

Arrhythmia Prediction and Diagnosis using Data Analysis

Presented By:

Project Group: P21

Mangalnathan Vijayagopal – mvijaya2

Nishcal Badarinath Kashyap – nkashya

Pawandeep Mendiratta – psmendir

Shreyas Chikkbapur Muralidhara - schikkb



Index:

- ❑ Introduction and Related Work
- ❑ Dataset
- ❑ Pre-Processing
- ❑ Feature Selection
- ❑ Support Vector Machine
- ❑ K – Nearest Neighbors
- ❑ 1D - Convoluted Neural Network
- ❑ Multi Layer Perceptron
- ❑ Results
- ❑ Conclusion
- ❑ References



Introduction

- ❑ To detect and predict the type of arrhythmia based on Electrocardiogram (ECG) tool using machine learning models and algorithms.

Related Work

- ❑ Automated Screening of Arrhythmia Using Wavelet Based Machine Learning Techniques
- ❑ Machine Intelligent Diagnosis of ECG for Arrhythmia Classification Using DWT, ICA and SVM techniques
- ❑ An integrated ECG feature extraction scheme using PCA and wavelet transform
- ❑ Heart rate dynamics distinguish among atrial fibrillation, normal sinus rhythm and sinus rhythm with frequent ectopy

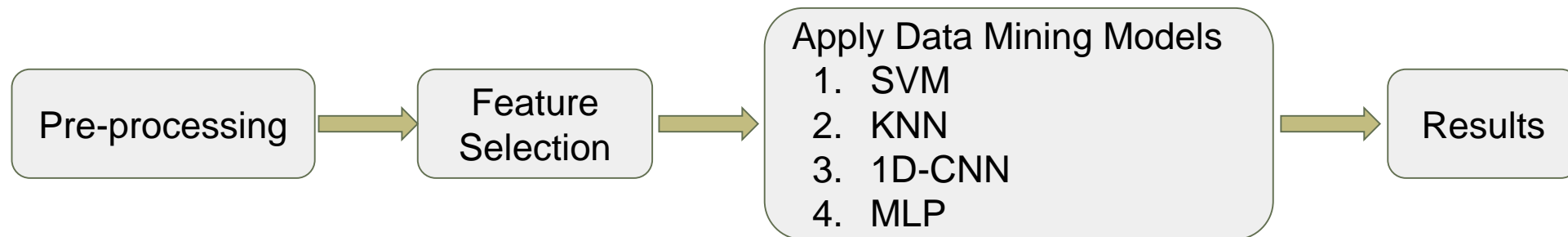


Data Set

<http://archive.ics.uci.edu/ml/datasets/Arrhythmia>

- ❑ Arrhythmia Data Set – Referenced from UCI Machine Learning Repository
- ❑ The data set contains 452 instances with 279 attributes
- ❑ The data set represents tabular form of ECG data of 452 patients along with patient information
- ❑ Multivariate dataset with Categorical, Integer and Real Attributes
- ❑ Class Label values range from 1 to 16 (Types of Arrhythmia)
- ❑ A train-test split in ratio 70:30 into training and testing data containing 316 and 116 records respectively.

