J. Electrical Systems 20-11s (2024): 3624-3634

Sheerinsithara A[1]*,

S Albert Antony Raj[2]

Risk Level Classification of Drug-Induced Arrhythmias and Long-QT Syndrome Diagnosis by SCLMISHCOLU-CNN and SBT-FUZZY

JES Journal of Electrical Systems

Abstract: Abnormal heart rhythms that are caused by some medications are called Drug-induced Arrhythmias (DA), which also affect the functioning of the heart. In the prevailing works, abnormal heart rhythms are examined grounded on an Electrocardiogram (ECG) signal only, but the consequences of DA are not focused. Therefore, grounded on ECG and arrhythmia's consequences data, a risk-level classification and a long-QT syndrome diagnosis model are proposed. Primarily, the ECG signal is preprocessed, followed by time series segmentation. Subsequently, to get the accurate P, Q, R, S, and T waves, the segmented signal is transformed into a waveform, and the time intervals between the wavelet components are estimated. Likewise, the segmented signal is also converted to image format, and the image is masked with the full heartbeat. Then, from the masked image, the features are extracted. In addition, the historical DA consequence data are preprocessed. Further, from the DA consequence's features, masked image features, and wave interval features, the optimal features are chosen. The SCLMish Collapsing Linear Unit-Convolutional Neural Network (SCLMishCoLU-CNN) classifier detects the normal and DA types grounded on the optimal features. Lastly, by using the Singleton Beta Trapezoidal Fuzzy (SBT-Fuzzy) algorithm, the risk level is identified from the detected output; also, grounded on QT intervals, the long-QT syndrome is diagnosed here. The robustness of the framework is proved by the analysis outcomes, thus achieving classification accuracy and precision of 99.79% and 99.49%, correspondingly.

Keywords: preprocessed, Collapsing, classification, consequence, segmentation

1. INTRODUCTION

Abnormal heart rhythms caused by some medications are referred to as DA. DA also results in heart failure, issues in blood circulation and blood vessels, hypertension, and impairment of cardiac valves ([19], [16]). In addition, an increase in the mortality rate of humans is caused by some therapeutic drugs [26]. Because of the malfunctioning of the heart system, DA generates irregular heartbeats [5]. Furthermore, serious cardiac side effects can be created by drug-induced life-threatening ventricular arrhythmias like torsades de pointes, which are related to QT prolongation [29]. But, the leading cause of death globally is DA. Therefore, to save the life of humans, diminishing the DA is crucial [15]. In addition, for the correct diagnosis, categorizing the risk level of the arrhythmia accurately is important [8].

In general, to record the activities of the heart, many image processing techniques like computed tomography, magnetic resonance imaging, and ECG are utilized. Amongst these, ECG is a popular one for drug-induced cardiac arrhythmias. Here, ECG shows the activity of the heart all the time [10]. By placing the electrodes on the skin, the ECG information about the heart rate, mental stress, and irregular intervals of the heartbeat are gathered [6]. The wave components, such as P, Q, R, S, and T waves are extracted to efficiently classify the arrhythmia types from the ECG signals [11]. In addition, to find the absence of wave components and irregular ventricular rate in the ECG signal, some morphological operations are also performed [27]. To categorize the types of arrhythmia disease, arrhythmia risk level classification frameworks like Deep Learning (DL) and Machine Learning (ML) frameworks are used in prevailing studies. From the above-mentioned approaches, ML frameworks, namely K-Nearest Neighbour (KNN), linear quadratic kernel Support Vector Machines (SVM), and Random Forests (RF) along with waveform-based signal processing features are used to categorize the arrhythmia utilizing ECG signals. But interpretability problems affect the ML models [30].

