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Stages-Based ECG Signal Analysis From Traditional Signal Processing to Machine Learning Approaches: A Survey

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ABSTRACT Electrocardiogram (ECG) gives essential information about different cardiac conditions of the human heart. Its analysis has been the main objective among the research community to detect and prevent life threatening cardiac circumstances. Traditional signal processing methods, machine learning and its subbranches, such as deep learning, are popular techniques for analyzing and classifying the ECG signal and mainly to develop applications for early detection and treatment of cardiac conditions and arrhythmias. A detailed literature survey regarding ECG signal analysis is presented in this article. We first introduce a stages-based model for ECG signal analysis where a survey of ECG analysis related work is then presented in the form of this stage-based process model. The model describes both traditional time/frequency-domain and advanced machine learning techniques reported in the published literature at every stage of analysis, starting from ECG data acquisition to its classification for both simulations and real-time monitoring systems. We present a comprehensive literature review of real-time ECG signal acquisition, prerecorded clinical ECG data, ECG signal processing and denoising, detection of ECG fiducial points based on feature engineering and ECG signal classification along with comparative discussions among the reviewed studies. This study also presents a detailed literature review of ECG signal analysis and feature engineering for ECG-based body sensor networks in portable and wearable ECG devices for real-time cardiac status monitoring. Additionally, challenges and limitations are discussed and tools for research in this field as well as suggestions for future work are outlined.

INDEX TERMS ECG analysis, cardiac arrhythmias, QRS and ST detection, ECG classification, deep learning.

I. INTRODUCTION

A. BACKGROUND AND MOTIVATION

Heart diseases, also called Cardiovascular Diseases (CVDs), are the main causes of high mortality rates. They arise with a lack of blood in the coronary artery that also supplies blood to the heart itself. CVDs result in irregular beats called arrhythmia and sudden death can occur depending on the severity of the arrhythmia condition. Electrocardiogram/Eletrokardiogram (ECG/EKG) demonstrates the electrical activity of the human heart and the ECG signal morphologies provide information about various types of arrhythmia based on different cardiac conditions. Fast and accurate identification of arrhythmia from the ECG wavegraph can potentially save many lives and much in terms of health care costs worldwide [1]. This motivated us to perform a detailed review of ECG analysis and present it in the form of a stages-based process model to further clarify and categorize the flow and significance of each phase of ECG signal analysis. With the enormous impact that effective ECG signal analysis offers on public health and economy, giving a perspective of hardware and software tools along with real-time monitoring using portable and wearable devices to analyze an ECG signal in the form of stages-based process is another motivation that led us to conduct this study.

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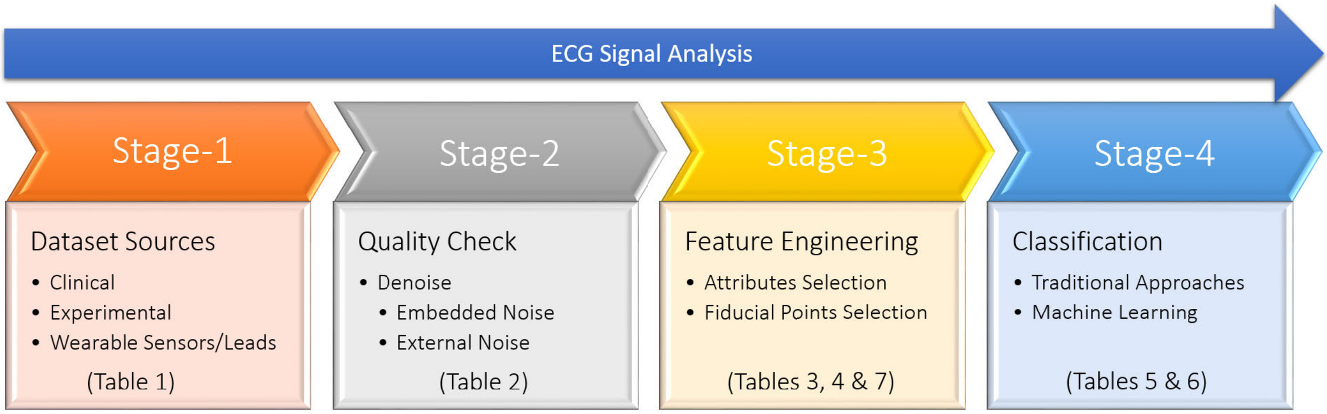

FIGURE 1. **Stages-based ECG signal analysis model.**

Analyzing the ECG signal and detecting different types of arrhythmia requires assistance from traditional signal processing and/or machine learning techniques for early treatment and prevention of CVDs. Advances in machine learning, in conjunction with computer-aided design (CAD) diagnostic systems [2], have many health applications such as data processing and retrieving relevant information from these data. These systems have increased the accuracy of early detection of CVDs and offer a significant reduction in cardiologist workload. Traditional and kernel-based neural network (NN) methods [3], [4] use handcrafted features to analyze the ECG waveform for processing, detection, and classification. Deep learning methods have overcome the problems of these time and resource-consuming processes and have improved feature engineering [5], [6], detection and classification by learning important features automatically that were manually determined in the past [7]. Whether it is real-time monitoring, detection, recognition, or classification, the ECG signal goes through different processes. We present these processes as a stages-based ECG signal analysis model, as depicted in Figure 1. The first stage describes different sources of ECG data, such as clinically prerecorded and sources of real-time ECG acquisition sensory data. In the second stage, we discuss different techniques reported in the literature to remove noise that has been introduced during the acquisition of the ECG signal at the first stage. Detection of fiducial points of the ECG signal is very crucial for classifying different heart conditions accurately. Identifying these fiducial points is part of the third stage of the ECG signal analysis process. Each wave and segment of the ECG signal has its importance in determining the type of arrhythmia in context. After the right selection of the data source and identifying the ECG fiducial points, different heart conditions can be detected and classified at the fourth stage of the ECG signal analysis process using traditional signal processing or machine learning methods. Each stage is discussed in more detail in section IV.

B. CONTRIBUTIONS

This study aims to contribute to the growing area of research for the detection of heart conditions and different arrhythmias by analyzing the ECG signal in real-time to prevent these conditions and exploring tele-health options and best practices. Our contributions to this area of research can be summarized as follows:

1) Present a detailed overview of the heart and its electrical activity by discussing ECG, its waveform and different arrhythmia types that can be retrieved from ECG
2) Present the stages-based ECG signal analysis process model from data acquisition source selection to the classification process. We present a comprehensive survey of ECG analysis work in the form and context of the introduced stages-based model.
3) Present a detailed literature review of ECG datasets (stage 1) that are used to evaluate machine learning classification algorithms in both research and portable wearable devices for real-time detection
4) Discuss and summarize denoising methods to clean the ECG signal to reduce false alarms and improve classification (stage 2). We present a comparison of different techniques and their usage in various research areas along with their reported performance evaluation metrics.
5) Present an overview of the latest research of traditional and machine learning features engineering-based ECG classification algorithms (stages 3 and 4) and summarize their performance metrics evaluated on different datasets
6) Discuss real-time monitoring systems using body sensors in portable and wearable devices, its feature engineering mechanisms, ECG sensor networks, and ECG classification for portable and wearable devices (relevant to all 4 stages, and mainly stage 3). We further outline the latest hardware of portable systems and wearable smart devices for real-time heart monitoring.
7) Discuss tools that are available to perform research in this area of interest
8) Discuss the challenges and limitations of this area of research and present a comparative summary table of this survey and other related survey papers in the field

C. PAPER ORGANIZATION

This article is organized as follows. In section II, the article selection and survey process for this article is described. In section III, we provide a detailed explanation of Electrocardiography. This section is further divided into four subsections. ECG leads and ECG waveforms are described in subsections III-A and III-B, respectively. ECG morphology for ischemia and infarction is explained in subsection III-C, and subsection III-D discusses the arrhythmia types. In section IV, we glance at prior related work published in the literature regarding both traditional time/frequency domain and advanced machine learning methods used in each stage of ECG signal analysis from data acquisition source to the classification process. This section is further subdivided into four subsections. Different data sources of ECG signal data acquisition for evaluating the beat detection and classification algorithms and their characteristics are explained in section IV-A. In section IV-B, the different techniques for signal smoothing and filtering noise from the ECG signal are described. Followed by feature engineering, section IV-C presents prior related work on traditional and machine learning-based approaches of ECG fiducial points and/or other features detection. In section IV-D, ECG classification models published in the literature are explained. Section V details the solutions reported in the literature regarding ECG signal acquisition, feature engineering, and classification using body sensor networks. Section VI elaborates on the devices and tools available for research and real-time monitoring systems/simulations. In section VII, a discussion of challenges and a comparative summary are presented, and in section VIII, the limitations are further discussed. Section IX concludes this article and describes future directions for the continuation of this research.

II. ARTICLE SELECTION AND SURVEY PROCESS

This article aims to review the work published in the literature in the last two decades regarding ECG analysis, from signal preprocessing, feature extraction to real-time classification. Relevant articles from 2000 to 2020 were collected from various resources and publishers including IEEE, MDPI, SPRINGER, ELSEVIER, SENSORS, PLOS and IOP. Different keywords, such as "ECG classification with machine learning" and "real-time monitoring systems for ECG" were used to collect the relevant articles. The review covers different stages that ECG data goes through, starting from the data acquisition source, denoising stage, feature engineering, to finally, the classification stage. Fiducial points such as R-peaks and QRS complex detected by different transforms and machine learning methods are also presented. ECG classification in real-time using machine learning and its subbranches are additionally presented. The initial number of retrieved articles was 180. The selection process was based on specific criteria, such as:

1) Being relevant to ECG
2) Being relevant to types of arrhythmia
3) Being relevant to machine algorithms related to ECG classification
4) Being relevant to ECG datasets
5) Being relevant to ECG feature engineering techniques
6) Being relevant to performance evaluation metrics of ECG classification algorithms

Fifty articles were excluded by reviewing the titles and abstracts of the retrieved articles based on the selection criteria.

