# Artificial Intelligence Based ECG Analysis Framework

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# Colloborators

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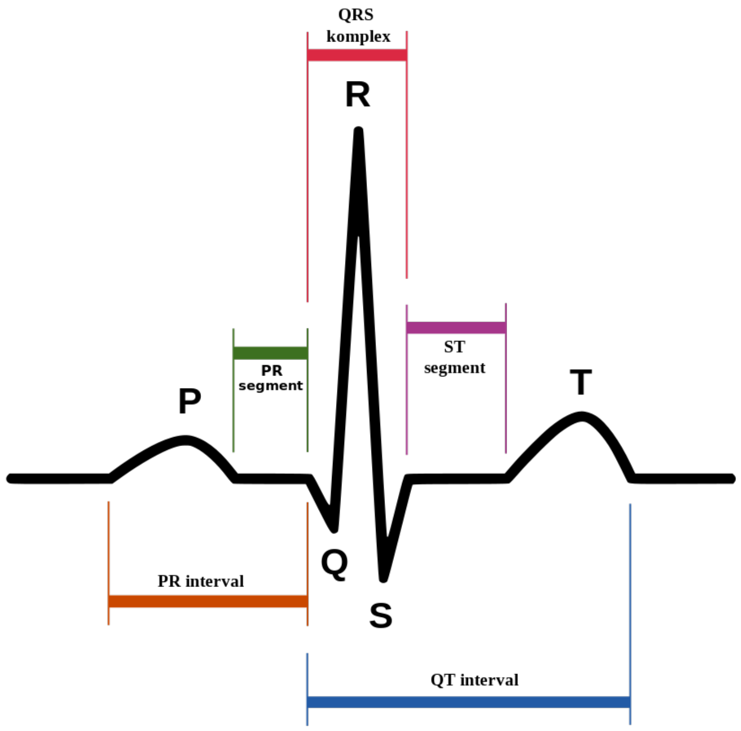
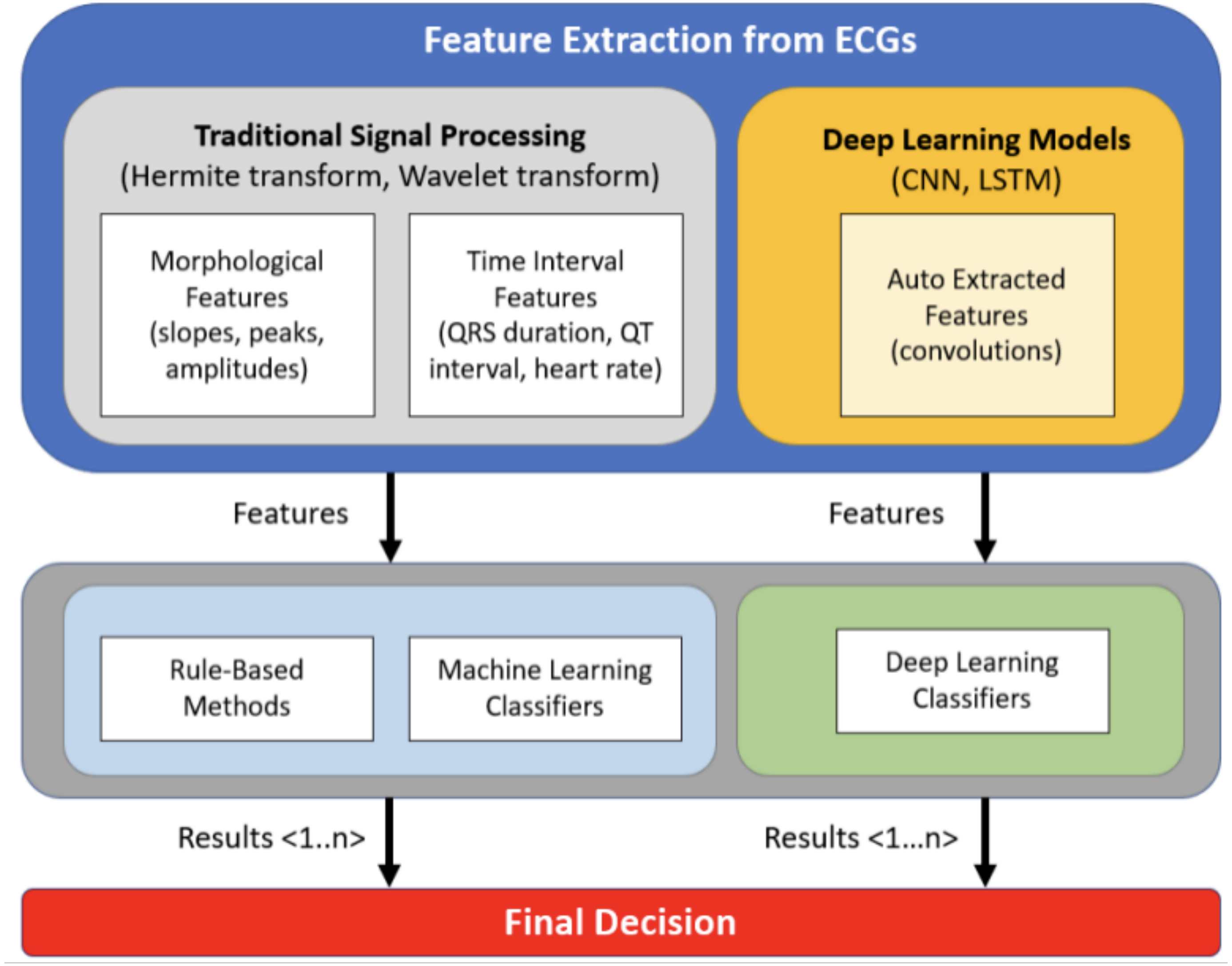
# What is ECG?

