SHORT-TERM ELECTRICAL LOAD FORECASTING FOR BANESHWOR FEEDER USING MACHINE AND DEEP LEARNING MODELS

Presenter,
Sujit Koirala

The Department Of Electrical Engineering
Masters Of Science In Power System Engineering

Tribhuvan University
Institute of Engineering
Pulchowk Campus

Table of contents

01 Introduction

Short-term electrical load forecasting is essential for planning and operating a reliable power system. It helps utilities manage demand, reduce costs, and improve overall efficiency. The Baneshwor Feeder serves a mix of households, businesses, and small industries, and its load pattern shifts with time, weather, and community activities. This project explores how modern machine learning and deep learning models can forecast its hourly demand more accurately than traditional methods.

Fig 1.1: Baneshwor Feeder View

02 Problem Statement

- Existing forecasting methods for the Baneshwor Feeder rely on manual estimates or traditional statistical models that struggle to capture nonlinear and rapidly changing load patterns.

- Weather changes, calendar effects, and local demand variations make the load behavior more complex, reducing the accuracy of current forecasting practices.

- Inaccurate forecasts lead to poor generation scheduling, higher operational costs, increased technical losses, and potential reliability issues in the distribution system.

- There is no systematic study that applies and compares advanced machine learning and deep learning models for short-term forecasting of this specific feeder.

03 Objectives

Build a Reliable Data Foundation

Collect and prepare historical load, weather, and calendar data for the Baneshwor Feeder. This ensures a complete and consistent dataset for developing accurate forecasting models.

Develop and Train Forecasting Models

Design and implement a set of machine learning and deep learning models, including SVR, Random Forest, XGBoost, LSTM, and GRU.

Evaluate and Identify the Best Forecasting Approach

Compare all models using standard performance metrics to determine which method delivers the most accurate and reliable short-term load forecasts

04 Methodology

01 — Data Acquisition

02 — Data Preprocessing

03 — Exploratory Data Analysis

04 — Model Development

06 — Model Training & Validation

07 — Performance Evaluation

4.1 Data Acquisition & Preprocessing

- Load Data: Hourly MW readings from Baneshwor Feeder.
- Weather Data: Temperature, Humidity, and Rainfall.
- Challenges: Missing Value, Nepali (BS) Date Format, Outliers

- Standardization: Converted all timestamps to Gregorian (AD).
- Cleaning: Handled missing values via Forward/Backward fill; detected outliers using IQR.
- Feature Engineering: Created Hour, Day, Month and Time Features from time.

4.1 Data Acquisition & Preprocessing

Time	MW	Air Temperature	Global Solar Radiation	Relative Humidity
2022-10-19 01:00	0.8	14.5	0	88.8
2022-10-19 02:00	0.8	14.4	0	87.9
2022-10-19 03:00	0.8	14	0	92.3
2022-10-19 04:00	0.8	13.2	0	95.8
2022-10-19 05:00	0.8	12.65	0	97.9
2022-10-19 06:00	1.2	12.1	0	100
2022-10-19 07:00	2	12	18.6	100
2022-10-19 08:00	2.3	14.3	171.3	92.9
2022-10-19 09:00	2.1	17.2	393.6	77

