ECG Anomaly Detection using Autoencoders

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AGENDA

- PROBLEM STATEMENT
- PROBLEM OVERVIEW
- END USERS
- SYSTEM APPROACH
- PROPOSED SOLUTION VALUE
- MODELLING
- RESULTS

PROBLEM STATEMENT

The Project addresses the critical need for accurate and timely detection of ECG anomaly. Existing detection methods are typically complicated, time-consuming and can have false positives, leading to challenges in early detection .

PROJECT OVERVIEW

The Project aims to develop an model that can detect anomalies in electrocardiogram (ECG) data. Autoencoders, a type of neural network, are used to reconstruct normal ECG signals and then identify any deviations from the normal patterns as anomalies. By training the autoencoder on a large dataset of normal ECG signals, deviations from normal patterns can be identified as anomalies. Deep learning techniques will be employed to enhance the accuracy of ECG anomaly detection, aiding in early diagnosis and treatment of cardiac disorders.

END USERS

- Healthcare Professionals
- Healthcare Institutions
- Patients
- Research Institutions
- Medical Device Manufacturers
- Healthcare Software Developers
- Telemedicine Providers
- Insurance Companies

PROPOSED SOLUTION VALUE

Our ECG anomaly detection solution utilizes a sophisticated autoencoder neural network, optimized for analyzing ECG data and identifying anomalies. With its specialized model design and unsupervised learning approach, our solution provides unique capabilities tailored for accurate anomaly detection in ECG signals.

✓ **Efficient Resource Utilization**
✓ **Accurate Anomaly Detection**
✓ **Timely Intervention**
✓ **Enhanced Diagnostic Insights**
✓ **Cost-Efficiency**

MODELLING

Autoencoder Architecture Design:

1.Encoder Layers:

The system processes ECG signal data through several dense layers. Initially, there's a layer with 32 units and ReLU activation, followed by one with 16 units and ReLU activation. Finally, a layer with 8 units and ReLU activation is applied. The resulting encoded representation captures essential features in the latent space of the ECG signal.

2.Decoder Layers:

The system reconstructs input signals from the latent space using a series of dense layers. Initially, there's a layer with 16 units and ReLU activation, followed by one with 32 units and ReLU activation. Finally, the output layer consists of 140 units with Sigmoid activation.

MODELLING-CONT.

3.**Loss Function:**

The calculated mean of the training loss values (Mean Absolute Error) provides insight into the reconstruction accuracy of the autoencoder model.

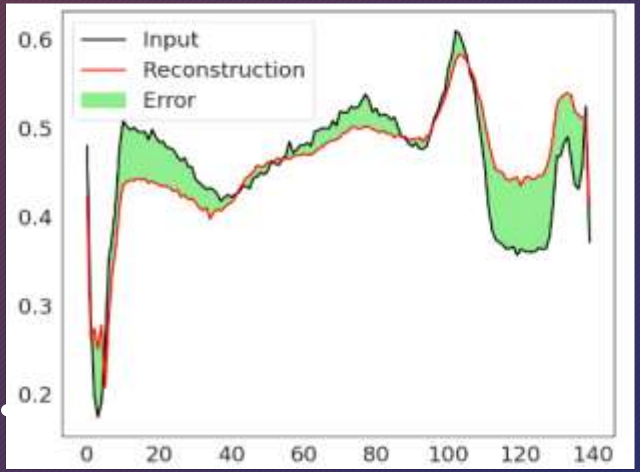
4.Training:

During training, the model iterates through 20 epochs, representing the complete pass of the training dataset through the neural network. Each training iteration utilizes a batch size of 512 samples for gradient updates. Additionally, model performance is monitored using validation data, typically derived from separate test data, throughout the training process.

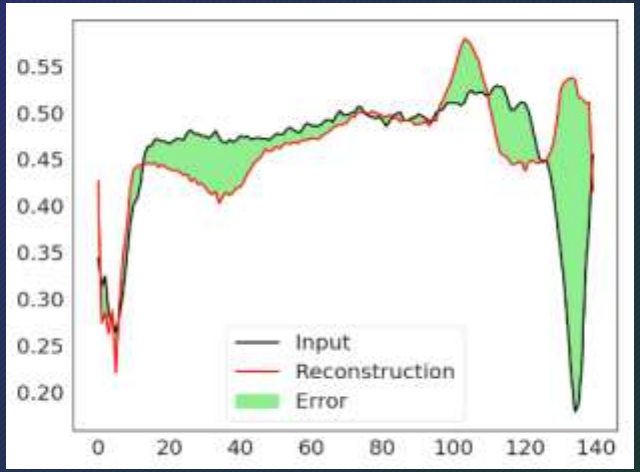
MODELLING-CONT.

5.Anomaly Detection:

Deviations or differences between the reconstructed signals and the originals serve as indicators of anomalies.



