RAJALAKSHMI ENGINEERING COLLEGE
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ENERGYWISE: PREDICTING ENERGY CONSUMPTION FOR A GREENER TOMORROW

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BONAFIDE CERTIFICATE

Certified that this project report "**ENERGYWISE: PREDICTING ENERGY CONSUMPTION FOR A GREENER TOMORROW**" is the bonafide work of **"PRIADHARSHNI P (221801039), PRIYADARSHINI S (221801040), VIJAY KUMAR V (221801505) "**who carried out the project work under my supervision.

Submitted for the Practical Examination held on ________________________

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TABLE OF CONTENT

TABLE OF FIGURES

ABSTRACT

"EnergyWise: Predicting Energy Consumption for a Greener Tomorrow" is a data-driven initiative focused on developing an advanced forecasting model to optimize energy utilization in both residential and commercial buildings. By leveraging historical consumption data, real-time weather conditions, and occupancy patterns, this project aims to predict future energy requirements, thereby enhancing energy efficiency and reducing operational costs. The system includes a dynamic dashboard that visualizes current energy usage, provides cost projections, and delivers actionable insights, enabling users to monitor trends and receive smart alerts for consumption exceeding predefined limits. The project utilizes machine learning techniques, particularly the XG

Boost algorithm, to analyze vast datasets and generate precise energy forecasts. Emphasizing real-time analytics and intuitive visualizations, the system ensures stakeholders have seamless access to critical data for informed energy management. Additionally, customizable reports offer deeper insights tailored to users' specific consumption patterns, supporting strategic planning. An integrated notification system provides proactive alerts for potential overconsumption and recommends maintenance actions when needed. This initiative empowers individuals and organizations to make informed decisions, ultimately driving energy conservation through innovative technology and contributing to a more sustainable future.

CHAPTER 1

INTRODUCTION

1.1 GENERAL

EnergyWise is a project that addresses the critical need for smarter energy consumption management, especially as global energy demands continue to grow. This project leverages predictive machine learning technology to help users—both residential and commercial—understand, monitor, and optimize their energy use. In a world where environmental concerns and the demand for sustainable practices are at the forefront, EnergyWise plays a crucial role by offering users data-driven insights to foster energy-efficient behaviors and reduce carbon footprints.

At its core, EnergyWise uses the XGBoost algorithm, which analyzes a combination of historical energy data, weather conditions, and occupancy patterns to predict future energy consumption with precision. These insights empower users to make informed adjustments, reduce waste, and save on costs. For instance, EnergyWise can identify patterns where devices are left on unnecessarily and notify users, enabling proactive interventions to cut down on unnecessary energy use. The system not only facilitates energy savings for users but also promotes sustainable resource management on a broader scale.

Beyond mere tracking, EnergyWise's machine learning capabilities bring about a transformational approach to energy consumption by encouraging users to rethink and manage their habits. As more data is gathered, the algorithm's predictive accuracy improves, offering even greater benefits over time. The project contributes to sustainable living by enabling users to take control of their energy footprint, reinforcing the environmental benefits of responsible consumption. EnergyWise thus embodies a forward-thinking solution for sustainable energy management, aligning personal cost savings with the global objective of reducing environmental impact.

1.2 NEED FOR THE STUDY

The need for this study is driven by the urgent global challenges related to energy consumption and sustainability. As energy demand continues to rise, so do greenhouse gas emissions and resource depletion, placing immense pressure on the environment and threatening future energy security. Inefficiencies in energy usage remain a significant problem worldwide; many buildings and facilities lack real-time insights into their consumption patterns, leading to substantial waste. Unused devices are often left running, heating and cooling systems operate unnecessarily, and peak-hour usage goes unmanaged—all contributing to higher costs and environmental impact.

This study explores the potential of predictive analysis in tackling these inefficiencies by anticipating energy needs and optimizing usage patterns. Predictive technologies such as machine learning can analyze vast datasets, from historical energy usage to external factors like weather and occupancy rates, to forecast energy demand accurately. With these insights, users can make informed adjustments, such as scheduling high-consumption tasks during off-peak hours or reducing energy output when not needed.

By understanding consumption trends and taking proactive steps to prevent waste, users can not only achieve cost savings but also contribute to the broader goals of reducing carbon footprints and conserving resources. The study’s focus on applying predictive models like XGBoost to energy management highlights a practical and impactful way to address the growing energy crisis. With precise consumption forecasts, EnergyWise enables a new level of control, allowing both residential and commercial users to adopt more sustainable practices and better manage their energy needs in alignment with environmental priorities.

