**Discussion**

The objective of this study was to determine the most effective machine learning model for predicting Overall Equipment Effectiveness (OEE) and Machine Maintenance Efficiency (MME) in a packaging equipment manufacturing industry. Using synthetic data generated with realistic parameter ranges, we evaluated the performance of ARIMA, GRU, and TCN models based on RMSE, MAE, and MAPE metrics.

One of the initial challenges we faced was the unavailability of real data from actual packaging equipment manufacturing companies. To address this, we generated synthetic data, ensuring that it closely mirrored real-world conditions by researching necessary parameters and their realistic value ranges. However, this approach introduces a limitation: synthetic data might not fully capture the complexities and nuances of actual operational data, such as interdependencies and temporal dynamics like seasonality or periodic maintenance cycles.

Our findings indicate that ARIMA, a traditional time series model, performed the worst. This result might be attributed to the synthetic nature of the data, as ARIMA often struggles with the complexity and non-linearity that could be inadequately represented in synthetic datasets. Conversely, both GRU and TCN models showed strong performance, with TCN slightly outperforming GRU. While these results are promising, they also raise concerns about whether such high accuracy and low error rates would be achievable with real-world data. The excellent performance of GRU and TCN on synthetic data might not fully translate to actual industrial settings where data is more complex and less predictable.

Future research should focus on validating our models using real-world data from manufacturing industries to understand their practical applicability better. Additionally, incorporating more parameters that influence OEE and MME, such as maintenance schedules, operator efficiency, and environmental factors, could further enhance model accuracy. Exploring hybrid models that combine different machine learning approaches might also capture both linear and non-linear patterns more effectively.

**Conclusion**

In conclusion, our study aimed to identify the best machine learning model for predicting OEE and MME in a manufacturing setting. We found that ARIMA was the least effective model, potentially due to the limitations of synthetic data. Both GRU and TCN models showed significant promise, with TCN slightly outperforming GRU. Despite the robust synthetic data generation and comprehensive evaluation metrics used in our study, the lack of real-world data poses a significant limitation. The synthetic data might not fully capture the interdependencies and temporal dynamics of actual processes, and the high performance of GRU and TCN on synthetic data may not be replicable with real-world data.

Future research should prioritize testing these models with real-world data and exploring additional parameters and hybrid models to enhance predictive accuracy. Incorporating real-world data will help validate the models' effectiveness and ensure their practical applicability in industrial settings. Additionally, expanding the scope of the models to include more comprehensive factors influencing OEE and MME could provide more accurate and reliable predictions. Ultimately, our findings offer a foundational understanding and direction for improving predictive maintenance and operational efficiency in the manufacturing industry, paving the way for future advancements in machine learning applications in this field.