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A HYBRID APPROACH OF A DEEP LEARNING TECHNIQUE FOR REAL–TIME ECG BEAT DETECTION

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This paper presents a new customized hybrid approach for early detection of cardiac abnormalities using an electrocardiogram (ECG). The ECG is a bio-electrical signal that helps monitor the heart's electrical activity. It can provide health information about the normal and abnormal physiology of the heart. Early diagnosis of cardiac abnormalities is critical for cardiac patients to avoid stroke or sudden cardiac death. The main aim of this paper is to detect crucial beats that can damage the functioning of the heart. Initially, a modified Pan–Tompkins algorithm identifies the characteristic points, followed by heartbeat segmentation. Subsequently, a different hybrid deep convolutional neural network (CNN) is proposed to experiment on standard and real-time long-term ECG databases. This work successfully classifies several cardiac beat abnormalities such as supra-ventricular ectopic beats (SVE), ventricular beats (VE), intra-ventricular conduction disturbances beats (IVCD), and normal beats (N). The obtained classification results show a better accuracy of 99.28% with an $F1$ score of 99.24% with the MIT–BIH database and a descent accuracy of 99.12% with the real-time acquired database.

Keywords: cardiac abnormalities, CAD, convolutional neural network (CNN), deep learning, ECG, supra-ventricular ectopic beats (SVE).

1. Introduction

Millions of people suffer from cardiac disorders every year in the world (CVDs, 2021; Allam *et al.*, 2022). An electrocardiogram (ECG) is a significant bio-signal that represents the heart's electrical activity and provides cardiologists with essential information about the heart's

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rhythm and function. The ECG signal is widely used as a standard tool for detecting and diagnosing heart disorders. Early detection of heart diseases can extend life and improve its through proper treatment. In ECG signals, medical attention is required for patients with abnormal morphology and heart rate since these abnormal cardiac rhythms may lead to life-threatening conditions (Acharya *et al.*, 2007).

Analyzing cardiac signals and diagnosing heart diseases is challenging in biomedical signal processing. Doctors find it hard to evaluate long ECG records in a short amount of time, and the human eye is not very suitable to detect continuous morphological changes in the ECG signal. From a practical standpoint, the examination of the ECG pattern may need to be done over several hours for a reliable diagnosis. The study is time-consuming, and there is a considerable risk of missing essential information due to the large volume of data. As a result, a strong and dependable computer-aided diagnosis (CAD) system is required. Some of the cardiac beat abnormalities in the ECG, such as supra-ventricular ectopic beats (SVE), ventricular beats (VE), and intra-ventricular conduction disturbances beats (IVCD), are shown in Fig. 1 (cf. Prakash *et al.*, 2021).

The paper is organized as follows: Section 2 describes the deep review of different ECG beat detection techniques, contributions of the work are discussed in Section 3, the ECG database used to evaluate the proposed model is explained in Section 4, Section 5 elaborates the proposed methodology for ECG beat detection, Section 6 presents the results and a discussion, and finally, conclusion are included in Section 7.