Table 4.1 Finalized Sample Dataset

4.2 Exploratory Data Analysis

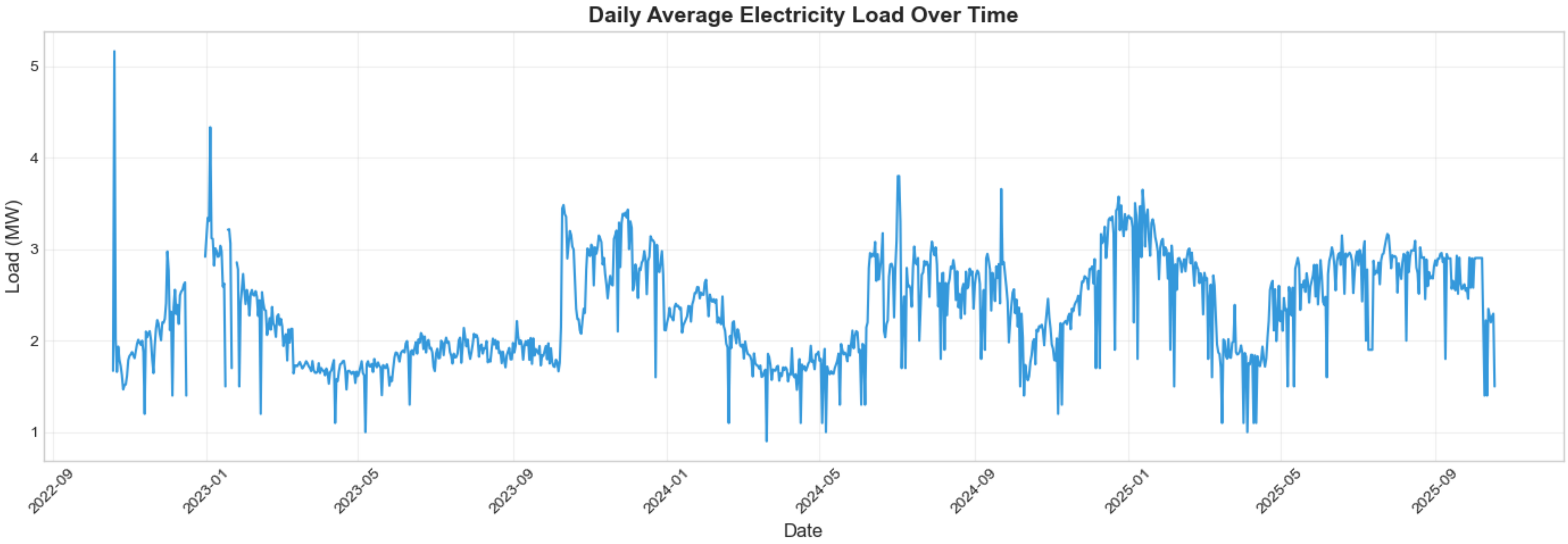
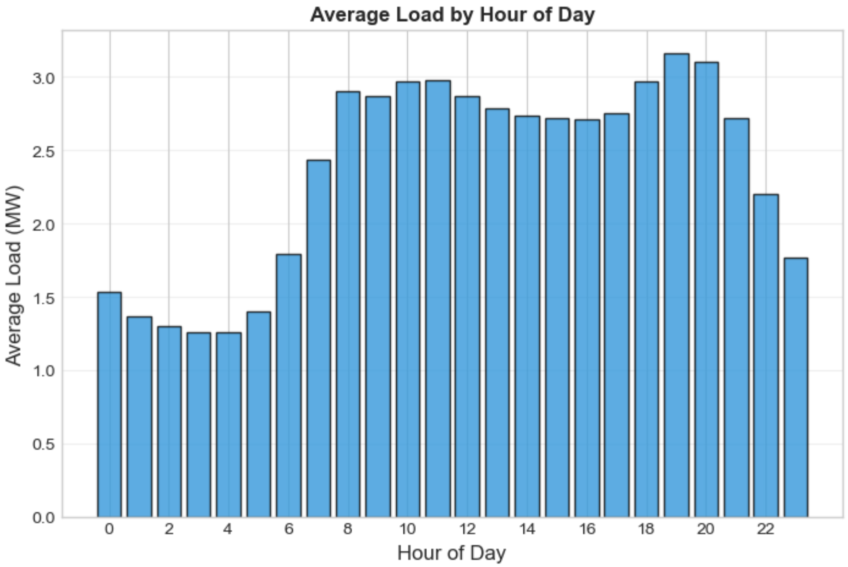