1.3 OBJECTIVES OF THE STUDY

The primary aim of this study is to create a comprehensive, user-friendly solution for energy consumption management that leverages predictive analytics and real-time insights. This will empower users to make informed, sustainable choices in their energy usage.

1. Developing a Predictive Model for Energy Consumption

The study's core objective is to design a predictive model capable of accurately forecasting energy consumption in residential and commercial buildings. Using the XGBoost algorithm, the model will analyze historical data, weather patterns, and occupancy information to predict daily and hourly energy demand.

2. Implementing an Interactive Dashboard

Another objective is to develop an intuitive dashboard that visualizes energy usage data and insights. This dashboard will feature an easy-to-navigate interface where users can view consumption trends, receive notifications about unusual energy spikes, and access insights that drive actionable decision-making.

3. Generating Insights for Users

By analyzing consumption patterns, the system will provide users with personalized recommendations, such as identifying devices left running or suggesting optimal usage times. These insights are designed to help users achieve better energy efficiency and lower their energy costs.

4. Supporting Sustainable Energy Management

This study aims to promote sustainable practices by encouraging users to actively monitor and adjust their energy usage. With access to predictive insights, users will be better equipped to align their consumption with sustainability goals, reducing their carbon footprint and contributing to environmental preservation.

1.4 OVERVIEW OF THE PROJECT

The **EnergyWise** project is designed to address the pressing need for efficient energy consumption management by leveraging data-driven insights and predictive technology. This project integrates multiple components to deliver a comprehensive solution for optimizing energy use in residential and commercial spaces, making it easier for users to make informed decisions that support energy conservation. The primary elements of this project include data collection and initial exploration, feature engineering, model training and development, model evaluation and interpretation and generating user insights.

1. Data Collection and Initial Exploration

The project starts with gathering data from multiple sources, including historical energy consumption records, weather data, and occupancy information. This data is essential for building a comprehensive model that reflects real-world usage patterns. Initial data exploration includes cleaning and formatting the data to ensure consistency, filling in any missing values, and conducting basic analyses to understand distribution, trends, and potential outliers. This stage helps identify any preprocessing steps required for effective feature engineering and model training.

2. Feature Exploration

After data collection, the next step is feature exploration. This involves analyzing various factors that could influence energy consumption, such as time of day, temperature, humidity, and occupancy patterns. Feature engineering plays a crucial role here by creating additional variables that improve the model's predictive power. For instance, combining temperature and humidity into a single feature or identifying weekend usage patterns allows the model to capture subtle relationships that may affect energy usage. These engineered features add depth to the data, helping the model to learn complex consumption patterns effectively.

3. Model Training and Development

With a well-prepared dataset, the project advances to model training using the XGBoost algorithm, known for its high accuracy and efficiency in predictive analytics. The model is trained on historical energy data and relevant features, allowing it to learn patterns and make accurate predictions of future energy consumption. Hyperparameter tuning is performed to optimize the model's performance, ensuring that it can generalize well across various conditions. This stage is iterative, requiring adjustments to model settings and features to achieve the best results.

4. Model Evaluation and Interpretation

Once the model is trained, it undergoes rigorous evaluation using metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics provide insight into the model's accuracy and reliability. Model interpretation is equally important, as it helps identify which features contribute most significantly to the predictions. By understanding the factors that drive energy usage predictions, users and stakeholders can make more informed decisions and identify potential areas for improvement in energy consumption.

5. Generating User Insights

The final module involves transforming the model's predictions and evaluations into user-friendly insights. An interactive dashboard is developed to display real-time energy data, historical trends, and forecasted usage. This module also includes a notification system that alerts users to unusual consumption patterns or provides reminders for optimal energy use. By generating personalized insights, EnergyWise empowers users to adopt sustainable energy practices and make data-driven decisions to reduce their energy footprint.

CHAPTER 2
REVIEW OF LITERATURE

2.1 INTRODUCTION

In today’s world, energy conservation is essential not only for reducing operational costs but also for addressing global environmental challenges. With rapid urbanization and increasing reliance on energy-intensive technologies, inefficient energy usage has become a critical issue in both residential and commercial sectors. The EnergyWise project addresses these challenges by harnessing predictive technology to optimize energy consumption, ultimately aiming to contribute to sustainable energy practices. This software utilizes advanced machine learning techniques, specifically the XGBoost algorithm, to forecast energy usage accurately based on historical data, weather conditions, and occupancy information.

