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Electrical Load Forecasting with Anomaly Detection and Explainability

S. Suganthi Shyam¹, S. Reshmaa², J. Jephitha Janish³

¹Assistant Professor / CSE, ^{2,3}UG Scholars, Department of Computer Science and Engineering, K.L.N. College of Engineering, Pottapalayam, Sivagangai, India

Abstract: Managing electricity efficiently has become a crucial part of modern living. Power usage constantly changes based on time, weather, and user behavior, making it difficult to predict and manage. Traditional forecasting methods like ARIMA or LSTM can predict trends but fail to explain why certain fluctuations occur or when abnormal consumption happens. This project — *Electricity Load Forecasting with Anomaly Detection and Explainability* — focuses on predicting energy consumption accurately while also detecting unusual usage patterns (called anomalies) and explaining the reasons behind them. The system uses a Transformer-based forecasting model to predict future electricity load, a statistical anomaly detector to find abnormal spikes or drops, and SHAP (SHapley Additive Explanations) to explain which features influence the results. A simple Streamlit dashboard displays real-time forecasting, anomaly visualization, and feature importance charts. This makes it easy for users and energy operators to understand power trends, reduce wastage, and maintain a more stable and efficient energy system.

Keywords: Electricity Load Forecasting, Transformer, Anomaly Detection, SHAP Explainability, Streamlit Dashboard, Smart Energy Management.

I. INTRODUCTION

Rapid urbanization, industrialization, and digitalization have caused exponential growth in energy consumption across sectors. Accurate electricity load forecasting is critical for effective power system planning, fault detection, and cost optimization [3]. Traditional models such as ARIMA and exponential smoothing are limited in handling nonlinear load fluctuations caused by dynamic user behavior, weather conditions, and special events [4]. Machine learning and deep learning methods, including LSTM and GRU networks, have shown improved accuracy for load forecasting tasks [5]. However, these models are computationally intensive, require long training times, and provide limited interpretability. This project addresses these challenges by combining three key techniques: Transformer-based forecasting to efficiently capture temporal dependencies and long-range patterns in load data. Anomaly detection using the Mean + 2×Standard Deviation method to identify unusual consumption spikes or drops. Explainable AI using SHAP to interpret the contribution of each feature, such as temperature, hour, or humidity, to the predictions. The system provides a unified framework for accurate, interpretable, and actionable energy analytics in smart grid applications.

II. METHODOLOGY

As can be seen in Fig. 1, the proposed Predictive Modeling and Forecasting of Electricity Load system is designed as a systematic step-by-step workflow to ensure high accuracy, explainability, and real-time adaptability. The process begins with data collection, where historical electricity consumption values along with external features such as temperature, humidity, and calendar information are fetched from reliable sources such as Kaggle datasets or smart meter APIs. This continuous data acquisition forms the backbone of the forecasting system and ensures that the model keeps pace with dynamic energy consumption patterns. Once the data is gathered, preprocessing steps are undertaken to clean and standardize the dataset for machine learning. This includes handling missing values through forward-filling, removing outliers to reduce noise, normalizing attributes using Min-Max scaling to maintain uniformity across features, and synchronizing timestamps to ensure temporal consistency. These steps are essential for providing the model with reliable and structured input that supports accurate learning. Following preprocessing, the feature engineering phase transforms raw electricity data into more informative features that capture short-term and long-term patterns. Features such as lag values, moving averages, hourly and daily load differences, temperature-humidity interactions, and day-type indicators are calculated. These derived features provide additional context to the model, allowing it to understand complex temporal relationships and seasonal variations that simple raw load data cannot convey. After preparing the dataset, the Transformer-based forecasting model is trained. The Transformer architecture leverages multi-head self-attention mechanisms to capture dependencies across long sequences of past load data efficiently.

