

Research Article

Hybrid BiGRU-BiLSTM Model for Real-Time ECG Arrhythmia Detection Using Wearable Sensors

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Abstract: Accurate and real-time detection of cardiac arrhythmias is essential for timely medical intervention. Advances in wearable devices and deep learning have made it feasible to continuously monitor electrocardiogram (ECG) signals, facilitating early identification of abnormal heart rhythms. For arrhythmia detection, this study presents a hybrid deep learning architecture combining Bidirectional Gated Recurrent Units (Bi-GRU) and Bidirectional Long Short-Term Memory (Bi-LSTM). To improve the extraction and classification of relevant features, the model incorporates Dilated Convolutional Neural Networks (DCNNs) alongside a hierarchical attention mechanism. The proposed framework achieves a maximum accuracy of 99.97%, surpassing the performance of conventional approaches. The proposed model achieved an accuracy of 99.97%, with a precision of 99.91%, a recall of 99.88%, and an F1-score of 99.89%. The hierarchical attention mechanism enhances interpretability by highlighting significant ECG segments contributing to classification decisions, ensuring transparency in clinical analysis. This method is well-suited for real-time implementation in wearable cardiac monitoring systems.

Keywords: Hybrid Deep Learning, BiGRU-BiLSTM, ECG Classification, Arrhythmia Detection, Wearable Sensors, Dilated CNN, Attention Mechanism

Introduction

Heart disease (CVD) is the leading cause of death and illness worldwide (Dang et al., 2019). Arrhythmia is among the most severe and potentially fatal CVDs. There are several types of arrhythmia, from tachycardia (too fast) to bradycardia to irregular patterns of heartbeat. Depending on their severity, cardiac arrhythmias can be benign or life-threatening (Yildirim et al., 2019). A clinical practitioner's ability to detect arrhythmia early is, therefore, crucial to saving lives (Islam et al., 2024). If an arrhythmia goes unnoticed or untreated, it may lead to life-threatening conditions like a stroke or heart attack. Arrhythmias can be detected by analyzing electrocardiograms (ECGs). Physiological signals have been continuously acquired in real-time by wearable sensors in recent years, enabling non-invasive monitoring of the heart. Healthcare systems that can make real-time decisions have been made possible by these advancements. ECGs are widely used diagnostic tools that record the heart's electrical activity during each heartbeat

(Jian et al., 2024). Three bipolar leads (I, II, III) are typically located on the left side of the device, three augmented unipolar leads (aVR, aVL, aVF) on the right side, and six chest leads (V1-V6) on the right side of the device. These leads collect signals from different angles across both horizontal and vertical planes, allowing for a thorough assessment of heart function. There are typically ten electrodes placed on the body of the patient to capture a complete and accurate picture of the cardiac rhythm (Irfan et al., 2022; Madan et al., 2022). In order to improve prediction accuracy, researchers frequently use ECG datasets to develop models for arrhythmia detection and classification (Andrés et al., 2022; Ardeti et al., 2023). Models can be built by detecting QRS complexes, RR intervals, and similarity between waveforms in ECG signals. The data are analyzed using time-domain and frequency-domain features, as well as statistical and morphological characteristics. SVMs, decision trees, random forests, K-Nearest Neighbor algorithms, Bayesian algorithms, and artificial neural networks are among the most commonly used algorithms. In addition,

cardiac dysfunction and arrhythmias are associated with sudden death. The study of ECG signals has thus drawn the attention of both computer enthusiasts and biomedical researchers. Considering the time and amplitude variations of the ECG signal, BLSTM models are utilized for time series analysis. Nevertheless, ELM-LRFs are among the fastest techniques for segmenting and classifying time series signals. FENGJUAN QIAO & Co. have proposed the DELM-LRF-BLSTM (Wang and Wu, 2022), a faster and more accurate hybrid deep learning model for recognizing ECG signals.