- Cardiovascular diseases are critical illnesses worldwide and cause 30% of deaths in the world according to the World Health Organization (WHO). Early detection of patients with this risk and a good understanding of the disease is very critical to improve diagnosis and treatment.
- Electrocardiogram (ECG) recordings capture the propagation of the electrical signals of the heart on the body surface. ECG shows a complex of P, Q, R, S, and T waves corresponding to each heartbeat. The changes in waves, the appearance of different waves from regular ones, and the changes in the times between waves give technicians, analysts, and doctors indications about heart diseases.

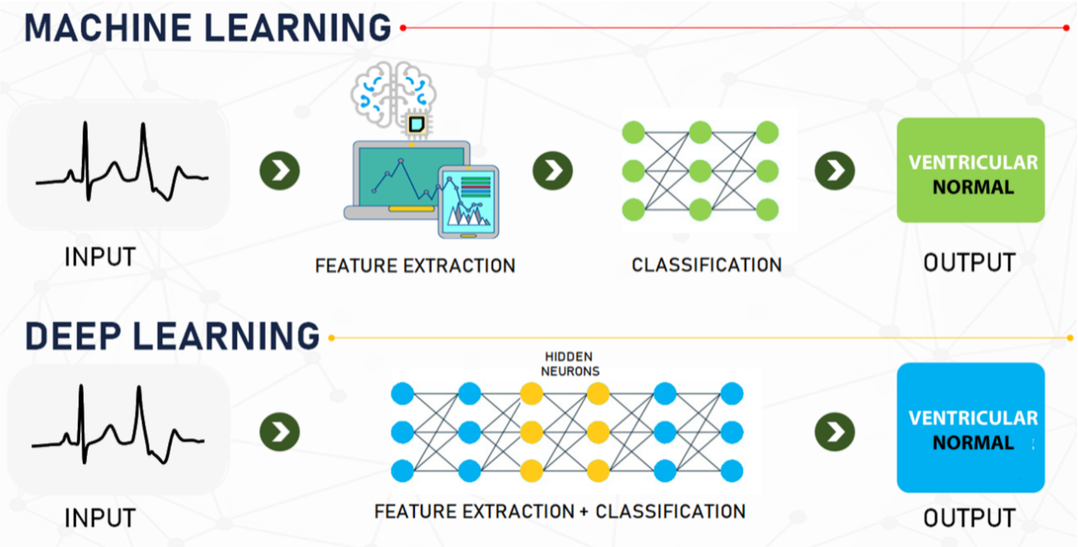


# ECG Analysis Overview



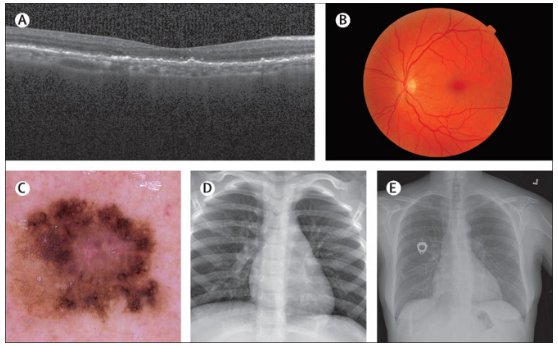
# Deep Learning

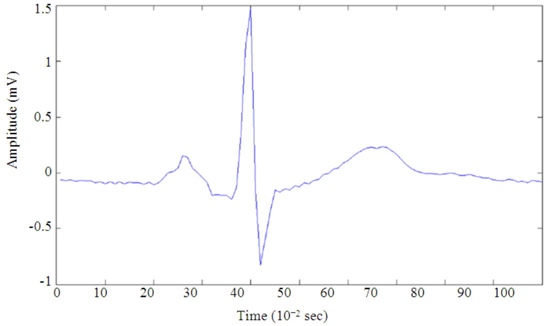
- Deep learning is a subset of machine learning where algorithms are inspired by the connectivity patterns of the human brain called Artificial Neural Networks (ANN).
- There are different deep learning architectures that have been applied to fields such as computer vision, speech recognition, natural language processing, and so on.
- Convolutional Neural Networks (CNN) is an architecture that has been used for image feature extraction.
- One other architecture is Recurrent Neural Networks (RNN) which has connections between its layers as a form of a directed graph, allowing the information carried in layers to remember. Long Short Team Memories (LSTM) are a special type of RNN, capable of remembering long-term dependencies.
