Rubiya et al. LGURJCSIT 2025

ISSN: 2521-0122 (Online)
ISSN: 2519-7991

LGU Research Journal of Computer Science & IT

doi: 10.54692/lgurjcsit.2025.092721
Vol (9): Issue (2), July – December 2025

Towards Clinically-Assisted Atrial Fibrillation Detection: A Multi-Class Classification Approach with Deep Learning and Enhanced Data Preprocessing using ECG Signals

Rubiya Shoukat, Saima Farhan*, Zarbakht Sadia, Ayesha Iqbal, Fatima Anjum

Department of Computer Science, Lahore College for Women University, Lahore, Pakistan

*Email: saima.farhan@lcwu.edu.pk

ABSTRACT

Atrial Fibrillation (AFiB) is the most prevalent kind of cardiac rhythm problem, and it is closely correlated with other heart-related disorders, including a high mortality rate and an increased risk of strokes. The early diagnosis and treatment of AFiB are of critical importance from a clinical standpoint. Automatic identification of AFiB based on electrocardiogram data assists in accurate and timely detection of the condition, which is a difficult undertaking. In recent years, with the growth of artificial intelligence, Deep Learning models have gained initial success in ECG data processing, particularly in the identification of AFiB. In the proposed approach, the objective is to devise a Deep Learning approach, based on CNN, with data augmentation technique to deal with imbalance data, as well as the Savitzky-Golay filter used for noise removal, in order to accurately predict AFiB from ECG signals. By using this approach, the ECG signals are classified into three classes, AFiB, Normal, and Other with an average accuracy of 97.87%. In addition, the performance of the suggested model has also been evaluated using several evaluation matrices to determine how well the model performed. The study has the potential to assist clinicians in the detection of common AFiB in real time on routine electrocardiogram monitoring.

KEYWORDS: AFiB, Arrythmia, Classification, CNN, Deep Learning, ECG

1. INTRODUCTION

Atrial Fibrillation (AFiB) is one of the most widespread type of arrhythmia, or cardiac rhythm problem that occurs when the heart beats abnormally, such as too slowly, too quickly, and irregularly irregular [1]. It has a significant factor in annual deaths of 17.8 million people who died of cardiovascular disease [2].

AFiB is a disorder that worsens over time. As a consequence of this, patients with paroxysmal AFiB have an increased risk of progressing to persistent or permanent AFiB [3] [4], making it essential to diagnose AFiB as soon as possible. Conventionally, 12 lead ECG is a significant instrument for diagnosing the AFiB in the clinical method that mainly relies on professional doctors with higher expertise and accurate devices. This detection of AFiB requires a long period of ECG monitoring that may last many hours or even days to analyze which is a time-consuming task. To overcome this limitation, different techniques are suggested to detect AFiB automatically. In the last decades, different machine learning techniques such as Support Vector Machine (SVM), the Principle Component Analysis (PCA), and Random Forest (RF), are used to classify arrhythmias but these techniques had some computational limitations in the learning process.

Recently, researchers began to use deep learning approaches to identify AFiB automatically with ECG signals which may reduce the time and improve the accuracy. The goal of deep learning approaches is to learn internal data representations. The major challenges faced in the detection of AFiB through ECG signals is the presence of noise in ECG signal and imbalance datasets. Most of the deep learning models are complex and requires significant amount of computational resources.

In this work, we propose a deep learning based Convolutional Neural Network (CNN) model to diagnose AFiB on a noisy and imbalanced dataset. Data augmentation techniques are applied on the dataset for balancing it. Subsequently, noise is eliminated from the dataset using noise removal technique. The balanced and cleaned data is then fed to the CNN model. The model gets trained on the data and generates predictions about AFiB on unseen data. The efficacy of the proposed model has been evaluated using a number of different metrics, including Accuracy, Recall, F1-score, Precision, and Confusion matrix, as well as AUC-ROC. This proposed technique bridges clinical insights with advanced computational modeling, ensuring that the deep learning framework aligns closely with real-world diagnostic needs for more accurate and interpretable atrial fibrillation detection.

The primary contributions of the research are given below:

- We have developed a simple and efficient CNN based deep learning approach for classifying ECG signal into three categories: AFiB, Normal and other, on a publicly available dataset.
- The proposed approach addresses the challenges of imbalanced data and noise in the ECG signals by utilizing data augmentation and noise removal techniques.
- The proposed method exhibited higher performance by achieving an accuracy of 97.87% in classifying ECG signals into three categories. Moreover, we have used multiple evaluation metrics to thoroughly understand its capabilities.
- It provides a major contribution in proactive AFiB treatment by accurate and efficient detection of AFiB.

2. LITERATURE REVIEW

Various methods like manual feature extraction, wavelets, and machine learning identify AFiB. Handcrafted features like heart rate, waves, and frequency have been the focus of ECG study for AFiB identification; these characteristics require expert interpretation [5][6]. AFiB can be identified through rhythm analysis using a Poincare plot of RR interval, with or without atrial activity analysis. This method produces better results on a variety of datasets [7].

Manual feature extraction for AFiB is noisy, inefficient, and has limited generalizability due to information loss. To improve manual feature extraction, independent component analysis [8], discrete wavelet transform [9], and entropy, have been applied. Zhang et al. employ recursive complicated networks for detection [10]. Researchers extensively analyze ECG signals to identify arrhythmias, including AFiB.

Machine learning techniques have recently been established for the identification of arrhythmias. An ensemble of Echo State Networks (ESNs) [11] processes heartbeat intervals and raw ECG waveforms as input with a single ECG lead and simple features processing. Yin et al. suggested a multi-domain ECG feature extraction [12] In this approach, six different wavelet coefficients' sample entropy values are utilized as nonlinear characteristics. The SVM classifier is used to make an automated diagnosis of arrhythmia based on these three features.

