https://doi.org/10.29042/2020-10-5-81-86

Helix (2020) 10 (5): 81-86

An Optimized Solution: Deep Residual Learning for ECG Signal Classification

✉ [1] P. Rama Santosh Naidu, [2] Dr. G. Lavanya Devi

[1] Department of Computer Science and Engineering, MVGR College of Engineering (A), Andhra Pradesh, India
prsn1988@gmail.com

[2] Department of Computer Science and Systems Engineering, Andhra University College of Engineering (A), Andhra Pradesh, India
lavanyadevig@yahoo.co.in

Received: 09th September 2020, Accepted: 14th October 2020, Published: 31st October 2020

Abstract

Time matters the most in medical diagnosis. Therefore, ECG has been extensively used in diagnosis and precise identification of several cardiac conditions. As continuation to the previous work, which concerned about feature extraction and classification of ECG signals applying CNN on distinct datasets, this paper presents residual learning model that makes training of networks easier and substantially deeper since the deeper neural networks are difficult to train. The proposed solution is classified into two types, one with no residual connection (Basic CNN) and the other analyzing the repetition of residual connections (Residual CNN) for displaying the variation in performance level of each model. The proposed model offers extensive observational proof indicating that residual model is an optimized framework that shows better results of accuracy from considerably increased depth. From the performance of the (Deep Residual CNN) we also see that we can better exploit these residual connections by making the model much deeper. Such a model can be conveniently used for constant monitoring of ECG in real time environment.

Keywords

Basic CNN, Residual CNN, Convolution Layer, Max Pool Block

Introduction

Deep Learning, to know the technique for cardiac arrhythmia (17 training) detection primarily depends on lengthy-length electrocardiography (ECG) sign analysis. Prevention of Cardiovascular disorder is major role of any medical device as about 50 million humans are liable to coronary heart disorder within the international. Despite the fact that automatic analysis of the ECG sign may be very famous, present-day strategies are not super. research is based totally on 1000 ECG sign fragments from the MIT - BIH Arrhythmia database for one lead (MLII) from 45 ladies and men. a way based totally on the assessment of 10-s ECG signal fragments (now not a single QRS complicated) is applied (on common, thirteen instances fewer classifications/evaluation). A whole quit-to-cease shape changed into designed in place of the hand-crafted characteristic extraction and choice applied in conventional strategies. Deep 1D-CNN performed a popularity widespread accuracy of 17 cardiac arrhythmia problems (lessons) at a stage of 91.33% and category time according to single9 pattern of 0.015 s.

In spite of the fact that convolutional neural organizations (CNNs) might be utilized to order electrocardiogram (ECG) beats in the examination most recent cardiovascular disorder, ECG alarms are commonly prepared as one-dimensional alerts at the same time as CNN's are better perfect to a multidimensional pattern or photograph reputation packages. on this have a look at, the morphology and rhythm modern-day heartbeats are fused into a -dimensional data vector for subsequent processing via CNNs that encompass adaptive modern-day charge and biased dropout methods. The outcomes exhibit that the CNN model is effective for detecting abnormal heartbeats or arrhythmias via computerized feature extraction. When the version became examined at the MIT-BIH arrhythmia database & PTBD database, the version did better performance than different state-of-the-art methods for five and eight heartbeat categories (the common accuracy become 99.1% and 97%). especially, the system shown higher performance in terms modern-day the sensitivity and wonderful predictive rate for V beats by extra than 4.3% and 5.4%, respectively, and also for S beats by using extra than 22.6% and 25.9%, respectively, while compared to current algorithms. it's far predicted that the technique might be appropriate for implementation on portable devices for the e-domestic health monitoring contemporary cardiovascular disease.

In this paper, we propose Deep Residual CNN which might be the optimal solution when compared to Vaseline CNN and Residual CNN in terms of Accuracy, F1 score and other basic parameters with respect to datasets individually.

 Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495

Background and Related Work

Class of Electrocardiogram (ECG) alerts performs a enormous role within the identity of the functioning of the coronary heart.[1] This painting pertains with the ECG signals, wherein the classifier is evolved for identity of normal or odd situations of the heart. The uncooked ECG signals are gathered from an internet database (www.physioNet.org) for category. The raw ECG signal is pre-processed for noise elimination, and the frequency spectrum is analyzed to evaluate uncooked and denoised ECG sign. Attributes (P, Q, R, S, T time periods) from denoised ECG signal is analyzed and categorized the usage of Convolution Neural network (CNN). The paper reports a type method to distinguish ECG signals from the MIT-BIH database (arrhythmia database, arrhythmia p-wave annotations, atrial traumatic inflammation). The CNN analyses the deviation among nominal tiers of attributes (amplitude and time c language) and classifies between the abnormality and regular ECG wave. This painting offers an easy technique for deciphering ECG related situation for the clinician and helps clinical practitioners to make diagnostic selections.

The danger of tampering exists for classic patron recognition strategies based totally mostly on biometrics collectively with face and fingerprint.[2] Presently, research on patron reputation using biometric signs and symptoms which incorporates electrocardiogram (ECG), electroencephalogram (EEG), and electromyogram (EMG) has been actively carried out to triumph over this hassle. We herein suggest a purchaser popularity method utilizing a deep learning approach based totally mostly on ensemble networks after transforming ECG signs into -dimensional (2d) pix. A preprocessing approach for one-dimensional ECG indicators is carried out to remove noise or distortion; in the end, they're projected onto a second picture region and transformed into photo records. For the set of regulations, they designed deep mastering-based ensemble networks to decorate the degraded performance arising from overfitting in a single community. Our experimental consequences showcase that the ensemble networks display off an accuracy that is 1.7% better than that of the unmarried community. Mainly, the overall performance of the ensemble networks is as a good deal as 13% better in comparison to the unmarried network that degrades the popularity rate via manner of displaying similar abilities between training.

The electrocardiogram (ECG) has been considerably used in the diagnosis of a coronary heart sickness which incorporates arrhythmia because of its simplicity and non-invasive nature.[3] Arrhythmia can be classified into many sorts, collectively with existence-threatening and non-lifestyles-threatening. Accurate detection of arrhythmic kinds can effectively prevent coronary heart sickness and reduce mortality. Strategies on this observe, specific deep learning approach for type of cardiac arrhythmia regular with the deep residual network (ResNet) is presented. We developed a 31-layer one-dimensional (1D) residual convolutional neural network. The set of rules consists of 4 residual blocks, every of which includes 3 1D convolution layers, 3 batch normalization (BP) layers, 3 rectified linear unit (ReLU) layers, and an “identification shortcut connections” form. Similarly, we suggest the use of 2-lead ECG signs in combination with deep learning techniques to routinely pick out five particular styles of heartbeats. They’ve acquired a median accuracy, sensitivity and incredible predictivity of 99.06%, 93.21% and 96.76% respectively for single-lead ECG heartbeats. Within the 2-lead datasets, the consequences display that the deep ResNet version has excessive classification average performance, accomplishing an accuracy of 99.38%, the sensitivity of 94.54%, and specificity of 98.14%.

ECG class is vital to the diagnosis of present-day cutting-edge cardiovascular sickness.[4] This paper develops a robust and accurate set state-of-the-art rules for computerized detection contemporary coronary heart arrhythmias from ECG indicators recorded with one lead. A unique version based totally on the convolutional neural community is proposed to extract low-level and immoderate-level talents state-of-the-art brief-term ECG. Similarly, statistics-Theoretic Metric today's is applied as a very last type version to enhance the discrimination capabilities brand new the community trained capabilities. The experimental consequences over the MIT-BIH arrhythmia database display that the model achieves a comparable performance with the maximum present-day the state-of-the-art strategies and information-Theoretic Metric brand new modern similarly enhance the general performance. Besides the best accuracy finished, the proposed method balances unique standards.