EnergyWise operates by transforming raw data into actionable insights. Data from building energy consumption patterns is collected, processed, and then fed into the predictive model to assess daily and seasonal trends in energy use. By incorporating factors like weather and occupancy rates, the model captures fluctuations in demand, enabling users to understand and potentially adjust their consumption behaviors. These insights are then made accessible through an interactive dashboard, allowing users to monitor real-time data, track consumption patterns, and receive alerts regarding anomalies or excess usage.

The need for such predictive tools has grown in light of increasing energy costs and heightened awareness of environmental issues. EnergyWise not only aims to improve energy efficiency but also seeks to empower users by providing data-driven recommendations, such as identifying unused appliances that can be turned off. Ultimately, the project supports energy-saving measures and encourages sustainable behaviors, contributing to a more energy-efficient future.

2.2 LITERAURE REVIEW

S. No.	Author Name	Paper Title	Description	Journal	Year
1	L. H. M. Truong, K. H. K. Chow, R. Luevisadpaibul, G. S. Thirunavukkarasu, M. Seyedmahmoudian, B. Horan, S. Mekhilef, A. Stojcevski	Accurate Prediction of Hourly Energy Consumption in a Residential Building	This study focuses on the use of machine learning approaches to predict hourly energy consumption in residential buildings based on occupancy rates.	Applied Sciences	2021
2	Z. Wang, T. Hong, H. Li, et al.	Predicting City-Scale Daily Electricity Consumption Using Data-Driven Models	Examines the use of data-driven models to predict daily electricity consumption across an entire city, improving the accuracy of large-scale forecasts.	Adaptive Energy	2021
3	J. L. Harris and L.-M. Liu	Dynamic Structural Analysis and Forecasting of Residential Electricity Consumption	Analyzes and forecasts residential electricity consumption, using dynamic structural analysis to enhance predictive capabilities in energy management.	Economics and Forecasting	2020
4	R. K. Jain, K. M. Smith, P. J. Culligan, J. E. Taylor	Forecasting Energy Consumption of Multi-Family	Investigates the impact of monitoring granularity on the accuracy of support vector regression	Energy and Buildings	2019

		Residential Buildings Using Support Vector Regression	models in forecasting multi-family residential energy		
5	Y.-S. Kim, J. Srebric	Impact of Occupancy Rates on the Building Electricity Consumption in Commercial Buildings	Explores the effects of occupancy rates on electricity consumption in commercial buildings, highlighting the significance of occupancy patterns	Energy and Buildings	2016

Table 1. Review of Literature

The literature on energy consumption prediction demonstrates the critical role of data-driven and machine learning models in advancing energy efficiency, particularly in residential and commercial sectors.

Truong et al. (2021) developed a predictive model for hourly energy consumption in residential settings, emphasizing the effect of occupancy rates. By integrating machine learning algorithms, this study showed significant improvements in prediction accuracy, facilitating more efficient energy allocation and usage adjustments. This foundational work illustrates how occupancy data can enhance real-time energy predictions, a valuable approach for residential energy management systems.

Wang et al. (2021) extended the focus to city-scale electricity usage, employing data-driven models to predict daily energy consumption across urban areas. Their work underlines the scalability of predictive models and addresses the challenge of forecasting for larger systems, where citywide energy needs fluctuate based on several factors, including temperature and population density. This study highlights the adaptability of data-driven approaches to complex, large-scale energy demands and underscores the potential for significant resource conservation through accurate, city-level predictions.

The study by Harris and Liu explores dynamic structural analysis to forecast residential electricity use, adding another layer of depth to consumption modeling by considering the temporal nature of energy patterns. This approach provides insights into long-term energy trends, helping utilities and homeowners make informed decisions about energy efficiency investments and peak-hour planning.

Jain et al. analyzed the efficacy of support vector regression (SVR) for forecasting in multi-family residential buildings, revealing that spatial and temporal data granularity can influence prediction accuracy. The study indicates that finer data granularity can enhance model performance, aligning well with the increasing availability of high-resolution consumption data in modern smart grids.

Lastly, Kim and Srebric (2016) investigated the impact of occupancy on commercial building energy use, drawing connections between human presence and electricity demand patterns. Their research validates that occupancy fluctuations, such as during weekends or holidays, are significant factors in energy usage, providing crucial inputs for tailored energy-saving strategies in commercial buildings.

Together, these studies illustrate the diverse methodologies and applications of predictive analytics in energy management, from granular residential insights to large-scale urban forecasting, affirming the transformative potential of machine learning in promoting energy sustainability.