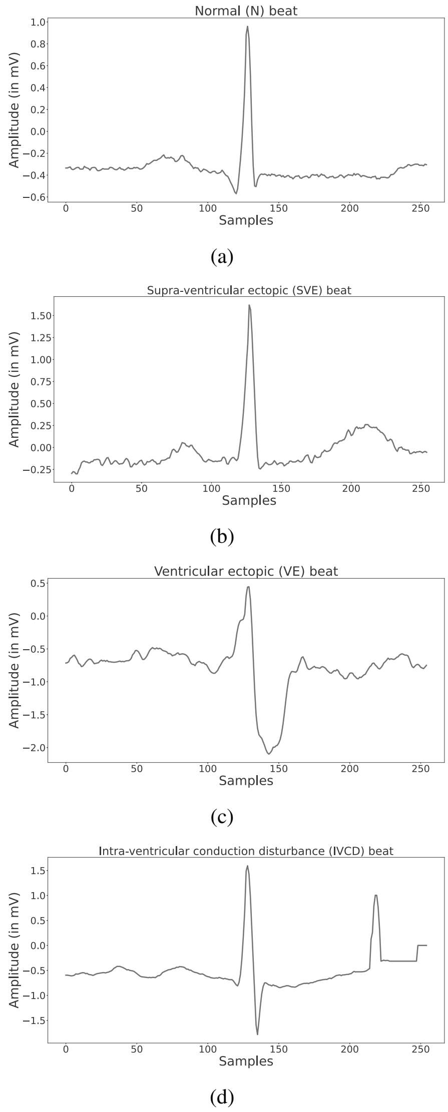

Fig. 1. Different ECG beats: N (a), SVE (b), ventricular (c), and IVCD ECG (d) (the number of samples is represented along the x-axis, whereas the amplitude is shown along the y-axis).

2. Review of the literature and motivations

Medical experts are used to analysing the ECG signal to identify the condition of the heart. CAD is an important tool for identifying cardiac disorders effectively to accommodate cardiac patients with proper medication. In the literature, many researchers have proposed different techniques to identify ECG abnormalities (Sahoo *et al.*, 2020; Shadmand and Mashoufi, 2016). The ECG abnormalities detection system mainly covers the following stages: data pre-processing, feature extraction, and classification. ECG signals are contaminated with various types of noise during acquisition (Sahoo *et al.*, 2020). Different signal pre-processing techniques are utilized in the literature to remove noise from the ECG signal (Mathews *et al.*, 2018; Khorrami and Moavenian, 2010; Uchaipichat *et al.*, 2016). After pre-processing, feature extraction is an important task to identify the particular type of cardiac arrhythmia.

The majority of the literature follows different techniques such as the discrete wavelet transform (DWT) (Khorrami and Moavenian, 2010), the discrete cosine transform (DCT) (Khorrami and Moavenian, 2010), the discrete Fourier transform (DFT) (Uchaipichat *et al.*, 2016), the Gaussian mixture model and the sparse decomposition method (do Vale Madeiro *et al.*, 2020) for extracting time domain, frequency domain and morphological features from the ECG signal. Techniques like principal component analysis (PCA) (Martis *et al.*, 2013a; 2013b; Rodrígez *et al.*, 2015), linear discriminant analysis (LDA) (Martis *et al.*, 2013b), independent component analysis (Martis *et al.*, 2013b; Elhaj *et al.*, 2016), kernel PCA (Rajagopal and Ranganathan, 2017), and genetic algorithms (GAs) (Kishore and Singh, 2015) have been used for feature reduction. Furthermore, the extracted features were fed to machine learning classifiers, such as neural networks (Elhaj *et al.*, 2016), support vector machines (SVMs) (Venkatesan *et al.*, 2018), radial basis function neural networks (RBFNNs) (Raj and Ray, 2018b), probabilistic neural networks (PNNs) (Rajagopal and Ranganathan, 2017), k-nearest neighbors (K-NN) (Hammad *et al.*, 2018), or random forest (RF) (Shimpi *et al.*, 2017).

Machine learning algorithms mainly depend on manual feature extraction methods, but it is very difficult to extract optimized features from the input. To overcome this problem, deep learning algorithms have come into existence to extract features automatically. Different deep learning algorithms, i.e., deep neural networks (DNNs) (Faust *et al.*, 2018; Mathews *et al.*, 2018), deep belief networks (DBNs) (Mathews *et al.*, 2018), and convolutional neural networks (CNNs) (Acharya *et al.*, 2017c; Bodyanskiy and Tyshchenko, 2019) are utilised in the earlier methods. ECG beats are classified into N, S, and V classes using ordinal pattern entropies by Bidias á Mougoufan *et al.* (2021). Ventricular arrhythmia alone is detected with more than 90% by Mandal *et al.* (2021).