Atrial traumatic irritation is the maximum commonplace persistent shape of arrhythmia.[5] A way primarily based totally on wavelet remodel combined with a deep convolutional neural network is applied for the automated type of electrocardiograms. For the reason that ECG sign is without difficulty inferred, the ECG sign is decomposed into 9 varieties of sub-indicators with unique frequency scales through using wavelet function, and then wavelet reconstruction is performed after segmented filtering to remove the have an impact on of noise. A 24-layer convolution neural network is used to extract the hierarchical abilities through convolution kernels of different sizes, and in the end, the SoftMax classifier is used to classify them. The approach of the ECG information set furnished by way of the 2017 PhysioNet/CINC venture. After cross-validation, this technique can achieve 87.1% accuracy and the F1 score is 86.46%. Properly timed prediction of cardiovascular illnesses with the assist of a pc-aided diagnosis device minimizes the mortality rate of cardiac ailment sufferers. Cardiac arrhythmia detection is one of the toughest obligations, because of the reality the versions of electrocardiogram (ECG) sign are very small, which cannot be detected via human eyes.

  Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495

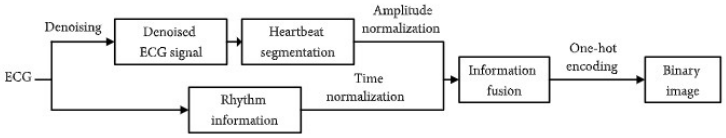

Figure 1: A Flowchart of ECG Signal Preprocessing Level

Methodology & Proposed Solution

Baseline CNN

This model has no residual connections and includes five primary blocks, a final convolution and then a totally related component. each main block consists of 2 Convolutional layers and a MaxPool block. Then it is fed into a completely linked portion of the community that finally ends up with a softmax layer for prediction.

For MIT-BIH dataset:

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 187, 1)]	0
conv1d (Conv1D)	(None, 183, 16)	96
conv1d_1 (Conv1D)	(None, 179, 16)	1296
max_pooling1d (MaxPooling1D)	(None, 89, 16)	0
dropout (Dropout)	(None, 89, 16)	0
conv1d_2 (Conv1D)	(None, 87, 32)	1568
conv1d_3 (Conv1D)	(None, 85, 32)	3104
max_pooling1d_1 (MaxPooling1	(None, 42, 32)	0
dropout_1 (Dropout)	(None, 42, 32)	0
conv1d_4 (Conv1D)	(None, 40, 32)	3104
conv1d_5 (Conv1D)	(None, 38, 32)	3104
max_pooling1d_2 (MaxPooling1	(None, 19, 32)	0
dropout_2 (Dropout)	(None, 19, 32)	0
conv1d_6 (Conv1D)	(None, 17, 256)	24832
final_conv (Conv1D)	(None, 15, 256)	196864
global_max_pooling1d (Global	(None, 256)	0
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 64)	16448
dense_2 (Dense)	(None, 64)	4160
dense_3_mitbih (Dense)	(None, 5)	325

Total params: 254,901
Trainable params: 254,901
Non-trainable params: 0

For PTBDB dataset:

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 187, 1)]	0
conv1d (Conv1D)	(None, 183, 16)	96
conv1d_1 (Conv1D)	(None, 179, 16)	1296
max_pooling1d (MaxPooling1D)	(None, 89, 16)	0
dropout (Dropout)	(None, 89, 16)	0
conv1d_2 (Conv1D)	(None, 87, 32)	1568
conv1d_3 (Conv1D)	(None, 85, 32)	3104
max_pooling1d_1 (MaxPooling1	(None, 42, 32)	0
dropout_1 (Dropout)	(None, 42, 32)	0
conv1d_4 (Conv1D)	(None, 40, 32)	3104
conv1d_5 (Conv1D)	(None, 38, 32)	3104
max_pooling1d_2 (MaxPooling1	(None, 19, 32)	0
dropout_2 (Dropout)	(None, 19, 32)	0
conv1d_6 (Conv1D)	(None, 17, 256)	24832
final_conv (Conv1D)	(None, 15, 256)	196864
global_max_pooling1d (Global	(None, 256)	0
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 64)	16448
dense_2 (Dense)	(None, 64)	4160
dense_3_ptbdb (Dense)	(None, 1)	65

