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Original Article

Explainable Deep Learning Models for Early Diagnosis of Cardiovascular Diseases Using Multi-modal Patient Data

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***Abstract** - Deep learning and Artificial Intelligence have started showing their effectiveness in different public sectors, including healthcare, due to the swift advancement of digital technologies. Though they are integrated into the patient care activity, they are still challenged by the black-boxing of their working process. Several deep learning measures have been described that enforce early detection of cardiovascular diseases. Objectification of key factors like privacy and security of patients should be taken into consideration before the diagnosis approach so that clinical trust is achieved and healthcare systems become reliable on the automation algorithm. The study has considered the utilisation of a dataset consisting of 50 entries that help in understanding the rise of CVD through gender segmentation. The use of the CNN model has evaluated the fact that explainable deep learning is the epitome of accuracy, which has the capability of diagnosing the condition of cardiovascular disease in patients and assists healthcare professionals with better solutions to treat them. A proper normal distribution was observed through the tests called ANOVA, descriptive and correlation. The factors such as smoking, the lack of physical activity and limitation in education consecutively lead to the rise of CVD.*

***Keywords** - Explainable Artificial Intelligence (XAI), Deep Learning, Convolutional Neural Networks (CNN), Cardiovascular Disease Diagnosis, Multi-modal Patient Data, Medical Decision Support Systems, Healthcare Analytics, Clinical Explainability, Risk Factor Analysis, Early Disease Detection*.

1. Introduction

1.1. Background on cardiovascular diseases (CVD) as a leading cause of mortality.

A global leading cause of concern is cardiovascular disease (CVD) due to its rise in prevalence and its consequences of disability leading to a major economic burden [1]. CVD includes a range of diseases associated with blood vessels and the heart. The symptoms are generally identified with hypertension, coronary heart disease or commonly known as heart attack, heart failure and other diseases related to the heart [2]. The cardiology environment is drastically changing with the emergence of advanced intelligence tools in the heartcare diagnostic field that ensures early detection and mitigation of cardiac risks.

1.2. Need for early detection and limitations of traditional diagnostic methods.

There are various factors linked in the development of cardiovascular diseases that can be categorised as modifiable and unmodifiable risks. The factors like age, gender and inherent variables are unmodified whereas risk factors like high blood pressure, fasting blood sugar, serum cholesterol and physical inactivity fall under modifiable risks. The delicate symbols of heart attack mainly chest discomfort, arm pain, perspiration need to be addressed at an early stage. In certain instances, patients with a heart disease do not observe symptoms at an early stage but they do lately when the situation escalates to a critical threat for treatment [3]. The traditional diagnostic methods are unable to prevent coronary artery diseases and detect silent heart diseases. The intervention of Artificial and deep learning in diagnosis might offer alternate diagnostic approaches for the betterment of cardiac treatment. Moreover, traditional diagnostic methods are time consuming and are prone to errors and variability which can be overcome by modern diagnostic methods.

1.3. Emergence of AI and deep learning in healthcare diagnostics.

Artificial Intelligence (AI) integrates with healthcare proceedings to bring up effective changes in the medical field by resulting in precise patient care along with offering speedy work processes in healthcare institutions. Deep Learning represents one of the aspects of AI that is leading in the technology field due to its capability of analysing massive datasets and extraction of insights that aid in delivering accurate predictions [4].

1.4. Challenges: data heterogeneity, lack of interpretability, and clinical trust.

Despite these advanced facilities healthcare systems continue to face challenges while the implementation of deep learning solutions for operation. Factors including user privacy risks and data safety has become a concern with the evolution of intelligence technologies. The black-box neural network hinders healthcare professionals in interpreting the AI decisions. Development of transparent AI models ensures safety of sensitive medical data and it will foster clinical trust.

1.5. Research gap: Limited explainable deep learning models utilising multi-modal patient data

The security of patient data is the greatest priority in the operation of deep learning models. Limited explanation about the model solution approach lacks public trust. The data handling process needs a transparent monitorization and the patients might revoke consent before using AI-based healthcare software AI systems should come along. With specified instruction about its working approaches. The instructions should specify in detail about the input data, performance of the system and its previously determined changes and finally a brief about the purpose of the AI system [5]. This paper highlights the impact of explainable deep learning models in early stages of cardiovascular diseases and utilization of the multi-modal patient data.