- RNNs and LSTMs are more suitable for sequential data such as text, time series, financial data, speech, audio, video, and so on. Therefore, they are commonly used for tasks such as natural language processing and time series processing. CNNs, on the other hand, are best suitable to work with spatial structures like images.

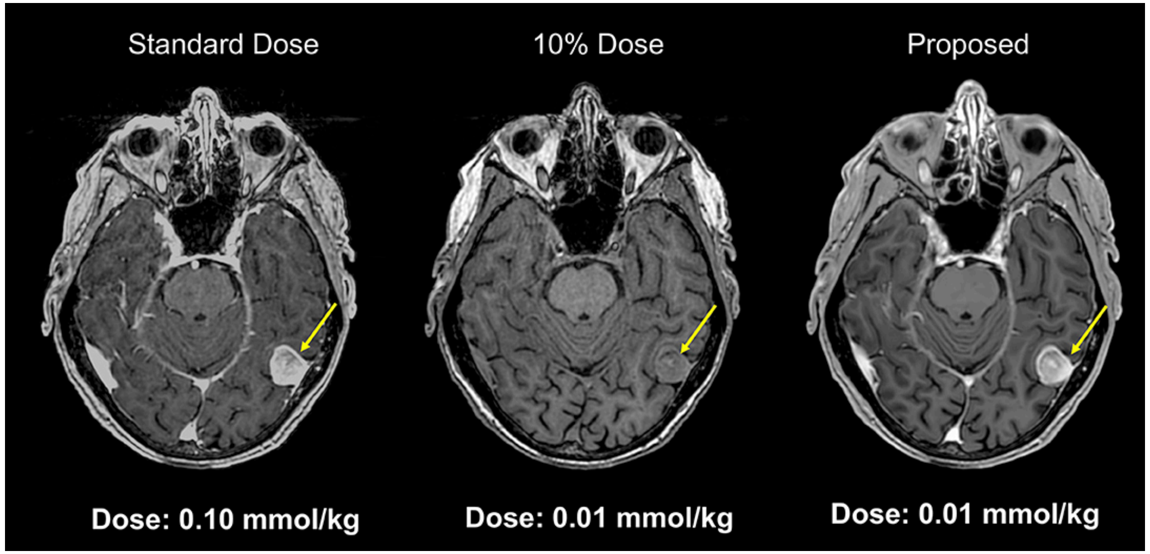


# Deep Learning in Medicine

- Advancements in deep learning have enabled the development of computer-based intelligent decision support systems and their more effective applications.
- Over the last few years, unlike traditional machine learning algorithms, deep learning models have shown their successes in many fields including signal processing.
- Deep learning methods have the potential to become essential tools for diagnosis and analysis in medicine. Despite the impressive results in areas like radiology, dermatology, and cardiology, deep neural networks are often criticized for being difficult to explain and for providing little to no insight into why they produce a given result (the so-called "**black box phenomenon**").
- Since doctors are accountable for their diagnoses, a black-box approach is unacceptable. We also used a technique called Grad-CAM to see which part the model focuses on when predicting the given input. That is, in our study, we tried to overcome the black box issues that are caused by the deep learning models.