Elhaj *et al.* (2016) and Venkatesan *et al.* (2018) reported descent performance of ECG abnormalities detection using machine learning classification schemes. Sahoo *et al.* (2017) proposed an RBNN based classifier with manual handcrafted features for classifying six types of ECG beats with an accuracy of 99.80%. Yang *et al.* (2018) proposed a system using principal component analysis (PCA) with a linear SVM classifier to classify five types of beats with an accuracy of 97.70%. A computer-based composite dictionary (CD) method of ECG analysis for detecting abnormalities with an accuracy of 99.21% is reported by Raj and Ray (2018a). A multi-resolution DWT hybrid technique with a multilayer-PNN classifier is used to classify LBBB and RBBB beats. Statistical features and an SVM classifier are used by Khalaf *et al.* (2015) to classify five beats with a performance of 98.60%.

Currently, deep learning techniques are becoming very popular to characterize heart abnormalities efficiently (Acharya *et al.*, 2018). In deep learning techniques, the initial layers are responsible for extracting features based on which the output layers carry out the evaluation and report the type of pattern. CNNs are often used in 2D data processing such as image processing, and speech recognition (Abdel-Hamid *et al.*, 2014). A deep learning-based one dimensional (1D) CNN (Kiranyaz *et al.*, 2015) technique has been utilized to detect cardiovascular diseases. Acharya *et al.* (2017c) also proposed a CNN model with nine layers to classify five cardiac beat abnormalities. Acharya *et al.* (2017b) proposed a novel automatic CNN model for classifying ECG beat abnormalities with an automatic feature extraction technique. Oh *et al.* (2018) introduced a new combination of a deep CNN with long short-term memory (LSTM) for classifying five types of variable length ECG beats and obtained a considerable accuracy of 98.10%. Automated deep feature extraction and classification of six ECG beats classes are provided by the hybrid CNN-LSTM system, which includes N, atrial fibrillation, atrial flutter, atrial premature beat, left bundle branch block (LBBB) and right bundle branch block (RBBB) (Obeidat and Alqudah, 2021).

Extensive literature is available on detecting cardiac abnormalities with machine and deep learning techniques, even though these existing techniques are suffering from one or more problems. The major complexities are as follows:

- the necessity of handcrafted features,
- huge data requirements for training,
- over-fitting and under-fitting of the network,
- complexity in the architecture,
- requirement of more depth to extract depth features,
- difficulty in hyper-parameter tuning,
- poor performance.

To overcome the above cited problems, a combination of automatic and manual feature extraction based hybrid models is proposed in this work.

3. Contributions of the proposed work

The proposed model considerably detects four input classes: non-ectopic (N), SVE and IVCD beats. The major contributions of the methodology proposed in this manuscript are as follows:

- In a real-time database, life-threatening arrhythmias are classified accurately with more than 99% accuracy with a good generalization capability.
- Some clinically important beats like IVCD are purely dependent on QRS width and R-peak; therefore, in addition to automatic extraction of the features, specific features are supplied externally to the deep learning network, which converts the conventional algorithm into a hybrid model.
- An automated computer-aided diagnosis tool is required for doctors to quickly identify an abnormality in in-patient health records with more accurate detection. This proposed tool will help process a large number of data in less time, allowing the doctor to start medication at the proper time for the patient.
- Highly crucial beats, SVE, VE, IVCD, and N, are specifically detected in this clinically significant work.

4. ECG database description

In this work, two types of databases are used to verify the performance of the proposed method, i.e., that of Massachusetts Institute of Technology–Beth Israel Hospital (MIT–BIH) and an acquired real-time database using BPL Digital Holter Trak 48.

4.1. MIT–BIH arrhythmia database. The database is prepared as per the Association for the Advancement of Medical Instrumentation (AAMI) standard. The IVCD beat is considered the combination of LBBB and RBBB. The database is prepared very carefully to balance the data set, which is useful in properly training the proposed deep learning network. First, the proposed methodology performance is tested on a benchmark MIT–BIH database, contains 48 ECG records, but four do not have adequate quality (#102, #104, #107, and #217). Hence only 44 ECG records are utilized for training and testing the network (Moody and Mark, 2001). A detailed database description is given in Table 1.

