Bulletin of Electrical Engineering and Informatics
Vol. 13, No. 2, April 2024, pp. 1325~1333
ISSN: 2302-9285, DOI: 10.11591/eei.v13i2.6102

The deep convolutional networks for the classification of multi-class arrhythmia

Muhamad Akbar[1,2], Siti Nurmaini[3], Radiyati Umi Partan[4]
[1]Doctoral Program of Engineering Science, Faculty of Engineering, Universitas Sriwijaya, Palembang, Indonesia
[2]Computer Science, Faculty of Engineering, Universitas Bina Insan, Lubuklinggau, Indonesia
[3]Intelligent System Research Group, Universitas Sriwijaya, Palembang, Indonesia
[4]Faculty of Medicine, Universitas Sriwijaya, Palembang, Indonesia

Article Info

Article history:

Received Feb 28, 2023
Revised Jun 14, 2023
Accepted Oct 12, 2023

Keywords:

Arrhythmia
Classification
Convolutional neural network
Modify dataset
Multiclass

ABSTRACT

An arrhythmia is an irregular heartbeat. Many researchers in the AI field have carried out the automatic classification of arrhythmias, and the issue that has been widely discussed is imbalanced data. A popular technique for overcoming this problem is the synthetic minority oversampling technique (SMOTE) technique. In this paper, the author adds some sampling of data obtained from other datasets into the primary dataset. In this case, the main dataset is the Massachusetts Institute of Technology–Beth Israel Hospital (MIT-BIH) arrhythmia database and an additional dataset from the MIT-BIH supraventricular arrhythmia database. The classification process is carried out with one-dimensional convolutional neural network model (1D-CNN) to perform multiclass and subject-class advancement of medical instrumentation (AAMII) classifications. The results obtained from this study are an accuracy of 99.10% for multiclass and 99.25% for subject-class.

Corresponding Author:

Muhamad Akbar
Doctoral Program of Engineering Science, Faculty of Engineering, Universitas Sriwijaya
Bukit Lama Kecamatan Ilir Barat I, Palembang, Indonesia
Email: muhamad.akbar@univbinainsan.ac.id

1. INTRODUCTION

Arrhythmia (cardiac arrhythmia) is a heart rhythm disorder, which is classified based on the rhythm of the heartbeat, such as a heartbeat that is too fast, too slow, or irregular [1], [2]. This arrhythmia is generally harmless. Most people experience an occasional irregular heartbeat, such as a fast or slow heart rate. However, some types of cardiac arrhythmia can cause health problems or even be life-threatening [3]. This arrhythmia occurs due to abnormal electrical activity of the heart. With an electrocardiograph (ECG), electrical activity in the heart can be recorded for a certain period by placing electrodes/sensors on the skin that have the potential to be recorded [4]. With the help of this ECG, cardiologists can detect, and visually analyze arrhythmias [5]. Cardiologists must diagnose and classify heart conditions from extensive ECG data to recognize this cardiac arrhythmia disorder. They take a long time to determine the type/class of heart conditions [6]. A computer-assisted ECG signal recognition method has been introduced to overcome this problem, which is a promising solution [7], [8].

The recognition of ECG signals for the classification of rhythm and beat arrhythmia uses an artificial intelligence approach, making it possible to see the classification results quickly. Especially with the rapid development of deep learning with the support of faster computing devices. Deep neural networks (DNNs) are becoming very popular for classification, segmentation, and detection problems [9]. In diagnosing a cardiac arrhythmia, several deep learning approaches are used, such as convolutional neural network (CNN), recurrent neural network (RNN), autoencoder [9], DNN, deep belief network (DBN), long-sort-term memory (LSTM), and gate recurrent unit (GRU) [10]. In recent studies, CNN is the deep learning model that is most widely used in the classification of arrhythmias, including in other medical cases; this is because CNN has a relatively good performance in classification and image detection [9], [11].

This paper describes a step to modify the Massachusetts Institute of Technology–Beth Israel Hospital (MIT–BIH) arrhythmia dataset to accelerate the classification process on imbalanced data against multiclass/class-oriented classification and reduce the accuracy gap between class-oriented and subject-oriented. This gap is a concern because previous studies have produced an inversely proportional accuracy gap between class-oriented and subject-oriented. Previous research resulted in a more significant multiclass/class-oriented accuracy value than the subject-oriented one. Previous research shows that the results of the multiclass classification do not positively affect the subject-oriented classification. In contrast, the smaller number of classes in the subject-oriented class should result in better accuracy. In addition to this study, we can see a comparison of the use of datasets for multiclass classification on unbalanced data. Comparisons were made by comparing synthetic data sampling techniques, such as synthetic minority oversampling technique (SMOTE) [9] or multiple memristor-based neural networks (MMNNs) [12], with additional minority data sampling techniques with other datasets. Several comparative experiments were carried out in this paper to test datasets suitable for multiclass classification and subject class classification advancement of medical instrumentation (AAMII) standard. The experiment was conducted to examine the modified dataset by performing a multiclass 16 class classification and comparing the results of the multiclass classification to the subject-oriented classification based on the standard AAMII.