As deep learning advances, particularly in Recurrent Neural Networks (RNNs), time-series signal analysis is undergoing a revolution. An LSTM network that reflects both forward and backward temporal relationships and a gated recurrence unit network (BiGRU) that captures the relationship between forward and backward time. Most of the existing CNN, GRU-, and LSTM-based efforts, even with their greater accuracy, fail to properly quantify the ECG feature space and demonstrate limited interpretability for real-time deployment. The current study aims to overcome these obstacles by promoting a combination of the hybrid BiGRU–BiLSTM and dilated CNN for feature extraction, and the hierarchical attention mechanism for interpretability. Incorporating these elements is anticipated to enhance the classification performance and computational speed of real-time ECG analysis. In this research, a heartbeat classification model based on ECG signals is introduced, employing a hybrid BiGRU–BiLSTM architecture and utilizing data from the MIT-BIH Arrhythmia Database. Based on data from the MIT-BIH's Arrhythmia Database and a hybrid BiGRU–BiLSTM architecture, an ECG-based heartbeat classification model is presented in this study. In order to enhance classification accuracy, the BiGRU and BiLSTM models are integrated in a way that leverages the complementary strengths of both architectures. This approach also enables real-time and remote monitoring of arrhythmias using ECG signals collected via wearable devices, thereby enhancing the ability to detect cardiac arrests early and intervene in a timely manner.

Related Work

A persistent chronic heart condition that affects older people, in addition to strokes, cardiac failure, and coronary artery disease, is an irregular heartbeat. A cardiac patient's electrocardiogram (ECG) plays an important role in diagnosing and classifying arrhythmia heartbeats. An algorithm to extract the required or desired features was developed by Dang et al. (2019) by combining a simple CNN on top of a multiscale fusion CNN on top of a simple CNN. Simple CNNs are used to test the capacity of single-dimensional CNNs to process ECG signals. They have numerous convolutional layers and straightforward architectures. CNNs for learning can

be enhanced by the MSF-CNN. A. MIT-BH database signals (N), supraventricular ectopics (S), ventricular ectopics (V), fusion beats (F), and unknown beats (Q) are used in this study, and six groups of ablation experiments are performed to evaluate the effectiveness of these signals (Butt et al., 2022).

Multiple classification models are constructed by combining convolutional neural networks with recurrent neural networks. Each model has additional layers, including RNN, LSTM, and GRU versions. 83.7% accuracy was achieved by the hybrid model composed of three layers of CNNs and GRUs (Ardeti et al., 2023). The classification of five types of heartbeats was also done using CNN and GRU in different architectures (Yao, 2021). Five types of heart rhythms were classified using a convolution layer with six local feature extraction modules (LFEMs), followed by Dense and SoftMax. About 99% of the classifications were accurate using this model. A DNN was proposed for analyzing an ECG signal filtered by Sannino and De Pietro (2018). In Luo et al. (2017) an image feature extraction method based on stacked autoencoders (AE) and DNN classifiers is presented in this paper. Despite rarely exceeding 95% accuracy, Ahmed et al. (2023) shows how restricted Boltzmann machines and deep belief networks can detect arrhythmias. Warrick et al. The phase-harmonic correlation coefficients of ECG channels were extracted using a recurrent neural network based on bi-directional LSTM units (Warrick et al., 2022). An extreme learning machine was employed to extract features by utilizing a gated recurrent neural network, whereas CNNs were used for feature extraction. In Oh et al. (2019), an end-to-end approach based on U-Nets was proposed, as was a modified version based on Winograd convolutions in Cheng et al. (2022). He et al. (2023) used transformations to improve model efficiency by using different learning paradigms. An architecture based on transformers was shown to be effective in Xia et al. (2023). In the same vein, a transformer-free convolutional approach was proposed, but it did not produce promising results.

The proposed hybrid BiGRU–BiLSTM architecture is markedly different from the previous CNN, GRU, and LSTM-based ECG classification methods. The integration of dilated convolutional layers and hierarchical attention mechanisms in this architecture allows the model to learn long-range temporal dependencies and the fine-grained local patterns of waveforms, and achieves enhanced interpretability. Moreover, my study is unique due to the use of hierarchical attention that results in increased transparency in decision-making, which has not been thoroughly investigated.

Methods

The purpose of this section is to outline a hybrid design

based on BiGRU and BiLSTM for detecting arrhythmias in real-time using wearable sensors validated with an MIT-BIH arrhythmia dataset. A five-step approach is followed: Acquiring data, preprocessing, designing model architecture, training and validating, and deploying it in real-time. 47 individuals provided 48 half-hour, two-channel ECG recordings for the training and evaluation of the proposed model. Heartbeats from both normal and arrhythmic patients are included in the dataset, which cardiologists have annotated in accordance with AAMI EC57 guidelines. A wearable-based ECG system can be modelled using these signals, as they represent real-life clinical scenarios. A wearable sensor, such as a smartwatch or chest patch, might capture ECG signals similar to those in the deployment.

