Chapter 4
Artificial Intelligence of Things for Early Detection of Cardiac Diseases

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4.1 Introduction

Much of the fatal illnesses are cardiovascular diseases (CVD) that might be coronary heart diseases. According to the World Health Organization (WHO) report, 17.9 million deaths related to CVDs were found in 2016, comprising 31% of all worldwide deaths. Medical scientific know-how is causing rapid strides in solving these problems and advances to solve those issues.

The past three decades have been characterized by an exponential growth in knowledge and advances in the clinical treatment of atrial fibrillation (AF). It is now known that AF genesis requires a vulnerable atrial substrate and that the formation and composition of this substrate may vary depending on comorbid conditions, genetics, sex, and other factors. Population-based studies have identified numerous factors that modify the atrial substrate and increase AF susceptibility. To date, genetic studies have reported 17 independent signals for AF at 14 genomic regions. Studies have established that advanced age, male sex, and European ancestry are prominent AF risk factors.

Other modifiable risk factors include sedentary lifestyle, smoking, obesity, diabetes mellitus, obstructive sleep apnea, and elevated blood pressure predispose to AF, and each factor has been shown to induce structural and electric remodeling of the atria. Both heart failure (HF) and myocardial infarction increase risk of AF and vice versa creating a feed-forward loop that increases mortality. Other cardiovascular outcomes attributed to AF, including stroke and thromboembolism, are well

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established, and epidemiology studies have championed therapeutics that mitigate these adverse outcomes. However, the role of anticoagulation for preventing dementia attributed to AF is less established

In the current clinical practice, the heart specialist adopts the ECG sign recordings and patient's questionnaire for the preliminary assessment of the patient's condition. However, this approach might also additionally fail to capture the severity of the ailment because of the restricted period of ECG recordings and the intermittent nature of cardiac arrest. Presently, artificial intelligence (AI) may also be able to solve this issue. There are many researches done in AI till date being used nowadays.

Natural intelligence shown or expressed by human beings and animals involves the consciousness and emotions. Artificial intelligence (AI) refers to the simulation of human intelligence in the machines which can be programmed to think like humans and mimic their actions. The term may also be called to any machine that exhibits the traits associated with a human mind such as learning, problem-solving, and speech recognition. The term artificial intelligence is linked with path of our everyday life.

Artificial intelligence (AI) and wearable technologies have been found to be big developments in the area of disease remediation. For the sake of everyday fitness treatment in an elderly population, if consumers can link a wearable monitoring app that can find suspicious electrocardiogram (ECG) signs and give a warning message to the hospital immediately, this tool can save you from several tragedies.

4.1.1 Objectives

The objectives of the chapter are as follows:

- Discussion on atrial fibrillation (AF).
- Study on various monitoring devices and applications.
- Cloud-based AI and database framework.
- Discussion on accuracy and efficiency of the framework.

4.1.2 Organization of Chapter

The remaining of the chapter is organized as follows: Section 4.2 includes related terminologies of reference articles referred to the study of our topic. Section 4.3 deals with the cloud-based AI and databases. Section 4.4 deals with cloud-based AI system. Section 4.5 deals with the experimental study and result comparisons. Section 4.6 concludes the application of novel artificial intelligence in the field of personalized care.

4.2 Related Terminologies

4.2.1 Wearable Heart Condition Monitoring Device for Artificial Intelligence of Things

The whole research establishes an artificial intelligence device for electrocardiogram (ECG) evaluation and detection of cardiac disorders [1]. The device consists of IoT-based front-end hardware, a smart device Application Personal Interface, a cloud database, and a cardiac disorder identification AI platform. This involves front end with IoT-based hardware, which detects portable ECG device consisting of an analogue front-end circuit and a Bluetooth module. The software on smart phones was unable to view users' actual ECG data more accurately, but it can automatically mark irregular notifications and early detection in real time. The cloud database server is used in order to store the ECG signal. It creates a big data archive for the AI algorithm to capture heart beat anomalies. The study's suggested algorithm depends on the convolutional neural network, and 94.96% is the familiar accuracy.

This research suggests a whole ecosystem of AIoT systems that is an interactive health care system that contains a database of hardware, apps, and cloud, which is intended to increase health. Compared to different algorithms, the AI-based cardiac disease classification model, which uses the advice of an expert cardiologist as a guide, has a simpler record of preprocessing success and an acceptable recognition sequence. Conversely, in order to resolve the problems of human variations and increase the responsiveness of the model, additional input from multiple therapeutic persons is required, which could be used to test the network and help control the role of preprocessing. Furthermore, this study takes a single lead ECG as the measure, so it cannot investigate a few forms of cardiac disease.

4.2.2 Large-Scale Arrhythmia Screening Artificial Intelligence System Focused on the Cloud

The significant source of arrhythmia is atrial fibrillation (AFib), and AFib patients have an increased risk of stroke [2]. These might result in sudden cardiac arrest. For screening arrhythmia, an artificial intelligence device, a cloud-based one specifically for AFib, is used to establish an efficient and sustainable technique for the detection of undiagnosed AFib. A cloud-based device for artificial intelligence (AI) which could exhibit arrhythmia screens in various outcomes. For a health checkup, a specialist combines the armband with the smart screen to display a vast number of participants within a small time period to receive news reports instantly. Hospital patients can take the bracelet home for a period of 7–14 days, screened with a smart phone app for tracking and getting the notifications. Both data from the systems may also be managed by an automated processing algorithm that removes unnecessary data and exports feedback for doctors to make final assessments.

4.2.3 Mobile Heart Attack Early Warning Approach Using Artificial Digital Stethoscope Intelligence Novel

The chapter reports the design of a mobile, low-cost device for early cardiac abnormality detection [3]. For monitoring coronary cardiac signals in actual and transferring it to our smartphone application for simultaneous cloud assessment, a special wireless stethoscope has been created here. Coronary heart sounds are preprocessed to detect improvements by algorithms such as audio slicing and segmentation and then transformed into top-notch spectrograms classified by our pre-trained cloud-based convolutional neural network (CNN).

4.2.4 Artificial Intelligence Management Allowed Smart Wearable Devices for CVD Early Diagnosis and Continuous Monitoring

Many researches addresses the therapy to regulate CVDs which are capable to timely monitor the patients [4]. Wearable devices are found to be an efficient way of overcoming the requirements of CVDs. In reality, even so, it is a basic pickup innovation that typically needs to be understood and cost-effective for which unique hints are determined to allow their still fully functional skills, such as solar-powered batteries in the unit. This will be used to evaluate the outcomes of implementing the era of wearable devices in the wellness of the patient with coronary heart diseases and their effects on the patients' lifestyle, as well as to aid for an assessment of the mechanism of the era of wearable devices on patients with cardiovascular diseases, to examine the effect of sophisticated artificial intelligence approaches on improving the speed and precision of wearable devices, and to discuss the potential problems of smart wearable devices that want to be solved.