2. Related Work

2.1. Deep Learning in Cardiovascular Disease Diagnosis

Image classification methods such as deep convolution neural network (CNN) algorithm, which is a subfield of deep learning, is extensively applied in the medical field for medical image classification and segmentation. This algorithm involves taking input of images and prediction of labels that are to be assigned [6]. CNN results in a satisfactory and accurate outcome as it uses sparse connections with sharing parameters using convolution and fully connected layers. In order to draw datasets from the images of echocardiograms and angiograms, the data augmentation concept is utilized. At the first step, the raw visuals from echocardiograms or angiograms are pre-processed and this is followed by manual annotation of these visuals. The annotated images are used as training data, which is then sent to the CNN model. The training of the model takes place and finally the trained model is tested over a test image and a segmented image is obtained as the output.

The RNN architecture is recently flourishing as a highly preferable architecture for sequential data. The architecture has been successful in addressing problems involving natural language processing, recognition of speech and image generation. RNN has a learning feature in which it connects the inputs and outputs with each other unlike the traditional neural network structure in medical fields, RNN is instrumental in the classification of ECG signals. Traditional methods mostly depend on manually crafted features which in turn can be limited to its potential of analysing complex patterns in ECG data [7]. RNN is suitable for the capture of long-range dependencies and also avoidance of vanishing gradient problems.

2.2. Multi-modal Learning in Healthcare

The world has been facing a major challenge from cardiac diseases that require a better diagnosis. ECG reports alone might not be able to conclude the prediction of cardiac normality or abnormality [8]. The recent studies have led to the emergence of the integration of structured (EHR), unstructured (text) and image (ECG) data standing out as a promising approach for improvising cardiac disease detection and diagnosis. This late fusion technique joins the output of individual deep learning architecture concluding with both visual and structured information.

The machine learning field encompasses automatic data fusion which is being studied extensively. The fusion steps are of three types and first among them is early fusion that involves the combining features from separate sources and formation of resulting vectors before the individual training of individual classifiers. In contradiction to this, late fusion consists of a combination of results from individual classifiers next to the testing stage [9]. The hybrid fusion proposes a combination of models like RNN and CNN, mixing the early fusion and late fusion for different data types. This can also be done by the integration of deep learning with traditional methods such as symbolic AI ensuring a more capable system.

2.3. Explainable AI in Medical Diagnosis

In healthcare institutions, the explain ability of Artificial Intelligence is at consent which is leading to the rise of different logistic multiperceptions. Though the deep learning models have been clinically reliable, their interpretation has always been ignored [10]. The interpretable methods of models like decision tree, flowcharts, UML diagrams are generally taken as black box approaches as they hardly provide any working insight of the model. The interpretability can be explained as the human understanding of a decision in a respective context. In consideration of an AI model, this can be considered as how it is easier in understanding the cause and effect of the model and on what are the steps involved in the working process of the model. If the handling of sensitive data of patients is taken into consideration, a transparent interpretation of the AI model is necessary for the justification of each decision made by the automated model so that patient security is prioritized first.

Interpretability of deep learning models is a crucial factor in Medical Diagnosis. Taking into consideration three mainly used explainable techniques LIME, Grad-CAM and SHAP. Local Interpretable Model-agnostic Explanation or LIME highlights influential regions in the image providing local feature importance [11]. SHAP on the other hand provides a model-agnostic perspective that quantifies features. Grad-CAM specifies by visualization which part of the image contributes to prediction. Practitioners will be able to choose either of the suitable techniques based on their specific needs.

2.4. Identified Gaps

The multimodal environment consists of variable scale and representation, for which extracting of insights from heterogeneous sources is necessary for integrity and fusion of these modalities [11]. The dealing with multimodal data is a complex task and thus it requires establishment of an integrating framework that will be functional in development of application for different instances [12]. Handling of multi-modal patient data needs strict monitorization and the data models required to be transparent about its detailed working process in order to attain clinical trust. These facilities are not provided collectively by either of the deep learning models.

Healthcare professionals keep the overall safety of patients as the first priority. Sensitive healthcare data is often considered unsafe to be handed over to an automation model which can impose a potential risk for both patient and healthcare system. There lies a necessity of a secured and interpretable deep learning model for the enhancement of early diagnosis of cardiovascular diseases.