Position encoding preserves temporal order, and feed-forward layers generate the predicted load for the next time step. The model is optimized using the Adam optimizer, with hyperparameter tuning applied to learning rate, number of attention heads, and feed-forward layer dimensions, ensuring a balance between accuracy and computational efficiency. Once trained, the anomaly detection module calculates deviations between predicted and actual load values. Any point exceeding the threshold defined as $\text{Mean} + 2 \times \text{Standard Deviation}$ is flagged as an anomaly, highlighting unexpected consumption patterns, meter errors, or potential faults in the grid. These anomalies are visually represented on the output dashboard, allowing operators to quickly identify and investigate abnormal behavior. Explainability is achieved using SHAP, which assigns contribution scores to each feature for every prediction. Positive SHAP values indicate features driving load increases, while negative values indicate reducing effects. Visualizing these contributions helps stakeholders understand why the model makes specific forecasts, bridging the gap between predictive accuracy and interpretability. Finally, all outputs are integrated into an interactive Streamlit dashboard, which provides three key visualizations: Forecasting Trends, Anomaly Indicators, and Feature Importance (SHAP). This modular design allows real-time updates as new data arrives, ensuring the system remains responsive to changing energy consumption patterns. In summary, the approach provides a seamless flow from raw data acquisition to actionable insights, combining robust preprocessing, informative feature engineering, advanced forecasting, anomaly detection, and explainable AI. The system serves as a practical and interpretable solution for electricity load prediction, supporting grid operators, energy analysts, and decision-makers in data-driven energy management and smart grid optimization.

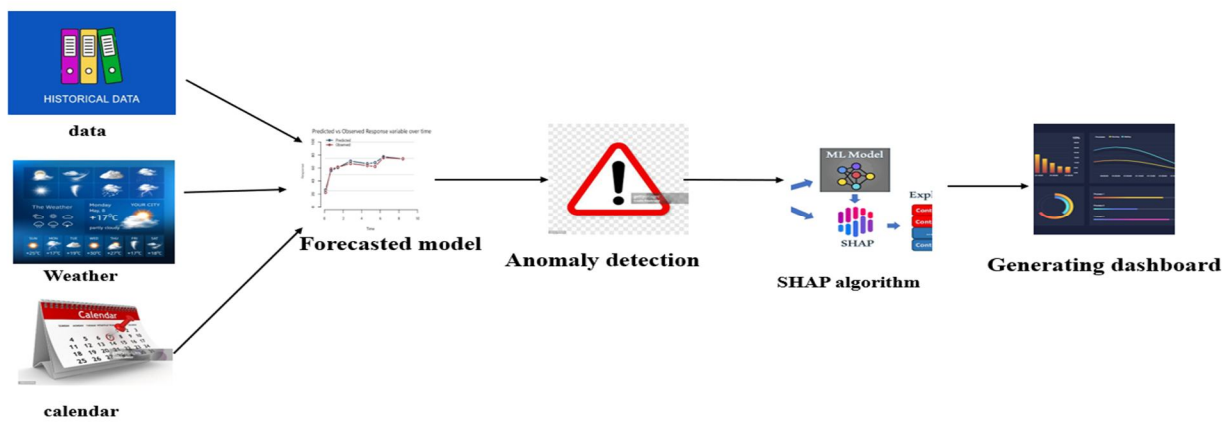


Fig. 1 Architecture Diagram

III. LITERATURE SURVEY

Various researchers have explored electricity load forecasting using diverse models and methodologies. Bhupatiraju and Ahn [1] proposed an explainability-driven feature engineering approach for mid-term load forecasting in ERCOT's SCENT region, demonstrating how carefully designed features can improve both prediction accuracy and interpretability. Yang et al. [2] employed a ConvLSTM-3D neural network with feature fusion, achieving optimized short-term load forecasts by capturing spatial-temporal dependencies, though the model required substantial computational resources. Giacomazzi et al. [3] utilized a Temporal Fusion Transformer (TFT) for short-term load forecasting, highlighting the impact of grid hierarchies on model performance. Their study showed that Transformer-based architectures could efficiently handle complex temporal patterns while remaining scalable across multiple grid levels. Wang et al. [4] introduced a time series decomposition-based method for interpretable electricity price forecasting, emphasizing the importance of separating trend, seasonality, and residual components to improve model transparency and decision-making. Zhang et al. [5] developed a hybrid deep learning model combining multiple architectures for short-term electricity load forecasting. While their approach improved accuracy, it incurred heavier computation and increased complexity. Lim et al. [6] proposed a Transformer-based framework for electricity demand forecasting in smart grids, demonstrating that self-attention mechanisms can efficiently capture long-term dependencies in load data and outperform traditional recurrent networks. Chen et al. [7] focused on anomaly detection in power systems using deep learning with attention mechanisms, showcasing the potential of combining forecasting and anomaly detection to identify abnormal consumption patterns and system faults. From these studies, it is evident that while deep learning models like ConvLSTM, TFT, and hybrid architectures achieve high prediction accuracy, they often require significant computational resources and are difficult to interpret.