MIT-BIH Arrhythmia Database: A 24-minute ECG recording is contained in each of the 48 samples of the MIT-BIH dataset. Arrhythmias are most often detected and classified using this dataset. The BIH Arrhythmia Research facility recorded 48 two-lead ECGs from 47 subjects. ECG recordings were digitized with an 11-bit resolution and recorded for 30 minutes over a range of 10 mV. It was collected by the Massachusetts Institute of Technology and Beth Israel Deaconess Medical Center in Boston. The single-lead ECG model in this study uses only Modified Limb Lead II (MLII) signals. Because lead MLII signals were not available in the ECG records of the remaining two patients, 46 patients' signals were used. It was possible to classify only 15 types of heartbeats into five major categories using original MIT-BIH data: N, S, V, and F. For removing the effect of patient overlap and also for fair evaluation of the results, we split the dataset per patient: 70% training, 15% validation, and 15% testing. This strategy avoids data leaking and helps to generalize the model. EKG and respiration signals were filtered (0.5–40 Hz), normalized by Z-score scaling, and segmented with a 2-s sliding window. To compensate for class imbalance, SMOTE was utilized to over-sample the minority classes.

Bi-GRU-Bi-LSTM Model

The following sections discuss the proposed BiGRU-Bi-LSTM layers. Below are brief descriptions of the BiGRU-Bi-LSTM layers. The proposed method combines two-way GRUs and LSTMs. The GRU maintains its capability for long periods and back propagates through constrained nonlinearities, so gradients are less likely to be lost. A Bi-GRU has two blocks, one with 64 units and one with 128 units. We returned the sequence as true after reducing the normal drop to 0.5. For categorizing ECG signals, bidirectional LSTM-GRU is frequently used. LSTM-GRUs transmit data backwards. Data flows automatically in both directions through bidirectional LSTM-GRUs. This results in Bi-LSTMs understanding the situation better (Dang et al., 2019). For scalability, we

utilized a Bi-LSTM (Yildirim et al., 2019):

$$\overrightarrow{b}_{g_t} = (\overrightarrow{GRU}_T * \overleftarrow{h}_{t-1}).x_t \quad (1)$$

$$\overleftarrow{b}_{g_t} = (\overleftarrow{GRU}_t * \overrightarrow{h}_{t-1}).x_t \quad (2)$$

$$b_{g_t} = (\overrightarrow{h}_t * \overleftarrow{h}_t) \quad (3)$$

The Bi-LSTM sequences in Eqn. (5) to (7) function as follows:

$$\overrightarrow{b}_{l_t} = (\overrightarrow{LSTM}_t * \overleftarrow{h}_{t-1}).x_t \quad (4)$$

$$\overleftarrow{b}_{l_t} = (\overleftarrow{LSTM}_t * \overrightarrow{h}_{t-1}).x_t \quad (5)$$

$$b_{l_t} = (\overrightarrow{h}_t * \overleftarrow{h}_t) \quad (6)$$

The LSTM and GRU encoders generate the following variables:

$$BG = bg_1, bg_2, \dots, bg_m \in R^{n*d} \quad (7)$$

$$BL = bl_1, bl_2, \dots, bl_n \in R^{n*d} \quad (8)$$

Dilated convolution is performed on Bi-GRU and Bi-LSTM outputs obtained from parallel execution. A Bi-LSTM-Bi-GRU algorithm processes ECG signals in this layer using their long-range features.

