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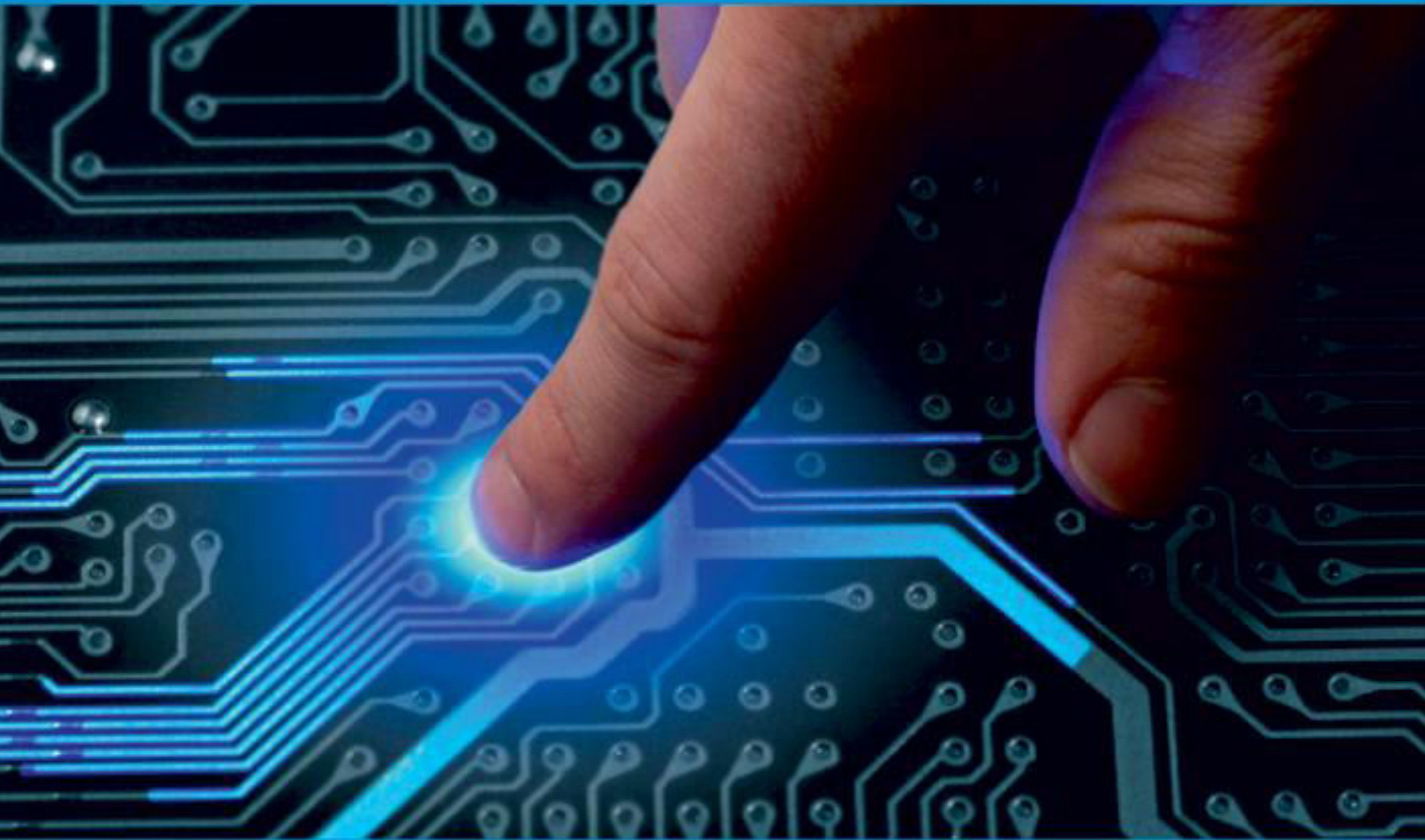

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Design and Development of ECG Analysis Using Machine Learning Techniques