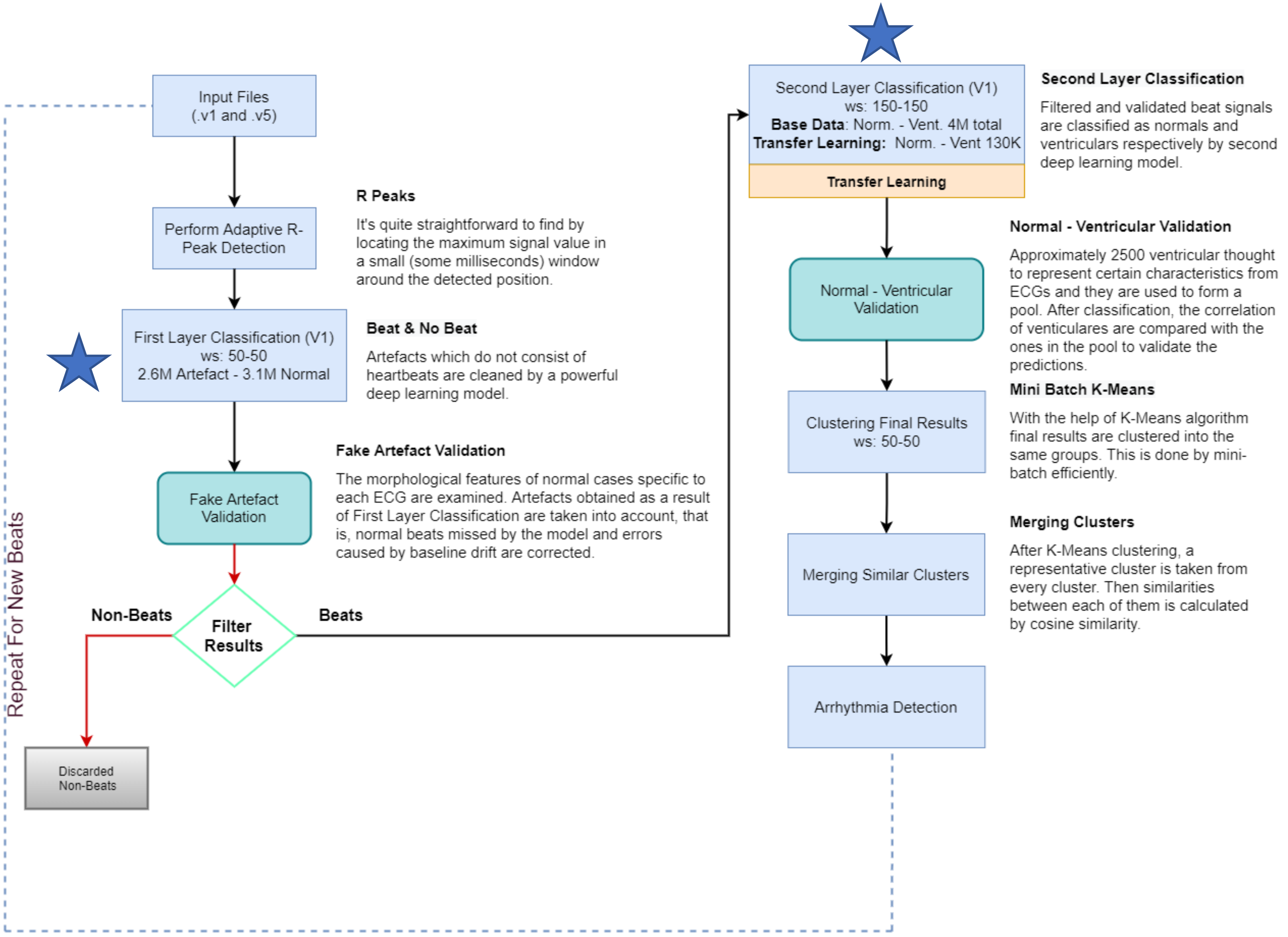


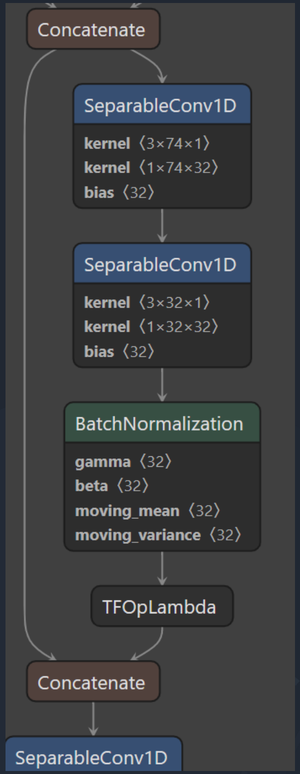



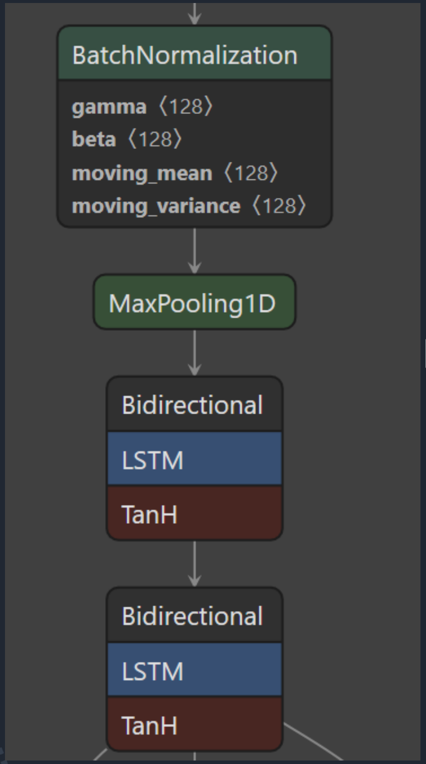
# Proposed ECG Analysis Framework

- Our framework consists of several processes to accomplish the best results. Firstly R-Peaks are detected with an adaptive algorithm. Then our first deep learning model (CNN + BiLSTM + Attention) classifies ECG signals as beats and no-beats. Then the predictions are validated with morphological features.
- The second deep learning model takes inputs with a window size 150-150 as classifying normal beats and ventricular beats are more complex. The same validation mechanism is also applied.
- After the classifications are completed, results are clustered with the help of the K-Means algorithm. After clustering, each cluster is checked whether they are similar enough to be merged. For this purpose, we employed cosine similarity as a metric.

