CS575 - Project Report

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Contents

OBJECTIVES

The study of the electrocardiogram (ECG) signal provides an insight to understand decreased heart function for many cardiac conditions. One area of study focuses on arrhythmias, which are any disturbance in the rate, regularity, site of origin or conduction of the cardiac electrical impulse. Arrhythmia detection is important and is often a basic stepping stone for diagnosis of other cardiac conditions.

In this study, we aim to develop a model for detecting arrhythmias by detecting presence of specific ectopic beats in a given ECG waveform, particularly the Premature Ventricular Contractions (PVCs).

Keeping in mind the inter-patient variability of ECG waveforms, we shall look for appropriate ways to incorporate patient-specific information into our models.

METHODOLOGY

Problem Foundation

Presence of certain ectopics heart-beats such as the Premature Ventricular Contractions (PVCs) can indicate the presence of arrhythmia. The major task is to separate out the abnormal or ectopic beats (V type) from normal or non-ectopic (N type) beats. Certain artifacts in the ECG waveform such as a wider QRS complex and ST-Depression are helpful in identifying the PVCs.

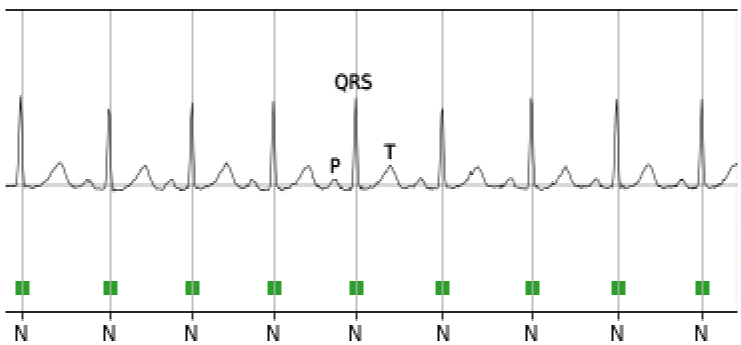


Fig 1: Normal Rhythm

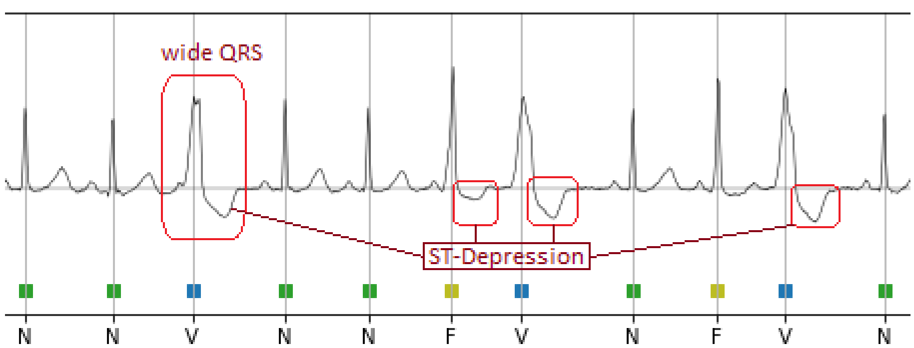


Fig 2: Premature Ventricular Contractions

Beat Representation

An ECG waveform may contain a variable number of heart-beats based on the duration of ECG recording and the heart rate of the patient. A heart-beat is considered to be the duration of a complete cycle of depolarization and repolarization of heart-muscles.

Each beat can be roughly located by detecting its R-peak on the waveform. Known algorithms such as the Pan-Tompkins algorithm can be employed to automatically detect the location of R-peaks on a given ECG waveform. R-peaks are accompanied by P-Waves and T-Waves on either side, which gives a rough location for start and end of a beat.

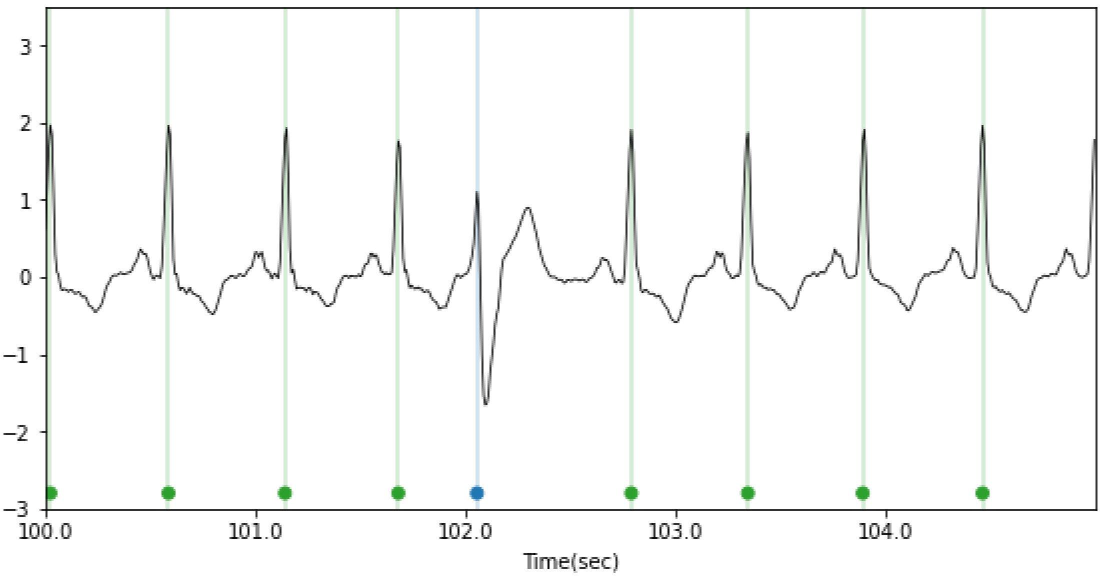


Fig 3: a signal slice of 5 sec duration from the record mitdb/233

Variance in Heart-Rate poses a problem in beat representation as each beat may vary in duration even within the same record. In this study, we looked at two ways of representing a beat:

1. **Fixed duration** on either side of the R-peak of the beat - 0.1 sec (12 samples) on the left and 0.4 sec (52 samples) on the right side. This is chosen so as to include the QRS complex and the ST segment of the beat.

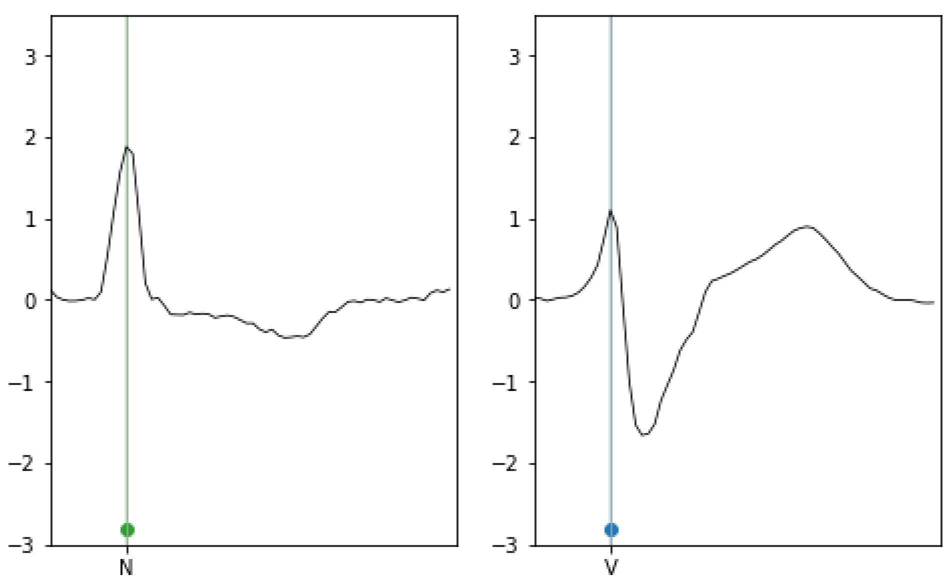


Fig 4: Fixed length representation of beats

2. **Variable duration** on either side of the R-peak of the beat, based on the occurrence of the previous and the next R-peak