4.2.5 Heart Disease Prediction Using Artificial Intelligence

Machine learning (ML) artificial intelligence is already found to be powerful in promoting the decision-making and forecasting of the vast volume of knowledge provided by means of the healthcare industry [5]. We have seen ML methods being used in new technologies in various Internet of Things (IoT) areas. Various studies give an insight into the prediction of coronary heart disease with ML techniques.

In this, a novel method aims at identifying main characteristics by ways of using system study technology to achieve the precision of disorder forecasting. With special configurations of abilities and many recognized classification methods, the prediction model is applied. Recognizing the production of raw patient information from coronary heart records will help save human lives and diagnose abnormalities in coronary heart problems early in the future. Computer study algorithms have been implemented to system data on this work and include a substitution and novel discernment of heart disease. In the clinical area, coronary heart disease estimation is challenging and potentially important. Even so, once the disease is diagnosed at the initial stage, the loss of life rate is routinely dramatically controlled, and prevention steps are followed as quickly as possible. Instead of only theoretical methods and models, further expansion of this analysis may be more useful to guide the studies to real-world datasets.

4.3 Cloud-Based AI and Database

A cloud-based artificial intelligence (AI) framework that can view heart condition displays screens in multiple scenarios. The cloud database server is used to capture the ECG signals of each individual, which forms a large-data AI algorithm database for cardiovascular disease detection. By means of an automated processing algorithm that eliminates redundant documents and export reports, all machine data can be processed for doctors to make final evaluations. More details are mentioned in Sect. 3.3.

4.3.1 Artificial Intelligence

Artificial intelligence (AI) [3] is a computational machine that is capable of conducting activities that typically involve human intelligence, like receiving environmental impressions and accomplishing goals using algorithms, pattern matching, heuristics, rules, cognitive computing, and deep learning (DL).

The continuing advancement of AI approaches, especially in the ML and DL subdomains, has increasingly drawn clinicians' attention to improving novel integrated, effective, and competitive strategies for delivering quality healthcare.

In cardiovascular medicine, imaging is the subject of concern and analysis in AI. In echocardiography, the benefits of using machine learning models lie in the elimination of inter- and intra-operator variability. It provides additional statistical information that could be too subtle for the human eyes to identify.

The relationship among cardiac CT and ML algorithms in people having these disorders has demonstrated the ability in clinical practice to take noninvasive methods and to identify functional knowledge beyond the characterization of atherosclerotic plaque. In addition to diagnostic imaging, automated identification of anomalies in electrocardiograms may be another interesting use of ML in cardiology.

4.3.2 Machine Learning

Machine learning (ML) [6] is a subset of AI that seeks to "teach" computers with the use of complicated computation and statistical algorithms to analyze vast datasets in a fast, accurate, and effective manner. Such models may recognize trends on new data that fit and render predictions based on current data they have already "learned from." It can be classified into three groups based on the way in which the predictive model learns and accumulates the data:

1. Supervised learning (e.g., logistic regression, Support Vector Machine, and neural networks): utilizes human-labeled databases that are typically often used build models that anticipate or describe potential events or know the most significant outcome variables. Figure 4.1 shows the block diagram of supervised learning.
2. Unsupervised learning (e.g., cluster analysis): in datasets through prior categorization of the training collection, the algorithm may recognize hidden framework (only when x is known). It identifies novel relationships within the results. Figure 4.2 shows the block diagram of unsupervised learning.
3. Reinforcement learning/semi-supervised learning: reward-driven learning (usually deployed in games and robotic apps), focused on atmospheric interactions where positive and negative reinforcements contribute toward the development of the predictive model. The computer must be designed with devices and facilities that not only promote learning but also take into account environmental features, such as sensors and cameras. Figure 4.3 shows the block diagram of reinforcement learning/semi-supervised learning.

