre-trained model. Furthermore, the proposed approach must be evaluated using various datasets to determine its efficacy.

Moreover, deep transfer learning was presented as a method to identify MI where a VGG-Net is used to analyze ECG data to extract features and fine-tune the model [14]. In addition, the author suggested using data augmentation and dropout methods in order to prevent the system overfitting and increase its accuracy. Then, the authors applied the model to the PTB database, which includes ECG recordings taken from individuals both with and without MI to assess the performance of their method. As a result, the method attained

99.22% MI detection rate. This illustrates the promise of deep transfer learning as a tool for efficient and accurate diagnosis in urban healthcare environments.

In addition, Almalchy *et al.* [58] proposed automated ECG diagnosis for AF using AlexNet due to its excellent performance and low training duration. Similar to previous studies, they converts a 30-second ECG recording to images before passing it to AlexNet. The authors also tested out the efficacy of data augmentation with transfer learning. However, they found that augmenting the ECG images affected the ECG features, leading to incorrect classification (51.59% accuracy). Transfer learning without data augmentation gives the best accuracy at 99.21%.

Singh and Sharma [18] presented a method for diagnosing atrial fibrillation that is based on transfer learning. The proposed approach commences with utilizing ResNet50 as a feature extractor and then proceeds to employ a fully connected neural network for classification purposes. This technique achieves a classification accuracy of up to 99% and demonstrated the potential use in aiding medical professionals in the early diagnosis of disease.

In another study, Weiman and Conrad [59] utilized ResNet-18V2, ResNet-34V2, and ResNet-50V2 as feature extractors, followed by a fully connected neural network for ECG classification, using the PTB Diagnostic ECG Database with five unique cardiac disease diagnoses. The results demonstrated that transfer learning can significantly improve the classification accuracy of ECG signals, achieving an overall accuracy rate of 95.64%. Additionally, authors indicate that transfer learning outperforms models developed from scratch, emphasizing its potential as a valuable tool for developing effective diagnostic solutions for cardiac diseases.

Using transfer learning, Pal *et al.* [60] constructed a system that they called CardioNet to categorize the many different forms of ARRs that may be seen on an ECG. By using the pre-trained weights from DenseNet, VGG, ResNet, and ResNetV2 architectures to fine-tune CardioNet on two separate ECG datasets the PTB Dataset and MIT-BIH ARRs the system achieved impressive accuracy rates. Among the models tested, DenseNet produced the highest accuracy rate of 98.92%, followed by VGG at 98.38% and ResNet and ResNetV2 at 96.1% and 95.2%, respectively.

Since there are not many biosignal datasets available, Jang *et al.* [61] argue that transfer learning may improve the performance of ECG analysis models even when there are just a few data points available. The authors examine the capabilities of GoogLeNet and convolutional auto encoder (CAE) by applying them to two separate ECG datasets and comparing their results. The authors claim that CAE is more successful than GoogleNet, achieving an accuracy of 85.70% as opposed to 81.10% for GoogleNet. The findings suggest, in general, that transfer learning is a potentially helpful strategy for developing effective ECG analysis models with low amounts of training data.

On the other hand, a method for categorizing different kinds of heartbeats from electrocardiogram (ECG) data by using deep transfer learning in conjunction with a convolutional neural network (CNN) and a short-time Fourier transform (STFT) technique was proposed in [4]. STFT was used in order to transform the 1D ECG data into 2D spectrogram images, and ResNet18 was utilized for the purpose of ARR classification. With an accuracy of 90.80% on the MIT-BIH ARR database, the suggested method shows promise for clinical diagnosis in ECG classification.

Furthermore, a new system called DVEEA-TL, which stands for "development and validation of embedded devices that prove ECG ARR by using transfer learning" was proposed in [38]. In this study, besides using the ECG dataset from Kaggle, the real-time ECG images were also acquired using a heart rate monitor sensor. The images were pre-processed and resized according to the AlexNet default parameters. The proposed system achieved 99.80% accuracy.

An automated cardiovascular diseases classifier was proposed in [62]. Data augmentation was used in this study to balance the ECG images dataset that contains several classes of heartbeat: normal, abnormal, MI, previous history of MI, and COVID-19. Three pre-trained transfer learning algorithms were used to classify the CVDs: DenseNet, VGG-16, and ResNet-50. Among these three, DenseNet gives the best performance with 93.33% accuracy.