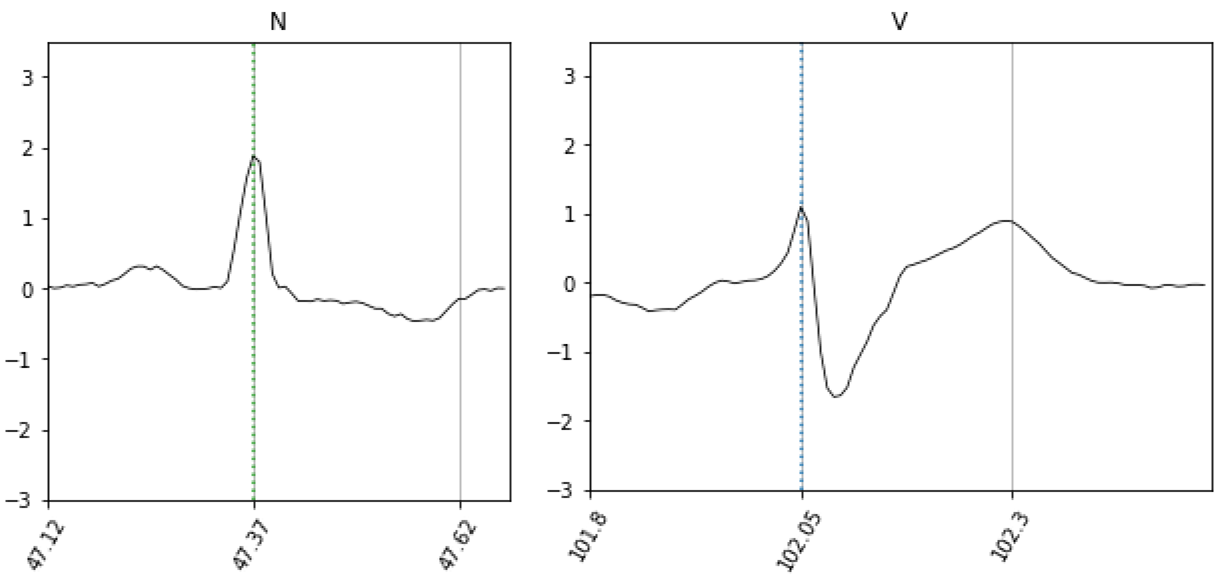


Fig 5: Variable length representation of beats

Inter-patient variability

ECG waveform shows high inter-patient variability. These arise due to various factors such as:

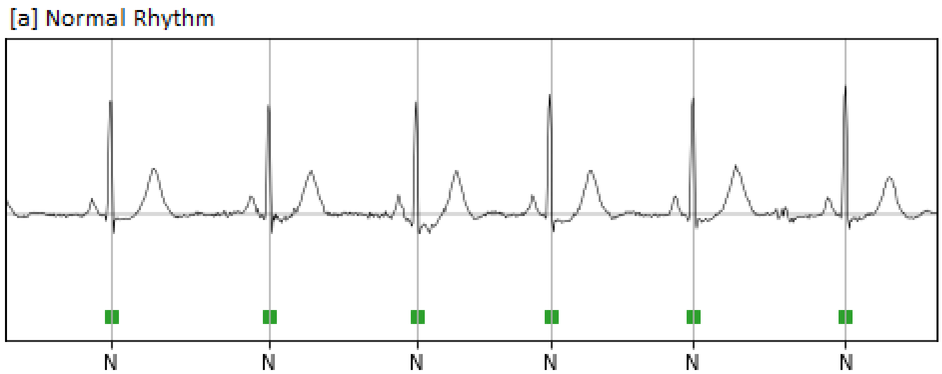
1. Age, Physical Condition, Rate of Metabolic Activities in the patient
2. Previous Injuries to Heart Muscles and/or Imbalance of regulatory Ions
3. Prescribed Medication that alter Heart Rate
4. Presence of Artificial Pacemaker

A classifier model has to be quite large in size to be able to capture these variability across a large population of patients. For this reason, we shall focus on developing **patient-specific** models that specialize for individual patients.

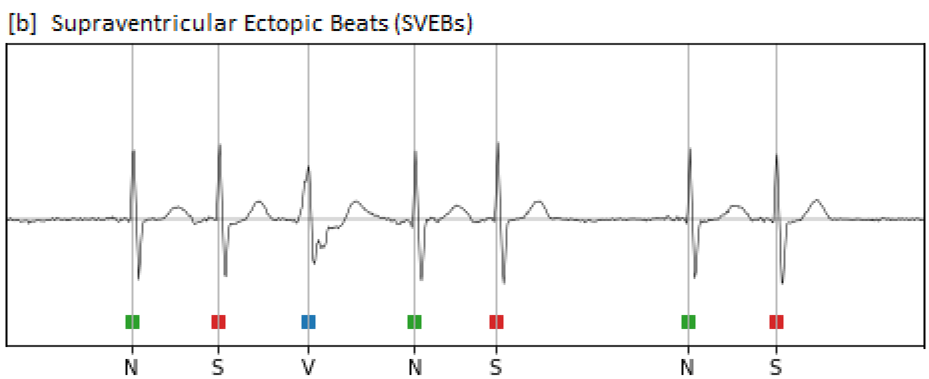
ECG DATA

The ECG Data used in this study was collected from MIT-BIH Arrhythmia Database available on PhysioNet [1] under open access. A total of 10 records were used from the database comprising around 5 hours of ECG signal. We used only the Lead II signal for our purpose. These databases are annotated with both timing information(R-peak location) and beat-labels which are verified by independent experts. **Class Labels** are described below.

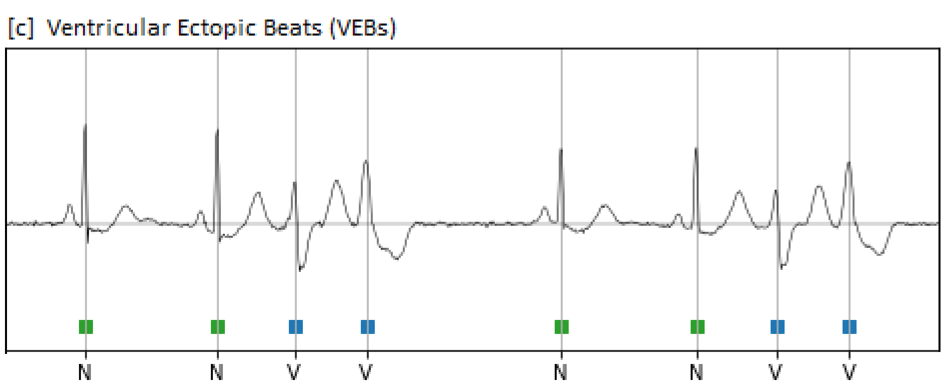
Class Label 'N' represents the Non-ectopic class - these beats are normal rhythm beats originating from the SA node - these include bundle branch blocks as well. **Represented as the normal class.**



Class Label 'S' represents the SupraVentricular Premature class - these beats are premature beats that originate from either anywhere in the atria(atrial premature) or from or near the AV node (nodal/junctional premature). **This class was NOT used.**



Class Label 'V' represents the Ventricular Premature class - these beats originate from the Purkinje fibers in the ventricles instead of the SA node. **Represented as the abnormal class.**



The following table shows the count of each type of beat in the selected set of records. All the records contain nearly 30 minutes of ECG signal.

RECORD	Total Beats	**N-Type**	**V-Type**	S-Type	F-Type	Q-Type	All Abnormal
mitdb_116	2410	2300	109	1	0	0	110
mitdb_215	3361	3193	164	3	1	0	168
mitdb_210	2648	2422	194	22	10	0	226
mitdb_214	2260	2001	256	0	1	2	259
mitdb_228	2051	1686	362	3	0	0	365
mitdb_221	2425	2029	396	0	0	0	396
mitdb_119	1985	1541	444	0	0	0	444
mitdb_203	2978	2527	444	2	1	4	451
mitdb_106	2025	1505	520	0	0	0	520
mitdb_233	3077	2229	830	7	11	0	848
Grand total	**25220**	**21433**	**3719**	**38**	**24**	**6**	**3787**

Table: Total count of beats in select dataset

Proposed Method #1 - Supervised Learning Method

In this method, a set of labeled beats are first estimated using an ARIMA model. The learned parameters are then modeled using Linear Discriminant Analysis (LDA) which creates a linear decision boundary for 2 classes. Once such a LDA-model is found, it can be used to classify future beats.