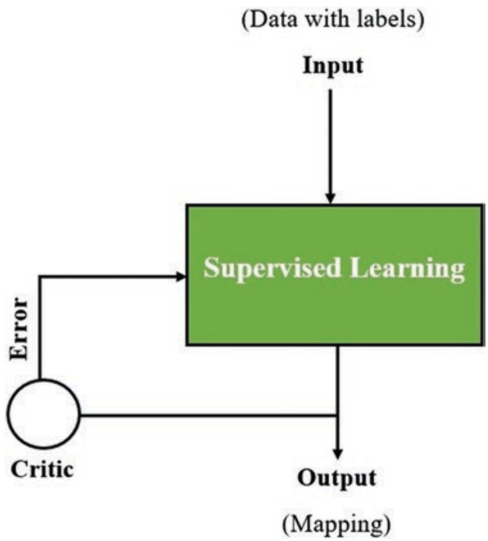

Fig. 4.1 Supervised learning

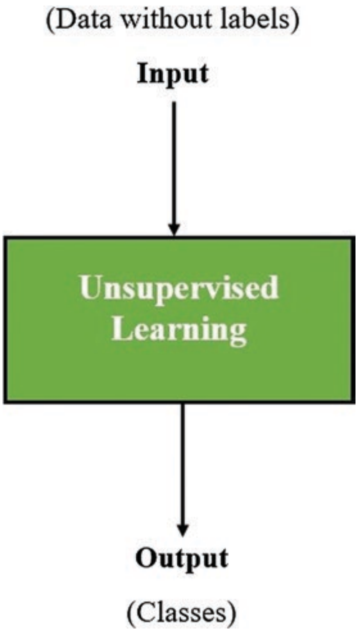

Fig. 4.2 Unsupervised learning

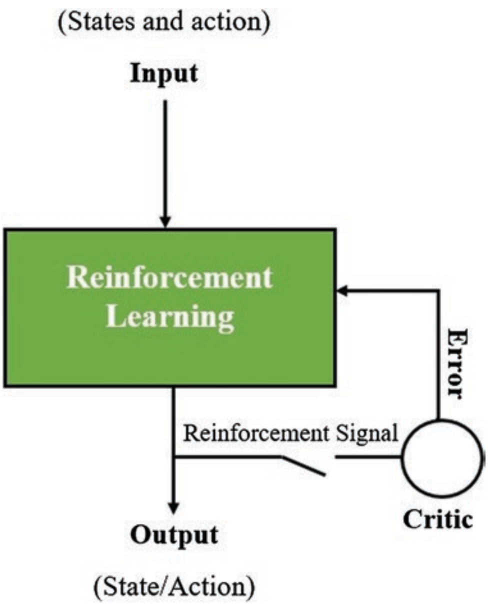

Fig. 4.3 Reinforcement learning/semi-supervised learning

4.3.3 Deep Learning

Deep learning (DL) [6] is a supervised approach to ML that utilizes neural networks which is defined by artificial algorithm process of capturing meaningful patterns of data collection. It imitates the complex human brain, being capable of learning from information with complex hierarchical representations that have multiple abstraction layers. The programmer incorporates known data into the machine which is designed to facilitate algorithms to effectively respond, even when exposed to completely new information. Via experience, the neural network knows and learns data, creates hierarchical structures, and offers advanced stages of input-output. This could catch dynamic nonlinear interactions among outcome variables of input-output. By calculating the weights toward the input and outcome data, the average error of results and their estimates can be minimized.

Based on their expertise, training, and cultural history, doctors diagnose them. At this stage, deep learning may be very effective and broadens and improves medical knowledge, particularly for nonexpert doctors.

Through utilizing more hidden layers, DL can investigate more complicated nonlinear patterns in the data than a classic neural network. For such a purpose, attributed to the rise in the volume and sophistication of data, especially in the field of imaging analysis, the applications of DL in the field of medical research have recently become popular.

In Facebook's image recognition software, DL also plays a leading role in speech recognition in Apple's Siri and Amazon's Alexa, Google brain and robots, etc.

Convolutional neural networks (CNN), recurrent neural networks, deep belief networks, and deep neural networks seem to be the most popular deep learning algorithms in the medical setting.

4.3.4 Value of Medical AI

In particular, laws and legislation have been established and enforced by governments and agencies around the world to create a safer medical climate for patients [3]. There are also many flaws in the modern medical system, including an unequal allocation of senior physicians, a high incidence of primary clinician misdiagnosis, lengthy preparation times for clinicians, scarcity of clinicians in undeveloped areas, and high medical costs for patients.

Even so, in recent times, with the growth and success of machine learning technologies, AI has steadily changed from concept to practicality. The numerous uses of AI in medicine are being illustrated. In turn, AI technology has been an influential factor that can impact the growth of the medical sector and increase the quality of medical services.

AI has numerous uses in the medical field [7, 8]. After that, AI will help doctors detect ailments and develop protocols for healing. Since being applied to traditional medical practices, AI can reduce the quantity of wrong diagnosis and improve diagnostic efficiency. Currently, with the advent of deep learning, AI has the ability to classify patient images and provide clinicians with more detailed diagnostic imaging information. Also, with the use of big data processing, AI systems can however generate very reliable results for patient forecasting (AI can analyze very large amounts of data which are impossible to analyze using standard data processing methods). AI would also help to encourage the development of drugs and improve the viability of new drugs being developed. Ultimately, the combination of AI and surgical robots will improve the accuracy of many complex and challenging operations. With the growth of AI, big data analytics, and cloud computing technologies, AI will deliver high-quality medical services to patients. In addition, the production of smart medicine and precision medicine will be strengthened by AI, shortening the time and cost of waiting for clients and receiving safe, affordable, and high-quality medical services. The implementation of AI deep learning in cardiovascular medicine will also benefit from the application of AI deep learning.

4.4 Cloud-Based AI System

The cloud infrastructure is intended to be able to provide a fast and efficient way to store the ECG data collected from wristband to a database [2]. Consequently, the system must also have functionality such as management, reporting, and editing as needed. To satisfy different screening requirements, the cell and web system architecture must be flexible to accommodate each one [9]. The United States licensed a wearable GUI. The Food and Drug Administration (FDA) was selected to record the 30 s ECG signals. Stored data can be transferred via Bluetooth Low Energy (BLE) to a mobile app within a few seconds. After the mobile app gets the collected info, the user can add his or her ID, date of birth, or several documents to produce a report. On the server side, after the file is obtained and imported into the algorithm, the ECG signal can be preprocessed with coding and filtering. Figure 4.4 shows the cloud-based AI system architecture [2].

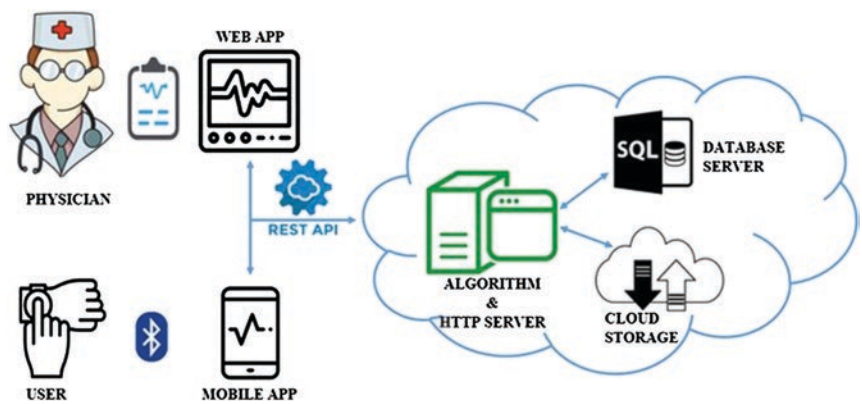

Fig. 4.4 The cloud-based AI system architecture

A technician or doctor on the website will review the final result. The wristband and smartphone app are connected by BLE opposed to a Bluetooth, which provides a simple connection and switch format with reduced power consumption. Following the data transferred toward the mobile app, the data can be sent to the server via HTTPS (Hypertext Transfer Protocol Secure) with additional documentation for further analysis.

4.4.1 Cloud Platform

In terms of cyber protection, Google Cloud Platform providers come under the framework of ISO 27001, 27,017, and 27,018 and help comply with the portability and transparency of Health Insurance Act [2]. The GCP compute engine service provides the size, efficiency, and cost to enable customers to build and operate virtual machines on Google infrastructure without problems. A consumer-friendly graphical user interface provides a highly flexible and efficient, quick, and completely controlled interface. To secure records, the database is designed to be automatically returned every day. To minimize the input-output burden of the database, the actual document transmitted by the mobile app should be stored in the Google Cloud Storage [10, 11]. Through this multiregional storage, the latency of the end users is being greatly reduced, and the service may be used to move data to cloud storage to reduce costs. With the server, database, and storage which are independently built over the GCP infrastructure, the cloud system could be replicated and transferred according to this model in a similar fashion, meaning that identical units could be customized for different purposes, such as medical facilities or public health centers.

