*Journal of Harbin Engineering University*
*ISSN: 1006-7043*

Vol 44 No. 12
December 2023

# ArithNet: A Promising Multi-Scale Feature Fused Convolutional Network for Arrhythmia Identification from Electrocardiogram Signals

**Subbaiah Shanmugasundaram [1], Sivakumar Subramanian [2], MuthuKumar.VP[3], Kavitha Muruganantham [4]**

[1]Department of MCA, SRM Institute of Science and Technology, Chennai, Tamilnadu, India
[2]Department of MCA, SRM Institute of Science and Technology, Chennai, Tamilnadu, India
[3]PG & Research Department of Computer Science and Applications, Vivekanadha College of Arts and Sciences for Women, Namakkal, Tamilnadu, India
[4]PG & Research Department of Computer Science and Applications, Vivekanadha College of Arts and Sciences for Women, Namakkal, Tamilnadu, India

**Abstract**
Arrhythmia is a highly prevalent chronic cardiac disorder in senior citizens and is related to the high severity including cardiovascular accidents, heart failure and myocardial ischemia. It is essential to instantly identify and categorize arrhythmia rhythms from Electrocardiogram (ECG) signals. From this viewpoint, a Multi-Scale Fusion-Convolutional Neural Network (MSF-CNN) was developed, which uses multi-scale features from the ECG signal for identifying arrhythmia classes. But, it needs a vast number of ECG signals and takes more time to train the model because of using cross-validation. As a result, this article designs a new lightweight end-to-end MSF-CNN with Long Short-Term Memory-Gated Recurrent Unit (LSTM-GRU) structure called an ArithNet model for recognizing arrhythmia automatically. In this model, two different training schemes are applied such as representation training and sequence residual training. At first, the ECG signal database is collected and preprocessed to remove the noisy signals. Then, the noiseless ECG waves are partitioned into regular (R), supraventricular ectopic beat (SV), ventricular ectopic beat (V), merging beat (M) and unfamiliar beat (U) based on the labeling from heart specialists. Such waves are given to the representation training, which extracts time-variant salient characteristics from the ECG signals. Moreover, the sequence residual training is performed, which extracts the temporal characteristics using bidirectional links. Further, the obtained salient and temporal characteristics are fused and categorized by the softmax layer to identify arrhythmia. Finally, the experimental results illustrate that the ArithNet on MIT-BIH and Arrhythmia Data Set achieves an accuracy of 93.09% and 92.84%, respectively than the other classical deep learning models for arrhythmia identification.
**Keywords:** Chronic cardio disorder, Arrhythmia,ECG signal,Multi-scale fusionCNN,LSTM-GRU,Representation learning,Sequence residual learning

## 1. Introduction

Arrhythmia is an essential set of cardiovascular disorders, which are categorized by deliberate, rapid, or abnormal heartbeats [1-2]. They might happen alone or combined with other cardiovascular disorders. Additionally, a few severe arrhythmias might happen abruptly and result in an unexpected fatality, stroke, cardiac arrest, or coronary artery disorders [3]. Arrhythmia leads to serious health problems and perhaps death if not treated promptly, since it is the top cause of death worldwide [4]. Though the exact etiology of heart disorder has yet to be resolved, many threat aspects contribute to its development. A variety of risk factors add to the possibility of acquiring cardiovascular disorder. Hypertension, drinking, dyslipidemia, mellitus, malnutrition, family history, age, and other factors are among the most important [5-6]. The recognition and categorization of patients at risk of cardiovascular disease is a key challenge in the healthcare sector.

In the case of cardiovascular disease recognition and categorization, early detection is crucial in the early stages of treatment, which reduces the risks associated with it. Cardiovascular disorders can be predicted using a range of blood tests and imaging studies [7]. Statistical data is also utilized to coordinate findings and predict the presence of sickness based on outcomes and procedures. The most frequent and critical diagnostic diagnostics are echocardiography (echo), Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) [8]. Although MRI and CT scans produce high-quality cardiac images, they are not used for prediction due to their lengthy collection time, limited availability and use of radiotherapy. The ECG is utilized to tackle this challenge since it is a graphical representation of the repolarization and depolarization of the ventricles and atria [9].

ECG is a quasi, low-cost and reliable diagnostic technique that reveals the particular variations in electric signal behavior over a period [10]. It is a key paradigm in arrhythmias recognition and prognosis. ECG signals have essential morphological features, which are typically captured by ECG assessment tools like echo, 24-hour Holter and smart sensor. Also, they are broadly utilized in the examination of heart activity [11]. Nowadays, arrhythmias are treated by the physical analysis of the ECG data. To recognize arrhythmias using ECG data without human intervention, forecasting tools should examine the structural features of ECG waves and the relationship among heartbeats. By using such relationships, the irregular heartbeats are identified and their categories are determined [12]. The Association for the Advancement of Medical Instrumentation (AAMI) [13] classifies ECG data into 5 types: R, SV, V, M and U. All ECG data have a distinct inference and need various desired therapy under various cardiac activity states.

Recently, visual examination depending on cardiologists is an essential diagnostic standard [14]. It takes a large number of skilled professionals to accurately detect the kind of signal, which not only tends to a difference between subjective assessment and the real condition but also takes a significant amount of time and power. So, it is critical for cardiologists to automatically recognize irregular cardiac rhythms before medical therapy.

During the earlier centuries, ECG signal detection and categorization have become a well-established technology that may successfully aid physicians in clinical diagnosis. Classical template matching approaches are used in the appropriate automated classification systems. Such approaches have established significant advances; however, the sophisticated feature mining procedure requires a significant amount of computational power [15]. Deep learning has been a popular object detection approach these days [16-17]. It is a complete training strategy, which did not need a time-consuming mining procedure. From this perspective, Dang et al. [18] developed multiple CNN frameworks such as a basic-CNN and 2 MSF-CNN structures, which substitute extra handcrafted attribute mining, assortment and categorization by classical machine learning models for arrhythmia recognition. Initially, multi-scale input signals were designed to enhance the generality of the framework through mining multi-scale wave characteristics. After that, the data preprocessing was performed based on the denoising and segmentation methods to remove the power-line interferences and segregate the pre-processed signal into 5 different waves. Also, data augmentation was applied to balance the data distribution by creating novel samples similar to the actual data for learning the CNN. Moreover, a strong MSF-CNN-based attribute mining was constructed to obtain the characteristics from ECG data and find the probability of 5 different ECG signal classes (i.e., R, SV, V, M and U). Based on the predicted signals, the arrhythmia is identified and diagnosed. On the other hand, CNN typically necessities a huge amount of data and time for the learning stage due to the use of cross-validation. So, this article aims to alleviate the difficulty of the cross-validation process and to increase the efficiency of identifying arrhythmia timely.