Process Flow

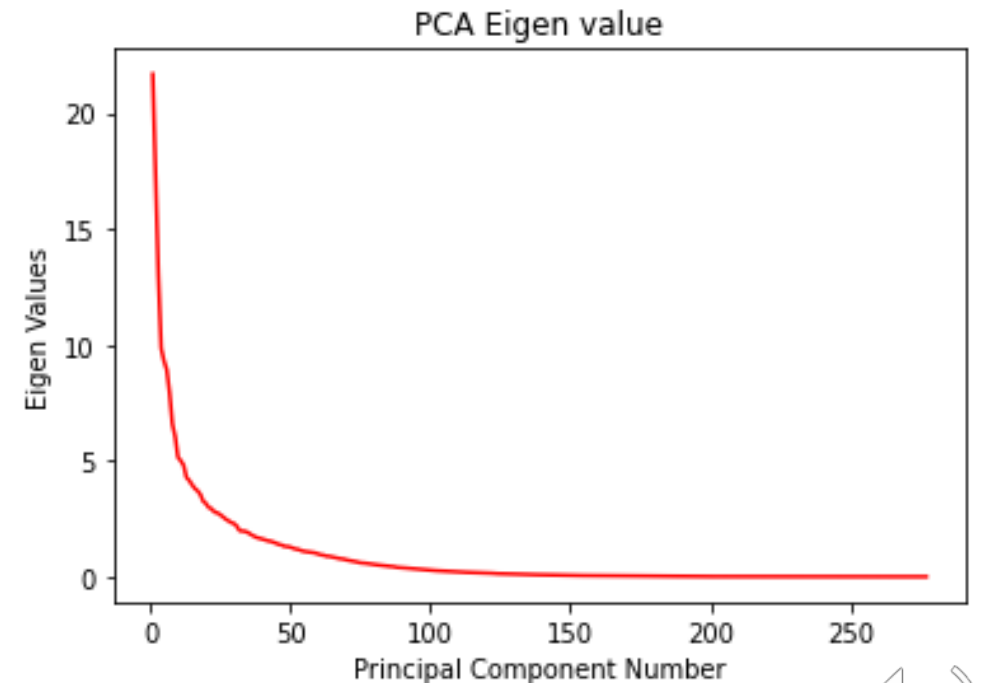


Pre-Processing

- ❑ Remove Unwanted Columns
- ❑ Replace Missing Values