Dash et al. [13] employed statistical approach to assess the RR interval's complexity, unpredictability, and variability using MIT-BIH AFiB dataset. Zabihi et al. [14] selected features

by employing an RF classifier. AFiB is identified using both the manually extracted and the neural networks extracted features [15]. The collected features are incorporated into the integration model, which also contains the submodels RF, Decision Tree, XGBoost, LightGBM, and GBDT. In the last decades, various machine learning algorithms including, K-nearest neighbors (KNN) [16], Principal Component Analysis (PCA) [17], Support Vector Machines (SVM) [18], and adaptive backpropagation neural network among others [19] have been proposed for automated classification of cardiac arrhythmias based on ECG signal. Research used feature fusion where traditional features and deep learning features are fused to improve efficiency [20]. Another approach used segment-based CNN [21] where SVM and CNN are utilized to classify ECG signals into AFiB, Normal, Other, and Noise on statistical features. Another DNNs technique is employed to identify 12-lead ECGs from hospitals and ECG wearable devices, and categorized them into AFiB, Non-ABIB and Others [22].

An Automatic AFiB detection approach has been made using Hybrid Network addresses imbalance MIT-BIH- AFiB data [23]. CNN extracts features and is classified by LSTM into AFiB, AV Junction Rhythm (J), Atrial Flutter (AFL), and Normal (N). Multi-feature extraction evaluates AFiB [24] using recursive complex networks with CNN and coherent operations with CNN and classify signals into Normal and AFiB.

Utilising a dual channel network model to extract hight-dimensional features and then a multi-branched network achieves generalization through training with a small amount of labelled data, and a large amount of unlabled data using a feature queue technique with global centroid [25].

Explainable Artificial Intelligence (XAI) is used to detect AFiB evaluating irregular rhythms [26]. Another approach enhance detection by calculating the gradient Set (GDS) of ECGs [27]. An effort has been made to compress the ECG signals using a Simple Deterministic Measurement Matrix (SDMM) and transpose projection operation to consume less energy [28]. A CNN is employed in order to identify AFiB based on these approximate signals, which has been verified accurate by the MIT-BIH AFiB Dataset [51][52][53][54][55].

MB-LSTM, a modified bidirectional long short-term memory is another efficient technique for detecting AFiB and Atrial Flutter. An Attention-Based Hybrid System uses ResNet and Bi-LSTM with an attention mechanism to improve performance, classifying signals into AFiB, Normal, Other, and Noise [29].

3. METHODOLOGY

The methodology includes several phases where each phase has its role in the process. The overall architecture of this research is comprised of the following stages: data collection, data preprocessing, data splitting, feature extraction, and application of a deep learning model. Each step is performed to get the corresponding output and all phases are interlinked. Figure 1. **Error! Reference source not found.** illustrates the suggested model's comprehensive architectural make-up in its entirety.

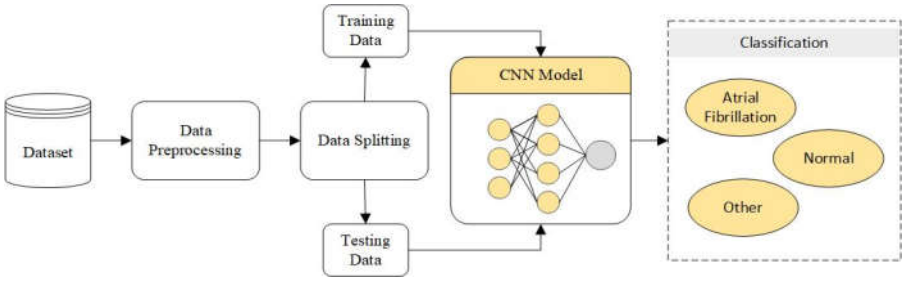


Figure 1. An overview of the proposed model

3.1. *Dataset*

The dataset for this research is an open-source dataset MIT-BIH Arrhythmia Database [30] which is also being widely used dataset in this current study. It consisted of the ECG records of 48 participants who are examined by the BIH Arrhythmia Laboratory between 1975 and 1979 on sample rate of 360 Hz, and the per-channel resolution is 10 mV. It includes heartbeat and rhythm annotations for a variety of arrhythmia conditions. This study focusses on three rhythms including Normal (N), Atrial Fibrillation (AFiB), and Other (O) labeled as 0, 1, and 2 respectively.

3.2. *Data Preprocessing*

In the proposed approach, the dataset used for AFiB detection is highly imbalanced and contains noise. To resolve these issues dataset undergoes following pre-processing steps to balance the dataset and eliminate noise.

3.2.1. Noise Removal (Savitzky Golay Filter)

Savitzky-Golay filter [31] is a method used to preprocess data to remove noise and improve classification models. It helps to remove artifacts like baseline wander from ECG signals and to perform data smoothing as a low pass filter. It requires a specific window size and polynomial order as input parameters. Figure 2. *a,* represents noisy signals, and *b* shows the filtered signals.

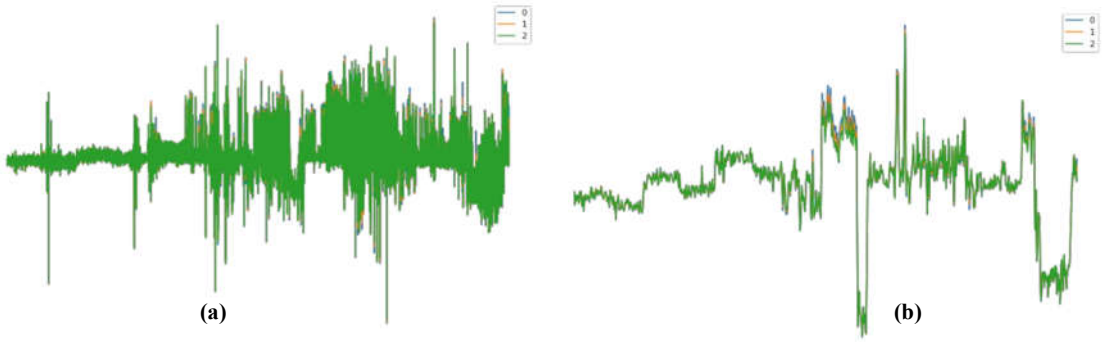


Figure 2. ECG signal (a) with noise and (b) after noise removal

3.2.2. Data Augmentation (SMOTe)

Imbalanced data during model training can lead to overfitting, hindering generalization. To counter this data augmentation is crucial. This study uses Synthetic Minority Over-Sampling Techniques (SMOTe) [32][33] to balance the data by oversampling for the minority class via interpolation. This ensures equal samples for AFiB, normal, and other rhythms, enhancing classification accuracy. **Error! Reference source not found.**

3.3. *Data Splitting*

For the purpose of training and validating the model, the dataset has been divided into a 80:20 ratio, with 80 percent of the data being employed for training and 20 percent of the data being utilized for validating the model.