[1]Department of Computer Applications, Faculty of Science and Humanities,
SRM Institute of Science and Technology, Kattankulathur -603203, INDIA. ORCiD ID:0009-0002-7706-4507
[2]Department of Computer Applications, Faculty of Science and Humanities,
SRM Institute of Science and Technology, Kattankulathur -603203, INDIA. ORCiD ID: 0000-0003-0363-4247
*Corresponding Author Email: sa7045@srmist.edu.in

Thus, to categorize the types of arrhythmias grounded on ECG signals, DL methods, namely Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and support vector neural networks are utilized. However, the aforementioned frameworks are prone to overfitting issues ([7], [4]). Therefore, to categorize the risk level of cardiac arrhythmia, One-Dimensional CNN (1D-CNN) is utilized. Nevertheless, owing to the imbalance of data, 1D-CNN produces poor outcomes [1]. But, to categorize the risk level of DA and to diagnose long QT syndrome, improvement is still required. So, to efficiently categorize the risk level of DA and diagnose the long QT syndrome, this paper proposed an efficient model grounded on SCL-MishCoLU-CNN and SBT-Fuzzy.

The rest of the paper is organized as: the prevailing works are conveyed in section 2, the proposed methodology is described in section 3, section 4 describes the results and discussion grounded on the performance metrics, and section 5 concludes the proposed work along with future work.

2. LITERATURE SURVEY

[22] used the ML framework for predicting the drug-induced long QT syndrome grounded on harmonized electronic health record data. For predicting the risk level of drug-induced QT prolongation, ML frameworks like RF, logical regression, and naïve Bayes were used. Thus, superior classification accuracy and F1-score were achieved in the prediction of drug-induced QT prolongation. However, grounded on a random weight basis, the data augmentation process was performed, thereby resulting in inaccurate data. Therefore, the model's performance was affected.

[2] described the detection of drug-induced QT-prolongation at risk of torsades de pointes. In this, to detect drug-induced QT prolongation, an explainable algorithm grounded on expert ECG interpretation and understanding of human visual perception was used. This work had high-performance values regarding the F1-score and Matthew's correlation coefficient. Furthermore, the beats of the ECG signals were segmented only by the explained framework, which can't examine the heartbeat in a specific time interval. Therefore, the accuracy ratio was decreased.

[24] monitored the detection of abnormal arrhythmias grounded on cardiac ECG signals. This work utilized 1D-CNN with 2 convolutional layers, two Fully Connected (FC) layers, and two down-sampling layers for detecting abnormal arrhythmia. Next, for efficient performance, the 1D data was converted into 2D data. Thus, the work's higher efficiency was demonstrated by the obtained results of the presented work. But this work had a limited number of features, thus decreasing the classification accuracy.

[21] presented an intelligent learning framework to enhance the classification of ECG signals as well as arrhythmia analysis. For categorizing cardiac arrhythmia, the presented model used a Hidden Markov Model (HMM). For extracting the features from the ECG signal, the wavelet-based method was developed. Thus, the cardiac arrhythmia was effectively categorized into left bundle branch block, normal, right bundle branch block, premature ventricular contraction, and atrial premature contraction by the wavelet-based model with very good accuracy. But, the HMM was restrictive and simplistic, which could create false outcomes owing to their wrong assumptions. Therefore, the model's performance was degraded.

[17] used wavelet transform with DL framework for the classification of ECG-based arrhythmia. In this, for detecting ECG-based arrhythmias, Continuous Wavelet Transform (CWT) with 2D CNN was suggested. As per the outcomes, the model efficiently detected the arrhythmia from short segments of ECG and achieved better results concerning sensitivity and specificity. However, the presented CWT with the 2D CNN model only proved their outcomes with a small dataset with fewer classes, so it might be unreliable for large datasets.

[18] suggested an effective ECG arrhythmia classification system utilizing transfer learning. To categorize the heartbeats for arrhythmia detection, the presented work utilized transfer learning. In this, to categorize 29 types of heartbeats for arrhythmia classification, the MIT-BIH arrhythmia dataset was utilized. Thus, the diverse irregular heartbeats or arrhythmias were superiorly categorized by the presented framework with a high accuracy ratio. Furthermore, owing to the transfer learning models' complex structure, it had computational complexities, thereby spoiling the model's performance.