Generally, the development of pre-trained transfer learning models over time has made it possible to seamlessly incorporate many of these models into existing popular open-source deep-learning platforms and toolkits. There are many available tools that can be used with transfer learning to develop detection systems for cardiovascular disease. Therefore, the platforms, frameworks, and toolkits that are compatible with the pre-trained transfer learning model and associated data sources are listed in Table 1. The overview of previous studies is shown in Table 2 [3], [4], [10], [14], [17]–[26], [32]–[38], [54]–[58], [60], [63]–[77] (in Appendix).

Table 1. Tools for transfer learning specific to cardiac disease

Tool	Descriptions	Sources
TensorFlow Hub	Open-source platform. Large repository of pre-trained models no initial training required.	https://www.tensorflow.org/
PyTorch Hub	Open-source ML library, easy to apply transfer learning via feature extraction and fine-tuning.	https://pytorch.org/
Keras	Open-source software library. Keras' API powers most transfer learning and fine-tuning workflows.	https://keras.io/
Hugging Face Transformers	Platform with APIs to use pre-trained models. Support framework interoperability between pytorch, tensorflow allow to share ML models and datasets.	https://huggingface.co/docs/transformers/index
NVIDIA TAO Toolkit	Built on tensorflow and pytorch easy integration with pre-trained models. No need AI expertise or large training datasets.	https://developer.nvidia.com/tao-toolkit
Transfer Learning Library	Based on pytorch easy integration with pre-trained models. Easily develop new algorithms or apply existing algorithms.	https://github.com/thuml/Transfer-Learning-Library
CardIO Toolbox	Deal with ECG signals in several different forms. AI-based PQRST segment detection, ECG feature calculation, and heart disease diagnosis. Able to work with python and the jupyter notebook.	https://doi.org/10.5281/zenodo.1156085
ECG-kit Toolbox	Works with different ECG file types. Statistical-based ECG wave segmentation and QRS complex identification. MATLAB-compatible and capable of heartbeat classification.	http://marianux.github.io/ecg-kit/

4. DISCUSSIONS

The proposed system in the reviewed papers includes but is not limited to the classification of ARR, MI, atrial fibrillation, and abnormal ECG. Since there are abundant publicly available ECG datasets, detailed analysis and consideration should be taken before choosing a database that is the most suitable for the study purposes and to avoid a negative impact on detection performance. Additionally, since ECG differs according to individual and demographic factors, adding self-collected data is recommended to allow a broad overview of CVD studies according to demographic division.

Most pre-trained transfer learning models take input in images or in a 2D ECG format. Hence, among the articles that were reviewed, some recommended efforts to transform a 1D ECG into a 2D ECG [18], [14], [60] or a time-frequency spectrogram image [4], [54], [61] image before feeding it to a model that had already been pre-trained were made. Despite this, Weiman and Conrad [59] opted not to change the input format of the ECG and instead chose to make just a minor adjustment to the convolutional layer, moving it from 2D to 1D. The accuracy attained for both input formats is good. This is an excellent chance to explore the reliance of the data input format on the performance of transfer learning. Additionally, there might be an influential factor in implementing CVD detection based on the combination of ECG input with different algorithms, which suggests further investigation.

ResNet, GoogleNet/Inception, AlexNet, VGG, and DenseNet are the top pre-trained models used in reviewed articles, as shown in Table 2. Most of the articles utilized 2D ECG in their studies, but several studies utilise 1D ECG and have succeeded in obtaining more than 90% accuracy [23]. Therefore, conducting further research on these models would be beneficial to establish an optimal pre-trained model for cardiovascular disease detection systems. In addition, Rouzrokh *et al.* [78] mentioned that transfer learning is more useful towards the performance of the detection model with similar imaging features, suggesting that transfer learning from medical data to medical data should be further studied to establish more effective approaches to detecting CVD.

5. CONCLUSION

This paper examines the latest advancements in CVD detection systems using ECG signals, focusing on pre-trained transfer learning models. It can be inferred that transfer learning can enhance the accuracy of cardiovascular disease detection, particularly when dealing with ECG signals. Additionally, transfer learning can address challenges associated with limited medical data and promote the development of more dependable and resilient detection systems. This approach can aid medical professionals in heart-related diseases and other diseases.