Fig 4.1 Daily Average Load Over Time

4.2 Exploratory Data Analysis



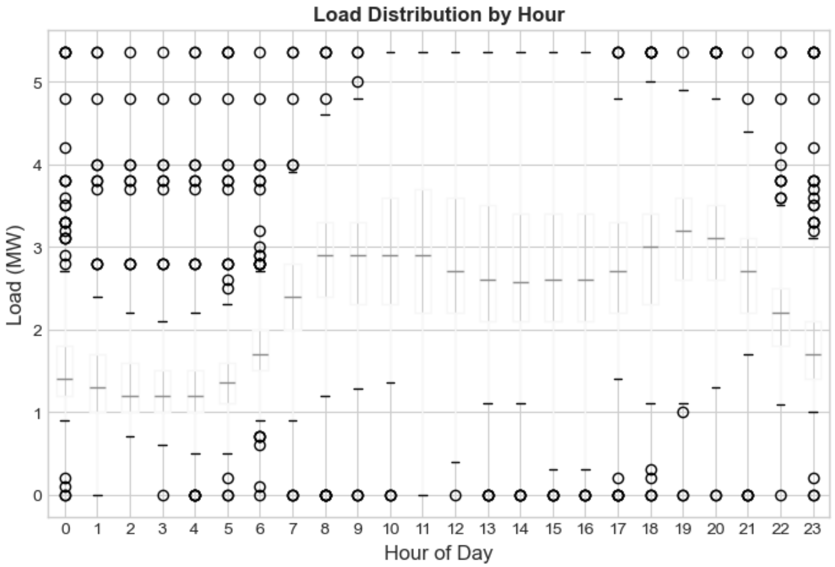


Fig 4.2 Average Load by House of Day and Load Distribution by Hour

4.2 Exploratory Data Analysis

Fig 4.3 Feature Relationship and Average Load by Month

4.2 Exploratory Data Analysis

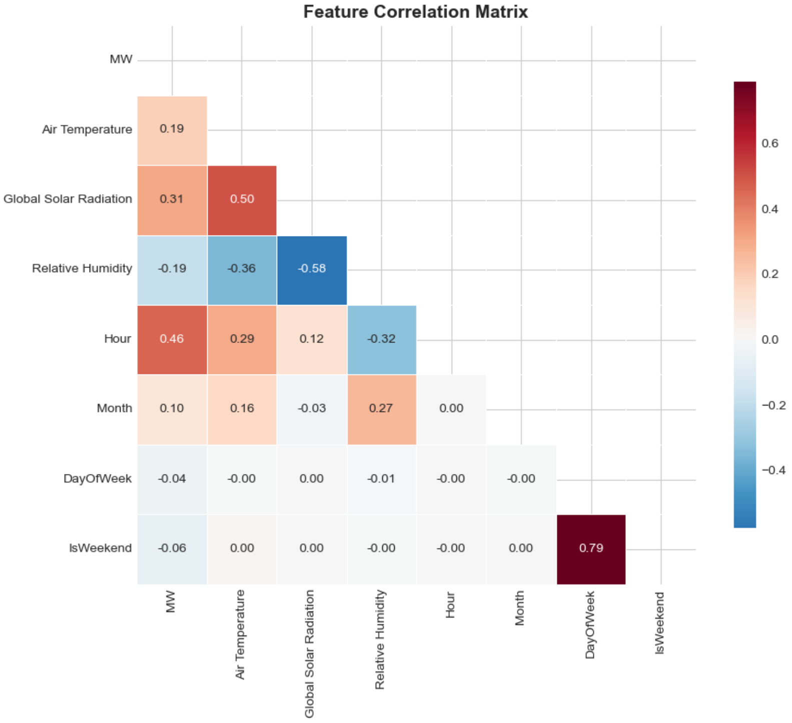


Fig 4.4 Feature Correlation Matrix

4.3 Model Development & Training

Machine Learning Models

- XGboost
- Random Forest
- Gradient Boosting
- SVR (Support Vector Regression)
- Ridge Regression
- Linear Regression

Deep Learning Model

- LSTM (Long Short-Term Memory)
- GRU (Gated Recurrent Unit)
- MLP (Multilayer Perceptron)