[25] utilized optimization-based actor-critic neural networks and spectral features for arrhythmia classification grounded on ECG signals. From the ECG signals, the wave components like P, Q, R, S, and T waves were identified. Subsequently, from the waves, the spectral and statistical features were extracted. Lastly, the arrhythmias were categorized by the actor-critic neural network. As per the outcomes, the model attained superior results concerning accuracy, sensitivity, and specificity. Moreover, the critic's value function of the actor-critic neural network could be inaccurate or inconsistent with the actor's policy. So, the policy gradient's quality was affected, which degraded the performance.

[9] introduced a cardiac arrhythmia classification framework utilizing Q-wavelet transforms-centered features and an SVM classifier. For efficient classification, the presented framework utilized tunable Q-wavelet-based features of ECG beats. To categorize the cardiac arrhythmias, the SVM classifier was suggested. The superior performance of the presented framework was demonstrated by the findings of the technique. But, for a large number of data, SVM was not suitable. SVM may underperform if more data were processed. Therefore, the model's efficiency was affected.

[28] explained a framework for arrhythmia recognition and classification utilizing combined parametric and visual pattern features of ECG morphology. In this, to automatically diagnose the arrhythmia, well-known classifiers like SVM, neural network, and KNN were used. An excellent accuracy ratio in the classification and recognition of arrhythmia was attained by the model. However, the variabilities of ECG wave components, such as P waves and T waves were not identified by the presented framework. Therefore, the classification ratio was decreased.

[12] used high-order spectrum and 2D Graph Fourier Transform (2D-GFT) for categorizing the ECG arrhythmia. To categorize the diverse arrhythmia heartbeats, the presented framework utilized an SVM-based radial basis function kernel. Grounded on bispectrum and 2D-GFT, the features were extracted. Thus, superior classification accuracy was achieved by the combination of bispectrum and 2D-GFT. Moreover, to remove the ECG signals' noise, the presented work had insufficient pre-processing methods, thereby affecting the classification outcomes of the model.

3. PROPOSED METHODOLOGY

From the ECG signal and arrhythmia consequences data, the features are extracted and selected by utilizing TDC-PCA and SSTOA, respectively. Subsequently, by using SCLMishCoLU-CNN, the normal and diverse types of arrhythmias are categorized. Lastly, SBT-Fuzzy identifies the risk level of DA and also diagnoses the long-QT syndrome. Figure 1 illustrates the proposed framework's architecture.

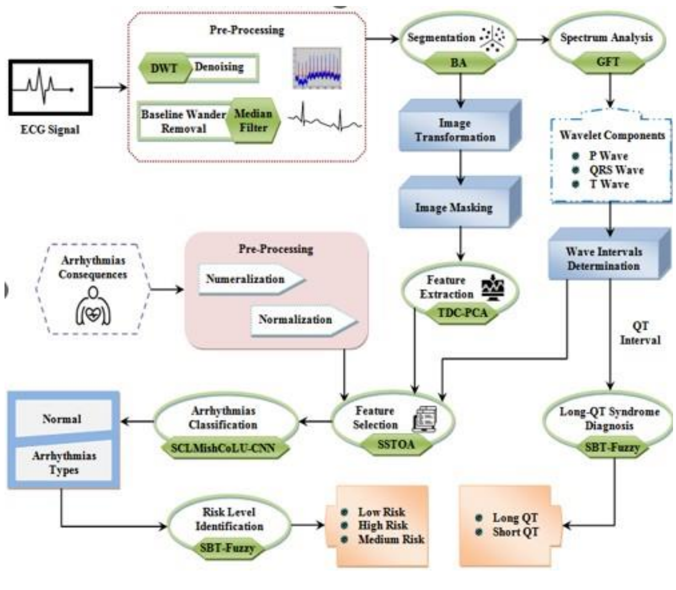


Figure 1: Structure of the proposed work

3.1. Preprocessing

Primarily, for categorizing the normal and diverse types of DA, the ECG signal is taken from the historical dataset to train the classifier. The ECG signal's preprocessing aids in eliminating the noises within the signal and also enhances the original waves of the ECG signal. The preprocessing is performed under two steps, such as denoising and baseline wander removal, which are explained below,

