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ORIGINAL PAPER

Detection of Cardio Vascular abnormalities using gradient descent optimization and CNN

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Abstract

Purpose The purpose of this study is to propose an advanced methodology for automated diagnosis and classification of heart conditions using electrocardiography (ECG) in order to address the rising death rate from cardiovascular disease (CVD).

Methods Buffered ECG pulses from the MIT-BIH Arrhythmia dataset are integrated using a multi-modal fusion framework, refined using Gradient Descent optimization, and classified using the K-Means technique based on pulse magnitudes. Convolutional Neural Networks (CNNs) are used to detect anomalies.

Results The study achieves an average accuracy of 98%, outperforming current state-of-the-art methods. Sensitivity, specificity, and other metrics show significant improvements. The results also show the type of Cardiovascular disease detected using Confusion matrix plots.

Conclusion The proposed methodology demonstrates the utility of advanced machine learning, particularly deep learning, in the assessment of cardiovascular health. Based on the MIT-BIH Arrhythmia dataset, this study contributes to the development of accurate and efficient diagnostic tools for addressing urgent cardiac health challenges.

Keywords Cardio vascular · ECG · Fusion · CNN · Gradient descent

1 Introduction

Out of the various ailments the Cardiovascular disease is considered to be the major reason for the death without any alarming also, conferring to the Centers for Disease Control & Prevention (CDC) as well as American Health Monitoring Organization [1]. Sometimes called as silent killer the Cardiovascular disease (CVD) is widely regarded as the significant factor of mortality worldwide [2]. The heart is considered to be the most important component of the circulatory system. The human heart is a muscular organ that pumps blood throughout the body to ensure that a person continues to have a beating heart. It achieves this goal by transporting oxygen and various other nutrients to the tissues, as well as by ridding the body of waste materials and carbon dioxide through the various pathways that make up the circulatory system [3]. The blood arteries that supply the heart muscle are being impeded by a blockage at this time. A heart attack is a catastrophic medical condition that has the potential to end a person's life.The absence of blood causes tissue to perish due to an inadequate supply of oxygen. Myocardial infarction is what medical professionals refer to as a "heart attack." A problem known as cardiovascular disease (CVD) is one that has an impact on both the heart and the blood vessels (Veins & arteries). In the twentieth century, heart disorders were responsible for ten percent of all deaths, and by the late twentieth century, the overall death rate from cardiac diseases had increased by twenty-five percent [4]. Men are more likely than women to acquire cardiovascular disease [5–7], particularly in middle or late age. CVDs are difficult to diagnose because of the multiple contributing factors that

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result in varying symptoms and severity of symptoms according on age, demography, and ethnicity. Extraordinary blood pressure, irregular pulse variation, cholesterol echelons, and other factors add to various kinds of cardiovascular disease (CVD) [8]. When a heart problem emerges, the first screening test is with electrocardiogram (ECG), that acts as the central analytical tool aimed at cardiovascular disease (CVD). The electrocardiograph captures electrical movement in heart throughout the examination, whichformerly displayed on visual drawing that depicts cyclical electrophysiological activities in the cardiac muscle [9–11].

Machine learning (ML) has recently gained significance in research and is used in a wide range of applications [12, 13]. Deep learning (DL) is among the most commonly utilised machine learning (ML) approaches within those applications [14–16]. To categorise ECG signals, many conventional machine learning techniques have been utilised. Several features from ECG recordings are extracted using several methods, including the Discrete Wavelet Transform (DWT) [17] as well as the Pan Tompkins algorithm [18]. Then a classification algorithm including such Support Vector Machine (SVM) [19] as well as Hidden Markov model (HMM) [20] are applied. These approaches, however, have two key limitations that impede the process of ECG classification jobs. First, the reliability using machine learning algorithms is significantly lower than those of a cardiologist. Recently, convolutional neural networks (CNNs) have shown amazing success in predicting cardiovascular abnormalities in ECG data [21]. CNNs have the significant advantage of being sophisticated enough to autonomously acquire racist and discriminatory structure from input variables without any data preparation [22–24]. The fundamental goal of this research is to create anwell-organized automated model for detecting heart disorders on ECG. The proposed CNN model could aid in reducing misdiagnosis and missed diagnoses in primary care settings, as well as improving efficiency and lowering labour costs in major general hospitals.

2 Literature review

In the referenced article [25] a technique for identifying CAD based on multi-domain piece combination of multichannel cardiac rigorous data. By adding entropy besides cross entropy structures to support vector machines (SVM), the accuracy was increased to 90.90 percent. In the referenced article [26] suggested that the band of heart echoes be captured with the help of imaginary part of cross power spectral density (ICPSD).

The referenced article [26, 27] proposed the Cleveland (Cleveland Clinic Foundation) databases for the year 2020. Using various machine learning approaches, a new hybrid method for predicting cardiovascular disease with an accuracy of 80% was developed. The purpose of proposedinvestigationstands not to interchange specialist physician, rather to aid the physician in gaining a second opinion besides determining its applicability in emergency circumstances.

In the referenced article [28] proposed a data mining technique to categorise and detect cardiac disease by means ofaamalgamation of imperialist reasonable algorithm and K-nearest neighbour, with a 91 percent accuracy. In comparison to other optimization algorithms, this technique can deliver a more optimal solution for genetic feature selection. Additionally, the categorization uses the K-nearest neighbour technique [29].

In the referenced article [30] proposed that Combination is a one-of-a-kind heart disease prediction method that combines all approaches into a learning algorithm with an efficiency of 89.2 percent. This study proposes a novel system to predict cardiac disease that hybridises all established methods into a single algorithm.

The authors proposed a cardiovascular ailment categorization approach based on the MLP (Multi Layer Perceptron) networks and the CNN network [31]. They examined the outcomes of two models that employed the very same given dataset but different classes. The MLP network and the CNN network both did poorly in this trial, with 88.7 percentage and 83.5 percent, respectively. In 2014, the researchers employed rough sets (RS) with quantum neural networks (QNN) to identify electrocardiogram (ECG) data [32, 33]. After that, a steepest descent method was utilised to train the QNN-based categorization modelling and forecasting test, the accuracy of these systems was 91.7 percent. In 2013, In the referenced article [34] the K-Nearest Neighbor & Genetic Algorithm for heart disease classification, with an accuracy of less than 90%. This approach's performance was evaluated using six medical data sets and one non-medical data set.

The accuracy of all of the offered approaches is less than 94 percent. As a result, the dynamic CNN approach for identifying cardiovascular disorders is proposed, in which optimised multi-channel cardiac sound signals are used to achieve high accuracy.