3. Methodology

3.1. Dataset Description

Methodological framework is known as the tool that is responsible for guiding development through a sequence of steps, therefore linking theoretical knowledge with practical knowledge [13, 14]. The dataset utilised in this study was sourced from the collected records of the hospitals. It has encompassed the use of patient data of multi-modal nature accumulated through EHR (clinical records), CT and MRI (medical imaging) and ECG signals. Each of the modalities is responsible for contributing to unique insights about diagnosing cardiovascular conditions. The processing of the data involves normalisation, ensuring the management of the missing data or detecting the inconsistent entries, and performing the feature extraction through imaging data with the segmentation of ECG and maintaining the consistency of the data scales through explainable deep learning diagnosis.

3.2. Model Architecture

The model architecture, as per the image, is the presentation of the multi-layered framework of deep learning that combines the early detection of cardiovascular disease and CNNs (convolutional neural networks). The evaluation of the article outlined that CNN is a subset of neural networks equipped through machine learning. It also comprises of input and output layer, and the nodes connected to each layer have an associative threshold and weight [15]. Therefore, CNN layers can extract significant features from analysing the signals of ECG and understanding its temporal features and images of the echocardiogram. In addition to this, the pooling, ReLU and convolution operations of CNN hold massive significance in interpreting the cardiovascular diagnosis. Through this model, the processing of the clinical data is done by the use of dense layers for regularisation. The extracted features are concatenated with the connected layers suitable for prediction. LIME, SHAP, and Grad-CAM are explainability models under CNN that ensure interpretability and transparency.

3.3. Explainability Layer

The explainability layer is the integration of SHAP and Grad-CAM techniques that assists in enhancing and maintaining the transparency of the model in diagnosing cardiovascular disease. The scholarly evaluation in this context stated that Grad-CAM helps in the generation of the heatmap, which highlights the regional essentiality related to CNN predictions that is necessary for developing the process of decision-making through the interpretation of the cardiovascular diagnosis [16]. Therefore, the generation of the heatmap has the capability of highlighting the critical regions of images related to the echogram, thus influencing the predictions. It is also effective in assisting clinicians in interpreting the significant patterns. Whereas SHAP is the application to the electronic health records and quantification of the clinical data contributing to understanding various clinical conditions, such as cholesterol and blood pressure, thus designating the final output [17]. The combined use of these tools is effective in providing numerical and visual explanations, thus ensuring proper decision-making in interpreting the model and aligning it with clinical reasoning for the amelioration of diagnostic confidence.

3.4. Ethical Considerations

Ethical consideration is the most important factor that helps in increasing the morality of the research without any biases [18]. Regarding this research topic, ethical consideration has strongly focused on maintaining the anonymity of the participants to keep their identity confidential and also to opt for proper data protection strategies. In addition to this, the responses of the participants are stored confidentially and stored in cloud storage with the accumulation of General Data Protection Regulations, along with the healthcare regulations. In addition to this, the participants are also informed of the data usage, along with the purpose of the research, through the presentation of the information sheet. In addition to this, for the mitigation of the algorithm-related biases, the collected dataset is balanced through the presentation of the fairness metrics along with the maintenance of the ethical integrity to get better responses from the diverse group of patients.