(i). Denoising

The unwanted noise occurring in the ECG signal is removed by the signal denoising, which alsorecovers the original signal. The denoising diminishes the error, enhances signal quality, and improves the model's overall performance. By utilizing the Discrete Wavelet Transform (DWT), the denoising is performed. A technique utilizedexamine the time series signal data is the DWT. The DWT is utilized because it has more efficient computational capability than the other transformation methodologies. DWT also has robust localization properties. The noises, which are out of the frequency band of the signal, are also suppressed by the DWT.

(ii). Baseline wander removal

Subsequently, a median filter removes the baseline wander noise that is a low-frequency noise in $\Re$. The median filter is a non-linear digital filter that is utilized to remove signal noises. The median filter is used for its ability to preserve important information while removing noise from the signal. The median filter can deal with spiky noise; also, it efficiently separates the peaks from a slowly changing baseline.

3.2. Segmentation

By utilizing the BA, the $\wp_{\Re}$ signal is segmented grounded on the time-series segmentation. For the identification of the number of heartbeats that happen in specific time intervals, time series-based segmentation is utilized. By utilizing observation signals, the BA can separate unknown and independent sources; so, BA is used here.

Further, for the improvement of wavelet determination, the obtained value is forwarded to a spectrum analysis phase.

3.3. Spectrum Analysis

By utilizing the GFT algorithm, the segmented signal (α) is transformed to the wave format in the spectrum analysis phase. To improve the accurate determination rate of P, Q, R, S, and T waves, the spectrum analysis is processed by measuring the strength and frequency of α. The GFT is utilized for its capability to analyze the frequency contents and select the spectrum components with the largest magnitudes by minimizing the approximation error. The GFT-based spectrum analysis is always grounded on the eigen decomposition of the graph laplacian (L).

3.4. Wavelet processing

In this, grounded on two processes, such as wavelet components and wave interval determination, the P, Q, R, S, and T waves from $\hat{\varsigma}$ are examined.

(a). Wavelet components: The waves, namely P, Q, R, S, and T are pointed out separately from $\hat{\varsigma}$. Two basic properties, namely scale and location are in the wavelets. The scale property explains how the wave is stretched, and the location property explains the position of the wave in the time-space. The time intervals amongst every single wave are estimated further grounded on the pointed P, Q, R, S, and T waves.

(b). Wave interval determination: Subsequently, to find the distance amongst every single wave, the time intervals among the P, Q, R, S, and T waves are determined. Grounded on the analysis, five diverse intervals (τ) are attained, namely PR interval, QT interval, RR interval, R peak, QRS duration

3.5. Long-QT syndrome diagnosis

Subsequently, by using the SBT-Fuzzy algorithm, the long-QT syndrome is diagnosed. Here, the SBT-Fuzzy algorithm utilizes the QT interval attained in the wave interval determination phase. As conventional fuzzing is easy and understandable, it is utilized here. It is also capable of rendering an efficient solution to complex problems. However, fuzzy had a tuning problem in the membership function. Therefore, the Singleton Beta Trapezoidal (SBT) membership function is used. Because of SBT's smoothness and concise notation, it is efficient for specifying fuzzy sets. The SBT-Fuzzy algorithm's process is explained below:

(i). Rule base: The set of if-then conditions, which are utilized for decision-making, is contained in the rule base. The condition for diagnosing long and short QT is provided below: If the distance between Q and T is 40 ms or 80 ms, then it is described as short QT; or else, it is described as long QT.

(ii). Fuzzification: To convert the crisp input, fuzzification is utilized. Here, the crisp input is the QT interval into a fuzzy input. To map the non-fuzzy input to the fuzzy inputs, the SBT membership function (ζ_{QT}) is used.

