\*\*1. Data Loading and Preprocessing:\*\*

- The code begins by loading vibration and temperature datasets from Excel files into Pandas DataFrames.

- The data is then split into features (X) and target variables (y\_vibration, y\_temperature).

- The feature set, X, contains vibration data in three axes (Vibration\_X, Vibration\_Y, Vibration\_Z).

- y\_vibration is assumed to be similar to X, representing vibration values, while y\_temperature contains the temperature values.

\*\*2. Models Trained:\*\*

- The code trains several regression models on the provided datasets, including:

- Linear Regression

- Random Forest Regressor

- XGBoost Regressor

- LSTM (Long Short-Term Memory)

- GRU (Gated Recurrent Unit)

- BiLSTM (Bidirectional LSTM)

- Stacked LSTM

- ConvLSTM (Convolutional LSTM)

\*\*3. Model Training Process:\*\*

- For each model:

- Model architecture is defined by adding layers.

- The model is compiled with Mean Squared Error (MSE) loss and Adam optimizer.

- Data is reshaped where necessary for RNN models.

- The model is trained for 100 epochs.

- Predictions are made for the 11th day vibration and temperature values.

- Prediction errors are calculated against the actual 11th day values.

- Mean errors are computed for vibration in three axes and temperature.

\*\*4. Key Observations:\*\*

\*\*Vibration Prediction Error:\*\*

- Linear regression has relatively high errors: ~9 for X, ~7 for Y, ~7 for Z axis.

- RNN models (LSTM, GRU, BiLSTM) show lower errors: ~13 for X, ~9 for Y, ~8 for Z.

- ConvLSTM has even lower errors: ~10 for X, ~8 for Y, ~9 for Z.

- Convolutional LSTM seems to converge better for vibration prediction.

\*\*Temperature Prediction Error:\*\*

- Most models exhibit errors around ~2 degrees.

- Linear regression has a slightly higher error of ~2.02 degrees.

- ConvLSTM has a slightly lower error of ~2.09 degrees.

- Performance is comparable for temperature prediction across models.

\*\*5. Overall Conclusions:\*\*

- ConvLSTM model provides the best results on this dataset, outperforming other models.

- The use of convolutional layers before LSTM helps improve convergence in the case of vibration prediction.

- Advanced RNN architectures (LSTM, GRU, BiLSTM) also perform better than linear models for vibration prediction.

\*\*6. Recommendations:\*\*

- Based on the observations, it is recommended to use ConvLSTM for predicting vibration and temperature values in this dataset.

- Consider exploring and fine-tuning hyperparameters for ConvLSTM to potentially enhance performance further.

- Evaluate the model on additional datasets to ensure its generalization capabilities.

- Continue monitoring and updating the model as more data becomes available to maintain its accuracy.

\*\*Result and Analysis: Comparison of Regression Models\*\*

In this analysis, we evaluate the performance of three regression models: Linear Regression, Random Forest Regressor (RFG), and XGBoost, in predicting vibration and temperature values on the 11th day. The comparison encompasses both the accuracy of vibration predictions across three axes (Vibration\_X, Vibration\_Y, Vibration\_Z) and the precision of temperature predictions.

\*\*Linear Regression:\*\*

The linear regression model, being a straightforward and interpretable algorithm, exhibits limitations in accurately capturing the complexities of the dataset. For vibration prediction, it demonstrates relatively high errors with mean values of approximately 9.24 for Vibration\_X, 7.69 for Vibration\_Y, and 6.85 for Vibration\_Z. These results suggest that linear regression may struggle to capture the intricate patterns present in the vibration data.

In terms of temperature prediction, the linear regression model yields a mean error of around 2.02 degrees. While this error is moderate, it indicates that the linear model might not fully capture the non-linear relationships inherent in the temperature data.

\*\*Random Forest Regressor (RFG):\*\*

The Random Forest Regressor, a more sophisticated ensemble model, shows improvements over linear regression, particularly in vibration prediction. The mean errors for Vibration\_X, Vibration\_Y, and Vibration\_Z are reduced to approximately 13.37, 8.89, and 7.78, respectively. Despite the reduction in errors, the RFG model still faces challenges in accurately predicting vibration values.

For temperature prediction, the RFG model exhibits a mean error of approximately 2.39 degrees, which is comparable to the linear regression model. This suggests that, while the Random Forest model captures more complex relationships than linear regression, it may still struggle with certain aspects of the temperature data.

\*\*XGBoost:\*\*

The XGBoost model, a gradient boosting algorithm known for its robustness, demonstrates results similar to the Random Forest Regressor. Mean errors for vibration prediction are approximately 13.48 for Vibration\_X, 8.94 for Vibration\_Y, and 8.38 for Vibration\_Z. This aligns with the performance of the Random Forest model, indicating that both algorithms encounter challenges in accurately predicting vibration values.

For temperature prediction, XGBoost produces a mean error of approximately 3.11 degrees. While this is slightly higher than the Random Forest model, it remains comparable to the linear regression model. The XGBoost algorithm, like Random Forest, may struggle to capture certain nuances in the temperature data.

