Recurrent Neural Network-based Model for Electrocardiogram Classification

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ABSTRACT

This paper presents the study of deep learning models for Electrocardiogram (ECG) classification. Abnormalities of heart diseases can detect and diagnose by ECG signal. Deep learning models have been interested for arrhythmia detection and classification from ECG signal. Recurrent Neural Networks (RNNs) represent a different category of artificial neural networks that incorporate feedback mechanisms. It makes suitable for capturing temporal dependencies in the time series data from ECG electrical signal. Long short-term memory (LSTM) network and gated recurrent unit (GRU) are types of RNN designs. The objective of this paper is to compare the performance of conventional RNN with LSTM and GRU models for capturing the long-term relationships in ECG data. Simulation results show that GRU model can classify the heart's diseases more accuracy than simple RNN and LSTM model.

***Keywords**: Deep learning, Electrocardiogram (ECG), Recurrent Neural Network (RNN), Gated recurrent unit (GRU). Long short-term memory (LSTM).*

1. INTRODUCTION

Electrocardiogram (ECG) is a tool for detecting and classifying heart diseases by capturing the heart's electrical signals through electrodes [1]. While ECG signal is abnormal that can diagnose for many pathology and can provide the information about the heart's condition such as the coronary artery disease, heart attack, abnormal heart rhythms, and heart muscle disease.

Deep learning techniques are used for the ECG interpretation by analyzing and interpret data from ECG time series data for the detection enhancement and precise classification. These characteristics allow the deep learning models to understand the different types of heart's problem [2]. In [3], the authors have been presented some conditions to detect as atrial fibrillation (AF) from heartbeats that requires the pattern identification.

Low cost systems based on deep learning models [4] have been offered the real-time monitoring with high accuracy of interpretation of ECG signals. Then, the use of deep learning model in ECG interpret [5] has been standardized for the patient's outcome improvement.

In this paper, three models of deep learning as RNN, GRU and LSTM are studied with the dataset of ECG signal. Section 2 presents briefly the ECG measurement and Section 3 describes three deep learning architecture. Section 4 shows the experimental results. Datasets are used for training and validation models. Simulation results will compare the performance of three deep learning models. Conclusion is in Section 5.

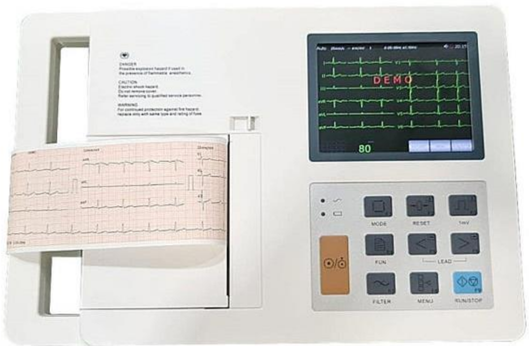

Fig. 1 *The 3-Channel ECG Machine [6]*

2. ECG MEASUREMENT

An ECG equipment records the electrical signals of the heart's activities in order to detect any abnormalities as shown in Fig. 1. During the test, sticky patches called electrodes are placed on the chest of patient, arms, and legs that are wired with an ECG machine. The results are typically presented a graph of heart's signals and activities, which shows the five components of ECG signal with its various intervals as follows.