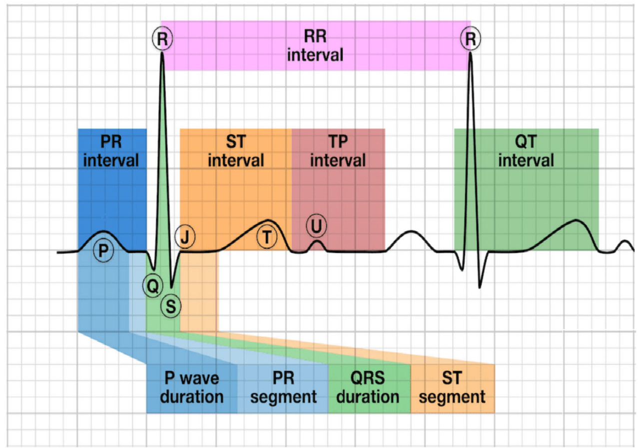

FIGURE 2. Electrocardiograph.

III. ELECTROCARDIOGRAPHY

Electrocardiography was invented by a Dutch physiologist Willem Einthoven more than a century ago. The Electrocardiogram (ECG) is the recording of electrical activity taking place in a cardiac cycle of the heart. It is captured on a graph paper shown in Figure 2 (two ECG cycles are shown in this figure). The electrical activity is in the form of small potential generated by the heart tissues, picked up through electrodes of the ECG leads. The miniature signals are amplified and recorded as ECG. The electrical activity is normally generated spontaneously by the specialized cells of the Sinoatrial Node (SA node) exhibiting automaticity. The generation of impulse is due to the reversal of electrical polarity of the cardiac cell wall, which is more positively charged on its outer surface in the normal resting state. This reversal produces negativity on the outer surface of the cell wall, which spreads as an impulse to the adjoining cardiac tissue. In addition to detecting ischemia and myocardial infarction (MI), ECG is also used for detecting arrhythmias and conduction disturbances. The worldwide use of modern medical therapy of acute MI (i.e., heart attack) and the development of interventional cardiology has substantiated the importance of ECG regarding its Specificity and Sensitivity in myocardial ischemia and MI [8], [9].

A. ECG LEADS

There are twelve ECG leads called conventional leads. Six leads are named as limb leads, and the remaining six leads

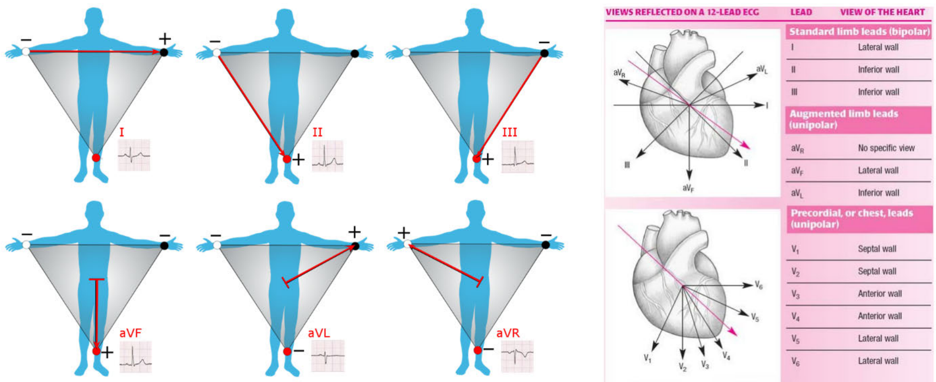

FIGURE 3. ECG leads.

are named as chest or precordial leads. The limb leads record the potential across the frontal plane, while the precordial leads record the potential across the horizontal plane, through their respective electrodes. Three limb leads are bipolar leads called standard limb leads, and the other three are called unipolar augmented leads. Each standard limb lead separately records the potential difference between two limbs as detailed below and illustrated in Figure 3.

1) Standard Lead I: between the left arm and right arm
2) Standard Lead II: between left leg and right arm
3) Standard Lead III: between left leg and left arm

Leads I, II and III have their positive terminals attached to the left arm, the left leg and the left leg, respectively. The three unipolar leads measure the voltage "V" on a single point in relation to an electrode attached to the right leg having zero potential. The potential detected by the unipolar limb lead terminals, are augmented and are denoted by small "a", as depicted in Figure 3. These augmented leads are "aVR: right arm", "aVL: left arm", "aVF: left leg" with their positive terminal being attached to the respective limb. The six unipolar precordial leads are attached to the chest wall and named V1-V6. The twelve conventional ECG leads can be considered to be reflecting a three-dimensional view of the electrical activity in the heart [8], [9].

B. ECG WAVEFORMS

The different ECG waves are named in an alphabetic order, called P, QRS, and T-U waves. Their shape, amplitude, and time intervals give important information regarding health and the state of the heart. The P wave reflects atrial depolarization. The QRS complex reflects ventricular depolarization. The repolarization of ventricles is reflected by the T-U wave. The electrocardiograph records a positive wave for an ECG lead whenever a depolarization current spreads toward the positive pole of the respective lead. In contrast, a negative wave appears in the case when the current spreads away from the pole.

C. MORPHOLOGY OF ECG IN ISCHEMIA AND INFARCTION

Before describing various ECG abnormalities, it would be appropriate to understand the ECG leads' orientation and arrangement, especially the limb leads, for localizing the ischemia and infarction as given below:

1) Lead I and aVL, V5-V6 are oriented toward the antero-lateral surface of the heart.
2) Lead II, III, and aVF are oriented toward the inferior surface of the heart.
3) Lead aVR is facing towards the cavity of the heart and normally shows the negative depolarization wave.

Regarding precordial (chest) leads, V1 and V2 are oriented toward the right ventricle. Leads V3 and V4 face the interventricular septum anteriorly. V5 and V6 face the left ventricle anterolaterally, with their positive terminals attached to the chest wall separately. MI mostly involves the ventricles, and the resultant QRS abnormalities are also accompanied by the ST-T abnormalities. In the early stage of MI, the ST-segment elevation occurs, and it settles down within a few days with the appearance of Q waves and/or the inversion of T-waves in the respective leads. The serially increasing ST elevation is significant as far as the medical treatment is concerned as compared to non-ST elevation MI (NSTEMI). The importance of ECG is well recognized in the diagnosis of myocardial ischemia and MI. The ECG findings are however, variable. Ischemia affects the electrical properties of the myocardial cell membrane, shortens the action potential and results in a difference of potential between the ischemic and the normal portion. This current of injury is reflected as changes in the ST-segment. These changes depend upon the severity and the location of ischemia or MI. The current of injury is directed toward the outer surface of the heart, in case the ischemia or MI is transmural. It, therefore, produces ST elevation in the leads with their positive terminals facing the affected portion of the heart. When those leads show the ST depression, the current of injury is flowing away from their positive terminals.

D. TYPES OF ARRHYTHMIA

Abnormal electrical impulses cause irregular heartbeats called cardiac arrhythmias. There are mainly two classes of arrhythmia. The first class is bradyarrhythmias, accompanied by low heart rates (less than 60 beats/minute). The second class is tachyarrhythmias with a heart rate greater than

TABLE 1. Stage 1: ECG dataset specifications.

Database [Ref.], Year	# of Files	# of Leads	# of Classes	Sampling Frequency fs (Hz)	Voltage	Duration of Recording	Collection Method/Device	Purpose
MITDB [11], 2001	48	2	5	360	5μV	30 min	Not Reported (NR)	Arrhythmias
ESCDB [12], 1992	90	2	NR	250	5μV	120 min	Holter Machine	Ischemia Detection, ST and T-Wave Changes
LTSTDB [13], 1998	86	2-3	NR	250	20 mV	24 hour	Holter Machine	ST-Segment Detection
QTDB [14], 1997	105	2	NR	250	5μV	15min	Holter Machine	ECG Delineation, Wave limit validation
TWADB [15], 2008	100	2-12	NR	500	5μV	2 min	NR	T-Wave Alternants
CSEDB [16], 2017	125	15	NR	500	1μV	10 sec	NR	Diagnostic ECG Analyzers
PTBDB [17], 1995	549	12	7	1k	16.38 mV		NR	MI Detection and Localization
TELE ECG	250	1	NR	500	5mV	5 sec	TeleMedCare Monitor	NR
AHA 1985 DB	80	NR	8	250	10 mV	30 min	NR	NR
MITNSTDB [18], 1984	2	NR	NR	360	NR	30 min	Acquired from MITBIH	Noisy ECG Signal Analysis
INCARTDB [19], 2001	75	12	9	257	NR	30 min	Holter Machine	NR
ChallengeDB2017 [20], 2017	3658	1	4	300	NR	9-61 sec	AliveCor	Atrial Fibrillation (AF) Detection
CPSCDB2018 [21], 2018	6877	12	9	500	NR	6-60 sec	NR	NR

100 beats/minute and is further divided into two types. The first type is supraventricular tachycardia, such as AV nodal tachycardia and AV junctional tachycardia. The second type is called ventricular arrhythmia such as premature ventricular beats, ventricular tachycardia and ventricular fibrillation.

Four types of arrhythmias can be grouped as normal, non-life-threatening, abnormal and life-threatening arrhythmia [10]. The Association for Advancement of Medical Instrumentation (AAMI) has divided the non-life-threatening arrhythmias into five classes: (N)- non ectopic, (S)-supraventricular ectopic, (V)-vetricular ectopic, (F)-fusion and (Q)-other unknown.

IV. RELATED WORK OF ECG SIGNAL ANALYSIS STAGES

In the past two decades, many researchers have conducted different experiments in each stage of the ECG signal analysis process. This article provides a thorough review of methods and approaches for each stage of ECG signal analysis. It compares their work in terms of selection criteria and evaluation metrics to give researchers in this field more insights and broader understandings of the contributions of related work.

