Power Quality Monitoring and Analysis Using Data Analytics and Artificial Intelligence

PRT840

Amanjeet Kaur Bhangu - S343399
Neelam Sharma - S366605
Ajay Kumar - S367729
Jagannath Shrestha - S372202

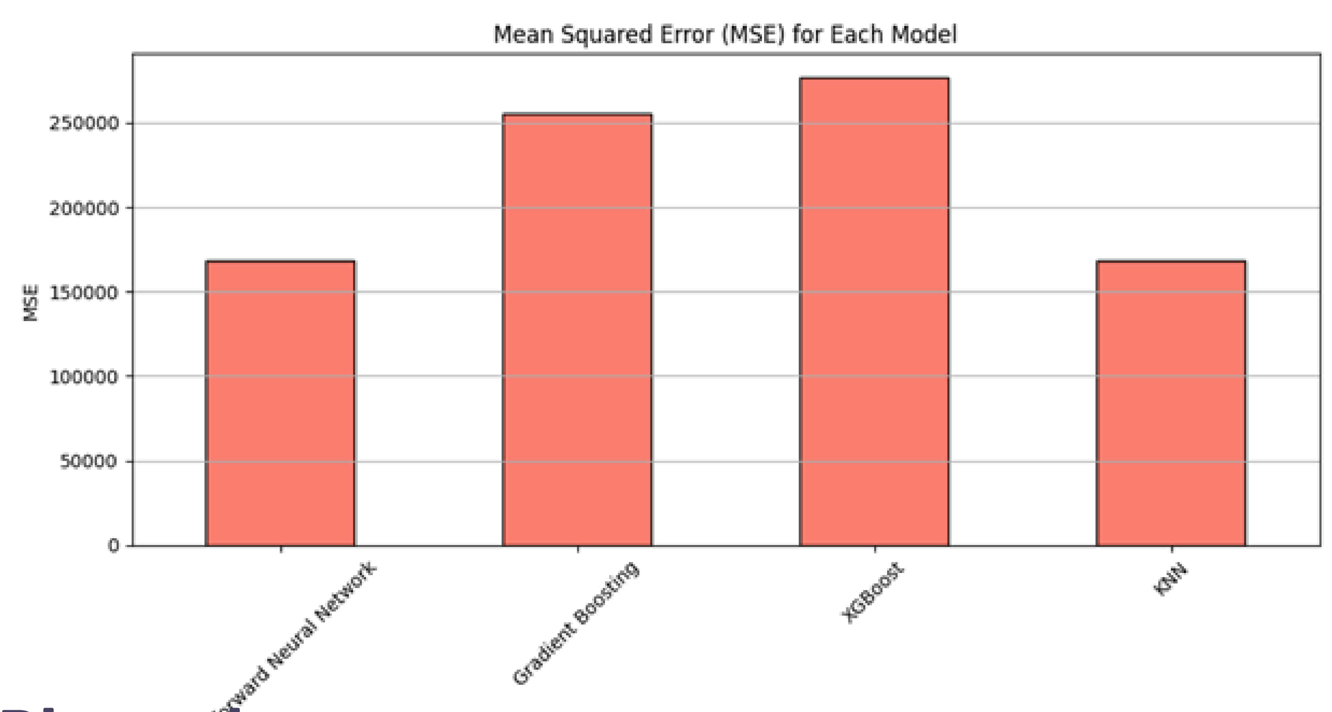
Objectives

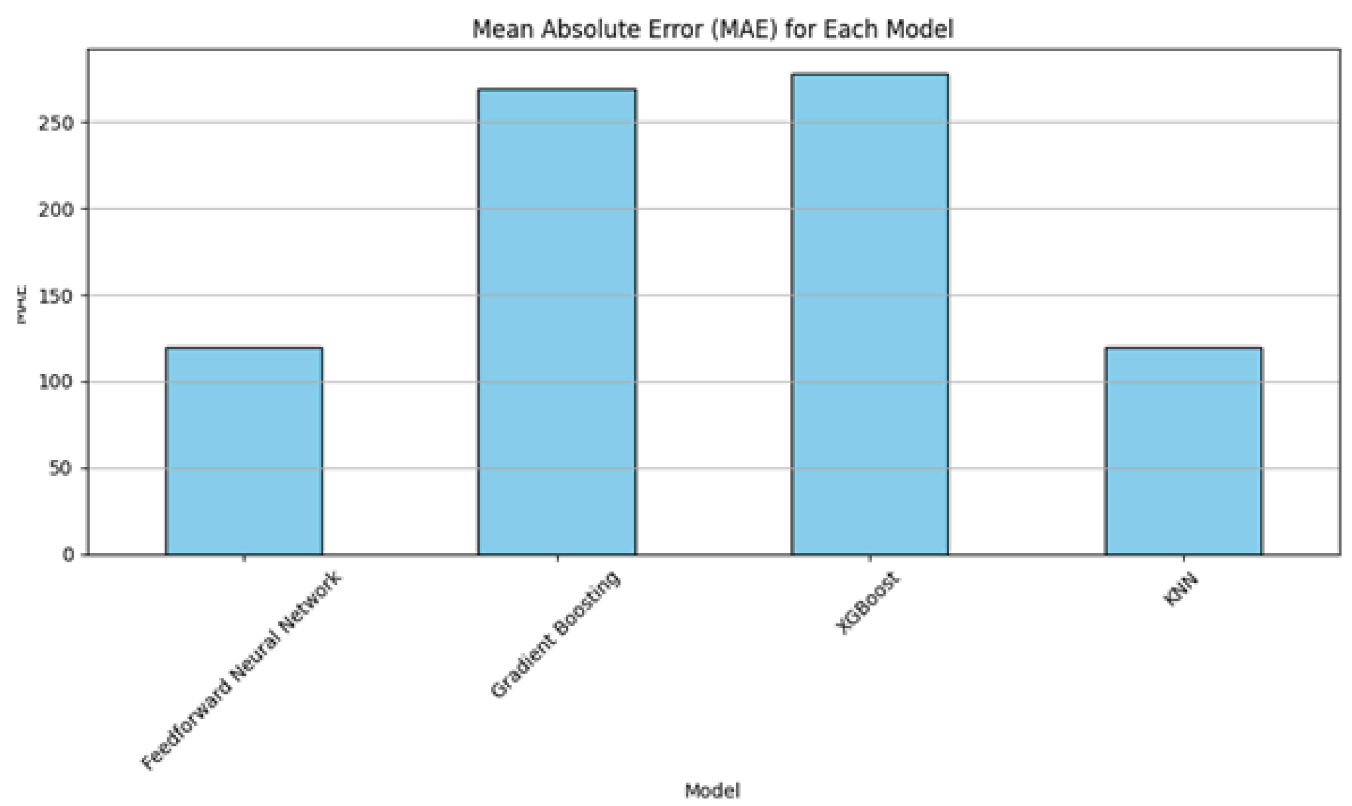
- Develop AI-driven monitoring tools that process power quality data in near real-time using machine learning and deep learning to detect potential grid disturbances.
- Implement a real-time online monitoring system to continuously measure power quality parameters, alerting operators to potential issues for preventive action.
- Utilize AI to predict and prevent disruptions, improving grid reliability through predictive and preventive maintenance.
- Ensure AI tools integrate with smart grid systems to enhance the conventional grid management system.

