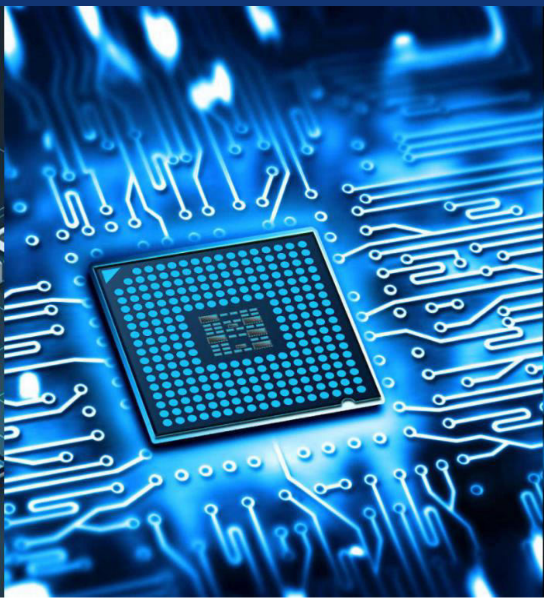
ISSN(O): 2320-9801
ISSN(P): 2320-9798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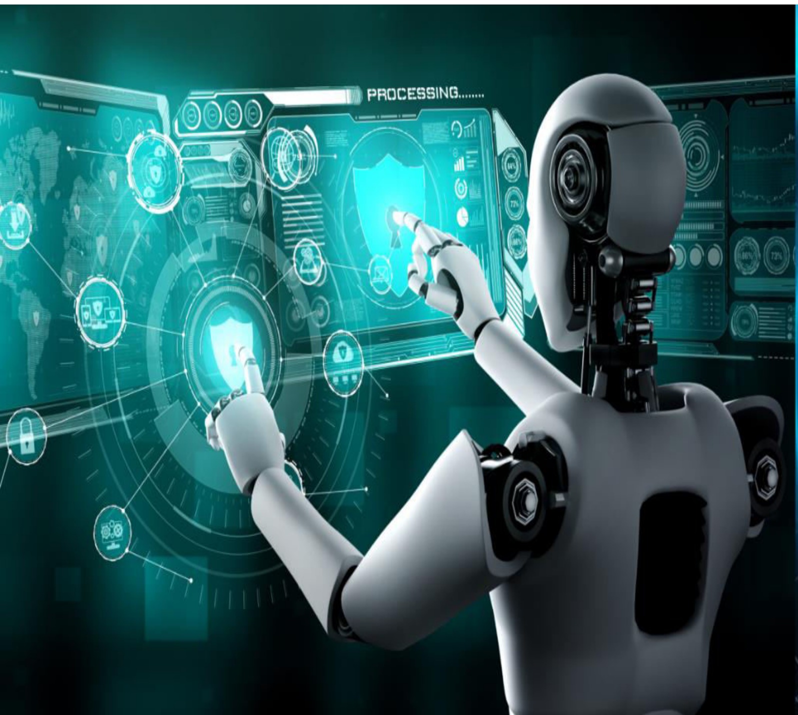

