**Time Series Forecasting Report on mechanized Agriculture dataset**

**Aim**

The goal was to forecast three key operational metrics from daily mechanized agriculture data:

1. Final Engine Hours (usage)
2. Number of Breakdowns (failures)
3. Tractors Sales Number (sales)

**Data Preparation and Feature Engineering**

* The raw daily data was cleaned and transformed.
* Lag features and rolling means were created for each target.
* Temporal features like day of week, month, and week of year were added.
* Log transformation was applied to Final Engine Hours to stabilize variance.

**Machine Learning Models**

* **Random Forest Regressor** was used for each target with basic and tuned hyperparameters.
* Grid Search improved performance significantly for engine hours.

**Results after tuning**

* **Final Engine Hours**: MAE of 151,018 and RMSE of 238,322
* **Tractor Sales**: MAE of 3.84 and RMSE of 5.12
* **Breakdowns**: MAE of 0.48 and RMSE of 0.62

**Deep Learning Model (LSTM)**

* A multi-output LSTM model was built using a 14-day window of scaled features.
* Model had one shared LSTM layer and separate dense outputs.

**Results (DL Model)**

* **Final Engine Hours**: MAE of 728,715 and RMSE of 1,051,306
* **Tractor Sales**: MAE of 3.40 and RMSE of 4.75
* **Breakdowns**: MAE of 0.42 and RMSE of 0.50

**Comparison Summary**

Machine learning models outperformed the LSTM in predicting Final Engine Hours, showing significantly lower error. However the LSTM model performed slightly better in predicting Tractor Sales and Number of Breakdowns capturing temporal patterns effectively.

**Recommendation**

Adopt a hybrid approach:

* Use ML models for predicting Final Engine Hours.
* Use the DL model for forecasting Tractor Sales and Breakdowns.

Further improvements may include: tuning LSTM architecture, trying other temporal models like TCNs or Transformers, and adding external factors like weather or fuel prices.