4.4 Performance Evaluation

Machine Learning Models

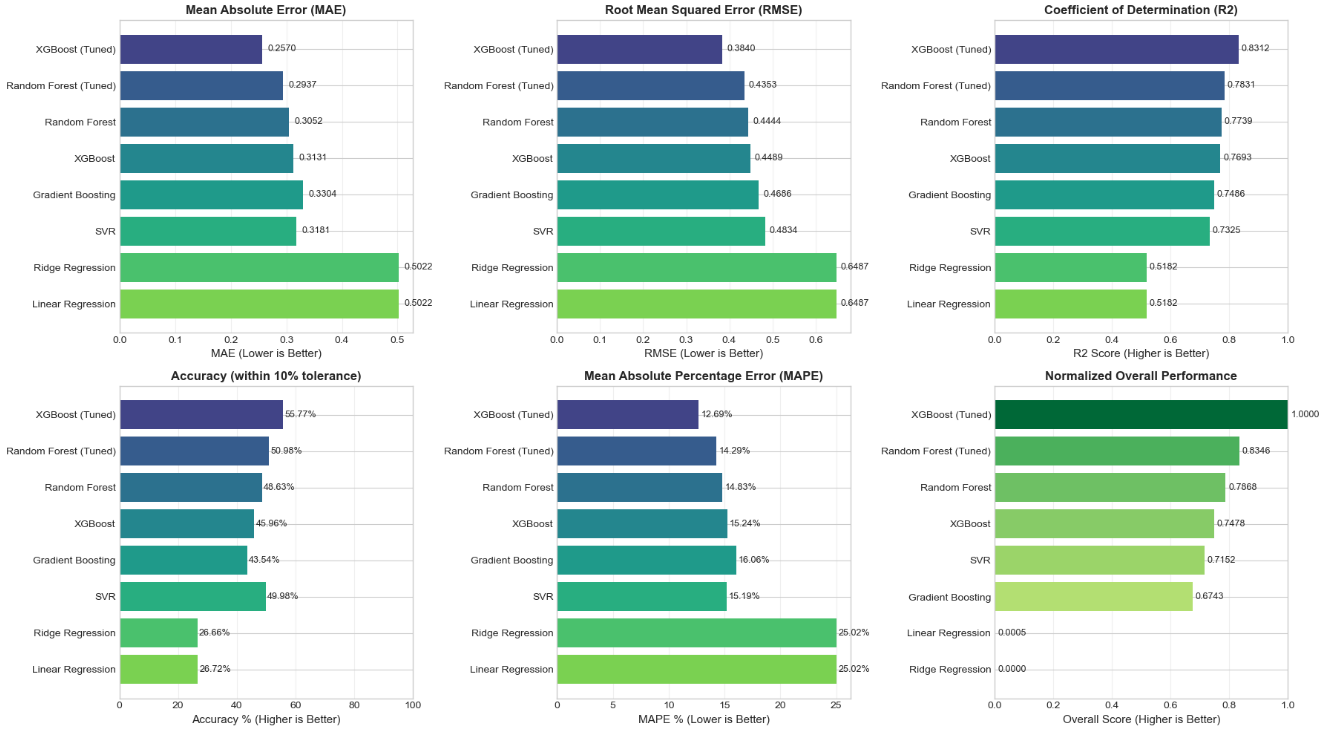


Fig 4.5 Machine Learning Models Evaluation Results

4.4 Performance Evaluation

Machine Learning Models

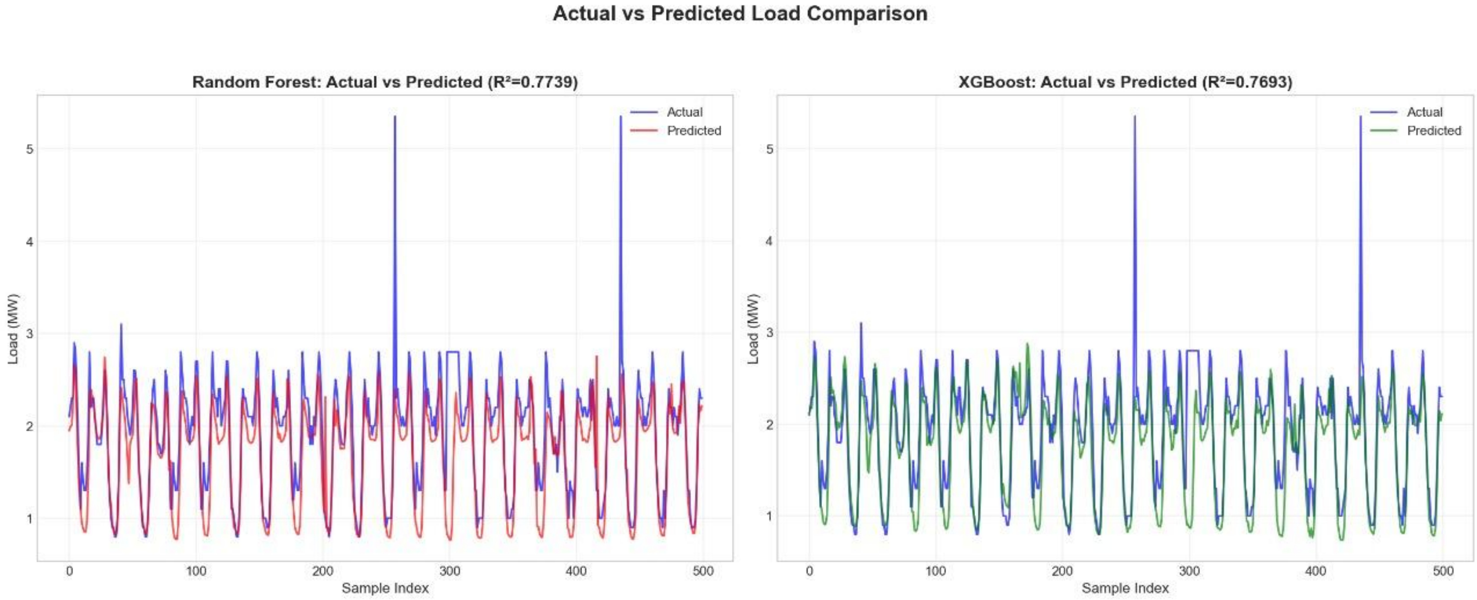


Fig 4.6 Machine Learning Models Actual vs Predicted Load

4.4 Performance Evaluation

Best Machine Learning Models

XGBoost (Tuned)

MAE (Mean Absolute Error)	: 0.256
RMSE (Root Mean Square Error)	: 0.384
MAPR (Mean Absolute Percentage Error)	: 12.69
R2 (Coefficient of Determination)	: 0.831
Accuracy	: 55.77%

