**AML\_Assignment\_3(Gorup-22)**

We constructed an aggregate of 14 models for time series data analysis. As a baseline, the first model produced a Mean Absolute Error (MAE) of 2.62 by relying on common sense methods.   
A little while later, we developed a thick-layer, beginner machine-learning model that achieved a barely advanced MAE of 2.82. As a result of leveling the time series data and eliminating the nonreligious environment, the thick subcaste model's interpretation was weak. Convolutional modeling was also attempted; it managed penurious effects by treating all data components marginally and, in fact, after pooling, which broke up the successional order of the data.

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Consequently, we acknowledged that time series data are better suited for intermittent neural networks or RNNs. The ability of intermittent neural networks (RNNs) to incorporate information from one method into their current decision-making process is a crucial feature. In the succession of data, this allows the network to find patterns and dependencies. Sequences of different durations may be modeled by the RNN because its internal structure functions as a mind that retains knowledge from one input at a time. However, it is sometimes too basic to be truly ultrapractical to use the Simple RNN for beginners. More specifically, Simple RNN consistently performs the most bleakly out of all the models, which is supported by the vivid representation. It has a considerable debt.

Simple RNN is supposed to be able to store data from all previous times, but because of the undesirable "evaporating grade case," it frequently struggles virtually, particularly in long networks. The network becomes almost untrainable in this scenario. More advanced RNN variations, such as the Long Short-term Memory (LSTM) and the Reopened Intermittent Unit (GRU), were created in response to this difficulty and incorporated into Keras. Because it can capture long-range relationships in successional data and is more computationally efficient when integrated with LSTMs, the straightforward GRU model we tested produced the most elegant results of all the models.

We performed six nonidentical LSTM models with different units in mounding intermittent layers (8, 16, and 32), and the model with 8 units showed the elegant interpretation. LSTMs are a well-known armature for handling time series data successfully. with order to improve delicacy and modify the forgetting situation, we also experimented with bidirectional data donation and assumed intermittent powerhouse to aid with overfitting. An equivalent MAE value was consistently shown by these LSTM models, and it was lower than that of the standard or common sense model.

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Finally, we attempted to integrate an RNN with a 1D complication model. Despite this, the mongrel model produced an advanced MAE of 3.75, most likely as a result of the complications that prevented the information from being in the correct sequence. Based on my compliances, it is recommended to replace basic RNNs for time series dissection, since they are unable to efficiently imprison long-term dependencies and struggle with the evaporating grade situation. Instead, advocate for more advanced RNN infrastructures that try to overcome these expostulations, such as LSTM and GRU.

Our experiments imply that GRU may extend more potent effects, even if LSTM is a popular method for processing time series data. The utilization of bidirectional data donation, intermittent powerhouse classes, and the number of units in stacked intermittent layers are examples of call tuning hyperparameters that are used to optimize GRU models. Similarly, it is recommended to focus on RNN infrastructures tuned for successional data, as combining RNN with 1D complexity did not produce the best results. Convolutional techniques are less effective in deconstructing time series data because they frequently skew the information.