In this paper, ArithNet, a new lightweight end-to-end MSF-CNN-LSTM-GRU model is designed with 2 distinct training strategies, namely representation training and sequence residual training for recognizing arrhythmia from ECG signal. The key contribution is to design an automatic end-to-end categorization of arrhythmia disorder from ECG signals by the lightweight MSF-CNN-LSTM-GRU architecture. It can capture salient characteristics directly from ECG signals with the smallest learning variables and memory. The representation training involves dynamic characteristic miner, frequency characteristic miner and pattern miner to jointly capture time-invariant salient characteristics from the ECG signals.

Also, the sequence residual training comprises bidirectional links and is utilized to capture temporal characteristics. Both salient and temporal characteristics are then concatenated and fed to the softmax classifier to identify arrhythmia on five different ECG signals. This novel ArithNet model can prevent the complexity of cross-validation tasks and increase the accuracy of arrhythmia identification rapidly.

The remainder of this manuscript is arranged as the following: Section II presents the different works associated with the arrhythmia identification and categorization models. Section III explains the ArithNet model whereas Section IV displays its validity. Section V outlines the entire study and discusses the upcoming enhancement.

## 2. Literature Survey

Abdalla et al. [19] designed a deep learning scheme to categorize various classes of arrhythmia. First, the ECG database was collected and preprocessed to remove noise and partition the signal by identifying the QRS complex. After that, data augmentation was applied to solve the imbalanced database. Further, the 1D-CNN was trained to extract the characteristics and categorize the arrhythmia classes. However, it needs to utilize the sequential framework to categorize the arrhythmia efficiently.

Yang & Wei [20] developed a novel technique integrated with the enhanced morphological characteristics to identify and categorize arrhythmias. Initially, the events of the ECG signals were identified. After that, parametric characteristics of ECG morphology were mined from the chosen ECG areas. Also, enhanced visible pattern characteristics were mined from the QRS complex morphology variations and a novel clustering-based feature mining scheme was applied. Moreover, those characteristic vectors were fed to the neural network, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) to categorize the arrhythmia class. But, it relies only on the visible patterns of the QRS complex, whereas changeability of other ECG waves was needed to increase the efficiency.

Wang et al. [21] designed a dual fully-connected neural network framework for the precise categorization of heartbeats. First, various characteristics were mined from the preprocessed ECG signals. After that, a 2-layer classifier was adopted in the categorization phase, wherein all layers have 2 independent fully-connected neural networks and the threshold condition was included in the second layer to categorize the arrhythmia. But, the sensitivity and precision were less for arrhythmia classes.

Chen et al. [22] developed a new Multi-information Fusion Convolutional Bidirectional Recurrent Neural Network (MF-CBRNN) to identify arrhythmia. It depends on the 2 parallel hybrid branches, which concurrently deliberate on the pulse-dependent data in the ECG signals and the slice-dependent data in the nearby parts of the rhythms. Morphological data were obtained from the specific ECG signals. Meanwhile, the nearby slice of the ECG beat was used to improve the temporal data. Then, a mixture of CNN and bidirectional LSTM were used in all branches to find the characteristics, which were merged to identify arrhythmia. But, the accuracy was not effective due to the limited amount of samples such as the categorization of the fusion beat type under the inter-patient model.

Li et al. [23] developed a rapid and precise categorization scheme called an Incremental Broad Learning (IBL) strategy depending on the biased dropout method to recognize arrhythmias. Initially, the morphological-rhythm characteristics of the denoised signal were obtained and fed to the IBL during the ECG signal processing. After that, the categorization effect of the node optimization framework was improved by adopting the target deactivation technique and integrating additional feature improvement nodes. But, the generalization of this scheme was not effective, since it was only suitable for the MIT-BIH ECG corpus.

Murugappan et al. [24] investigated the ECG morphological characteristics to identify the abrupt cardiac arrest. Initially, ECG signals were divided into a 1-min period and processed to determine the onset of ventricular fibrillation. Afterward, the nonlinear characteristics were captured from the R peak to T-end rhythms. Such characteristics were categorized using the SVM, subtractive fuzzy clustering and Neuro-fuzzy categorizer to recognize the abrupt cardiac arrest. But, the training samples were limited and there were no rich characteristics regarding the arrhythmia which results in imprecise classification.

Li et al. [25] designed a Multi-tag attribute Selection scheme using ECG (MS-ECG), which devices an analysis hypothesis of ECG characteristics depending on the kernelized fuzzy rough sets to select the best characteristic subgroup and adjust the ECG feature space. Also, a Multi-tag Categorization scheme of arrhythmia using ECG (MC-ECG) was developed based on the multi-objective optimization scheme, which finds the correlations among arrhythmia disorders and evaluates the mapping correlation between ECG characteristics and arrhythmia disorders to categorize the multiple labels of arrhythmia. But, the accuracy was less because it trains only standard machine learning algorithms for categorization.

Darmawahyuni et al. [26] developed a generalization model of deep learning for ECG signal categorization in intra and inter-patients' scenarios. Also, a 1D-CNN structure was adopted to categorize ECG signals according to the rhythm and beat characteristics. On the other hand, the preprocessing was not effective in the scenario of ECG signals that contain several leads, noises and sampling frequencies. Also, the partition of the different wave categories from the ECG signals was not conducted before the categorization.

Mathunjwa et al. [27] designed an efficient ECG recurrence plot-based arrhythmia categorization scheme. First, the ECG time series were partitioned and transformed by the recurrence plot. Then, 2-level categorization was adopted in which the ResNet18 structure was used in the initial level to identify noise and ventricular fibrillation while the ResNet50 was used in the second level to identify regular, atrial fibrillation, premature atrial contraction and premature ventricular contractions. But, the classification efficiency was influenced by the imbalanced data. Also, the memory requirement and network complexity were high because of color ECG scans.