- ❑ Attribute Scaling – Normalize values to the range of 0 to 1

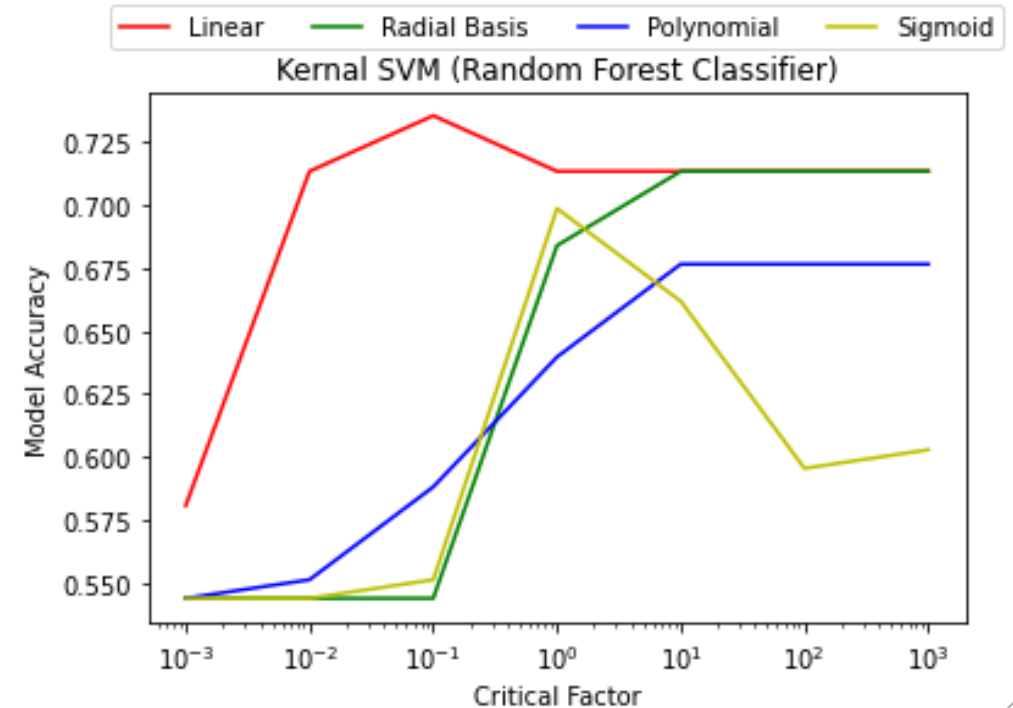
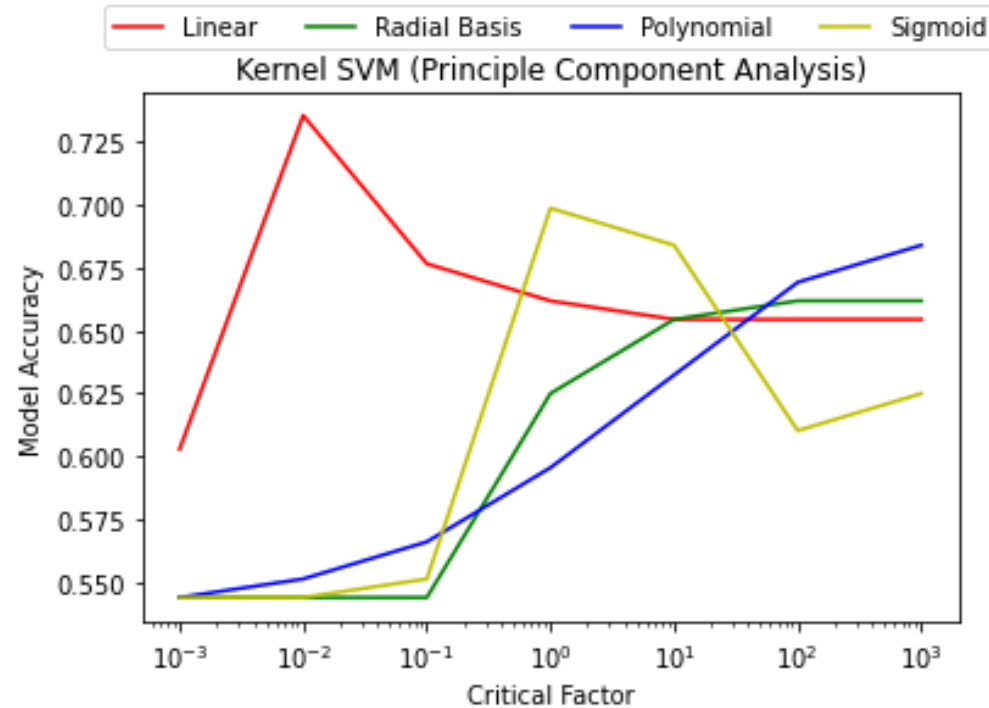
Feature Selection