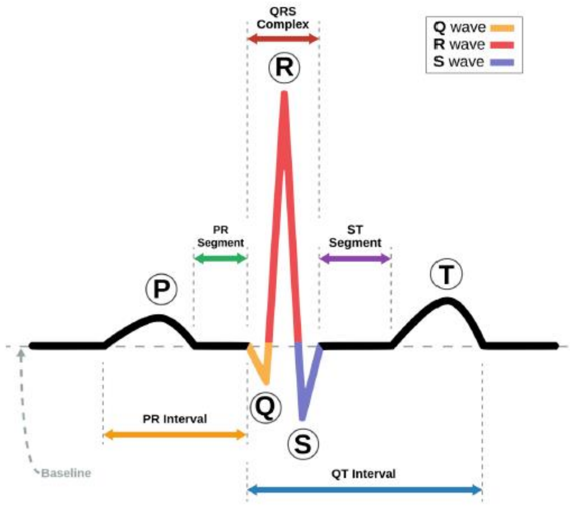

Fig. 2 *ECG Signal with its intervals [7]*

Following [7], P-wave from Fig. 2 shows the atria's depolarization and subsequent contraction. QRS complex consists of Q-wave, R-wave and S-wave. The QRS complex remarks the electrical signal transmission through the ventricular myocardium. T-wave is the recovery phase that the change of its shape will be caused the various troubles as electrolyte imbalances or drug effects.

PR interval in Fig. 2 shows the time an electrical wave takes to travel from the atria to the atrio-ventricular (AV) node and then to the ventricles. QT interval denotes the duration for ventricular depolarization and repolarization. ST segment is the time elapsed between depolarization and repolarization of ventricles.

3. DEEP LEARNING MODELS

In this paper, all three deep learning models are studied as follows.

3.1 RNN model

Following [7], Recurrent Neural Network (RNN) is a type of artificial neural networks (ANN) that have feedback loops, making them suitable for understanding temporal relationships in time series data. RNN has some feature of cyclic connections, distinguishing them from traditional feedforward neural networks.

RNN is designed to recognize patterns in sequences of data. They have a memory that captures information about what has been calculated so far. This memory allows RNN to use prior inputs to influence the current output. Summary of RNN architecture shows in Fig. 3 and RNN network presented in Fig. 4, respectively.

3.2 GRU model

Gated Recurrent Unit [8] is a kind of RNN designed to address the vanishing gradient problem commonly found in traditional RNN. This capability has enhanced their ability to recognize long-term dependencies in data. GRUs control the information flow by selectively useful information and deleting irrelevant data. They are distinguished by their update and reset gates. Summary of GRU architecture shows in Fig. 5 and GRU network presented in Fig. 6, respectively.

Model: "RNN_Model"

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 187, 256)	66048
dropout (Dropout)	(None, 187, 256)	0
simple_rnn_1 (SimpleRNN)	(None, 128)	49280
dropout_1 (Dropout)	(None, 128)	0
dense (Dense)	(None, 5)	645

Total params: 115,973
Trainable params: 115,973
Non-trainable params: 0

Fig. 3 *RNN model summary*

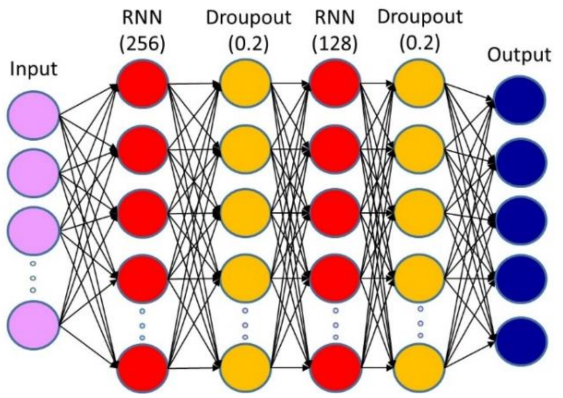

Fig. 4 *RNN network*

3.3 LSTM model

Long Short-Term Memory Network (LSTM) is a type of RNN model for sequential data since it can recall information over long periods of time [9]. Memory cells that store information and gates that control the flow of information into and out of these cells are two of the special features of LSTMs. These gates allow LSTMs to learn and retain longer sequences. Especially, these features can gain for overcome the vanishing gradient problem common in standard RNNs [10].

Summary of LSTM architecture shows in Fig. 7 and LSTM network presented in Fig. 8, respectively.