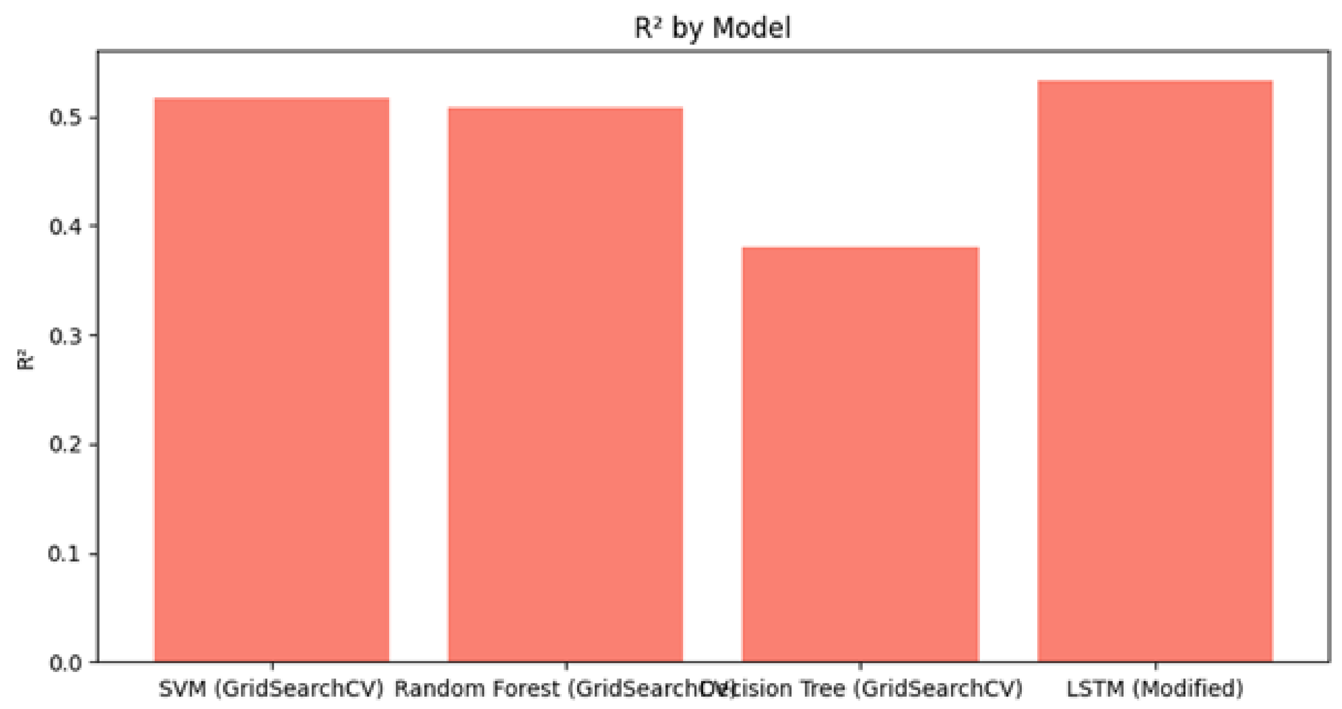
Introduction

The aim of this project is to improve power quality analysis as well as the monitoring of smart grid using data analytics and artificial intelligence (Remigio et al., 2022). The suggested project is to develop an AI-based system for continual detection, categorization, and mitigation of power quality problems (Nair et al., 2022). This system intended to synchronize with the smart grid infrastructures that are currently in place and will regulate the movement of power and prevent disruption of power flow (De Oliveira & Bollen, 2023).

Model	MSE	MAE	R^2
SVM (GridSearchCV)	0.012638	0.093606	0.516276
Random Forest (GridSearchCV)	0.012847	0.091834	0.508243
Decision Tree (GridSearchCV)	0.016192	0.101714	0.380239
LSTM (Modified)	0.012191	0.090156	0.533360
SVM	0.012638	0.093606	0.516276
Random Forest	0.012939	0.091795	0.504732
Decision Tree	0.021749	0.115188	0.167522
LSTM	0.012434	0.090776	0.524083







Results

The Feedforward Neural Network (FNN) performed best overall, showing the lowest MSE and MAE, and an R^2 value close to 1, indicating superior prediction accuracy. Gradient Boosting, XGBoost, and KNN also performed reasonably well, but with higher errors compared to FNN. KNN, interestingly, achieved similar results to FNN in some cases, demonstrating its competitiveness for this type of structured dataset.