This model is completely linear and highly flexible as it allows us to encode variable length beats in terms of fixed number of ARIMA parameters. The only patient-specific information required is the estimated LDA model and optionally the type of ARIMA model. These LDA models are easy to update dynamically and thus suitable for long term active learning.

Preceding section illustrates the method on record **mitdb/116**.

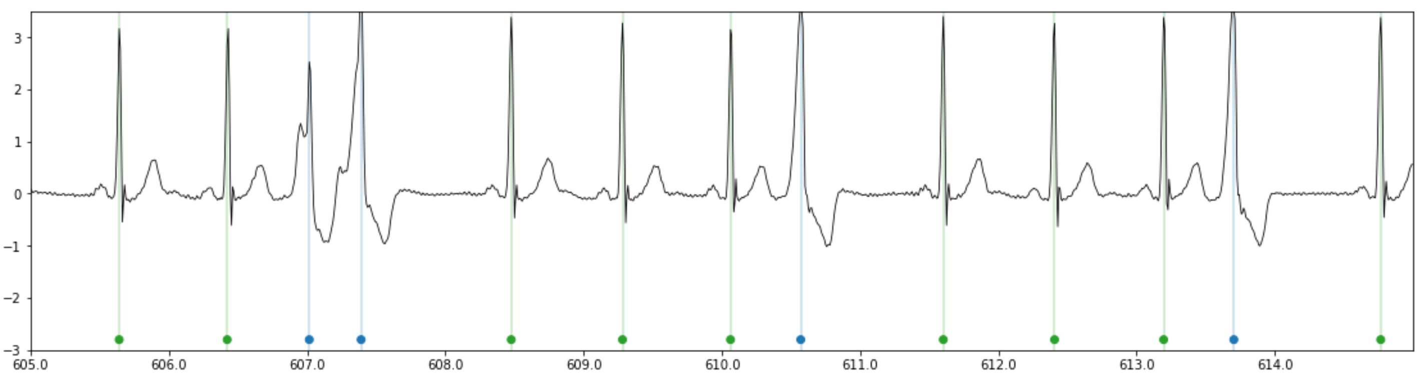


Fig 6: ten second ECG waveform from the record mitdb/116

For this method we shall use variable length beats. Fig 7 shows a Normal beat from the selected record.

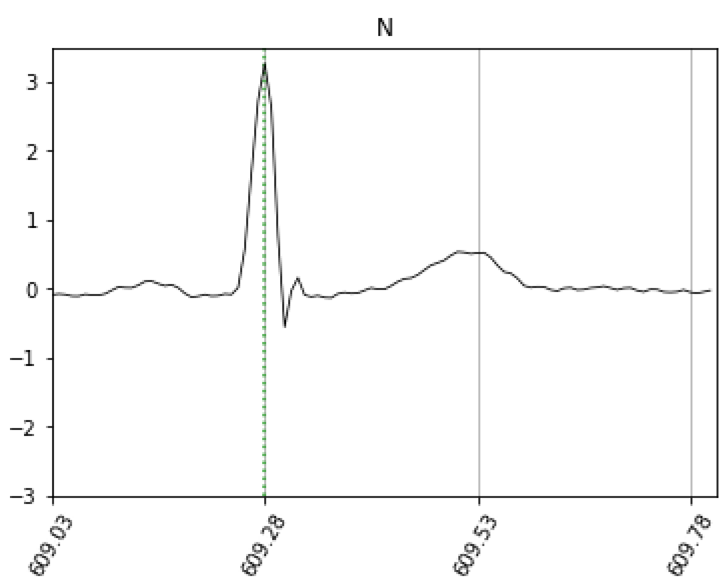


Fig 7: beat at mitdb/116/809

Checking for stationarity using ADF test.

```
ADF-Test Hypothesis    Series is Non-Stationary
Test Statistic                                              -2.60168
p-value                                                    0.0926514
#Lags Used                                                        12
Number of Observations Used                                       87
Critical Value (1%)         (-3.5078527246648834, Hypothesis: True)
Critical Value (5%)          (-2.895382030636155, Hypothesis: True)
Critical Value (10%)        (-2.584823877658872, Hypothesis: False)
dtype: object
ADF-Test Result   True
```

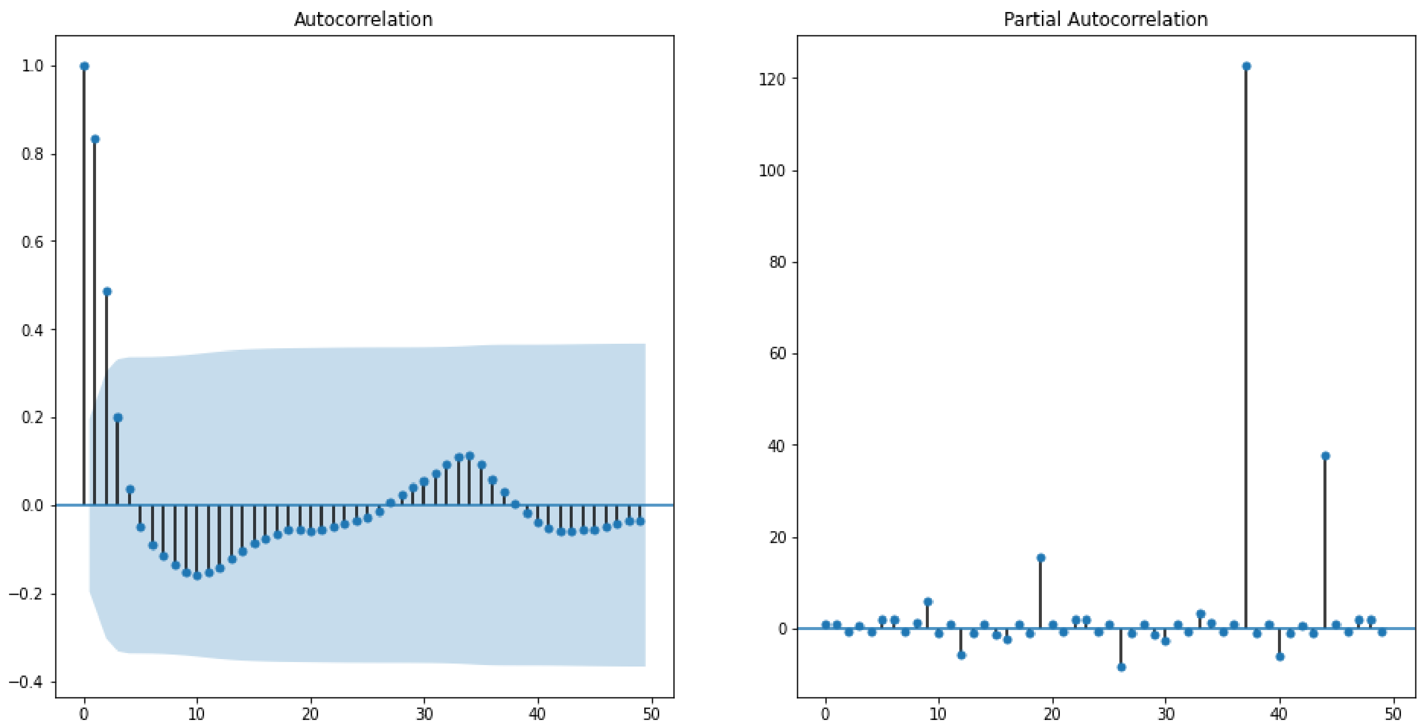


Fig 8: ACF and PACF for Normal beat [mitdb/116/809]

Use differencing to convert to stationary series and check for stationarity using ADF test again.

```
ADF-Test Hypothesis     Series is Non-Stationary
Test Statistic                                           -3.59521
p-value                                                0.00585332
#Lags Used                                                     12
Number of Observations Used                                    86
Critical Value (1%)        (-3.5087828609430614, Hypothesis: False)
Critical Value (5%)         (-2.895783561573195, Hypothesis: False)
Critical Value (10%)       (-2.5850381719848565, Hypothesis: False)
dtype: object
ADF-Test Result    False
```