4. EXPERIMENTS AND SIMULATION RESULTS

ECG dataset is used in all three models to classify the heart's disease [11], [12]. This dataset consists of

Model: "GRU_Model"

Layer (type)	Output Shape	Param #
gru (GRU)	(None, 187, 256)	198912
dropout_2 (Dropout)	(None, 187, 256)	0
gru_1 (GRU)	(None, 128)	148224
dropout_3 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 5)	645

Total params: 347,781
Trainable params: 347,781
Non-trainable params: 0

Fig. 5 *GRU model summary*

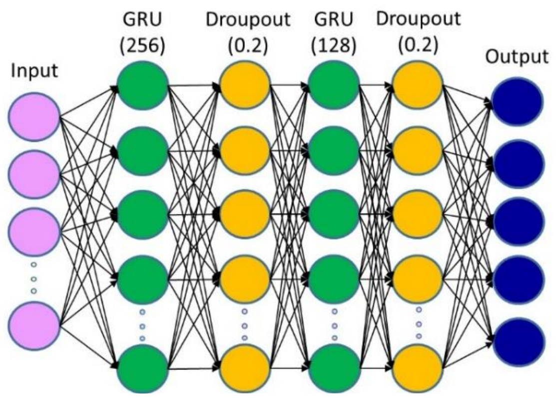

Fig. 6 *GRU network*

ECG signal collected from patients with the cardiac conditions. A set of ECG signal in Fig. 9 comprises with the normal condition shown in Fig. 9(a), the premature ventricular contraction (PVC) shown in Fig. 9(b), the fusion of paced and normal in Fig. 9(c), the atrial premature (AP) in Fig. 9(d) and the fusion of ventricular and normal shown in Fig.9(e), respectively.

This experiments are following the multiple stages, including data collection, preprocessing, model training, and evaluation. Each model RNN, GRU, and LSTM follow 4 steps as follows.

4.1 Data preprocessing

A sample of ECG dataset [11], [12] including with 5-class of ECG signal as the normal condition, premature ventricular contraction, fusion of paced and normal, atrial premature and the fusion of ventricular and normal. It is loaded and encoded in form of step of preprocessing.

4.2 Model training and Hyper-parameter tuning

All RNN, GRU and LSTM are tailored with architecture shown in Figs. 3, 5, 7, respectively. RNN model consist of two RNN-model layers, with the first containing 256 units and the second containing 128 units

```
Model: "LSTM_Model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 187, 256)          264192

 dropout (Dropout)           (None, 187, 256)          0

 lstm_1 (LSTM)               (None, 128)               197120

 dropout_1 (Dropout)         (None, 128)               0

 dense (Dense)               (None, 5)                 645

=================================================================
Total params: 461,957
Trainable params: 461,957
Non-trainable params: 0
```

Fig. 7 *LSTM model summary*

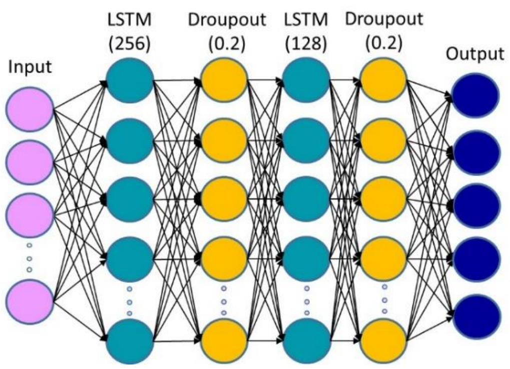

Fig. 8 *LSTM network*

In a similar fashion, GRU model consist of two GRU-model layers, with the first containing 256 units and the second containing 128 units. Then, LSTM model follows a similar structure, with two LSTM layers having 256 and 128 units, respectively. Dropout for each model is of 0.2.

Hyper-parameter tuning stand for a number of epochs used, batch size and learning rate to enhance the models. Training process starts with 10 epochs with 32 batch size. Adam optimizer is applied while training. Activation function is used by Softmax for classified 5 outputs shown in Fig. 9. There are five outputs by five classes of ECG dataset as 1) normal, 2) Premature Ventricular Contraction (PVC), (3) fusion of paced and normal, (4) atrial premature and (5) Fusion of paced and normal.