Madan et al. [28] developed a hybrid deep learning-based model to automatically recognize and categorize arrhythmia from ECG signals. Initially, 1D-ECG signals were converted into 2D Scalogram images using Continuous Wavelet Transformation (CWT) to remove the noise and capture the characteristics. After that, 2D-CNN and the LSTM network were combined to categorize arrhythmias. But, the computation difficulty was high because of using CWT.

## 3. PROPOSED METHODOLOGY

This part explains the ArithNet model for arrhythmia identification and diagnosis briefly. Figure 1 illustrates the schematic representation of this study. Initially, different ECG recordings with healthy and arrhythmia patients are collected from the available websites to construct training and test sets. Secondly, different preprocessing methods are conducted to enhance and augment the training ECG samples. Thirdly, those training samples are utilized for training the ArithNet classifier and the trained classifier is considered to categorize the test samples into various classes of arrhythmia disorder.

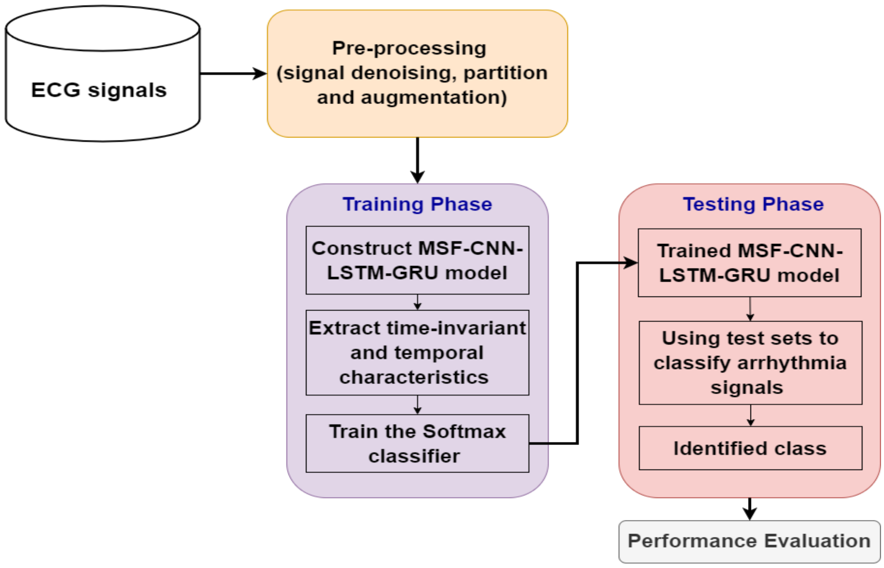


**Figure 1. Schematic Representation of ArithNet-based Arrhythmia Identification and Diagnosis System**

### 3.1. Database description

In this study, two benchmark databases are considered, including:

1. MIT-BIH arrhythmia database: It is a public PhysioBank corpus [29-31], which is broadly considered to investigate the identification and categorization of ECG signals. It comprises 48 half-hour ECG recordings captured from 47 participants and all have 2 leads (lead II and V) created from various sensors. Such participants involve 19 women aged from 23 to 89 and 26 men aged from 32 to 89. The ECG recordings have 17 categories: regular sinus pulse, pacemaker pulse and 15 categories of heart disorders (for all classes, a minimum of 10 signal fragments are acquired). The recordings were digitized at 360 pulses/sec and 11-bit resolution/channel over a 10mV. All recordings were independently labeled by 2 or many specialists; discrepancies have been solved to get the machine-understandable benchmark labels for all heartbeats (approximately 110,000 labels) contained in the corpus. For the evaluation, 1000, 10-second (3600 pulses) pieces of the ECG data (non-overlapping) have been arbitrarily chosen. The waves obtained from a single lead, i.e. the MLII are only utilized.
2. Arrhythmia Data Set: It is also a public corpus [32-33] used to categorize the existence and non-existence of arrhythmia in one of the 16 classes. It has 279 elements, 206 of which are linear ranged and the remaining is nominal. Class 1 is the normal ECG class, Classes 2 to 15 are the various categories of arrhythmia and Class 16 is the remaining uncategorized ones.

### 3.2. Signal preprocessing

The real raw ECG signals from the acquired databases are processed by different methods including denoising, signal partition and augmentation [18] to create the new databases. First, denoising is performed by applying median and low-pass filtering techniques to remove noise and disturbances, respectively triggered by patient respiration or movement. Then, the noise-free ECG waves are split into 5 distinct groups: R, SV, V, M and U based on the labeling by cardiologists [18]. The signal partition includes 251 examples (collection X) and 361 examples (collection Y). The real unprocessed ECG recordings are denoised and split into a group of rhythms located on the R-peak, excluding the initial and final heartbeats. All pulses are made up of 251 examples (60 ahead of the R-peak and 190 behind the R-peak), with a combined P-, Q-, R-, S- and T-peak. Such recordings having 251 samples are called collection X. Similarly, the real raw recordings with denoising are split into 361 heartbeat samples (120 ahead of the R-peak and 240 behind the R-peak). Those recordings with 361 samples are called collection Y.

Moreover, data augmentation methods such as time-shift and noise augmentation methods are applied to balance the different groups of ECG recordings by creating new signals in similar groups [18]. It must be observed that this process creates new samples in addition to actual samples, which are applied only to the learning task. During testing, the real samples are leveraged without augmentation [18].

### 3.3 Fundamentals of deep learning structure

*CNN:*

The typical structure of CNNs has 6 units: the convolutional (CNV) unit, Pooling Unit (PU), Rectified Linear Unit (ReLU), batch regularization, Fully Connected (FC) and softmax unit [18]. All CNV layers have many convolution operations and every variable is adjusted via the back-propagation strategy. The major task of this CNV function is to transform the given signals to the hidden unit attribute region; therefore, various characteristics are mined from the given recordings. The PU intends to minimize the number of feature maps based on max and mean-pooling functions. The ReLU activation executes nonlinear transformation from the result of the CNV unit. Then, batch regularization is used to regularize the results of the pooling layer, which supports the network learning converges quicker when its inputs are whitened. The FC layer executes the weighted amount of the characteristics from the preceding units and the attribute region is transformed to the basic indicator region using the linear conversion. Finally, the softmax function is applied to map several scalars to a probability distribution, which is the class of a given input signal (i.e., R, SV, V, M and U). Additionally, a residual training module is adopted in the 1D signal investigation to recognize shortcut links, which provides all layers fit a residual mapping rather than requiring all staked units to immediately fit a targeted original mapping [18]. The residual training module is split into identity mapping and residual mapping. Table 1 summarizes the final configuration of the CNN structure.