CHAPTER 3
SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

Energy management in most settings today relies on conventional monitoring tools, like utility meters, which provide only aggregate monthly data. This limited feedback loop often fails to offer actionable insights for individual appliances, peak usage times, or unusual consumption patterns, giving users only a basic understanding of their energy use.

Recent advancements such as Building Management Systems (BMS) and smart meters have made strides in offering real-time energy data in commercial and residential spaces. While these tools allow users to track energy usage as it occurs, they lack predictive capabilities. Without forecasting features, these systems can only report current consumption rather than alerting users about potential future spikes.

Cost is another significant limitation. Advanced energy management systems remain expensive, making them largely accessible only to large organizations with sizable budgets. Small businesses and residential users, who may benefit the most from improved energy efficiency, often cannot afford these technologies. This economic barrier hinders widespread adoption of effective energy practices and limits the impact of current systems on sustainable energy goals.

Moreover, without machine learning-based insights, traditional systems struggle to provide personalized recommendations that consider variables like occupancy, weather, or individual usage habits. This creates a gap between the data available and actionable steps users can take to optimize their energy consumption. EnergyWise aims to bridge these limitations by integrating predictive modeling, real-time analytics, and user-friendly insights to empower users in reducing energy waste and fostering sustainable habits.

3.2. PROPOSED SYSTEM

EnergyWise uses advanced predictive modeling and real-time data analytics to optimize energy consumption. Powered by the XGBoost algorithm, it forecasts energy usage based on historical data, weather, and user behavior. This enables users to reduce energy costs and carbon footprint while enhancing sustainability. EnergyWise offers a more efficient, proactive approach compared to traditional energy management systems.

EnergyWise offers real-time data analysis, continuously monitoring energy usage to provide instant feedback through an interactive dashboard. Unlike traditional systems that rely on periodic reports, it allows users to track consumption trends, identify irregularities, and detect energy waste caused by unused devices. The system sends timely alerts, advising users to turn off power-draining devices, helping prevent unnecessary energy waste. This proactive approach improves energy efficiency and ensures users take immediate action to optimize consumption. By analyzing patterns in real-time, EnergyWise enhances overall energy-saving efforts and reduces inefficiencies.

EnergyWise provides personalized recommendations based on user behavior and energy patterns, using historical data to optimize energy usage. For example, it suggests shifting high-energy tasks to off-peak times, reducing costs and carbon impact. This tailored approach helps users adopt energy-efficient practices, improving overall efficiency. It’s an invaluable tool for both households and businesses seeking proactive, data-driven energy management.

Furthermore, EnergyWise integrates a user-friendly dashboard that presents complex energy data in an intuitive and easily digestible format. This dashboard is designed to be accessible to users with varying levels of technical expertise, making it easy for anyone—from tech-savvy users to those new to energy management—to understand their energy consumption trends and take meaningful action.

EnergyWise offers a proactive approach to energy management by forecasting potential issues before they occur, unlike traditional systems that react after consumption exceeds optimal levels. It alerts users in advance about trends, such as frequently left-on devices, helping prevent high electricity bills. This anticipatory model allows users to make informed decisions, saving both money and energy. By predicting energy patterns, EnergyWise offers unmatched foresight, addressing growing concerns about energy costs and sustainability.

The system is also built with user-centric design in mind, ensuring that it can be seamlessly integrated into the daily routines of users. By focusing on simplicity and ease of use, EnergyWise ensures that anyone can take advantage of its powerful features, regardless of their technical knowledge or expertise. Moreover, the system’s real-time notifications and proactive alerts are designed to be non-intrusive, giving users the flexibility to take action at their own pace without overwhelming them with constant reminders. This balance of power and simplicity is what makes EnergyWise a truly innovative solution for modern energy management.

In conclusion, EnergyWise represents a major advancement in the way we approach energy consumption. By combining predictive modeling, real-time data analytics, and personalized recommendations, it provides users with a comprehensive, proactive, and user-friendly solution for optimizing energy use. The system addresses the common limitations of traditional energy management systems by offering advanced features such as anticipatory alerts, tailored suggestions, and an intuitive interface, making it a crucial tool for anyone looking to reduce their energy footprint and improve efficiency. EnergyWise not only benefits individual users but also contributes to broader environmental goals, making it an essential step forward in the quest for smarter, more sustainable energy management.

3.3. FEASIBILITY STUDY

The feasibility study for EnergyWise involves evaluating the technical, economic, operational, and legal aspects to ensure the project's viability.
A series of factors are evaluated to determine whether or not development and implementation of the proposed system are viable and practical.