3.4. *Proposed CNN Architecture*

The proposed study provides a multilayered CNN architecture for AFiB classification. It is a five-layered network followed by batch normalization and three more layers: the flatten layer, the dense layer with the Rectified Linear Units (ReLU) activation function, and the dense layer or the output layer with the softmax activation function for classification purpose.

Figure ***3***. depicts the structural design of the proposed model.

Figure ***3. Structure of proposed AFiB detection model***

Table 1 shows the detailed parameters of each layer.

3.4.1. Input Layer

The input layer in the proposed model is critical since it lays the groundwork for all following levels. A convolutional layer 1 extracts features from input signals using a ReLU activation function and 64 kernels before forwarding it to the next layer.

3.4.2. *Convolution Layers (Conv1D)*

In this work, 1D convolution kernel processes the 1D ECG data layer-by-layer, maintains similar diamentions of input and output layers by using ReLU and padding. Convolution layer output is obtained from offset and nonlinear activation function, represented by the equation (1).

$$\boldsymbol{h_i^{l,k} = f(b_i^{l.k} + \sum_{n=1}^{N} W_{n,i}^{l,k} * x_{i+n-1}^{l-1,k})} \quad (1)$$

Where $h_i^{l,k}$ is the ith neuron's output in layer l, f being activation function, and $b_i^{l.k}$ represents neuron offset in layer l. $x_{i+n-1}^{l-1,k}$ shows neuron's output in layer $l-1$, and $W_{n,i}^{l,k}$ represents the kth convolution kernel in the lth layer.

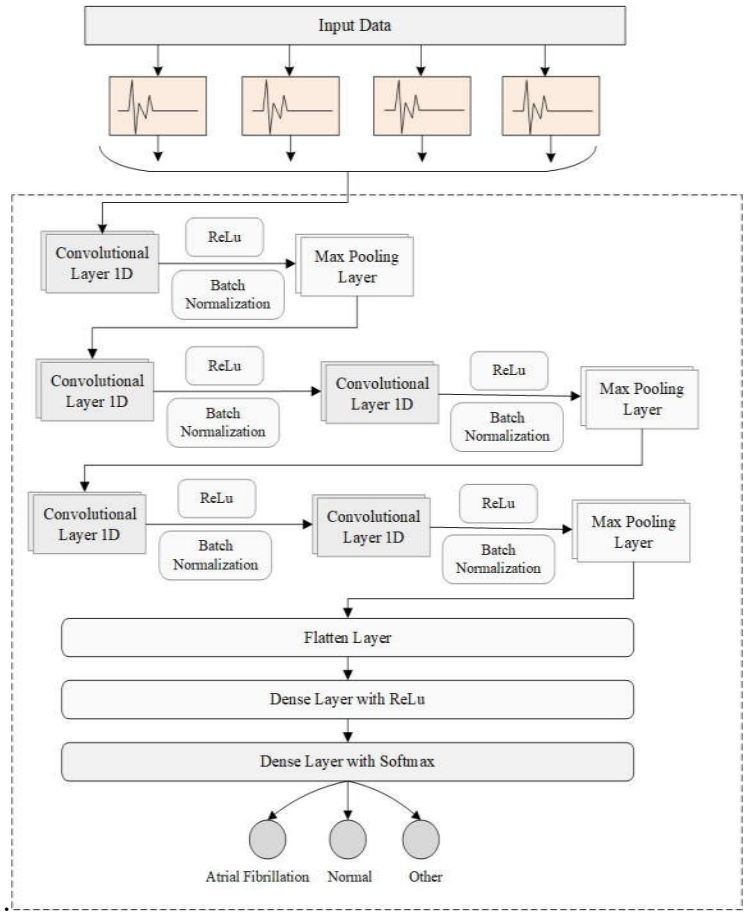


Figure 3. Structure of proposed AFiB detection model

Table 1. Parameters of each layer in the CNN model

Layers	Parameters	Activation

Conv1D	Filter 64 / kernel 6	ReLU
Maxpooling	Pool_size 3 / stride 2	
Conv1D	Filter 128 / kernel 3	ReLU
Conv1D	Filter 128 / kernel 3	ReLU
Maxpooling	Pool_size 2 / stride 2	
Conv1D	Filter 256 / kernel 3	ReLU
Conv1D	Filter 256 / kernel 3	ReLU
Maxpooling	Pool_size 2 / stride 2	
Dense	1024	ReLU
Dense (main_output)	3	Softmax

3.4.3. ReLU Activation function

Activation functions in convolutional layers target more complex features within the input signals [34] [35]. They are applied to learn the interlinear units, and hyperbolic tangent functions [36]. ReLU activation functions are a popular choice in deep learning applications [37]. The proposed method uses ReLU as it provides simplicity while enabling faster and more efficient model training. Mathematically, it is represented by equation (2).

$$y = \max(0, x) \tag{2}$$

It is applied to feature maps to enhance the non-linear properties of the training model and the entire network without affecting the respective fields of the convolutional layers.

3.4.4. Batch Normalization

The proposed approach has introduced batch normalization layers after every convolutional layer to enhance the training model's performance. This reduces training time and improves the model's ability to kearn from input signals.

3.4.5. Max-Pooling Layer

Max-pooling down-samples the most prominent features within a patch. The proposed model adds pooling layer after every two consecutive convolutional layers to gradually reduce the spatial size of the representation, thereby decresing computational demands, reducing parameters, and mitigating overfitting. This process can be mathematically expressed as equation (3).

$$o_i^{l,k} = f(\alpha_i^{l.k} pool(\, x_i^{l-1,k}) + \, b_i^{l,k}) \tag{3}$$

Where $b_i^{l,k}$ the activation function is represented by f, the weight and bias are represented by, α_i, b_i respectively, and $pool(\ x_i^{l-1,k})$ indicates the maximum-pooled input from the preceding layer.

3.4.6. Fully-connected layer (Flatten)

The fully-connected layer connects all features extracted from multiple convolutional and pooling layers. It flattens the output from previous layers before processing further. The fully-connected layer helps map the representation from the input to the output.

3.4.7. Dense Layer with ReLU Activation Function

The dense layer [38] is most commonly used layer in CNNs**.** The dense layer in the proposed study employs the ReLU activation function [39]. Each neuron in a dense layer is directly connected to every neuron in the preceding layer.