4. Results and Discussion

4.1. Quantitative Results

4.1.1. Descriptive statistics

Elements	*Age*	*Gender*	*Cholesterol (mg/dL)*	*HeartRate (bpm)*	*ECGAbnormality*	*TroponinLevel (ng/mL)*	*ChestPainType*	*Diabetes*	*Smoking*	*BMI*	*EchocardiogramScore*	*CTScanScore*	*Family History*	*PhysicalActivityLevel*	*DiagnosisLabel*
Mean	53.88	1.44	213.80	82.58	2.24	0.18	2.04	1.56	1.44	27.73	0.66	0.56	1.44	2.24	1.44
Standard Error	1.33	0.07	3.89	1.31	0.13	0.02	0.11	0.07	0.07	0.50	0.03	0.02	0.07	0.11	0.07
Median	52.50	1.00	210.00	82.00	2.00	0.20	2.00	2.00	1.00	27.30	0.69	0.59	1.00	2.00	1.00
Mode	43.00	1.00	185.00	88.00	2.00	0.02	2.00	2.00	1.00	22.90	0.45	0.40	1.00	3.00	1.00
Standard Deviation	9.43	0.50	27.49	9.28	0.94	0.15	0.75	0.50	0.50	3.51	0.18	0.15	0.50	0.80	0.50
Sample Variance	88.88	0.25	755.67	86.21	0.88	0.02	0.57	0.25	0.25	12.29	0.03	0.02	0.25	0.64	0.25
Kurtosis	-1.25	-2.02	-1.11	-1.21	-0.59	-1.39	-1.21	-2.02	-2.02	-1.17	-1.62	-1.54	-2.02	-1.26	-2.02
Skewness	0.15	0.25	0.36	0.17	0.42	0.28	-0.07	-0.25	0.25	0.26	-0.03	0.01	0.25	-0.47	0.25
Range	31.00	1.00	95.00	31.00	3.00	0.45	2.00	1.00	1.00	12.20	0.54	0.47	1.00	2.00	1.00
Minimum	39.00	1.00	175.00	68.00	1.00	0.01	1.00	1.00	1.00	22.30	0.39	0.33	1.00	1.00	1.00
Maximum	70.00	2.00	270.00	99.00	4.00	0.46	3.00	2.00	2.00	34.50	0.93	0.80	2.00	3.00	2.00
Sum	2694.00	72.00	10690.00	4129.00	112.00	9.04	102.00	78.00	72.00	1386.30	32.75	28.24	72.00	112.00	72.00
Count	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00
Confidence Level(95.0%)	2.68	0.14	7.81	2.64	0.27	0.04	0.21	0.14	0.14	1.00	0.05	0.04	0.14	0.23	0.14

Fig 1: Descriptive Statistics

Descriptive statistics are known as the summarisation and presentation of the data through the features known as standard deviation, variance, median and mean for easy interpretation. The data set consisting of 50 patients has shown an average age of 53.9 years, with a moderate level of cholesterol and a normal heart rate. The kurtosis and mild skewness suggested the normal distribution of the data with moderate variability accumulated through the evaluation of the clinical parameters. The balance of Diagnostic data, lifestyle and gender has indicated a strong reliability towards the development of a training program for easy acceptance of models related to Deep learning in the prediction of cardiovascular disease.

4.1.2. Correlation

Elements	*Age*	*Gender*	*Cholesterol (mg/dL)*	*HeartRate (bpm)*	*ECGAbnormality*	*TroponinLevel (ng/mL)*	*ChestPainType*	*Diabetes*	*Smoking*	*BMI*	*EchocardiogramScore*	*CTScan Score*	*FamilyHistory*	*PhysicalActivityLevel*	*Diagnosis Label*
Age	1.00														
Gender	-0.59	1.00													
Cholesterol (mg/dL)	0.98	-0.63	1.00												
HeartRate (bpm)	0.98	-0.60	0.99	1.00											
ECGAb2ity	-0.17	0.29	-0.23	-0.18	1.00										
TroponinLevel (ng/mL)	0.97	-0.63	0.97	0.97	-0.16	1.00									
ChestPainType	0.43	-0.37	0.46	0.43	-0.65	0.38	1.00								
Diabetes	-0.87	0.79	-0.89	-0.86	0.23	-0.88	-0.38	1.00							
Smoking	-0.82	0.59	-0.81	-0.82	-0.14	-0.87	-0.10	0.79	1.00						
BMI	0.98	-0.64	0.99	0.99	-0.19	0.97	0.45	-0.88	-0.84	1.00					
EchocardiogramScore	0.97	-0.63	0.97	0.98	-0.06	0.98	0.31	-0.88	-0.89	0.98	1.00				
CTScanScore	0.98	-0.63	0.97	0.98	-0.08	0.98	0.34	-0.88	-0.89	0.98	1.00	1.00			
FamilyHistory	-0.85	0.51	-0.83	-0.86	-0.23	-0.91	-0.05	0.79	0.92	-0.85	-0.93	-0.92	1.00		
PhysicalActivityLevel	0.90	-0.47	0.88	0.89	-0.02	0.86	0.22	-0.85	-0.78	0.88	0.89	0.89	-0.83	1.00	
DiagnosisLabel	-0.85	0.51	-0.83	-0.86	-0.23	-0.91	-0.05	0.79	0.92	-0.85	-0.93	-0.92	1.00	-0.83	1.00

