Questions

1. Model Evaluation and Making Predictions
   - Why is it important to evaluate a model on a test set?
     - To have an unbiased performance evaluation
     - To test how well the model generalize on unseen data
     - Check if the model is overfitting the train set as well if its Hyperparameter are well tuned and not biased to the train/eval set.

   - Could you identify overfitting or underfitting while evaluating the model?
   - Overfitting:
     - The model error quickly reaches a plateau and flattens out.
     - Training error is further slowly decreasing but the validation error remains more or less the same.

   - Do you think the choice of evaluation metric impacts the model performance? If yes, how could you explain it?
     - Each evaluation metric offers a different setup of properties e.g. :
       - Sensitivity to different aspects of the data
         - Outlier Sensitivity e.g. mse are more sensitive to outliers because of quadratic increase
         - If a dataset is imbalanced metrics like accuracy might not cover the full model behaviour.
           - Precision, recall and f1-score provide better insights into the performance across different classes
     - Evaluation metrics are typically chosen based on the specific goals

   - How do you interpret the evaluation metrics to understand the model's performance?
     - Mean Squared Error:
       - MSE measures the average squared difference between the predicted values and the actual target
       - Sensitive to Outliers
     - Root Mean Squared Error:
       - Provides a more interpretable value of error compared to MSE because it is on the same scale as the original data
     - Root Mean Squared Logarithmic Error:
       - Considers the relative error between the predicted and actual value
       - Larger penalty for underestimation of the actual variable than overestimation

2. SHAP Analysis
   - What is the significance of SHAP in model interpretation and understanding feature importance?
     - Main approach: Treating the model as a black box and observe how changes in input affect the output.
     - SHAP values explain the prediction of an instance by computing the contribution of each feature to the prediction. This helps in understanding how the model makes decisions.
     - This offers Interpretability of the model decisions and a understanding of how important each feature is for estimating the target.

   - Think about some other ways that could help you understand feature importance.
     - Permutation Importance:
       - Involves random shuffling of one feature in the test set and check how does it influence the model performance. This can give an indication of how important that feature is for its original prediction
       - Saliency Maps:
         - Highlight which part of the input data have the most impact for the predictions made by the model
       - Attention Mechanism:
         - To identify the importance of different time steps in the input sequence.
         - Have to be implemented into the model architecture.

- Would your feature importance technique work with LSTMs? If yes. how?
  - Permutation Importance:
    - Yes, can be applied by shuffling each feature over its sequence separately and then analyse how does it affects the outcome of the model.
  - Saliency Maps:
    - Yes, it can help identifying which time steps or features within each time step are most influential for the model prediction.
  - Attention Mechanism:
    - In LSTMs with an attention layer, the attention weights can be interpreted as a measure of the importance of each time step in the input sequence. Higher weights indicate that the model is paying more attention to those specific parts of the sequence.

Answer these questions after doing your analysis on heart beat data.

1. What is the difference in model performance when model evaluation is done on a different evaluation metric rather than MSE?
   - Different evaluation metrics can provide different perspectives on how well a model is performing, depending on what aspect of the model's predictions we're interested in.
   - MSE: 0.0208, is quite small because our error lies between 0 and 1, and a value squared that is smaller than 1 gets even smaller. Thats why MSE is kinda biased to our scaling, not telling us so much from its raw value.
   - RMSE: 0.1441, tells me that our average error is about 14,41% of the range of our target variable because we scaled the data between 0 and 1. So looks not that well like the first insight of MSE.
   - RMSLE: 0.0198, another metric which penalised relative differences between target and error. Seems quite low.

2. What is your interpretation of feature importance done using SHAP?

3. What is your interpretation of feature importance done using your feature importance technique? How is the result different from SHAP analysis?

- Using Permeation Importance for Feature Importance by shuffling each datapoint each feature through its sequence to see how the error behaves.
- Mean Squared Error on Testset: 0.0199
- Shuffling Features:
  - Heart_Beat: -0.00010676 => shuffling reduced the error slightly over the whole test set, indicating its not a helpful feature
  - Steps: 0.00378982 => shuffling increased error, indicating its an important feature (most important feature)
  - Intensity_1h_before: 0.00026332
  - hour_of_the_day: 0.00158409 (second important feature)