Topic	Summary	Novelties	Shortcomings
Energy Demand Forecasting Using Machine Learning Perspective (Bangladesh)	Investigates ML-based energy demand forecasting using LSTM, SARIMAX, and Fbprophet on 11 years of power generation data. LSTM showed the best accuracy.	- Comparative analysis of LSTM, SARIMAX, and Fbprophet. - Focus on Bangladesh's energy challenges. - Emphasizes LSTM's superior performance.	- Data from 2003-2014 may not reflect current patterns. - Limited input variables beyond historical demand. - Insufficient clarity on data preprocessing. - Lacks justification for LSTM's complexity. - Findings may not generalize to other countries.
Short-Term Electrical Load Prediction Using Hybrid DL Model	Proposes a CNN-LSTM hybrid model for short-term load forecasting in Mymensingh, Bangladesh. Model outperformed vanilla NN and GRUs with the lowest MAPE.	- First hybrid CNN-LSTM approach for STLF. - Region-specific study in Bangladesh. - Direct comparison with PGCB's forecasting method.	- Limited to Mymensingh Division, restricting generalizability. - Feature selection rationale could be stronger. - Model complexity affects interpretability. - Relies mainly on MAPE; could include RMSE/MAE. - Limited discussion on hyperparameter tuning.
Long-Term Energy Demand Analysis Using ML Algorithms (Bangladesh Case Study)	Uses ML models (Random Forest, KNN, XGBoost, Light-GBM) for long-term energy demand forecasting in Dhaka. KNN performed best (R^2 = 0.9447, RMSE = 163.9).	- First ML-based long-term demand study in Bangladesh. - Detailed hyperparameter tuning documentation. - Comparative analysis of multiple models. - Uses a large dataset with consumer segmentation.	- Only three years of data, limiting insights. - Lacks interpretability discussion. - No comparison with traditional statistical models. - Overfitting concerns with Random Forest. - Lacks feature importance analysis.
Medium-Term Energy Demand Analysis Using ML	Applies ML to medium-term demand forecasting in a sub-district of Dhaka using KNN, Light-GBM, RF, MLR, and XGBoost. KNN was the most accurate (72%) but slowest.	- Addresses energy demand in a developing country. - Compares multiple ML models. - Focus on medium-term forecasting. - Granular data analysis (tariffs, building types). - Uses meteorological & tariff data.	- Limited to a small geographic area. - May lack key socioeconomic and building-related factors. - Does not optimize ML models extensively. - No external validation with independent data. - KNN has high computational cost.