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ABSTRACT: Cardiovascular disease is the leading cause of death world-wide and the electrocardiogram (ECG) is a major tool in the diagnosis. Delineation of electrocardiogram gives various necessary features which consists of intervals and segments (RR interval, PR interval, QT interval, QRS width, ST segment) and amplitudes (QRS, P and T). These ECG parameters help in guiding the clinicians to diagnose accurately. Compared to determining whether ECG is normal or not, diagnosing heart disease is a more challenging task. Traditional ECG signal analysis and classification relies on the guidance of experienced medical experts, which is a time-consuming and labour- consuming job. Therefore, there is a growing need for fully automated ECG analysis using machine learning. However, the development of such algorithms requires large training datasets and clear benchmark procedures. One such dataset is the PTB-XL ECG dataset from PhysioNet. In this project, a deep neural network was developed for the classification of ECG signals. Training was carried out for models namelyInception 1D, ResNet 1D and accuracy was calculated. Features based on the ECG waveform shape and heart beat intervals are used as inputs to the classifiers. The dataset was divided into training, validation, and test sets in proportions of 70%, 15%, and 15%, respectively. For the project to be user-friendly a GUI is developed which accepts input in the form of a signal file, our trained model classifies the input signal as normal or abnormal and the result displayed on the screen. The Inception 1D performed better with precision 0.71, recall 0.64 and 92.45% AUC than ResNet 1D precision 0.72, recall 0.65 and 91.91% AUC since the models are trained with a dataset with large data diversity.

KEYWORDS: ECG; Inception 1D; ResNet 1D

I. INTRODUCTION

The analysis of electrocardiographic signals (ECG) is one of the most important steps in diagnosing cardiac disorders. Research into methods of ECG signal diagnostics has been developed for decades. An electrocardiogram is a commonly employed non-invasive physiological signal used for screening and diagnosing cardiovascular disease. Traditionally, ECG usually means a 12-lead ECG taken while lying down. However, other devices can record the electrical activity of the heart such as a Holter monitor but also some models of smartwatch are capable of recording an ECG. ECG signals can be recorded in other context with other devices. In a conventional 12-lead ECG, ten electrodes are placed on the patient’s limbs and on the surface of the chest. The overall magnitude of the heart’s electrical potential is then measured from twelve different angles (“leads”) and is recorded over a period of time (usually ten seconds) [1]. In this way, overall magnitude and direction of the heart’s electrical depolarization is captured at each moment throughout the cardiac cycle.The ECG machine is designed to recognise and record any electrical activity within the heart [2].

An ECG can detect:

• Arrhythmias – where the heart beats too slowly, too quickly, or irregularly
• Coronary heart disease – where the heart’s blood supply is blocked or interrupted by a build-up of fatty substances
• Heart attacks – where the supply of blood to the heart is suddenly blocked
• Cardiomyopathy – where the heart walls become thickened or enlarged

OBJECTIVE:

- To explore existing standard ECG analysis datasets
- To explore existing denoising techniques to remove noise present in input signal

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- To design and develop arrhythmia classification systems using deep learning models
- Compare and contrast developed methods on standard datasets

II. RELATED WORK

Wei and Seong [4] presents evolvable block-based neural networks (BbNNs) for personalized ECG heartbeat pattern classification. A BbNN consists of a 2-D array of modular component NNs with flexible structures and internal configurations that can be implemented using reconfigurable digital hardware such as field-programmable gate arrays (FPGAs). Signal flow between the blocks determines the internal configuration of a block as well as the overall structure of the BbNN. Network structure and the weights are optimized using local gradient-based search and evolutionary operators with the rates changing adaptively according to their effectiveness in the previous evolution period. Such adaptive operator rate update scheme ensures higher fitness on average compared to predetermined fixed operator rates. The Hermite transform coefficients and the time interval between two neighboring R-peaks of ECG signals are used as inputs to the BbNN. A BbNN optimized with the proposed evolutionary algorithm (EA) makes a personalized heartbeat pattern classifier that copes with changing operating environments caused by individual difference and time-varying characteristics of ECG signals. Simulation results using the Massachusetts Institute of Technology/Beth Israel Hospital (MIT-BIH) arrhythmia database demonstrate high average detection accuracies of ventricular ectopic beats (98.1%) and supraventricular ectopic beats (96.6%) patterns for heartbeat monitoring, being a significant improvement over previously reported electrocardiogram (ECG) classification results.Dayong et al.[5] presents a system for detection of cardiac arrhythmias within ECGsignals, based on a Bayesian artificial neural network (ANN) classifier. The Bayesian(or probabilistic) ANN classifier is built by the use of a logistic regression model andthe backpropagation algorithm based on a Bayesian framework. Its performance forthis task is evaluated by comparison with other classifiers including Naive Bayes, decision trees, logistic regression, and RBF networks. A paired t-test is employed incomparing classifiers to select the optimum model. The system is evaluated usingnoisy ECG data, to simulate a real-world environment. It is hoped that the systemcan be further developed and fine-tuned for practical application.