Transformer-based models combined with explainable AI and anomaly detection now offer a balanced solution, providing accurate, interpretable, and real-time electricity load forecasts. The proposed system in this project leverages a Transformer-based forecasting model, integrated anomaly detection, and SHAP-based explainability to provide a robust, efficient, and transparent energy analytics framework suitable for smart grid applications.

IV. DATA COLLECTION AND PREPROCESSING

This module is responsible for gathering both historical and real-time electricity consumption data from households or facilities, along with relevant external factors such as weather conditions, calendar information, and special events. The preprocessing step ensures that the collected data is clean, consistent, and formatted for time-series modeling. It handles missing or noisy values, normalizes the data, and applies feature engineering techniques such as lag features, rolling averages, and trend indicators. By providing high-quality and structured inputs, this module lays a strong foundation for accurate and reliable load forecasting.

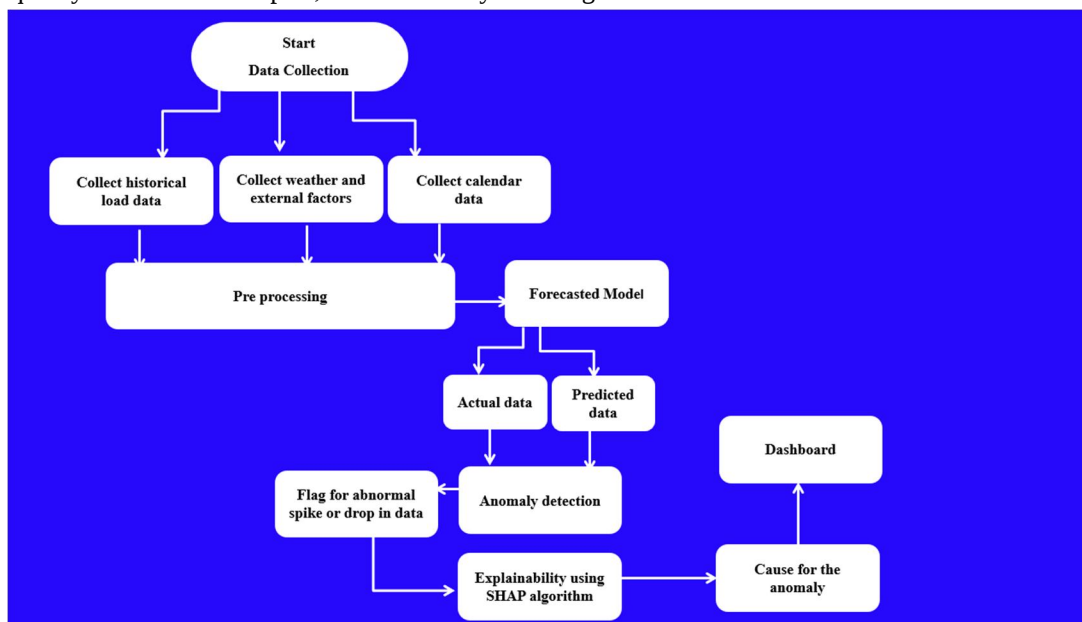


Fig. 2 Data Flow Diagram

V. TRANSFORMER FORECASTING MODEL

The Transformer Forecasting Model forms the core predictive engine of the system. Utilizing self-attention mechanisms, it captures both short-term fluctuations and long-term dependencies in electricity consumption. Unlike conventional statistical models, the transformer efficiently processes large datasets and adapts to complex temporal patterns, making it suitable for multi-horizon forecasts. This module can handle daily, weekly, and seasonal cycles, ensuring robust predictions across different time scales. Continuous learning from incoming data allows the model to improve and remain accurate over time.