(iii). Inference engine: For making decisions, the inference engine is responsible. It decides which rule is utilized for the input. Grounded on the set of rules, the inference engine defines the input and assigns values to the output.

(iv). Defuzzification: Defuzzification again converts the fuzzy values attained in the inference engine into crisp values. The output achieved from the SBT-Fuzzy is provided as, $\Pi = \{\Pi_{long}, \Pi_{short}\}$ Here, the long QT and short QT are represented as $\Pi_{long}\ and\ \Pi_{short}$, correspondingly.

3.6. Feature extraction

Subsequently, for classifying the DA, the features from α_{map} are extracted to effectively train the classifier. For extracting the features from α_{map}, the TDC-PCA is deployed. The conventional Principal Component Analysis (PCA) is used for its ability to find the significant features in the data, which are utilized to build predictive models. However, during feature extraction, the PCA lost some information. Therefore, for the covariance matrix, a Tied Diagonal Covariance (TDC) based vector is created. Within a linear number of function evaluations, the TDA can learn a rescaling factor of the issue in the coordinates of the vector.

3.7. Preprocessing

To enhance the efficiency of the classification, the preprocessing is performed grounded on two processes, such as numeralization and normalization. The preprocessing steps are described as follows.

Stage 1: Numeralization: For transforming the strings or the characters present in the historical data into an integer form, the numeralization of Ω is performed.

Stage 2: Normalization: For easier analysis, the normalization process is used to set the different ranges of Ω_{num} into a particular range. $\Omega_{nor} = \frac{(\Omega_{num} - \min(\Omega_{num}))}{(\max(\Omega_{num}) - \min(\Omega_{num}))}$ Where, the lowest and highest range of Ω_{num} are signified as $\min$ and $\max$, correspondingly. Subsequently, it is provided to the feature selection process.

3.8. Feature selection

Further, by utilizing SSTOA, the optimal features from the processed ECG signal data and arrhythmias consequences data are chosen. The conventional STOA is deployed for its ability to balance between the exploration and exploitation phases, which aids in avoiding the local optimal solution. However, STOA randomly selects the numbers that cause premature convergence issues. To resolve this problem, a slash distribution function is used. The slash distribution is a useful distribution for simulation; also, when compared with a normal distribution, it has heavier tails.

3.9. Arrhythmias classification

In this, by utilizing ε_{opt}, the classification of DA is described from the pre-trained SCLMishCoLU-CNN. Because of conventional CNN's efficiency in video and image processing, it is deployed. The CNN utilizes a convolutional technique that applies a filter to extract the relevant features from ε_{opt} . But, while processing with a small dataset, CNN has an overfitting problem and poor performance. Therefore, the sigmoid activation function is replaced with SCLMishCoLU activation. The SCLMishCoLU is for creating complex mappings betwixt the network's inputs and outputs that are vital for learning and modeling complex data.

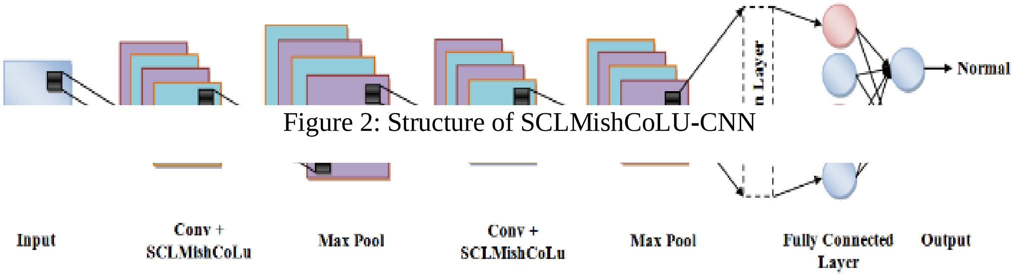


Figure 2: Structure of SCLMishCoLU-CNN

Figure 2: SCLMishCoLU-CNN's structure

Input layer: The input layer (Γ_{inp}) takes the optimal features (ε_{opt}) as the input, and the dimension of Γ_{inp} is grounded on the size of ε_{opt} .