3 Methodology and description

The Proposed system initiates its operation by acquiring the ECG samples of Heart from different nodes and reshapes for proper sequence of buffering the ECG Pulses. The Buffered ECG pulses are suitably fused by multi-modal fusion frame work to combine all the pulses of similar magnitude and modalities. The fused ECG pulses are optimized with the robust neural network optimization technique like Gradient Descent optimization technique. Then, the optimized ECG pulses are clustered into different classes based on their pulse magnitudes by K-Means. The classification features are extracted from the optimized ECG pulses and are subjected to the abnormality's detection and classification by the Convolutional Neural Network by way ofpresented Fig. 1.

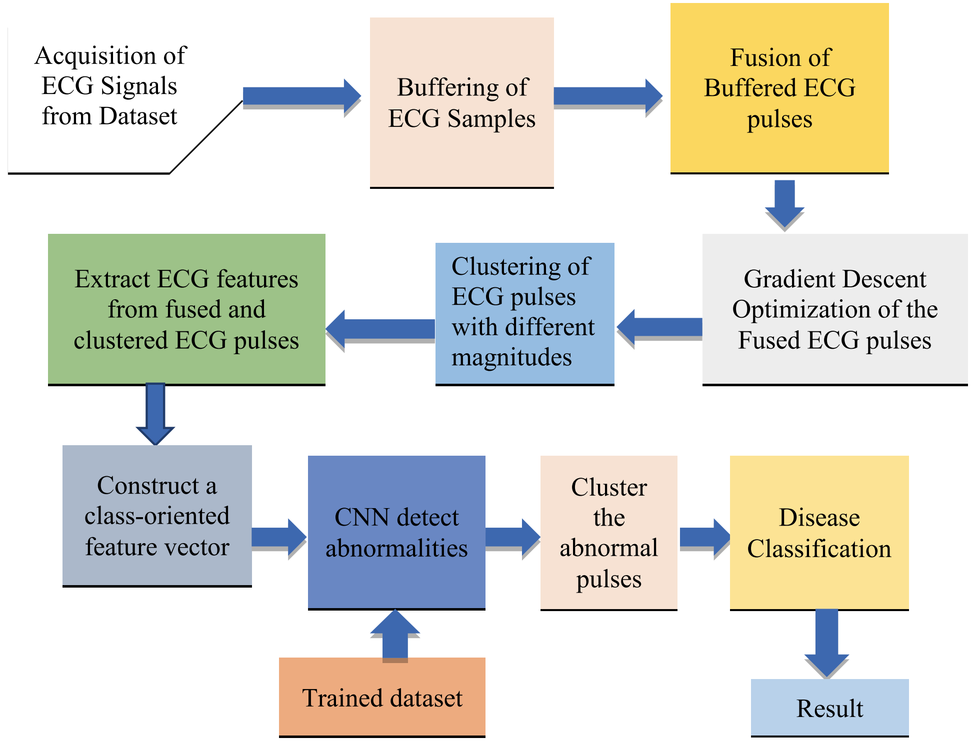


Fig. 1 Proposed block diagram

The detected abnormalities are again clustered into variant groups for disease classification. Finally, the classification results are conveyed with psychovisual and quantitative parameters such as Sensitivity, Specificity, Accuracy, PSNR, MSE etc.

The dataset includes an ECG as well as a variety of additional pulsatile and non-pulsatile signals. A training dataset was made public for the study, but a testing dataset was kept hidden in order to evaluate the Challenge entries. The training dataset included 100 human records, comprising patients with various issues as well as healthy participants. All of the recordings included an ECG signal as well as three to seven physiological signals captured concurrently. The purpose of the challenge was to create an algorithm that takes a record as input and outputs the observed heart beat annotations. To assess performance, the output annotations were compared to the reference annotations.

The disease should be categorised as heart attack, heart failure, heart valve, pericardial, or vascular disease by comparing input signals to the training dataset. If the patient has no diseases, it indicates that the heart is healthy.

4 Quantative metrics

Quantitative metrics include accuracy, positive anticipated value, sensitivity, specificity, negatively expected values, positive likelihood, negative likelihood, and so on.

4.1 Accuracy

In measuring technology, the process of measuring a degree of correct or accuracy in relation to the real measured variable with multiple measurements. The degree of accuracy can increase by employing probability. The accuracy is calculated by using true positive, true negative, false positive and false negative values as shown in Eq. 1.

$$\text{Accuracy} = \frac{(Tp + Tn)}{(Tp + Fp + Fn + Tn)} \tag{1}$$

4.2 Sensitivity

The sensitivity tests the proportion of positives correctly defined as percentage of sick people. In clinics the sickness of people is judge by through percentage level, if the percentage is more than the specificity. The sensitivity of a test has an ability to distinguish the patient cases correctly. calculate the fraction of true positive in-patient cases as shown in Eq. 2.

$$\text{Sensitivity} = \frac{Tp}{Tp + Fn} \tag{2}$$

4.3 Specificity

The test has ability to define the healthy cases correctly, it calculates the proportion of true negative (T_n) in healthy cases, it measures the proportion of high values (positives) that are correctly defined by using Eq. 3. This can correctly identify the persons which are not sick.

$$\text{Specificity} = \frac{Tn}{Tn + Fp} \tag{3}$$

5 Experimental investigation and analysis

The proposed system detects cardiovascular diseases like Heart Attack, Heart Valve, Vascular diseases, Pericardial and Heart Failure by using optimized multichannel cardiac sound signals. To detect and classify the cardiovascular diseases, initially the ECG signals are acquired. In this work the ECG signals of 4 patients represented asP-l, P-2, P-3 and P-4 are acquired from public database like Kaggle and are shown in Fig. 2.