Deep CNN Layer

The Deep CNN receives spatial information not obtained from normal CNNs, which perform convolution directly on pretrained weights. This Dilated CNN layer obtained output from concatenating BiGRU and BiLSTM. Eqn. (10) to (12) present the combined feature representations obtained from both the BiLSTM and BiGRU layers:

$$RV_{Bi-GRU} = BG = bg_1, bg_2, \dots, bg_m \in R^{n*d} \quad (9)$$

$$RV_{Bi-LSTM} = BL = bl_1, bl_2, \dots, bl_n \in R^{n*d} \quad (10)$$

$$RV_l = Concatenation(RV_{Bi-GRU}, RV_{Bi-LSTM}) \quad (11)$$

An input sequence scalar component, d . Each intermediary architecture's output can be viewed as its final component:

$$RV^1 = [rv_1^l, rv_2^l, \dots, rv_n^l] \in R^{n*d}, \in (1, L) \quad (12)$$

The total number of convolution blocks is denoted by L , with each block containing k filters, and the i^{th} block is analyzed further:

$$W^l \in R^{k*w*k}, W^l R^{k*w*d} \quad (13)$$

A single filter of size k is applied along with the w

input vectors to construct the convolutional matrix. The adjustment between two consecutive blocks is described as follows:

$$RV = F(W^1, RV^{l-1}) \quad (14)$$

The operation involves sliding filter kernels across input sequences of length w , treating them as fixed-size windows, where f represents an algebraic transformation function. The value $rv_1^l \in RV^l$ is formally computed as follows:

$$rv_t^l = ReLU(W^l \oplus [rv_{t+1r}^{l-1}]_{t=0}^{w-1}) \quad (15)$$

The symbol \oplus represents the convolution operation, and r refers to the depth of the network layer in the CNN model. Rectified linear units (*ReLU*) are an activation function that applies a non-linear transformation to introduce sparsity and improve learning efficiency. In the BiGRU-BiLSTM-based deep architecture, each convolutional block is increased with the maximum number of layers of 2^{L-2} , where L is the total number of layers. Every block has a maximum $(w - 1)2^{L-2}$ width. The weights of a deep learning layer usually increase exponentially with network depth rather than linearly. The receiving field is calculated by $(W - 1) * 2^{L-2}$. The output feature maps, denoted by $RV^1, RV^2, \dots, \dots, \dots, RV^L$ represent hierarchical representations of the input. The final output of the CNN layer is generated via vector routing, with the convolutional outcome labelled as rv_1^N .

In the current implementation, the convolutional layer produces the following hierarchical output:

$$RV^1 = [rv_1^l, rv_2^l, \dots, \dots, rv_n^l] \in R^{n \times k}, l \in (1, L)$$

i^{th} convolutional block produces $R^{n \times k}, l \in (1, L)$ as its output. An RV n -gram feature derived from a filter mapping is denoted by the symbol:

$$CV^1 = [CV_1^l, CV_2^l, \dots, \dots, CV_n^l] \in R^{M \times d_v}$$

Where M represents the total target convolution blocks, and d_v is the dimensionality of the output features. The objective is to transform the set RV^l to CV^l to improve the interpretability of the learned features and facilitate accurate information categorization. The predicted feature vector, $\widehat{rv}_{j|l}$, is obtained by applying a linear transformation using the matrix W_j . Where:

$$\widehat{rv}_{j|l} = rv_i * W_j \quad (16)$$

This transformation enables the model to effectively translate raw vector features into a form suitable for downstream classification tasks. This approach enhances

the efficiency of information flow and control within the routing mechanism by normalizing large vector representations into unit vectors and extending smaller ones as needed. An iterative hierarchical routing strategy is employed across two convolutional layers to compute the intermediate feature representations. The inclusion of a hierarchical attention mechanism further improves the interpretability of extracted features by combining long-range dependencies learned from the BiLSTM-BiGRU layers with locally significant features captured by the dilated CNN layer. This synergy between global and local features enhances classification accuracy in ECG signal analysis. Within the softmax-based routing process, the initial routing coefficient b_{ij} is initialized to zero and dynamically updated using the scaling factor a_{ij} , as defined in Eqn. (17) and (18). The final agreement value of a_{ij} is determined by the characteristics and size of the input samples, allowing the model to assign appropriate attention weights during feature aggregation:

$$a_{ij} = rv_i * \widehat{rv}_{j|l} \quad (17)$$

$$b_{ij} = b_{ij} + a_{ij} \quad (18)$$

Hierarchical attention layer: This layer is designed to generate a focused and aggregated output by processing each target convolution as input. For every target convolution vector $cv_i \in R^{d_v}$ Within the set CV , an attention weight I is computed to represent the significance and contribution of each CV to the overall classification task. The attention mechanism quantifies this relevance using the formulation provided in Equation (19):