**Table 1. Configuration of Hyperparameters for CNN**

| Hyperparameters | Range |
|---|---|
| Batch range | 256 |
| Training rate | 0.001 |
| Number of epochs | 35 |
| Activation function | ReLU |
| Optimizer | Adam |
| Loss factor | Cross-entropy |

*LSTM-GRU:*

In the LSTM-GRU structure, the LSTM is initially applied to solve the vanishing gradient issue in the back-propagation. It comprises 3 gates such as input $(i_t)$, forget $(f_t)$ and output $(o_t)$ gates, whereas the GRU comprises 2 gates such as update gate $(u_t)$ and reset gate $(r_t)$. The result of the LSTM is given to the GRU. Let $\sigma$ is the sigmoid function, $w_x$ is the weight for the corresponding gate $x$, $h_{t-1}$ is the result of the preceding LSTM unit at time $t-1$, $x_t$ is the input at present time $t$, $b_x$ is the bias for the corresponding gate $x$, $C_t$ is the memory (cell outcome) at $t$, $\tilde{C}_t$ is the nominee (cell input) for storage at $t$.

The LSTM has 3 gates ($i_t, f_t$ and $o_t$). GRU has 2 gates ($u_t$ and $r_t$). The hidden units of LSTM-GRU are $\tilde{C}_t$, $\tilde{h}_t$ and $h_t$. The weights of LSTM are $w_i, w_f, w_o$ and $w_c$. The weights of GRU are $w_u, w_r, w_o$ and $w_{C_t}$. LSTM-GRU has biases $b_i, b_f, b_o$ and $b_c$. Also, $tanh$ is the hyperbolic tangent function and the scalar products of 2 vectors are defined by $\circ$.

If $x_t$ is fed to the input layer, then it is multiplied by $w_i$ and $h_{t-1}$ is multiplied by $w_i$, which is further included with $b_i$. The $h_{t-1}$ keeps the data of preceding layers $t-1$. It provides the sigmoid operation and transforms range from 0 to 1, as well as, modifies the cell condition.

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \quad (1)$$

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f) \quad (2)$$

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$

Eqns. (4) & (5) define how to create the outcome from 0 to 1 by the sigmoid activation factor. $\tilde{C}_t$ and $C_t$ are utilized to confirm what data is preserved in storage and what data is neglected. $\tilde{C}_t$ is multiplied using $tanh$ and confirms which range is highly important.

$$\tilde{C}_t = tanh(w_C \cdot [h_{t-1}, x_t] + b_C) \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (5)$$

Eqns. (6) and (7) define that $C_t$ is fed to the initial unit of the GRU $(u_t)$ in which $u_t$ and $h_{t-1}$ are multiplied by a weight and the resultant data is passed to $r_t$.

$$u_t = \sigma(w_u \cdot [C_t] + w_u \cdot [h_{t-1}]) \quad (6)$$

$$r_t = \sigma(w_r \cdot [C_t] + w_r \cdot [h_{t-1}]) \quad (7)$$

Eqns. (8)-(10) defines that $h_t$ decides data be stored. The stored data is further given to the output unit. This unit has $tanh$ as an activation function, which is utilized to capture time-invariant and temporal characteristics. Adam is applied as a fine-tuner and the Mean Squared Error (MSE) is an error factor.

$$h_t = u_t \circ h_{t-1} + (1 - u_t) \circ \tilde{h}_t \quad (8)$$

$$\tilde{h}_t = tanh(w_{C_t} + r_t \circ w_{C_t}[h_{t-1}])$$

(9)

$$h_t = o_t * tanh(h_t)$$

(10)

Table 2 provides the absolute setting of the LSTM-GRU structure.

**Table 2. Configuration of hyperparameters for LSTM-GRU**

| Hyperparameters | Range |
|---|---|
| Batch range | 256 |
| Training rate | 0.001 |
| Number of epochs | 35 |
| Number of hidden units | 4 |
| Hidden neurons | 128 |
| Dropout percentage | 0.5 |
| Activation factor | $tanh$ |
| Outcome neuron | 1 |
| Outcome unit activation factor | Linear |
| Fine-tuner | Adam |
| Error factor | MSE |

**3.4 Design of ArithNet for arrhythmia identification**

After preprocessing, both ECG signal collections X and Y are fed to the ArithNet classifier to identify arrhythmia samples. The key concept of the ArithNet is to create a robust feature mining for capturing characteristics from ECG recordings. This network can simply adapt to various databases by transfer learning strategy. The structure of the ArithNet as depicted in Figure 2 majorly relies on the CNN-LSTM-GRU structure. It has 3 parallel CNV modules for representation training, whereas 7 CNV layers, 2 residual learning modules, 2 max-pooling layers, single global mean pooling, 2 LSTM-GRU modules, 2 FC layers and one softmax layer for sequence residual training.