4.4.2 Cardiac Disease Detection Algorithm

To reduce noise, the raw ECG data was filtered by band transfer, and the QRS peaks were identified using an adaptive threshold system [2]. A cardiac disease detector with a threshold of 0.725 can process the RR interval from the peaks to establish the segmentation of cardiac disease [2].

4.4.3 Screening Method

The screening system may be classified into two classifications: one to test and generate results upon instantaneous data transfer and the other to be used at home [2]. The calculation process was demonstrated to the respondents orally, and informed written consent was obtained. Once uploaded to the municipal health data registry, personal identity-related information would be secure. In order to analyze information from the wristband and connect it to the server, the immediate home measuring tool should be included for the smartphone. On-site screening is carried out by licensed technicians. In rapid estimation, they assist the condition and link the details of the topic to the measurement record [12]. The web app helps technicians, as per the specifications, to search data or change information on it. The document can be created to be used as a basis for final diagnosis by the doctor.

4.4.4 Application of AI in CVD

In cardiovascular medicine [3], AI technologies were used, such as precision medicine, clinical prediction, cardiac imaging research, and intelligent robotics. The application of AI in cardiovascular medicine has exciting outcomes.

4.4.4.1 Precision Medicine

For remote follow-ups, drug alerts, real-time condition therapy, and earlier indication warnings [6], AI would be implemented mainly on the focus from the patient's viewpoint. At the very same time, it helps to capture voice information (such as patient history), connect clinicians' electronic medical record systems, and reduce clinicians' workload. Cognitive systems (machine learning devices or deep learning algorithms that can solve challenges without any human assistance) help doctors make accurate decisions and also predict health future performance [13, 14]. A detailed treatment strategy that customizes healthcare for each patient is more likely to be introduced with the aid of AI. People agree that doctors would not be replaced by AI. Clinicians, on the other hand, must learn about using AI technologies and obtain expertise in the clinical practice of implementing AI to enhance the evaluation and management of cardiovascular diseases by big data processing, helping to enter the age of precision medicine. Precision medicine, which is more necessary to be completed with the aid of AI, can tailor healthcare for each particular patient. It is believed that AI is not going to substitute clinicians.

4.4.4.2 Clinical Predictions

AI can help doctors make very reliable patient forecasts via machine learning and big data analytics [5]. Data from Dawes TJW indicates that for patients with heart disease, AI may estimate future periods of death. In their research, AI program reported the findings of cardiac magnetic resonance imaging (MRI) tests and blood tests of 256 patients with heart disease. The program calculated the motion of 30,000 points in each heartbeat, which are marked on the heart structures. AI might anticipate the abnormal symptoms that lead to patient mortality by comparing this information with the 8-year clinical history of the patients [15, 16]. In comparison, their program was capable of predicting patients' survival rates for the next 5 years, and the estimation accuracy of patients' survival for the next year could comfortably exceed 80%. The estimation accuracy of the doctors, nevertheless, was just 60%. In addition, it established a predictive model for 10,030 suspected coronary heart disease (CHD) patients with the use of deep learning to determine the probability of death for the next 5 years. Their findings found that the AI-based risk assessment is superior to standard clinical decision and coronary computed tomographic angiography.

4.4.4.3 Cardiac Imaging Analysis

Cardiac imaging analysis [6] has demonstrated great growth opportunities in recent years, with the emergence of deep learning. Deep learning will discuss coronary angiography, echocardiography, and electrocardiography (ECG). The main treatment for cardiovascular disease in recent times has been heart surgery, especially CHD and acute coronary syndrome (ACS). While using deep learning, AI will be able to identify coronary atherosclerotic plaques more accurately than clinicians in the near future [17]. In comparison, for echocardiographic image analysis, AI will also be used, requiring automatic scale estimation inside each chamber and left ventricular (LV) function inspection. Moreover, systemic disorders, like valvular disease, may be measured to better identify the type and staging of diseases.

4.4.4.4 Intelligent Robots

With the advent of surgical robotics [6], the computer was ready to assist doctors conduct bladder graft surgery and hysteromyoma resection. In the future, the incorporation of AI and minimally invasive surgical systems, along with the da Vinci surgical robot, would make robotic surgery more realistic, minimize patient trauma, improve surgical protection, and shorten hospital stays. In contrast, AI could perform cardiac interventional procedures on patients rather than physicians with this kind of combination, like percutaneous coronary intervention (PCI) procedures and atrial fibrillation catheter ablation, which can use automatic subtraction angiography to reduce the radiation exposure of clinicians [18, 19]. By using reinforcement learning, particularly for use in repetition exercises, the knowledge of AI will be much superior to that of a human being. The AI can also practice more easily than human doctors how to perform procedures. In brief, the use of AI and surgical robotics at the same time will make the traditional medicine revolution simpler.

AI techniques such as machine learning, deep learning, and cognitive computing, especially in cardiovascular imaging, will change the practice of cardiology and cardiovascular medicine (e.g., how we produce information, analyze data, and make decisions).

4.4.4.5 Echocardiography

Throughout the diagnosis and treatment of cardiovascular disorders, but in the effective research method of cardiac development and function, the task of echocardiography is critical [6]. Even so, this also relies mostly on operator and knowledge with inter-variability. Throughout the study of medical echocardiography, AI technology, specifically machine learning, offers new ways to expand the accuracy of image analysis, particularly between nonexpert clinicians. A broad variety of complex disease dynamics can be defined by ML models that learned to learn unique attributes in an image, taking into account each pixel and their experiences.

ML models can automatically reflect unused data obtained by the advent of multidimensional imaging modalities (such as 3D echocardiography and speckle tracking) [20]. This leads to the advantages of decreasing analytical time and increasing reproducibility.

3D echocardiographic automatic evaluation can indeed be performed out by Heart Model, a software program that implements a model-based algorithm. In a few seconds, the software-integrated algorithm can quickly allocate the accompanying (i) volumes of the left chamber (atrium and ventricle), (ii) systolic flow, and (iii) LV ejection fraction from the 3D echocardiographic information obtained. In addition, from a certain eco-3D dataset, the app often attains the atrium volume simultaneously, providing a fuller estimation of the atrium function relative to traditional measurement methods. Another notable component to the analysis is that it was designed to examine eco-3D datasets acquired in single-beat mode. This may be particularly efficient in patients where 3D interpretation is difficult, such as those with repeated arrhythmias or those with respiratory problems.