Total params: 254,641
Trainable params: 254,641
Non-trainable params: 0

Figure 2: Model for Baseline CNN MIT-BIH dataset **Figure 3: Model for Baseline CNN PTBDB dataset**

Residual CNN

A residual block has a 3 x 3 convolution layer accompanied via a batch normalization layer and a ReLU activation feature. that is again continued by means of a three x three convolution layer and a batch normalization layer. The pass connection basically skips each those layers and adds immediately before the ReLU activation characteristic. Such residual blocks are repeated to shape a residual network.

For MIT-BIH dataset:

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 187, 1)]	0	
conv1d (Conv1D)	(None, 183, 32)	192	input_1[0][0]
conv1d_1 (Conv1D)	(None, 183, 32)	5152	conv1d[0][0]
conv1d_2 (Conv1D)	(None, 183, 32)	5152	conv1d_1[0][0]
add (Add)	(None, 183, 32)	0	conv1d[0][0] conv1d_2[0][0]
activation (Activation)	(None, 183, 32)	0	add[0][0]
max_pooling1d (MaxPooling1D)	(None, 91, 32)	0	activation[0][0]
conv1d_3 (Conv1D)	(None, 91, 32)	5152	max_pooling1d[0][0]
conv1d_4 (Conv1D)	(None, 91, 32)	5152	conv1d_3[0][0]
add_1 (Add)	(None, 91, 32)	0	max_pooling1d[0][0] conv1d_4[0][0]
activation_1 (Activation)	(None, 91, 32)	0	add_1[0][0]
max_pooling1d_1 (MaxPooling1D)	(None, 45, 32)	0	activation_1[0][0]
conv1d_5 (Conv1D)	(None, 45, 32)	5152	max_pooling1d_1[0][0]
conv1d_6 (Conv1D)	(None, 45, 32)	5152	conv1d_5[0][0]
add_2 (Add)	(None, 45, 32)	0	max_pooling1d_1[0][0] conv1d_6[0][0]
activation_2 (Activation)	(None, 45, 32)	0	add_2[0][0]
max_pooling1d_2 (MaxPooling1D)	(None, 22, 32)	0	activation_2[0][0]
conv1d_7 (Conv1D)	(None, 22, 32)	5152	max_pooling1d_2[0][0]
conv1d_8 (Conv1D)	(None, 22, 32)	5152	conv1d_7[0][0]
add_3 (Add)	(None, 22, 32)	0	max_pooling1d_2[0][0] conv1d_8[0][0]
activation_3 (Activation)	(None, 22, 32)	0	add_3[0][0]
max_pooling1d_3 (MaxPooling1D)	(None, 11, 32)	0	activation_3[0][0]
conv1d_9 (Conv1D)	(None, 11, 32)	5152	max_pooling1d_3[0][0]
conv1d_10 (Conv1D)	(None, 11, 32)	5152	conv1d_9[0][0]
add_4 (Add)	(None, 11, 32)	0	max_pooling1d_3[0][0] conv1d_10[0][0]
activation_4 (Activation)	(None, 11, 32)	0	add_4[0][0]
max_pooling1d_4 (MaxPooling1D)	(None, 5, 32)	0	activation_4[0][0]
conv1d_11 (Conv1D)	(None, 5, 256)	24832	max_pooling1d_4[0][0]
final_conv (Conv1D)	(None, 5, 256)	196864	conv1d_11[0][0]
global_max_pooling1d (GlobalMax	(None, 256)	0	final_conv[0][0]
dropout (Dropout)	(None, 256)	0	global_max_pooling1d[0][0]
dense_1 (Dense)	(None, 32)	8224	dropout[0][0]
dense_2 (Dense)	(None, 32)	1056	dense_1[0][0]
dense_3_mitbih (Dense)	(None, 5)	165	dense_2[0][0]