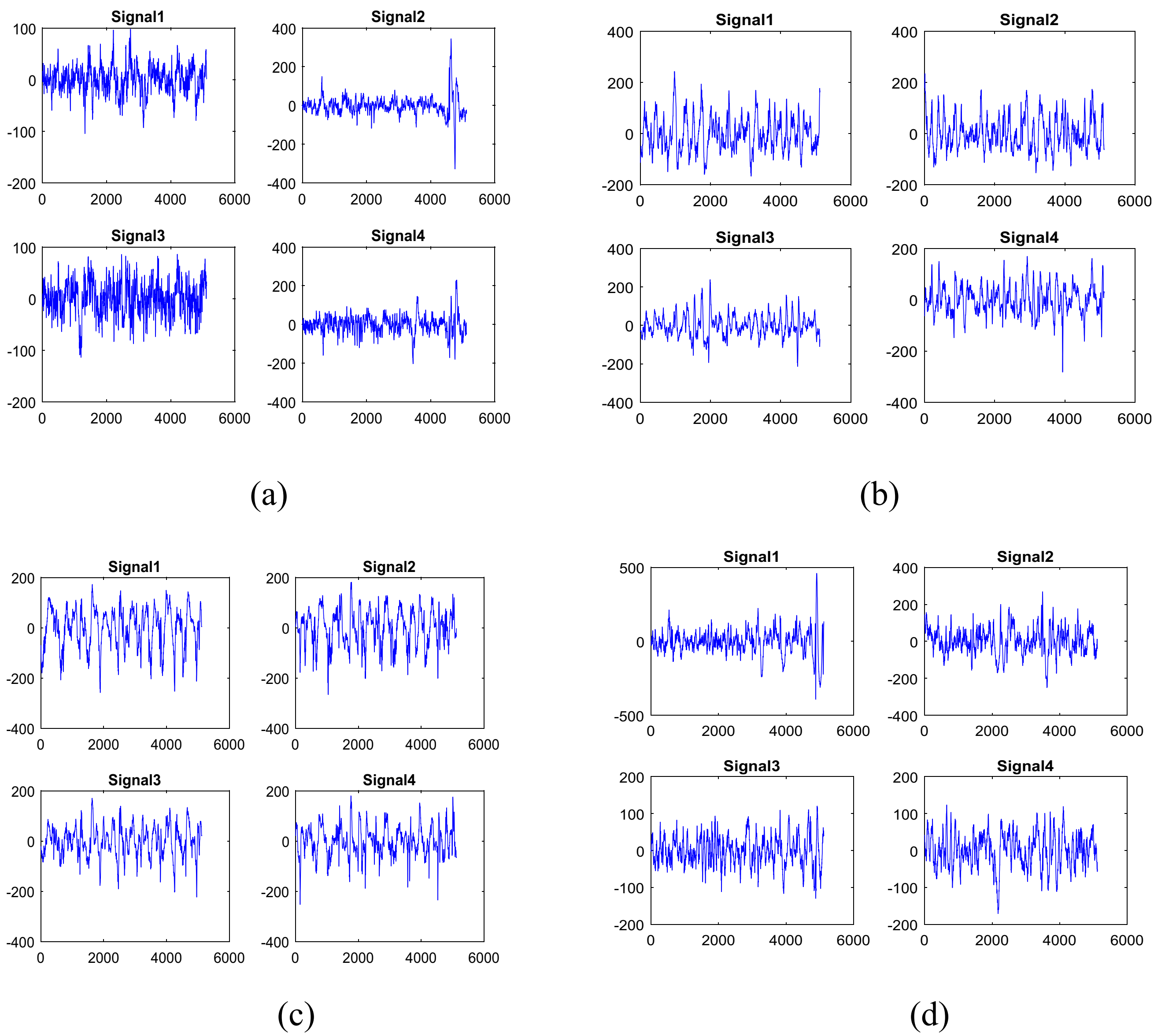


Fig. 2 ECG signals **a** P-1, **b** P-2, **c** P-3, **d** P-4

ECG accounts the electrical movement of heart over time. ECG signals remain now widely used as a screening tool for detecting and diagnosing a variety of cardiac abnormalities. It has also become an important component of any comprehensive medical examination. The ECG signal provides extensive information about the heart's structure and function. ECG signals which were taken from various nodes of the patient are presented in Fig. 2.

After acquiring of ECG signals at different nodes of the patient are stored at buffer. After recording all the ECG signals then, they are fused. The process of combining two or more entities into a singular entity is known as fusion.

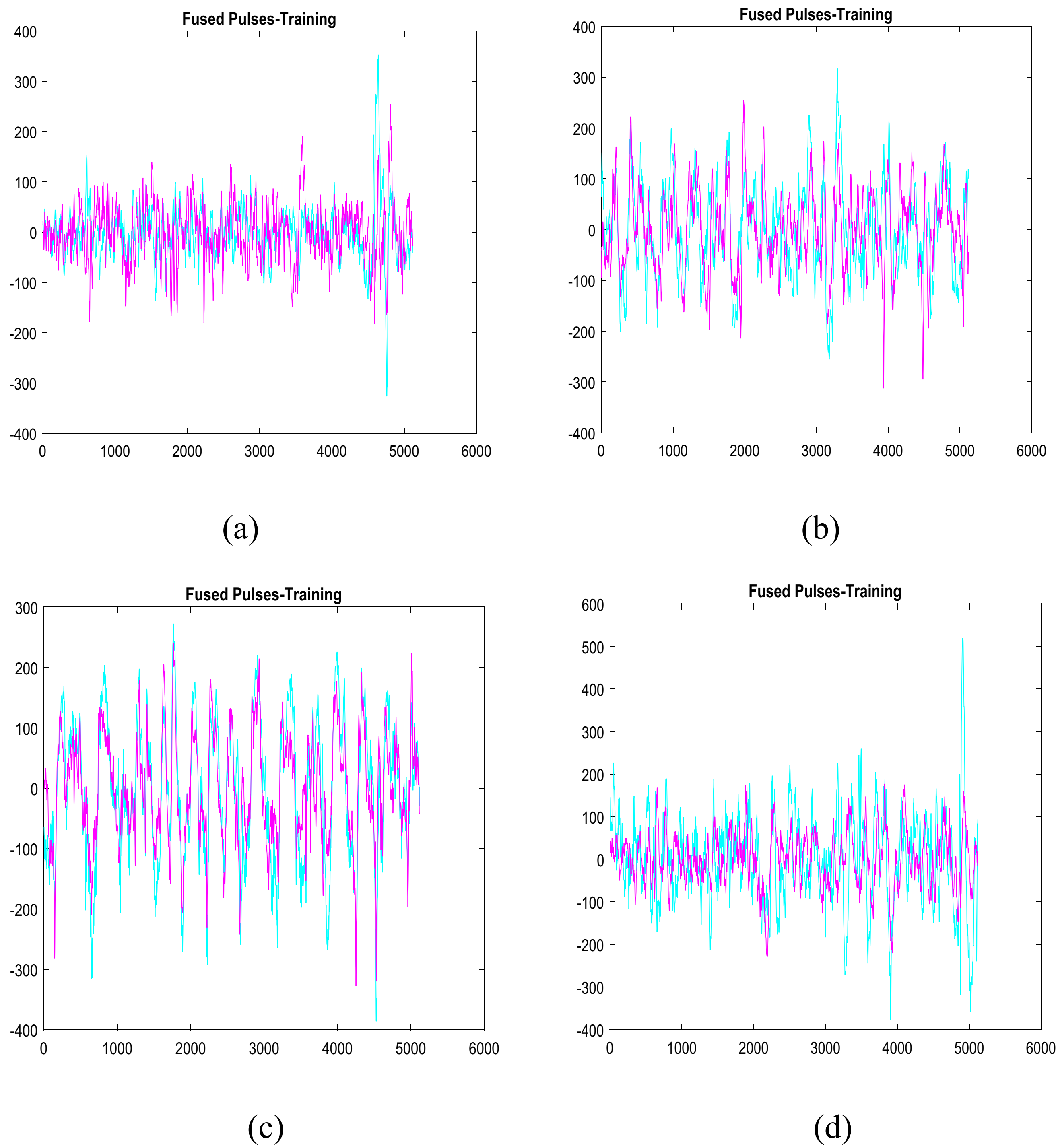


Fig. 3 Fused ECG Signals **a** P-1, **b** P-2, **c** P-3, **d** P-4

Fusion can enable or enhance the approximation to more complex structured results. Multimodal fusion combines data from a variety of sheathes into a single command. Usually for a single patient 4 ECG signals are acquired at 4 different nodes. To process all 4 signals at a time it is complicated. so, to reduce the complexity of the process the