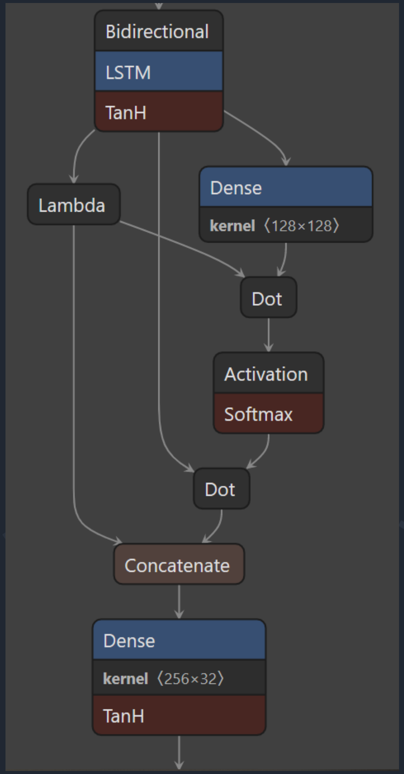





Residual Connections




Bidirectional LSTM Layers



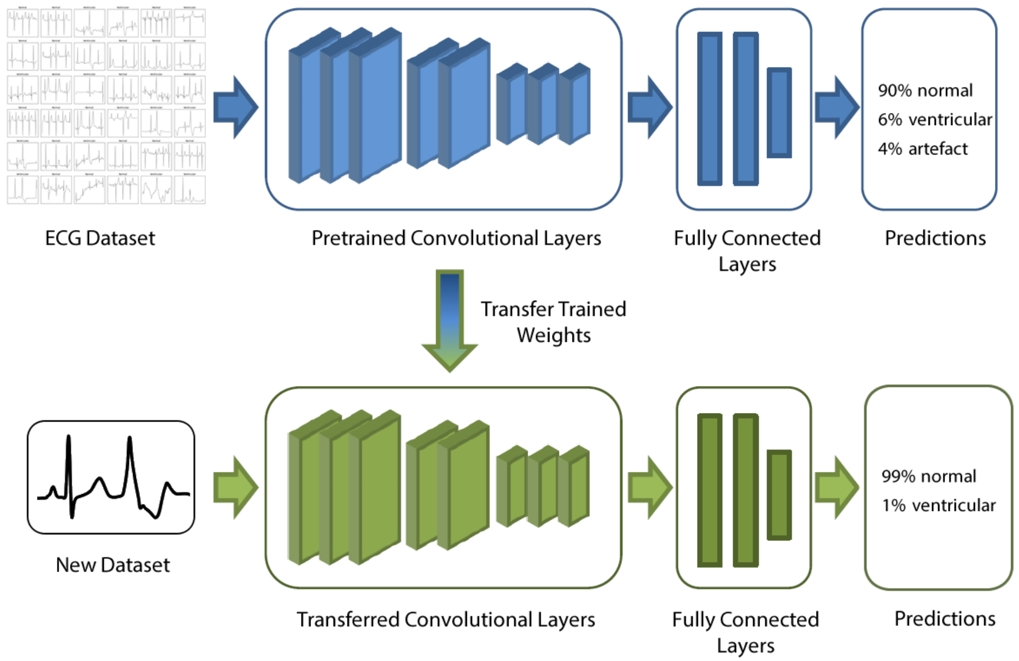

Attention Mechanism

# Proposed Combination Network and Deep Learning Models

- Our study utilized state-of-the-art deep learning architectures which consist of 1D Separable Residual Convolutional connections followed by BiLSTM layers and attention mechanism.
- Convolution layers are used as feature extractors to extract morphological features of the input ECG signals.
- Extracted features from signals are considered as a sequence, that is, BiLSTM layers used for remembering important features in sequences.
- Finally, an attention layer is utilized to help LSTM layers to help them to remember and forget properly. The attention layer is used to extract the most distinctive feature from the sequence after the LSTM layers.