Testing using normal data



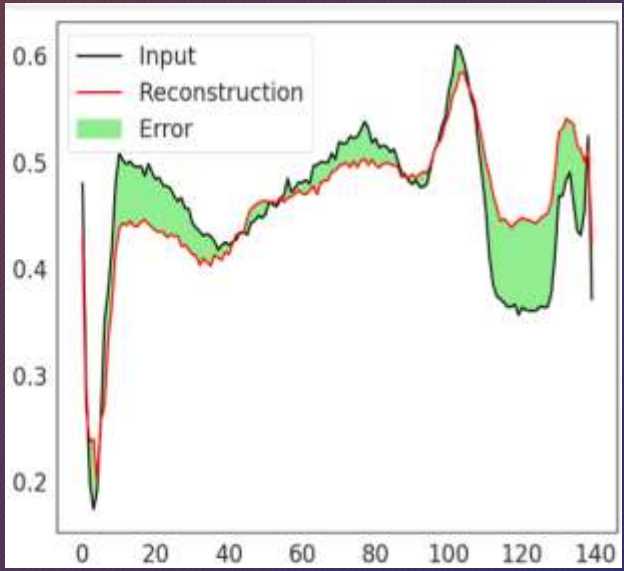
Testing using abnormal data

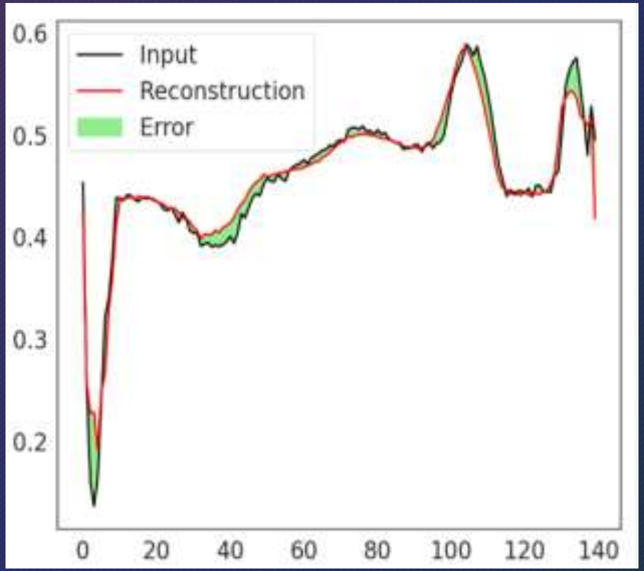
MODELLING-CONT.

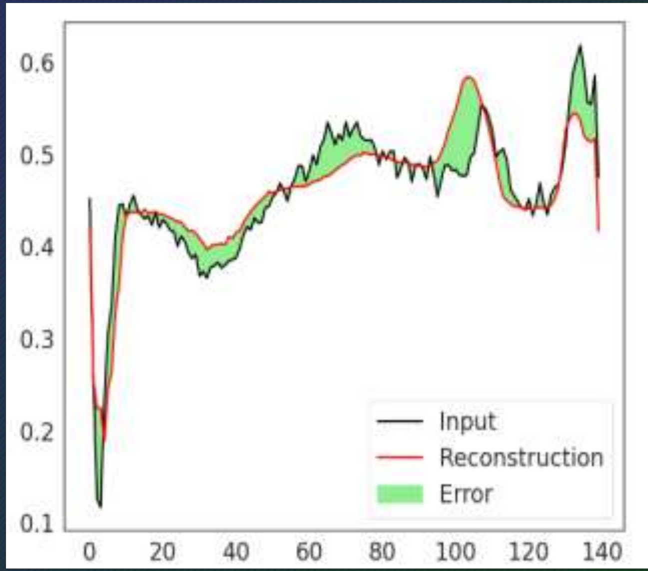
6.Model Evaluation: Metrics like MSE, accuracy, precision, recall, F1-score, ROC-AUC for performance assessment.

```
Accuracy: 0.945
Precision: 0.9922027290448343
Recall: 0.9089285714285714
F1 Score: 0.9487418452935694
AUC Score: 0.9499188311688314
```