III. DATASET

Electrocardiography (ECG) is a key diagnostic tool to assess the cardiac condition of a patient. Automatic ECG interpretation algorithms as diagnosis support systems promise large reliefs for the medical personnel - only on the basis of the number of ECGs that are routinely taken. However, the development of such algorithms requires large training datasets and clear benchmark procedures. In our opinion, both aspects are not covered satisfactorily by existing freely accessible ECG datasets. This is a large dataset of 21837 clinical 12-lead ECGs from 18885 patients of 10 second length, where 52% are male and 48% are female with ages covering the whole range from 0 to 95 years (median 62 and interquantile range of 22). The dataset is complemented by extensive metadata on demographics, infarction characteristics, likelihoods for diagnostic ECG statements as well as annotated signal properties. The value of the dataset results from the comprehensive collection of many different co-occurring pathologies, but also from a large proportion of healthy control samples. Among them there are examples of the following ECG signals: NORM-normal ECG, CD-myocardial infarction, STTC-ST/T change, MI-conduction disturbance, HYP-hypertrophy.

Fig. 1 The diagnostic superclass distribution.

Records	Superclass	Description
9528	NORM	Normal ECG
5486	MI	Myocardial Infarction
5250	STTC	ST/T Change
4907	CD	Conduction Disturbance
2655	HYP	Hypertrophy

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IV. IMPLEMENTATION

The first stage describes different sources of ECG data, such as clinically prerecordedand sources of real-time ECG acquisition sensory data. In the second stage, we discussdifferent techniques reported in the literature to remove noise that has been introducedduring the acquisition of the ECG signal at the first stage. Detection of fiducial pointsof the ECG signal is very crucial for classifying different heart conditions accurately.Identifying these fiducial points is part of the third stage of the ECG signal analysisprocess.

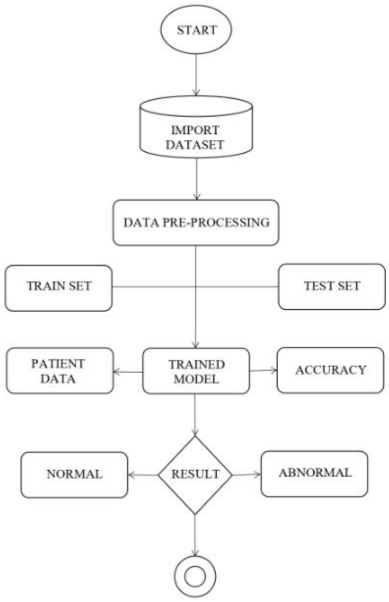

Fig. 2 Methodology

Each wave and segment of the ECG signal has its importance in determiningthe type of arrhythmia in context. After the right selection of the data source andidentifying the ECG fiducial points, different heart conditions can be detected andclassified at the fourth stage of the ECG signal analysis process using deep learningmodels. The above Figure 2 describes the methodology of this work in which data isdivided into test set and train set after data preprocessing. The data is given as inputto trained model which calculates the accuracy and displays the result as normal orabnormal.

1. Deep learning approaches:
   a) Inception 1D

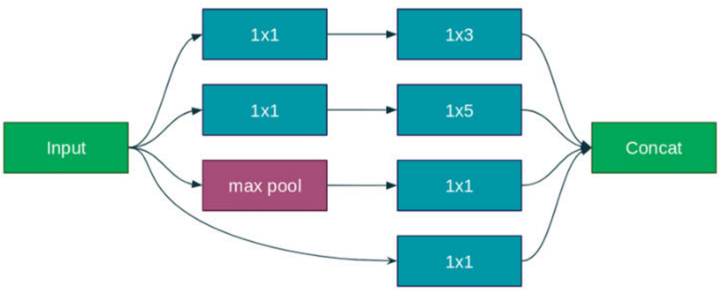

Fig. 3 Inception 1D

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An inception network is a deep neural network with an architectural design Figure 3 that consists of repeating components referred to as Inception modules.Whendesigning the Inception network, few principles and ideas guided the researchers.