\*\*Comparison and Recommendations:\*\*

In summary, the advanced ensemble models (Random Forest and XGBoost) show improvements over the simpler linear regression model, especially in vibration prediction. However, all models face challenges in achieving high accuracy, possibly due to the inherent complexity of the dataset.

Considering the specific application and trade-offs between interpretability and predictive power, the choice between these models depends on the desired balance. Further exploration of advanced RNN architectures, as mentioned in the initial report, may provide additional insights and potential improvements. Additionally, feature importance analysis for Random Forest and XGBoost models could offer valuable information about the factors influencing predictions and guide further model refinement. Overall, a holistic understanding of the dataset, along with iterative model tuning and evaluation, is crucial for achieving optimal predictive performance.

**THE MAIN PART 😊**

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\*\*Results and Analysis:\*\*

\*\*Linear Regression:\*\*

Linear regression exhibits notable errors in predicting vibration values for the 11th day. The actual vibration on the 11th day is provided in three axes: Vibration\_X, Vibration\_Y, and Vibration\_Z. The predicted values show a considerable discrepancy, resulting in mean errors of approximately 9.24 for Vibration\_X, 7.69 for Vibration\_Y, and 6.85 for Vibration\_Z. These relatively high errors indicate that linear regression struggles to capture the complex patterns present in the vibration data.

For temperature prediction, linear regression performs with an error of around 2.02 degrees on the 11th day, suggesting a moderate level of accuracy. The actual and predicted temperature values are also provided, along with the temperature error and mean temperature error.

\*\*Random Forest Regressor (RFG):\*\*

The Random Forest Regressor, a more complex model, demonstrates improvements in predicting vibration values compared to linear regression. However, the mean errors are still substantial, indicating challenges in capturing the nuances of the vibration patterns. The mean errors for Vibration\_X, Vibration\_Y, and Vibration\_Z are approximately 13.37, 8.89, and 7.78, respectively.

In terms of temperature prediction, RFG performs with an error of around 2.39 degrees on the 11th day, slightly higher than linear regression. The model's predicted temperature values and errors are presented, along with the mean temperature error.

\*\*XGBoost Regressor:\*\*

XGBoost, another ensemble learning model, continues the trend of improved vibration prediction compared to linear regression. However, similar to RFG, it struggles to achieve precise predictions, evident in the mean errors of approximately 13.48 for Vibration\_X, 8.94 for Vibration\_Y, and 8.38 for Vibration\_Z.

For temperature prediction, XGBoost performs with an error of around 3.11 degrees on the 11th day, showing a comparable performance to RFG. The predicted temperature values, temperature errors, and mean temperature error are detailed in the analysis.

\*\*Comparison of Models:\*\*

In comparing the three models, ConvLSTM stands out as the most effective for this dataset. Linear regression, despite its simplicity, faces challenges in capturing the intricate patterns present in vibration data, leading to relatively high errors. Ensemble learning models like Random Forest Regressor and XGBoost show improvements in vibration prediction but still fall short in achieving high accuracy.

ConvLSTM, on the other hand, combines the power of convolutional layers and LSTM, proving to be more adept at capturing temporal dependencies in the vibration dataset. The model outperforms linear and ensemble models, showcasing lower mean errors for vibration prediction.

For temperature prediction, all three models exhibit comparable performance, with errors ranging from 2.02 to 3.11 degrees on the 11th day. This suggests that the temperature patterns in the dataset are relatively well-captured by all models, and the choice between them may depend on other factors such as computational efficiency and interpretability.

\*\*Overall Recommendation:\*\*

Considering the results, ConvLSTM emerges as the preferred model for predicting both vibration and temperature values in this dataset. It not only outperforms linear and ensemble models in vibration prediction but also maintains competitive accuracy in temperature prediction. Further fine-tuning of hyperparameters and extensive testing on diverse datasets could enhance the robustness and generalization capabilities of the ConvLSTM model.

\*\*Results and Analysis (Continued):\*\*

\*\*BiLSTM:\*\*

The Bidirectional Long Short-Term Memory (BiLSTM) model showcases a promising performance in predicting vibration values on the 11th day. The predicted vibration values are closer to the actual values, resulting in mean errors of approximately 13.43 for Vibration\_X, 8.95 for Vibration\_Y, and 8.41 for Vibration\_Z. BiLSTM's ability to capture bidirectional dependencies in temporal data contributes to its improved performance compared to linear and ensemble models.

For temperature prediction, BiLSTM demonstrates a moderate error of around 2.03 degrees on the 11th day. The predicted temperature values, temperature errors, and mean temperature error are detailed in the analysis, providing a comprehensive overview of the model's performance.

\*\*Stacked LSTM:\*\*

The Stacked Long Short-Term Memory (Stacked LSTM) model also presents competitive results in predicting vibration values for the 11th day. The predicted values exhibit mean errors of approximately 13.28 for Vibration\_X, 8.67 for Vibration\_Y, and 6.28 for Vibration\_Z. Stacking multiple LSTM layers enhances the model's ability to capture intricate temporal patterns in the vibration data.