A. STAGE1: DATA ACQUISITION SOURCE/DATASET

When it comes to ECG signal analysis for feature extraction and/or beat classification based on different arrhythmias, the dataset selection drives the motive. The attributes that are recorded with the ECG signal help in deciding which features would be extracted or explored further. Annotation, type, lead number, and the number of leads used in the recording, number, age, and gender of patients and their health condition are all attributes that give direction to the rest of the stages of the ECG signal analysis process for its classification. This stage covers various ECG data acquisition sources as the input to the stages-based model, with a special emphasis on the source of the data (rather than the electronics of the data acquisition circuitry).

ECG analysis is mostly performed on PC-based tools and evaluated on publicly available databases. These databases contain different morphological patterns for recorded ECG signals. Some databases used tele-health monitors to record these ECG signals under certain recording conditions. ECG recording specifications for these databases are summarized in Table 1. Research has shown that ECG classification based on the single-lead recording in some cases can be as effective as twelve-lead ECG records. This makes the ESC-ST-T database popular for researchers as it has recordings from a single lead, which is the limb lead and could be used to evaluate wearable ECG sensors and devices' performances. The CSE database is the second most cited database, according to Scopus.

B. STAGE2: DENOISING

ECG analysis and classification requires prerecorded or real-time ECG signals as the primary input. In both cases, ECG data acquisition is achieved by attaching sensors and leads to the body. During the ECG signal acquisition, noise is also captured along with the original signal, which significantly affects the quality and classification of ECG. Removal of noise is called denoising, and it has been a top interest of

TABLE 2. Stage 2: Summary and comparison of various ECG denoising techniques.

Method [Ref.], Year	Noise	Performance Metrics	Database
HDL-Based FIR Filter [22], 2016	Gaussian White Noise	NR	MITDB
Kalman Filter [23], 2016		1.28_{mse}	
Wavelet Filter [24], 2009		$99.51\%_{acc}$	
Unbiased FIR [25], 2019	Equipment induced noise	$99.3\%_{acc}$	
SSRLS [26], 2016	Power-line Interference	20_{SNR}	
ANF [27], 2019		0.44_{rmse}	
Non-linear FFT Filter [28], 2013		$2.5\text{sec}_{\text{convergence rate}}$	Simulated ECG Signal
NN-Based DAE [29], 2019	Added Noise to Datasource	0.063_{rmse}	MITSTDB

researchers to remove noise from the ECG signal for accurately identifying different anomalies. Conventional methods to denoise the ECG signal include applying band-pass filters (0.05-45Hz) with sample entropy to verify the quality. Noise can cause false alarms that are crucial to assessing the health status. Noise can be in any form but can be categorized into two primary forms: internal embedded noise and external noise. External noise can be either power-line noise or any other white noise. In ECG analysis, noise is usually removed after acquiring data from data sources. There are many different methods to clean the noisy signal. The quality of the ECG signal can be checked with the Structural Similarity Matrix (SSIM) [30] and assessed with measures such as the signal to noise ratio (SNR). Other performance metrics reported by researchers in the ECG denoising stage include Accuracy (acc), Mean Square Error (mse), Root Mean Square Error (rsme), or Convergence Rate.

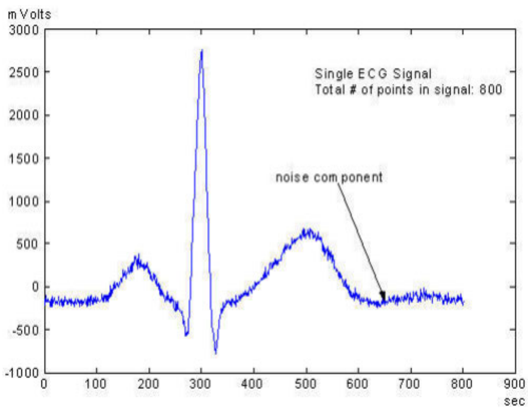

FIGURE 4. Noisy electrocardiograph.

As summarized in Table 2, various filters such as the Finite Impulse Response (FIR) filter, Adaptive Notch Filter (ANF), and other filter-based approaches have been adopted by researchers in the recent studies to remove noise from the ECG signal. Whether it is traditional leads with cables or a wireless body sensor, any equipment can introduce noise into the ECG signal, as shown in Figure 4. Authors in [25] have attempted to remove internal noise by smoothing the ECG signal using the FIR filters and have achieved 99.3% accuracy. On the other hand, external Power-Line Interference (PLI) is the most disturbing noise that the ECG signal is susceptible to. PLI is a significant source of noise in the frequency range of 50-60 Hz. State Space Recursive Least Square Adaptive Filter (SSRLS), ANF, and Fast Fourier Transform (FFT) Filter-based denoising of power-line interference is performed by [26]–[28], [31] and unknown external disturbances are removed by adaptive control schemes in [32]. Other external white noise can be removed by Hardware Descriptive Language (HDL)-based Finite Impulse Response (FIR) filters and NN-based Denoising Autoencoders (DAE) [22]–[24], [29].

C. STAGE3: FEATURE ENGINEERING

ECG classification requires proper detection of fiducial points in its waveform. The QRS complex is an important wave in the ECG signal that reflects the ventricular contraction activity of the heart. Its shape gives the basis for automated detection of different characteristics, which is the starting point for different classification methods. QRS complex detection provides a foundation for almost all automated ECG analysis algorithms. However, there are difficulties in accurate QRS detection due to its physiological variability and presence of different sources of noise in the ECG signal. The derivative-based approaches had higher performance index for low-frequency noises, while algorithms based on digital filtering performed well for high frequency noise. In the last decade, many traditional signal processing and machine learning approaches have been proposed towards Feature Engineering (FE) to detect the QRS complex, ST-Segment, R-peak, and other fiducial points. The following two sections present these approaches published in the reported literature.

1) TRADITIONAL SIGNAL PROCESSING APPROACHES

The QRS complex is a crucial part of the ECG signal, and its detection is first in detecting other fiducial points and extraction of all kinds of other features. Any QRS detector should detect different QRS morphologies that further helps to classify the ECG signal to detect different types of arrhythmias. Once the ECG signal passes through the denoising stage, a clean, good quality ECG signal is achieved. The ECG signal would then go through a feature engineering stage where fiducial points such as the R-R interval, ST-segment, J-point, and T-wave are detected. Figure 2 shows the fiducial points along with different ECG waves and the R-peaks between the R-R interval in a two-cycle ECG. Furthermore, to improve identifying ST-segment changes, the J-point and heart rate features are additional characteristics that play an essential role in ECG beat classification. ST-segment is an integral part of the ECG cycle that gives information about ischemic diseases. MI and angina are life-threatening conditions that result in changes and abnormalities in the ST-segment.

In this section, we present different methods and techniques reported in the literature that detect the QRS complex, ST-segment, and other fiducial points. Wavelet Transform (WT) is one of the popular methods that has been adopted by many researchers to detect different points of the ECG signal. Wavelet transform decomposes and transforms the signal into space where both time and frequency information about the signal can be observed at the same time. There are other transforms such as Wigner distribution and Fourier Transform that provide this information as well, but WT and its time and frequency representation can be of interest if a particular portion is essential to study. For example, the QRS complex in ECG can provide event-related information, and by knowing its time intervals, ECG fiducial points can be identified, and features can be extracted. WT was introduced to overcome some shortcomings and as an alternative to the Short Time Fourier Transform (STFT). When it comes to the analysis of a signal with computational efficiency, the Discrete Wavelet Transform (DWT) provides information for both analysis and synthesis of the signal with less computation time. DWT is easier to implement, and its foundations date back to 1976 when Croiser, Galand, and Esteban came up with the technique to decompose time domain signals into discrete representations. DWT represents the signal in both the time and frequency domain. This transform became a popular tool to analyze biomedical signals such as ECG. DWT transforms the ECG signal into different levels of resolution by decomposing the signal. This scaled signal can then be analyzed further using different filters to extract different points. Details about WT, DWT and its other variations such as Continuous Wavelet Transform (CWT), Cross Wavelet Transform (XWT), and others are provided in [33]. Nonetheless, WT can be represented by Equation 1, where * denotes the complex conjugate.

$$F_{(a,b)} = \int_{-\infty}^{\infty} f(t)\psi^{*}_{(a,b)}(t)dt \tag{1}$$

Heuristic-based methods using different transforms have been proposed as QRS detection techniques in [34]–[37]. The best Sensitivity of 99.95% is achieved by the DWT based windowing method presented by [38]–[41]. A delineation algorithm [42] in conjunction with the DWT based windowing method has outperformed QRS, P, and T-wave detection evaluated on multiple databases with a Sensitivity of 99.84%. Different fiducial points detection by windowing algorithms have been proposed by [43]–[45]. Their best accuracy of 99% is comparable to the DWT based windowing methods. Methods based on Time Domain (TD) [46]–[48], Mathematical Morphology (MM) [49]–[51] with Very-Large-Scale-Integration (VLSI) [52], Gaussian filter based Synthesized Mathematical Model (SMM) [53] and derivative based [54] methods have reported the best Sensitivity of 99.81%, yet a bit lower than DWT based methods. The Karhunen-Loeve Transform (KLT), along with the Legendre Polynomials-based Transform (LPT) employed in [55], [56] have been useful to detect the ST-segment, but their Sensitivity is much lower than [34]. To improve the QRS detection, more than one threshold in the wave is normally required. However, the Phasor Transform (PT) can reliably be used to detect R-peaks regardless of the amplitude. This is an advantage of detecting low-amplitude QRS complexes in ECG signals [57]. A modified wavelet transform called Dyadic Wavelet Transform (DyWT) takes the convolution of the ECG and gives dyadically time-scaled wavelets of the signal being analyzed. DyWT is similar to the Hamilton-Tomplins (HT) algorithm with a couple of advantages over it. Authors in [58] and [59] have used DyWT and multiwavelet transforms to detect the QRS complex but achieved average accuracy levels. The detection of the QRS complex with the derivative-based algorithm [54] compares the feature with a threshold value computed by heuristically found rules. The best method with the highest Sensitivity to detect QRS complex has been proposed by [39], [60] which was based on multilead Area Curve Length (ACL)-based DWT and FIR filters using adaptive thresholds, whereas [34] achieved the highest Sensitivity in detecting the ST-segment using wavelet transforms evaluated on the same dataset of MITDB. Table 3 illustrates a list of these traditional signal processing approaches that extract ECG signal features with reported performance metrics of Sensitivity (sen), Specificity (spe), Positive Predictive Value (ppv), F1-score (F1), Mean Error (me), Error (err), Root Mean Square Error (rmse) and Accuracy (acc).