3.4.8. Softmax (Dense Layer)

In the last phase, SoftMax classifies using logistic regression [40]. CNN uses a simple softmax classifier to classify signals. The softmax Layer is a form of squashing function that limits output values to 0 and 1. It's a multi-class sigmoid that calculates probability for many classes.

3.4.9. Loss Function

Loss function being crucial component of a neural network quantifies the error between the model's predicted outputs and the desired outcomes. In this study, the categorical cross-entropy loss function [41] is employed. Suitable for multi-class classification models. It is applied to output labels encoded as one-hot vectors of zeros and ones. Equation (4) presents the loss function.

$$Loss = -\sum_{i=1}^{output\ size} y_i . log\hat{y}_i \quad (4)$$

where: y_i is the true label for the ith class and $\hat{y}_i$ is the predicted probability for the ith class.

3.5. *Development Platform*

To develop a system for automatic AFiB detection, Python is employed in conjunction with Anaconda [42] and Jupyter Notebook [43]. The system operated on a Windows 10 machine equipped with 8GB RAM, and a Core i7-7500U CPU. The following libraries are used:TensorFlow, Keras, Numpy, Matplotlib

4. Results and Discussion

The performance of the proposed method has been evaluated using several evaluation metrics such as accuracy, precision, recall, F1-score, confusion metric, and AUC-ROC.

4.1. *Experimental Setup*

Each trial uses 32 batch-size and 10 iterations per epoch, with updating the network's weight using a cross-entropy loss function and Adam optimizer. Moreover, ReLU and SoftMax activation functions are incorporated. Hyperparameters are detailed in Table 2.

Table 2. Hyperparameters for the CNN model

Hyperparameters	Values
Batch Size	32
Epochs	10
Loss	Categorical_CrossEntropy
Optimizer	Adam
Non-linearity function	ReLU SoftMax

4.2. *Experiments*

To assess the effectiveness of the proposed model in identifying cases of AFiB, two distinct experiments has been carried out. These experiments yielded an overall accuracy of 97.87% for the proposed model.

4.2.1. Experimental results of proposed model without noise removal

This experiment evaluated the proposed model's performance in the presence of noise. No noise removal strategy is applied during data preprocessing..The goal is to assess whether the model can make good prediction if noise is present? Interestingly, the model achieved an accuracy of 90.03% which is remarkable considering the noise. The results of this experiment are provided in Table 3. Moreover, accuracy, AUC-ROC graph, "precision vs recall curve", and confusion matrix are presented in Figure 4.

Table 3. Experimental results before noise removal

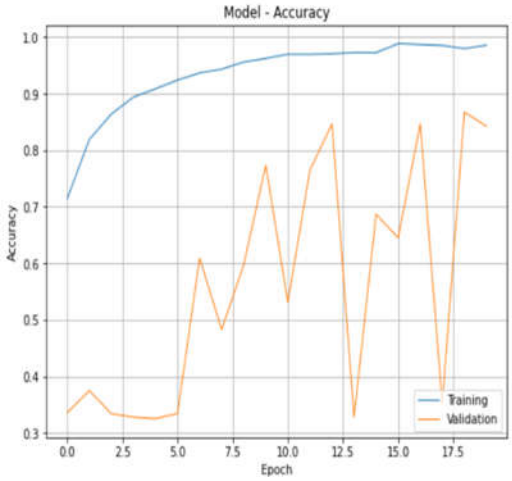
Accuracy	Class	Precision (%)	Recall (%)	F1-score (%)
90.93%	AFiB	92.00	94.00	93.00
	Normal	99.00	85.00	91.00
	Other	84.00	94.00	89.00
	Weighted Avg	92.00	91.00	91.00

4.2.2. Experimental results of proposed model with noise removal

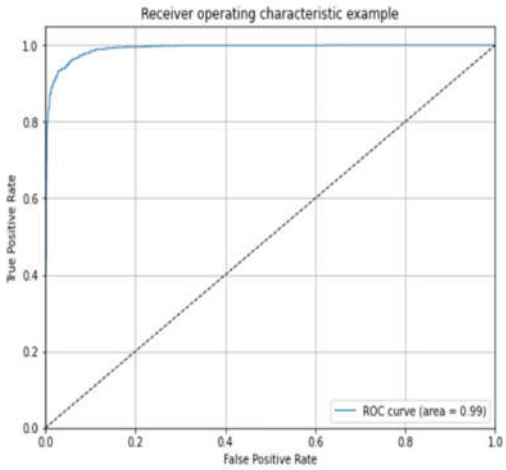
This experiment incorporated a noise removal technique, Savitzky-Golay filter, during preprocessing to assess its impact on performance. The findings indicate that the model performed exceptionally well, achieving a high accuracy of 97.87%. The experimental results are summarized in **Error! Reference source not found.**. Moreover, accuracy, AUC-ROC graph, "Precision vs Recall curve", and Confusion Matrix are presented in Figure 5.

Table 4. Experimental results after noise removal (Savitzky-Golay filter)

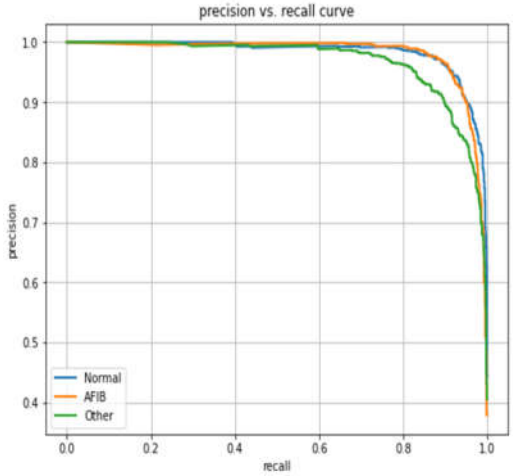
Accuracy	Class	Precision (%)	Recall (%)	F1-score (%)
97.87%	AFiB	99.00	96.00	97.00
	Normal	95.00	97.00	96.00
	Other	94.00	95.00	94.00
	Weighted Avg	96.00	96.00	96.00