Convolutional layer: Next, the output of Γ_{inp} is provided as the input to the convolutional layer (Γ_{conv}). The convolutional layer is responsible for the feature extraction process. Γ_{conv} encompasses some filters, which are known as kernels that are convolved with Γ_{inp} to capture the relevant features of Γ_{inp} .

Pooling layer: Then, by using the pooling layer (Γ_{pool}) operation, the spatial dimension in Γ_{conv} is diminished. While discarding the unwanted information, the pooling layer performs a max pooling operation to retain the important information.

Flatten layer: The flatten layer (Γ_{flat}) is the crucial component in SCLMishCoLU-CNN as Γ_{flat} allows the network to learn the complex patterns from Γ_{pool} and aids in making predictions. The Γ_{flat} converts the feature maps from Γ_{pool} to a format, which is understood by the FC layer.Where, the multi-dimensional and one-dimensional feature arrays are signified as $g'\, and\ \hat{g}$, correspondingly.

Fully connected layer: The FC layer $\left(\Gamma_{ful}\right)$ uses $\hat{g}\Gamma_{flat}$ from Γ_{flat}; also, grounded on the features extracted in the previous layers, the FC layer $\left(\Gamma_{ful}\right)$ predicts the output classes. The FC layer connects the extracted information from the previous layer to the output layer and categorizes the input with the desired pre-trained labels.

Output layer: The relevant results for the input are attained in the output layer $\left(\Gamma_{out}\right)$. The output of SCLMishCoLU-CNN is achieved as the normal and diverse types of DA like normal beat, left bundle branch block beat, right bundle branch block beat, premature ventricular contraction, and atrial premature beat. Subsequently, the output from Γ_{out} is then forwarded for identifying the risk level of achieved arrhythmias.

3.10. Risk level identification

Grounded on Γ_{out}, the risk levels of the attained DA classes are identified using the SBT-Fuzzy algorithm. Concerning the process discussed in the long-QT syndrome diagnosis phase, the risk levels of the DA are identified. However, the input provided to the SBT-Fuzzy is the attained DA classes from Γ_{out} .By examining (age=υ), (chest pain type=υ), (shortness of breath=υ), (heart rate=υ), and AD classes, the risk levels are identified. From the historical dataset, the υ value is attained. The SBT-Fuzzy predicted the risk level as low risk, high risk, and medium risk grounded on the υ value. Next, the framework's performance outcomes are discussed further.

4. RESULTS AND DISCUSSION

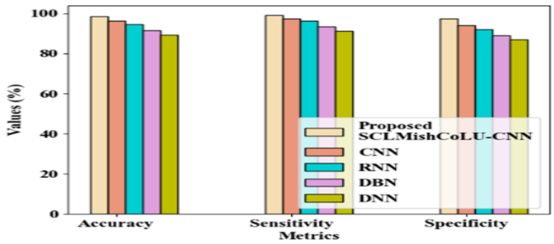
Here, the proposed model's performance is assessed by contrasting it with conventional methodologies grounded on performance metrics. The proposed methodology is implemented in the working platform of PYTHON.

4.1 Dataset Description

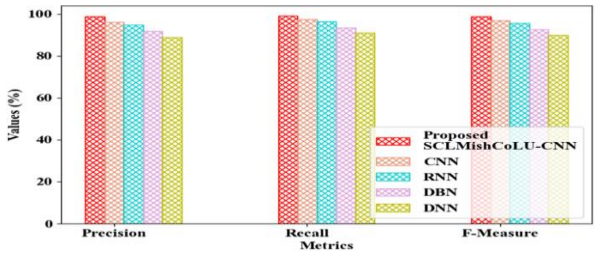
Two datasets, such as the Cleveland Clinic heart disease dataset and the MIT-BIH arrhythmia database are used by the proposed framework. These datasets are gathered from publicly available sources, which are mentioned in the reference section. 704 ECG signals are encompassed in the MIT-BIH arrhythmia database. Likewise, from the Cleveland Clinic heart disease dataset, 704 heart disease data are taken. From the whole data, 80% of the data is used for training, and for testing, 20% of the data is used.