4.3 Evaluation Metrics

For model evaluation, loss and accuracy curves are suggested to analyze for model performance.

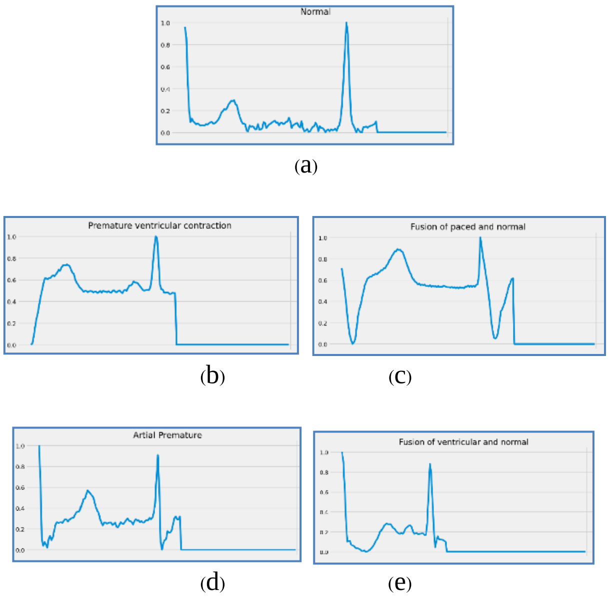

Fig. 9 *Five classes of ECG dataset; (a) normal, (b) Premature Ventricular Contraction (PVC), (c) fusion of paced and normal, (d) atrial premature and (e) Fusion of paced and normal.*

4.4 Experimental Execution

For experiments, we assume that the training set is used at 80% for training and 10% for testing and 10% for validation.

Performance of RNN, LSTM and GRU models are simulated by training-validation losses and training-validation accuracy as shown in Fig. 10. Performance of RNN model with training and validation losses is presented in Fig. 10(a) and the curves of training and validation accuracy is shown in Fig. 10(b). It is found that RNN model happens the average of accuracy about 82.76%, but the loss is still high around 64.38%.

Performance of LSTM model with training and validation losses is presented in Fig. 11(a) and the curves of training and validation accuracy is shown in Fig. 11(b). Noted that LSTM model shows the average of accuracy about 93.84%, but the loss is a bit high at 23.33%.

Meanwhile, performance of GRU model with training and validation losses is presented in Fig. 12(a) and the curves of training and validation accuracy is shown in Fig. 12(b). Noticed that GRU model shows the average of accuracy about 98.11%, but the loss is low at 7.02%.

5. CONCLUSION

We have presented the deep learning model based on recurrent neural network for ECG classification with five classes of heart's disease. It is concluded that GRU model can maintain a high accuracy rate for ECG tasks with datasets. This experiment investigates the impact of GRU model compared to RNN and LSTM models for ECG classification. GRU achieves an accuracy of 98.11% when a loss of 7.02%.