RESULTS

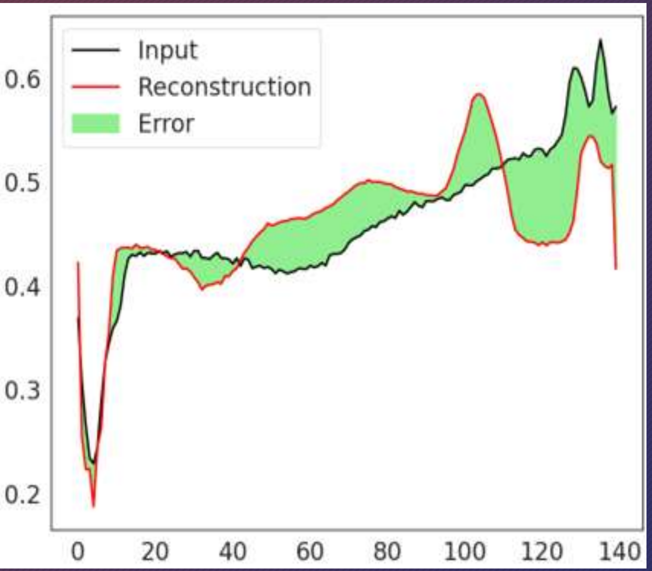


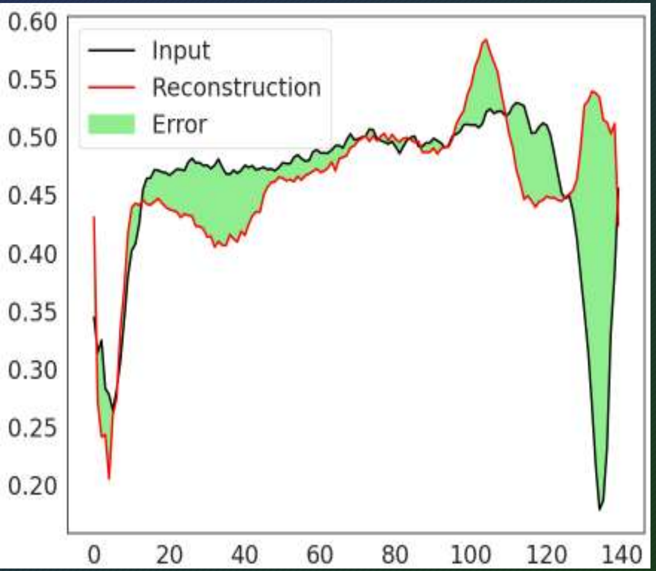




Normal

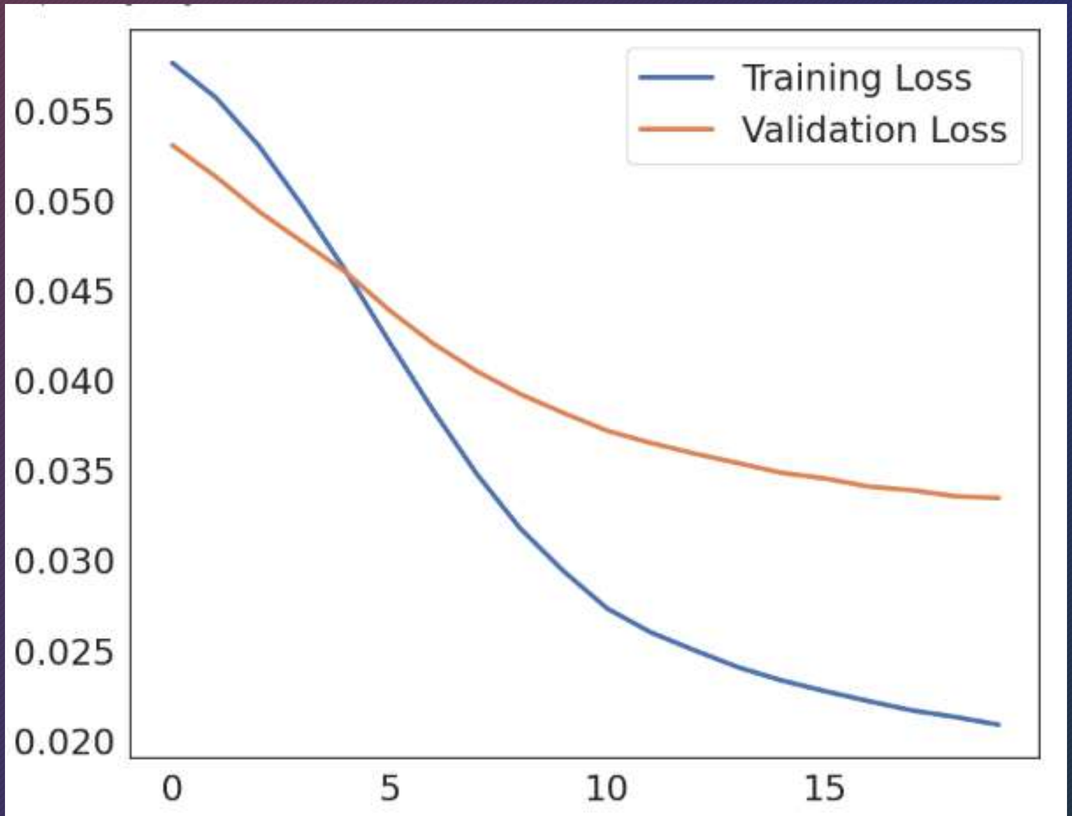
RESULTS-CONT.





Anomaly

RESULTS-CONT.



Training and Validation Loss

If the reconstruction error is greater than one standard deviation from the normal training example, classify the ECG as abnormal.