Predicted vs Actual Load

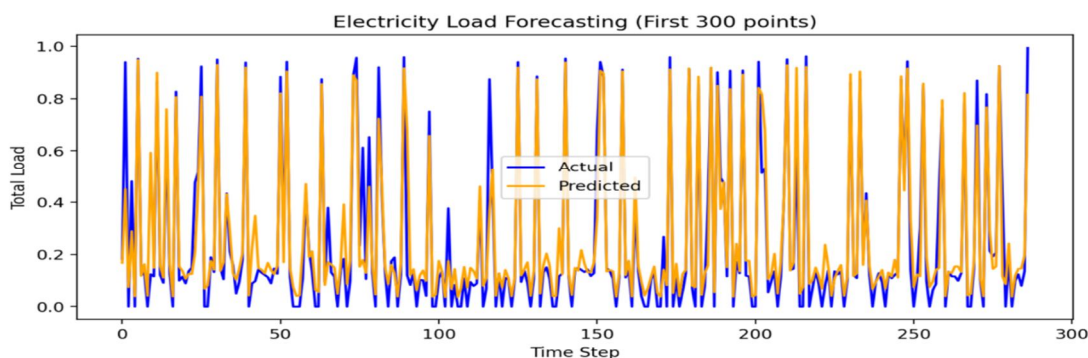


Fig. 3 Forecasted Model

VI. ANOMALY DETECTION MODULE

The Anomaly Detection Module identifies unusual load behaviors by comparing predicted consumption values with actual readings. Deviations beyond a predefined threshold are flagged as anomalies, which could indicate equipment malfunctions, unusual consumption spikes, or potential energy theft. Each anomaly is assigned a severity level and triggers alerts for timely corrective actions. The module's adaptive thresholds account for seasonal or daily variations, maintaining high reliability and reducing false positives.

Anomaly Detection in Load Data

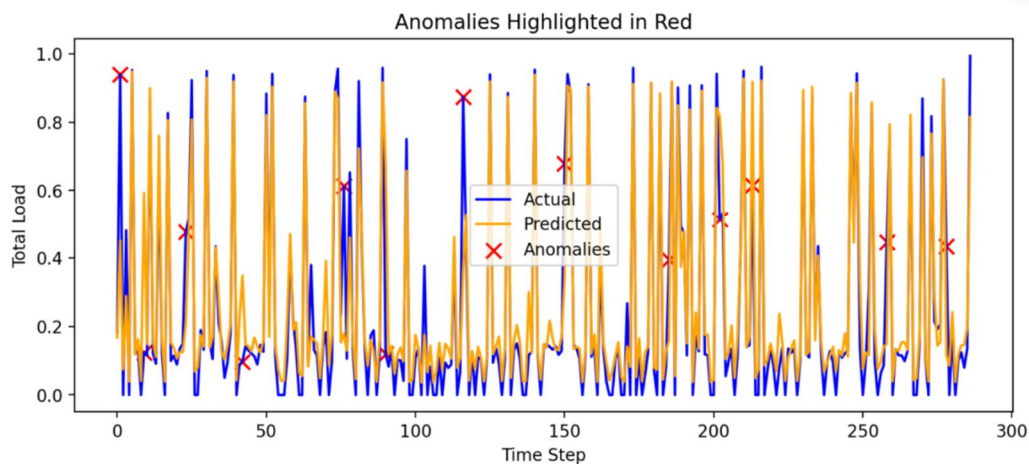


Fig. 4 Anomaly Detection

VII. EXPLAINABILITY MODULE

This module integrates Explainable AI (XAI) techniques, such as SHAP, to provide transparency into the forecasting model. It highlights the contribution of each input feature—like temperature, time of day, or historical load—to the predictions and detected anomalies. Visualizations such as feature importance charts and contribution breakdowns help operators understand why the model made certain predictions, enhancing interpretability, trust, and informed decision-making in energy management.