- Highly performant deep neural networks need to be large. For a neural networkto be considered large, it had to have several more layers within the networkand units within these layers.
- Convolutional neural networks benefit from extracting features at varying scales.The biological human visual cortex functions by identifying patterns at differentscales, which accumulates to form lager perceptions of objects. Therefore, multiscale convnet have the potential to learn more.
- Consideration of the Hebbian Principle — neurons that fire together, wire together.The above listed guidelines come with some technical drawbacks. Large networks areprone to overfitting, and chaining multiple convolutional operations together increasesthe computational cost of the network.

b) ResNet 1D

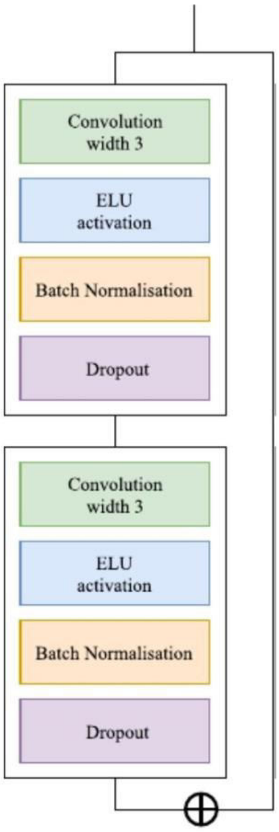

Fig. 3 ResNet 1D

This model have something called Residual blocks. Many Residual blocks are stackedtogether to form a ResNet as shown in Figure 3. We have "skipped connections"which are the major part of ResNet. The following Figure 5.4 denotes how a residualnetwork works. The idea is to connect the input of a layer directly to the outputof a layer after skipping a few connections. We can see here, x is the input to thelayer which we are directly using to connect to a layer after skipping the identityconnections and if we think the output from identity connection to be F(x). Then wecan say the output will be,

$$F(x) + x \qquad (4.1)$$

One problem that may happen is regarding the dimensions. Sometimes the dimensionsof x and F(x) may vary and this needs to be solved. Two approaches can be followedin such situations. One involves padding the input x with weights such as it nowbrought equal to that of the value coming out. The second way includes using aconvolutional layer from x to addition to F(x).

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This way we can bring down the weights same dimensions of that coming out.When following the first way, the equation turns to be,

$$F(x) + w1.x \tag{4.2}$$

Here w1 is the additional parameters added so that we can bring up the dimensionsto that of output coming from the activation function. The skip connections in ResNetsolve the problem of vanishing gradient in deep neural networks by allowing thisalternate shortcut path for the gradient to flow through.It also helps the connections by allowing the model to learn the identity functionswhich ensures that the higher layer will perform at least as good as the lower layer,and not worse. The complete idea is to make,

$$F(x) = 0 \tag{4.3}$$

So that at the end we have,

$$Y = X \tag{4.4}$$

as result. This means that the value coming out from the activation function ofthe identity blocks is the same as the input from which we skipped the connections.

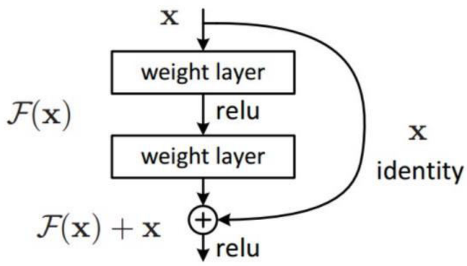

Fig. 4 Residual Network

V. RESULT

The result chapter of this report presents the observations and accuracies achieved onclassification of ECG signals via two deep learning models Inception 1D and ResNet1D.Since this work was carried out on PTB-XL dataset therefore relevant literaturematerial was studied and implementation methods were used as the basis for thiswork. The choice of Inception 1D and ResNet 1D models was based on the higherefficiency and learning capability of these models. Inception 1D proved to be workingbetter.The table 6.1 gives the summary of the results obtained.Figure 6and 7 shows the confusion matrix of Inception 1D and ResNet 1D.Figure 8 to 11 shows the loss-accuracy graph of two deep learning models Inception1D and ResNet 1D. As observed in the Figure 5, the Inception 1D model providesmore accurate result when compared with ResNet 1D.