4.2. Acquired real-time ECG database. In addition to that, the proposed method is also tested with the acquired real-time ECG database. In this work, to study the long term analysis of ECG signals, a real-time private database has been created with the support of the GGH (Govermment General Hospital), Guntur, using BPL Digital Holter Trak 48. The data acquisition system uses a 1024 Hz sampling frequency with 12 lead, three-channel configurable, powerful software devices. The database consists of 34 recordings from 15 individuals; 10 were male, and five were female between 27 to 60. Each ECG record comprises a 24 hour long duration signal. The generated ECG data were clinically verified by expert physicians and given annotations manually as per the AAMI standard. A detailed database description is given in Table 2.

5. Proposed methodology for ECG beat detection

In this work, computer-aided diagnosis (CAD) system apps are developed to detect cardiac abnormalities such as N, SVE, VE and IVCD long term fragments of ECG signals. The following three steps are involved in the detection of cardiac arrhythmia from the ECG signal: (i) an ECG database, (ii) pre-processing and R-peak detection, (iii) feature extraction and classification jointly implemented using a deep learning algorithm. Figure 2 describes the block diagram of the applied methodology for detecting cardiac beat abnormalities.

5.1. Pre-processing and R-peak detection. In pre-processing, the detection of the QRS complex is the first step toward automated computer-based ECG signal analysis. The Pan–Tompkins algorithm (Pan and Tompkins, 1985) is used to find the R-peak locations of the ECG signal. After R-peak detection, ECG beats are segmented based on the R-peak location of the pre-processed signal. Annotations are also added to all the extracted ECG beats to train deep learning algorithms. An additional enhancement of the ECG signal is also implemented in this work with the fast Fourier transform (FFT); it can be achieved with the help of the methodology shown in Fig. 3.

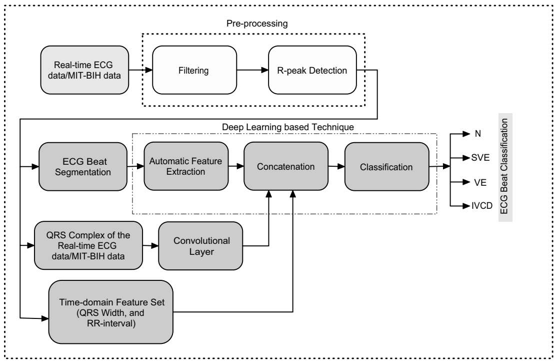

Fig. 2. Block diagram of the proposed beat detection system.

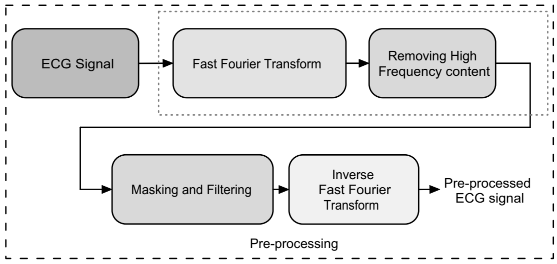

Fig. 3. Pre-processing of the original ECG beat.

The ECG signal is usually distorted by artifacts like baseline wander, power line interference (50/60 Hz), and electromyography noise. These must be removed before the ECG can be used for diagnosis. An FFT based band-pass filter with a band of 0.05–100 Hz is employed to isolate the ECG data accurately from noise. Therefore, a frequency below 100 Hz is retained by frequency thresholding. Masking and filtering are used to remove noise between the QRS complex of the frequency domain by a statically appropriate threshold (Sinha *et al.*, 2021). Finally, the time domain ECG beat is reconstructed by taking the inverse FFT of the filtered signal. The pre-processed method is followed as in the work of Kumar *et al.* (2014).

5.2. Customized deep learning neural network (DNN) for classification. CNNs can be used to classify electrocardiogram beats (Acharya *et al.*, 2017a; Tan

Table 1. Details of different beats in MIT–BIH.