- ❑ Principal Component Analysis
Top 88 features were chosen based on PCA output
- ❑ Random Forest
Top 99 features were chosen based on
Random Forest output



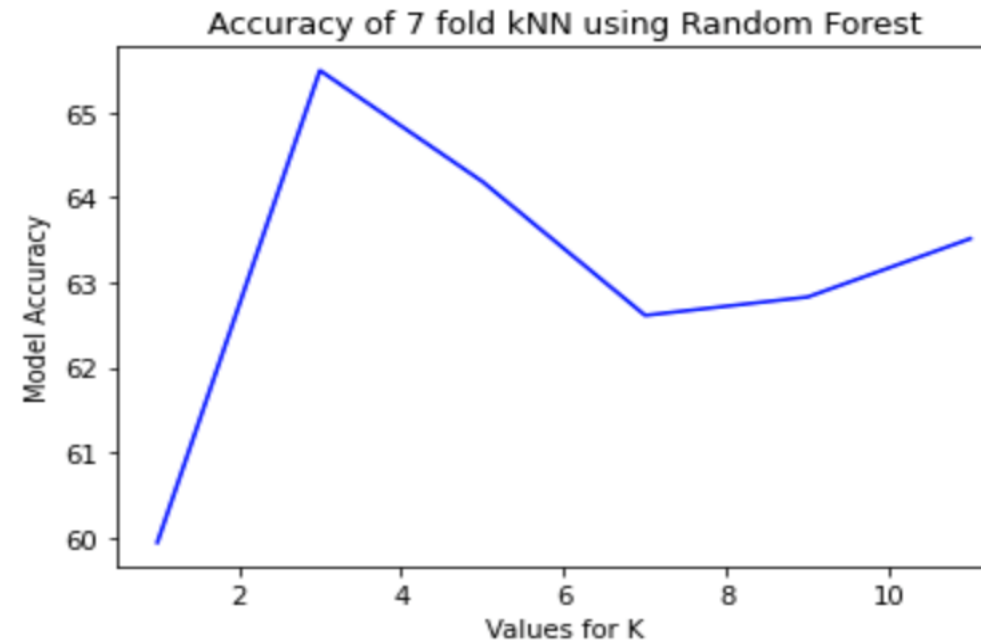
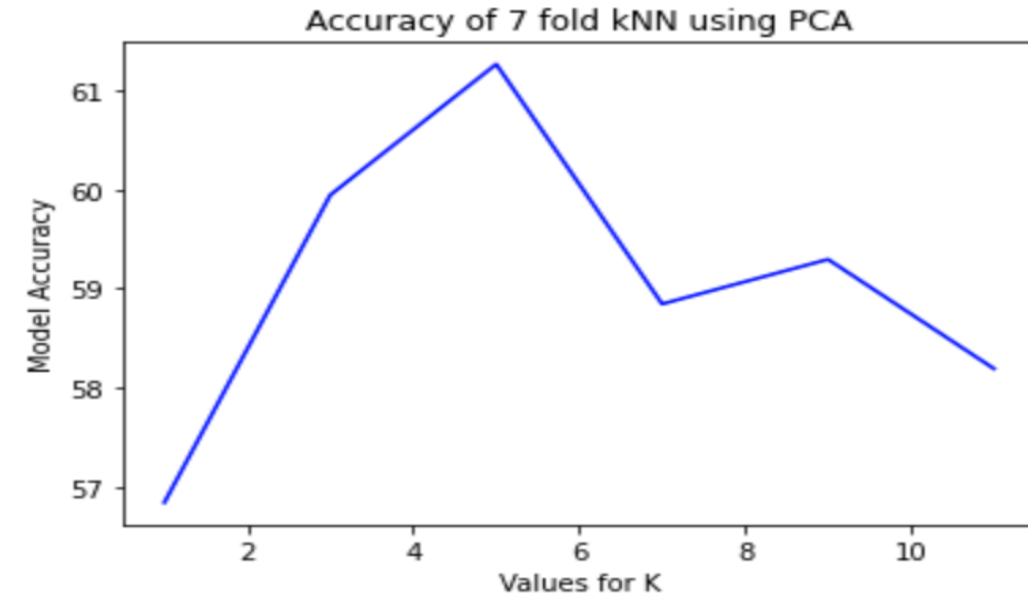
Support Vector Machines

- For SVM , we trained the model with different kernel functions: Linear, Polynomial, Gaussian RBF and Sigmoid kernel function.
- Linear Kernel function gave us the best performance of 73.53 %