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APPENDIX

Table 2. Overview of previous studies

Ref	Applications	Database	Modality	AlexNet	GoogleNet / Inception	VGG	ResNet	DenseNet	SqueezeNet	MobileNet	EfficientNet	Other[a]
[63]	MI	Ali Haider	ECG images	/					/			
[21]	MI	Ali Haider	ECG printed images		/		/					
[22]	MI	Ali Haider	ECG images			/	/	/		/		
[3]	MI	Ali Haider; PTB	ECG printed images		/		/	/			/	
[20]	MI	GCI; PTB	ECG spectrogram		/							/
[35]	MI	GCI; PTB	ECG spectrogram		/							
[32]	MI	Hualizen Tzu Chi	ECG images		/	/	/	/		/		
[34]	ARR and MI	ICBEB; GCI	ECG spectrogram		/							
[64]	ARR	MIT-BIH Long-Term AF; MIT-BIH AFib	ECG spectrogram							/		
[18]	ARR	MIT-BIH AFib; MIT-BIH NSR	ECG images				/					
[54]	ARR	MIT-BIH AFib; MIT-BIH VT; MIT-BIH NSR; European ST-T	ECG spectrogram					/				
[65]	ARR	MIT-BIH ARR	ECG images					/				
[66]	ARR	MIT-BIH ARR	ECG spectrogram				/					
[67]	ARR	MIT-BIH ARR	ECG images				/					
[23]	ARR	MIT-BIH ARR	ECG raw data	/	/		/					
[17]	ARR	MIT-BIH ARR	ECG images	/			/		/			
[68]	ARR	MIT-BIH ARR	ECG spectrogram			/						
[69]	ARR	MIT-BIH ARR	ECG spectrogram		/	/	/	/		/	/	
[70]	ARR	MIT-BIH ARR	Beat Score Map (BSM) image			/						
[4]	ARR	MIT-BIH ARR	ECG spectrogram				/					
[71]	ARR	MIT-BIH ARR, MIT-BIH NSR, BIDMC CHF	ECG scalogram	/								
[72]	ARR	MIT-BIH ARR; INCART ARR	ECG images				/					
[23]	CHD (ARR, cardiomyopathy, and ischemia)	MIT-BIH ARR; MIT NSR	ECG error signal images	/	/	/	/					/
[73]	ARR	MIT-BIH ARR; MIT-BIH LT; MIT-BIH Long-Term AF	ECG raw data		/							
[25]	ARR	MIT-BIH ARR; MIT-BIH NSR; BIDMC CHF	ECG raw data, ECG scalogram	/	/		/	/	/			/
[74]	ARR and congestive heart failure	MIT-BIH ARR; MIT-BIH NSR; MIT-BIH AFib; BIDMC CHF	ECG scalogram			/						
[75]	ARR	MIT-BIH ARR; MIT-BIH NSR; MIT-BIH VT; BIDMC CHF	ECG scalogram	/								
[76]	ARR	MIT-BIH ARR; MIT-BIH SV; QT; INCART	ECG images								/	
[38]	ARR	MIT-BIH ARR; Own dataset (RT-CarArr)	ECG images	/								
[19]	ARR	MIT-BIH VT; MIT-BIH VFib; MIT-BIH ARR; CUDB	ECG images	/	/	/						
[36]	ARR	Own	ECG images		/		/	/				/
[37]	ARR	Own	ECG images							/		

Table 2. Overview of previous studies (continue)

Ref	Applications	Database	Modality	AlexNet	GoogleNet / Inception	VGG	ResNet	DenseNet	SqueezeNet	MobileNet	EfficientNet	Other[a]
[26]	ARR and Congestive Heart Failure	MIT-BIH ARR; MIT-BIH NSR; BIDMC CHF	ECG scalogram, spectrogram, attractor, and Poincare plot	/	/				/			
[77]	ARR	PhysioNet 2017	ECG spectrogram								/	
[24]	ARR	PhysioNet 2017	ECG spectrogram and scalogram		/		/	/	/			
[55]	ARR	PhysioNet 2017	ECG spectrogram	/	/	/	/					
[57]	ARR	PhysioNet 2017	ECG spectrogram	/								
[58]	ARR	PhysioNet 2017	ECG images	/								
[33]	ARR	PhysioNet 2017; The First China ECG Intelligent Competition	ECG raw data				/					
[56]	ARR	PTB	ECG spectrogram	/		/	/					
[10]	MI	PTB	ECG spectrogram		/							
[14]	MI	PTB	ECG images			/						
[60]	ARR	PTB; MIT-BIH ARR	ECG images					/				

*Others consist of the pre-trained network that has been once among 44 papers reviewed, which includes MnasNet, NasNet, and ShuffleNet.

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