Furthermore, one-dimensional convolutional neural network model (1D-CNN) with deep residuals as a feature was used to create a model in this dataset classification test experiment. The rest of the paper is organized as follows. In section 2, previous research done on the multiclass and subject-oriented classification of arrhythmia is presented. In section 3, our method is presented. In sections 4 and 5 we present our results and then the conclusion.

2. LITERATUR REVIEW

The most popular databases used in arrhythmia classification are the MIT-BIH arrhythmia database (MITDB) [13], MIT-BIH supraventricular arrhythmia database (SVDB) [14], UCI arrhythmia dataset [15], St-Petersburg Institute of Cardiological technics 12-lead arrhythmia database (INCARTDB) [16], and Physikalisch Technische Bundesanstalt (PTB) ECG database [17]. Some researchers even compare the classification model in several databases to produce a model that can perform a good arrhythmia classification [18], [19]. In the existing literature [9], researchers have conducted studies to classify arrhythmias into five categories. This category is based on the association for the AAMI [20]. Separately from this category, several researchers also classified arrhythmia based on segmentation or heartbeat categories extracted from all or part of the MIT-BIH arrhythmia database [21]. This category is often called "multiclass classification"; this "multiclass-classification" evaluation has been widely adopted by [9], [22]. One of the challenges in doing this multiclass classification is imbalanced data. For example, of the 109,494 total beat annotations in the MIT-BIH dataset, 75,052 (68.5%) are regular beats, and the remaining 34,442 annotations are divided into 19 different classes. In classifying the 16 classes of arrhythmia beats, there are three classes with samples below 100. Moreover, there are even two classes that only have a minimal number of samples, such as the atrial escape beat (e) class with 16 samples and the Q class (unclassifiable beat) with a sample of 33. This minority sample makes the classification process with unbalanced data training produce many errors. To solve this imbalanced data problem, many researchers use the SMOTE technique [9], [23] by adding synthetic sampling, such as research conducted by Luo *et al*. [9]. This researcher uses the HCRNet model with the MIT-BIH dataset in the classification 9 type beat arrhythmia resulting in an accuracy of 99.01% and a sensitivity of 99.58%. In this study, the SMOTE technique was used to overcome imbalanced data. In this study, researchers used classes N, A, E, F, j, L, Q, R, and V, where classes E, F, j, and Q were minority classes with very few samples, as shown in Table 1. Researchers used the SMOTE technique with 10-fold cross-validation using the HCRNet model to conduct training. Furthermore, as a comparison, this researcher also classified five classes, N, SVEB, VEB, F, and Q, with an accuracy of 98.7%. The summary of the literature review can be seen in Table 1.

In the classification of multiclass arrhythmia with a large number of classes, Shi *et al*. [24] classified 15 classes. This researcher uses the approach of combining deep learning models, namely CNN and LSTM, using multiple input layers. The dataset used is MIT-BIH by classifying classes N, L, R, A, V, P, a, !, F, j, f, E, J, e, and Q. In class-oriented or multiclass, the accuracy is 99.26.% and accuracy for subject-oriented five classes is 94.20% by classifying according to standard AAMII, namely N, S, V, F, and unclassified beats (Q).

The study of multiclass arrhythmia with 16 classes can be seen in the study of Raj and Ray [25]. This researcher classified the classes N, L, R, A, V, P, a, !, F, x, j, f, E, J, e, and Q. This researcher used a sparse decomposition technique with PSO optimized least-square twin SVM. The multiclass accuracy results were 99.11% and 89.93% for AAMII-based subject-oriented accuracy.

Table 1. Literature review

Author	Year	Approach	Problem identified	Advantage
Luo *et al*. [9]	2021	HCRNet: 9 classes	Minority classes with very few samples resulting in unbalanced data.	SMOTE technique with 10-fold cross validation can increase the accuracy value.
Shi *et al*. [24]	2020	CNN-LSTM: 15 classes	Misclassified class in subject-oriented scheme.	Improved network structure. This model can be used for multiple inputs. RNN and LSTM can be used for extracting features and sequential features.
Raj and Ray [25]	2018	LSTSVM-PSO: 16 classes	Less number of training sample in subject-oriented scheme.	New feature extraction method using the sparse technique to efficient analysis ECG signals. The optimization techniques can evaluate two analysis schemes of classification.