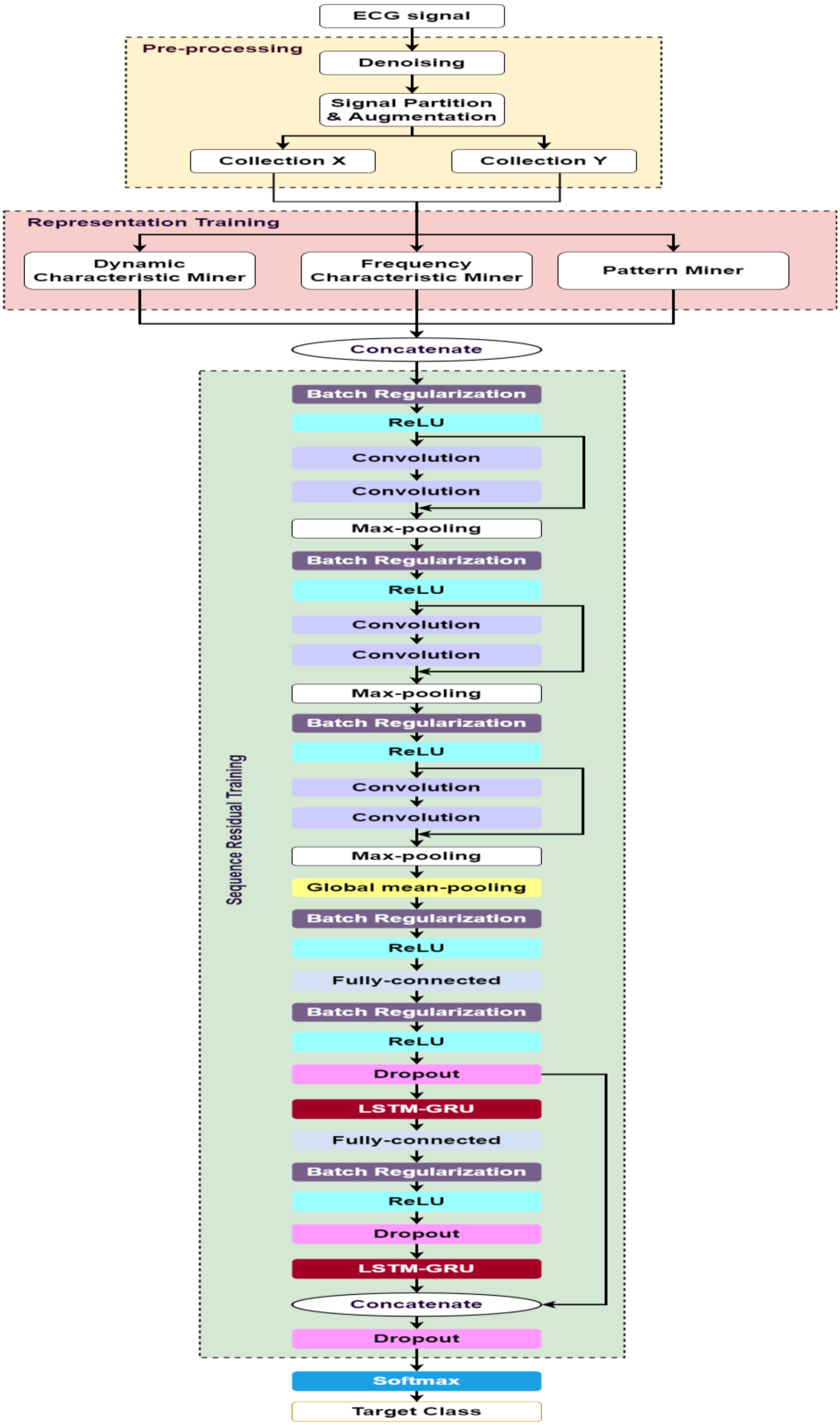


**Figure 2. Overview structure of proposed ArithNet model**

The representation training is performed to capture time-invariant characteristics from all ECG recordings. It has 3 parallel CNN such as dynamic characteristic miner, frequency characteristic miner and pattern miner. The frequency characteristic miner has 4 1D CNV units and 2 max-PUs including the major kernel dimension of sampling rate $S_r \times 4$ and stride dimension $S_r/2$ for the 1D CNV unit to obtain the occurrence elements. The successive kernel and stride dimensions are selected by hyperparameter adjustment.

Likewise, the pattern miner involves 4 1D CNV units and 2 max-PUs. But, the fine-grained CNV including kernel and stride dimensions assigned as $S_r/2$ and $S_r/16$, correspondingly are utilized to find the emergence of different ECG waves. The successive kernel and stride dimensions are selected using hyperparameter adjustment. The incoming signals are redesigned into a 2D tensor and passed to the dynamic characteristic miner. It has 2D CNV units, batch regularization, max-pooling and squeeze-expansion units. So, the results from these 3 CNNs are aggregated and passed to the sequence residual training module.

The sequence residual training is performed to capture the sequential characteristics from the series of characteristics mined in the preceding module. In this training, 2 blocks of LSTM-GRU are applied to train sequential data that facilitates the encoding of history and upcoming data using 2 separate LSTM-GRUs. A skip link is used to execute the residual operation and facilitate the fusion of temporal characteristics and earlier captured characteristics from the CNNs. The aggregated characteristics vector is then passed to the softmax unit, which determines the probability of five different ECG signal waves and identifies the arrhythmia disorder categories. Thus, this ArithNet model is trained and applied to identify and categorize the arrhythmia heartbeats from the test ECG signals.

## 4. EXPERIMENTAL RESULT

This part examines the efficacy of the ArithNet model by implementing it in MATLAB 2019a using the MIT-BIH and Arrhythmia Data Set (discussed in Section 3.1). As well, a comparative analysis is carried out to understand the improvement of the ArithNet model contrasted to the existing models, including MSF-CNN [18], MF-CBRNN [22], IBL [23], 1D-CNN [26] and CNN-LSTM [28]. The evaluation metrics used to measure the success of the proposed and existing models include:

- Accuracy: It is the proportion of the number of exact identifications of normal and arrhythmia cases to the overall cases analyzed.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)} \quad (11)$$

In Eq. (11), the amount of normal beats properly classified normal is TP, while the amount of arrhythmia beats properly classified as arrhythmia is TN. Also, FP represents the amount of arrhythmia beats improperly classified as normal, whereas FN represents the amount of normal beats improperly classified as arrhythmia.