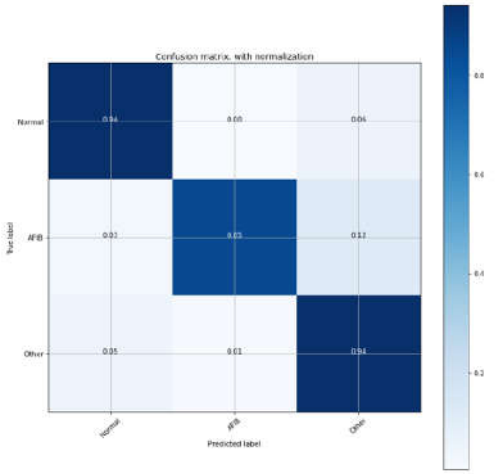
a. Accuracy



b. AUC-ROC graph

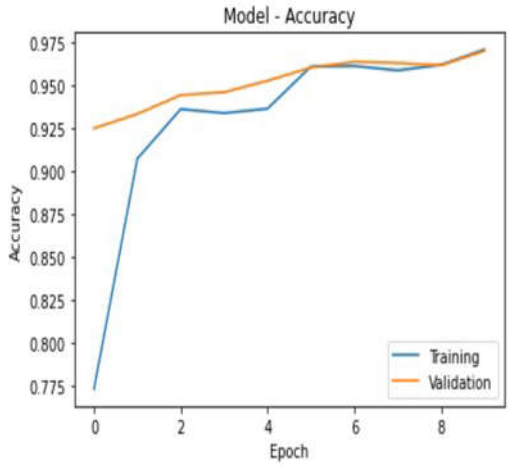


c. Precision vs Recall curve

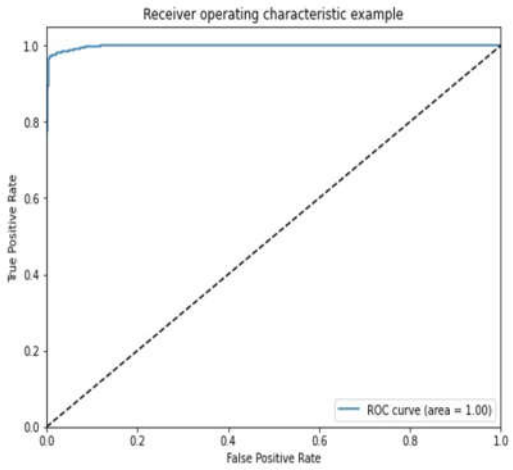


d. Confusion Matrix

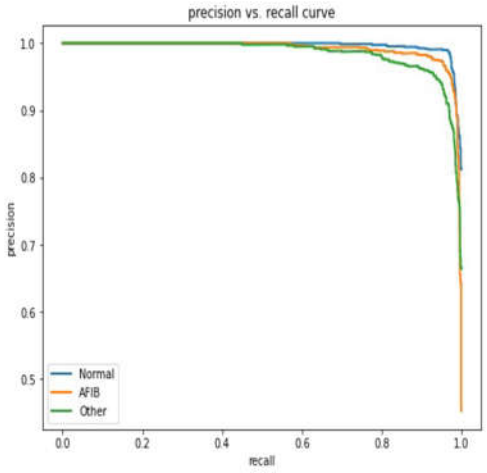
Figure 4. Results achieved from the proposed model without noise filter applied



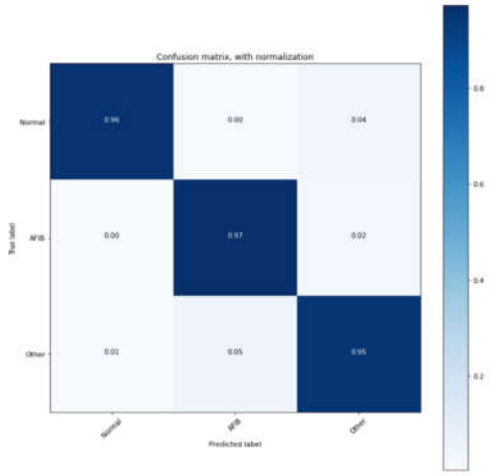
a. Accuracy



b. AUC-ROC graph



c. Precision vs Recall curve



d. Confusion Matrix

Figure 5. Results achieved from the proposed model with noise filter applied

4.3. *Discussion*

The proposed approach for detecting AFiB using ECG signals has significantly improved performance. Data augmentation and a noise removal filter in the preprocessing phase contribute to a robust model. Tested on the imbalanced MIT-BIH dataset, it achieved an impressive 97.87% accuracy by using the CNN model with data augmentation and noise removal strategy, compared to 90.93% in earlier experiments without noise removal. Most of existing studies relies on binary classification. However, the proposed methodology has a better outcome as it achieves higher accuracy for identifying multiclass classification of AFiB by applying an effective noise removal filter that is not even much used in previous research.

Authors	Dataset	Classes	Preprocessing	Methodology	Accuracy
[44]	BCG data	AFiB, sinus rhythm (SR)	Signal transformation, Feature sequences generation, Statistical feature calculation.	SVM	96.80%
[45]	Real-time data collected using Smartphone	AFiB, Healthy	Feature extraction, Feature analysis	Accelerometer RMS filter and gyroscope sensors	97.40%
[46]	MIT-BIH AF database (AFDB)	AFiB, Other	Noise reduction (pulse rejection filter)	RF	97.60%
[47]	MIT-BIH arrhythmia database.	AFiB, Other	Noise reduction (wavelet transform and sliding window filtering)	Feedforward Neural Network	83.00%
[48]	MIT–BIT Dataset	AFiB, Normal Sinus Rhythm (NSR), Noisy	——	Artificial Neural Network	93.10s%
[49]	Long-term AF database	Abnormal (AFiB),	——	Stacked LSTM	92.00%
[50]	MIT-BIH Arrhythmia Database	AFiB, Normal Sinus Rhythm (NSR)	RRI sequences calculated	CNN and RNN	96.95%
Proposed approach	**MIT-BIH Arrhythmia Database**	**AFiB, Normal, Other**	**Data augmentation (SMOTe), Noise Removal (Savitzky-Golay filter)**	**CNN (with data augmentation, and cross-entropy)**	**97.78%**

contains a comparison between the proposed model and some current approaches.