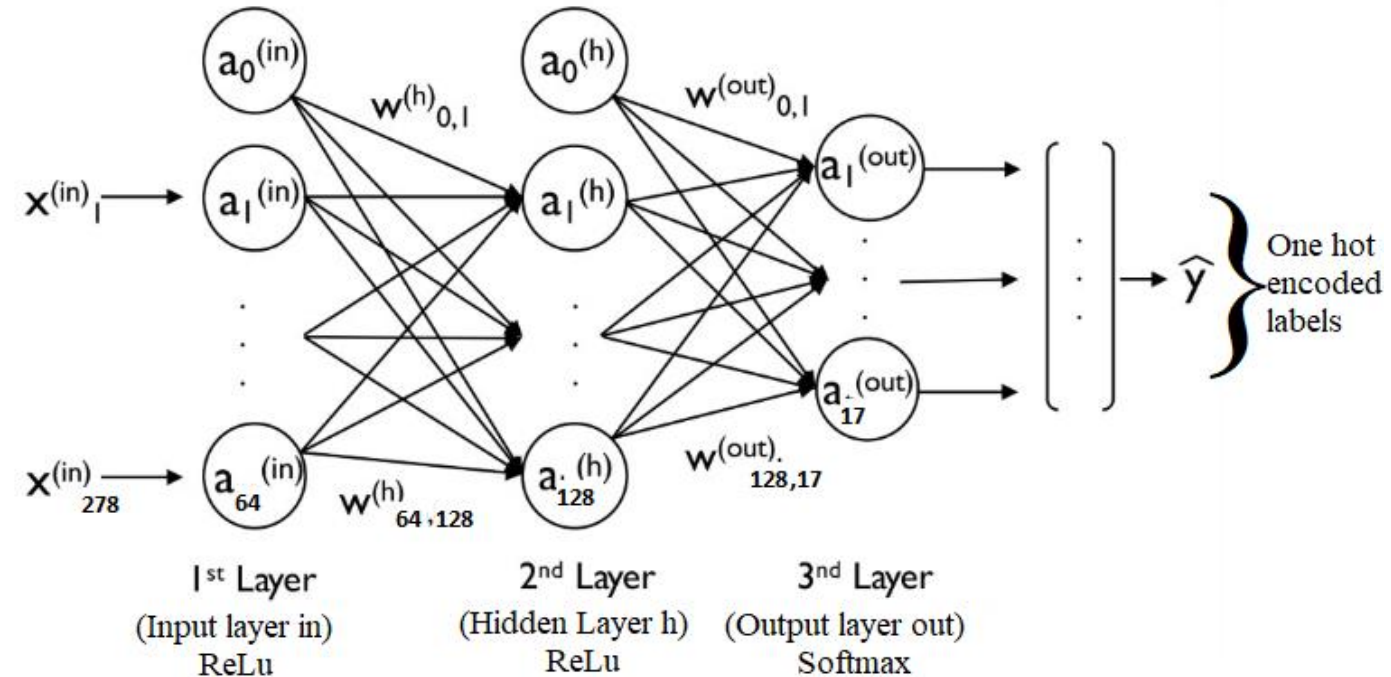
K Fold K Nearest Neighbor

Principal Component Analysis	
Hyperparameters	
Folds	7
Accuracy(5 NN)	61.26
Random Forest Classifier	
Hyperparameters	
Folds	7
Accuracy(3 NN)	65.51



Multi Layer Perceptron - Method

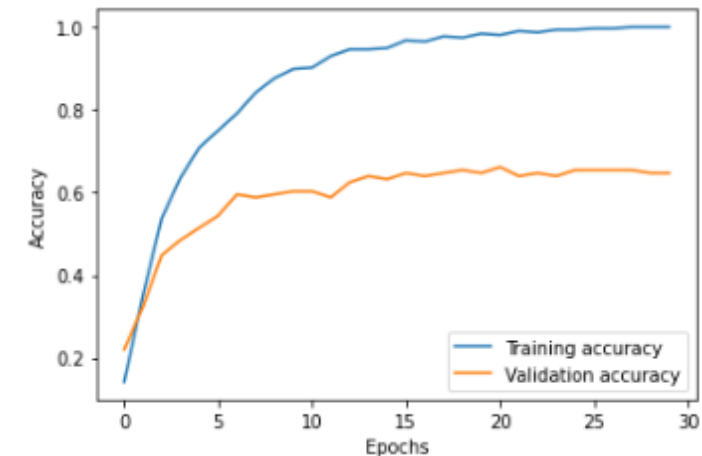
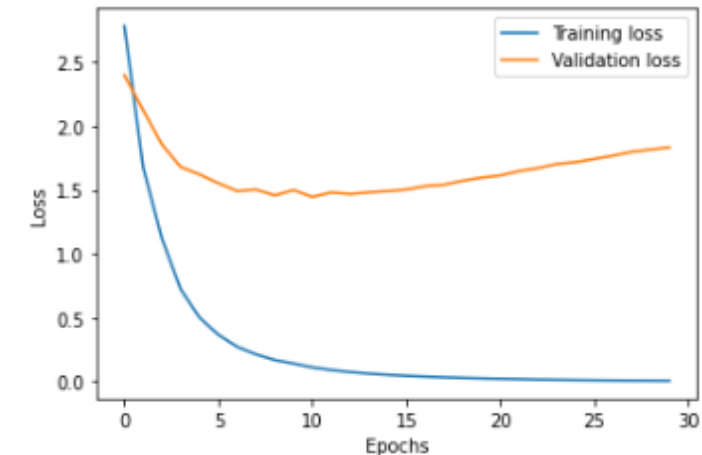
- ❑ Feed forward Neural network with 2 fully connected layers with ReLU activation. Predictions generated from Final Softmax layer.
- ❑ Weighted Loss Function for compensating imbalanced class.
- ❑ Hyper-parameters:
 - ❑ Optimizer – Adam
 - ❑ Learning Rate – 0.01
 - ❑ Batch size – 8
 - ❑ Epoch - 30
 - ❑ Neurons per layer – [64, 128, 17]