3. METHOD

The method used in this research consists of 7 phases: selection and merging of records for datasets, preprocessing, heartbeat segmentation, and feature classification. The overview of the proposed classification method is shown in Figure 1. The first phase is entering several records from the additional dataset into the main dataset. The main dataset is the MIT-BIH arrhythmia database (MITDB), and an additional one is the MIT-BIH SVDB. The MIT-BIH arrhythmia database obtained 110,159 annotations from 48 records, then added 14 records from the MIT-BIH Supraventricular (record number 801, 849, 851, 852, 854, 855, 860, 865, 868, 870, 878, 879, 887, and 892) the total number of annotations became 146,257. The next step is examing sample heart rate data, a sample illustration of signal and R peaks can see in Figure 2.

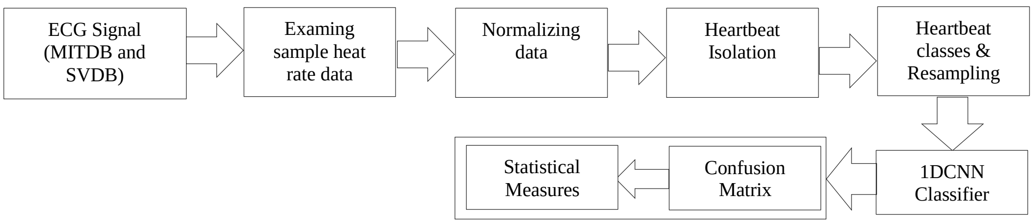

Figure 1. Flowchart of the proposed classification method

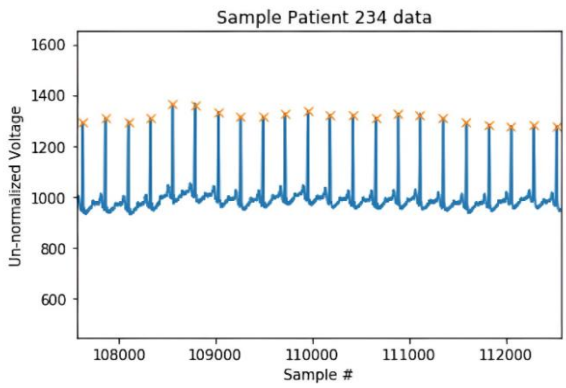

Figure 2. Raw ECG data for patient 234 with unnormalized voltage recording

The next phase is preprocessing, which starts by normalizing from 0 to 1 using (1):

$$zi = \frac{xi - \min(x)}{\max(x) - \min(x)} \quad (1)$$

Where z is the normalized value, and x is the sample data. This normalization makes every data have the same or close scale. After normalizing, the next step is to do a cutoff frequency from 20 Hz to 60 Hz by implementing a moving average and a butterworth low pass signal filter. Figure 3 illustrates the normalization process from the original signal to norm 3.

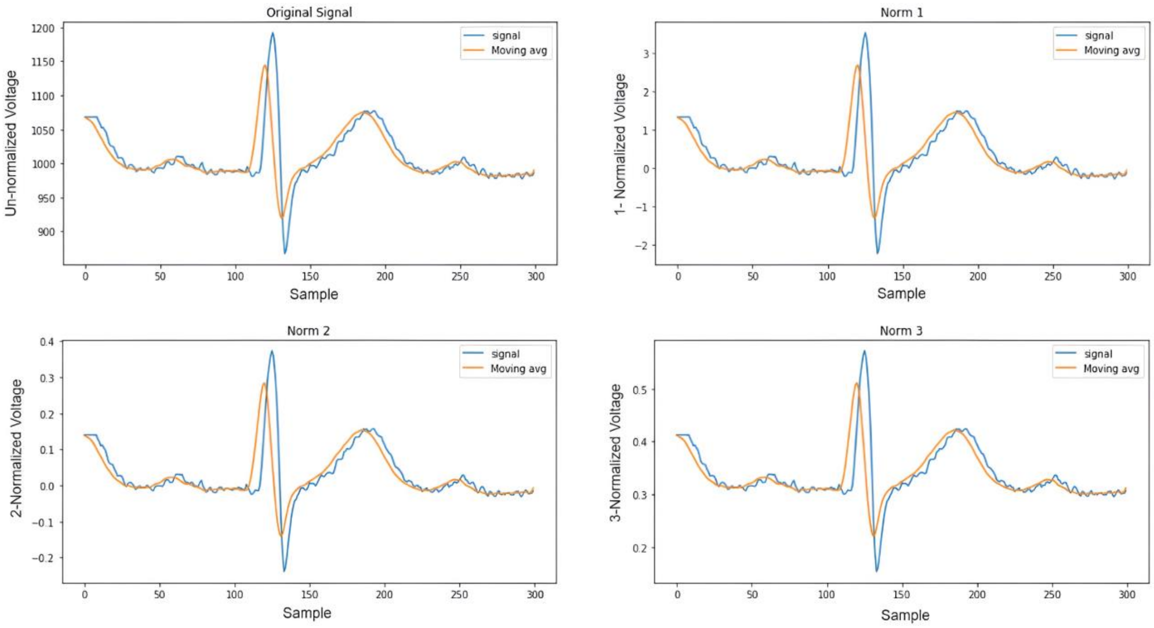

Figure 3. Normalization process (norm: 3 selected)