VIII. VISUALIZATION AND DASHBOARD MODULE

The Visualization and Dashboard Module offers a user-friendly interface for monitoring real-time electricity forecasts, anomalies, and feature explanations. Interactive charts display load trends, bar graphs illustrate anomaly distribution, and heatmaps capture seasonal variations. The dashboard also provides notifications and alerts for significant deviations, enabling proactive management. Users can filter and explore data by region, time period, or appliance category, making the system actionable and highly informative for smart grid operators.

IX. RESULTS AND DISCUSSION

The proposed Transformer-based electricity load forecasting system demonstrates substantial improvements in prediction accuracy, adaptability, and interpretability compared to conventional models like ARIMA and LSTM. The model effectively captures complex temporal dependencies in historical electricity consumption, weather variables, and calendar features, enabling highly reliable next-step load predictions. The forecasted electricity load graph, showing that predicted values closely track actual consumption trends. The model's ability to anticipate demand fluctuations in real time allows for optimized energy management, reduced wastage, and enhanced operational efficiency. The forecasting mechanism dynamically adapts to varying consumption patterns across hours and days, reflecting the system's robustness in handling diverse load behaviors. Anomaly detection results are presented. Points where actual consumption deviates significantly from predicted values—beyond the mean plus two standard deviations—are flagged as anomalies. These deviations can indicate abnormal energy usage, equipment malfunctions, or unexpected consumption patterns. By detecting anomalies early, the system enables proactive interventions and supports improved grid reliability. Figure displays SHAP-based explainability visualizations integrated into the dashboard. This feature allows users to interpret the contribution of each input factor—such as temperature, humidity, hour of the day, and day of the week—to the predicted load.

Stakeholders can monitor trends and deviations for the first 300 data points, helping validate the model's predictions and providing actionable insights for energy optimization in smart homes, commercial facilities, or industrial setups. Overall, the system successfully integrates accurate forecasting, anomaly detection, and transparent explainability within a single framework. Leveraging the Transformer model ensures computational efficiency and parallel processing of temporal data, while SHAP visualizations and interactive dashboards enhance interpretability. These results confirm that the system is highly effective for real-time energy management and can significantly contribute to smart grid optimization.