S.No	Name of the beat	Number of beats
1	Non-ectopic beat (N)	9,492
2	Supra-ventricular ectopic beat (SVE)	3,528
3	Ventricular ectopic beat (VE)	6,540
4	Intra-ventricular conduction disturbances (IVCD)	7,728

Table 2. Details of different beats in real-time acquired data.

S.No	Name of the beat	Number of beats
1	Non-ectopic beat (N)	2,230
2	Supra-ventricular ectopic beat (SVE)	1,099
3	Ventricular ectopic beat (VE)	1,318
4	Intra-ventricular conduction disturbances (IVCD)	780

et al., 2018; Acharya *et al.*, 2017b; Kowal *et al.*, 2021). ECG signals are typically processed as two-dimensional signals; hence CNNs are better suited for multidimensional patterns or image recognition applications (Abdel-Hamid *et al.*, 2014; Sahoo *et al.*, 2022). A CNN is a deep feed-forward artificial neural network that can automatically extract deep features from data without manually extracting them (Patro *et al.*, 2020).

The deep learning neural network (DNN) classifier model maps the input features to the respective classes. The deep learning algorithm is used to classify the ECG signal. The algorithm automatically extracts the features of the ECG signal which can exactly identify the arrhythmia class. A customized deep CNN is used to classify different types of arrhythmia. In this model, different layers are used to design the model, (i) a convolutional layer, (ii) a rectifier linear unit (ReLu), (iii) a soft-max layer, and (iv) a dense layer. The CNN architecture includes 11 layers: three convolutional layers, one max-pooling layer, three flatten layers, and three dense layers. Each convolutional layer provided the feature maps and was followed by a down-sampled max-pooling layer. The final layer includes fully connected layers consisting of 30 and four output neurons (Venkata Phanikrishna *et al.*, 2021). The detailed architecture of the proposed methodology is shown in Fig. 4.

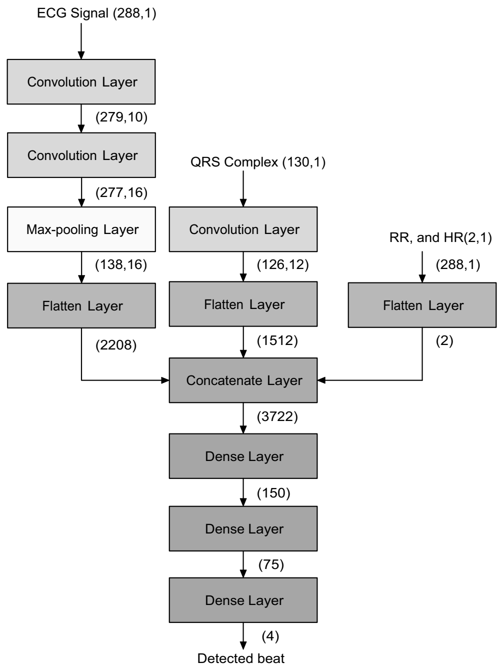

Fig. 4. Block diagram of the proposed architecture.

6. Results and a discussion

Experiments in this work are executed on the Python platform with the Open CV, Keras with Tensor Flow GPU libraries as the back end. The hardware utilized in this work with the configuration of a desktop computer has an NVIDIA Quadro M4000 8 GB graphics processing unit (GPU), Intel i7 processor, and 32 GB of DDR3 memory. The performance of the proposed work is evaluated on two databases. Different types of inputs are processed through three parallel CNN models so that they can work better together. The applied inputs are a raw ECG, QRS complex, and RR, and the HR interval of the ECG. The Softmax function and a classification layer are used to separate outputs for each class. Two different learning parameters were used in the CNN model applied, and the results were compared. First, a 3×10^{-3} initial learning rate was applied, and this value has not been changed during the training; the momentum parameter was taken as 0.2 and the maximum epoch set as 50. Ten-fold cross-validation was applied with these layer parameters. Secondly, a 0.01 initial learning rate was used. This value was dropped with a factor of 0.2 during training; the momentum parameter was taken as 0.2, and the maximum epoch was set as 300. The numbers of majority class