- Precision: It is calculated by

$$Precision = \frac{TP}{TP + FP} \quad (12)$$

- Recall: It is determined as:

$$Recall = \frac{TP}{TP + FN} \quad (13)$$

- F-score ($F$): It is calculated by

$$F = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (14)$$

### 4.1 Accuracy

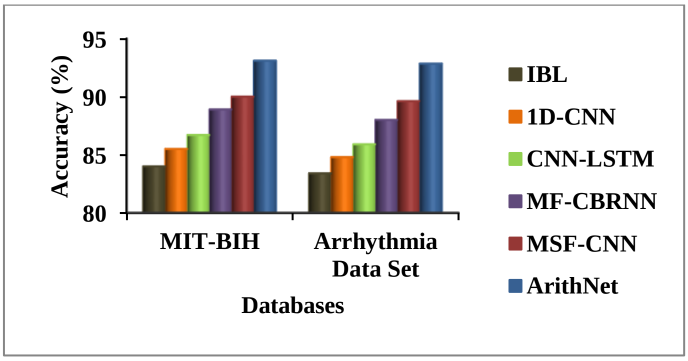


**Figure 3. Comparison of accuracy**

Figure 3 displays the accuracy (in %) realized by the different arrhythmia identification and classification models applied to 2 different databases. It addresses that the accuracy of the ArithNet model on the MIT-BIH database is 10.82% greater than the IBL, 8.88% superior to the 1D-CNN, 7.37% superior to the CNN-LSTM, 4.71% superior to the MF-CBRNN and 3.43% greater than the MSF-CNN models. Similarly, the accuracy of the ArithNet model on the Arrhythmia Data Set is 11.32% greater than the IBL, 9.48% greater than the 1D-CNN, 8.08% greater than the CNN-LSTM, 5.5% greater than the MF-CBRNN and 3.6% greater than the MSF-CNN models. This is because of capturing both time-invariant and temporal characteristics along with the deep features from the ECG recordings to classify arrhythmia classes.

**4.2 Precision**

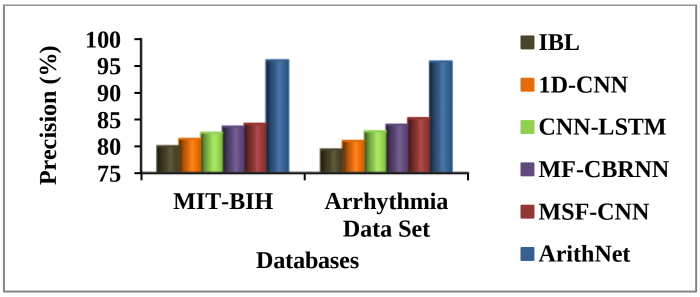


**Figure 4. Comparison of precision**

In Figure 4, the precision (in %) of the ArithNet model is compared with various arrhythmia identification and classification models applied to 2 different databases. It observes that the precision of the ArithNet model on the MIT-BIH database is 20.04% better than the IBL, 18% better than the 1D-CNN, 16.39% better than the CNN-LSTM, 14.77% better than the MF-CBRNN and 14.06% superior to the MSF-CNN models. Similarly, the accuracy of the ArithNet classifier on the Arrhythmia Data Set is 20.65% better than the IBL, 18.27% better than the 1D-CNN, 15.74% better than the CNN-LSTM, 14.02% better than the MF-CBRNN and 12.39% better than the MSF-CNN models due to the implementation of representation training and sequence residual training processes

.

**4.3 Recall**

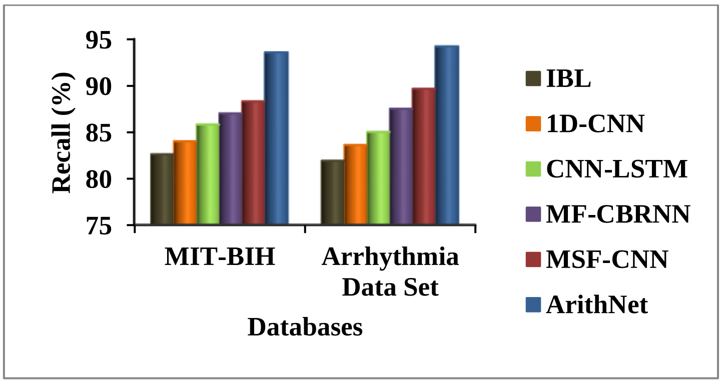


**Figure 5. Analysis of recall**

Figure 5 demonstrates the recall (in %) obtained by the different arrhythmia identification and classification models applied to 2 different databases. It analyzes that the recall of the ArithNet model on the MIT-BIH database is 13.28% larger than the IBL, 11.39% larger than the 1D-CNN, 9.06% larger than the CNN-LSTM, 7.55% larger than the MF-CBRNN and 5.97% larger than the MSF-CNN models. Similarly, the recall of the ArithNet model on the Arrhythmia Data Set is 15.03% larger than the IBL, 12.69% larger than the 1D-CNN, 10.84% larger than the CNN-LSTM, 7.67% larger than the

MF-CBRNN and 5.1% larger than the MSF-CNN models. This realizes that the ArithNet model increases the recall of identifying and categorizing arrhythmia classes compared to the other models because of improving the feature learning tasks.

**4.4 F-score**

Figure 6 portrays the f-score (in %) achieved by the different arrhythmia identification and classification models applied to 2 different databases. It indicates that the f-score of the ArithNet model on the MIT-BIH database is 16.58% higher than the IBL, 14.62% higher than the 1D-CNN, 12.62% higher than the CNN-LSTM, 11.06% higher than the MF-CBRNN and 9.95% higher than the MSF-CNN models. Similarly, the f-score of the ArithNet model on the Arrhythmia Data Set is 17.81% higher than the IBL, 15.44% higher than the 1D-CNN, 13.26% higher than the CNN-LSTM, 10.79% higher than the MF-CBRNN and 8.66% higher than the MSF-CNN models.

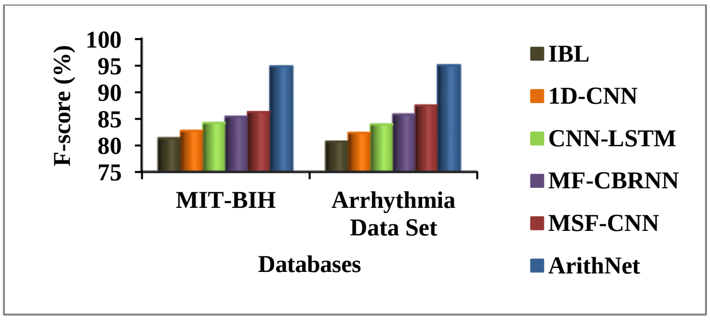


**Figure 6. Comparison of F-score**

Thus, it summarizes that the ArithNet model maximizes the efficiency of identifying and categorizing arrhythmia classes compared to all existing models due to the consideration of both representation and sequence residual training stages, which enhances the feature mining and classification.