2) MACHINE LEARNING APPROACHES

Various irregular conditions of the heart are categorized as different arrhythmias, and analyzing the ECG signal can guide through the classification process for each type of arrhythmia. A trained cardiologist can classify the ECG signal to its appropriate arrhythmia class by analyzing ECG signal through visual inspection. However, this traditional process takes much time from the moment patients experience symptoms at home or workplace to the time they visit the Emergency Room (ER) and wait for the ECG to be recorded and analyzed by the doctor. This delay in the process of ischemic or MI detection is crucial to health and could be prevented if faster methods are developed. The growing technology and automation have made this possible by detecting ECG conditions with mathematical computing and artificial neural networks (ANN). However, these smart technologies heavily rely on proper detection of fiducial points of which, QRS complex is an important morphology and a dominant feature of the ECG signal. The detection of QRS in the ECG signal has been the interest of researches for more than 40 years.

TABLE 3. Stage 3: Feature engineering with traditional signal processing approaches.

Fiducial Points [Ref.], Year	Detection Method	Performance Metrics	Dataset
ST-Segment [34], 2015	Wavelet Transform	$99\%_{sen}$	MITDB
QRS-Complex [35], 2011		$[99.77\%_{sen}, 99.86\%_{ppv}]_{MITDB}, [99.81\%_{sen}, 99.56\%_{ppv}]_{ESCDB}$	MITDB, ESCDB
QRS-Complex [36], 2004		$[99.8\%_{sen}, 99.86\%_{ppv}, 0.34_{me}]_{MITDB}, [99.92\%_{sen}, 99.88\%_{ppv}, 0.20_{me}]_{QTDB}, [99.61\%_{sen}, 99.48\%_{ppv}, 0.90_{me}]_{ESCDB}$,	MITDB, QTDB, ESCDB
QRS, ST-Segment [37], 2015		$0.09sec_{QRS\ duration}, 0.11sec_{ST\ duration}$	MITDB, ESCDB
QRS, R-peak [38], 2012	DWT	$99.64\%_{sen}, 99.82\%_{ppv}, 0.54_{err}$	MITDB
QRS-Complex [39], 2011	DWT-Based ACL	$99.94\%_{sen}, 99.91\%_{ppv}, 0.14_{err}$	
ST-Segment, J-Point [40], 2011	DWT-Based Windowing	$[93.33\%_{acc}]_{ESCDB}, [96.35\%_{acc}]_{MITDB}$	ESCDB, MITDB
QRS-Complex [41], 2008	DWT	$90.75\%_{sen}, 89.2\%_{ppv}$	ESCDB
QRS, P and T-Wave [42], 2009	DWT-Based Windowing	$99.84\%_{sen}, 99.8\%_{ppv}, 0.0113_{err}$	MITDB, ESCDB, QTDB and TWADB2008
QRS-Complex [58], 2010	DyWT with Matlab	$86.25\%_{acc}$	CSEDB
QRS-Complex [59], 2017	Multiwavelet Transform	$93.35\%_{acc}, 98.5\%_{sen}, 97\%_{ppv}, 0.04428_{err}$	MITDB
ST-Segment [55], 2016	KLT and LPT	$[90\%_{acc}, 91\%_{sen}]_{KLT}, [82\%_{acc}, 85\%_{sen}]_{LPT}$	LTSTDB
ST-Segment [56], 2004	KLT-Based Modular Detector	$[81.3\%_{sen}, 89.2\%_{ppv}]_{ESCDB}, [78.9\%_{sen}, 80.7\%_{ppv}]_{LTSTDB}$	ESCDB, LTSTDB
QRS, P and T Waves [57], 2010	Phasor Transform	$99.81\%_{sen}, 99.89\%_{ppv}, 0.017_{err}$	QTDB
QRS-Complex [49], 2009	MM	$99.81\%_{sen}, 99.8\%_{ppv}, 99.61\%_{Detection\ Rate}$	MITDB
QRS-Complex [50], 2006	MM	$0.21_{err}, 99.97\%_{Detection\ Rate}$	
QRS-Complex [51], 2010	MM	$85.76\%_{Detection\ Rate}$	
QRS-Complex [52], 2012	MM+VLSI Detector	$99.76\%_{sen}, 99.82\%_{ppv}, 99.57\%_{Detection\ Rate}$	
QRS-Complex [53], 2020	Gaussian + SMM	0.17_{rmse}	MITDB, QTDB
QRS and R-Peak [43], 2018	Windowing Algorithm	$94.3\%_{acc}, 96\%_{sen}, 97.3\%_{ppv}, 0.3_{err}$	MITDB
P, Q, R, S, T waves [44], 2014		$99\%_{acc}$, P$[96.72\%_{sen}]$, Q$[97.12\%_{sen}]$, R$[96.04\%_{sen}]$, S$[97.32\%_{sen}]$, T$[97.56\%_{sen}]$,	
R-Peak, ST-Segment [45], 2015		$90.1\%_{acc}$	ESCDB
R-Peak, QRS [54], 2012	Derivative Based Approach	$99.8\%_{sen}$	PTBDB
ST-Segment [46], 2016	TD	$91.37\%_{sen}, 45.53\%_{ppv}$	ESCDB
ST-Segment [47], 2019	TD	NR	
QRS, ST-Segment [48], 2012	TD Morphology and Gradients	$[0.04_{err}]$QTDB, $[0.06_{err}]$PTDB	QTDB, PTBDB
QRS-Complex [60], 2015	FIR-Based Adaptive Thresholds	$[99.9\%_{sen}, 99.87\%_{ppv}]$MITDB, $[99.84\%_{sen}, 99.71\%_{ppv}]$ESCDB	MITDB, ESCDB

The recent and advanced high computing developments, such as GPU has evolved software-based QRS detection techniques. Many Artificial Intelligence (AI) algorithms have been proposed to detect the QRS complex, ST-segment, and other fiducial points. Within the past two decades, software detection approaches of ECG fiducial points have replaced the hardware detectors. The QRS complex has been detected using variational mode decomposition (VMD), K-Nearest Neighbor (KNN), Naive Bayes (NB) and Support Vector Machine (SVM) based approaches in [61], [62] where

TABLE 4. Stage 3: Feature engineering with machine learning approaches.

Fiducial Points [Ref.], Year	Detection Method	Performance Metrics	Dataset
Fragmented-QRS and R-peak [61], 2018	VMD and KNN, NB, SVM	$86\%_{sen}$, $89\%_{ppv}$, $88\%_{acc}$	QTDB
QRS [62], 2007	Entropy-Based SVM	[$99.7\%_{Sen}$,$97.75\%_{ppv}$] 1-lead, [$99.93\%_{sen}$,$99.13\%_{ppv}$] 12-lead	CSEDB
ST-Deviation [41], 2008	Ensemble NN	$90.75\%_{sen}$, $89.2\%_{ppv}$	ESCDB
ST-Segment and T-Wave [63], 2016	DT and RUSBoost	$86\%_{sen}$, $94.85\%_{ppv}$, $77\%_{acc}$, 0.6_{F1}	
ST-Changes [64], 2018	Google's Inception V3 2-D CNN	$82.64\%_{sen}$, $80.34\%_{ppv}$, $87.38\%_{F1}$	LTSTDB

TABLE 5. Stage 4: ECG classification with traditional algorithms.

Class [Ref.], Year	Algorithm	Performance Metrics	Dataset
Normal, Abnormal [24], 2009	Modified Tompkins	$99.51\%_{acc}$, 0.0049_{err}	MITDB
Normal, Abnormal [65], 2010	Adaptive-profiling	$97.47\%_{acc}$, $99.8\%_{sen}$, $99.79\%_{ppv}$, 0.0258_{err}	
Normal, Abnormal [3], 2013	PCA, ICA	$99.28\%_{acc}$, $97.97\%_{sen}$, $99.21\%_{ppv}$	
Normal, Abnormal [66], 2016	MDL	$93.33\%_{acc}$, $100\%_{sen}$, $81.81\%_{spe}$, $90.47\%_{ppv}$	
Normal, Abnormal [67], 2013	Threshold based	$97.6\%_{acc}$, $97.3\%_{sen}$, $98.8\%_{spe}$	PTBDB
Normal, Ischemic [68], 2016	Threshold based	$98.12\%_{sen}$, $98.16\%_{spe}$	ESCDB
Normal, Abnormal [69], 2019	Regression	$97\%_{sen}$, $88\%_{spe}$, $97\%_{ppv}$	Sample Collection

the best Sensitivity of 99.93% was achieved with 12-lead ECG data and 99.79% with single-lead ECG. On the other hand, ST-segment and its changes have been detected using Decision Tree (DT) [63] and Google's Inception based 2-D Convolutional Neural Network (CNN) [64], but didn't perform well in Sensitivity as compared to [41] which employed the ensemble NN-based isoelectric level detector. These different methods are summarized in Table 4 with reported performance metrics of Sensitivity (sen), Specificity (spe), Positive Predictive Value (ppv), F1-score (F1), Error (err), Root Mean Square Error (rmse) and Accuracy (acc).

D. STAGE4: CLASSIFICATION

Once the ECG signal is acquired and has been passed through noise filtration and feature engineering stages, the last stage of ECG signal analysis process classifies the ECG signal into its different classes using the detected fiducial points and based on the problem of interest. This section discusses both traditional and machine learning approaches reported in the literature to classify the ECG signal.