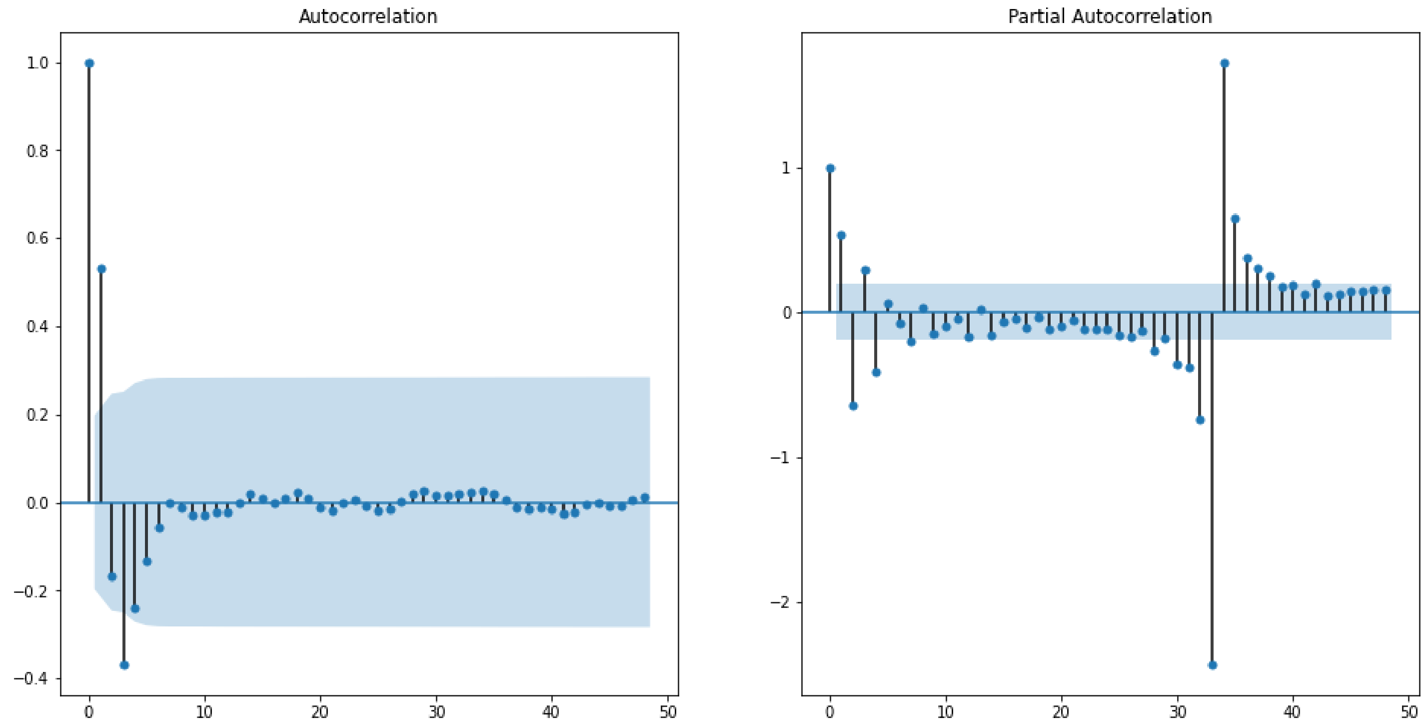


Fig 9: ACF and PACF for Normal beat [mitdb/116/809] after differencing

Perform similar analysis on an abnormal beat. Fig 10 shows an Abnormal beat from the selected record.

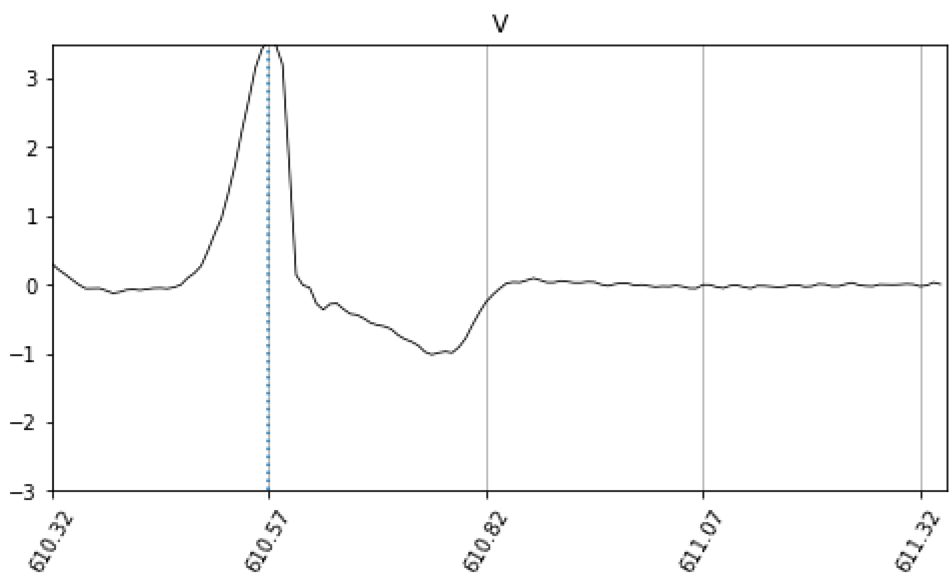


Fig 10: beat at mitdb/116/811

Checking for stationarity using ADF test.

```
ADF-Test Hypothesis      Series is Non-Stationary
Test Statistic                                               -2.62276
p-value                                                      0.088384
#Lags Used                                                         12
Number of Observations Used                                        85
Critical Value (1%)           (-3.5097356063504983, Hypothesis: True)
Critical Value (5%)           (-2.8961947486260944, Hypothesis: True)
Critical Value (10%)         (-2.5852576124567475, Hypothesis: False)
dtype: object
ADF-Test Result     True
```

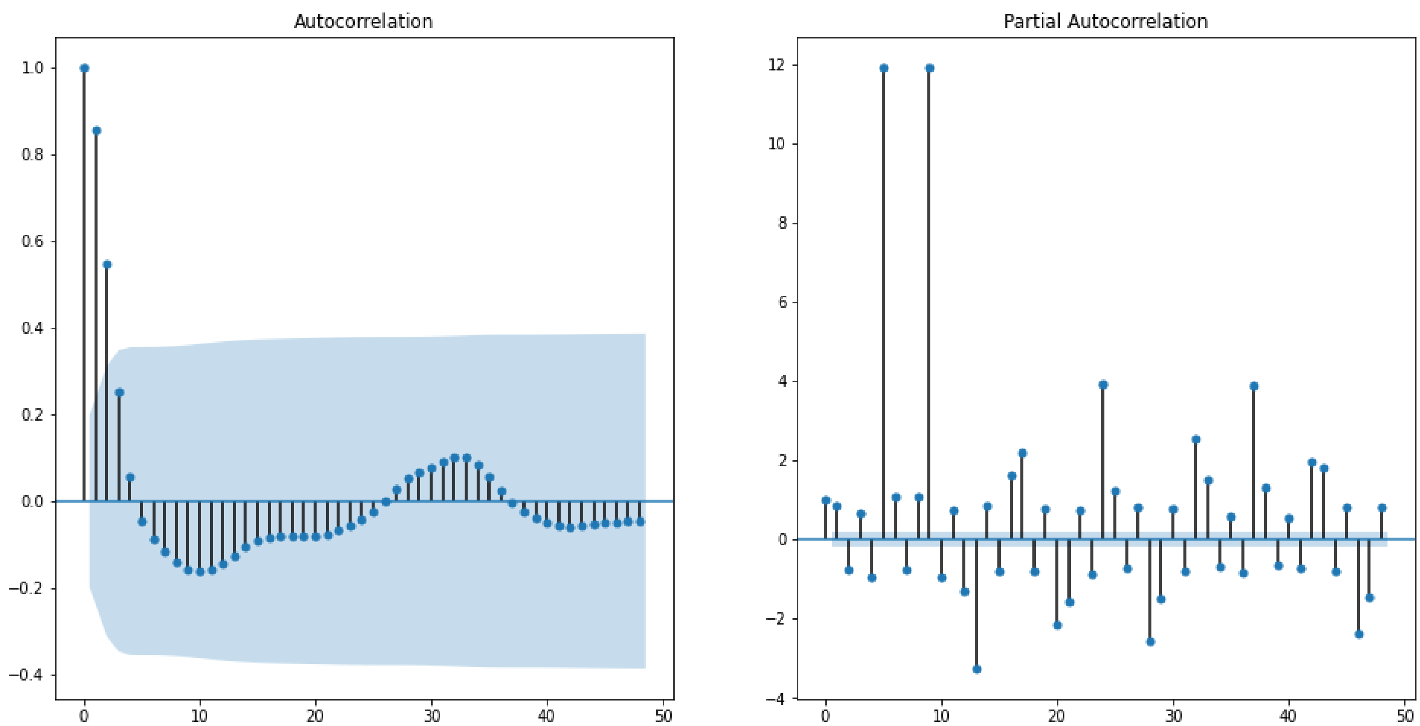


Fig 11: ACF and PACF for Abnormal beat [mitdb/116/811]