Models	Precision	Recall	f1-score	Support	AUC
Inception 1D	0.71	0.64	0.65	2163	0.9245
ResNet 1D	0.72	0.65	0.65	2163	0.9191

Fig. 5 Summary of results obtained with two deep learning models

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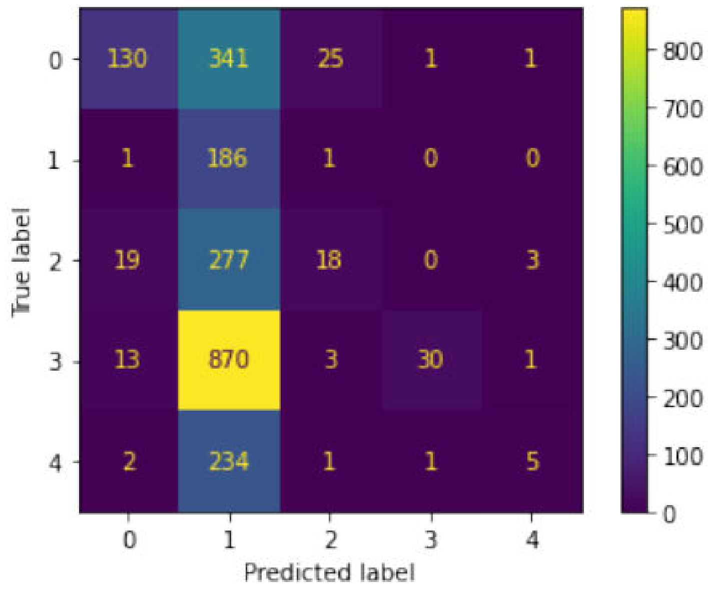

Fig. 6 Confusion matrix of Inception 1D

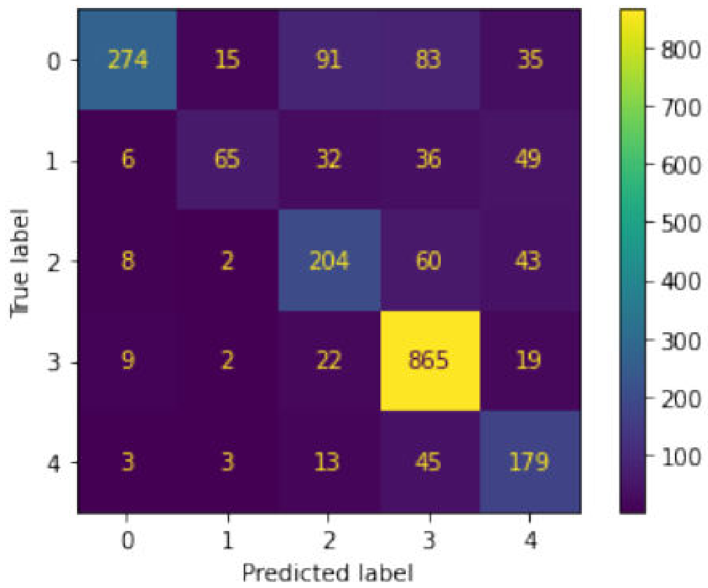

Fig. 7 Confusion matrix of ResNet 1D

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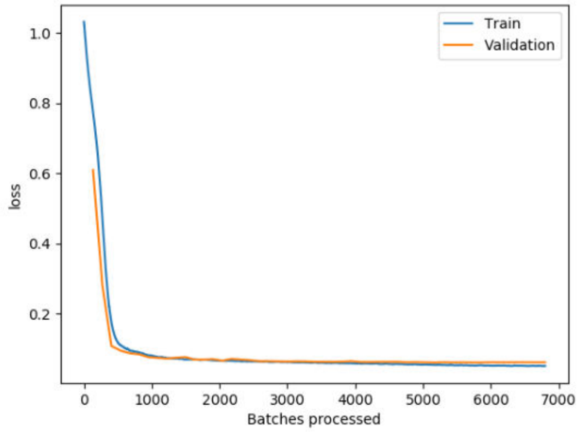