Table 5. Comparison of the proposed approach with the existing approaches

Authors	Dataset	Classes	Preprocessing	Methodology	Accuracy
[44]	BCG data	AFiB,	Signal transformation, Feature sequences	SVM	96.80%

		sinus rhythm (SR)	generation, Statistical feature calculation.		
[45]	Real-time data collected using Smartphone	AFiB, Healthy	Feature extraction, Feature analysis	Accelerometer RMS filter and gyroscope sensors	97.40%
[46]	MIT-BIH AF database (AFDB)	AFiB, Other	Noise reduction (pulse rejection filter)	RF	97.60%
[47]	MIT-BIH arrhythmia database.	AFiB, Other	Noise reduction (wavelet transform and sliding window filtering)	Feedforward Neural Network	83.00%
[48]	MIT–BIT Dataset	AFiB, Normal Sinus Rhythm (NSR), Noisy	——	Artificial Neural Network	93.10s%
[49]	Long-term AF database	Abnormal (AFiB),	——	Stacked LSTM	92.00%
[50]	MIT-BIH Arrhythmia Database	AFiB, Normal Sinus Rhythm (NSR)	RRI sequences calculated	CNN and RNN	96.95%
Proposed approach	**MIT-BIH Arrhythmia Database**	**AFiB, Normal, Other**	**Data augmentation (SMOTe), Noise Removal (Savitzky-Golay filter)**	**CNN (with data augmentation, and cross-entropy)**	**97.78%**

5. CONCLUSION

This study presents a new approach using CNN with data augmentation (SMOTe) and a noise removal filter to detect AFiB, normal rhythm, and other rhythms. The study utilized an open source MIT-BIH dataset for classification. The proposed CNN-based framework with data augmentation and noise filtering achieved superior performance compared to existing studies, demonstrating its potential for real-time clinical AFiB detection.The model's performanace is assessed through experiments, one without noise removal, and the other with a noise filter applied. The results show the model outperformed previous approaches with 97.87% accuracy when the noise filter is

applied. However, the proposed method still achieves a remarkable score without a noise filter. Therefore, we conclude that the proposed approach outperforms previous studies and has the capability for multiclass classification of AFiB with high accuracy. In the future, a more generalized model can be explored which can detect various types of arrhythmia, such as atrial flutter, junctional rhythm, and atrial tachycardia, amongst others.

REFERENCES

1. Lines JST, Cai X, Nielsen BF. *Computing the Electrical Activity in the Heart.* Monographs in Computational Science and Engineering. (2006). doi: https://doi.org/10.1007/3-540-33437-8_3 .
2. Kaptoge S, Pennells L, De Bacquer D, Cooney MT, Kavousi M, Stevens G,. *World Health Organization Cardiovascular Disease Risk Charts: Revised Models to Estimate Risk in 21 Global Regions.* Lancet Global Health. ;7:e1332–45 (2024).doi: https://doi.org/10.1016/s2214-109x(24)00210-9 .
3. Lip GYH, Li Saw Hee FL. *Paroxysmal Atrial Fibrillation.* QJM.94:665–78.0 (2001).doi: https://doi.org/10.1111/j.1742-1241.1999.tb11680.x .
4. Parkash R, Verma A, Tang AS. *Persistent Atrial Fibrillation: Current Approach and Controversies.* Current Opinion in Cardiology;25:1–7. (2010).doi: https://doi.org/10.1097/hco.0b013e3283336d52 .
5. Cerutti S, Mainardi LT, Porta A, Bianchi AM. *Analysis of the Dynamics of RR Interval Series for the Detection of Atrial Fibrillation Episodes.* Computers in Cardiology;77–80.(1997).DOI: https://doi.org/10.1109/cic.1997.647834 .
6. Rincon F, Grassi PR, Khaled N, Atienza D, Sciuto D. *Automated Real-Time Atrial Fibrillation Detection on a Wearable Wireless Sensor Platform*. in Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biological Soc. EMBS;2472–5. (2012).doi: https://doi.org/10.1109/embc.2012.6346465 .
7. Tuboly G, Kozmann G, Kiss O, Merkely B. *Atrial Fibrillation Detection With and Without Atrial Activity Analysis Using Lead-I Mobile ECG Technology.* Biomedical Signal Processing and Control;66:102462. (2021).doi: https://doi.org/10.1016/j.bspc.2021.102462 .
8. Prasad H, Martis RJ, Acharya UR, Min LC, Suri JS. *Application of Higher Order Spectra for Accurate Delineation of Atrial Srrhythmia.* in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC);57–60.(2013).doi: https://doi.org/10.1109/embc.2013.6609436 .
9. Lee J, Reyes BA, McManus DD, Mathias O, Chon KH. *Atrial Fibrillation Detection Using An Iphone 4S*. IEEE Transactions on Biomedical Engineering;60:203–6.(2013).doi: https://doi.org/10.1109/tbme.2012.2208112 .
10. Barnard TE. *Legendre Polynomial Expressions for the Probability Density Function of Magnitude-Squared Coherence Estimates.* IEEE Transactions on Acoustics, Speech, and Signal Processing.;29:107–8. (1981).doi: https://doi.org/10.1109/tassp.1981.1163516 .
11. Vicente R, Ribeiro HV, Rosa RR, Alfaras M, Soriano MC, Ortín S. *A Fast Machine Learning Model for ECG-Based Heartbeat Classification and Arrhythmia Detection.* Frontiers in Physics;7:472268.(2019).doi: https://doi.org/10.3389/fphy.2019.00103 .
12. Yin L, Chen F, Zhang Q, Ma X. *Arrhythmia Classification Based on Multi-Domain Feature*

Extraction. Journal of Physics. Confernece Series;1237:022062.(2019).doi: https://doi.org/10.1088/1742-6596/1237/2/022062 .