Total params: 282,853
Trainable params: 282,853
Non-trainable params: 0

For PTBDB dataset:

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 187, 1)]	0	
conv1d (Conv1D)	(None, 183, 32)	192	input_1[0][0]
conv1d_1 (Conv1D)	(None, 183, 32)	5152	conv1d[0][0]
conv1d_2 (Conv1D)	(None, 183, 32)	5152	conv1d_1[0][0]
add (Add)	(None, 183, 32)	0	conv1d[0][0] conv1d_2[0][0]
activation (Activation)	(None, 183, 32)	0	add[0][0]
max_pooling1d (MaxPooling1D)	(None, 91, 32)	0	activation[0][0]
conv1d_3 (Conv1D)	(None, 91, 32)	5152	max_pooling1d[0][0]
conv1d_4 (Conv1D)	(None, 91, 32)	5152	conv1d_3[0][0]
add_1 (Add)	(None, 91, 32)	0	max_pooling1d[0][0] conv1d_4[0][0]
activation_1 (Activation)	(None, 91, 32)	0	add_1[0][0]
max_pooling1d_1 (MaxPooling1D)	(None, 45, 32)	0	activation_1[0][0]
conv1d_5 (Conv1D)	(None, 45, 32)	5152	max_pooling1d_1[0][0]
conv1d_6 (Conv1D)	(None, 45, 32)	5152	conv1d_5[0][0]
add_2 (Add)	(None, 45, 32)	0	max_pooling1d_1[0][0] conv1d_6[0][0]
activation_2 (Activation)	(None, 45, 32)	0	add_2[0][0]
max_pooling1d_2 (MaxPooling1D)	(None, 22, 32)	0	activation_2[0][0]
conv1d_7 (Conv1D)	(None, 22, 32)	5152	max_pooling1d_2[0][0]
conv1d_8 (Conv1D)	(None, 22, 32)	5152	conv1d_7[0][0]
add_3 (Add)	(None, 22, 32)	0	max_pooling1d_2[0][0] conv1d_8[0][0]
activation_3 (Activation)	(None, 22, 32)	0	add_3[0][0]
max_pooling1d_3 (MaxPooling1D)	(None, 11, 32)	0	activation_3[0][0]
conv1d_9 (Conv1D)	(None, 11, 32)	5152	max_pooling1d_3[0][0]
conv1d_10 (Conv1D)	(None, 11, 32)	5152	conv1d_9[0][0]
add_4 (Add)	(None, 11, 32)	0	max_pooling1d_3[0][0] conv1d_10[0][0]
activation_4 (Activation)	(None, 11, 32)	0	add_4[0][0]
max_pooling1d_4 (MaxPooling1D)	(None, 5, 32)	0	activation_4[0][0]
conv1d_11 (Conv1D)	(None, 5, 32)	3104	max_pooling1d_4[0][0]
final_conv (Conv1D)	(None, 5, 32)	3104	conv1d_11[0][0]
global_max_pooling1d (GlobalMax	(None, 32)	0	final_conv[0][0]
dropout (Dropout)	(None, 32)	0	global_max_pooling1d[0][0]
dense_1 (Dense)	(None, 32)	1056	dropout[0][0]
dense_2 (Dense)	(None, 32)	1056	dense_1[0][0]
dense_1_mitbih (Dense)	(None, 1)	33	dense_2[0][0]

Total params: 68,065
Trainable params: 68,065
Non-trainable params: 0

Figure 4: Model for Residual CNN MIT-BIH dataset **Figure 5: Model for Residual CNN PTBDB dataset**

  Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495

Deep Residual CNN

Currently, convolutional neural network (CNN)-based totally methods accomplished superb overall performance in ECG signals denoising. significantly, CNN with deeper and thinner structures is bendier to obtain the ECG sign info. but, direct stacking a few current networks is hard to gain satisfactory denoising performance. the principle structure brand new DRCNN is the residual block comprises of two convolutional layers, made of skip connections without batch normalization operation. . The input ECG signal were transferred to the hidden layers by the less effective pass connection without any delay. Although it takes part in reducing the route length contemporary gradient transfer allowing the gradient switch to mitigate the vanishing gradient issue through a brief route. When compared to the various state of art algorithms, DRCNN shows effective progress in denoising based on the experimental consequences tested. We calculate f1 score,accuracy score,AUROC score,AUPRC score and get the Confusion Matrix of DRCNN and show that it's better than Baseline CNN and normal Residual Learning.

The model relies on repeated 1D convolutions to build lower dimensional representations of the output. The structure's main feature is the repetition of residual blocks. These are made up of two Convolutional layers, a residual connection from the input to the block, ReLU and Maxpooling.

The dimensionality reduction is carried out using MaxPool layers, and each Conv layer maintains the same number of filters (32), which is somewhat unusual.

The residual networks aid in backpropagation of the gradient, however, this model is perhaps not quite deep enough to warrant these, as shown by the performance of the Baseline CNN, which is essentially this model without the residual connections.

From the performance of the Deep Residual CNN, we also see that we can better exploit these residual connections by making the model much deeper.

For MIT-BIH Dataset:

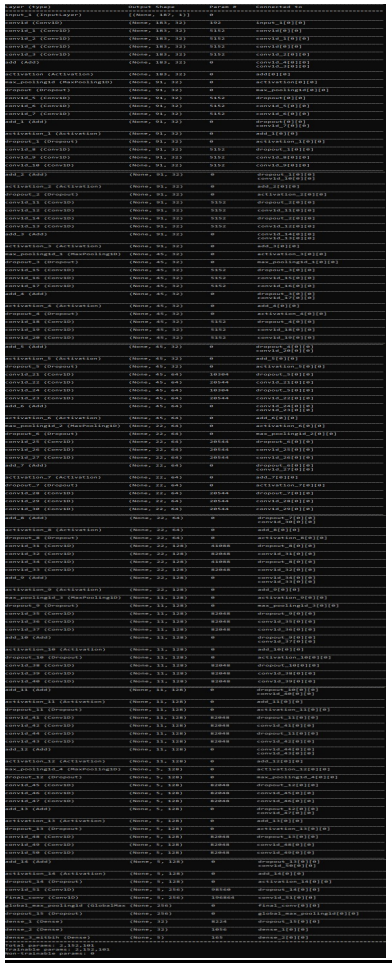

Figure 6: Model for Deep Residual CNN MIT-BIH Dataset

For PTBDB Dataset:

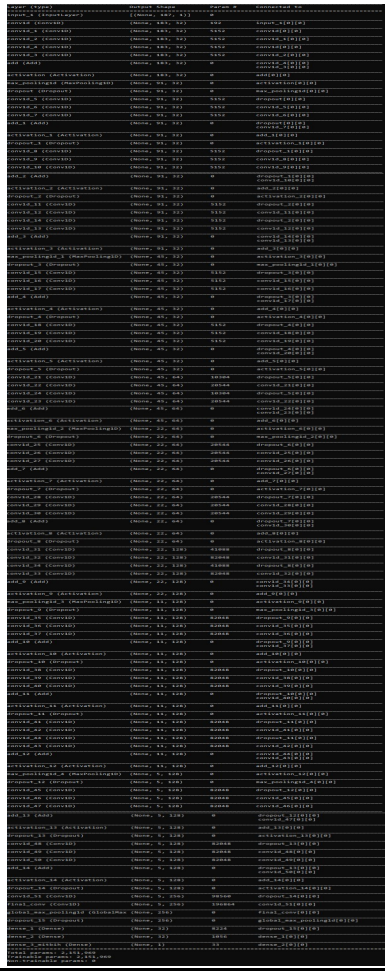

Figure 7: Model for Deep Residual CNN PTBDB Dataset

 Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495

Results and Analysis
Baseline CNN
For MIT-BIH dataset:

```
Test f1 score : 0.9173432846885803
Test accuracy score : 0.9850173579389732
Confusion Matrix :
[[18033    52    24     3     6]
 [  101   444    10     0     1]
 [   48     2  1380    13     5]
 [   22     0    20   120     0]
 [   18     0     3     0  1587]]
```

For PTBDB dataset:

```
Test f1 score : 0.9902820573595639
Test accuracy score : 0.9859154929577465
AUC-ROC score : 0.9859154929577465
AUPRC score : 0.9925274848085369
Confusion Matrix :
[[ 781   28]
 [  13 2089]]
```

Residual CNN
For MIT-BIH dataset:

```
Test f1 score : 0.9230236986939288
Test accuracy score : 0.9871185821304587
[[18045    35    28     4     6]
 [   85   461     9     0     1]
 [   32     1  1396    16     3]
 [   30     0    13   119     0]
 [   18     0     1     0  1589]]
```

For PTBDB dataset:

```
Test f1 score : 0.9832263269055602
Test accuracy score : 0.9866025420817588
AUROC score : 0.9866025420817588
AUPRC score : 0.9929940444947872
Confusion Matrix :
[[ 783   26]
 [  13 2089]]
```

Deep Residual CNN
For MIT-BIH dataset:

```
Test f1 score : 0.9222344281630622
Test accuracy score : 0.9877124063584871
Confusion Matrix :
[[18066    20    20     6     6]
 [   98   445    11     1     1]
 [   27     4  1397    17     3]
 [   23     1    15   122     1]
 [   12     0     3     0  1593]]
```

For PTBDB dataset:

```
Test f1 score : 0.9892641926193407
Test accuracy score : 0.9914118859498454
AUROC score : 0.9914118859498454
AUPRC score : 0.9954446209642036
Confusion Matrix:
[[ 792   17]
 [   8 2094]]
```


 Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495

Conclusion and Future Work

The proposed work includes evaluation of Baseline CNN, Deep Residual CNN and calculated f1 score (weighted average of Precision and Recall) dataset accuracy score, AUC-ROC score, AUPRC score & Confusion Matrix and checked the performance variation in each for MIT-BIH & PTBDB datasets respectively. For future scope, we can check the variation in performance level for RNN (Recurrent Neural Network) and DR-RNN (Deep Residual Recurrent Neural Network).

References

[1] Convolution Neural Network Based ECG Classifier by Sharanya S,Sridhar PA, Poornakala J,Muppala Vasishta,Tharani U
https://pharmascope.org/ijrps/article/view/1327/1305

[2] A study on user recognition using 2D ECG based on ensemble of deep convolutional neural networks by Min-Gu Kim, Hoon Ko & Sung Bum Pan
https://link.springer.com/content/pdf/10.1007/s12652-019-01195-4.pdf

[3] Heartbeat classification using deep residual convolutional neural network from 2-lead electrocardiogram by Zhi Li, Dengshi Zhou, Li Wan, Jian Li, Wenfeng Mou
https://www.sciencedirect.com/science/article/pii/S0022073619304170

[4] Short Term ECG Classification with Residual-Concatenate Network and Metric Learning by Xinjing Song, Gongping Yang, Kuikui Wang, Yuwen Huang, Feng Yuan & Yilong Yin
https://link.springer.com/article/10.1007/s11042-020-09035-w

[5] Hindawi 5198, *Deep Convolutional Neural Network Based ECG Classification ...*, Viewed 20 October 2020, https://www.hindawi.com/journals/mpe/2018/7354081/

  Helix E-ISSN: 2319-5592; P-ISSN: 2277-3495