Use differencing to convert to stationary series and check for stationarity using ADF test again.

```
ADF-Test Hypothesis      Series is Non-Stationary
Test Statistic                                               -3.63859
p-value                                                    0.00506472
#Lags Used                                                         12
Number of Observations Used                                        84
Critical Value (1%)           (-3.510711795769895, Hypothesis: False)
Critical Value (5%)          (-2.8966159448223734, Hypothesis: False)
Critical Value (10%)         (-2.5854823866213152, Hypothesis: False)
dtype: object
ADF-Test Result     False
```

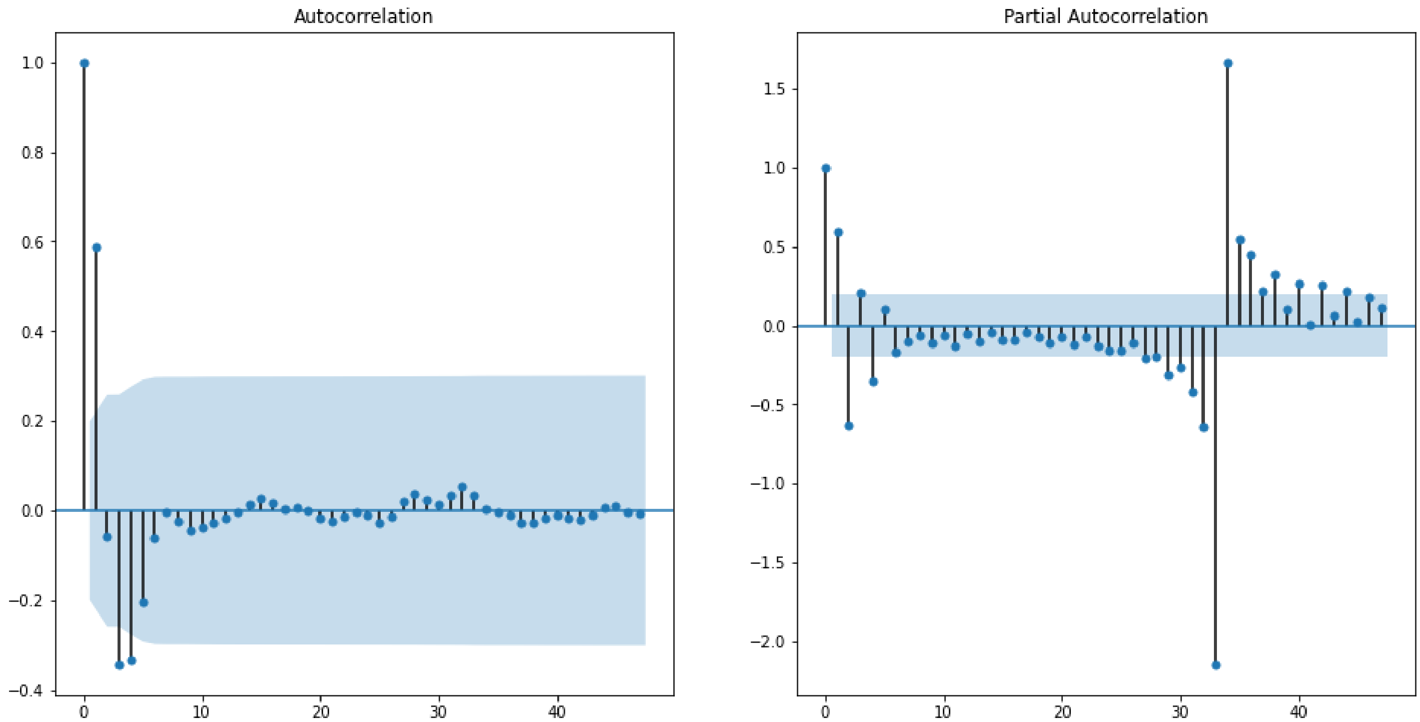


Fig 12: ACF and PACF for Normal beat [mitdb/116/811] after differencing

Record mitdb/116 contains a total of **2412** beats out of which **2302** are Normal (N-Type) and **109** are Abnormal (V-type).

Label	# beats
N	**2302**
S	1
V	**109**
F	0
Q	0
Total	2412

>> Label Count mitdb/116

An ARIMA model with (p,d,q) = (4,1,4) was chosen to estimate parameters for the beats of this record. 80 beats were chosen randomly from each of N and V classes for training. An LDA model was trained on the estimated ARIMA params for all the 80 beats. The LDA Result are as follows:

```
LDA Score: 0.9875
```

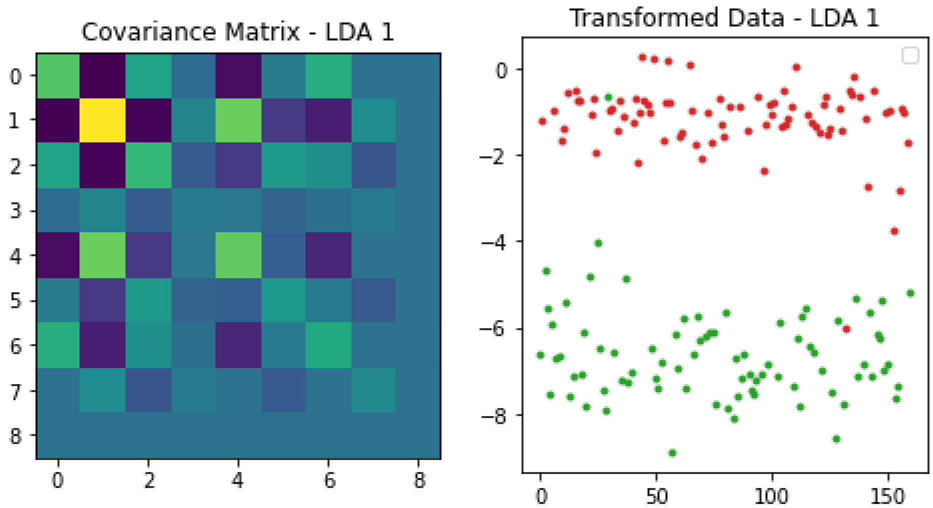


Fig 13: LDA Training Results

The trained LDA model is now tested on another set of 200 beats randomly selected from both classes of the same record. The test results are described below:

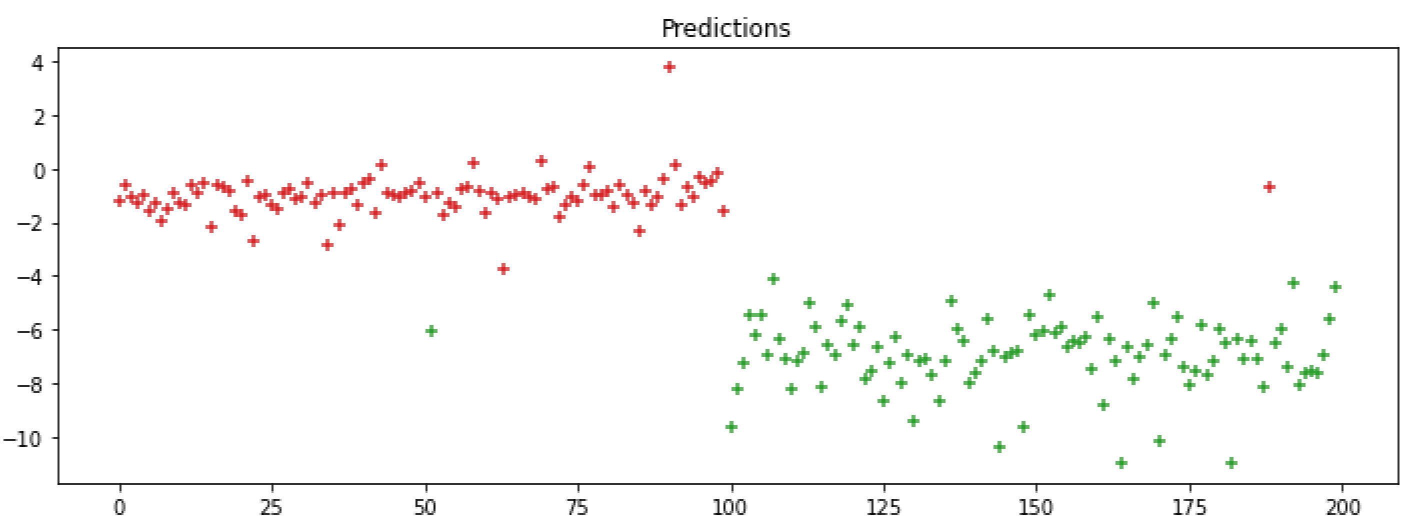
Confusion Matrix [N/A]