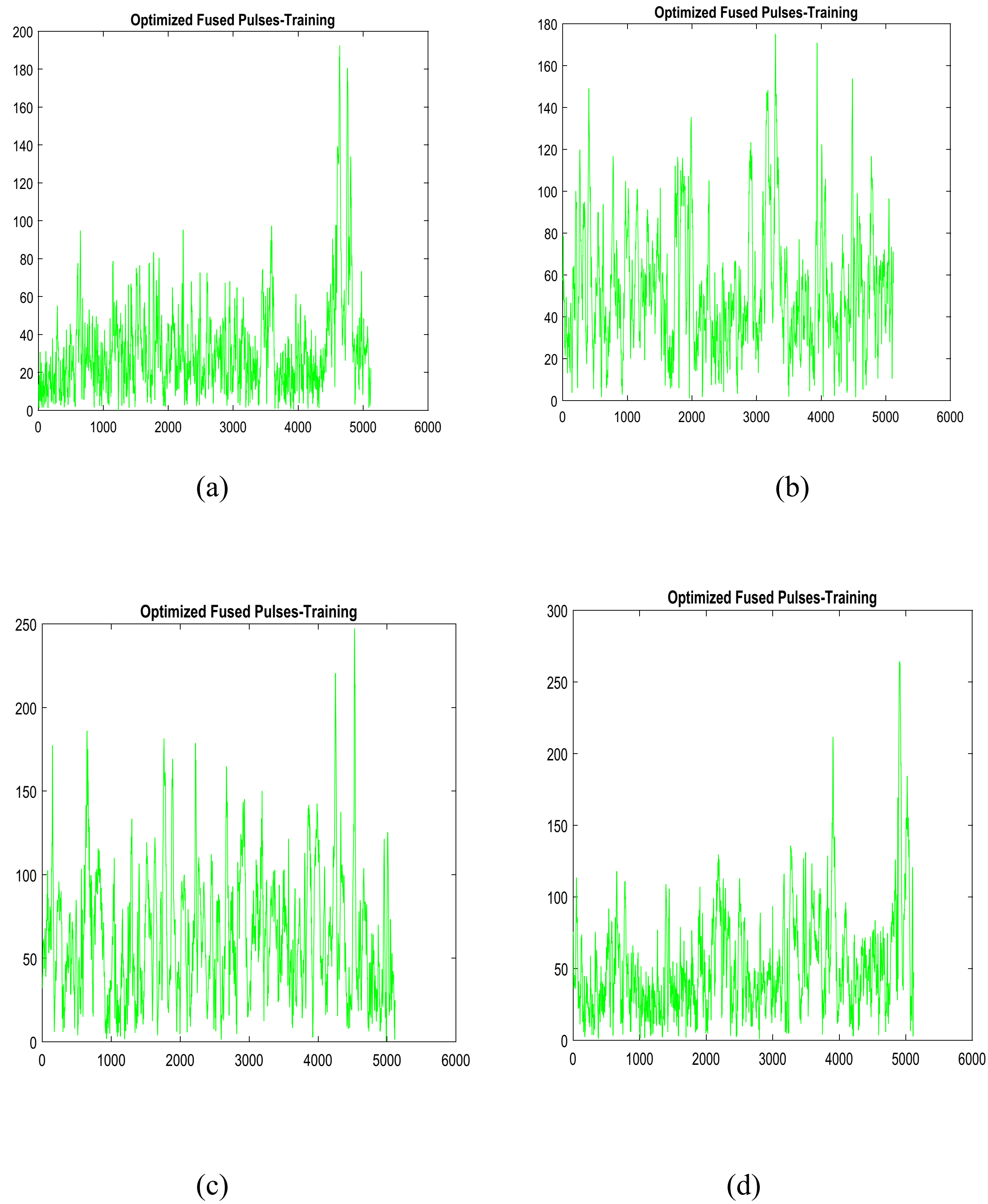


Fig. 4 Optimized ECG signals **a** P-1, **b** P-2, **c** P-3, **d** P-4

4 ECG signals of patients are fused. A multimodal fusion strategy enhances heartbeat detection by utilizing additional information present in the various physiological signals.

The fused signals of patient-1, patient-2, patient-3 and patient-4 are shown in Fig. 3.

From the fused signals, the optimal features are selected by optimization algorithm. An optimization algorithm is theprocedure that associates various explanations iteratively pending an optimal or satisfactory solution is determined. Gradient descent is a very well optimization algorithm for

