Report on Predictive Modeling of Remaining Useful Life (RUL)

Introduction

This report outlines the approach taken to predict the Remaining Useful Life (RUL) of engines using machine learning models, specifically LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) networks. This report serves as a comparative study between the two Deep Learning architectures. The goal is to assess the performance of these models in terms of accuracy, precision, recall, and other relevant metrics. The dataset that we will be using is CMAPSS dataset, specifically the FD001 dataset

Data Preprocessing

Data Preparation

The dataset consists of operational and sensor data collected from engines. Initial steps included handling missing values and transforming data into sequences suitable for time series analysis. We defined sequences based on a fixed window size, which allows the model to learn patterns over time.

Data preprocessing includes handling missing value, normalization of the values, replacing nulls or NaN values with suitable statistical values.

Feature Engineering

Several features were engineered to improve model performance which were derived from the features present in the dataset. Some of them were,

- **Exponential Moving Averages**: Computed for sensor readings to smooth out short-term fluctuations also giving importance or more weightage to more recent readings..
- **Lag Features**: Captured the dependencies within the data.

Model Training

Two models, LSTM and GRU, were trained on the dataset. The models were evaluated based on their performance on a test set, and metrics such as accuracy, precision, recall, and F1-score were computed.

 LSTM **Performance**: Achieved an accuracy of 98.12%, precision of 0.99%, and recall of 0.98%.

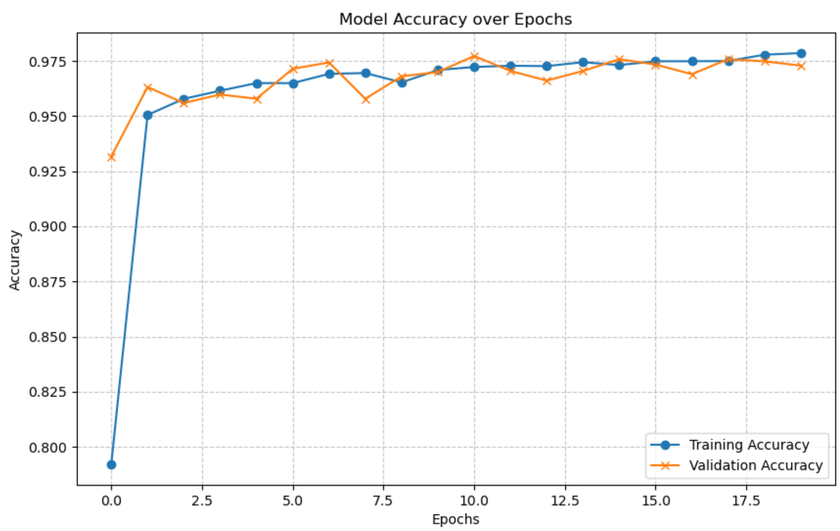
 GRU **Performance**: Outperformed LSTM with an accuracy of 98.12%, precision of 0.99%, and recall of 0.99%