The following process is to perform isolation based on finding the peak point on the R wave using a christov-segmenter. The MITDB and SVDB databases already have labels marking all signal peaks, and this segmentation is used in applications to compute the average heartbeat of a patient. The next step is identifying and determining the classes that will be carried out in the multiclass-oriented classification process. Class selection for classification refers to the research conducted by Ye *et al*. [21] with classes, as shown in Table 2.

Table 2. Hearth beat classification arrhythmia for 16 classes

Number	Label/Class	Description
1	N	Normal beat
2	L	Left bundle branch block beat
3	R	Right bundle branch block beat
4	A	Atrial premature beat
5	V	Premature ventricular contraction
6	/	Paced beat
7	a	Aberrated atrial premature beat
8	!	Ventricular flutter wave
9	F	Fusion of ventricular and normal beat
10	x	Non-conducted P-wave (block APB)
11	j	Nodal (junctional) escape beat
12	f	Fusion of paced and normal beat
13	E	Ventricular escape beat
14	J	Nodal (junctional) premature beat
15	e	Atrial escape beat
16	Q	Unclassifiable beat

In subject-class-oriented or subject-oriented class categories, class groups are made based on AAMII. Class classification is based on class grouping based on standard AAMII as follows: i) class N: consists of classes N, L, R, e, and j; ii) class S: consists of classes S, A, a, and J; iii) class V: consists of classes V and E; iv) class F: consists of class F; and v) class Q: consists of classes Q, /, and f. After the heartbeats are isolated and labeled, the data is zero padded in the maximum heartbeat sample length range and then the signal is re-sampled from 360 Hz to 125 Hz. This is done to reduce the amount of data and maintain signal integrity.

The final step is featuring classification. In this case, classification is done with a 1-dimensional deep convolutional network model. In the process of experimenting, the data will use a batch size ranging from 32 to 512. It is important to note that the training batch size will contain the same data per class. This is done using the weight-based sampling method, where the class weight is the same as the inverse of the calculation, for the validation and test sets that are evaluated with the actual distribution.

The choice of 1D CNN is because this algorithm is very effective in identifying features from the smallest segment of all datasets and determining the location of features from irrelevant segments [24]. This model is built with blocks containing two convolution Kernels 32×5×1 and a final max pooling layer Kernel with sizes 5 and 2 strides. The convoluted output layer contains a fully connected dense layer with an activation function, ReLU, for the initial dense. For dense final use, the SoftMax activation function has 16 output classes for multiclass classification and 5 for subject-oriented classification. Furthermore, between the dense, there are dropouts to reduce overfitting. This model can be seen in Figure 4. In this model, the loss criteria are negative log loss in the Pytorch framework and use the average stochastic gradient descent (ASGD) optimizer with lambda values=0.0001 and alpha=0.75. The ideal learning rate for this classification is 0.01.