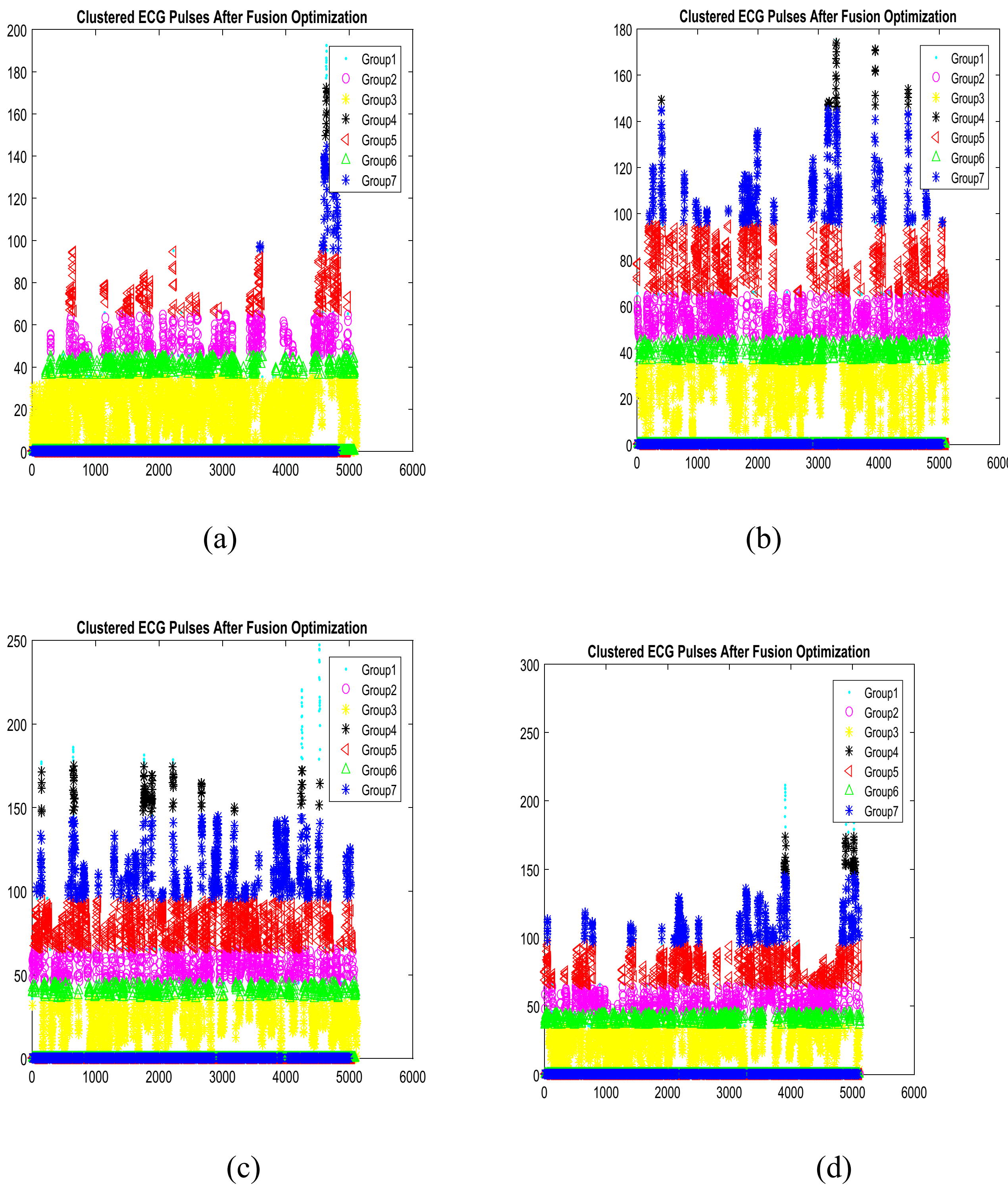


Fig. 5 Clustered ECG pulses **a** P-1, **b** P-2, **c** P-3, **d** P-4

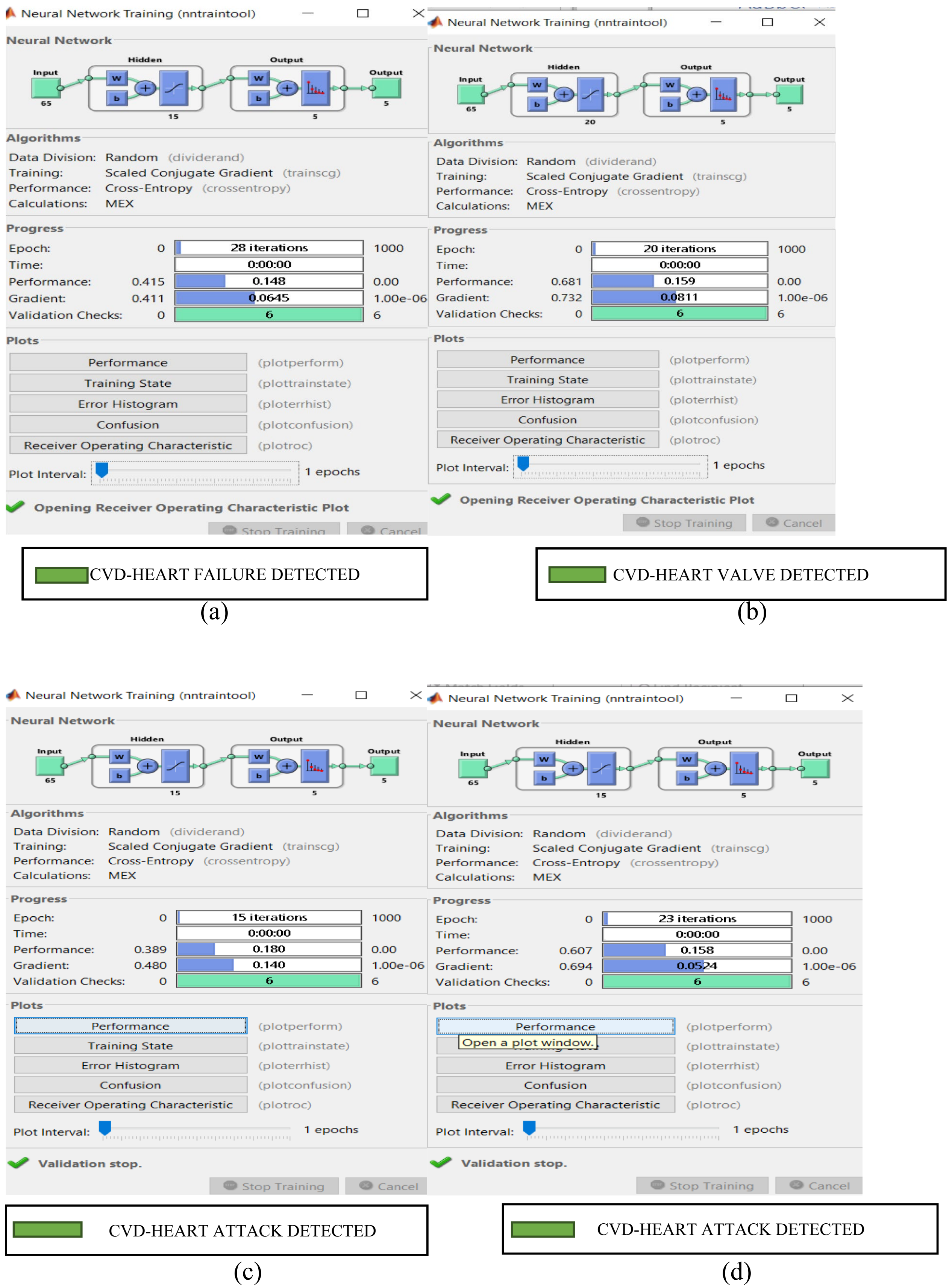


Fig. 6 Training Phases of CNN **a** P-1, **b** P-2, **c** P-3, **d** P-4

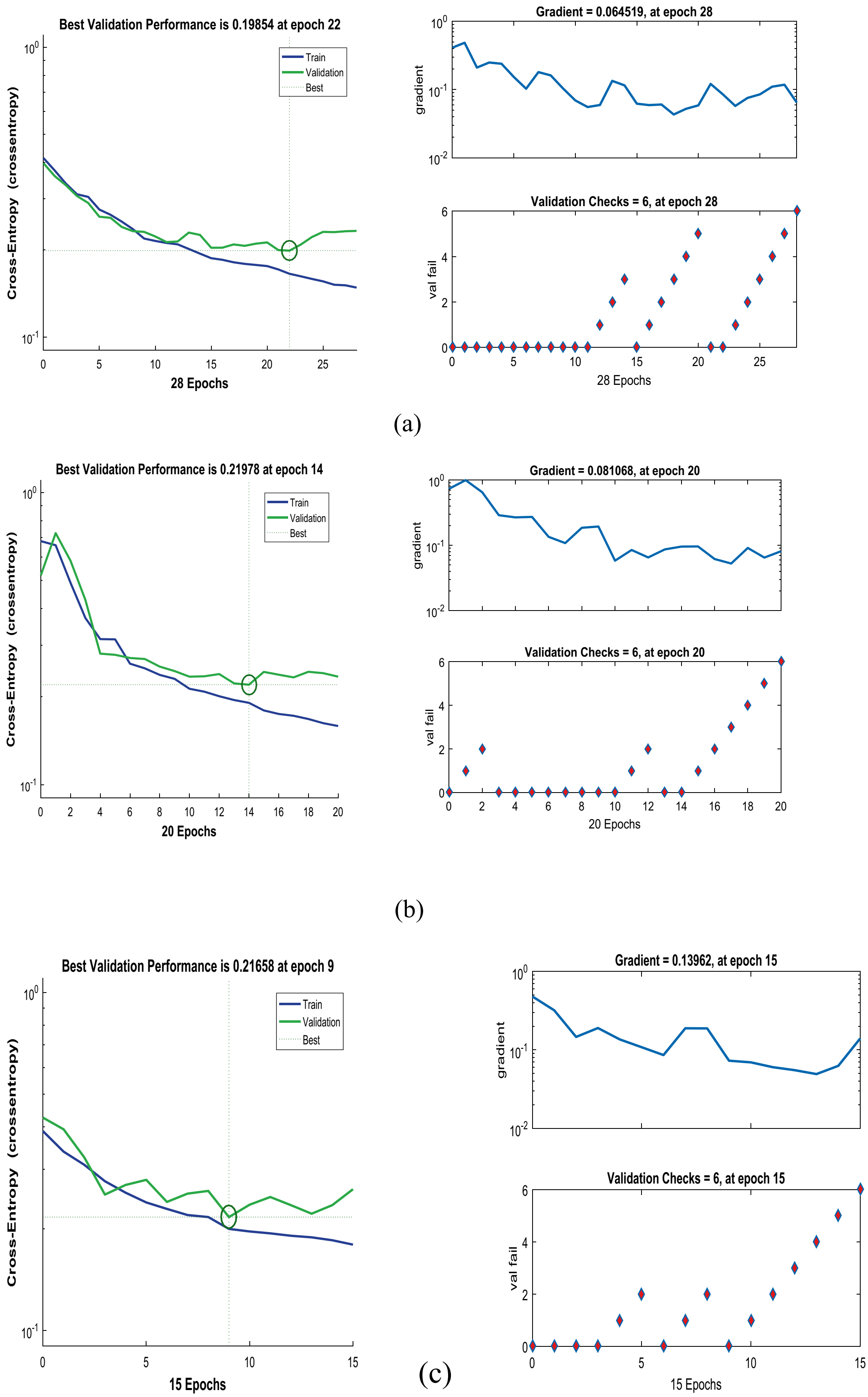
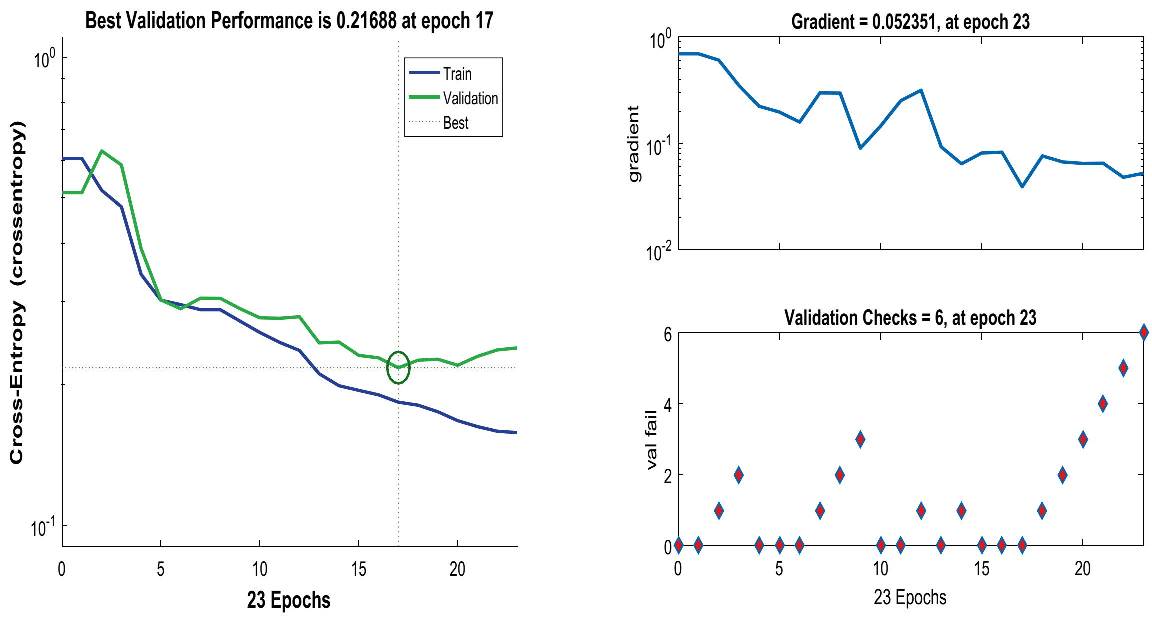


Fig. 7 Best Validation Performance and Training State **a** P-1, **b** P-2, **c** P-3, **d** P-4



(d)

Fig. 7 (continued)

training neural networks and machine learning techniques. So, in this work, from fused ECG Signals the optimal features are selected by gradient descent optimization technique. The optimized signals of different patients are shown in Fig. 4.