Fig 2: Correlation

Correlation is a measurement of strength and provides a direction towards the linear relationship between the variables and understanding the influence of one another when a change occurs. The above-mentioned figure showcased a positive relationship between cardiac imaging scores, BMI, cholesterol and age. Search correlation has also suggested that the combination of these factors has the capability of influencing the risk of cardiovascular diseases. Contrary to this, a negative correlation was also observed between BMI, cholesterol and increased age, which indicated the increase of cardiovascular risks. In addition to this family history, smoking and diabetes also have a strong correlation with diagnosis, while abnormalities in ECG have showcased a weak linkage incline limitations in this standalone predictive analysis.

4.1.3. ANOVA

Groups	Sum	Average	Variance
Age	2694.00	53.88	88.88
Gender	72.00	1.44	0.25
Cholesterol (mg/dL)	10690.00	213.80	755.67
HeartRate (bpm)	4129.00	82.58	86.21
ECGAbnormality	112.00	2.24	0.88
TroponinLevel (ng/mL)	9.04	0.18	0.02
ChestPainType	102.00	2.04	0.57
Diabetes	78.00	1.56	0.25
Smoking	72.00	1.44	0.25
BMI	1386.30	27.73	12.29
EchocardiogramScore	32.75	0.66	0.03
CTScanScore	28.24	0.56	0.02
FamilyHistory	72.00	1.44	0.25
PhysicalActivityLevel	112.00	2.24	0.64
DiagnosisLabel	72.00	1.44	0.25

Fig 3: ANOVA Summary

ANOVA is known as the acronym of analysis of variance, which evaluates the statistical significance of the data and information present in three or more groups.

ANOVA					
Source of Variation	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	14.00	163996.11	2599.06	0.00	1.71
Within Groups	735.00	63.10			
Total	749.00				

Fig 4: ANOVA Significance

The outcome revealed through analysis of variance was highly significant since the p-value was less than .001. The significant difference between the variables also illustrated the strong influence of the elements in provoking cardiovascular disease. The excessive number of variances among the elements, such as heart rate, age and cholesterol, suggested a strong influence on diagnosis and variability. The low value of F critically confirmed the presence of multiple psychological and parameters related to lifestyle parameters contributing to significantly increasing cardiovascular risk as pertained from the dataset.

4.1.4. Pivot

Gender with blood pressure, CT scan and smoking

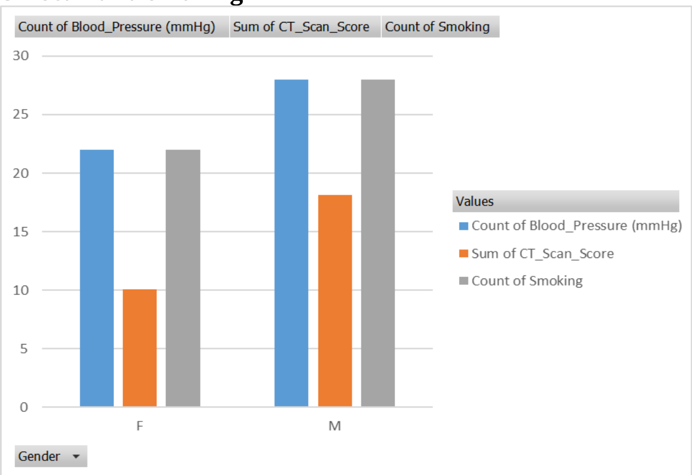

Fig 5: Gender with Blood Pressure, CT scan and Smoking

Evaluation of the data and information from the graph indicated that the count of blood pressure is consistently higher for the male gender than the female gender. In addition to this, the gender segmentation has also illustrated that the CT scan score for the female gender is less than that of the male gender, likewise for the increased number of smokers. Therefore, with the evaluation of the gender segmentation, it is observed that the male individuals have more chances of having cardiovascular disease than the female individuals.