ML models of clinical echocardiography practice may benefit from a broad range of cardiovascular diseases. Also, it demonstrates that supervised learning algorithms might more appropriately distinguish athlete's heart and hypertrophic cardiomyopathy from traditional measurement systems using STE (Secure Terminal Equipment) data. Some other possible area of use for ML models of echocardiography is heart valve disease (HVD). HVD is an extremely frequent disease that may benefit from ML cardiac imaging incorporation via early detection, treatment, or surgical preparation. It assessed that without the need to measure the left ventricular outflow tract (LVOT), AI will allocate the aortic valve area (AVA) to aortic valve stenosis from other echocardiographic information; a high accuracy (0.95) was acquired.

Recent research has also shown that AI tools can be used to improve HF diagnosis, identification, intensity estimate, and estimation through echocardiographic data and clinical factors of side effects, especially in patients with retained ejection fraction.

4.4.4.6 Magnetic Resonance Imaging

One of the fields of cardiac MRI [6] which has more potential for the implementation of ML models is ventricular segmentation. It enables volumetry to be quantified and diagnostic monitoring accuracy and reproducibility to be increased. For the automated classification and extraction of the right ventricular (RV) chamber, deep learning algorithms (i.e., convolutional neural networks and stacked autoencoders) trained by cardiac MRI datasets were used to predict the performance of such algorithms [21]. Likewise, for left ventricular segmentation, especially for cardiac cine MRIs, multiple artificial neural networks were successfully introduced. Subacute or chronic myocardial scar recognition is another use of ML in cardiac MRI.

4.4.4.7 Cardiac Computed Tomography

In the treatment and risk assessment of coronary artery disease (CAD) [6] and atherosclerosis, methodologies for ML image processing in cardiac CT are progressively utilized (e.g., coronary artery calcium scoring and fractional flow estimation). A noninvasive way of diagnosing coronary heart disease is coronary computed tomographic angiography (CCTA). It usually exaggerates the severity of stenosis compared with intrusive angiography, and where fractional flow reserve (FFR) is used as a guideline, angiographic stenosis does not really immediately indicate hemodynamic importance [22]. So many ML models have therefore been found to evaluate noninvasive FFR and enhance CCTA efficiency by correctly reclassifying hemodynamically nonsignificant stenosis.

Automatic coronary artery calcium scoring in CCTA using ML models provides additional therapeutic benefit by reducing false positive and inter-observer uncertainty in order to characterize coronary plaque. Some other use of ML to cardiac CT in the prognosis and management of myocardial infarction is the use of texture analysis techniques.

The early findings of the SMARTool project have implemented a new approach focused on ML treatment outcomes and quantitative biomechanics for CAD patient care (diagnosis, prognosis, and treatment) [23]. A retrospective and prospective ML study (clinical, biohumoral, CCTA imaging, lipidomics, etc.) was conducted to differentiate patients from those at low to moderate to high risk. The CAD diagnostic module is focused on 3D coronary artery reconstruction and noninvasive smart FFR estimation, while CAD projections are focused on complicated numerical models of plaque formation.

4.4.4.8 Applications in Electrocardiography

In addition to diagnostic imaging, electrocardiography [6] is other area which may also benefit again from incorporation of ML to its practices. The most commonly used method to detect abnormalities of electric cardiac function is the electrocardiogram (ECG). ML models, in particular the DL subfield, have made it possible to detect irregularities automatically in electrocardiograms, reducing interpretation time and reliance on human heterogeneity [24]. In order to help classify the heart rhythm, supervised learning algorithms were largely designed. Essential features like PhysioNet Project's MIT-BIH Arrhythmia allow the ability to both exercise and test the various algorithms. In addition, in the unsupervised learning analysis, the learning can take place in queries that do not have a default classification [25]. Data not historically named is viewed with this methodology and subsequently divided into subgroups of ECG phenotypes with various approaches. Specifically, by compiling data with identical architectures, ECG phenotypes correlated with arrhythmic risk markers for hypertrophic cardiomyopathy have been established and categorized.

4.5 Experimental Study

For medical trials that can be performed by patients at Tainan Hospital, Ministry of Health and Welfare, the assessment of this AIoT method is sent to the Ministry of Health and Welfare. Each section can be tested in these tests, including the wearable ECG-sensing method, application user interface, cloud service, and AI-based method.

4.5.1 System Design

In order to minimize the risk of major heart attacks, the Artificial Intelligence of Things (AIoT) system aims to test actual ECG signals throughout this review. A smart machine user interface, a cloud database, and an AI-based cardiac disease monitoring algorithm for real-time identification, low power consumption, and long-term use, as well as a compact front-end ECG-sensing platform form the complete device design. Figure 4.5 shows the device block of the acquisition and implementation of ECG signals [1].

4.5.2 Wearable ECG Monitoring Device

This study proposes a monitoring hardware structure that involves a low-energy analogue front-end circuit, an integrated commercial energy management (IC) circuit, and a commercial Bluetooth module [1]. A self-designed chip system (SOC),