13. Dash S, Chon KH, Lu S, Raeder EA. *Automatic Real Time Detection of Atrial Fibrillation.* Annals of Biomedical Engineering;37:1701–9.(2009).doi: https://doi.org/10.1007/s10439-009-9740-z .
14. Zabihi M, Rad AB, Katsaggelos AK, Kiranyaz S, Narkilahti S, Gabbouj M. *Detection of Atrial Fibrillation in ECG Hand-Held Devices Using a Random Forest Classifier.* Computing in Cardiology Conference (CinC);44:1–4.(2017).doi: https://doi.org/10.22489/cinc.2017.069-336 .
15. Shen M, Zhang L, Luo X, Xu J. *Atrial Fibrillation Detection Algorithm Based on Manual Extraction Features and Automatic Extraction Features.* Computing in Cardiology Conference (CinC).;428:012050.(2020).doi: https://doi.org/10.1088/1755-1315/428/1/012050 .
16. Park J, Lee K, Kang K. *Arrhythmia Detection from Heartbeat Using K-Nearest Neighbor Classifier.* IEEE International Conference on Bioinformatics and Biomedicine.doi: https://doi.org/10.1109/bibm.2013.6732594 .
17. Maglaveras N, Stamkopoulos T, Diamantaras K, Pappas C, Strintzis M. *ECG Pattern Recognition and Classification Using Non-Linear Transformations and Neural Networks: A Review*. International Journal of Medical Informatics;52:191–208.(1998).doi:https://doi.org/10.1016/s1386-5056(98)00138-5 .
18. Khazaee A, Ebrahimzadeh A. Heart *Arrhythmia Detection Using Support Vector Machines.* Intelligent Automation and Soft Computing;19:1–9.(2013).doi: https://doi.org/10.1080/10798587.2013.771456 .
19. Maglaveras N, Stamkopoulos T, Pappas C, Strintzis MG. *An Adaptive Backpropagation Neural Network for Real-Time Ischemia Episodes Detection: Development and Performance Analysis Using the European ST-T Database.* IEEE Transactions on Biomedical Engineering;45:805–13.(1998).doi: https://doi.org/10.1109/10.686788 .
20. Shi J, Chen C, Liu H, Wang Y, Shu M, Zhu Q. *Automated Atrial Fibrillation Detection Based on Feature Fusion Using Discriminant Canonical Correlation Analysis*. Computational and Mathematical Methods in Medicine:6691177.(2021).doi: https://doi.org/10.1155/2021/6691177 .
21. Nguyen QH, Nguyen BP, Nguyen TB, Do TTT, Mbinta JF, Simpson CR. Stacking *Segment-Based CNN with SVM for Recognition of Atrial Fibrillation from Single-Lead ECG Recordings.* Biomedical Signal Processing and Control;68:102672.(2021).doi: https://doi.org/10.1016/j.bspc.2021.102672 .
22. Cai W, Chen Y, Guo J, Han B, Shi Y, Ji L, et al. *Accurate Detection of Atrial Fibrillation From 12-Lead ECG Using Deep Neural Network.* Computers in Biology and Medicine;116:103378.(2020).doihttps://doi.org/10.1016/j.compbiomed.2019.103378 .
23. Petmezas G, Haris K, Stefanopoulos L, Kilintzis V, Tzavelis A, Rogers JA,. *Automated Atrial Fibrillation Detection Using a Hybrid CNN-LSTM Network on Imbalanced ECG* Datasets. Biomed. Signal Process. Control;63:102194.(2021).doi: https://doi.org/10.1016/j.bspc.2020.102194 .
24. Chen X, Cheng Z, Wang S, Lu G, Xv G, Liu Q,. *Atrial Fibrillation Detection Based On Multi-Feature Extraction and Convolutional Neural Network for Processing ECG Signals*. Computer Methods and Programs in Biomedicine:106009.(2021).doi: https://doi.org/10.1016/j.cmpb.2021.106009 .

25. Du M, Yang Y, Zhang L. *Diagnosis of Atrial Fibrillation Based on Unsupervised Domain Adaptation.* Computers in Biology and Medicine;164:107275. (2023).doi:https://doi.org/10.1016/j.compbiomed.2023.107275 .
26. Jo YY, Cho Y, Lee SY, Kwon J myoung, Kim KH, Jeon KH, et al. *Explainable Artificial Intelligence to Detect Atrial Fibrillation Using Electrocardiogram.* International Journal of Cardiology2021;328:104–10.(2021).doi: https://doi.org/10.1016/j.ijcard.2020.11.053 .
27. Wang H, Dai H, Zhou Y, Zhou B, Lu P, Zhang H, *An Effective Feature Extraction Method Based on GDS for Atrial Fibrillation Detection*. Journal of Biomedical Informatics;119:103819.(2021).doi: https://doi.org/10.1016/j.jbi.2021.103819 .
28. Zhang H, Dong Z, Sun M, Gu H, Wang Z. *TP-CNN: a Detection Method for Atrial Fibrillation Based on Transposed Projection Signals With Compressed Sensed ECG.* Computer Methods and Programs in Biomedicine;210:106358.(2021).doi: https://doi.org/10.1016/j.cmpb.2021.106358 .
29. Jiang M, Gu J, Li Y, Wei B, Zhang J, Wang Z,. *HADLN: Hybrid Attention-Based Deep Learning Network for Automated Arrhythmia Classification.* Frontiers in Physiology;12:683025.(2021).doi: https://doi.org/10.3389/fphys.2021.683025 .
30. Moody GB, Mark RG. *The Impact of the MIT-BIH Arrhythmia Database.* IEEE Engineering in Medicine and Biology Magazine.;20:45–50.(2001).doi: https://doi.org/10.1109/51.932724 .
31. Awal MA, Mostafa S, Ahmad M. P*erformance Analysis of Savitzky-Golay Smoothing Filter Using ECG Signal.* Signal Processing (2011).doi: https://doi.org/10.1016/j.sigpro.2005.02.002 .
32. Pandey SK, Janghel RR. *Automatic Detection of Arrhythmia from Imbalanced ECG Database Using CNN Model with SMOTE.* Australasian Physical & Engineering Sciences in Medicine;42:1129–39. (2019).doi: https://doi.org/10.1007/s13246-019-00815-9 .
33. Chawla N V., Bowyer KW, Hall LO, Kegelmeyer WP. *SMOTE: Synthetic Minority Over-Sampling Technique*. Journal of Artificial Intelligence Research;16:321–57.(2002).doi; https://doi.org/10.1613/jair.953 .
34. Wang Y, Li Y, Song Y, Rong X. *The Influence of the Activation Function in a Convolution Neural Network Model of Facial Expression Recognition.* Applied Sciences, Vol. 10, Page 1897 2020;10:1897.(2020).doi: https://doi.org/10.3390/app10051897 .
35. He Z, Liu X, He H, Wang H. *Dual Attention Convolutional Neural Network Based on Adaptive Parametric ReLU for Denoising ECG Signals with Strong Noise. Annual* International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) 2021;779–82.(2021) .doi: https://doi.org/10.1109/embc46164.2021.9630123 .
36. Lau MM, Hann Lim K. Review of Adaptive Activation Function in Deep Neural Network. IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES);686–90.(2019).doi: https://doi.org/10.1109/iecbes.2018.8626714 .
37. Lin G, Shen W. *Research on Convolutional Neural Network Based on Improved Relu Piecewise Activation Function*. Procedia Computer Science;131:977–84.(2018).doi: https://doi.org/10.1016/j.procs.2018.04.239 .
38. Yıldırım Ö, Baloglu UB, Acharya UR. *A Deep Convolutional Neural Network Model for Automated Identification of Abnormal EEG Signals.* Neural Computing and Applications;32:15857–68.(2020).doi: https://doi.org/10.1007/s00521-018-3889-z .
39. Maghsood S. Mohammad L., Marjan S., Antonio C., Sara A.A. *SARAF: Searching for*