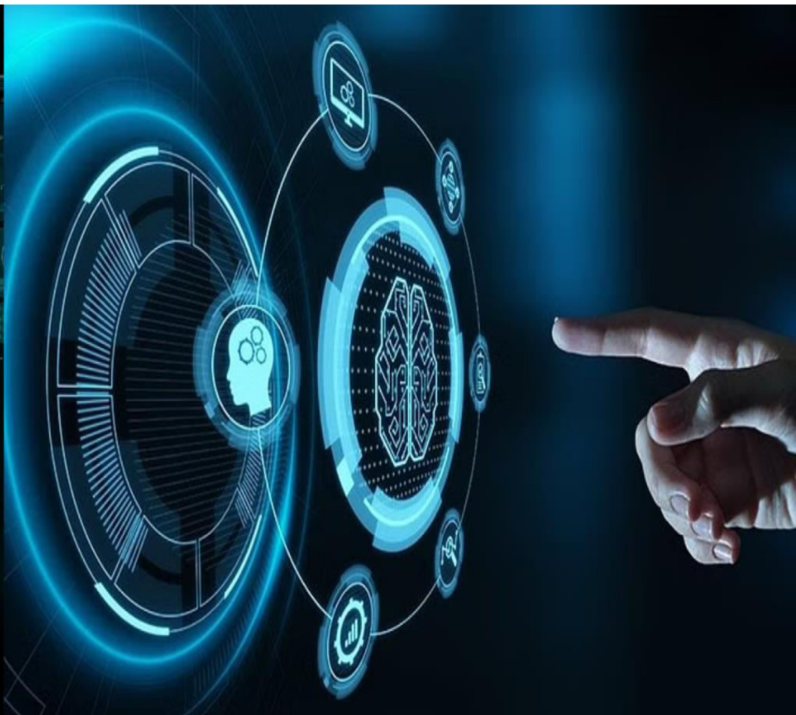

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Volume 14, Issue 7, July 2026

© 2026 IJIRCCE | Volume 14, Issue 7, July 2026 DOI: 10.15680/IJIRCCE.2026.1407021

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Sustainable Energy Solutions: Predicting Residential Electricity Consumption Using Deep Learning Techniques

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ABSTRACT: Residential electricity consumption has significantly increased due to global population growth, urbanization, and the widespread use of household appliances, creating challenges in maintaining stable power supplies. This project presents a deep learning-based approach for accurately predicting residential electricity consumption, addressing these challenges by leveraging advanced techniques such as Convolutional Neural Networks (CNN), Bidirectional Gated Recurrent Units (BiGRU), and Self-Attention (SA). The model is trained on a comprehensive dataset from the UCI Machine Learning Repository, ensuring robust generalization and reliability. To enhance accuracy, data preprocessing steps like normalization technique are applied, preserving temporal dynamics and improving model efficiency. CNN layers extract crucial spatial patterns from electricity consumption data, while BiGRU layers capture long-term dependencies in both forward and backward directions, and the Self-Attention mechanism refines feature selection by emphasizing key temporal correlations. The model is rigorously evaluated using real-world electricity consumption datasets, demonstrating superior predictive performance over traditional statistical and machine learning models. By enabling precise and reliable forecasting, this approach aids in optimizing energy distribution, reducing power outages, enhancing grid stability, and contributing to sustainable energy management.

KEYWORDS: Residential Electricity Consumption, Deep Learning, CNN, BiGRU, Self-Attention, Energy Forecasting, Time Series Prediction, Min-Max Normalization, Sustainable Energy.

I. INTRODUCTION

Electricity is the backbone of modern civilization, powering homes, industries, and commercial establishments. As global energy demands continue to rise, efficient energy management has become a key concern for governments, power suppliers, and consumers alike. The residential sector accounts for a significant portion of total electricity consumption, with household usage patterns influenced by lifestyle changes, economic development, seasonal variations, and advancements in home automation. The increasing reliance on electrical appliances such as air conditioners, heating systems, and smart home devices has further exacerbated energy consumption levels. A major challenge in energy management is balancing electricity supply and demand. Power generation companies must accurately predict future consumption to avoid energy wastage, grid failures, and blackouts. Unexpected fluctuations in electricity demand can lead to increased operational costs and resource inefficiencies. Inaccurate forecasts may result in underproduction, leading to power shortages, or overproduction, causing excess energy to go unused.

II. LITERATURE REVIE

Accurate electricity demand forecasting has become indispensable for modern power systems, playing a vital role in optimizing energy generation, improving grid reliability, and supporting the integration of renewable energy sources. As power grids evolve to incorporate more distributed generation and renewable energy, the need for precise load prediction has intensified. Traditional forecasting techniques, including statistical models like ARIMA and conventional machine learning algorithms such as support vector machines, have historically formed the backbone of load prediction systems.