Multi Layer Perceptron - Result

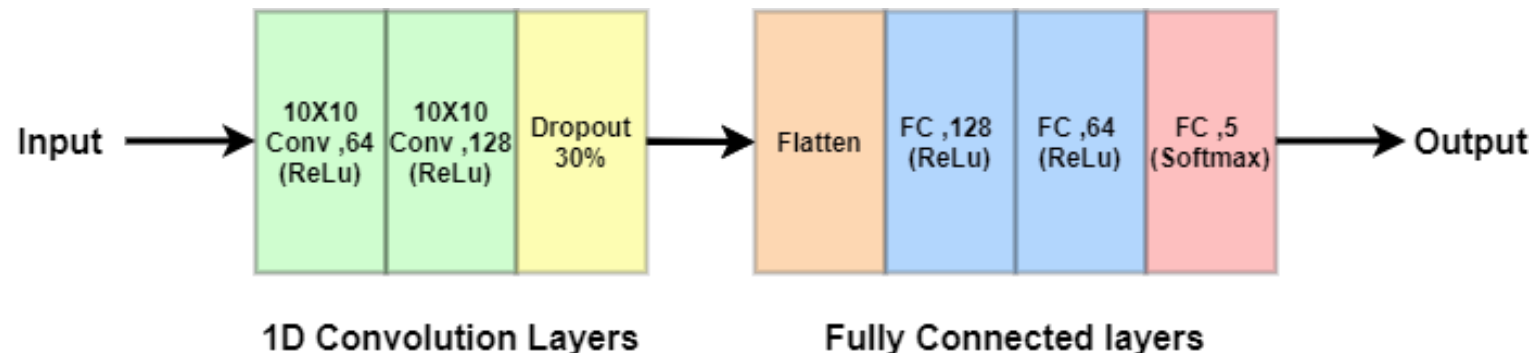
- Test Accuracy for model is 66.91%, while the validation accuracy is 68.63%

Classification Report for model				
	precision	recall	f1-score	support
1	0.74	0.85	0.79	74
2	0.40	0.46	0.43	13
3	0.80	1.00	0.89	4
4	0.75	0.75	0.75	4
5	0.67	0.50	0.57	4
6	0.43	0.38	0.40	8
7	0.00	0.00	0.00	1
8	0.00	0.00	0.00	1
9	1.00	0.67	0.80	3
10	0.75	0.40	0.52	15
14	1.00	1.00	1.00	1
15	0.50	1.00	0.67	1
16	0.00	0.00	0.00	7
accuracy			0.67	136
macro avg	0.54	0.54	0.52	136
weighted avg	0.65	0.67	0.65	136