$$e_i = a(q, cv_i) \quad (19)$$

The probability distribution over the convolution pool CV is determined, where q represents the query or pattern vector from the training data, and k denotes the relevance score or likelihood associated with each convolutional feature in the pool. As a result of these relevance scores, a weighted sum of features can be computed, which is then passed on to the downstream classification layer. This process yields a fixed-length, attention-based aggregated feature vector for the final prediction:

$$o = \sum_i (a_{ij} * cv_j) \quad (20)$$

Prediction Layer: In this layer, y represents the target class label, and $P(y|S)$ is the probability distribution. A softmax activation function is used to produce a normalized probability distribution over the possible classes from the aggregated feature vector o generated from the attention mechanism:

$$o = \sum_i (a_k cv_o_i) \quad (21)$$

Input and prediction layers are depicted sequentially in the architecture. To evaluate the model's performance, real-world ECG data is utilized. Initially, the raw ECG signals undergo preprocessing, which includes filtering, noise reduction, and Z-score normalization. To execute and classify the signals sequentially, the preprocessed signals are transformed into deep learning frameworks. The implementation of the proposed model was based on TensorFlow and performed training on an NVIDIA GPU with 16GB RAM. The average time required for inference per ECG segment was around 0.23 ms, which has significant potential for low-power wearable devices. The experiments were repeated five times to assess consistency. Standard deviation has remained below 0.02, indicating the model is stable and robust.

Results and Discussion

ECG signals are used in this section to evaluate the performance of the hybrid BiGRU-BiLSTM model that has been proposed to detect arrhythmias. In addition to accuracy and loss, key performance metrics are used to assess the model's effectiveness. It is benchmarked against baseline models to highlight its classification capability, generalizability, and suitability for real-time deployment in wearable health monitoring systems. Figures 1(a) and 1(b) illustrate the progression of accuracy and loss over the course of training. As shown, the model's accuracy steadily improves and begins to stabilize after approximately 70 epochs, indicating effective learning. The loss curves in Figure 1(b) exhibit a similar trend: Training loss flattens around 65 epochs, while the validation loss, although initially volatile, stabilizes after 75 epochs. Although the model was configured to run for 150 epochs, training was automatically stopped at the 105th epoch using an early stopping mechanism, as further improvements were marginal. The validation process was carried out with a learning rate of 0.00015, yielding results that align well with expectations for the MIT-BIH Arrhythmia Dataset.

In all four heartbeat classes, Normal, Supraventricular, Ventricular, and Fusion, the hybrid BiGRU-BiLSTM achieved consistently high performance. A high accuracy rate, a high precision rate, a high recall rate, and a high F1-score indicate reliable classification performance. This model demonstrated both robustness and effectiveness across five repeated experiments, achieving an average accuracy of 99.51%. As shown by the precision, recall, and F1-scores, the model is capable of distinguishing between normal (N) and abnormal (S, V, F) heartbeats. Notably, the model achieved near-perfect scores for the N class, reflecting excellent recognition of normal rhythms. Although the performance for S and V beats was slightly lower, it remained at an impressively high level, ensuring reliable detection of arrhythmic patterns. In addition, an

in-depth examination of the class-wise performance indicates that supraventricular and ventricular classes exhibit relatively low recall values in comparison to the other classes, which can be explained by the class imbalance problem.