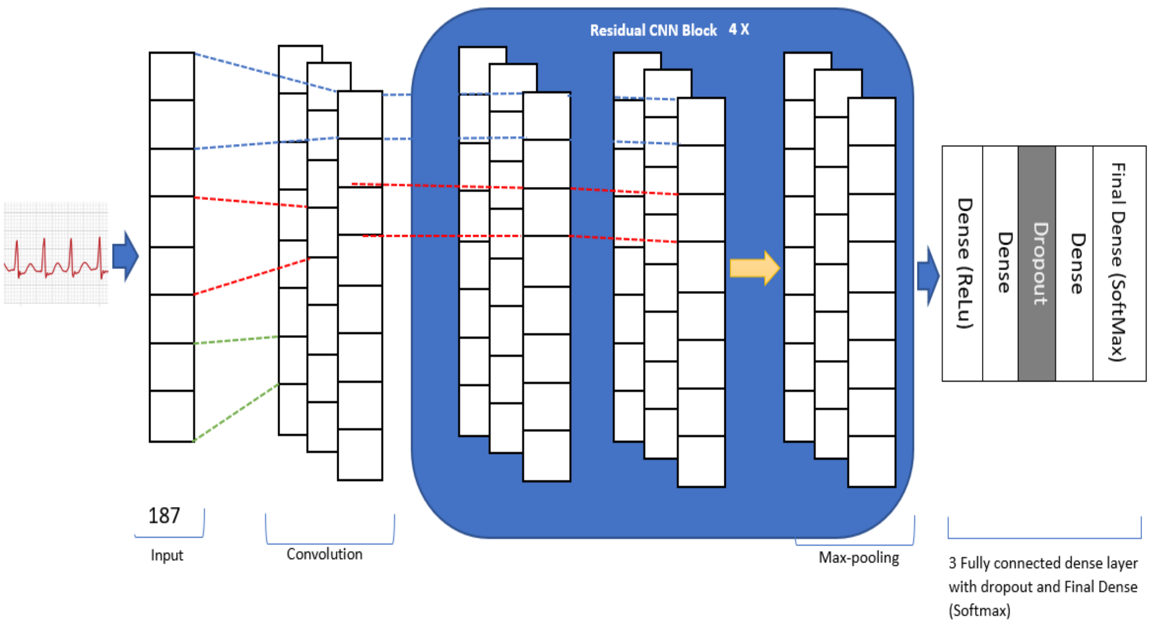

Figure 4. Architecture 1D CNN model

4. RESULTS AND DISCUSSION

The results of the preprocessing signal obtained that the average heart rate was 83.71 bpm for 62 patients (combined results of 48 MITDB patients and 14 SVDB patients). The average heart rate length is 278.35 samples (0.77 s per beat). In the classification process, the best results from the data composition are divided into 70:10:20, namely 70% training set, 10% validation set, and 20% for the testing set. The batch size 32 produces train size batched=2,955, validation size batched=328 and test size batched=803. Batch size 32 is selected from the best testing results with the ASGD optimizer. The ASGD optimizer was chosen due to the best classification results between SGD and root mean square propagation (RMSprop) being tested, which can be seen in Table 3. To maintain the consistency of accuracy with the amount of data and implement various batch sizes, we used a fixed number of the epoch at as much as 200 epochs, with model testing as much as 200 epochs, five times. Table 3 shows the best results from the experiments carried out.

Table 3. Evaluation results of multi and subject class scheme

Class	Precision	Recall	F1-score
Multiclass scheme			
N	0.99	0.99	0.99
L	0.99	0.99	0.99
R	1	0.99	0.99
A	0.91	0.94	0.92
V	0.98	0.98	0.98
/	1	1	1
A	0.82	0.93	0.79
!	0.87	1	0.93
F	0.91	0.9	0.91
x	0.94	0.94	0.94
J	0.8	0.8	0.8
f	0.97	0.99	0.98
E	1	1	0.96
J	0.84	1	0.94
e	1	1	1
Q	0.64	0.83	0.67
Subject-class scheme			
N	1	1	1
S	0.90	0.94	0.92
V	0.99	0.98	0.98
F	0.91	0.92	0.91
Q	1	1	1

In multiclass classification, classes J and Q have low precision values, but all classes have good values for sensitivity. This low precision score is due to the lack of training and testing data samples. In contrast to multiclass, the evaluation score is above 93% in the subject class. This result proves that the classification in the subject class is better, subject class roc table and confusion matrix shown in Figure 5. The figure shows how the training loss and validation loss are close to 0. Furthermore, in the confusion-matrix that there is still misclassification in class F. The summary results of subject class scheme and multi class scheme classification with 3 optimizers can be seen in Table 4. Here it can be seen that the ASGD optimizer can provide better accuracy.