1) TRADITIONAL ECG CLASSIFICATION APPROACHES

ECG beat classification of Normal and Abnormal beats have been attempted by threshold-based techniques [67], [68]. A modified Pan-Tompkins [70] based adaptive thresholding approach was presented in [65]. DWT is also used to classify ECG with the help of Principle Component Analysis (PCA) and Independent Component Analysis (ICA), as described in [3]. However, the Multimodel Decision Learning (MDL) algorithm has achieved better Sensitivity of 100% in classifying ECG as Normal and Abnormal when evaluated on the MIT-BIH arrhythmia dataset. These different methods are summarized in Table 5.

2) MACHINE LEARNING CLASSIFICATION APPROACHES

AI and Machine Learning (ML) is a branch of computer science that deals with the intelligent behavior of computers. It comprises of different methods that allow computers to learn an efficient representation of data with the help of different algorithms. AI is used for prediction or classification and could be performed using unsupervised or supervised learning with different goals. While unsupervised learning focuses on underlying structure discovery, supervised learning involves the classification of multiple categories such as "Normal versus Abnormal rhythm". Supervised learning heavily relies on datasets with labeled/structured data. Every predictive modeling requires feature selection called predictor variables. AI has been proven to be very useful in FE.

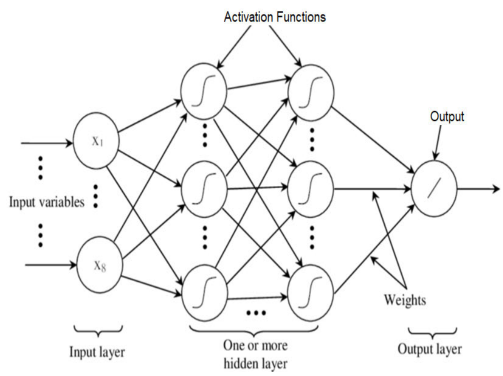

FIGURE 5. Neural network.

ANN are models of machine learning inspired by the human brain. The NN shown in Figure 5 consists of multiple layers, including an input layer followed by one or more hidden layers and an output layer. Each layer has multiple nodes called neurons, which are weighted sums of the output from the previous layer neurons. That is how each layer is connected to the next layer. The weighted sum at each neuron is further passed through an activation function such as Sigmoid, Relu, TanH or Softmax. Depending on the model and goal, the appropriate activation function is selected. The output is calculated by the weighted sum from the input to the last layer which is called forward pass or forward propagation. The error is then calculated based on the predicted output and the labeled output. Each weight is then updated to reduce the error using different methods such as Stochastic Gradient Descent (SGD), Adam, and so forth. This process is called back pass or backpropagation. One complete cycle of forward and backpropagation is called iteration or epoch. The number of epochs depends on the convergence of error and is determined with repetitive experiments or heuristically. NN can be optimized if used in feedback systems, as presented by [113].

In this study, we present the known AI-NN and techniques that have been reported in the recent literature for ECG analysis and classification of its different abnormalities. With the help of ANNs, complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) [110] and multi-module neural network system (MMNNS) [2], attempts have been made to classify different types of arrhythmias into Normal versus Abnormal from the ECG signal analysis using Ensemble Decision Tree (DT) [108] and particle swarm optimization (PSO) based Fast forward neural networks (FFNN) [109].

Support Vector Machine (SVM) is, to some extent, similar to ANN and creates a hyperplane from high-dimensional space and then linearly separates classes. Therefore, SVM is generally known as a linear classifier. Researchers have detected arrhythmias using SVM [96], [98], [101] with Sequential Minimal Optimization-SVM (SMO-SVM)) [102], Multi-class Support Vector Machine (MSVM)/Complex Support Vector Machine (CSVM) [104] and in conjunction with other ML methods such as Ensemble-SVM [97]. Even though SVM is a linear classifier, it can still capture nonlinear relationships in the cardiovascular functionalities, often making highly accurate predictions such as classifying ECG as Normal versus Abnormal [99], [100] and detecting different heartbeats [103]. However, it has computational limitations in the sense that it can be difficult in high-dimensional space and results in non-probabilistic classification such as divided outcomes. Other methods, such as isotonic regression, have overcome this problem.

Convolutional Neural Network (CNN) is a branch of machine learning and an extension to ANN with multiple layers of the network as depicted in Figure 6. Its application to cardiology goes back more than twenty years [114], [115]. In cardiology, and especially in ECG analysis, CNN has many applications such as detection of arrhythmias [85], [87], ST-changes detection [86] and

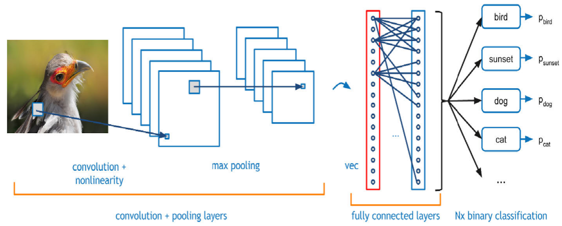

FIGURE 6. Convolutional neural network.

Normal versus Abnormal [116] classification. There are many variations to CNN and few are stated in this article to detect arrhythmias with Residual CNN [88], Recurrent Neural Network (RNN) and Long-Short Term Memory (LSTM) network [89], [90], [92]–[95] as well as detecting MI [91] events.

Deep neural networks also called deep learning [117] is a subbranch of machine learning and also considered an extension to ANN and special cases of CNN. It is a non-linear classifier that learns complex features from the data automatically and is becoming state-of-the-art for feature engineering. Its nonlinear representation learning of features makes it very compelling. Deep learning is emerging due to the availability of Graphical Processing Unit (GPU)-based computing. It has a wide variety of applications such as biometrics authentication, object detection, classification, compression, image classification, and other computer vision related technology fields. Deep learning has great potential of applications in cardiology such as ECG arrhythmia detection with Deep-CNN [71], [72], [74], [76], [77], [79], [80], Robust Deep Dictionary Language (RDDL) [73], Deep Brief Network with Restricted Boltzmann Machine (DBN+RBM) [75] and Deep Neural Network (DNN) [78]. MI detection is performed with Deep-CNN [81] and Deep Neural Network (DNN) [82] while detecting heartbeats is performed by DNN in [83]. There is a variety of neural networks; LeCun *et al.* [6] presented a detailed introduction to deep learning. Other machine learning methods such as Decision Tree Detection, Genetic Algorithm (GA), KNN and Probabilistic Neural Network (PNN) are used to detect ischemic [105], [106] events, MI [107] and arrhythmia using PCA and Linear Discriminant Analysis (LDA) [4], respectively. These different methods are summarized in Table 6 with reported performance metrics of Sensitivity (sen), Specificity (spe), Positive Predictive Value (ppv), F1-score (F1), Error (err), Root Mean Square Error (rmse) and Accuracy (acc).

V. REAL-TIME MONITORING

The main cause of death in the United States due to Cardiovascular Diseases (CVD) is accounted for 17.9% of national expenditure. This number is projected to be 45.1% by 2035 totaling to $1.1 trillion [118]. Portable and wearable battery-operated smart devices and wireless sensors have the potential to be integrated with devices such as mobile phones, smartwatches, ePatch, and wearable

TABLE 6. Stage 4: ECG classification with machine learning algorithms.