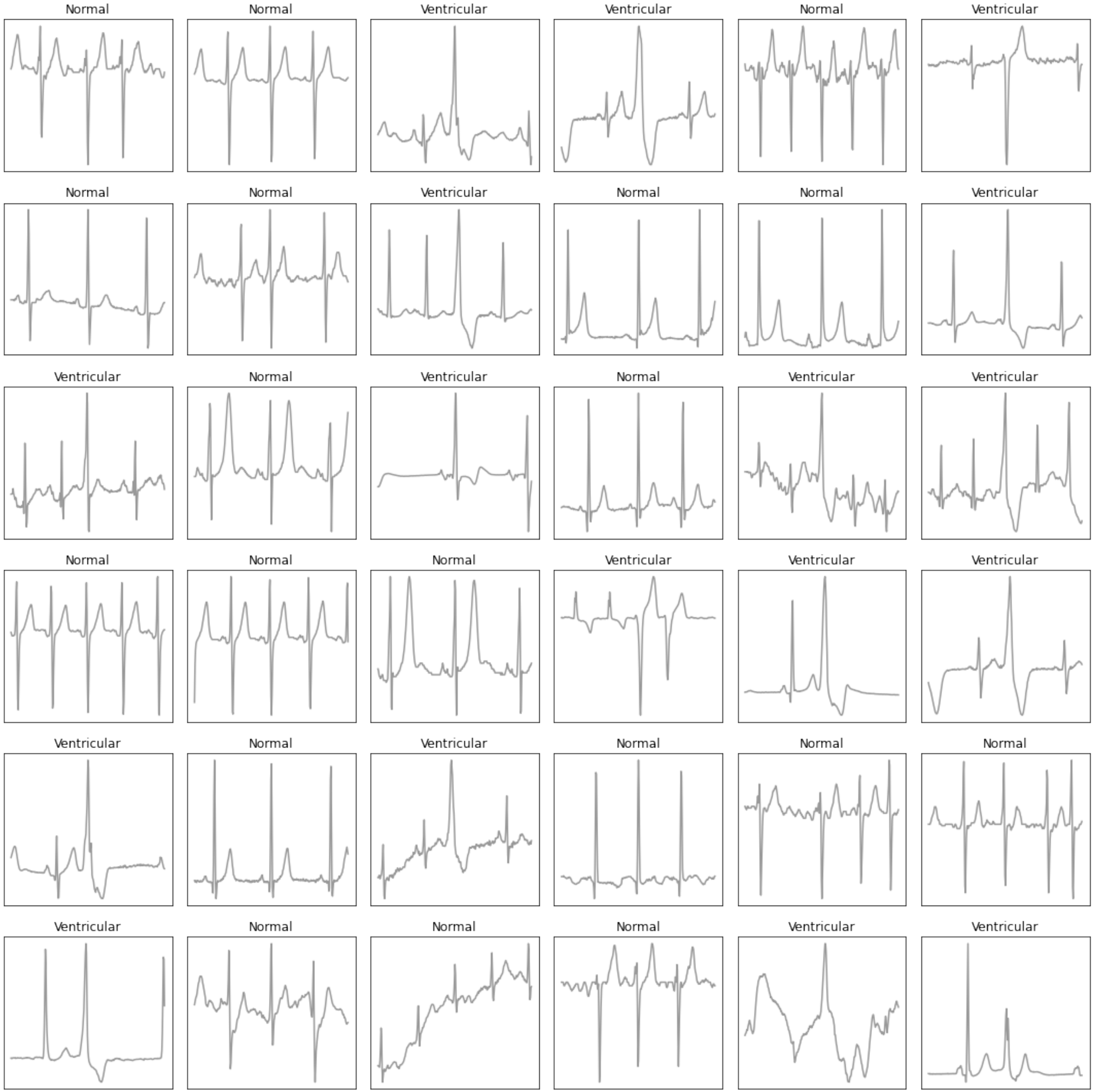
# Transfer Learning

- Transfer learning is a machine learning technique to re-use pre-trained models for new objectives. That is, layers and weights of a pre-trained model are used as a starting point in model creation.
- In this way, we make use of the information readily available in the parameters of a previously trained model. In addition, training a new model takes considerably less amount of time. For instance, obtaining a model which was already trained on ECG signals can help the convergence of the new model as the datasets are similar.
- In our study, we utilized transfer learning where we had pre-trained models on a huge dataset. Instead of writing models from scratch, the weights of pre-trained models were used.



# Dataset

- The dataset used in this project consists of 1500 ECG recordings in total. Each signal is recorded for 24 hours.
- In order to feed deep learning models by provided data, we sliced each signal with defined fixed window size.
- We selected window size according to the complexity of the problem.
- **First Layer Training Dataset (50-50 win. size):** 2.6 million artefacts, 3.1 million heartbeats.
- **Second Layer Training Dataset (150-150 win. size):** 4 million ventricular and normal heartbeats in total and Transfer Learning was performed with 130k heartbeats.