6. ACKNOWLEDGEMENT

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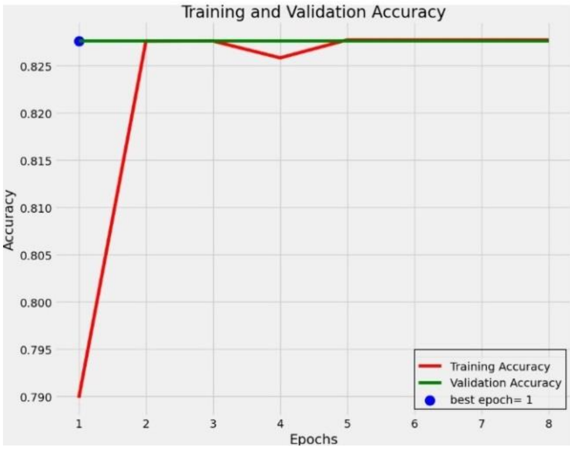
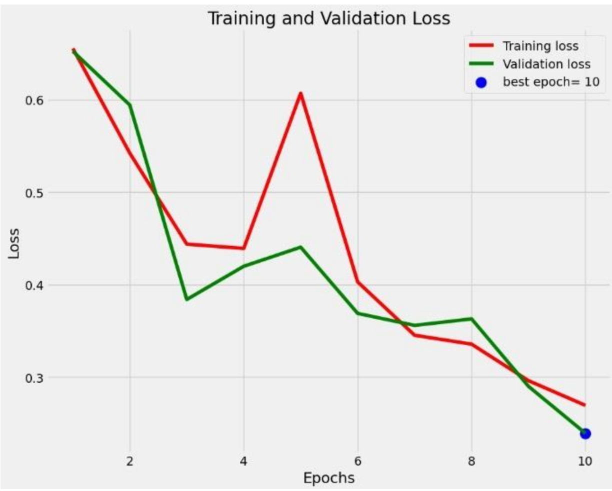
(a)

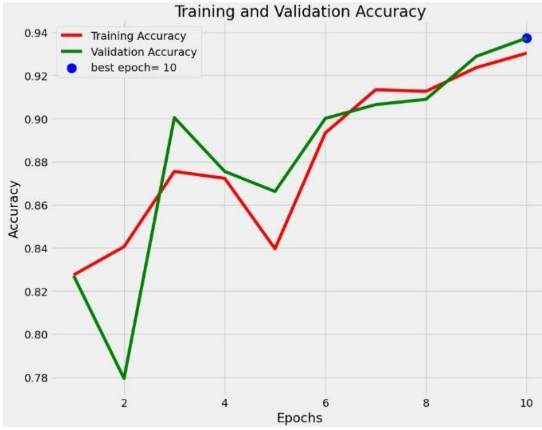


(b)

Fig. 10 *Training and Validation Losses and Accuracy for RNN model*

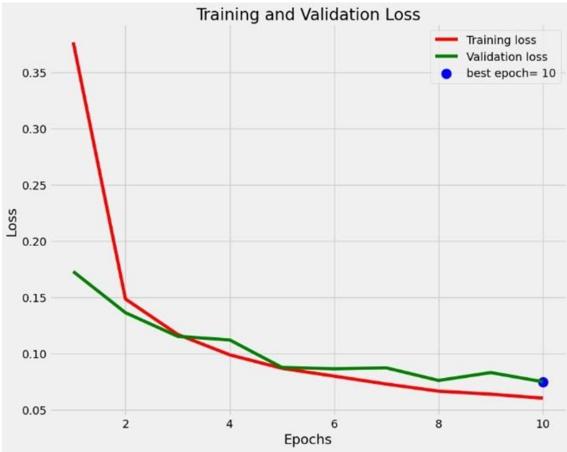


(a)

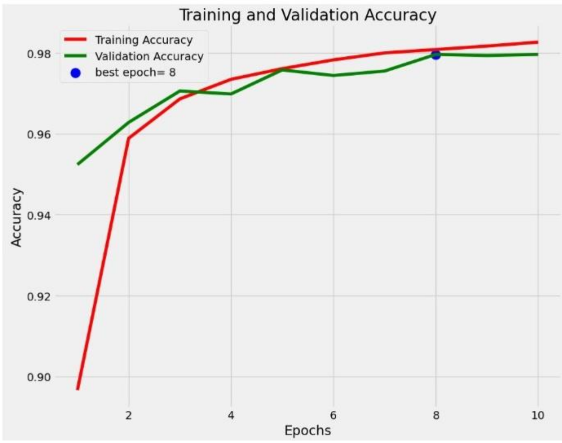


(b)

Fig. 11 *Training and Validation Losses and Accuracy for LSTM model*



(a)



(b)

Fig. 12 *Training and Validation Losses and Accuracy for GRU model*

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