Class [Ref.], Year	Algorithm	Performance Metrics	Dataset
N, S, V, F, Q [71], 2017	Deep-CNN	$[95.14\%_{acc}, 91.64\%_{sen}, 96.01\%_{spe}, 85.17\%_{ppv}]N$, $[96.82\%_{acc}, 98.04\%_{sen}, 98.77\%_{spe}, 94.76\%_{ppv}]S$, $[97.84\%_{acc}, 94.07\%_{sen}, 98.74\%_{spe}, 95.08\%_{ppv}]V$, $[97.97\%_{acc}, 95.21\%_{sen}, 98.67\%_{spe}, 94.69\%_{ppv}]F$, $[99.16\%_{acc}, 97.39\%_{sen}, 99.61\%_{spe}, 98.40\%_{ppv}]Q$	MITDB
N, S, V, F, Q [72], 2019	Deep-CNN + Batch weighted loss	$99.79\%_{acc}, 94.65\%_{sen}, 99.36\%_{spe}, 97.71\%_{ppv}$	
N, S, V, F, Q [73], 2017	RDDL	$97\%_{acc}$, $[100\%_{sen}, 67.2\%_{spe}]F$, $[16.9\%_{sen}, 100\%_{spe}]S$, $[90.1\%_{sen}, 100\%_{spe}]V$	
N, L, R, V, S [74], 2020	Deep-CNN + $2D^2PCA$	$98.81\%_{acc}, 98.33\%_{sen}, 99.09\%_{spe}, 98.34\%_{ppv}$	
S, V [75], 2018	DBN+RBM	0.047_{err}, $[93.63\%_{acc}, 88.62\%_{sen}]S$, $[95.87\%_{acc}, 85.54\%_{sen}]V$	
N, AF, Other [76], 2018	Deep-CNN	$84.24_{acc}, 0.83_{F1\text{-}score}$	ChallengeDB 2017
N, AF, Other [77], 2020		86_{F1}, $[0.93_{err}]N$, $[0.82_{err}]AF$, $[0.79_{err}]Other$	
N, AF, Other [78], 2019	DNN	$[0.91_{N}, 0.81_{A}, 0.75_{O}]_{F1}$	
AF [79], 2018	Deep-CNN	$76.47\%_{sen}, 93.6\%_{ppv}$	ChallengeDB 2001
Multi-class [80], 2019		$[98.24\%_{PTBDB}, 97.7\%_{MITDB}, 99.71\%_{ChallengeDB2001}]_{acc}$	PTBDB, MITDB, ChallengeDB2001
Normal, MI [81], 2017		$93.5\%_{acc}, 93.71_{sen}, 92.83_{spe}, 98.03\%_{ppv}$	PTBDB
MI [82], 2019	DNN	$93.3\%_{sen}, 89.7\%_{spe}, 93.6\%_{ppv}$	
Heartbeats [83], 2020		$0.006_{mse}, 99.34\%_{acc}, 93.83\%_{sen}, 99.57\%_{spe}, 89.81\%_{ppv}, 91.44\%_{F1}$	MITNSTDB
Control, AF, VF, ST [84], 2018		$97.23\%_{acc}, 97.02\%_{sen}, 97.76\%_{ppv}, 97.35\%_{F1}$	MITDB, ESCDB
S, V [85], 2015	CNN	$[97.6\%_{acc}, 60.3\%_{sen}, 99.2\%_{spe}]S$, $[99\%_{acc}, 93.9\%_{sen}, 98.9\%_{spe}]V$	MITDB
ST-Change [86], 2018		$89.6\%_{auc}, 84.4\%_{sen}, 84.9\%_{spe}$	LTSTDB
Multi-class [87], 2018		$81\%_{acc}, 81\%_{f1\text{-}sore}$	CPSCDB2018
N, S, V, F, Q [88], 2020	Residual CNN	$[99.06\%_{acc}, 93.21\%_{sen}, 96.76\%_{ppv}]1\text{-}Lead$, $[99.38\%_{acc}, 94.54\%_{sen}, 98.14\%_{spe}]2\text{-}Lead$	MITDB
S, V [89], 2018	RCNN	$[99.1\%_{acc}, 92.7\%_{sen}, 99.3\%_{spe}, 80.2\%_{ppv}]S$, $[99.6\%_{acc}, 98.8\%_{sen}, 99.6\%_{spe}, 95.5\%_{ppv}]V$	
Multi-class [90], 2020		$83.5\%_{F1}$	CPSCDB2018
MI Detection [91], 2020	End-to-end CNN	$98.21\%_{acc}, 97.5\%_{sen}, 98.01\%_{spe}$	PTBDB
N, L, R, V, S [92], 2018	CNN+LSTM	$98.1\%_{acc}, 97.5\%_{sen}, 98.7\%_{spe}$	MITDB
Multi-class [93], 2020		$97.15\%_{acc}, 95.40\%_{sen}, 96.80\%_{spe}, 95.56\%_{ppv}$	
Multi-class [94], 2018	RNN+LSTM	$74.15\%_{F1}$	CPSCDB2018
Multi-class [95], 2020	LSTM	$90\%_{acc}$	CSEDB2020
Arrhythmia Beats [96], 2016	SVM+GA	$0.0163_{rmse}, 97.3\%_{acc}, 97.5\%_{sen}, 99.32\%_{spe}, 97.41\%_{ppv}$	MITDB
Heartbeats [97], 2020	Ensemble SVM	$94.4\%_{acc}, 65.26\%_{sen}, 93.25\%_{spe}, 66.24\%_{F1}$	
Multi-class [98], 2020	SVM	$99.27\%_{acc}, 96.22\%_{sen}, 99.58\%_{spe}$	
Normal, Abnormal [99], 2016	SVM+NN	$0.3_{err}, 98.91\%_{acc}, 98.91\%_{sen}, 97.85\%_{spe}$	
Normal, Abnormal [100], 2018	SVM	$96\%_{acc}$	
N, S, V, F, Q [101], 2015		$98.49\%_{acc}$, $[99.57\%_{N}, 97.91\%_{S}, 92.18\%_{V}, 76.54\%_{F}, 97.22\%_{Q}]_{acc}$	
N, S, V [102], 2017	SMO-SVM	$99.20\%_{acc}, 98.01\%_{sen}, 99.49\%_{spe}$	
N, LBBB, RBBB, Q [103], 2017	SVM+NN	$0.0042_{err}, 98.39\%_{acc}, 96.86\%_{sen}, 98.92\%_{spe}$	
N, V, S, F [104], 2015	MSVM+CSVM	$[86\%_{acc}]MSVM$, $[94\%_{acc}]CSVM$	ESCDB
Normal, Ischemic [105], 2007	DT+Fuzzy Model	$91.7\%_{acc}, 91.2\%_{sen}, 92.2\%_{spe}$	ESCDB, MITDB
Ischemic [106], 2004	MDA-based GA	$91\%_{sen}, 91\%_{spe}$	ESCDB
MI [107], 2012	KNN	$98.8\%_{acc}, 99.97\%_{sen}, 99.9\%_{spe}$	PTBDB
Arrhythmia [4], 2013	PNN+PCA+LDA	$99.71\%_{acc}, 97.98\%_{sen}, 99.1\%_{spe}$	MITDB
Normal, Abnormal [108], 2014	ANN+Ensemble DT	$[98.73\%_{acc}]ANN$, $[99.4\%_{acc}]Ensemble$	MITDB, QTDB, ESCDB
Normal, Abnormal [109], 2019	ANN+PSO+FFNN	$93.6\%_{acc}, 92\%_{sen}$	MITDB
N, L, R, V, S [110], 2019	ANN+CEEMDAN	$99.9_{acc}, 99.7_{sen}, 99.9_{spe}$	
S, V [2], 2019	ANN+MMNNS	$[[97.3\%_{acc}, 64.4\%_{sen}, 98.6\%_{spe}, 63.7\%_{ppv}]S]_{MITBDB}$, $[[98.8\%_{acc}, 91\%_{sen}, 99.3\%_{spe}, 90\%_{ppv}]V]_{ESCDB}$	MITDB, ESCDB
Ischemic [111], 2002	ANN+PCA	$90\%_{sen}, 90\%_{spe}$	ESCDB
N, S, V, F, Q [112], 2016	Random Forest	$94.61\%_{acc}$, $[94.67\%_{sen}, 99.73\%_{ppv}]N$, $[20\%_{sen}, 0.16\%_{ppv}]S$, $[94.2\%_{sen}, 89.78\%_{ppv}]V$, $[50\%_{sen}, 0.52\%_{ppv}]F$, $[0\%_{sen}, 0\%_{ppv}]Q$	MITDB

handheld monitoring devices. The integration provides continuous ECG monitoring and can improve real-time monitoring, detection, and early treatment of different cardiovascular diseases. These portable and wearable sensors are capable of recording and analyzing the ECG signal to detect the QRS complex as well as other ECG characteristics. ECG monitoring and analysis can be achieved in three different ways. For the purpose of this article, we are labeling them as three separate systems.

1) System 1: As shown in Figure 7, a recorder is used that acquires the ECG signal to be diagnosed later in an offline mode. Devices like Holter, GE MAC5500, GE's SEER Digital Holter, Philips's Digitrack, BIOPAC MP150, ePatch by DELTA and Midmark's IQmark are few of the popular devices that provide several hours bedside or body attached acquisition. The data acquired is analyzed offline by algorithms such as wavelet transforms [119]–[124]. In many cases, a doctor would analyze the data. Limitations to such a method include non-real-time classification.

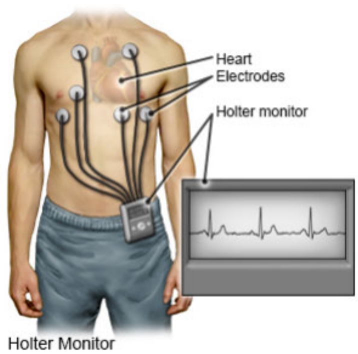

FIGURE 7. System 1.

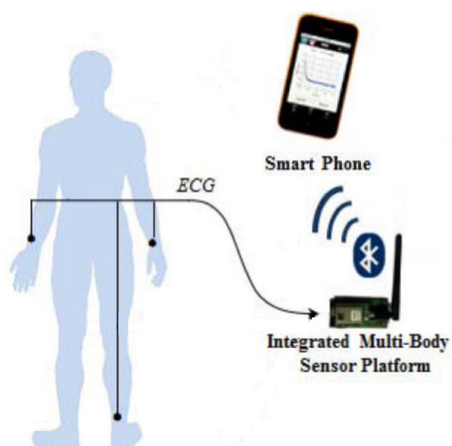

FIGURE 8. System 2.

2) System 2: As shown in Figure 8, these systems use real-time detection and diagnosis of the device itself. Examples of such devices include smartwatches, smartphones, Nuvant Corventis PiiX, AliveCor, SmartCardia INYU and MyThrob System on Chip (SoC) in which the R-peaks are detected using Relative-Energy-based WeArable R-Peak Detection (REWARD) [125], and wavelet transform [126], [127], ST-segments using SVM [128], and the QRS complex is detected using WT [129]. Diagnosis is performed on the smart device itself using appropriate classification methods. However, these types of systems put a burden on the device in terms of computational complexity, memory, and battery life.

3) System 3: As shown in Figure 9, these systems use a three-layer structure discussed later in this section. ECG is acquired with attached patches, portable or wearable sensors and is sent to a coordinator such as Personal Digital Assistant (PDA), smartphone or a controller that processes the ECG data and sends it to a central location with live connection for further diagnosis and classification. Jurik and Weaver [130] have explained this in a three-tier form. Limitations of this method are the lack of real-time feedback for early treatment.