Adversarial Robust Activation Functions. 6th International Conference on Machine Vision and Applications (2017).doi: https://doi.org/10.1145/3589572.3589598 .

40. Gu J, Wang Z, Kuen J, Ma L, Shahroudy A, Shuai B, *Recent Advances in Convolutional Neural Networks.* Pattern Recognition;77:354–77.(2018).doi: https://doi.org/10.1016/j.patcog.2017.10.013 .
41. Partan R. *Cardiac Arrhythmias Classification Using Deep Neural Networks and Principle Component Analysis Algorithm*, Proceedings of Computers in Cardiology Conference, (2023). doi: https://doi.org/10.1109/cic.1993.378434
42. Rolon-Mérette D, Ross M, Rolon-Mérette T, Church K. *Python for Research in Psychology Introduction to Anaconda and Python: Installation and setup*. The Quantitave Methods of Psychology.16. (2020).doi: https://doi.org/10.20982/tqmp.16.5.s003 .
43. Randles BM, Pasquetto I V., Golshan MS, Borgman CL. *Using the Jupyter Notebook as a Tool for Open Science: An Empirical Study*. ACM/IEEE Joint Conference on Digital Libraries (JCDL) (2017).doi: https://doi.org/10.1109/jcdl.2017.7991618 .
44. Wen X, Huang Y, Wu X, Zhang B. *A Feasible Feature Extraction Method for Atrial Fibrillation Detection from BCG.* IEEE Journal of Biomedical and Health Informatics;24:1093–103.(2020).doi: https://doi.org/10.1109/jbhi.2019.2927165 .
45. Lahdenoja O, Hurnanen T, Iftikhar Z, Nieminen S, Knuutila T, Saraste A, *Atrial Fibrillation Detection via Accelerometer and Gyroscope of a Smartphone.* IEEE Journal of Biomedical and Health Informatics;22:108–18.(2018).doi: https://doi.org/10.1109/jbhi.2017.2688473 .
46. Hirsch G, Jensen SH, Poulsen ES, Puthusserypady S. *Atrial Fibrillation Detection Using Heart Rate Variability and Atrial Activity: A Hybrid Approach.* Expert Systems with Applications;169:114452.(2021).doi: https://doi.org/10.1016/j.eswa.2020.114452 .
47. Chen Y, Zhang C, Liu C, Wang Y, Wan X. *Atrial Fibrillation Detection Using a Feedforward Neural Network.* Journal of Medical and Biological Engineering;42:63–73.(2022).doi: https://doi.org/10.1007/s40846-022-00681-z .
48. Khriji L, Fradi M, Machhout M, Hossen *A. Deep Learning-Based Approach for Atrial Fibrillation Detection.* Lecture sNotes in Computer Science;12157 LNCS:100–13.(2020).doi: https://doi.org/10.1007/978-3-030-51517-1_9 .
49. Sun L, Wang Y, He J, Li H, Peng D, Wang Y. *A Stacked LSTM for Atrial Fibrillation Prediction Based on Multivariate ECGs.* Health Information Science and Systems;8:1–7. (2020).doi: https://doi.org/10.1007/s13755-020-00103-x .
50. Andersen RS, Peimankar A, Puthusserypady S. *A Deep Learning Approach for Real-Time Detection of Atrial Fibrillation.* Expert Systems with Applications;115:465–73.(2019) .doi: https://doi.org/10.1016/j.eswa.2018.08.011 .
51. Ansari Y, Mourad O, Qaraqe K, Serpedin E.*Deep learning for ECG Arrhythmia detection and classification: an overview of progress for period 2017-2023*. Frontiers in Physiology, 15;14:1246746. 2023. doi: 10.3389/fphys.2023.1246746.
52. Sun, LC., Lee, CC., Ke, HY. *Deep Learning for the Classification of Atrial Fibrillation Using Wavelet Transform-Based Visual Images*. BMC Medical Informatics and Decision Making , 349. 2022. doi:https://doi.org/10.1186/s12911-025-02872-5.
53. Elzana D., Zhilbert T., *A Deep Learning Approach to Multi-Class ECG Interpretation,* Conference: 2025 10th International Conference on Smart and Sustainable Technologies (SpliTech.). 2025. doi: 10.23919/SpliTech65624.2025.11091679.

54. Aldughayfiq B, Ashfaq F, Jhanjhi NZ, Humayun M.*A Deep Learning Approach for z Fibrillation Classification Using Multi-Feature Time Series Data from ECG and PPG.* Diagnostics (Basel). Jul 21;13(14):2442. 2023. doi: 10.3390/diagnostics13142442.
55. Jaechan L., Dong H., Ki H. C., *RS-Centric Beat-Wise Atrial Fibrillation Detection In Ecg Signals Using Deep Neural Networks,* Computers in Biology and Medicine, Volume 192, Part B,110282, 2025. doi:https://doi.org/10.1016/j.compbiomed.2025.10282.
56. Muhammad Sohail Irshad, Tehreem Masood, Arfan Jaffar, Muhammad Rashid, Sheeraz Akram, Abeer Aljohani, *Deep Learning-Based ECG Classification for Arterial Fibrillation Detection,* Computers, Materials and Continua, Volume 79, Issue 3, Pages 4805-4824. 2024. doi:https://doi.org/10.32604/cmc.2024.050931.