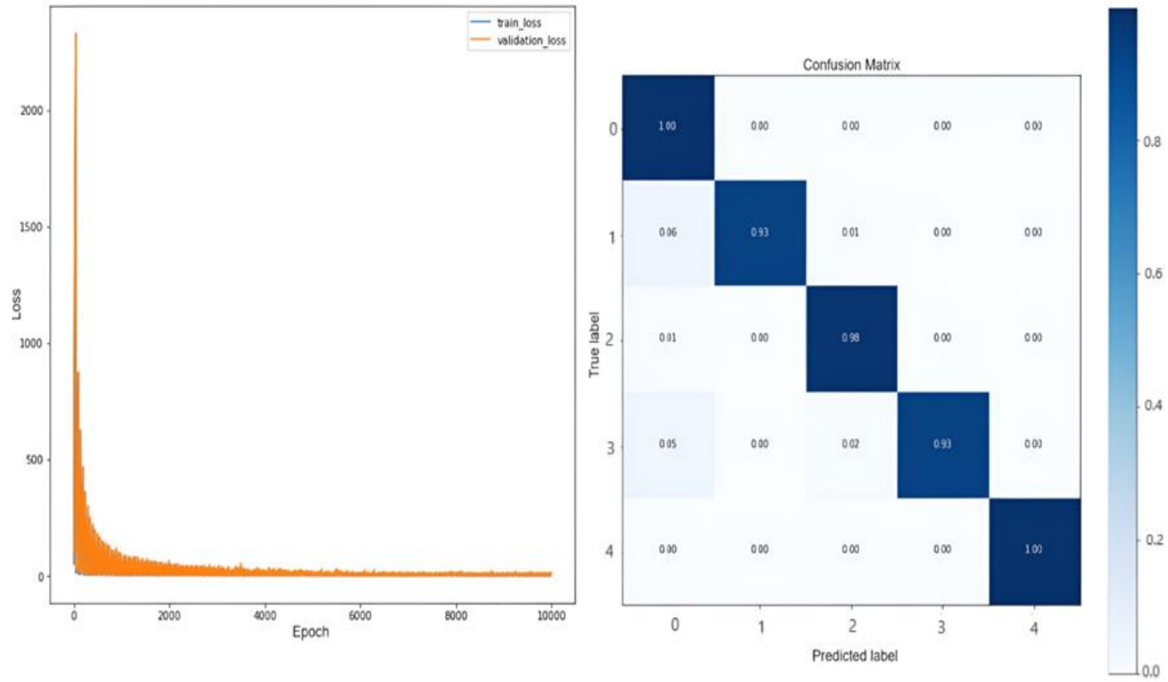

Figure 5. Subject class ROC and confusion matrix

Table 4. The classification results from 3 optimizers

Optimizer	Batch size	Classes	Accuracy
ASGD	32	16	0.9910
SGD	32	16	0.9888
RMSprop	512	16	0.9803
ASGD	32	5	0.9925
SGD	32	5	0.9916
RMSprop	320	5	0.9903

The results of the classification of this model compared with previous researchers can be seen in Table 5. Table 5 shows that the results of the multiclass accuracy of the model made are close to the results of Raj's research [25] with the number of classes 16. However, for a smaller number of classes, this model already beat the accuracy value of Luo *et al*. [9] with the number of classes only nine, but the accuracy value is only 99.01. With an excellent multiclass accuracy value, this model is superior when classifying subject classes (5 classes), as shown in Table 5.

Table 5. Comparison classification with other methods

Literature	Classifier	Classes	Acc (%)	Ppv	Recall	F1 score
Luo *et al*. [9]	HCRNet	9	99.01	99.44	99.58	99.51
Raj and Ray [25]	LSTSVM-PSO	16	99.11	85.88	91.47	88.15
Shi *et al*. [24]	CNN-LSTM	15	99.26	84.97	87.77	-
Proposed	**1DCNN**	**16**	**99.10**	**91.62**	**95.50**	**92.43**
Luo *et al*. [9]	HCRNet	5	98.7	99.53	99.28	99.38
Raj and Ray [25]	LSTSVM-PSO	5	89.93	49.29	72.35	52.50
Shi *et al*. [24]	CNN-LSTM	5	98.4	77.08	92.97	-
Proposed	**1DCNN**	**5**	**99.25**	**97.20**	**96.80**	**97.00**

In Table 5, the model created can provide outstanding accuracy values for subject-class classification compared to previous research results with an average accuracy above 99%, which is 99.25%. This result shows that this model can perform classification with sufficient accuracy for multiclass and subject classes. This paper uses a different technique in dealing with imbalanced data in the minority class in classifying arrhythmias compared to previous studies. The study modified the MIT-BIH arrhythmia (MITDB) dataset by adding 14 records from the SVDB dataset. This dataset has 62 patient records with a total of 146,257 annotations. The modification can increase minority classes. Such as supraventricular premature/entropic beat (S) and unclassifiable beat (Q) classes. This is done to improve classification accuracy and make the gap between multiclass or class-oriented and subject-oriented classifications that are not too far apart. This is based on the results of previous studies such as the research of Shi *et al*. [24] and Raj and Ray [25], who did classification 15 and 16 classes; the difference in accuracy between multiclass and subject-oriented looks quite far. The results of Raj and Ray's accuracy for 16 classes are 99.11% and 89.93 for subject-oriented with an accuracy gap of 9.18%, and Shi's accuracy results for classification 15 classes are 99.29% for multiclass and 94.20% for subject-oriented with a gap of 5.09%. From previous studies, both Luo [9], Shi *et al*. [24], and Raj and Ray [25] have a higher multiclass accuracy ratio compared to subject-class accuracy. It differs from the research in this paper, which produces a better subject-class accuracy value than the multiclass classification.

According to Shi *et al*. [24], although the accuracy value in the classification of 15 classes (multiclass) got excellent results, namely 99.26%, in the subject class, it got a relatively low accuracy of 98.4%. The problem is that there is still a class N misclassification as S. In addition, the number of F classes is too limited. Raj and Ray [25], the value of sensitivity and F1 score for class Q in the subject class is still a shallow point. This is what causes the poor subject-class accuracy scores. In contrast, in this study, the accuracy of the subject class is higher than that of multiclass. This research shows that multiclass classification can support classification in the subject class.