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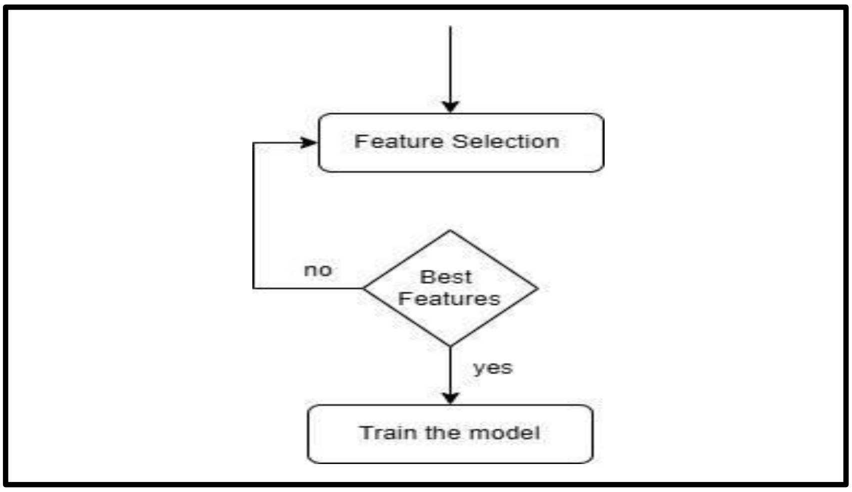
While these methods provided reasonable accuracy for stable grid conditions, they face significant limitations in capturing the complex, non-linear patterns present in contemporary electricity consumption data. Modern consumption patterns are influenced by numerous dynamic factors including weather conditions, economic trends, shifting consumer behaviors, and the increasing penetration of intermittent renewable generation. These complexities render traditional linear models inadequate for today's forecasting challenges, necessitating more sophisticated approach

Predicting Residential Electricity Consumption Using CNN-BiLSTM-SA Neural Networks‖ by MENG-PING WU AND FANWU from IEEE, introduces a hybrid deep learning model, CNN-BiLSTM-SA, designed for residential electricity consumption prediction. The model combines three key components: CNN (Convolutional Neural Networks), BiLSTM (Bidirectional Long ShortTerm Memory), and Self-Attention (SA). The CNN component is responsible for learning local timedependent patterns in electricity consumption, while BiLSTM helps capture long-term dependencies by processing both past and future data sequences. The Self-Attention mechanism enhances the model by focusing on the most important time steps, improving the interpretability and predictive accuracy of the model. The results indicate that CNN-BiLSTM-SA outperforms other models, achieving lower mean absolute error (MAE) and root mean square error (RMSE), demonstrating its effectiveness in capturing both short-term and long-term consumption patterns.

III. FLOWCHARTS

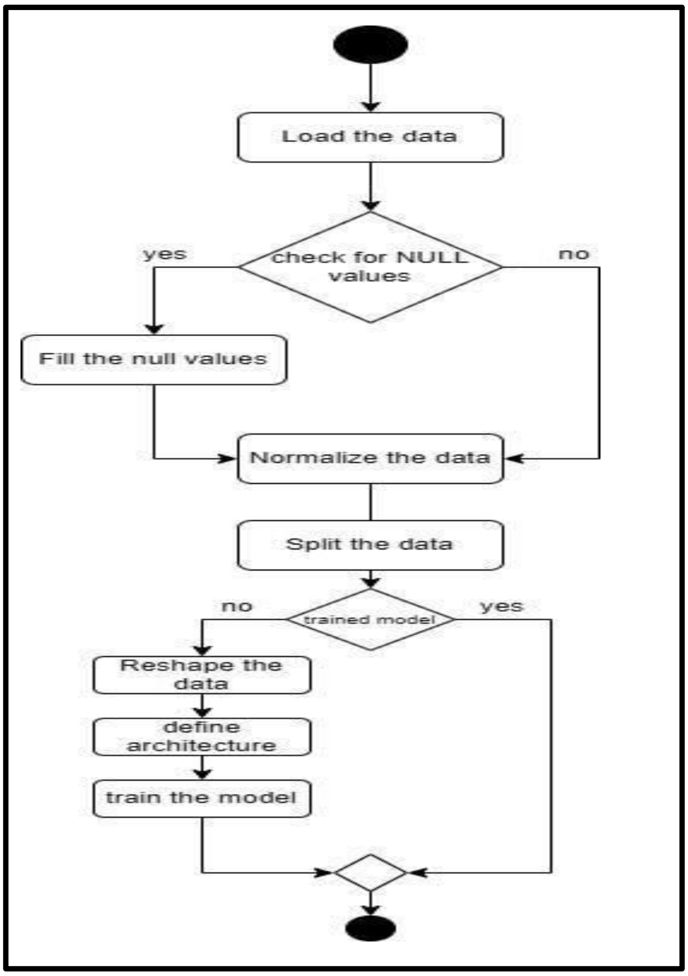
A. Flowchart for Feature Selection



Flowchart for feature selection

- Feature selection is an important step in machine learning because it can help to improve the performance of a model.
- By selecting only the most relevant features, you can reduce the amount of data that the model needs to train on, which can help to prevent overfitting.
- Overfitting is a problem that occurs when a model is too closely fit to the training data and does not perform well on new data.
- Feature selection can also help to improve the interpretability of a model.
- By understanding which features are most important to the model, you can gain insights into the relationships between the features and the target variable.