T\P	0	1
0	99	1
1	1	99

Performance for 2 classes

Class	#True	#Pred	TPs	FNs	FPs	TNs	ACC	PRE	SEN	SPF	F1S
0	100.0	100.0	99.0	1.0	1.0	99.0	0.99	0.99	0.99	0.99	0.99
1	100.0	100.0	99.0	1.0	1.0	99.0	0.99	0.99	0.99	0.99	0.99

Total Predictions	200	
Correct Predictions	198	**99.0 %**
Incorrect Predictions	2	1.0 %



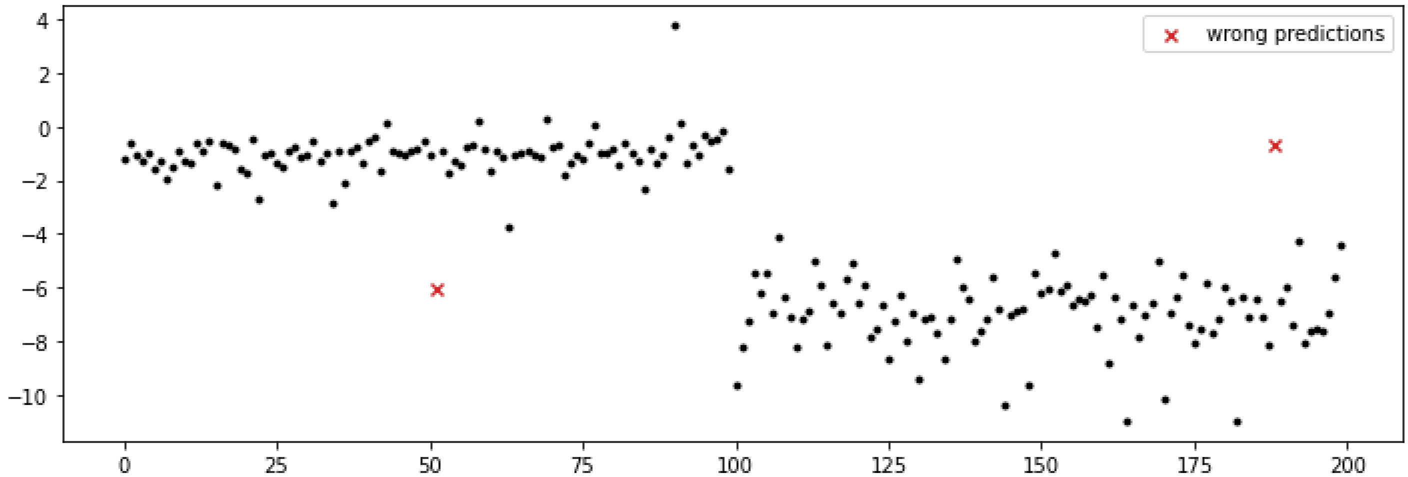


Fig 14: Test Results for LDA models

The Linear Supervised Model shows good performance for record mitd/116. Test results for all the records are described in the results sections.

Results

Following are the results for the Linear model on full records. Each patient-specific model is trained with 80 of each normal and abnormal beats from a record. For testing, 100 beats of each type were chosen randomly.

Record	LDA Score	Accuracy	Precision	Sensitivity
116	0.98125	0.985	0.9899	0.98
215	0.96875	0.965	0.94286	0.99
106	0.99375	0.96	0.95098	0.97
203	0.73125	0.72	0.68966	0.80
210	0.9	0.89	0.85455	0.94
233	0.94375	0.88	0.82203	0.97
214	0.95626	0.915	0.93684	0.89
228	0.975	0.935	0.93939	0.93
221	1.0	0.985	0.97087	1.0
119	1.0	1.0	1.0	1.0
Average	**0.945**	**0.9235**	**0.9097**	**0.947**

Proposed Method #2 - Semi-Supervised Learning Method

In this method, we used an LSTM-based encoder to first learn the Normal Rhythm of a patient. A threshold on reconstruction error of the decoder is applied to classify beats as Normal or Abnormal.

This method uses the fixed length beat representation and overcomes the problem with anomaly beat representation as it does not require abnormal beats to be already present in a record. Labeled data is only required initially to encode the normal rhythm of the patient and optionally to decide the threshold for classification.

For illustration, the same beats from the previous method are used. Fig 15 shows the same beats from the previous method, represented in fixed length representation.

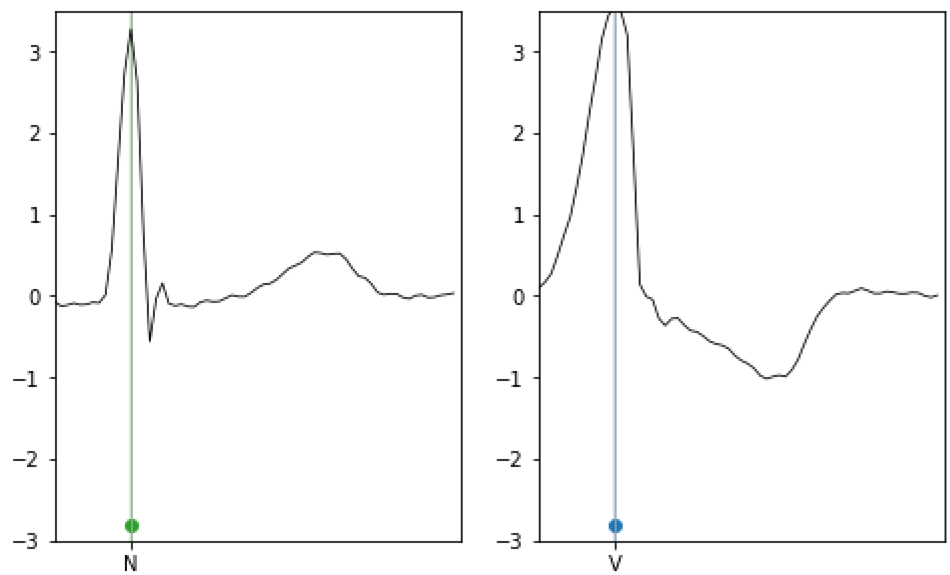


Fig 15: Beats - mitdb/116/809 [N] and mitdb/116/811 [V]

Checking for stationarity using ADF test.

For Normal Beat

```
ADF-Test Hypothesis     Series is Non-Stationary
Test Statistic                                              -2.88517
p-value                                                       0.0471
#Lags Used                                                        11
Number of Observations Used                                       52
Critical Value (1%)            (-3.562878534649522, Hypothesis: True)
Critical Value (5%)            (-2.918973284023669, Hypothesis: True)
Critical Value (10%)          (-2.597393446745562, Hypothesis: False)
dtype: object
ADF-Test Result    False
```