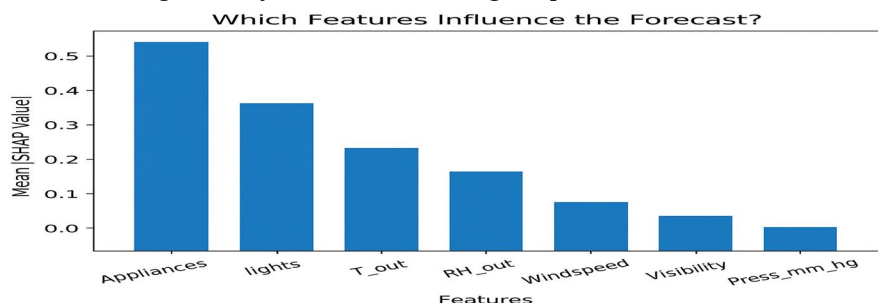


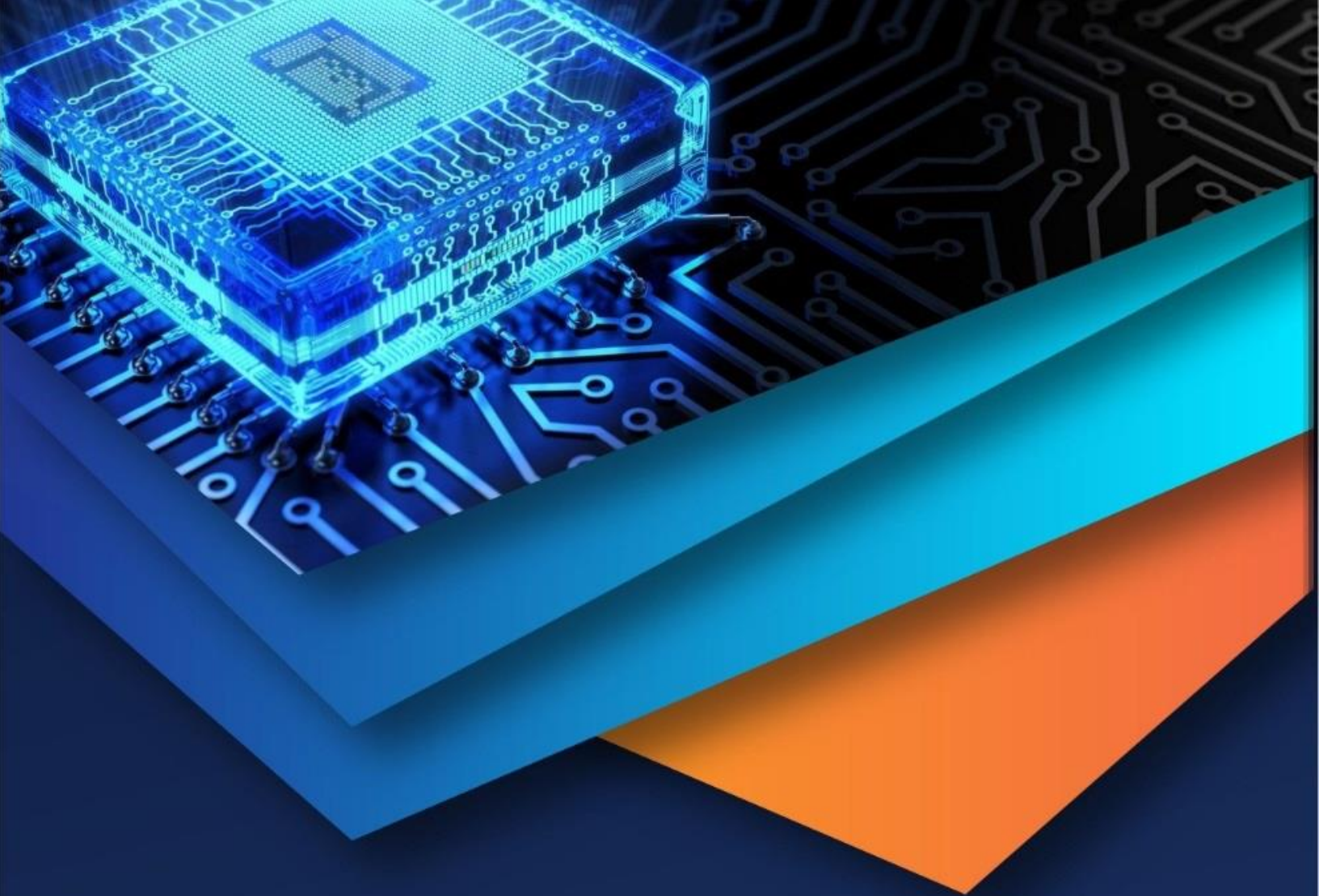
Fig. 5 Visualization

X. CONCLUSION

The Forecasting of Electricity Load system effectively demonstrates the effectiveness and stability of applying a Transformer-based architecture combined with anomaly detection and explainable AI for modern energy analytics. The model not only delivers high forecasting accuracy but also ensures interpretability and computational efficiency, addressing key limitations of conventional statistical methods and deep learning models. By incorporating robust feature engineering—such as lag values, moving averages, weather-related parameters, and calendar information—the system is able to capture both short-term fluctuations and long-term trends in electricity consumption. The anomaly detection module enables the identification of abnormal load patterns, which may indicate equipment faults, sudden consumption spikes, or meter errors, thereby enhancing operational monitoring and grid reliability. Real-time data retrieval from smart meters or open-source datasets ensures that the system remains flexible and adaptive to changing consumption patterns. SHAP-based explainability provides transparent insights into the contribution of each feature toward the predicted load, bridging the gap between predictive performance and interpretability. The evaluation metrics, including Mean Squared Error (MSE) and visual comparisons of predicted versus actual loads, validate the reliability, stability, and robustness of the proposed model. This system can be further extended by integrating renewable energy parameters, hybrid modeling techniques, and cloud-based dashboards for scalable real-time deployment. In conclusion, the project establishes a usable, interpretable, and real-time electricity load forecasting framework that supports intelligent decision-making, grid optimization, and anomaly detection in modern smart grid environments.

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