B. Flowchart for training the model



Flowchart for training the model

Depicts the flowchart for the model training process, starting with loading the dataset. The data is then checked for any NULL values. If NULL values are detected, they are filled using appropriate techniques such as mean, median, or mode. If no NULL values are found, the process moves directly to data normalization, where all feature values are scaled to a similar range to improve model performance. After normalization, the data is split into training and testing sets to evaluate the model's performance. If a trained model is already available, the process proceeds to evaluation. Otherwise, the data is reshaped to fit the model's input format, and the model architecture is defined with suitable layers and hyperparameters. Finally, the model is trained on the training data, ensuring that the model is well-prepared for evaluation and making accurate predictions.

IV. METHODOLOGY

The proposed system uses a hybrid CNN-BiGRU-SA deep learning model to accurately predict residential electricity consumption from time-series data.

Data Preprocessing

Missing values are removed or handled.

Data is normalized to improve model performance.

Time-series sequences are created and divided into training and testing datasets.

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CNN Feature Extraction
A Convolutional Neural Network (CNN) extracts important local temporal features from the electricity consumption data.
Convolution and pooling layers reduce dimensionality while preserving meaningful patterns.

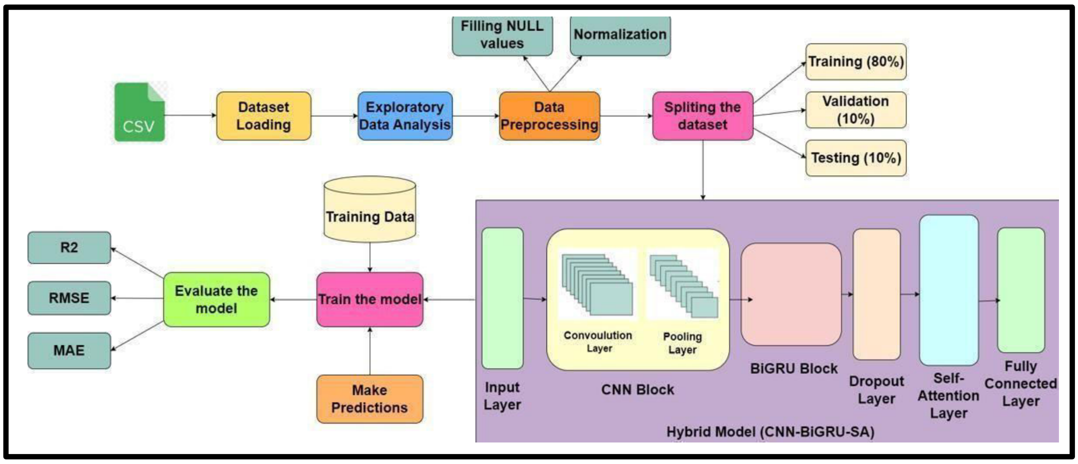
BiGRU Learning
The extracted features are passed to a Bidirectional Gated Recurrent Unit (BiGRU).
BiGRU processes the sequence in both forward and backward directions to capture long-term dependencies and improve prediction accuracy.

Self-Attention Mechanism
A Self-Attention (SA) layer assigns higher importance to relevant time steps.
This enables the model to focus on critical consumption patterns while reducing the influence of less important information.

Prediction and Evaluation
The final output layer predicts future residential electricity consumption.

V. CONTENT DIAGRAM OF THE PROJECT

The content diagram provides an overview of the system's architecture and workflow for the Residential Electricity Prediction project. It outlines the different stages, from loading the dataset to model evaluation and prediction System Architecture Represents the system architecture of the Residential Electricity Prediction project, illustrating the complete workflow from data loading to model evaluation. As depicted in Fig 3, the architecture begins with a data ingestion, then subjected to standard preprocessing techniques including missing value imputation, normalization, and time alignment to ensure the data is suitable for model training.



The preprocessed data is fed into the CNN block, where convolutional layers learn spatial features from short-term consumption patterns. The feature maps generated are then passed to the BiGRU module, which models the temporal progression and contextual relationships in both past and future directions.