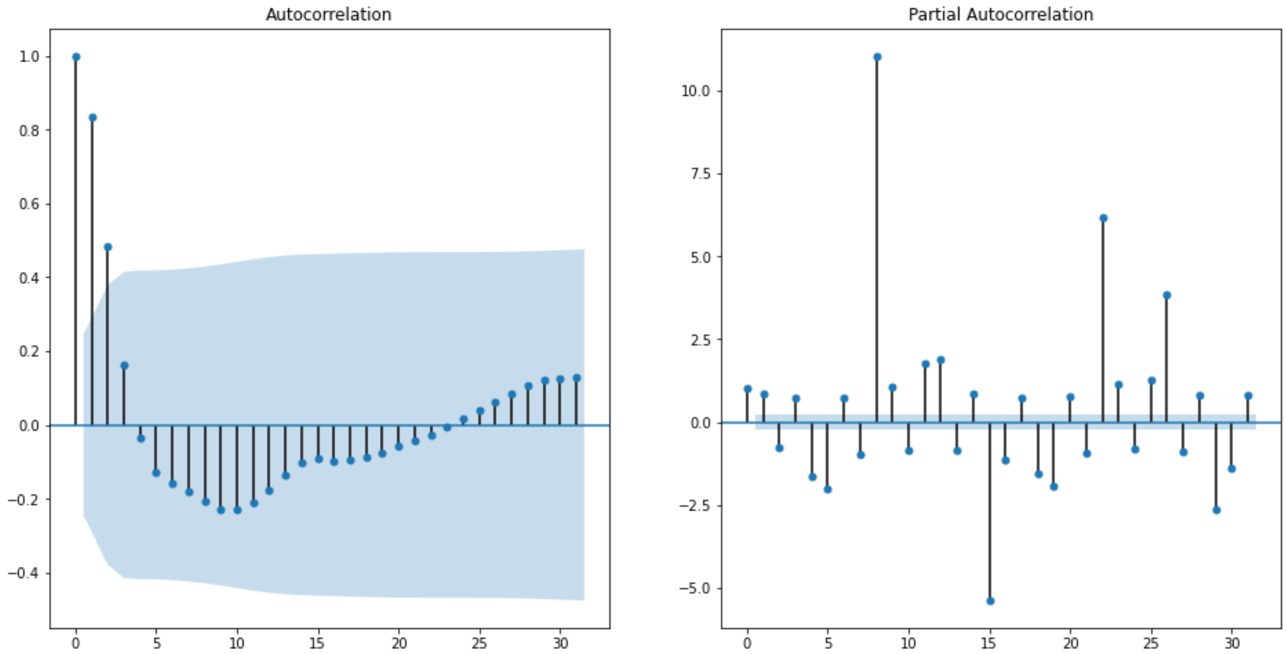


Fig 16: ACF and PACF for Normal beat [mitdb/116/809] for fixed length representation

For Abnormal Beat

```
ADF-Test Hypothesis      Series is Non-Stationary
Test Statistic                                  -2.97249
p-value                                        0.0375445
#Lags Used                                            11
Number of Observations Used                           52
Critical Value (1%)          (-3.562878534649522, Hypothesis: True)
Critical Value (5%)         (-2.918973284023669, Hypothesis: False)
Critical Value (10%)        (-2.597393446745562, Hypothesis: False)
dtype: object
ADF-Test Result    False
```

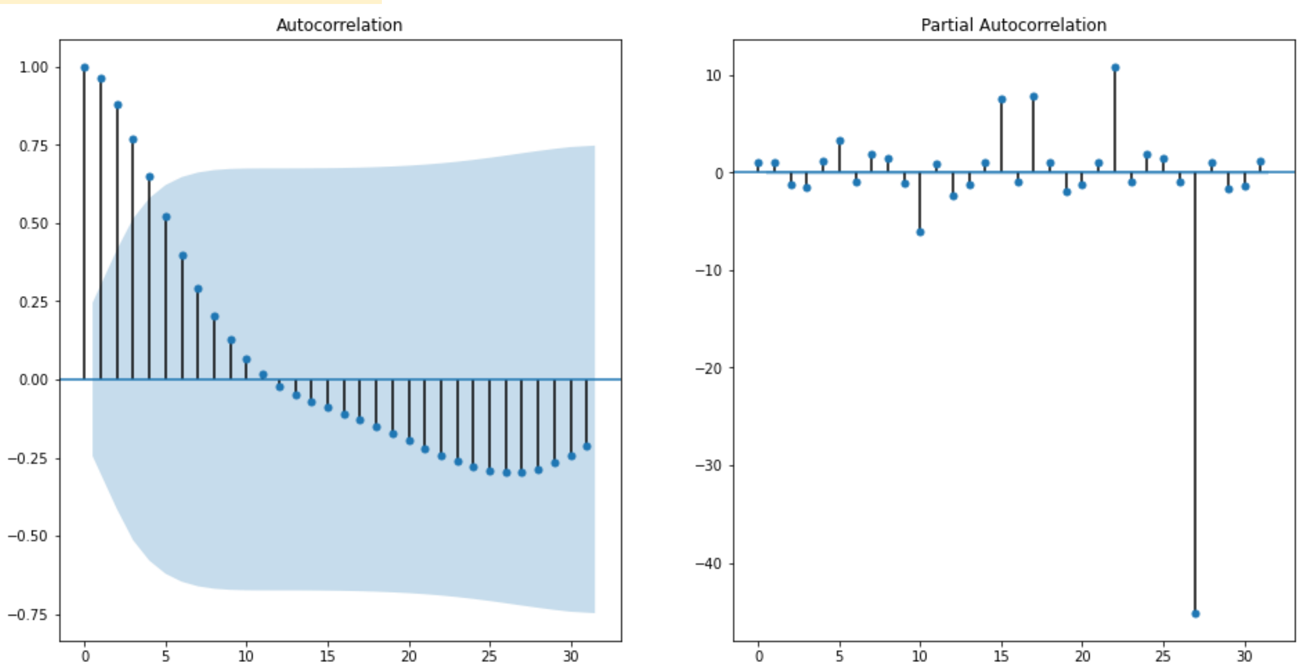


Fig 17: ACF and PACF for Abnormal beat [mitdb/116/811] for fixed length representation

An **LSTM-based encoder-decoder** model with 1 LSTM layer of 64 units each is used to learn the normal beats. The model has a total of 49,985 trainable parameters. The model was first trained on the beat mitdb/116/811 (N) and tested on some normal and abnormal beats.

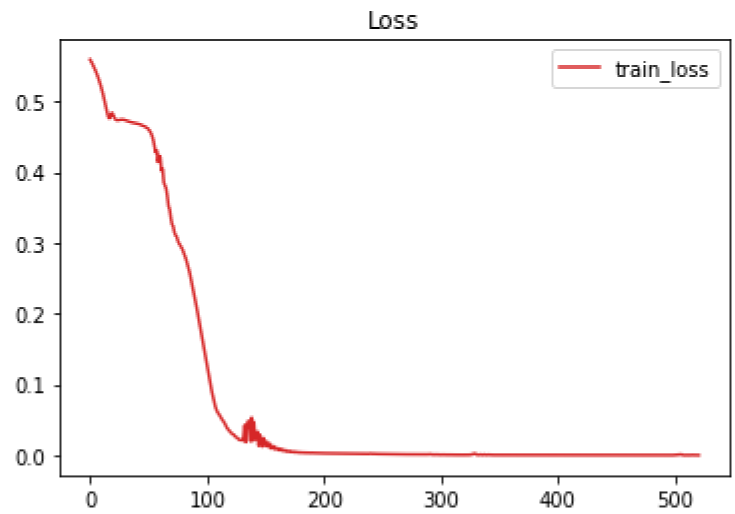


Fig: 18: Training Loss for LSTM-Encoder-Decoder

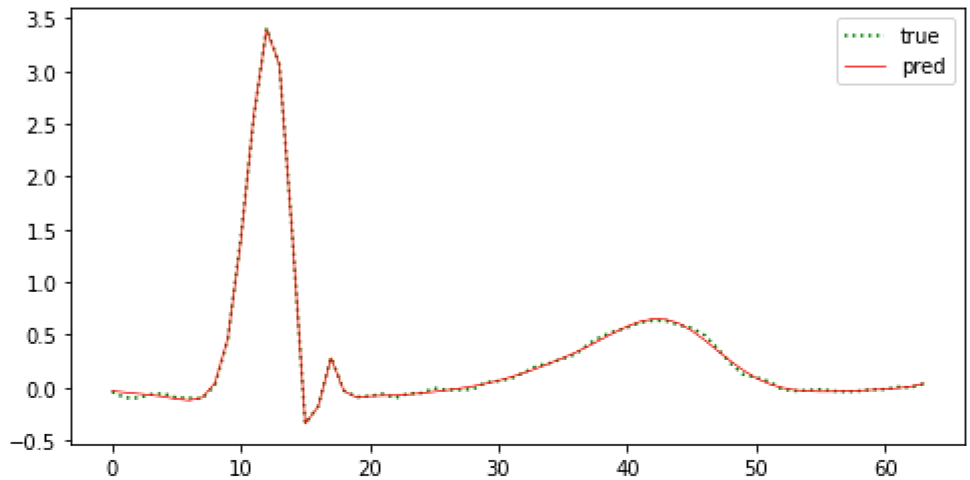


Fig 19: Reconstruction of training beat [mitdb/116/809] (N)