1D – Convolutional Neural Network - Method

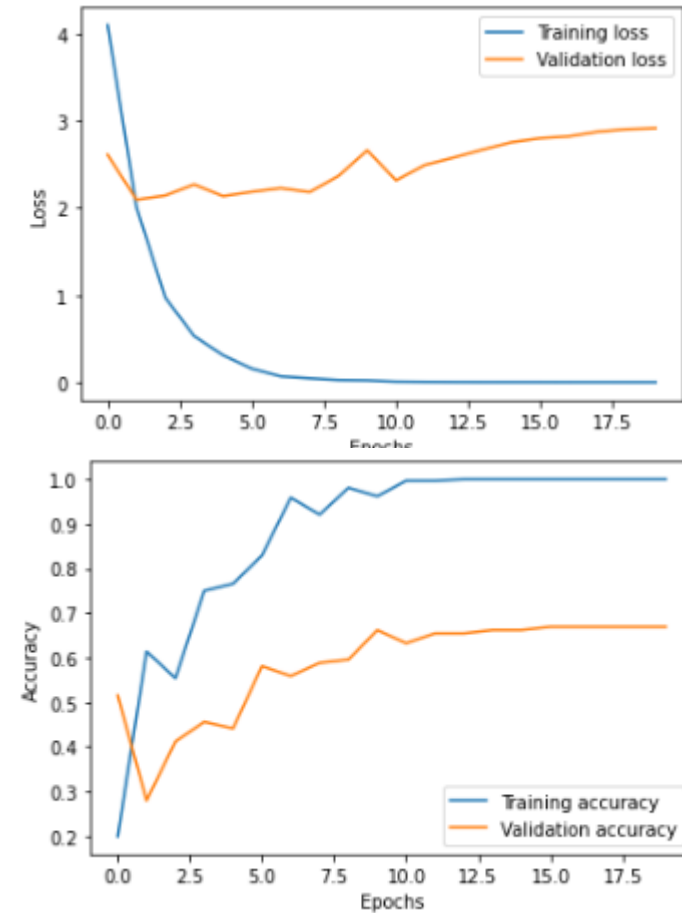
- ❑ Model is divided into 2 blocks
 - ❑ Convolution block – 1D Convolution layers and Dropout.
 - ❑ Fully Connected block – Extract features required for class prediction.
- ❑ Compiling model with Weighted Loss Function to penalize misclassification of imbalanced classes.
- ❑ Hyper-parameters:
 - ❑ Optimizer – Adam
 - ❑ Learning Rate – 0.01
 - ❑ Batch size – 16
 - ❑ Epoch - 20



1D – Convolutional Neural Network - Result

- Test Accuracy for model is 69.85%, while the validation accuracy is 70.63%

Classification Report for model				
	precision	recall	f1-score	support
1	0.70	0.92	0.80	74
2	0.54	0.54	0.54	13
3	0.80	1.00	0.89	4
4	1.00	0.75	0.86	4
5	0.50	0.25	0.33	4
6	0.67	0.25	0.36	8
7	0.00	0.00	0.00	1
8	0.00	0.00	0.00	1
9	1.00	0.67	0.80	3
10	0.80	0.53	0.64	15
14	0.00	0.00	0.00	1
15	0.00	0.00	0.00	1
16	0.00	0.00	0.00	7
accuracy			0.70	136
macro avg	0.46	0.38	0.40	136
weighted avg	0.65	0.70	0.66	136



Discussion

- ❑ For SVM, the data is linearly separated. From our work, we conclude that linear kernel works best for the data set by comparing accuracy scores with other multi-dimensional kernels.
- ❑ For KNN, this was a novel approach which was not implemented in prior related work.
- ❑ Random Forest is equally good as PCA for feature selection.
- ❑ None of the related work referenced has implemented 1D-CNN and MLP.



References

- [1] A. Das, F. Catthoor and S. Schaafsma, "Heartbeat Classification in Wearables Using Multi-layer Perceptron and Time-Frequency Joint Distribution of ECG," 2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE), Washington, DC, USA, 2018, pp. 69-74.\newline
- [2] N. Kalkstein, Y. Kinar, M. Na'aman, N. Neumark and P. Akiva, "Using machine learning to detect problems in ECG data collection," 2011 Computing in Cardiology, Hangzhou, 2011, pp. 437-440. \newline
- [3]Martis, R.J., Krishnan, M.M.R., Chakraborty, C. et al. Automated Screening of Arrhythmia Using Wavelet Based Machine Learning Techniques. J Med Syst 36, 677–688 (2012). <https://doi-org.prox.lib.ncsu.edu/10.1007/s10916-010-9535-7>
- [4] U. Desai, R. J. Martis, C. G. Nayak, Sarika K. and G. Seshikala, "Machine intelligent diagnosis of ECG for arrhythmia classification using DWT, ICA and SVM techniques," 2015 Annual IEEE India Conference (INDICON), New Delhi, 2015
- [5]R. J. Martis, C. Chakraborty and A. K. Ray, "An Integrated ECG Feature Extraction Scheme Using PCA and Wavelet Transform," 2009 Annual IEEE India Conference, Gujarat, 2009, pp. 1-4.



THANK YOU!