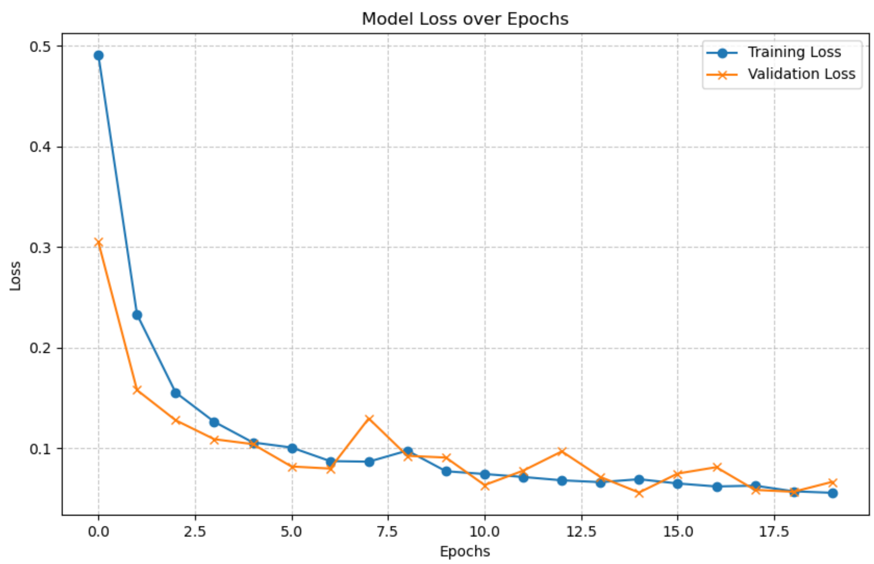
Results

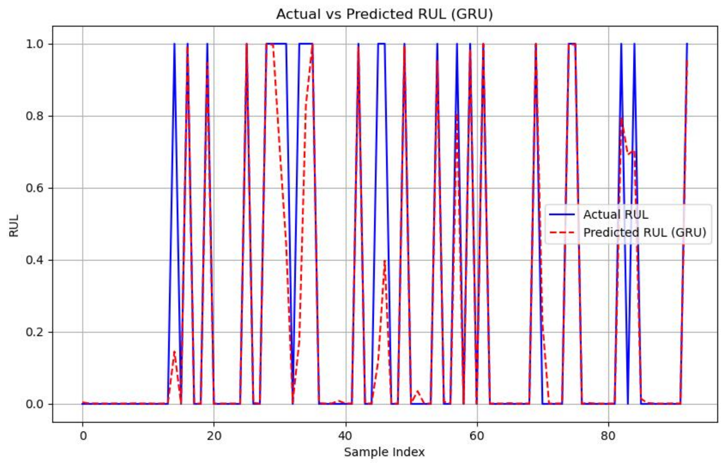
Performance Metrics

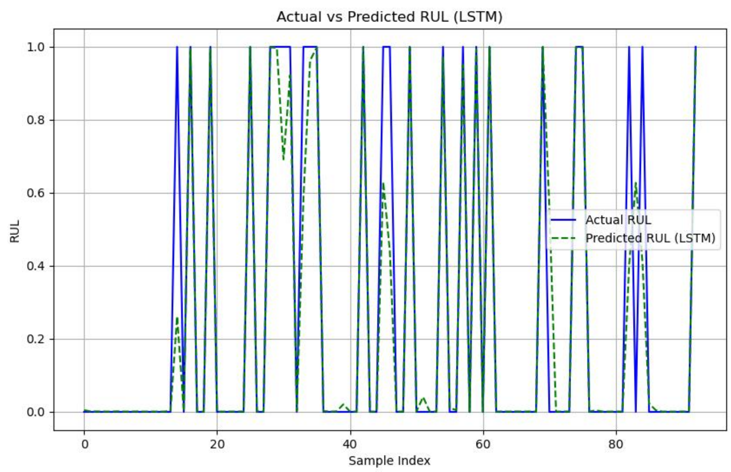
The results indicated that the GRU model slightly outperformed the LSTM model across several metrics:

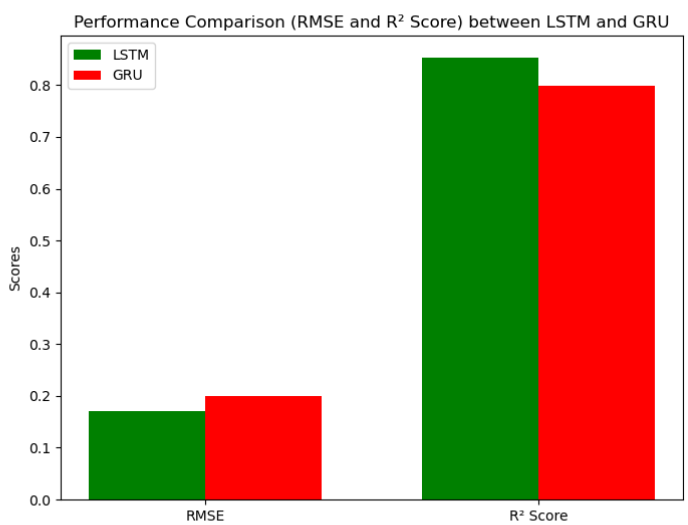
- **Accuracy**: GRU showed higher accuracy on the test set.
- **Precision**: The GRU model demonstrated better precision,suggesting fewer false positives.
- **Recall**: GRU also had a higher recall, indicating its effectiveness in identifying positive s.