**5. Conclusion**

In this study, the ArithNet model was designed based on the representation training and sequence residual training to identify arrhythmia classes from the ECG signals. Initially, distinct ECG recordings were acquired from the freely available databases and preprocessing methods were applied to eliminate the noises from the acquired ECG signals. After that, those signals were divided into R, SV, V, M and U waves according to the labels from cardiologists. Each signal was passed to the MSF-CNN-LSTM-GRU structure, wherein both representation and sequence residual training processes were executed to capture time-invariant and temporal features efficiently. Moreover, those features were aggregated and learned by the softmax function to identify the probabilities of different arrhythmia classes. Further, the investigational results realized that the ArithNet on MIT-BIH and Arrhythmia databases has 93.09% and 92.84% accuracy compared to the conventional arrhythmia identification models.

**References**

[1] R. P. Wong, E. A. Tinsley, M. A. Waclawiw, H. K. Krull and D. A. Lathrop, “National, heart, lung, and blood institute support of cardiac arrhythmia research,” Heart Rhythm, vol. 13, no. 7, pp. 1570-1572, 2016, doi: 10.1016/j.hrthm.2016.03.001.

[2] K. Tara and M. H. Islam, “Advances of cardiac state-inducing prototype and design of GUI to anatomize cardiac signal for ascertaining psychological working competence,” Sensing and Bio-Sensing Research, vol. 30, pp. 1-13, 2020, doi: 10.1016/j.sbsr.2020.100376.

[3] C. H. Papadopoulos, D. Oikonomidis, E. Lazaris and P. Nihoyannopoulos, “Echocardiography and cardiac arrhythmias,” Hellenic Journal of Cardiology, vol. 59, no.3, pp. 140-149, 2018, doi: 10.1504/IJCAT.2021.117285.

[4] S. S. Virani, A. Alonso, H. J. Aparicio, E. J. Benjamin, M. S. Bittencourt, C. W. Callaway and C. W. Tsao, “Heart disease and stroke statistics-2021 update: a report from the American Heart Association,” Circulation, vol. 143, no. 8, 2021, doi: 10.1161/CIR.0000000000000950.

[5] M. P. Brandão, P. Sa-Couto, G. Gomes, P. Beça and J. Reis, "Factors associated with cardiovascular disease risk among employees at a Portuguese higher education institution," International Journal of Environmental Research and Public Health, vol. 19, no. 2, pp. 848, 2022, doi: 10.3390/ijerph19020848.

[6] S. Maffei, A. Meloni, M. Deidda, S. Sciomer, L. Cugusi, C. Cadeddu and IGENDA Study Group, "Cardiovascular risk perception and knowledge among Italian women: lessons from IGENDA protocol," Journal of Clinical Medicine, vol. 11, no. 6, pp. 1695, 2022, doi: 10.3390/jcm11061695.

[7] B. Patel and A. N. Makaryus, "Artificial intelligence advances in the world of cardiovascular imaging," In Healthcare, Vol. 10, No. 1, pp. 154. MDPI, 2022, January, doi: 10.3390/healthcare10010154.

[8] M. Y. Khanji, N. Aung, C. A. A. Chahal and S. E. Petersen, "COVID-19 and the UK Biobank—opportunities and challenges for research and collaboration with other large population studies," Frontiers in Cardiovascular Medicine, vol. 7, pp. 156, 2020, doi: 10.3390/healthcare10010154.

[9] S. Aziz, S. Ahmed and M. S. Alouini, "ECG-based machine-learning algorithms for heartbeat classification," Scientific reports, vol. 11, no. 1, pp. 18738, 2021, doi: 10.1038/s41598-021-97118-5.

[10] V. Randazzo, J. Ferretti and E. Pasero, "Anytime ECG monitoring through the use of a low-cost, user-friendly, wearable device," Sensors, vol. 21, no. 18, pp. 6036, 2021, doi: 10.3390/s21186036.

[11] X. Zhang, K. Gu, S. Miao, X. Zhang, Y. Yin, C. Wan and Y. Liu, "Automated detection of cardiovascular disease by electrocardiogram signal analysis: a deep learning system," Cardiovascular Diagnosis and Therapy, vol. 10, no. 2, pp. 227, 2020, doi: 10.21037%2Fcdt.2019.12.10.

[12] S. A. Mahmoudinejad and N. Safdarian, "Evaluating morphological features of electrocardiogram signals for diagnosing of myocardial infarction using classification-based feature selection," Journal of Medical Signals and Sensors, vol. 11, no. 2, pp. 79, 2021, doi: 10.4103%2Fjmss.JMSS_12_20.

[13] Y. Xia and Y. Xie, "A novel wearable electrocardiogram classification system using convolutional neural networks and active learning," Ieee Access, vol. 7, pp. 7989-8001, 2019, doi: 10.1109/ACCESS.2019.2890865.

[14] K. C. Siontis, P. A. Noseworthy, Z. I. Attia and P. A. Friedman, "Artificial intelligence-enhanced electrocardiography in cardiovascular disease management," Nature Reviews Cardiology, vol. 18, no. 7, pp. 465-478, 2021, doi: 10.1038/s41569-020-00503-2.

[15] S. M. Mathews, C. Kambhamettu and K. E. Barner, "A novel application of deep learning for single-lead ECG classification," Computers in biology and medicine, vol. 99, pp. 53-62, 2018, doi: 10.1016/j.compbiomed.2018.05.013.

[16] Y. Liang, S. Yin, Q. Tang, Z. Zheng, M. Elgendi and Z. Chen, "Deep learning algorithm classifies heartbeat events based on electrocardiogram signals," Frontiers in Physiology, vol. 11, pp. 569050, 2020, doi: 10.3389/fphys.2020.569050.

[17] S. Śmigiel, K. Pałczyński and D. Ledziński, "Deep learning techniques in the classification of ECG signals using r-peak detection based on the PTB-XL dataset," Sensors, vol. 21, no. 24, pp. 8174, 2021, doi: 10.3390/s21248174.

[18] H. Dang, Y. Yue, D. Xiong, X. Zhou, X. Xu and X. Tao, "A deep biometric recognition and diagnosis network with residual learning for arrhythmia screening using electrocardiogram recordings," IEEE Access, vol. 8, pp. 153436-153454, 2020, doi: 10.1109/ACCESS.2020.3016938.