4.2 Performance estimation of the proposed SCLMishCoLU-CNN

In this, the proposed model's performance estimation is contrasted with conventional techniques, namely CNN, Deep Belief Network (DBN), Recurrent Neural Network (RNN), and Deep Neural Network (DNN). The proposed SCLMishCoLU-CNN's sensitivity, specificity, accuracy, precision, recall, and f-measure are analogized with the traditional methods as illustrated in Figure 3. High sensitivity, specificity, accuracy, precision, recall, and f-measure values of 91.23%, 86.95%, 89.20%, 88.88%, 91.15%, and 89.90%, respectively, were attained by the proposed model. Likewise, regarding precision, recall, accuracy, sensitivity, specificity, and f-measure, low values were also attained by other prevailing works. So, the SCLMishCoLU-CNN achieved high values concerning the performance metrics, which demonstrates the effective classification of arrhythmias. To render superior classification without any overfitting problems, the SCLMishCoLU activation function is included with the CNN. Therefore, amongst all methodologies, the SCLMishCoLU-CNN stands out as the top-performing technique.



(a)



(b)

Figure 3: Performance assessment of the proposed model based on performance metrics

Techniques	Training time (ms)	FPR	FNR
Proposed SCLMishCoLU-CNN	37226	2.2406	0.9204
CNN	42243	5.2358	2.5824
RNN	47647	7.7412	3.6402
DBN	53374	10.9542	6.5924
DNN	58384	13.0402	8.8284

Table 1: Comparison by performance metrics

Table 1 displays the proposed SCLMishCoLU-CNN's comparison with the existing works concerning the False Positive Rate (FPR), training time, and False Negative Rate (FNR). FNR and FPR aid in assessing the model's error rate. The SCLMishCoLU-CNN has a low FNR and FPR values of 0.9204 and 2.2406, correspondingly. In addition, the proposed model took less training time of 37226ms, which shows the efficiency of the model, while other prevailing works have the highest average FPR, training time, and FNR values of 9.2428, 50412 ms, and 5.4108, respectively. Hence, when contrasted with other prevailing methods, the proposed model supremely classified the arrhythmia with low false rates and less training time.

4.3 Performance evaluation of the proposed SBT-Fuzzy

To prove the model's decision-making capability, the proposed model's performance evaluation is validated in this section.The graphical representation of the proposed SBT-Fuzzy with the prevailing works regarding defuzzification time and fuzzification time is illustrated in Figure 4. The risk level of arrhythmia with a less defuzzification and fuzzification time of 2365ms and 2451ms, correspondingly, are efficiently categorized by the proposed SBT-Fuzzy. But, the conventional works, namely sigmoid fuzzy, triangular fuzzy, gaussian fuzzy, and trapezoidal fuzzy attained an average fuzzification time of 7698ms and defuzzification time of 7558.75ms, which is greater than the proposed framework. To resolve the tuning difficulties, the SBT membership function is encompassed with fuzzy rules. Hence, the proposed model gave superior outcomes when compared with other existing works.