5. CONCLUSION

The arrhythmia classification process has been carried out by many researchers using the help of AI. The problem of imbalanced data is the main problem for researchers. This paper presents an alternative solution by adding several records from the existing dataset to the dataset that will be used as a training and testing dataset. In this study, the authors added 14 SVDB database records into MITDB. The classification process uses 1DCNN, which can provide high accuracy in this classification. The experiment was performed by classifying beat arrhythmia in multiclass and subject-class (AAMII). This research was conducted to demonstrate that multiclass accuracy can enhance subject-class accuracy. The result of multiclass accuracy is 99.10% and subject-class accuracy is 99.25. In contrast to previous studies, which resulted in multiclass accuracy higher than subject-class accuracy, this study provides better accuracy in subject-class. Therefore, this model can be used as an alternative to solve the problem of imbalanced data in arrhythmia classification.

ACKNOWLEDGEMENTS

We would like to express my very great appreciation to Universitas Bina Insan and *Lembaga Penelitian dan Pengabdian kepada Masyarakat Bina Insan* (LPPM) for support during the development of this research work.

REFERENCES

[1] G. Sannino and G. De Pietro, "A deep learning approach for ECG-based heartbeat classification for arrhythmia detection," *Future Gener. Comput. Syst.*, vol. 86, pp. 446–455, Sep. 2018, doi: 10.1016/j.future.2018.03.057.

[2] M. Sraitih, Y. Jabrane, and A. H. El Hassani, "An Automated System for ECG Arrhythmia Detection Using Machine Learning Techniques," *J. Clin. Med.*, vol. 10, no. 22, p. 5450, Nov. 2021, doi: 10.3390/jcm10225450.

[3] S. Parvaneh, J. Rubin, S. Babaeizadeh, and M. Xu-Wilson, "Cardiac arrhythmia detection using deep learning: A review," *J. Electrocardiol.*, vol. 57, pp. S70–S74, Nov. 2019, doi: 10.1016/j.jelectrocard.2019.08.004.

[4] K. Rakesh and R. Singh, "A Review on ECG System Design," *Int. J. Res.*, vol. 1, no. 9, 2014.

[5] V. Bhagyalakshmi, R. V. Pujeri, and G. D. Devanagavi, "GB-SVNN: Genetic BAT assisted support vector neural network for arrhythmia classification using ECG signals," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 33, no. 1, pp. 54–67, Jan. 2021, doi: 10.1016/j.jksuci.2018.02.005.

[6] C. K. Jha and M. H. Kolekar, "Cardiac arrhythmia classification using tunable Q-wavelet transform based features and support vector machine classifier," *Biomed. Signal Process. Control*, vol. 59, p. 101875, May 2020, doi: 10.1016/j.bspc.2020.101875.

[7] A. Y. Hannun *et al.*, "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network," *Nat. Med.*, vol. 25, no. 1, pp. 65–69, Jan. 2019, doi: 10.1038/s41591-018-0268-3.

[8] G. Wang *et al.*, "A global and updatable ECG beat classification system based on recurrent neural networks and active learning," *Inf. Sci.*, vol. 501, pp. 523–542, Oct. 2019, doi: 10.1016/j.ins.2018.06.062.

[9] X. Luo, L. Yang, H. Cai, R. Tang, Y. Chen, and W. Li, "Multi-classification of arrhythmias using a HCRNet on imbalanced ECG datasets," *Comput. Methods Programs Biomed.*, vol. 208, p. 106258, Sep. 2021, doi: 10.1016/j.cmpb.2021.106258.

[10] Z. Ebrahimi, M. Loni, M. Daneshtalab, and A. Gharehbaghi, "A review on deep learning methods for ECG arrhythmia classification," *Expert Syst. Appl. X*, vol. 7, p. 100033, Sep. 2020, doi: 10.1016/j.eswax.2020.100033.

[11] D. Zhang, Y. Chen, Y. Chen, S. Ye, W. Cai, and M. Chen, "An ECG Heartbeat Classification Method Based on Deep Convolutional Neural Network," *J. Healthc. Eng.*, vol. 2021, pp. 1–9, Sep. 2021, doi: 10.1155/2021/7167891.

[12] J. Jiang, H. Zhang, D. Pi, and C. Dai, "A novel multi-module neural network system for imbalanced heartbeats classification," *Expert Syst. Appl. X*, vol. 1, p. 100003, Apr. 2019, doi: 10.1016/j.eswax.2019.100003.

[13] G. B. Moody and R. G. Mark, "MIT-BIH Arrhythmia Database," *Hardvard-MIT Div. Health Sci. Technol.*, 1992, doi: 10.13026/C2F305.

[14] S. D. Greenwald, "The MIT-BIH Supraventricular Arrhythmia Database," *physionet*, 1992, doi: 10.13026/C2V30W.