# Experimental Setup

### HW Configuration

Model training process is done on the laptop that have following specs:

GTX 1660Ti GPU 6GB, 16GB Ram, Python 3.8, TensorFlow 2.5.0

### Training time

Training time differs for each model as shape of the inputs are not the same.

1st Model: 1 day 2 hours (Whole dataset)

2nd Model: 1 day 18 hours (Whole dataset)

2nd Model Transfer Learning: 1 day 4 hours (Transfer Learning)

### Training parameters (#of epochs, batch_size)

1st Model: 25 epochs with a batch_size of 256

2nd Model: 27 epochs with a batch_size of 128

### Total number of parameters

1st Model: 169,932

2nd Model: 169,932

Architecture is same for both models. With only 169K params, models achieve to a promising performance.

# Experimental Results

- The results obtained by the deep learning models were shown in tables in terms of precision, recall, and F1-Score.
- We had baseline models that were trained on 1500 ECGs, more precisely, trained on more than 3M+ signals.
- In the second experiment, our models only had Convolutional and LSTM layers. Their results are shown in Table 1.
- We realized that using pretrained weights as a starting point increases the overall accuracy. Table 2 shows the results of transfer learning approach.
- Lastly, for increasing the overall performance, model's architecture was changed by adding the attention mechanism. We added an attention layer  to the models and repeated the training process to see the improvement in accuracy.
- Attention is a mechanism that helps LSTM layers to remember & forget properly by selecting the most distinct features.
- It can be seen that both of the models achieve over %99 performance.

| Model # | Precision | Recall/Sensitivity | F1-Score |
|---|---|---|---|
| First DL Model | 0.9891 | 0.9889 | 0.9890 |
| Second DL Model | 0.9844 | 0.9856 | 0.9850 |

Table 1. Results of baseline model

| Model # | Precision | Recall/Sensitivity | F1-Score |
|---|---|---|---|
| First DL Model | 0.9997 | 0.9997 | 0.9997 |
| Second DL Model | 0.9961 | 0.9974 | 0.9967 |

Table 2. Results of transfer learning

| Model # | Precision | Recall/Sensitivity | F1-Score |
|---|---|---|---|
| First DL Model | 0.9999 | 0.9998 | 0.9998 |
| Second DL Model | 0.9964 | 0.9976 | 0.9970 |

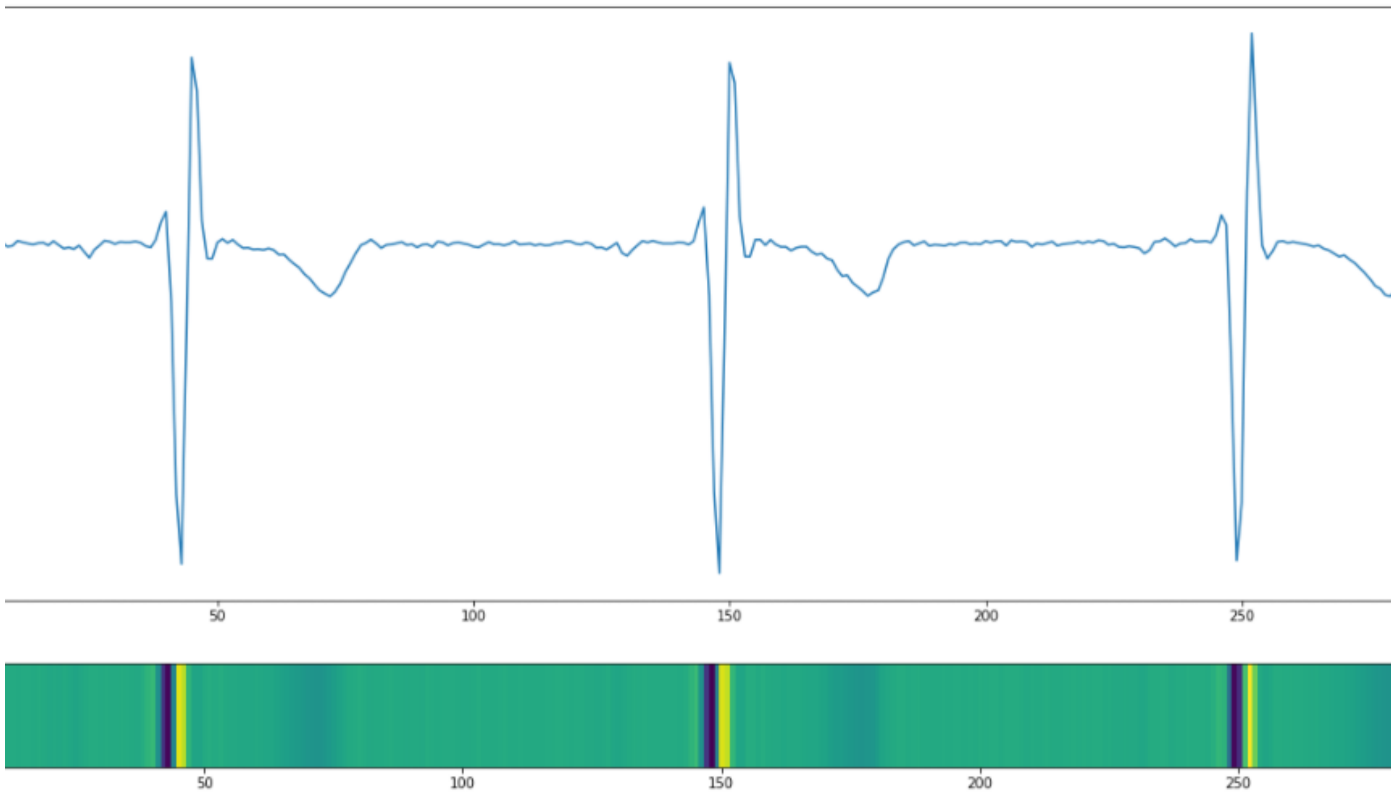
Table 3. Results of TL + attention mechanism