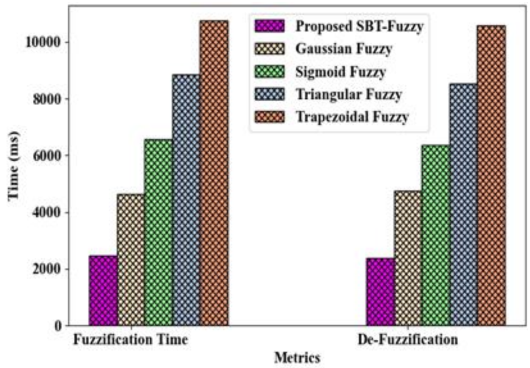


Figure 4: Graphical representation of Fuzzification vs Defuzzification

4.4 Comparative analysis of the proposed model

In this, to prove the model's efficiency, the proposed model is analogized with prevailing works. In Table 2, the proposed framework's comparison with the related works is provided. The SCLMishCoLU-CNN is utilized to effectively categorize the arrhythmia in the proposed work. High f-measure, accuracy, and specificity of 98.92%, 98.59%, and 97.56%, correspondingly, are achieved by the proposed SCLMishCoLU-CNN. A very low accuracy of 93.19% was attained by other related works like deep CNN. In addition, a very low f-measure of 91% was achieved by the prevailing Artificial Neural Network (ANN), thereby leading to misclassifications. Likewise, low accuracy, f-measure, and specificity values are also attained by other prevailing works, such as General Sparsed Neural Networks (GSNN), two-dimensional CNN, and 2DCNN-LSTM. Thus, efficient outcomes in the classification of arrhythmia were attained by the proposed model.

Study	Method	Dataset used	Accuracy (%)	F-measure (%)	Specificity (%)
Proposed model	SCLMishCoLU-CNN	Cleveland Clinic heart disease dataset and MIT-BIH arrhythmia database	98.59	98.92	97.56
[14]	ANN	MIT-BIH arrhythmia database	91	91	98
[3]	Deep CNN	MIT-BIH arrhythmia database	93.19	-	93.98
[23]	1D CNN and 2D CNN	MIT-BIH arrhythmia database	97.8	98	-
[20]	GSNN	MIT-BIH arrhythmia dataset	98	98	-
[13]	2DCNN-LSTM	MIT-BIH cardiac arrhythmia database	98	98	98

Table 2 : Comparative analysis of the proposed model

5. CONCLUSION

An effective framework for categorizing the risk level of arrhythmia and diagnosing the long QT syndrome by utilizing SCLMishCoLU-CNN and SBT-Fuzzy is proposed in the paper. Pre-processing, feature extraction, feature selection, time series-based segmentation, spectrum analysis, image transformation and masking, arrhythmia classification, and risk level classification of arrhythmia were performed in the proposed model. Here, the Cleveland Clinic heart disease dataset and MIT-BIH arrhythmia database were utilized for training the proposed methodology. After completing the execution of all processes, the proposed methodology attained a high accuracy and a precision of 98.59% and 98.63%, correspondingly, which demonstrated the accurate classification of arrhythmia. In addition, less time (1523ms) was taken by the proposed SBT-Fuzzy for rule generation concerning the risk level classification. Therefore, as per the outcomes, the proposed work performed better than the prevailing works. The proposed work focused on diagnosing the arrhythmia utilizing ECG signals and arrhythmia consequences only. However, the arrhythmia that relies upon emotional stress, strenuous exercise, and type and class of drugs were not focused.

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BIOGRAPHIES OF AUTHORS

	**Sheerinsithara A** is pursuing Ph.D in Computer Science from SRM Institute of Science and Technology. She completed her B.Sc in computer science from Madurai Kamaraj University in 2012 and received MCA degree in Computer Science from Mother Teresa University, Kodaikanal in 2015. She has good programming skills and is proficient in subjects such as software engineering, operating systems and database management systems. Her research work mainly focuses on Deep Learning techniques involved in disease detection using ECG Signals. She can be contacted at email: sa7045@srmist.edu.in.
	**Prof. S. Albert Antony Raj** holds a PhD degree in Computer Science from Manonmaniam Sundaranar University, Tirunelveli. He is currently working as Deputy Dean in Computer Applications department, SRM Institute of Science and Technology. He has over 25 years of teaching experience and 10 years of research experience and is also proficient in many technical areas such Data Structures, Computer Algorithms, Operating System, Compiler Design, Computer Networks, Programming Languages, Net Programming. He has published various research papers in International Journals and conferences which are indexed in Scopus and Web of Science. He can be contacted at email: alberts@srmist.edu.in