[15] "UCI Machine Learning Repository: Arrhythmia Data Set," Arrhythmia. Accessed: Mar. 02, 2020. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Arrhythmia

[16] "St.-Petersburg Institute of Cardiological Technics 12-lead Arrhythmia Database," physionet. Accessed: Nov. 27, 2018. [Online]. Available: https://archive.physionet.org/physiobank/database/incartdb/

[17] R.-D. Bousseljot, D. Kreiseler, and A. Schnabel, "The PTB Diagnostic ECG Database," *physionet.org*, 2004, doi: 10.13026/C28C71.

[18] E. Merdjanovska and A. Rashkovska, "Cross-Database Generalization of Deep Learning Models for Arrhythmia Classification," in *2021 44th International Convention on Information, Communication and Electronic Technology (MIPRO)*, IEEE, Sep. 2021, pp. 346–351, doi: 10.23919/MIPRO52101.2021.9596930.

[19] M. M. Al Rahhal, Y. Bazi, M. Al Zuair, E. Othman, and B. BenJdira, "Convolutional Neural Networks for Electrocardiogram Classification," *J. Med. Biol. Eng.*, vol. 38, no. 6, pp. 1014–1025, Dec. 2018, doi: 10.1007/s40846-018-0389-7.

[20] J. R. Annam, S. Kalyanapu, S. Ch., J. Somala, and S. B. Raju, "Classification of ECG Heartbeat Arrhythmia: A Review," *Procedia Comput. Sci.*, vol. 171, pp. 679–688, 2020, doi: 10.1016/j.procs.2020.04.074.

[21] C. Ye, B. V. K. V. Kumar, and M. T. Coimbra, "Heartbeat Classification Using Morphological and Dynamic Features of ECG Signals," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 10, pp. 2930–2941, Oct. 2012, doi: 10.1109/TBME.2012.2213253.

[22] A. Mustaqeem, S. M. Anwar, and M. Majid, "Multiclass Classification of Cardiac Arrhythmia Using Improved Feature Selection and SVM Invariants," *Comput. Math. Methods Med.*, vol. 2018, pp. 1–10, 2018, doi: 10.1155/2018/7310496.

[23] M. D. Mazhar Qureshi *et al.*, "Multiclass Heartbeat Classification using ECG Signals and Convolutional Neural Networks," in *2022 2nd International Conference on Digital Futures and Transformative Technologies (ICoDT2)*, IEEE, May 2022, pp. 1–6, doi: 10.1109/ICoDT255437.2022.9787419.

[24] H. Shi, C. Qin, D. Xiao, L. Zhao, and C. Liu, "Automated heartbeat classification based on deep neural network with multiple input layers," *Knowl.-Based Syst.*, vol. 188, p. 105036, Jan. 2020, doi: 10.1016/j.knosys.2019.105036.

[25] S. Raj and K. C. Ray, "Sparse representation of ECG signals for automated recognition of cardiac arrhythmias," *Expert Syst. Appl.*, vol. 105, pp. 49–64, Sep. 2018, doi: 10.1016/j.eswa.2018.03.038.

BIOGRAPHIES OF AUTHORS

Muhamad Akbar received Engineering Degree in Informatics Engineering from the Indonesian College of Science and Technology in 1995. Received master's degree in Internet Studies from the Faculty of Humanity CURTIN University, Australia in 2005. Currently a researcher at the AI Laboratory of the Faculty of Engineering and Senior lecturer at Bina Insan University, South Sumatra, Palembang, Indonesia. His research interests include deep learning, machine learning, image processing, and human computer interaction. He can be contacted at email: muhamad.akbar@univbinainsan.ac.id.

Siti Nurmaini received the master's degree in Control System from the Institut Teknologi Bandung (ITB), Indonesia, in 1998, and the Ph.D. degree in Computer Science from the Universiti Teknologi Malaysia (UTM), in 2011. She is currently a Professor with the Faculty of Computer Science, Universitas Sriwijaya, Indonesia. Her research interests include biomedical engineering, deep learning, machine learning, image processing, control systems, and robotic. She can be contacted at email: siti_nurmaini@unsri.ac.id.

Radiyati Umi Partan is a rheumatologist, staff at the Department of Internal Medicine, Faculty of Medicine, Sriwijaya University in Palembang, South Sumatra Indonesia. Member of the Indonesian Rheumatology Association and the Indonesian Osteoporosis Association. Graduated from the Faculty of Medicine, Sriwijaya University in 1997. She completed specialist in Internal Medicine in 2008. Received master's degree in Pharmacology, a post-graduate program at Sriwijaya University in 2010. Obtained a Doctoral degree and subspecialty in Rheumatology at Brawijaya University and completed it in 2016. Currently, she is in clinical practice and conducting several researches, particularly in rheumatology. Her research interests include osteoporosis, osteoarthritis, and systemic lupus erythematosus. She can be contacted at email: radiyati.u.p@fk.unsri.ac.id.