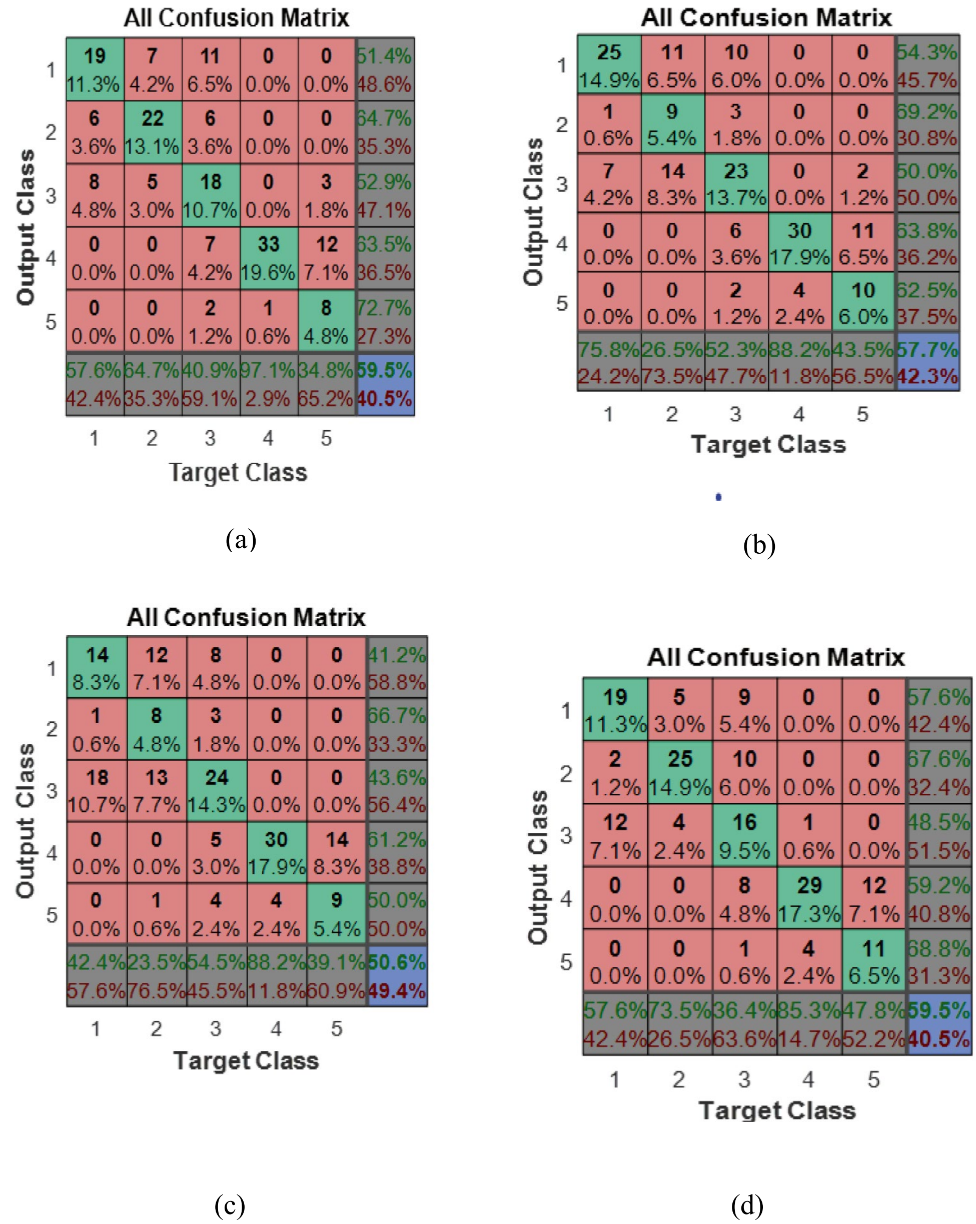
After selecting the optimal features then those features are extracted by clustering technique. Clustering is the procedure of dividing a group or set of data points addicted to multiple groups consequently that data points in the similar group remain more related than data points in former groups.The K-Means algorithm splits the given dataset into aexistedamount of clustersand the optimized ECG signals are clustered based on its magnitude by using K-Means algorithm. The total amount of clusters is 7 and from those clusters the features are extracted such as maximum, mean, median, cross entropy and gradient from different clusters. Clustered ECG signals of different patients are shown in Fig. 5.

After all the features are extracted then those features are fed to classification process where CNN is used to classify the cardiovascular diseases.The Convolutional Neural Network has an input layer, a hidden layer, and an output layer. It can learn, save, and form connections among inputs and outputs. The neural network begins by adjusting the weights associated with all correlations. Certain data sets were used to train the network. Figure 6 shows the training phase of neural network. The total number of epochs used to train the features which are obtained from clusters.

After classification of the diseases, the results are validated by constructing the features as cross entropy and gradient. In the validation performance curve and training state if the cross entropy and gradient values are approximately zero then the model is perfectly trained otherwise not trained well. Best line should be a dotted line, best line represents that other line should lie on or near these lines then we can confirm that training has to be done successfully. Any line meets or passes near to the best dotted line it means the convergence has achieved. Cross Entropy feature is used in classification tasks. The cross entropy and gradient values of patient-1, patient-2, patient-3 and patient-4 are shown in Fig. 7.

The confusion matrix defines the performance of a classification method. A confusion matrix shows how many correct and incorrect predictions the model made. The amount of valid predictions for each class is distributed diagonally. Figure 8 depicts the confusion matrix for 4 patients.

Fig. 8 Confusion Matrix **a** P-1, **b** P-2, **c** P-3, **d** P-4



Finally, ROC curve is used to observe the effectiveness and strength of the developed model. Receiver operating characteristics demonstrates the tradeoff amongst the true positive rate in addition to false positive rate. All the receiver operating characteristics are obtained after training, validation and testing.If the ROC curve was near to one then it indicates the system is perfect as shown in Fig. 9.

In Table 1 it clearly observed that nearly 98% of accuracy, approximately 64% of sensitivity and nearly 62% of specificity are obtained for all the patients. The parameters of all the patients are shown in Fig. 10.