Subsequently, the sequence output from the BiGRU layer is refined using the Self-Attention layer, which adaptively emphasizes critical time steps in the data. This selective attention mechanism ensuresthe modeul focuses on the most impactful parts of the input sequence for accurate forecasting.

The final output is generated through a fully connected (dense) layer, which maps the refined features to a future electricity consumption prediction. The model is evaluated using common performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2), ensuring the reliability and precision of the forecasted results.

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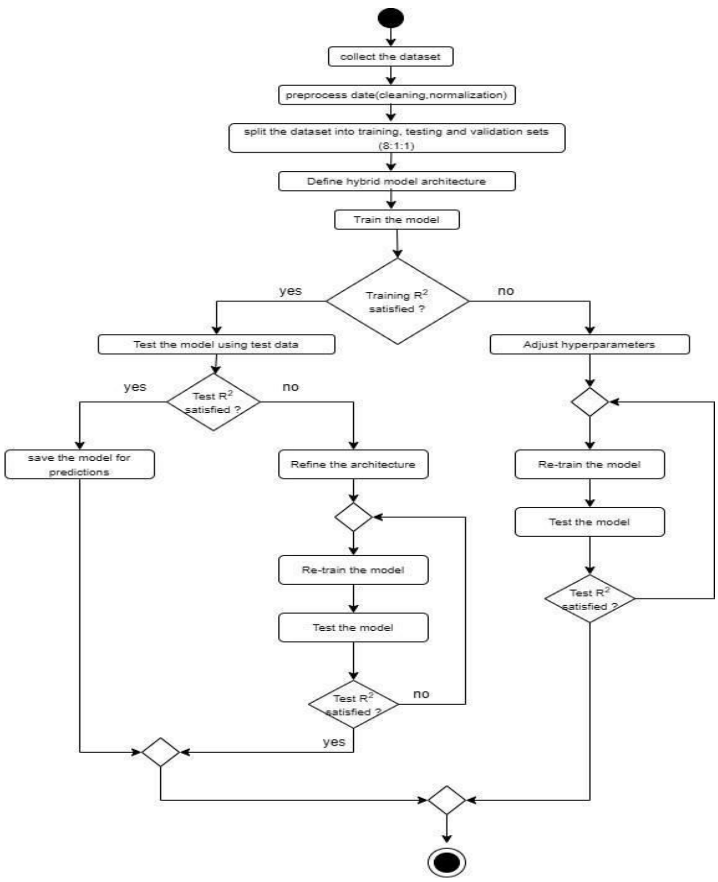
The model architecture comprises a combination of convolutional layers for spatial feature extraction, stacked BiGRU layers for capturing bidirectional temporal dependencies, and a selfattention mechanism to emphasize significant time steps.

VI. MODULE DESIGN

The module design and organization of the **Residential Electricity Consumption Prediction System** ensure a well-structured and modular approach, enhancing the maintainability and scalability of the system. The system is divided into multiple modules, each handling specific functionalities.

- **User Module:**
  ○ Handles user registration, login, and logout functionalities. o Ensures secure authentication and session management.
- **Prediction Module:**
  ○ Manages data collection and sends input data to the model.
  ○ Retrieves and displays prediction results.
- **ModelHandler Module:**
  ○ Loads the pre-trained CNN-BiGRU-SA hybrid model. o Processes user input data and returns prediction results.
- **DataHandler Module:**
  ○ Stores prediction results and user consumption history. o Retrieves previous consumption data when requested.
- **Dashboard Module:**
  ○ Provides an interactive interface for users. o Displays previous consumption in both graphical and tabular formats.