Beyond the traditional analysis of ECG, the automated analysis is receiving significant attention and has gone through substantial advances. Deaths by cardiovascular diseases have an economic fallout, and its burden is expected to rise due to unhealthy lifestyles and the growing population of the world. This requires continuous supervision and medical care of cardiovascular diseases and comes with the cost of medical equipment. Wireless body sensor network (WBSN) technologies provide scalable and cost-effective solutions to this problem. They are able to measure the ECG signal continuously, provide real-time monitoring by sending data to a centralized location, integrate the data with the person's medical history, and provoke early diagnosis and medical support. Wearable devices and its automated ECG analysis have gained both academic and industrial attention in supporting a fairly new term Next Generation Mobile Cardiology (NGMC). Such attention resulted in the development of many wearable and portable devices both for commercial and research purposes. Similar to the American Heart Association [131] which offers practice standards for bedside ECG monitoring at hospitals, any sensor that receives the ECG signal must follow the Food and Drug Administration (FDA) regulation under 21 CFR 870.2360, class II Code DRX and 501(k) for marketing clearance. Real-time monitoring usually follows the structure of System 3 for ECG signal analysis and diagnosis in real-time for early detection and treatment, which undergoes the process of three layers:

1) Layer 1: Body Sensors: As shown in Figure 10, this layer consists of sensors attached to the patient's body to sense the ECG signal and send it to the next layer. Portable and wearable monitoring devices for ECG, also called ECG patch monitoring (EPM), cleared by FDA are limited by recording capabilities such as being only a single lead. AD8232 with three leads,

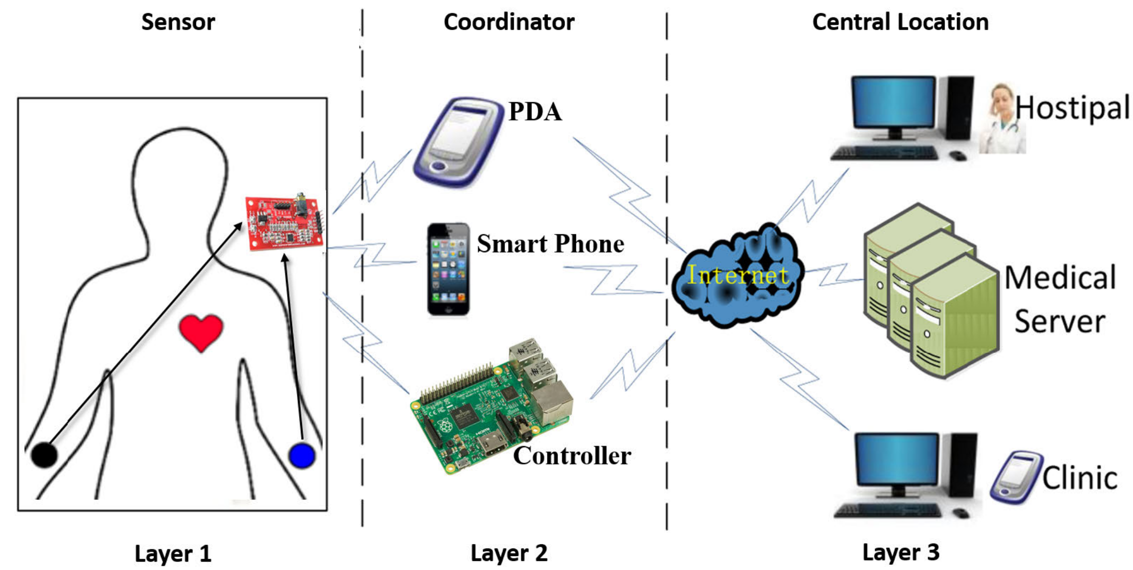

FIGURE 9. System 3: Wireless body sensor network.

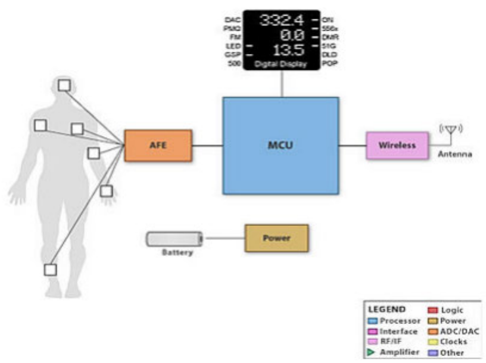

FIGURE 10. Body sensors.

Zio Patch [132], Sensium Life Pebble and two-channel Shimmer3 [133] which is a Bluetooth based wireless sensor are a few popular devices that are used as sensors attached to the body surface for ECG acquisition, detection of the QRS complex [134], [135] and sending the ECG signal to the coordinator.

2) Layer 2: Coordinator: Devices such as Arduino, ADuCM361 and TI MSP430 controllers receive the data from previous layers using directly attached cables or over radio protocols such as wireless IEEE802.11x, Bluetooth IEEE802.15.1, and Zigbee IEEE802.15.4 [136] for graphical representation, which then sends the data to the next layer over a data network such as GSM. Sending data over these protocols consume and require bandwidth. Compressing the ECG signal without compromising data is essential to reduce the overall energy consumption of the coordinator role of portable devices. Techniques like Quad Level Vector (QLV) [127], lossless compression by [137], or huffman coding can be used to compress the ECG signal while keeping its features intact.

3) Layer 3: Diagnoses: This layer receives the data from previous layers for analysis and diagnosis of ECG conditions. This could be a remote server with GPU computing or a cloud hosted solution such as Amazon Web Services (AWS) Core IoT, Thingspeak and Ubidots for graphical representation or analysis with AI algorithms for diagnosis of different heart conditions.

Major improvements in monitoring systems of cardiac activity have been taking place by the deployment of AI algorithms, ischemia monitoring, noise reduction schemes and detection with reduced number of leads. Tele-healthcare is gaining wide attention with the growing technology of body sensors and its integration with portable and wearable devices. It may become standard procedure for the treatment of certain health conditions as the technology matures and gains further acceptance. The different features of ECG, detected with different methods, sensors, hardware platforms and their evaluations on different databases is summarized in Table 7 along with reported performance metrics of Sensitivity (sen), Specificity (spe), Positive Predictive Value (ppv), F1-score (F1), Error (err), Root Mean Square Error (rmse) and Accuracy (acc).

VI. RESEARCH TOOLS

When it comes to evaluating detection or classification algorithms, researchers use PC-based software to train, test, and evaluate their methods. There are computer-based software such as Labview, Python, and Matlab that include a lot of libraries which can be used to evaluate an algorithm. These tools provide methods to import prerecorded ECG signals from the publicly available databases discussed in section IV-A. However, the "R" tool can be used to analyze datasets itself. Even though datasets come with explanations of the recording environment and other details, by using "R," one can have different views to see the attributes,

TABLE 7. Stage 3: Feature engineering methodologies for real-time monitoring.

Fiducial Points [Ref.], Year	Detection Method	Performance Metrics	Sensor	Platform	Application	Dataset
R-Peak [125], 2019	REWARD+WT	$99.33\%_{sen}$, $99.28\%_{ppv}$, $2.74\%_{err}$	Silicon EFM32	Emulator Board	Simplicity Studio	QTDB
R-Peak [126], 2018	Maximum Value-based Formula	NR	OLIMEX Shield EKG-EMG	Smartphone	Android SDK	Sensor Data
R-Peak [127], 2009	QLV	$95.63\%_{sen}$, $97.04\%_{ppv}$	MITDB Data	TI MSP430 Microcontroller	NR	MITDB
QRS,R-Peak [138], 2007	First and Second Derivative	NR		NokiaN91, Siemens C75, Nokia 6280	Java	
QRS,P,T-Wave [139], 2018	LocalMaximum Point + LocalMinimum Point	$99.17\%_{sen}$, $99.55\%_{ppv}$, $1.28\%_{err}$		Opal Kelly XEM6001 FPGA	Verilog	
QRS [119], 2010	Wavelet-Transform	$99.8\%_{sen}$, $99.86\%_{ppv}$, $35\%_{err}$		ASIC CMOS IC	NR	
QRS [120], 2012		$99.57\%_{sen}$, $99.57\%_{ppv}$	ePatch	Delta	Matlab + WFDB	
QRS [121], 2011		NR	CC2420 Zigbee Transceiver	TI MSP430 Micro controller	TinyOS with C and Java	Sensor Data
QRS,P,T-Wave [122], 2011		$99.97\%_{sen}$, $98.72\%_{ppv}$	Shimmer		FreeRTOS with CCE Compiler	QTDB
QRS [134], 2017	First and Second Derivative	$100\%_{sen}$, $99.51\%_{ppv}$			Matlab + WFDB	
QRS [123], 2012	Wavelet-Transform	$78\%_{sen}$, $87\%_{ppv}$		IcyHeart SoC	NR	CSEDB2017
QRS [140], 2012		$89.5\%_{sen}$, $80.6\%_{spe}$		Smartphone	Android SDK	MITDB
QRS [135], 2013	First and Second Derivative	570-700us$_{\text{time required}}$	Front End Circuit		Java	
QRS [129], 2017	jqrs Detector	$83\%_{F1}$	AliveCor		SVM	ChallengeDB2017
ST-Segment [128], 2010	SVM + PCA	$96\%_{acc}$			HeartToGo	ESCDB
Arrhythmias [141], 2015	Context-Aware System	$97.7\%_{acc}$, $94.7\%_{sen}$	Self-Design Sensor		Designed Application	Sensor Data

annotations and analyze the datasets differently. On the other hand, there are emulator boards sometimes called Open Source HardWare (OSHW) such as Arduino Mega 2560, Duino Olimexino-5510, TI MSP430-T5510 and many other available tools for experimental and testing purposes. Emulation software is required with each of these for programming purposes so that the ECG acquisition and processing can be performed. Arduino IDE and MSPSim are examples of emulation software. ECG sensors such as AD8232 can be used with these boards using patch, clip or cup electrode ECG cables to acquire the ECG signal and process it using these emulators. However, on-board (on-chip) analysis and classification of ECG requires further processing capabilities. There are boards called System on Module (SOM) such as RK3188 and AM335X with ARM Cortex Quad-Core processor on-board to provide embedded processing of algorithms along with System on Chip (SOC) boards such as NXP Nexperia-8550. Android provides a developmental platform that can be used to develop applications on ARM Cortex based OSHW and SOM boards. There are also portable simulators available such as AliveCor, Fluke ProSim 8 ECG Patient Simulator, TriSmed TSM3000B, and many others [142] that can be used to acquire ECG and perform some tests in real-time. Moreover, 12 lead ECG portable simulators are available for testing purposes, such as Zoll CS1201. A similar 12-lead portable simulator is designed and proposed by [143].

VII. DISCUSSION

Emerging of AI with traditional and advanced algorithms has allowed numerous improvements in many real-world tasks. Consider a logistic regression example. For instance, the estimation of statistical values and coefficients requires strong assumptions such as collinearity among variables and independent observations, in which case the statistical inference may hinder the performance of a model. AI algorithms overcome such assumptions with improved prediction and classification. Thus, cardiology can benefit from AI and machine learning in conjunction with other real-time monitoring systems.

TABLE 8. Comparative summary of ECG survey papers.