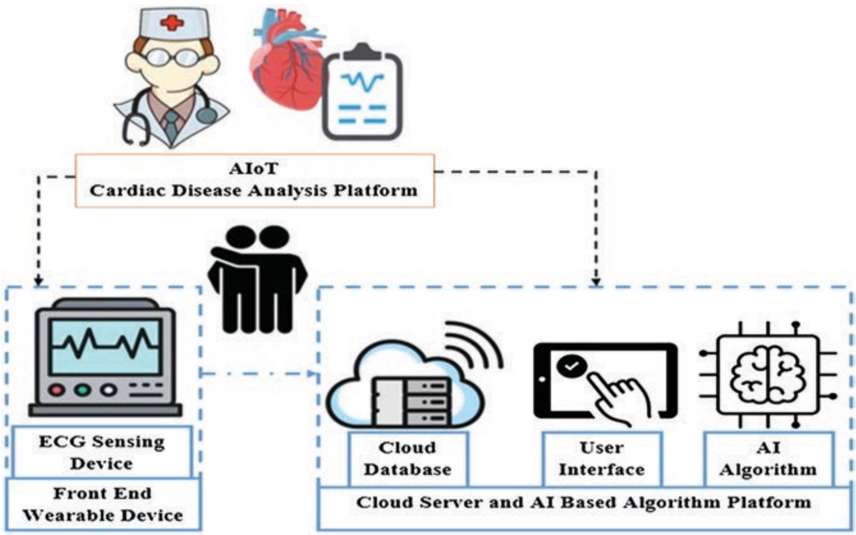

Fig. 4.5 Device block of the acquisition and implementation of ECG signals

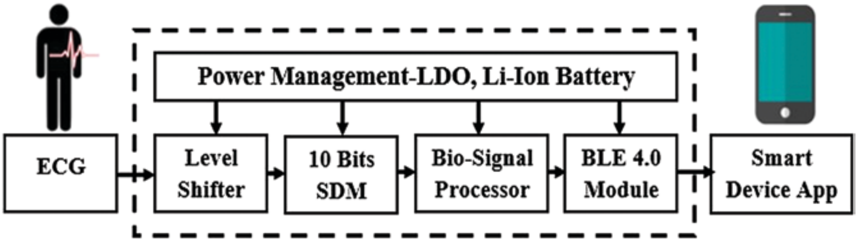

Fig. 4.6 Block diagram of the front-end system of the deployed ECG acquisition

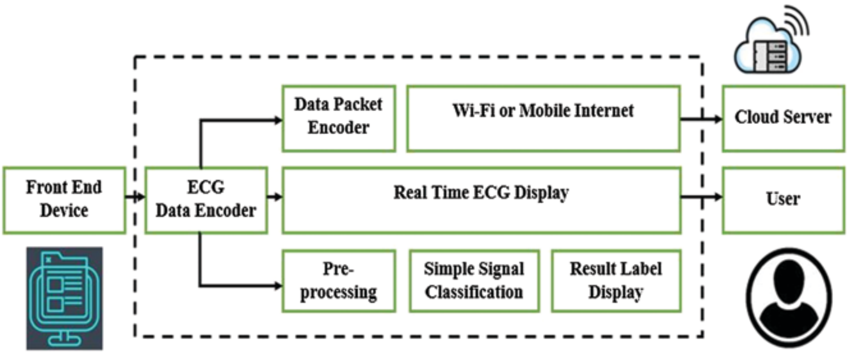

Fig. 4.7 The smart device APP structure

with a 10-bit sigma-delta analogue to digital converter, a degree shifter, and digital signal processing units, is the analogue front-end circuit [26]. The commercial Bluetooth module incorporates Bluetooth Low Energy 4.0 to transmit the ECG signal obtained from the front-end SOC automatically to the APP. The compact single-lead ECG tracking unit is connected to the chest with wet silver chloride electrodes and can be used for up to 24 h of daily use. Figure 4.6 shows the block diagram of the front-end system of the deployed ECG acquisition [1].

4.5.3 User Interface on Smart Device APP

A device interface also includes three key elements: an ECG display feature, an AI-based function, and a function for receiving and transmitting data [1]. The real-time ECG signal can be represented on the computer, and the AI method has been utilized to distinguish the user's ECG signal with different heart problems in a similar way. By taking into account the processing capacity of current electronic devices, the smart device classification defines the two effective classifications: usual and abnormal. Figure 4.7 shows the smart device APP structure [1].

For the extra category, to receive an additional specific arrhythmia form from the user's ECG signal, the category may be filled out over the cloud server. Not only will the collected ECG data be processed on local mobile devices and transmitted to the cloud servers. All data can be encrypted and produced with time stamps in the sake of data confidentiality and rightness.

4.5.4 Cloud Server and Database

The server [1] contains a large-data database that also comprises three sections: AI-based algorithm of data retrieval, online user interface, and cardiac condition analysis. Initially, data storage is responsible for handling data plans from intelligent front-end systems, and the data packages are decrypted as ECG indicators [27]. Moreover, as per the quantified artifacts and the time stamps, the ECG signals could be saved one at a time. Next, the web user interface shows a systematic data platform for doctors, patients, and patients' families. Physicians can determine the state of patients more clearly through the retained ECG records, and family members can understand something about their everyday ECG signs. Finally, for many minutes, the AI-based algorithm can identify uncommon signals from a lot of information. In general, around 100 thousand pulses a day are generated by a person, and many of them are ordinary ECG signals; only some are erratic [31, 32]. Despite this cause, physicians face a major challenge in identifying long-term ECG data successfully. The AI-based method can easily identify irregular signals displayed on the web user interface via this cloud platform. Figure 4.8 shows the cloud sever and database structure [1].

There are two elements within the structure of this method: data preprocessing and the CNN model. Standard ECG signal processing, such as time frequency analysis, feature extraction, and R-peak and QRS complex detection, is not really performed in addition to making the CNN model provide improved feature learning. Three steps are used in the preprocessing method suggested in this analysis: noise reduction, baseline removal, and image creation, as seen in Fig. 4.9 [1].

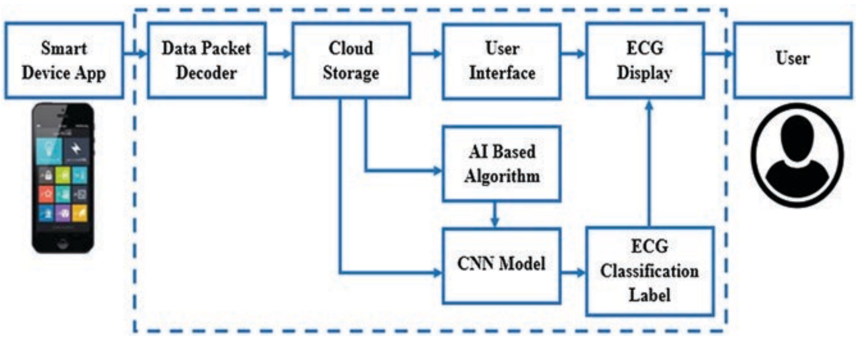

Fig. 4.8 The cloud sever and database structure

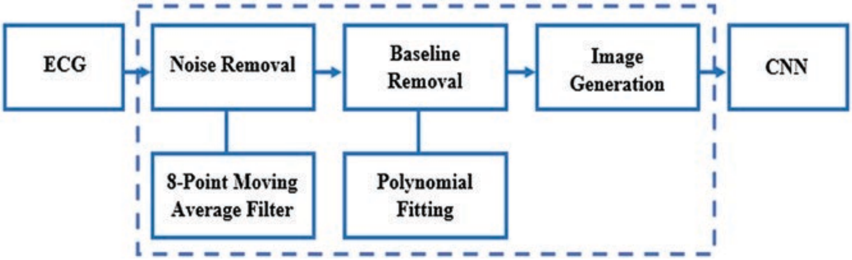

Fig. 4.9 The preprocessing structure

4.5.5 Comparative Study

It is also generally used by the Ministry of Health and Welfare for medical studies to validate the procedure that the Ministry of Health and Welfare can perform for patients at Tainan Hospital. Each portion could be evaluated in such trials, along with the wearable ECG-sensing device, software user interface, cloud server, and AI-based arrhythmia classification method.