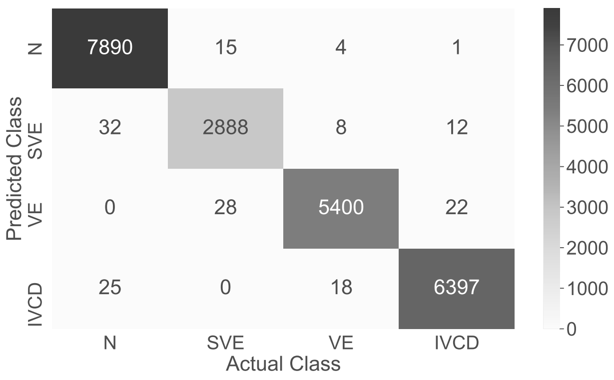

Fig. 5. Confusion matrix of the proposed network with the MIT–BIH database.

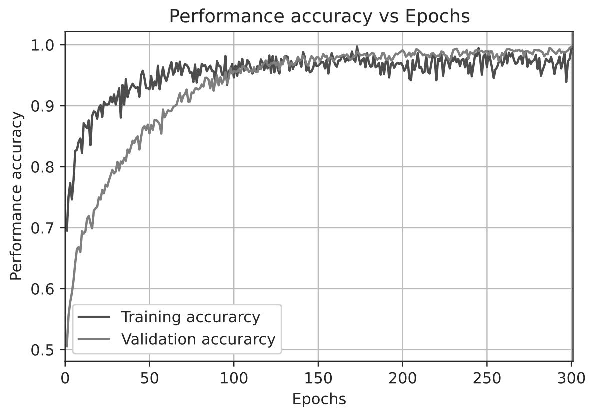

Fig. 6. Training and cross-validation curves of the proposed network.

Table 3. Performance matrix of the proposed method with the standard data set.

Class	Acc (%)	Sen (%)	Spe (%)	Ppr (%)
N	99.74	99.28	99.61	99.58
SVE	99.63	98.53	99.51	99.68
VE	99.78	99.44	99.84	99.91
IVCD	99.73	99.45	99.57	99.88

Table 4. Performance matrix of the proposed method with a real-time data set.

Class	Acc (%)	Sen (%)	Spe (%)	Ppr (%)
N	99.00	98.95	99.56	98.11
SVE	99.44	99.26	99.10	99.09
VE	99.87	99.02	99.05	97.80
IVCD	99.47	99.14	99.28	97.30

samples were subdivided to match the number of minority class samples. The training was continued until all of the majority class samples were used in the train. The network utilized the MIT–BIH standard database. 80% of the data were utilized for the training cum validation phase in the total data set from the total data.

In the field of deep learning, a confusion matrix, also known as a contingency table or an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning, it is usually called a matching matrix). Each matrix column represents the instances in a predicted class, while each row represents the instances in an actual class. The name stems from the fact that it makes it easy to see if the system is confusing two classes (i.e., commonly mislabeling one as another). A confusion matrix is generated based on the MIT–BIH database shown in Fig. 5. Each row in the confusion matrix represents instances in the true class, and each column stands for instances in the predicted class. The training and cross-validation curves of the proposed methodology are shown in Fig. 6.

In Table 3, different performance metrics of the proposed work are reported. The performance of the proposed method was evaluated in terms of metrics such as accuracy, sensitivity, specificity and positive predictivity:

$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}, \tag{1}$$

$$\mathrm{Sen} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \tag{2}$$

$$\mathrm{Spe} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}, \tag{3}$$

$$\mathrm{Ppr} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}. \tag{4}$$

i.e., TP, FP, TN, and FN are truly positive, false positive, true negative, and false negative, respectively, calculated from the generated confusion matrix. The proposed deep learning methodology successfully classifies the beats into four classes, i.e., N, SVE, VE, and IVCD, with a promising performance greater than 99% accuracy. The proposed deep learning method reports an accuracy of 99.28% with an F1 score of 99.24%. The accuracy cum loss curve of the proposed deep learning model is shown in Fig. 6. Overall, the suggested deep learning method had a very strong overall accuracy of 99.28% for long term ECG data compared with other similar works (Table 5).