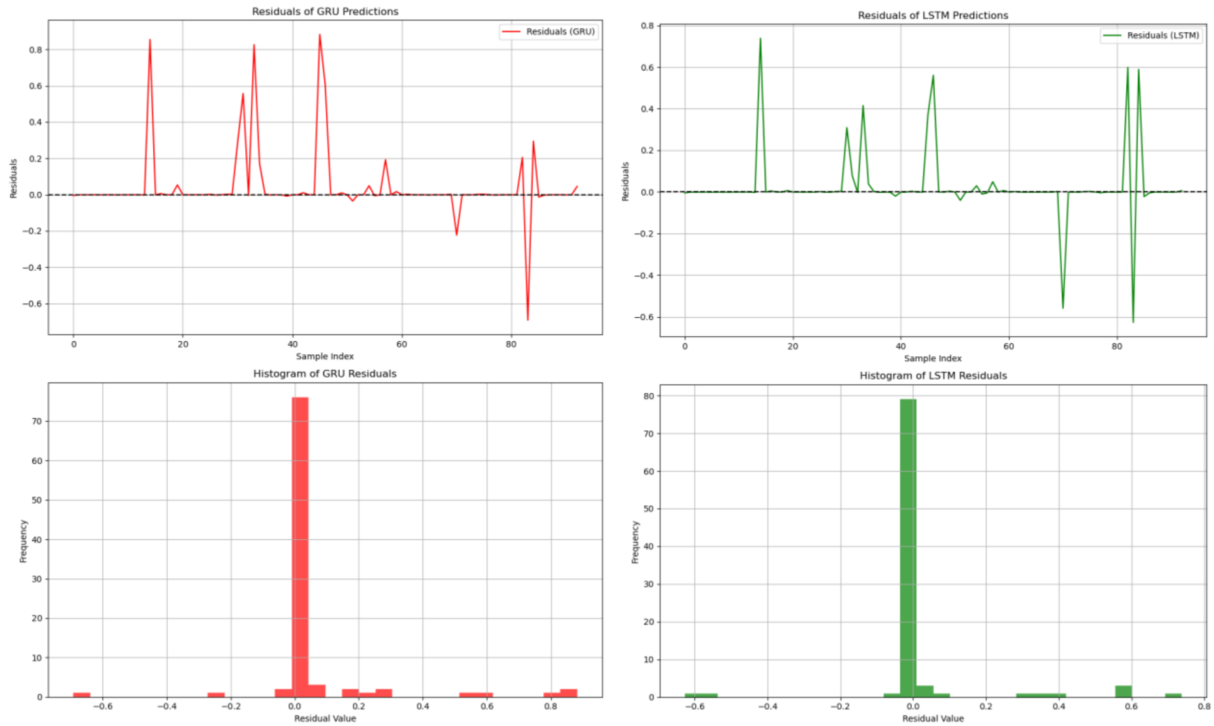

Actual vs Predicted RUL (GRU)
RUL
Sample Index
Actual RUL
Predicted RUL (GRU)
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80


Actual vs Predicted RUL (LSTM)
RUL
Sample Index
Actual RUL
Predicted RUL (LSTM)
0.0
0.2
0.4
0.6
0.8
1.0
0
20
40
60
80


Performance Comparison (RMSE and R² Score) between LSTM and GRU
LSTM
GRU
Scores
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
RMSE
R² Score

Residual Analysis

Residuals were calculated to understand the prediction errors better. The standard deviation of the residuals indicated the variability of errors for both models. Confidence intervals were plotted to visualize the reliability of predictions.



Conclusion

The GRU model demonstrated slightly better performance than the LSTM in predicting the RUL of engines. Its higher precision and recall make it a more reliable option for this task. The analysis also highlights the importance of careful feature engineering and model evaluation in predictive modeling.

Future work could involve experimenting with hyperparameter tuning, exploring additional features, or incorporating ensemble methods to further enhance model performance.