4.5.5.1 Wearable Device

It is an ECG sensor system with an ECG-sensing-enabled front-end device that measures 84.55 mm × 39.38 mm × 18.31 mm [1]. The calculation of the ECG is single lead with a length of 24 h. It is connected to the patient's chest portion that also involves a low energy consumption analogue front-end circuit, with an integrated commercial energy management (IC) circuit and a commercial Bluetooth module. The single-lead wearable ECG tracking device is connected to silver chloride moist electrodes on the chest which could use up to 24 h of daily use.

4.5.5.2 User Interference APP

In the personal interference APP [1], the upper section shows the original information from the individual's ECG signal, whereas the bottom portion shows the performance results of the algorithm for arrhythmia classification. Each ECG signal can be identified as an irregular or frequent ECG signal. The actual ECG signal can be viewed on the computer, and the AI algorithm is often utilized to identify the consumer's ECG signal into particular heart conditions in the same way. The smart device section explains the most effective classifications by taking modern mobile devices' processing capacity into account: usual and abnormal.

4.5.5.3 Cloud Server and Database

The online user interface could extract the consumer's historic ECG data and go through more consultations with physicians [1]. The online user interface is somewhat identical to the UI of the smartphone. The top and bottom sections then represent the ECG original information and, accordingly, derive values from the arrhythmia group method. Each ECG data could've been categorized as several ECG forms, comprising of numerous types of irregular heartbeats that vary substantially from the APP user experience.

4.5.5.4 AI-Based Algorithm

Various data preprocessing operations are required in order to provide a sufficient input dataset [1]. First, with and without noise removal, is the variance between the data. It is discovered by using a common filter for eight-point shifting. Second, by polynomial fitting, baseline removal is completed [33]. This research establishes a single-dimensional CNN. With four convolution layers and three completely connected layers, the CNN edition is undoubtedly intended, taking into account the probabilities of recognizing this variant by digital IC layout and the effect after many tests. The load decay, learning rate, and learning rate decay parameters are determined as 0.0001, 0.1, and 0.9 after each epoch, depending on multiple test results.

Not only the information from medical studies, as well as the dataset, is processed by the CNN-based version. Outcomes are illustrated in Tables 4.1 and 4.2 [1]. The typical reliability of the data and the findings from clinical trials was 95.73% and 94.96%. In Table 4.3, associations between this discovery and past research are seen [1].

Table 4.1 Open-source database testing result

	NSR	AFib	AFL	FA	Accuracy
NSR	272	9	0	0	96.69%
AFib	15	371	3	0	95.37%
AFL	9	1	69	1	93.24%
FA	0	0	0	7	100%

Table 4.2 Clinical trial database testing result

	NSR	AFib	AFL	FA	Accuracy
NSR	9531	130	15	17	98.35%
AFib	16	249	9	5	89.24%
AFL	0	0	0	0	–
FA	0	0	0	0	–

Table 4.3 Performance comparison

	2019	2017	2016	2015
Classification target	NSR, AFib, AFL, FA	NSR, AFib, AFL, VFib	NSR, AFib, AFL, VFib	AFib, AFL, VFib
Model	CNN	CNN	Rotation forest	Decision tree
Accuracy	Clinical trial testing is 94.96% MIT-BIH testing is 95.35%	94.9%	98.37%	96.3%
Testing database	Clinical trails	Open source	Open source	Open source

4.6 Conclusion and Future Scope

Today, cardiovascular diseases are the most important challenges of healthcare worldwide. The early detection of cardiovascular disease, which will help to an extent, reduced the occurrence of sudden cardiac arrest. Prevention and control of cardiovascular diseases require a pervasive and complete device for recording data. Information of patient's records is one of the most important data, which must be classified for easy and fast remedy process. From this study, it is observed that the usage of artificial intelligence for early detection of cardiac disease detection is more effective to reduce sudden death. Through the use of AI application, abnormal heart rate can be detected. In addition to predicting prognosis, some studies have shown the incredible ability of AI in the analysis of coronary artery disease and cardiomyopathy and in the assessment of cardiac function over the past few years. In multiple unique cardiac areas, cardiac AI has recently shown its potential to outperform human vision. These trends in cardiac imaging advanced the day-by-day exercise of cardiac imaging and could significantly display its effect in the near future. The challenging problem with the devices is general acceptance, privacy problems, effective management, etc. To clarify the AI-based optimizations on the device, this analysis aims to verify the results as soon as possible in the future. As the technology would develop exponentially, it will be an enormous aid in building high-quality and readily available healthcare. The artificial intelligence in the field of cardiology brings a wide possibility also to provide new personalized care.

References

1. Lin, Y. J., Chuang, C. W., Yen, C. Y., Huang, S. H., Huang, P. W., Chen, J. Y., & Lee, S. Y. (2019). Artificial Intelligence of things wearable system for cardiac disease detection. In *2019 IEEE International Conference on Artificial Intelligence Circuits and Systems (AICAS)* (pp. 67–70). IEEE.
2. Tseng, C. H., Lin, C., Chang, H. C., Liu, C. C., Serafico, B. M. F., Wu, L. C., Lin, C. T., Hsu, T., Huang, C. Y., & Lo, M. T. (2019). Cloud-based artificial intelligence system for large-scale arrhythmia screening. *Computer, 52*(11), 40–51.