				ECG Signal Analysis - Stages							
[Ref.], Year	Publisher	# of Citations	# of Reviewed Papers	Stage1: Dataset Sources	Stage2: Quality Check	Stage3: Feature Engineering	Stage4: Classification	Real-Time Monitoring	Research Tools	Focus Area	Performance Metrics
[144], 2016	Elsevier/ Journal	338	67	MITBIH	×	✓	✓	×	×	Heartbeat detection	sen, ppv, acc
[145], 2017	IEEE/ Conference	1	31	MITBIH, PTB, ESCDB	×	✓	×	×	×	MI detection	sen, ppv, acc
[146], 2015	IEEE/ Conference	19	27	×	✓	×	✓	×	×	Denoising	NR
[147],2019	IEEE/ Conference	1	20	MITBIH, ESCDB	×	✓	✓	×	×	Beat classification	sen, ppv, acc
[148], 2015	IEEE/ Conference	113	39	MITBIH	×	✓	✓	×	×	Arrhythmia detection	sen, ppv, acc, rmse, mse
[149], 2014	SciEP/ Journal	57	98	MITBIH, QTDB, ESCDB, CSEDB	×	✓	×	×	✓	QRS detection	sen, ppv, acc
[150], 2020	Elsevier/ Journal	3	45	MITBIH	✓	✓	✓	×	×	Arrhythmia detection	sen, ppv, acc
[151], 2016	IEEE/ Conference	18	31	MITBIH, QTDB, ESCDB, PTBDB	✓	✓	✓	×	×	Heartbeat detection	sen, ppv, acc
[152], 2017	IJCA/ Journal	28	24	MITBIH	×	×	✓	×	×	Arrhythmia detection	sen, ppv, acc
[153], 2010	ARXIV/ Journal	161	19	MITBIH	×	✓	×	×	×	Feature extraction	sen, ppv, acc
[154], 2013	Springer/ Journal	234	27	×	×	×	×	✓	✓	Real-Time monitoring	×
[155], 2018	IEEE/ Journal	7	19	×	×	✓	✓	×	×	Feature extraction	×
[156], 2018	IEEE/ Journal	34	41	MITBIH, MITNSTDB, TELE ECG, PICC*, MITBIHSTC*, Fantasia*, MACE*, MIMIC-II*	✓	✓	✓	×	×	Denoising, Classification	sen, ppv, acc
[157], 2017	IEEE/ Journal	30	14	PTBDB, ESCDB, LTSTDB	✓	✓	✓	×	×	MI detection	sen, ppv, acc
This article	IEEE/ Journal	N/A	107	MITBIH, ESCDB, LTSTDB, QTDB, TWADB, CSEDB, PTBDB, TELE ECG, AHADB, MITNSTDB, INCARTDB, CHALLENGE-DB2017, CPSC-DB2018	✔	✔	✔	✔	✔	4-Stage ECG analysis model survey, ECG data acquisition source, Denoising, All fiducial points, Classification, Real-Time monitoring, Research tools, ECG morphology study	sen, ppv, acc, spe, f1-score, err, mse, rmse

* PhysioNet in Cardiology Challenge2011 (PICC) [158], MIT-BIH ST Change (MITBIHSTC) [159], Fantasia [160], Motion Artifact Contaminated ECG (MACE) [161], Multiparameter intelligent monitoring in intensive care-II (MIMIC-II) [162]

High computing capabilities and mobile connectivity of electronic devices have provided a surge in mobile health technologies that are geographically independent with smart and wearable devices. Real-time data streaming has enhanced clinical care in an automated fashion with decision support tools. However, the lack of a framework for cost, regulatory standard, and security protocols is a big hurdle in the adaption of these modern technologies in real life. Efforts need to be established to overcome these barriers to take full advantage of mobile health, tele-health, real-time monitoring and care in the field of medicine and specifically, cardiology [163].

Various techniques have been reviewed in this article for ECG analysis to show the automated detection of ECG fiducial points and classifying related conditions such as MI. However, not all studies have performed their experiment with the same lead(s) and/or databases. Some have used single-lead ECG [81], [164], [165], and others have used 12-leads [107], [166], [167] to introduce their models and analysis of ECG. Another major challenge is that generally all 12 ECG leads are required to accurately identify the ST-segment changes for MI. This is while 12-lead ECG is mostly used in clinical settings and inconvenient for real-time monitoring with portable/wearable ECG devices. Highly accurate, time dependent sequential data interpolation methods may be required to represent the ECG data from other leads using only a single lead.

To better understand the contributions of this study, we present a comparative summary table (Table 8) that lists our contributions in comparison with other related survey papers in the field. ECG is a well researched area and to date, many ECG survey papers have been published. Reputable ECG survey papers with high number of citations were selected for this comparative summary. The main focus area of each survey paper is listed in the table of comparison. The table clearly depicts that this study has reviewed a larger number of papers, collectively, regarding ECG databases, real-time monitoring and research tools in each stage of the ECG signal analysis process model, as shown in Figure 1. This survey also stands out among others in terms of more focused areas and performance metrics included in the comparative study with respect to other reported survey and review papers. Comprehensively reviewing ECG signal analysis techniques in the structure of a stages-based model, the detailed study on research tools for ECG analysis as well as the study of real-time ECG monitoring systems along with elaborated discussions of the challenges/limitations are among the main contributions of this survey paper. This survey sheds light on ECG research avenues in a stages-based ECG signal analysis process model where new and experienced researchers can refer to initiate or further continue progressing in this competitive area.

Performance metrics such as accuracy and f1-score are among the well-known measures of assessing the efficiency of ECG analysis systems. On the other hand, systems engineering and system dynamics are other quantitative and qualitative approaches to evaluate the effectiveness of ECG analysis systems in a broader context [168]. In such approaches, nonlinear feedback relationship models are designed, where in addition to the ECG system's device and analysis algorithm factors, other societal (patient care and well-being), environmental (green resources and energy) and economic (cost) factors also play a significant role in determining the overall effectiveness of the ECG analysis system.

VIII. LIMITATIONS

After carefully reviewing a large body of existing papers in the field of ECG signal analysis where numerous ideas have been compared and contrasted, one can observe that traditional signal processing approaches may not perform as accurate as recent deep and machine learning approaches. On the other hand, deep/machine learning approaches generally have higher computational complexities and therefore would require higher cost processors to operate. The main limitations of various ECG studies can be quantitatively noted in terms of performance metrics (such and accuracy and f1-score, etc.), and time and computational complexity (generally reported in Big O notations). Remedies to these limitations involve tradeoff in the design procedure and possibly employing an ensemble of techniques. Other limitations include concerns regarding the lack of a globally unified regulatory standardization for the number of ECG leads, databases, ECG analysis platforms, unified performance metrics and security protocols, among others.

This comprehensive literature study, though uncovers the massive body of research regarding ECG signal analysis, also reveals certain challenges and unsettleties in this competitive research field. The lack of consistent ECG signal distributions among devices/datasets as well as the lack of unified metrics used to report the performance of different techniques are among the top concerns. With the variety of ECG devices used in medical and research settings, the distribution of ECG data varies, making one ECG analysis technique practically not suitable for ECG data captured differently. In general, deep/machine learning techniques require that the development set used for training be from the same distribution of the test set to prevent high variance. Thus, there is a need for a unified standard or a common-ground framework for ECG signal analysis - starting from the data distribution to quantification of results - where researchers and/or industries developing portable and wearable ECG devices must follow to compare the ideas and results with one another and build-up from there to achieve better performance of ECG signal classification. Real-time ECG tele-health and early treatment can be improved with the assurance of accreditation or certification of such framework or standard. Moreover, bio-data augmentation of the heart functionality from the ECG signal, especially required in heart surgery settings as well as medical schools for education and research purposes, can significantly benefit from such unified standard.

In the context of this survey paper, additional limitations include the fact that with the enormous body of ECG studies existing in the literature, only a portion has been has been reviewed. We have made best efforts to provide a comprehensive review of the majority portion of the body of ECG research and wide range of ECG analysis literature, but there are more methods and techniques used to analyze the ECG signal that can further be reviewed and verified. The selection of related survey papers for the purpose of comparing the contributions and advantages of this study (Table 8) with other related survey papers consists of highly reputable journals. However, we rely on integrity of these work for what they have reported. Verifying the results reported in other related work is beyond the scope of this survey paper.

IX. CONCLUSION AND FUTURE WORK

ECG is an important tool and can be used to diagnose abnormalities of the heart function. Early diagnosis of MI can save lives and is a challenging task, but with CAD and machine learning techniques, automated diagnosis of MI can be achieved with ECG analysis and classification. This article presented a comprehensive review of different traditional and machine learning methods used in every stage of ECG signal analysis, specifically for the ECG classification task. Both automated and somewhat automated machine learning techniques to detect ECG fiducial points such as R-peaks and QRS complexes have been presented. Deep learning techniques show more efficient detection and classification results in the recently published work.

We have introduced a stages-based model for ECG signal analysis in this article where the bulk of any ECG literature can be categorized into one or more stages of the presented model. In this survey paper, researchers are directed to the huge corpus of ECG research literature with insights on how the ECG signal goes through different stages/processes and what is included in each stage in terms of data acquisition, and the methods/techniques and algorithms related to each stage of ECG signal analysis. A variety of software and hardware tools for research in this field have also been outlined. In addition, the major challenges and limitations have been discussed and suggestions have been provided for future research.

We summarized a variety of deep learning methods for ECG analysis recently published in the literature in a tabular form. From our survey, the majority of researchers have used MITDB to evaluate their methods of ECG analysis and classification based on one dimensional ECG data. However, very little attention is paid towards the 2-D image-based classification of ECG in the literature surveyed. Building upon our recently published preliminary work in this area [116], we plan to further explore deep CNNs for 2-D image-based ECG classification to distinguish multiple classes of ECG beats.

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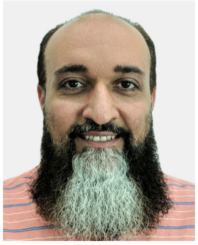

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