6.1. Performance of the network on real-time acquired ECG data. The same network is tested with the acquired real-time ECG database. The database is collected with the BPL Digital Holter Trak 48 instrument. It is a 12-lead, 3-channel Holter monitor that can record data from patients for 24–48 hours. The procedure during the collection of the ECG is shown in Fig. 7. A total of 5,427 beats were collected from different patients.

Fig. 7. Real-time ECG data acquisition using the BPL Holter ECG (Trak 48 12 Channel/Lead).

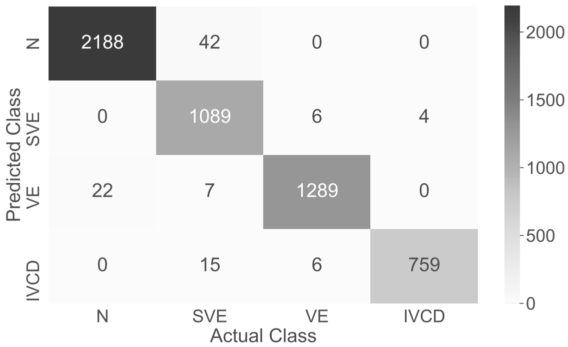

Fig. 8. Confusion matrix of the proposed network on real-time data.

To verify the generalization capability of the network, after training and testing with the MIT–BIH database, the same network is tested with the acquired real-time ECG database.

The confusion matrix with the real-time dataset is shown in Fig. 8. The network can classify the beats applied with a performance accuracy of 99.12%. It can process the beats with decent accuracy. The performance matrix of the proposed method on the real-time database is shown in Table 4. A detailed comparison of the proposed method with the existing approaches is shown in Table 5. There are several uncertainties that need to be quantified in this proposed work: (i) the selection and collection of the training data, (ii) estimating the depth of the network, and (iii) uncertainties pertaining to the performance of the model depending on the operational data.

7. Conclusion

The proposed hybrid deep learning strategy approach can classify various long-duration ECG heartbeats, which are crucial for detecting cardiac arrhythmia. The developed model classified four ECG beats, integrating them into a CAD ECG system for fast and accurate diagnosis. Our system first extracts R-peak locations, followed by heartbeat segmentation. Finally, the other end of the system provides beat-by-beat classification results using the deep learning technique. The proposed model tested over 10,000 beats for four classes of cardiac abnormalities such as N, SVE, VE and IVCD. The obtained classification results show an overall descent accuracy of 99.65%, with an F1 score of 0.99. The network performance with real-time data is also descent, i.e., 99.44%, which shows the network's generalization capability is good. Deploying such models in hospitals to analyse huge volumes of ECG data would reduce physicians' workload and would be very helpful for early diagnosis of cardiac abnormalities. In the future, the authors want to deploy the whole end-to-end system on an Android based platform to design mobile based health care.

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Table 5. Performance comparison of the proposed method with the existing literature.

S.no	Authors	Technique	Dataset	No.of classes	Accuracy (%)
1	Li *et al.*, 2016	SVM classifier with GA	MIT	3	97.30
2	Sahay *et al.*, 2019	ANN classifier with PSO	MIT	2	93.60
3	Jiang *et al.*, 2019	ANN+MMNNS	MIT ESC	2	97.30
4	Li and Zhou, 2016	Random forest classifier	343434 MIT	4	
5	Liu *et al.*, 2018	Convolutional neural network	CPSC	2	81.0
6	Xie *et al.*, 2018	Recurrent neural network	MIT	343434 2	99.10
7	Hasan and Bhattacharjee, 2019	Deep-CNN	PTB	4	98.24
8	Wu *et al.*, 2020	Deep-CNN	Challenge	2	93.20
9	Asgharzadeh-Bonab *et al.*, 2020	Deep-CNN with 2D PCA	MIT	5	98.81
10	Proposed work*	Hybrid Deep-CNN model	MIT Real-time acquired ECG DB	4	99.28 99.12

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