MAE: 0.9320333448865205

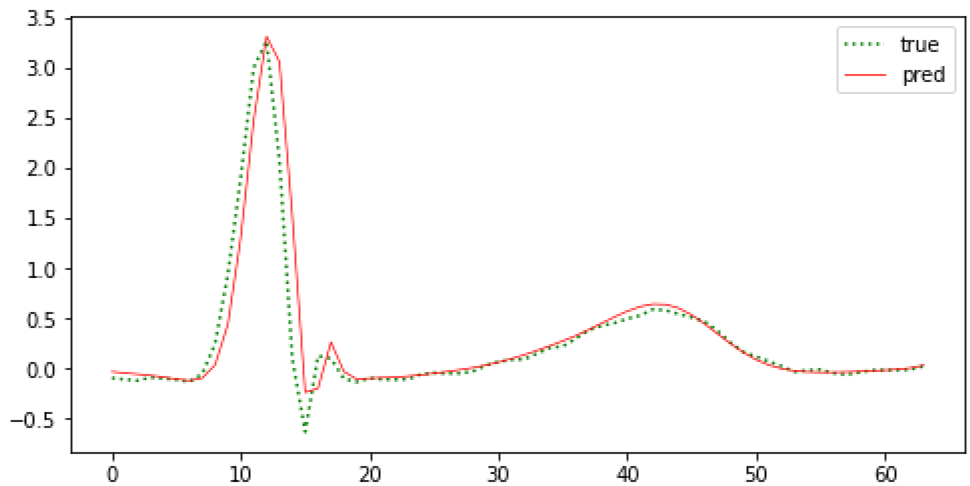


Fig 20: Reconstruction of Normal beat [mitdb/116/813] (N)

MAE: 6.676851023021376

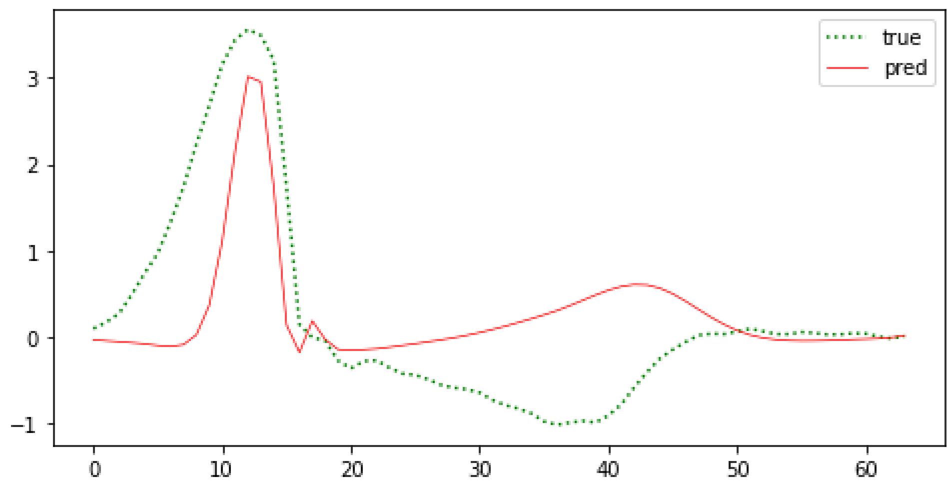
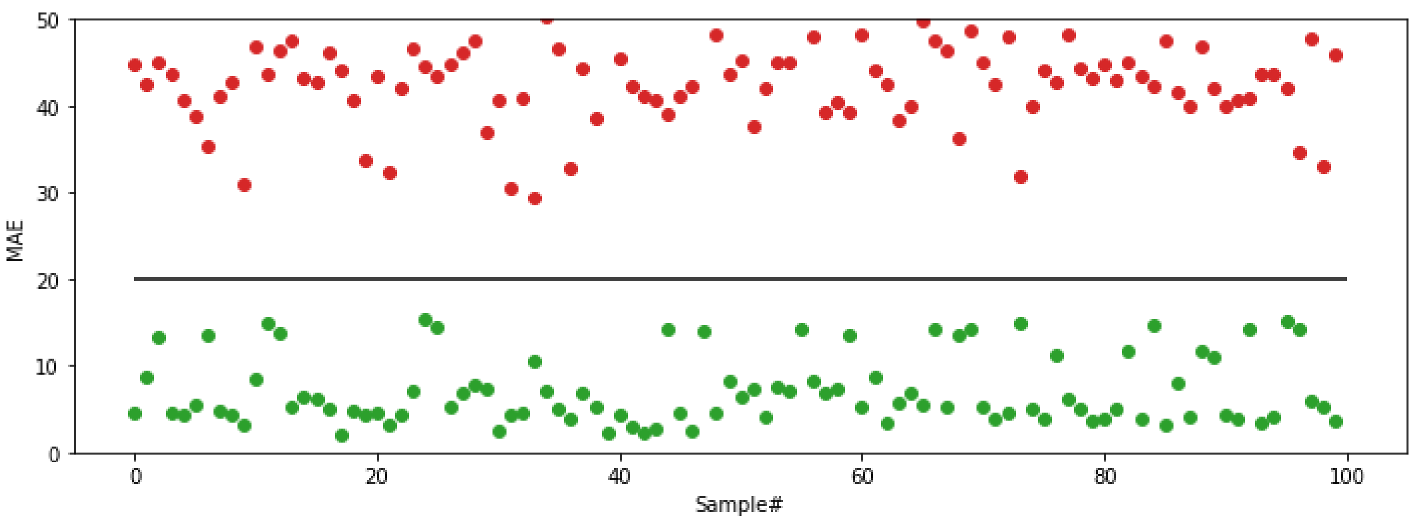


Fig 22: Reconstruction of Abnormal beat [mitdb/116/811] (V)

`MAE: 42.20973327757446`

Deciding a threshold on reconstruction error may require some labeled data from the abnormal class. Using 100 labed beats from each class we find that an MAE of 20 might be a good limit for classification for this particular record.



The LSTM-encoder-decoder model is flexible and can be trained on most recently generated patient data as long as labeled normal rhythm beats are available.

Results

Following are the results for LSTM encoder decoder on full records. Each patient-specific LSTM model is trained with 100 normal beats from a record. For testing and deciding a threshold, an equal number of beats from the both classes are chosen randomly, depending upon the number of abnormal beats present in a record. The MAE threshold is chosen such that it covers 98% of normal beats.

Record	Training Loss	# beats for Testing	MAE Threshold	Test Accuracy(%)
116	0.0186	109	8.24	98.16
215	0.0048	164	5.22	98.78
210	0.0040	195	6.05	96.67
233	0.0063	830	19.79	88.73
214	0.0063	256	9.07	93.36
228	0.0032	362	6.59	98.34
221	0.0062	396	4.40	98.98
119	0.0076	444	6.59	98.98
203	0.0198	444	20.34	88.28
106	0.0190	520	7.69	97.98
Average				**95.826**

CONCLUSION

In this study, two time-series based models were proposed for PVC detection in ECG signals. Both the models show almost similar overall accuracy of 95% in these experiments. It can be observed that model performance varies for each record. Hence the choice of model is flexible for each patient. Both the models are patient-specific, due to which they are lightweight and suitable for use with real time ECG monitoring devices. The models capture patient specific information by encoding heart-beats for a patient.

The models can be expanded upon by finding ways of encoding parts of beat specifically for detecting other types of abnormalities like the Supra-Ventricular Ectopic Beats which are very sensitive to the part of beat being observed and the heart-rate. More ways of encoding patient data can be considered which may include personal information like age, gender etc and as well include historic medical data of the patient.

The ECG data used in this study is more than 40 years old (recorded in 1975-1979) and quite noisy. Presence of noise in some ECG signals causes the performance of the models to degrade sometimes. Modern ECG equipment usually have in-built systems to remove noisy artifacts like electrical interference and baseline wander. Other types of noise that may arise while handling the equipment include loose electrode connection and too much movement in the patient while recording. An improvement would be to make the model more robust to such sources of noise.

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