# Explainable AI - GradCAM

- Most of the time deep learning models are treated as black-boxes as they fail to explain why they made that prediction based on a given input. GradCAM technique aims to enlighten this issue by drawing a heatmap on class activation maps.

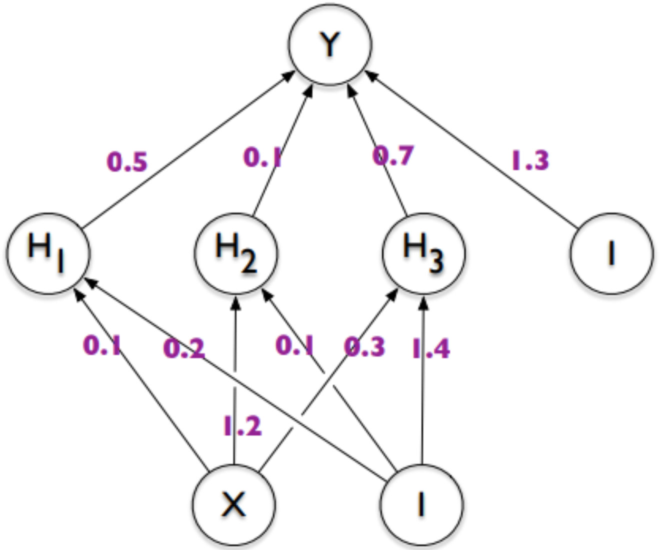
- Grad-CAM is a conventional technique for creating a class-specific heatmap based on a particular input image, a trained CNN, and a chosen class of interest. Grad-CAM is directly related to CAM. Grad-CAM is compatible with any CNN architecture as long as the layers are differentiable.

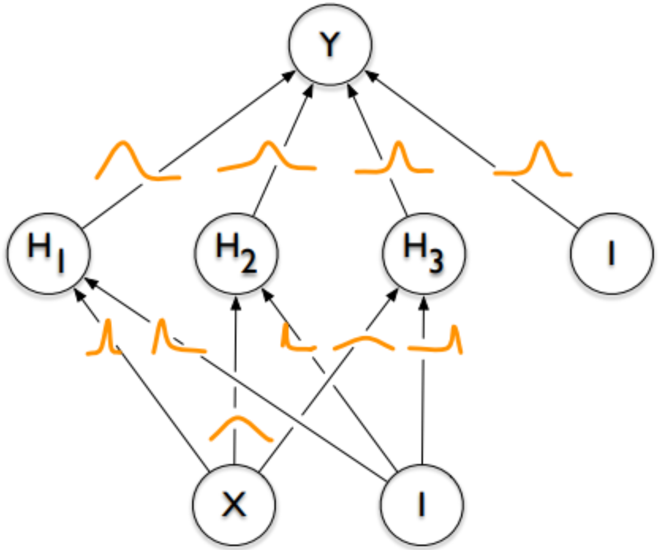
- Yellow points show where the model is focused when predicting a given input. That is, we can see the areas where the network paid attention.



# Future Work "Bayesian Deep Learning"

- Common deep learning models are often too confident for their predictions. This is caused by the final layer activations. In other words, normal deep learning models fail to capture uncertainty in both predictions and data.
- In traditional deep learning models, weights and biases are just point estimates. On the other hand, Bayesian deep learning aims to learn probability distributions that can represent the data.
- With the help of the Bayes theorem and proper frameworks, we can integrate deep learning and Bayes theorem.



Thank you for listening…