[19] F. Y. Abdalla, L. Wu, H. Ullah, G. Ren, A. Noor, H. Mkindu and Y. Zhao, "Deep convolutional neural network application to classify the ECG arrhythmia," Signal, Image and Video Processing, vol. 14, pp. 1431-1439, 2020, doi: 10.1007/s11760-020-01688-2.

[20] H. Yang and Z. Wei, "Arrhythmia recognition and classification using combined parametric and visual pattern features of ECG morphology," IEEE Access, vol. 8, pp. 47103-47117, 2020, doi: 10.1109/ACCESS.2020.2979256.

[21] H. Wang, H. Shi, K. Lin, C. Qin, L. Zhao, Y. Huang and C. Liu, "A high-precision arrhythmia

classification method based on dual fully connected neural network," Biomedical Signal Processing and Control, vol. 58, pp. 101874, 2020, doi: 10.1016/j.bspc.2020.101874.

[22] A. Chen, F. Wang, W. Liu, S. Chang, H. Wang, J. He and Q. Huang, "Multi-information fusion neural networks for arrhythmia automatic detection," Computer methods and programs in biomedicine, vol. 193, pp. 105479, 2020, doi: 10.1016/j.cmpb.2020.105479.

[23] J. Li, Y. Zhang, L. Gao and X. Li, "Arrhythmia classification using biased dropout and morphology-rhythm feature with incremental broad learning," IEEE Access, vol. 9, pp. 66132-66140, 2021, doi: 10.1109/ACCESS.2021.3076683.

[24] M. Murugappan, L. Murugesan, S. Jerritta and H. Adeli, "Sudden cardiac arrest (SCA) prediction using ECG morphological features," Arabian Journal for Science and Engineering, vol. 46, pp. 947-961, 2021, doi: 10.1007/s13369-020-04765-3.

[25] Y. Li, Z. Zhang, F. Zhou, Y. Xing, J. Li and C. Liu, "Multi-label classification of arrhythmia for long-term electrocardiogram signals with feature learning," IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-11, 2021, doi: 10.1109/TIM.2021.3077667.

[26] A. Darmawahyuni, S. Nurmaini, M. N. Rachmatullah, B. Tutuko, A. I. Sapitri, F. Firdaus and A. Predyansyah, "Deep learning-based electrocardiogram rhythm and beat features for heart abnormality classification," PeerJ Computer Science, vol. 8, pp. e825, 2022, doi: 10.7717/peerj-cs.825.

[27] B. M. Mathunjwa, Y. T. Lin, C. H. Lin, M. F. Abbod, M. Sadrawi and J. S. Shieh, "ECG recurrence plot-based arrhythmia classification using two-dimensional deep residual CNN features," Sensors, vol. 22, no. 4, pp. 1660, 2022, doi: 10.3390/s22041660.

[28] P. Madan, V. Singh, D. P. Singh, M. Diwakar, B. Pant and A. Kishor, "A hybrid deep learning approach for ECG-based arrhythmia classification," Bioengineering, vol. 9, no. 4, pp. 152, 2022, doi: 10.3390/bioengineering9040152.

[29] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," IEEE engineering in medicine and biology magazine, vol. 20, no. 3, pp. 45-50, 2001, doi: 10.1109/51.932724.

[30] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," circulation, vol. 101, no. 23, pp. e215-e220, 2000, doi: 10.1161/01.CIR.101.23.e215.

[31] https://physionet.org/content/mitdb/1.0.0/

[32] H. A. Guvenir, B. Acar, G. Demiroz and A. Cekin, "A supervised machine learning algorithm for arrhythmia analysis," In Computers in Cardiology 1997, pp. 433-436, IEEE, 1997, September, doi: 10.1109/CIC.1997.647926.

[33] https://archive.ics.uci.edu/ml/datasets/Arrhythmia

**BIOGRAPHIES OF AUTHORS**

| | |
|---|---|
|  | Dr. Shanmugasundaram Subbaiah, received his Bachelor Degree (B.Sc.(C.S)) from University of Madras, Chennai in 1995 and he completed his Master degree M.C.A. in Bharathidasan University, Trichy in 1998 and M.Phil.(C.S) in Bharathidasan University, Trichy in 2005. He did his Ph.D. in Anna University, Chennai in 2014. He is working as Associate Professor in Computer Science Department at SRM Institute of Science and Technology (Deemed to be University), Chennai. His Research Area is Data Mining. His Area of Interest is Big Data Analytics, Internet of Things and Computer Networks. His experience is more than 21 years. He organized various International/National Level Conferences, Technical Symposium, Workshops and Seminars. He is a lifetime member in Indian Society of Technical Education. He received fund from EDI to conduct awareness programme in Computer Science Subjects and applied for workshop, seminar and awareness programme for funding agencies namely UGC, |

| | |
|---|---|
| | ICMR and EDI. His paper is published in various journals and presented paper in various conferences. He can be contacted at email: subbaias@srmist.edu.in. |
| | |
|  | Dr. Subramanian Sivakumar is an Assistant Professor in the Department of Computer science and application (MCA), in SRM Institute of Science and Technology (Deemed to be University), Ramapuram Campus, Chennai. He received his B.Sc. Computer Science from Madras University and his post graduate degree M.C.A from Anna University. He has completed his PhD from Bharathiar University. He has 13 years of experience in Teaching and one year working as a Database Trainee from Eagel Software India Pvt Ltd, Chennai. His research interests include Network Security, Cyber Security, Mobile Adhoc networks, Vehicular Ad-hoc networks, Sensor Network. He can be contacted at email: sivakums11@srmist.edu.in. |
| | |
|  | Mrs. Muruganantham.Kavitha received her Bachelor's degree (B.Sc(C.S)) from Gobi Arts & Science College (Autonomous), Bharathiar University in 2003. She received her Master Degree (M.C.A) from Gobi Arts & Science College (Autonomous), Bharathiar University 2006 and she completed M.Phil (CS) in Bharathiar University in the year of 2008. Also, she qualified in SET exam conducted by the Bharathiar University in the year of 2012. Currently, she is pursuing Part time Ph.d(C.S) in Vivekanandha College Of Arts And Sciences for Women (Autonomous) in Periyar University. Her area of research includes data mining and big data. She has published her research paper in various journals. She can be contacted at email: sankavis@gmail.com. |