4.4 Performance Evaluation

Deep Learning Models

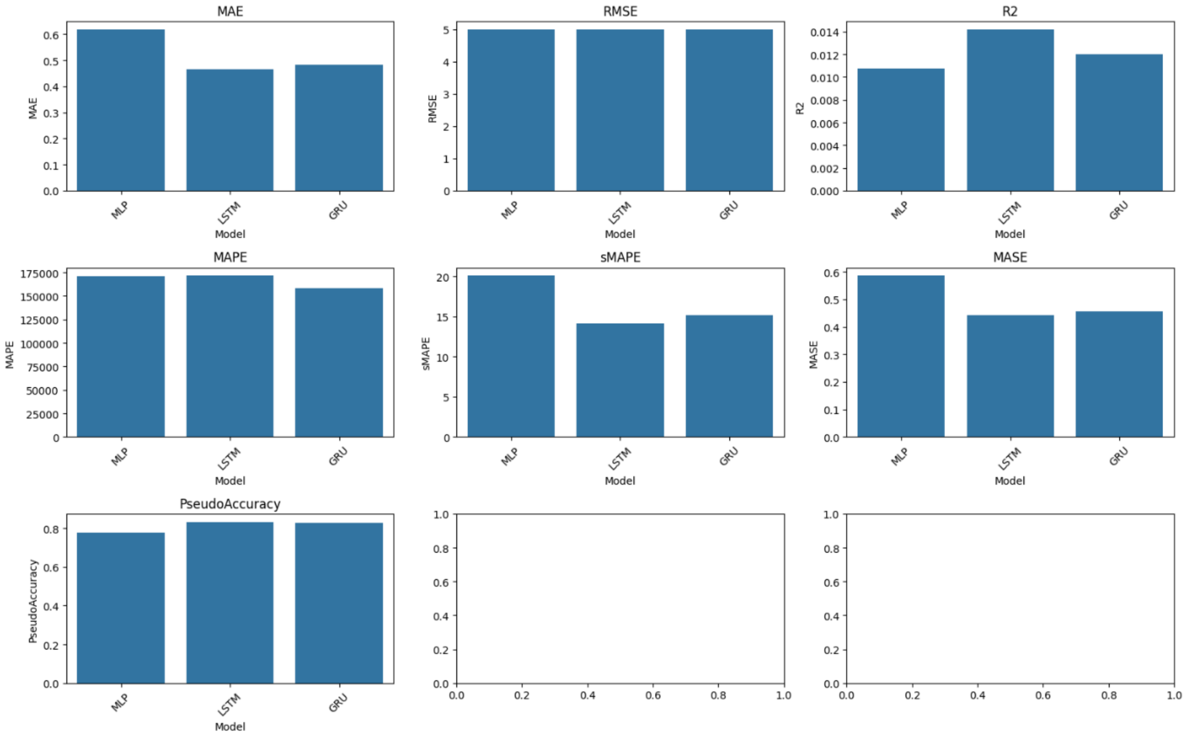


Fig 4.7 Deep Learning Models Evaluation Results

4.4 Performance Evaluation

Deep Learning Models

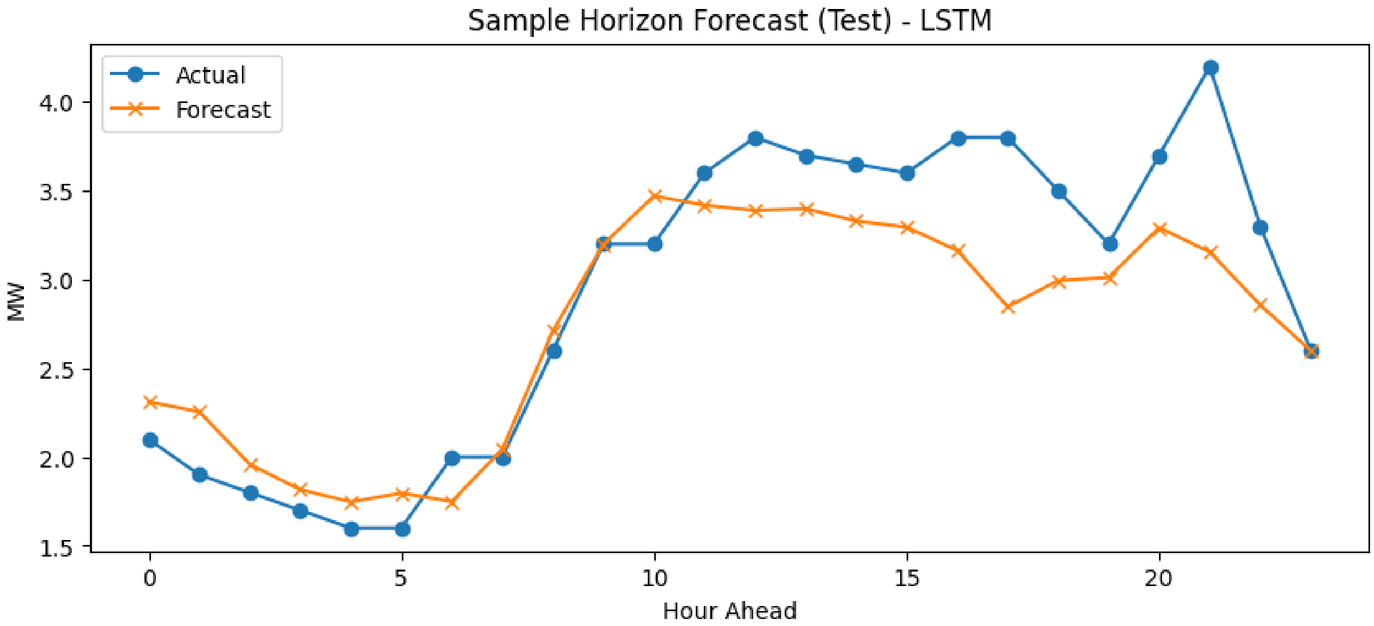


Fig 4.7 LSTM Model Sample Forecast vs Actual

4.4 Performance Evaluation

Best Deep Learning Models

LSTM (Long Short-Term Memory)

MAE (Mean Absolute Error)	: 0.467
RMSE (Root Mean Square Error)	: 0.498
MAPR (Mean Absolute Percentage Error)	: 14.15
R2 (Coefficient of Determination)	: 0.014
Accuracy	: 83.30%