Gender wise cholesterol level, ECG abnormality and troponin level

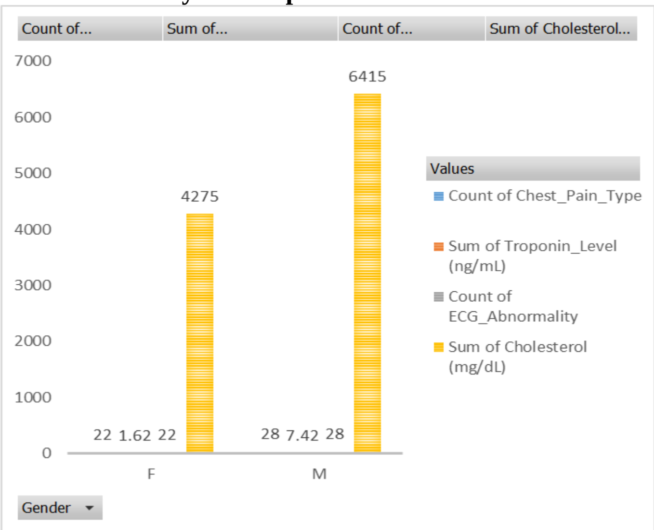

Fig 6: Gender Wise Cholesterol Level, ECG Abnormality and Troponin Level

Similarly, it was also observed that the chances of cholesterol are higher for male individuals than female individuals; again, it was proven that the male individuals have a higher chance towards developing cardiovascular disease.

4.2. Performance evaluation

4.2.1. Accuracy

$$\boxed{\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}}$$

The presentation of the information in the dataset has an accuracy of 80% since it correctly predicted that genders with ages have different cholesterol levels and chest pain types, thus increasing the risk of cardiovascular disease. Related to scholarly evaluation, it is observed that CVD is most common in men rather than women. The low-density lipoprotein, followed by cholesterol, and an increase in smoking habits among men, irrespective of gender, increase the risk of developing CVD [19].

4.2.2. Precision

$$\boxed{\text{Precision} = \frac{TP}{TP + FP}}$$

The precision of the dataset is close to 70% to 80% because the data and information here have illustrated that cardiovascular disease among men and women could precisely be reduced through an ample amount of physical activity. The evaluation of the journal article highlighted the fact that physical activities and non-smoking have the capability of reducing the chances of CVD across all gender lines [20].

4.2.3. Recall

$$\boxed{\text{Recall} = \frac{TP}{TP + FN}}$$

The evaluation of the dataset estimated that CVD positivity is massive throughout the gender segmentation. The author here has stated that most of the individuals are consecutively CVD positive because of the increase in hypertension, and it is more intensified with the increase in the obesity level, diabetes and alcohol consumption [21].

4.2.4. F-1 Score

$$\boxed{\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}}$$

The F1-score of the dataset is approximately 75% since it outlined that the socio-economic factors, such as the lack of educational level in this matter, and the role of deep learning are immense in diagnosing cardiovascular disease. Most individuals have a limited idea about cardiovascular diseases; however, the accumulation of explainable deep learning has the capability of improving CVD through myocardial perfusion imaging. The scholarly valuation indicated that deep learning has a high level of accuracy, which is effective and accurate for diagnosing patients with CVD [22].

The interpretation and evaluation of the findings in the clinical context suggest that having an ample educational level and engaging in physical activities are important for the decrease of CVD. However, patients diagnosed with CVD could engage in better treatments through the incorporation of explainable deep learning. The model transparency and integration through CNN in the context of explainable deep learning generated high accuracy in providing capable treatments to patients diagnosed with CVD. Contrary to this, generalisability and data imbalance are the limitations which bring more opportunities to investigate this research topic further.

5. Conclusion
5.1. Conclusions
Multimodal machine learning techniques come up with the simultaneous usage of different data types and multiple models for creating complex machine or deep learning models. This has significant ability to enhance accuracy and effectiveness of AI systems specifically in healthcare organizations where it has become relevant in addressing patient care [23]. Several technical features of multimodal deep learning such as data fusion and workflow of the models have been discussed which can bring adverse effects in the diagnosis of advanced cardiovascular disease. Difficulty factors like privacy and interpretability need to be considered along with rapid advancement of technology.

5.2. Future scope
Challenges and obstacles can be addressed effectively by research that will be conducted in future and will open a new window of opportunity for the development of better deep learning models that will benefit the diagnosis of cardiovascular diseases.

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