Report on Predicting Hospital Length of Stay (HLOS) Using Multi-Layer Perceptron (MLP) and Recurrent Neural Network (RNN)

1. Data Preprocessing and Statistics

Number of Rows and Columns

508 rows and 59 columns - Data-at-admission dataset

4064 rows and 36 columns – Days-breakdown dataset

Mean of Each Column (After pre-processing)

Age: *66.02*, Height: *166.91 cm*, Weight: *80.26 kg*, Systolic BP*: 129.36 mmHg*, Diastolic BP: *75.57 mmHg*, Heart Rate: *97.4 bpm*, Respiratory Rate*: 24.9 breaths/min*, Oxygen Saturation: *93.1%*, Temperature: *37.77°C*, Motor Score: *5.9*, Verbal Score: *4.76*, Eye Score: *3.94,* WBC: *8.03 x10^9/L*, RBC: *4.62 x10^12/L,* Haemoglobin: *129.88 g/L*, MCV: *86.02 fL*, MCH: *28.28 pg*, MCHC: *328.58 g/L*, RDW: *13.97%*, Platelet Count*: 230.87 x10^9/L*, PT: *14.61 sec*, ALT: *51.2 U/L*, AST: *61.39 U/L*, Serum Creatinine: *114.77 µmol/L*, Sodium: *135.33 mmol/L*, Potassium: *3.88 mmol/L*, Total Bilirubin: *10.63 µmol/L*, Lactate: *2.33 mmol/L*, PaO2: *77.9 mmHg*, PaO2/FiO2: *1.5*, pH: *7.34*, ESR: *61.8 mm/h*, INR: *1.15*, Ferritin: *1003.75 µg/L*, CRP: *109.12 mg/L*

Blank Columns:

1. high_senstivity_cardiac_troponin 2. hs_crp

These columns were dropped as they were of no use.

Key Features for Estimating HLOS

Based on intuition and domain knowledge, the following features are hypothesized to play an important role in estimating HLOS: **Systolic and Diastolic Blood Pressure, Respiratory Rate and Oxygen Saturation, Temperature, Heart Rate**, **Comorbidities (e.g., Diabetes, Hypertension)**

Model Training and Evaluation

Multi-Layer Perceptron (MLP): For the MLP model, we achieved a **Mean Squared Error (MSE) of 11.01** and an **R-squared value of 0.91**. These results indicate that the model fits the data well, explaining approximately 91% of the variance in hospital length of stay (HLOS) predictions. While the MSE suggests a relatively small prediction error, further hyperparameter tuning and feature selection could improve the model's performance.

Recurrent Neural Network (RNN): For the RNN model, the final training loss was **35.05**, indicating the model's performance on the training data. Through hyperparameter tuning, the best combination of parameters was found to be **Units**: 10, **Activation**: Tanh, **Optimizer**: RMSprop, **Batch Size**: 32, **Epochs**:200. Using these hyperparameters, the model achieved a **best MSE of 88.42** on the validation set, and a **final MSE of 36.24** on the training data. The results suggest that the model fits the training data reasonably well, but further tuning may be needed to improve generalization on unseen data.

Empirical Results and Observations

After applying both the MLP and RNN models on the pre-processed dataset, the following empirical results were obtained:

1. Multi-Layer Perceptron (MLP):The MLP model performed well, with a relatively low MSE and a high R^2 score, indicating that the model captured most of the variance in the data. The predictions from the MLP model show strong agreement with the actual hospital length of stay (HLOS) values.
2. Recurrent Neural Network (RNN): The RNN model, designed to capture sequential patterns in the patient data, had a higher MSE than the MLP. However, this is expected as RNNs tend to perform better with more complex temporal relationships. The RNN model struggled slightly with the variability in the sequence length, which may have contributed to higher errors.

Overall Satisfaction

MLP Model: The low MSE and high R^2 suggest the model effectively captures the relationships between features and HLOS.
RNN Model: The higher MSE indicates the model struggled with temporal dependencies, requiring further refinements like better sequence alignment and padding.

MLP and RNN Trial Results Summary
The MLP model was evaluated using 5 separate trials, with the following results:

- **Average MSE**: 118.51
- **Standard Deviation of MSE**: 3.63

The performance across trials was consistent, indicating a relatively stable model. Increasing the maximum number of iterations could potentially improve the results, but given the current findings, the MLP model provides satisfactory performance for this dataset.

The RNN model was evaluated over 5 trials, resulting in the following performance metrics:

- **Average MSE**: 128.14
- **Standard Deviation of MSE**: 15.49

The RNN model's MSE values fluctuated across the trials, with a higher variance compared to the MLP model. This suggests that the RNN struggled to consistently capture the temporal patterns within the data. Adjusting the model's architecture, such as the number of units or layers, or further tuning the hyperparameters, could potentially improve its performance.

Scope for Improvement

- **Feature Engineering**: Additional feature engineering, including the creation of interaction terms or more domain-specific features, could help improve the models' performance.
- **Hyperparameter Tuning**: While some hyperparameter tuning was conducted, more extensive grid search or random search could yield better results, particularly for the RNN model.
- **Sequence Alignment for RNN**: Improving the handling of sequences, such as by using more sophisticated padding or truncation strategies, could allow the RNN to better capture patient progress over time.
- **Model Architecture**: More advanced architectures like GRU or LSTM networks, which are tailored for sequential data, could improve the RNN's ability to model temporal dependencies.