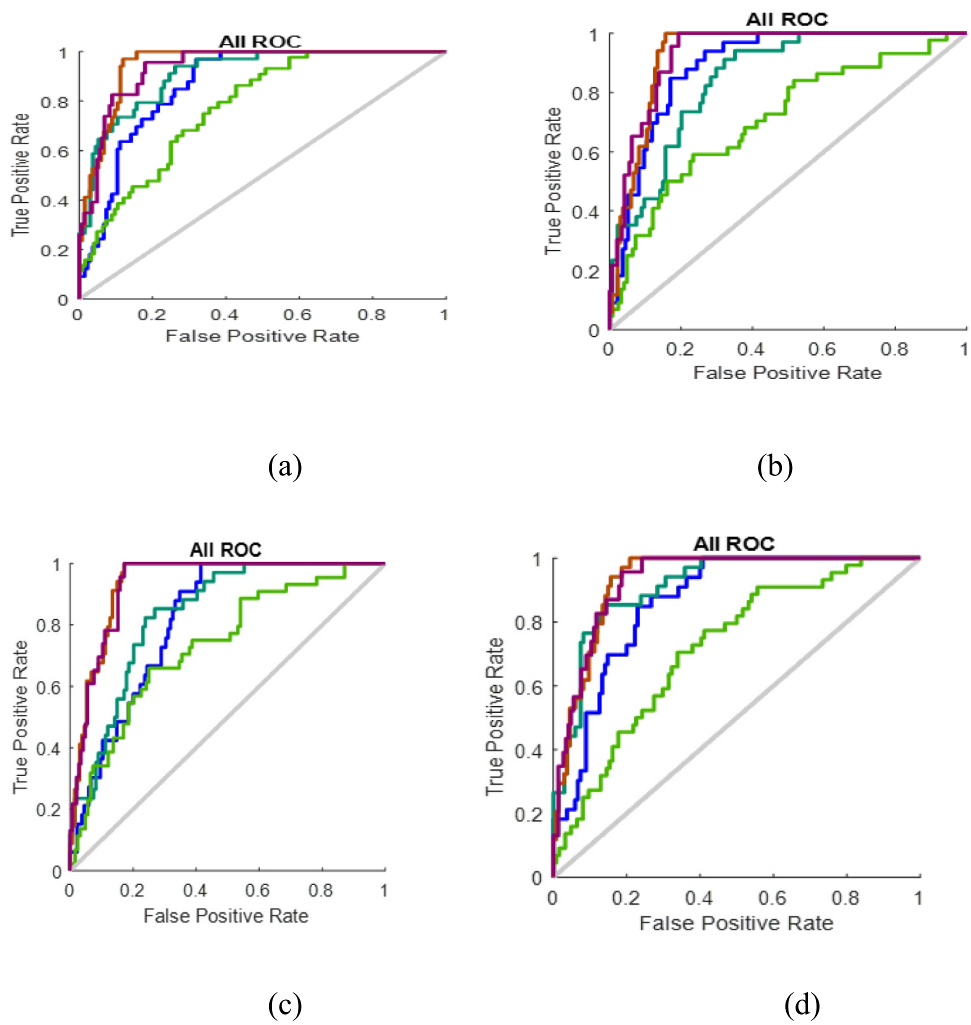


Fig. 9 Receiver operating characteristics **a** P-1, **b** P-2, **c** P-3, **d** P-4

Table 1 Statistical Parameters of four patients

Patient Details	Patient 1	Patient 2	Patient 3	Patient 4
Accuracy	98	97	96.5	98.5
Sensitivity	65.625	62.375	64.10	63.625
Specificity	62.45	60.25	62.15	61.35
Maximum	192.44	175.10	247.311	250.79
Mean	31.89	53.07	62.55	66.91
Median	25.58	47.36	58.10	56.70
RMS	40.08	60.63	72.68	79.05
Diseases Classification	Heart Failure	Heart Valve	Heart Attack	Heart Attack

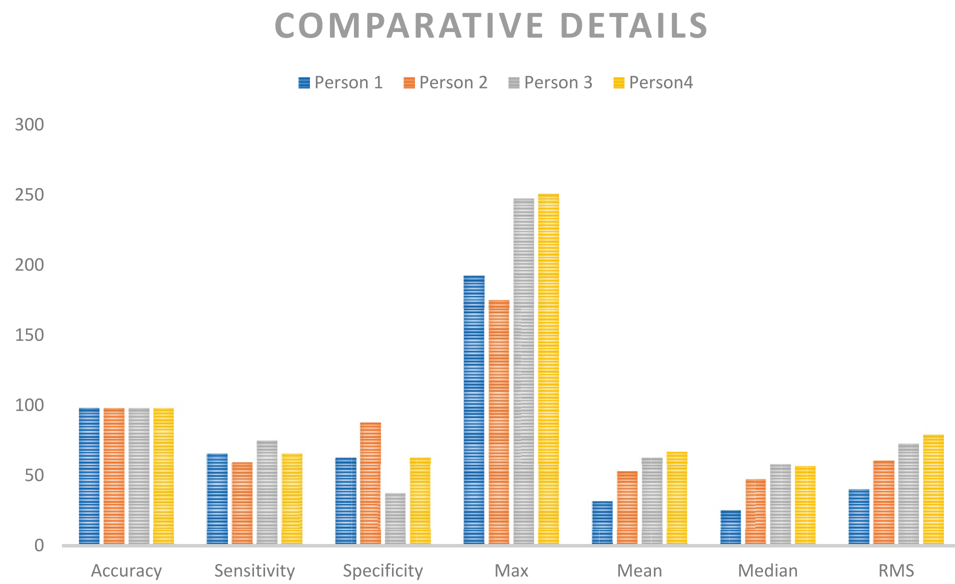


Fig. 10 Statistical Parameters graph for four patients

6 Conclusion

Cardiovascular Disease (CVD) is among the top causes of death in both men and women worldwide. The rising prevalence of the these disorders and their complications has a severe impact on the community and places a significant physical and financial strain on the worldwide community. Heart sound impulses provide crucial information about the health of the heart. Heart sound signals offer information that can be utilised to detect cardiovascular illness. In this work a novel method was proposed to detect cardiovascular diseases usingmulti-channel cardiac sound signals along with optimization technique.

In this work, the ECG samples of different patients from Kaggle database were acquired and buffered and reshaped for the proper sequence of ECG pulses. The buffered ECG pulses were fused by multi modal fusion frame work by combined all the pulses of similar magnitude and modalities.The fused ECG pulses were optimized by Gradient Descent optimization technique and clustered into different classes based on their pulse magnitudes by K-Means technique.The features were extracted from the clustered ECG pulses and subjected to the abnormality detection and classification by the Convolutional Neural Network. Finally, the performance parameters such as sensitivity, specificity, Accuracy, cross entropy, gradientare computed and compared. Future study should aim to increase the sensitivity and specificity of individual classifications by altering various factors. This study could be improved by training a larger dataset on more cardiac abnormalities then testing the identification ratio with DNNs. Advanced characteristics on ECG images can be extracted utilising image capture, adaptive image enhancement, including various boundary classification techniques on a variety of cardiac-related concerns with the help of medical specialists and new technical tools.Another major task for future scholars will be to learn domain adaptation.

Author contributions All authors have participated in (a) conception and design, or data analysis and interpretation; (b) drafting the paper or critically reviewing it for significant intellectual content; and (c) approval of the final result. This manuscript is not currently being reviewed by another journal or other publishing venue and has not been submitted to one. All authors are not affiliated with any entity that has a direct or indirect financial interest in the subject matter mentioned in the research.

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Data availability The processed data are available upon request from authors.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable

Consent to publish Not applicable.

Conflict of interests Authors have no conflicts of interest to declare.

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