Discussion

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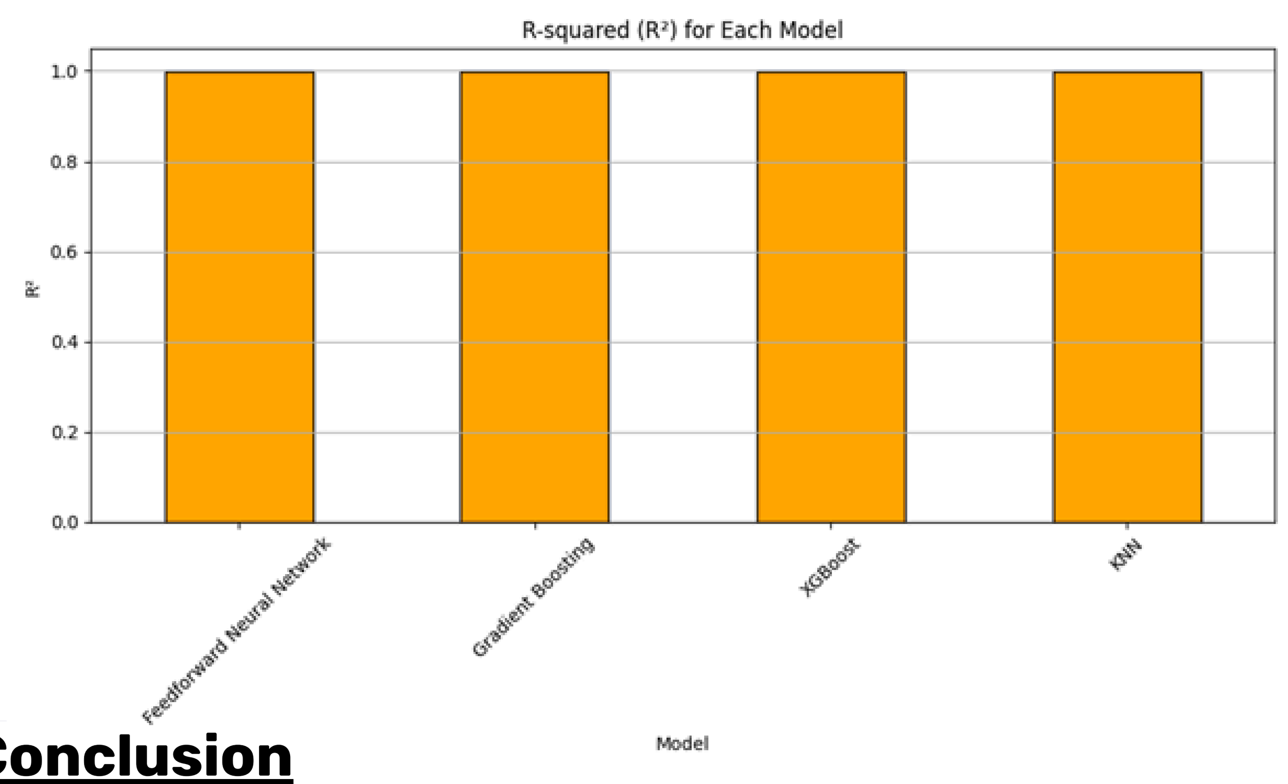