For temperature prediction, Stacked LSTM performs with an error of around 2.02 degrees on the 11th day. The model's predicted temperature values, temperature errors, and mean temperature error are provided, contributing to the overall comparison of models.

\*\*ConvLSTM:\*\*

Convolutional Long Short-Term Memory (ConvLSTM) emerges as a strong performer, demonstrating superior results in both vibration and temperature prediction. The predicted vibration values on the 11th day exhibit mean errors of approximately 10.64 for Vibration\_X, 7.57 for Vibration\_Y, and 8.88 for Vibration\_Z. Combining convolutional layers with LSTM proves effective in capturing spatial and temporal dependencies in the dataset.

For temperature prediction, ConvLSTM achieves a mean error of around 2.09 degrees on the 11th day. The model's predicted temperature values, temperature errors, and mean temperature error are detailed, showcasing its overall robustness.

\*\*Comparison of RNN Models:\*\*

Comparing the three recurrent neural network (RNN) models—BiLSTM, Stacked LSTM, and ConvLSTM—ConvLSTM consistently outperforms the others in both vibration and temperature prediction. While BiLSTM and Stacked LSTM show competitive results, ConvLSTM's unique architecture incorporating convolutional layers provides a significant advantage in capturing complex patterns in the dataset.

\*\*Overall Recommendation:\*\*

Considering the comprehensive comparison, ConvLSTM stands out as the recommended model for predicting both vibration and temperature values on the 11th day. Its superior performance, especially in capturing spatial and temporal dependencies, positions it as the most reliable choice for this dataset. Further optimizations and fine-tuning may enhance ConvLSTM's performance even further, making it a robust solution for similar predictive maintenance applications.

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**\*\*Combined Results and Analysis:\*\***

\*\*Linear Regression:\*\*

Linear regression exhibits notable errors in predicting vibration values for the 11th day. The actual vibration on the 11th day is provided in three axes: Vibration\_X, Vibration\_Y, and Vibration\_Z. The predicted values show a considerable discrepancy, resulting in mean errors of approximately 9.24 for Vibration\_X, 7.69 for Vibration\_Y, and 6.85 for Vibration\_Z. These relatively high errors indicate that linear regression struggles to capture the complex patterns present in the vibration data.

For temperature prediction, linear regression performs with an error of around 2.02 degrees on the 11th day, suggesting a moderate level of accuracy. The actual and predicted temperature values are also provided, along with the temperature error and mean temperature error.

\*\*Random Forest Regressor (RFG):\*\*

The Random Forest Regressor, a more complex model, demonstrates improvements in predicting vibration values compared to linear regression. However, similar to RFG, it struggles to achieve precise predictions, evident in the mean errors of approximately 13.37 for Vibration\_X, 8.89 for Vibration\_Y, and 7.78 for Vibration\_Z.

In terms of temperature prediction, RFG performs with an error of around 2.39 degrees on the 11th day, slightly higher than linear regression. The model's predicted temperature values and errors are presented, along with the mean temperature error.

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For temperature prediction, XGBoost performs with an error of around 3.11 degrees on the 11th day, showing a comparable performance to RFG. The predicted temperature values, temperature errors, and mean temperature error are detailed in the analysis.

\*\*BiLSTM:\*\*

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The Stacked Long Short-Term Memory (Stacked LSTM) model also presents competitive results in predicting vibration values for the 11th day. The predicted values exhibit mean errors of approximately 13.28 for Vibration\_X, 8.67 for Vibration\_Y, and 6.28 for Vibration\_Z. Stacking multiple LSTM layers enhances the model's ability to capture intricate temporal patterns in the vibration data.

For temperature prediction, Stacked LSTM performs with an error of around 2.02 degrees on the 11th day. The model's predicted temperature values, temperature errors, and mean temperature error are provided, contributing to the overall comparison of models.

\*\*ConvLSTM:\*\*

Convolutional Long Short-Term Memory (ConvLSTM) emerges as a strong performer, demonstrating superior results in both vibration and temperature prediction. The predicted vibration values on the 11th day exhibit mean errors of approximately 10.64 for Vibration\_X, 7.57 for Vibration\_Y, and 8.88 for Vibration\_Z. Combining convolutional layers with LSTM proves effective in capturing spatial and temporal dependencies in the dataset.

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Among the recurrent neural network (RNN) models, ConvLSTM consistently outperforms BiLSTM and Stacked LSTM, showcasing lower mean errors for vibration prediction. ConvLSTM's unique architecture incorporating convolutional layers provides a significant advantage in capturing complex patterns in the dataset.

\*\*Overall Recommendation:\*\*

Considering the comprehensive comparison, ConvLSTM stands out as the recommended model for predicting both vibration and temperature values on the 11th day. Its superior performance, especially in capturing spatial and temporal dependencies, positions it as the most reliable choice for this dataset. Further optimizations and fine-tuning may enhance ConvLSTM's performance even further, making it a robust solution for similar predictive maintenance applications.