Fig. 8loss vs Batch processed in ResNet1D

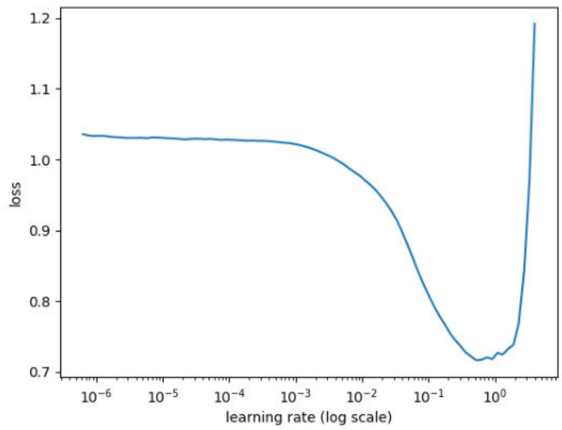

Fig. 9loss vs learning rate in ResNet1D

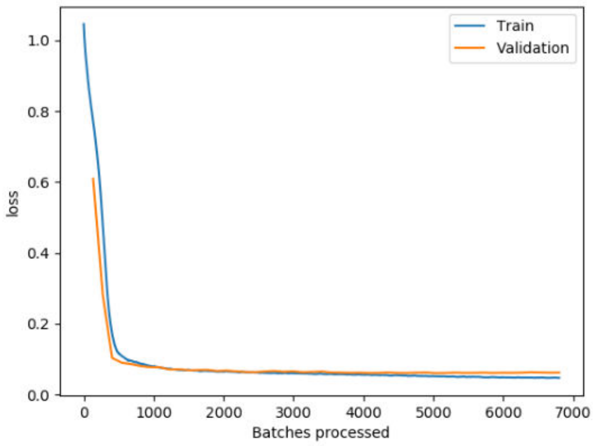

Fig. 10loss vs Batch processed in Inception 1D

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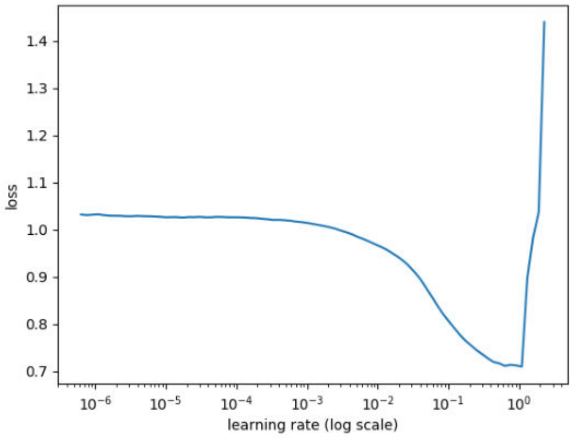

Fig. 11loss vs learning rate in Inception 1D

VI. CONCLUSION

Diseases affecting the heart have also become common day by day as a result of abad lifestyle involving medical conditions such as diabetes and hypertension. ECGis the gold standard that is widely used for the diagnosis and prognosis of variousheart conditions. However, manual inspection of ECG signals is a difficult task andcan be subjective, time-consuming and susceptible to inter-observer variability. Theextraction and segmentation of features in the ECG plays a significant role in thediagnosis of most heart disease. Classification systems are becoming increasinglypopular; our main task is automatically analyzing different heart diseases using deeplearning methods to improve diagnostic accuracy.PTB-XL dataset is used for our project. At first, different sources of ECG isacquired. Then noise that has been introduced during acquisition of ECG is detectedand denoising is done. The data is preprocessed in the next stage. We had split thisdata into test and train set. Training is performed using the two deep learning modelsnamely Inception 1D and ResNet 1D. ResNet 1D model with 92.45% AUC providedmore accurate result than that of the Inception 1D with 91.91% AUC which helpedto classify the ECG signal as normal and abnormal and the loss graphs are plottedfor the same.

REFERENCES

[1] Sandra ´ Smigiel, Krzysztof Pa lczy´ nski and Damian Ledzi´ nski. Deep Learning Techniquesin the Classification of ECG Signals Using R-Peak Detection Based on the PTB-XLDataset. 2021.

[2] Hugo Plácido da Silva, Carlos Carreiras, Andre Lourenco, Ana Fred and Ana L. N.Fred. Off-the-person electrocardiography: performanceassessment and clinical correlation. 2015.

[3] C. K. Roopa and B. S. Harish. A Survey on various Machine Learning Approaches forECG Analysis. 2017.

[4] Wei Jiang and Seong G. Kong. Evolvable block-based neural networks (BbNNs) forpersonalized ECG heartbeat pattern classification. 20074

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