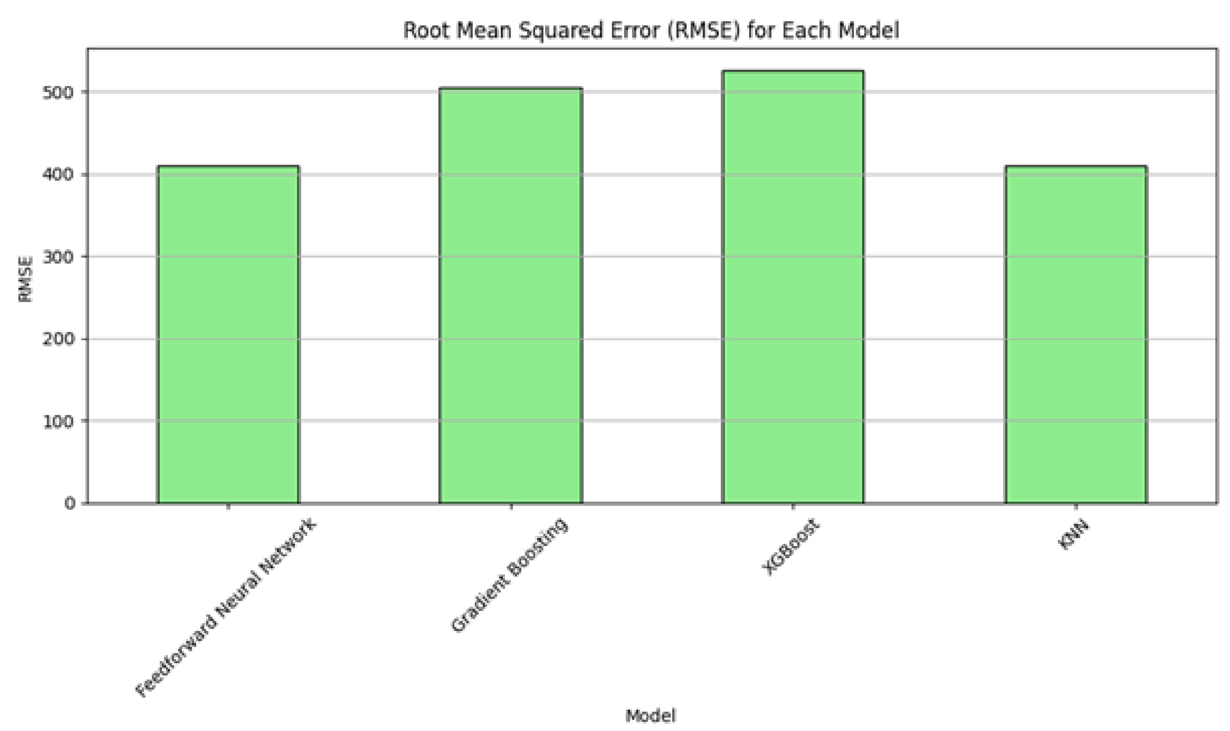

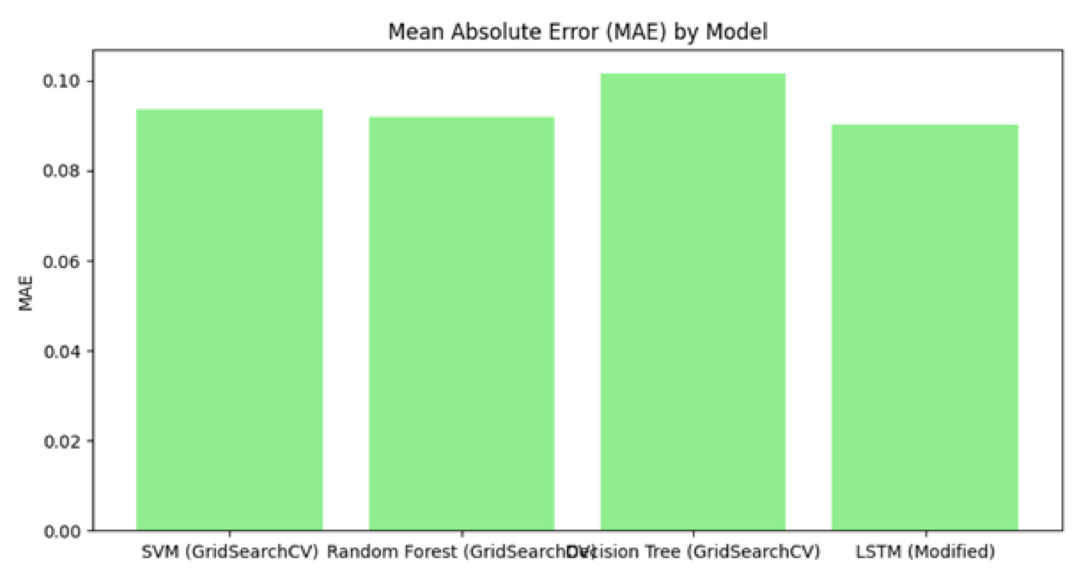

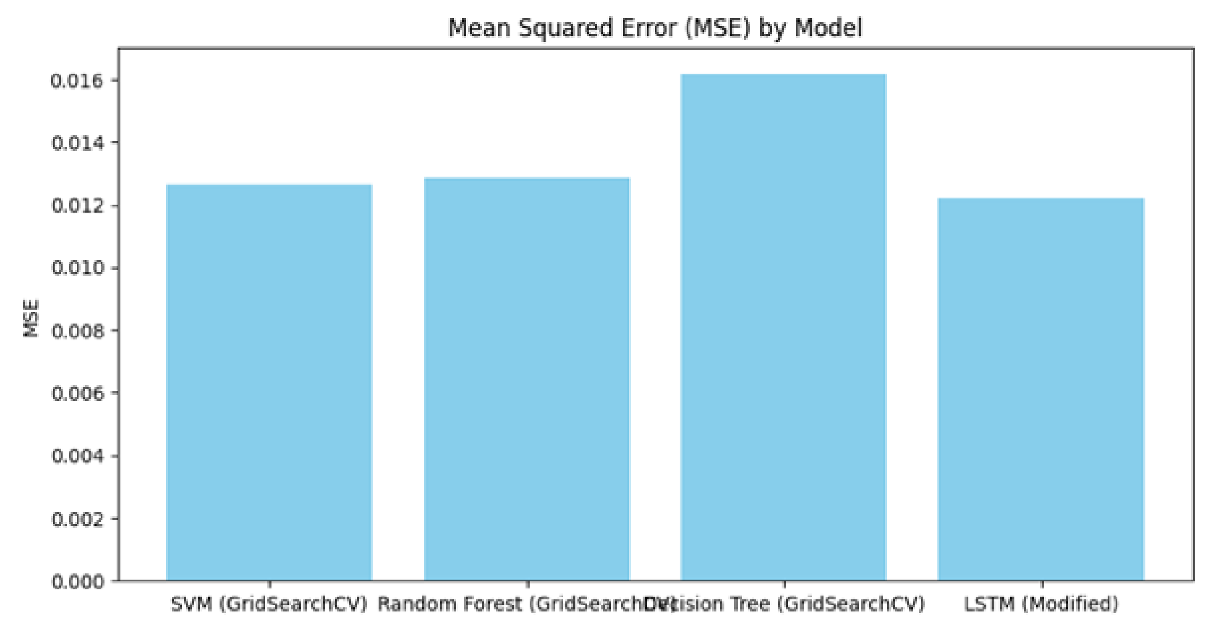

Conclusion

The FNN emerged as the most reliable model, offering highly accurate energy demand predictions with minimal errors. KNN also demonstrated significant potential due to its low complexity and competitive performance. Future work could focus on fine-tuning these models for improved results and exploring their applications in other contexts of smart grid management.

References

- Kumar, S. et al. (2023) - Discusses the role of smart meters and sensors in monitoring power quality in smart grids.
- Li, J. et al. (2022) - Explores the integration of cloud environments for data storage and analysis in power systems.
- Zhang, T. et al. (2023) - Describes the application of Convolutional Neural Networks (CNNs) in identifying spatial patterns in power quality data.
- Das, P. et al. (2021) - Focuses on AI's predictive capabilities for grid reliability and preventive maintenance.