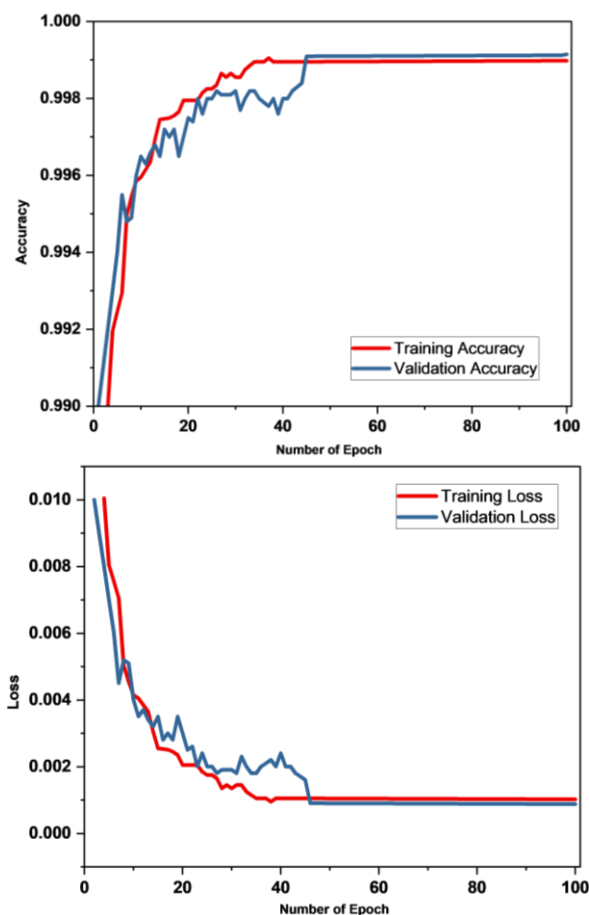


Fig. 1: Performance analysis for MIT-BIH dataset (a) Accuracy versus number of epochs and (b) Loss versus number of epochs

Moreover, the result of the generation of hierarchical attention maps shows the model's capability to concentrate on the QRS complexes and abnormal waveform segments, ultimately providing insight into model predictions for clinicians. Based on the MIT-BIH Arrhythmia Dataset, the model's generalization and stability are confirmed. Figure 2 illustrates how the model consistently achieved 98.97% accuracy across all runs, with consistently high precision, recall, and F1-scores -- especially for normal beats, where these metrics exceeded 99%, confirming its suitability for real-world ECG classification.

Table 1 illustrates how deep learning models can be utilized to detect cardiac arrhythmias using various databases. The proposed model detects cardiac

arrhythmias with the same effectiveness and competence as existing research on the MIT-BIH datasets.

Wearable systems such as smart watches and chest patches benefit from the lightweight architecture and dilated CNN layers that ensure efficient memory usage and fast response times.

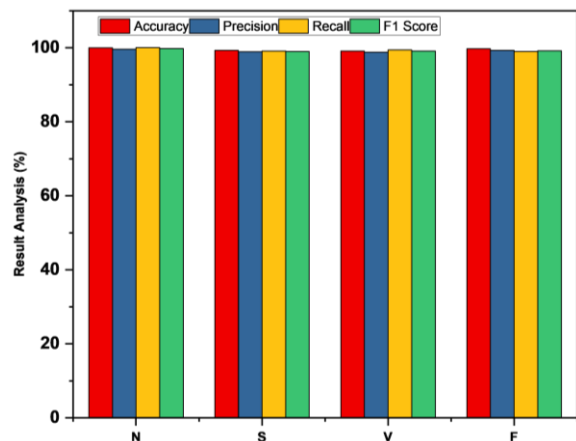


Fig. 2: Comparative performance analysis based on the number of classes

Table 1: Comparative result analysis

Article	Method	Dataset	Accuracy (%)
Islam et al. (2022)	CNN-BI-LSTM-Bi-GRU-CCE	MIT-BIH	99.90
Khan et al. (2023)	CNN	MIT-BIH	92.86
Islam et al. (2024)	CAT-Net	MIT-BIH	99.14
Proposed Model	Proposed Model	MIT-BIH	99.97

Conclusion

We present a hybrid BiGRU-BiLSTM deep learning framework for detecting real-time arrhythmias based on ECG signals collected from wearable sensors. The proposed model effectively integrates BiGRU's sequential learning capabilities with BiLSTM's robust long-term dependency modelling capabilities. An enhanced feature extraction and classification mechanism is further enhanced by the addition of a dilated convolutional layer and a hierarchical attention mechanism. A series of extensive experiments on the MIT-BIH Arrhythmia Dataset validates the model's accuracy, with consistently high precision, recall, and F1 scores for every class of heartbeats. It is demonstrated that the architecture can be applied to real-time implementation on resource-constrained wearable devices, showing strong generalization and stability across multiple runs. The hierarchical attention mechanism makes the model's predictions easier to interpret, so clinicians can determine

which signals influence classification outcomes. This framework will be tested on additional datasets, evaluated for energy efficiency on embedded hardware, and integrated with explainable AI techniques for transparent decision-making in future research.

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Authors Contributions

Prem Narayan Singh: The implementation and writing of the paper done by me.

Rajendra Prasad Mahapatra: Supervised each and every steps of writing research article. Author contributed in reviewing it critically for significant intellectual content.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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