4.4 Performance Evaluation

Best Over All Models

XGBoost (Tuned)

Best generalization, Best error metrics, Best accuracy, Best balance between complexity and performance

- Captures nonlinear relationships effectively
- Handles weather-driven patterns well
- Robust to irregular temporal behavior
- Explains 83.1% of variance in load data

4.4 Performance Evaluation

Over All Model Ranking

Rank	Model	MAE	RMSE	R^2	Category
1	**XGBoost (Tuned)**	**0.257**	**0.384**	**0.8312**	ML
2	**Random Forest (Tuned)**	0.293	0.435	0.7831	ML
3	Random Forest	0.305	0.444	0.7739	ML
4	XGBoost	0.313	0.448	0.7693	ML
5	Gradient Boosting	0.330	0.468	0.7486	ML
6	SVR	0.318	0.483	0.7324	ML
7	Ridge Regression	0.502	0.648	0.5182	ML
8	Linear Regression	0.502	0.648	0.5182	ML
9	LSTM	0.467	0.498	0.014	DL
10	GRU	0.482	0.499	0.012	DL
11	MLP	0.618	0.499	0.011	DL

Table 4.2 ML and DL over all Models Ranking

5 Conclusion

- The study successfully developed and evaluated ML and DL models for short-term load forecasting of the Baneshwor Feeder.
- Ensemble ML models particularly **XGBoost (Tuned)** achieved the highest forecasting accuracy across all evaluation metrics.
- Deep learning models (LSTM, GRU, MLP) underperformed due to limited dataset size and weaker temporal patterns.
- Feature engineering, especially time-based and cyclical features, significantly improved ML performance.
- The final recommended model for practical deployment is **XGBoost (Tuned)** due to its high accuracy, robustness, and operational efficiency.

6 Future Work

- Incorporate additional exogenous variables such as rainfall, wind speed, socio-economic events, and special holidays to improve forecasting accuracy.

- Explore advanced deep learning architectures like **Transformers**, **Temporal Fusion Transformers (TFT)**, and **N-BEATS** for better sequence modeling.

- Develop an end-to-end real-time forecasting system with automated data ingestion and live model deployment.

- Integrate the model with NEA’s load management system to support decision-making and demand-side planning.

Thanks!

Do you have any questions?

Presenter,
Sujit Koirala

The Department Of Electrical Engineering
Masters Of Science In Power System Engineering

Tribhuvan University
Institute of Engineering
Pulchowk Campus

References

- Acharya, S., Luintel, M. C., & Badrudoza, M. (n.d.). Short-term load forecasting of Gothatar feeder of Nepal Electricity Authority using Recurrent Neural Network. Publisher not specified.
- Desai, S., Dalal, T., Kadam, S., & Mishra, S. (2021). Electrical load forecasting using machine learning. IEEE (ICSCAN 2021).
- Singla, M. K., Gupta, J., Nijhawan, P., & Oberoi, A. S. (2019). Electrical load forecasting using machine learning. International Journal.
- Saglam, M., Lv, X., Spataru, C., & Karaman, O. A. (2024). Instantaneous electricity peak load forecasting using optimization and machine learning. Energies.
- Matrenin, P., Safaraliev, M., Dmitriev, S., Kokin, S., Ghulomzoda, A., & Mitrofanov, S. (2022). Medium-term load forecasting in isolated power systems based on ensemble machine learning models. Energy Reports.
- Aguilar Madrid, E., & Antonio, N. (2021). Short-term electricity load forecasting with machine learning. Information.
- Cordeiro-Costas, M., Villanueva, D., Eguía-Oller, P., Martínez-Comesaña, M., & Ramos, S. (2023). Load forecasting with machine learning and deep learning methods. Applied Sciences.
- Guo, W., Che, L., Shahidehpour, M., & Wan, X. (2021). Machine-learning-based methods in short-term load forecasting. The Electricity Journal.
- Chapagain, K., Acharya, S., Bhusal, H., Katuwal, S., Lakhey, O., Neupane, P., Sah, R. K., Tamang, B., & Rajbhandari, Y. (2021). Short-term electricity demand forecasting for Kathmandu Valley, Nepal. Kathmandu University Journal of Science, Engineering and Technology.