3. El Khatib, M. M., & Ahmed, G. (2019). Management of Artificial Intelligence enabled smart wearable devices for early diagnosis and continuous monitoring of CVDS. *International Journal of Innovative Technology and Exploring Engineering, 9*(1).
4. Nasrabadi, A., & Haddadnia, J. (2016). Predicting heart attacks in patients using artificial intelligence methods. *Modern Applied Science, 10*(3), 66.
5. Sharma, D., Sahu, S., & Pande, A. (2020). Mobile solution for early detection of heart diseases using artificial intelligence and novel digital stethoscope. *International Journal of Engineering and Technology, 9*(5).
6. Romiti, S., Vinciguerra, M., Saade, W., AnsoCortajarena, I., & Greco, E. (2020). *Artificial intelligence (AI) and cardiovascular diseases: An unexpected Alliance*. Cardiology Research and Practice.
7. Duverney, D., et al. (2002). High accuracy of automatic detection of atrial fibrillation using wavelet transform of heart rate intervals. *Pacing and Clinical Electrophysiology, 25*(4), 457–462.
8. Petrėnas, A., Marozas, V., & Sörnmo, L. (Oct. 1, 2015). Low-complexity detection of atrial fibrillation in continuous long-term monitoring. *Computers in Biology and Medicine, 65*, 184–191.
9. Goldberger, A. L., et al. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation, 101*(23), E215–E220.
10. Steinhubl, S. R., et al. (2018). Effect of a home-based wearable continuous ECG monitoring patch on detection of undiagnosed atrial fibrillation: The mSToPS randomized clinical trial. *JAMA, 320*(2), 146–155.
11. PMCC. (1997). *Electrocardiogram (ECG) – what to expect*. [Online]. Available: https://www.uhn.ca/PMCC/PatientsFamilies/Clinics_Tests/CG/Pages/what_expect.aspx 19. Mayo Clinic, “Electrocardiogram (ECG or EKG),” 2019. [Online].
12. Ahmad, B. A., Khairatul, K., & Farnaza, A. (2017). An assessment of patient waiting and consultation time in a primary healthcare clinic. *Malaysian Family Physician, 12*(1), 14–21.
13. Xia, H. N., Asif, I., & Zhao, X. P. (2013). Cloud-ECG for real time ECG monitoring and analysis. *Computer Methods and Programs in Biomedicine, 110*(3), 253–259.
14. Wang, X. L., Gui, Q., Liu, B., Jin, Z., & Chen, Y. (2014). Enabling smart personalized healthcare: A hybrid mobile-cloud approach for ECG telemonitoring. *IEEE Journal of Biomedical and Health Informatics, 18*(3), 739–745.
15. Yang, Z., Zhou, Q., Lei, L., Zheng, K., & Xiang, W. (2016). An IoT-cloud based wearable ECG monitoring system for smart healthcare. *Journal of Medical Systems, 40*(12), 286.
16. Satija, U., Ramkumar, B., & Manikandan, M. S. (2017). Real-time signal quality-aware ECG telemetry system for IoT-based health care monitoring. *IEEE Internet of Things Journal, 4*(3), 815–823.
17. Clifford, G. D., Behar, J., Li, Q., & Rezek, I. (2012). Signal quality indices and data fusion for determining clinical acceptability of electrocardiograms. *Physiological Measurement, 33*(9), 1419–1433.
18. Hamilton, P. (2002). Open source ECG analysis. In *Proc. Conf. Computers Cardiology, Memphis, TN*,101–104
19. Lin, C., et al. (2019). Robust fetal heart beat detection via R-peak intervals distribution. *IEEE Transactions on Biomedical Engineering*. https://doi.org/10.1109/TBME.2019.2904014
20. Desai, U., Martis, R. J., Acharya, U. R., Nayak, C. G., Seshikala, G., & Ranjan, S. K. (2016). Diagnosis of multiclass tachycardia beats using recurrence quantification analysis and ensemble classifiers. *Journal of Mechanics in Medicine and Biology, 16*(01).
21. Acharya, U. R., Fujita, H., Adam, M., Oh, S. L., Tan, J. H., Sudarshan, V. K., & Koh, J. E. W. (2016, October). Automated characterization of arrhythmias using nonlinear features from tachycardia ECG beats. *IEEE International Conference on Systems, Man, and Cybernetics*, 533–538.
22. Andreu-Perez, J., Leff, D. R., Ip, H. M., & Yang, G.-Z. (2015). —From wearable sensors to smart implants-–towards pervasive and personalized healthcare||. *IEEE Transactions on Biomedical Engineering, 62*(12), 2750–2762.

23. Oresko, J. J., Jin, Z., Cheng, J., Huang, S., Sun, Y., Duschl, H., & Cheng, A. C. (2010). A wearable smartphone-based platform for real-time cardiovascular disease detection via electrocardiogram processing. *IEEE Transactions on Information Technology in Biomedicine, 14*(3), 734–740.
24. Alkeshuosh, A. H., Moghadam, M. Z., Al Mansoori, I., & Abdar, M. (2017, September). Using PSO algorithm for producing best rules in diagnosis of heart disease. In *Proceedings of the International Conference on Computer Applications (ICCA)* (pp. 306–311).
25. Al-milli, N. (2013). Backpropogation neural network for prediction of heart disease. *Journal of Theoretical and Applied Information Technology, 56*(1), 131–135.
26. Devi, C. A., Rajamhoana, S. P., Umamaheswari, K., Kiruba, R., Karunya, K., & Deepika, R. (2018, July). Analysis of neural networks based heart disease prediction system. In *Proc. 11th Int. Conf. Hum. Syst. Interact. (HSI), Gdansk, Poland* (pp. 233–239).
27. Abdullah, A. S., & Rajalaxmi, R. R. (2012, April). A data mining model for predicting the coronary heart disease using random forest classifier. In *Proceedings of International Conference on Recent Trends Comput. Methods, Commun. Controls* (pp. 22–25).
28. Anooj, P. K. (Jan. 2012). Clinical decision support system: Risk level prediction of heart disease using weighted fuzzy rules. *The Journal of King Saud University Computer and Information Sciences, 24*(1), 27–40.
29. Baccour, L. (June 2018). Amended fused TOPSIS-VIKOR for classification (ATOVIC) applied to some UCI data sets. *Expert Systems with Applications, 99*, 115–125.
30. Cheng, C. A., & Chiu, H. W. (2017, July). An artificial neural network model for the evaluation of carotid artery stenting prognosis using a national-wide database. In *Proceedings of the 39th Annual International Conference on IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 2566–2569).
31. Esfahani, H. A., & Ghazanfari, M. (2017, December). Cardiovascular disease detection using a new ensemble classifier. In *Proceedings of IEEE 4th International Conference on Knowledge Based Engineering and Innovation (KBEI)* (pp. 1011–1014).
32. Dammak, F., Baccour, L., & Alimi, A. M. (2015, August). The impact of criterion weights techniques in TOPSIS method of multi-criteria decision making in crisp and intuitionistic fuzzy domains. *Proceedings of IEEE International Conference on Fuzzy Syst. (FUZZ-IEEE), 9*, 1–8.