System Workflow



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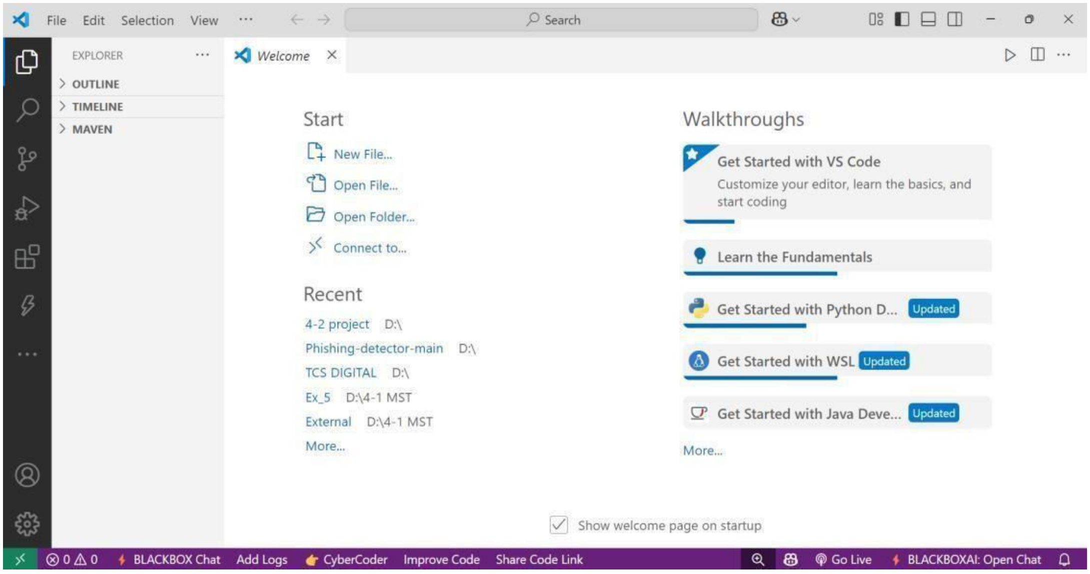
IMPLEMENTATION DETAILS

The project code was developed and executed using **Visual Studio Code (VS Code)**, a powerful and lightweight code editor that offers support for Python and Flask applications. VS Code provides an integrated terminal, debugging capabilities, and seamless Git integration, making it an ideal environment for implementing machine learning models and web applications.



Screen 1: Visual Studio Code Interface

VS Code Features:

- **Code Editing and Debugging:** VS Code provides IntelliSense for code completion and debugging tools for error identification.
- **Terminal and Extensions:** The built-in terminal allows running Python scripts directly, while extensions like Python and Jupyter Notebook enable easy switching between environments.
- **Version Control:** Seamless integration with Git allows efficient version control and project management.

VS Code's versatility, combined with its ability to support multiple programming languages and frameworks, made it the preferred platform for developing and deploying the Residential Electricity Prediction System.

LIMITATIONS

- Computational complexity increases due to the combination of CNN, BiGRU, and Selfattention, making it less suitable for low-resource environments.
- Deep learning models require large amounts of high-quality training data, and limited or inconsistent data may lead to overfitting and reduced predictive accuracy.
- Model performance is highly sensitive to hyperparameter tuning, and inadequate tuning may result in suboptimal outcomes.
- The complexity of the model may pose challenges when scaling it for real-time applications or larger datasets, requiring efficient system optimization.
- Real-time energy monitoring and data collection from smart meters and IoT devices raise potential data privacy and security concerns

VII. CONCLUSION

The **Residential Electricity Prediction System** was successfully designed and implemented using a CNN-BiGRU-SA hybrid model to predict electricity consumption patterns with high accuracy. The model effectively combines convolutional neural networks (CNN) to extract meaningful features from the input data and bidirectional gated

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recurrent units (BiGRU) to capture sequential dependencies, further enhanced by a self-attention mechanism that emphasizes relevant temporal information. The Flask-based frontend provides an interactive interface, allowing users to input relevant data, visualize predictions, and receive actionable insights. The entire system has been rigorously tested and validated to ensure that it meets the specified functional and non-functional requirements, making it a reliable tool for residential electricity consumption forecasting. The system's capability to analyze large volumes of time-series data and generate accurate predictions can assist users in better understanding their energy consumption patterns, ultimately enabling them to make informed decisions for optimizing their energy usage. Additionally, the performance of the model was evaluated using appropriate metrics, and the testing phase ensured that the system operates efficiently under various scenarios, making it ready for real-world deployment.

To further enhance the Residential Electricity Prediction System, future improvements can focus on integrating a real-time energy monitoring dashboard, enabling users to visualize live electricity consumption trends and generate real-time alerts for abnormal usage patterns. This enhancement can be achieved by incorporating IoT devices such as smart meters, which can automate data collection and continuously feed real-time information into the system. By leveraging IoT devices for real-time data acquisition, the system can dynamically analyze consumption patterns, detect anomalies, and notify users about any irregularities. This feature will empower users to take timely actions to optimize energy consumption and reduce unnecessary power usage. These improvements will transform the system into a more intelligent and proactive solution, providing users with real-time insights and greater control over their energy consumption.

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