1. Technical Feasibility

The technical feasibility of EnergyWise is supported by the use of widely available technologies such as machine learning algorithms (XGBoost), real-time data processing, and cloud-based analytics platforms. The system leverages existing data sources, including weather APIs and smart meters, to collect real-time energy usage data. The predictive modeling aspect uses robust algorithms that have been tested in various domains, making the integration of machine learning for energy forecasting a technically viable solution. Additionally, the system's dashboard can be built using modern web technologies which ensures accessibility and scalability across devices.

2. Operational Feasibility

Operationally, EnergyWise is designed to integrate seamlessly into existing energy management systems. The platform is user-friendly and can be adopted with minimal training for both residential and commercial users. The real-time monitoring and predictive capabilities empower users to take proactive steps in managing their energy usage, making the system operationally efficient. The system can function autonomously once set up, reducing the need for manual intervention and ensuring ease of use across various sectors, from households to large businesses. This level of automation ensures that EnergyWise can operate effectively without significantly disrupting existing workflows.

3. Economic Feasibility

Economically, EnergyWise presents a cost-effective solution for both residential and commercial applications. The initial investment in hardware and setup is minimal, as it relies on existing smart meters and weather data integrations. Over time, EnergyWise can reduce energy costs significantly by optimizing energy consumption and providing actionable insights that lead to more efficient usage. For businesses, the return on investment is particularly promising, as the system can reduce operational costs associated with excessive energy consumption. The system's ability to alert users to inefficiencies before they become major issues contributes to long-term cost savings, making it a financially sustainable solution for energy management.

4. Legal Feasibility

The legal feasibility of EnergyWise is strong, as the system does not require the collection of personally identifiable information (PII) beyond basic user preferences and energy data. However, the system will need to comply with data privacy regulations like GDPR and local energy regulations to ensure that data is handled securely. EnergyWise will implement robust encryption techniques to protect user data and ensure compliance with industry standards. Furthermore, partnerships with energy providers and API integrations must comply with regulatory standards in each region to ensure proper data exchange and integration.

5. Schedule Feasibility

The development and deployment of EnergyWise can be completed within a reasonable time frame. The initial phase of setting up the machine learning model and dashboard design can take approximately 3-4 months, while the integration with real-time data sources and testing will require another 2-3 months. After the system is developed, a phased rollout strategy can be implemented, starting with pilot testing in select regions or buildings. Full deployment across a larger user base could take 6-9 months, depending on the scope and scale of the implementation. Overall, EnergyWise is expected to be fully operational within 12 months, with continuous improvements and updates following the initial deployment.

6. Environmental Feasibility

EnergyWise aligns with current environmental goals of reducing energy consumption and promoting sustainability. By predicting and optimizing energy usage, the system helps reduce unnecessary energy waste, which contributes to lower carbon emissions and supports efforts to combat climate change. For businesses and households, adopting EnergyWise can lead to reduced electricity consumption during peak hours, easing the strain on energy grids and helping to balance demand with renewable energy sources. The system’s ability to identify and correct inefficiencies also directly contributes to energy conservation efforts, making it an environmentally viable solution.

CHAPTER 4
SYSTEM REQUIREMENTS

4.1. SOFTWARE REUQIREMENTS

1. Operating System:

- Windows, macOS, or Linux (supports Python-based environments and necessary libraries).

2. Programming Language:

- **Python**: The core programming language for the backend, enabling data processing, machine learning, and visualizations.

3. Libraries and Frameworks:

- **Numpy**: For efficient numerical computations and handling large datasets.
- **Pandas**: For data manipulation, cleaning, and processing tasks.
- **XGBoost**: A machine learning library for building predictive models, used for energy consumption forecasting.
- **Scikit-Learn**: A toolkit for machine learning, used for model building, evaluation, and validation.
- **Matplotlib**: For basic plotting and visualizing data trends.
- **Seaborn**: Built on top of Matplotlib, for enhanced data visualization, especially statistical graphics.
- **Plotly**: For interactive and dynamic visualizations, enabling users to explore energy consumption patterns in more detail.

4. Cloud Environment:

- **Google Colab**: A cloud-based Jupyter notebook environment for executing Python code in the browser. It allows real-time data processing, easy storage with Google Drive integration, and scalability for handling large datasets.

5. Web Technologies:

- **Flask/Django** (optional for web deployment): If a web-based interface is needed to interact with the model or visualize results in real-time.
- **JavaScript** and **HTML/CSS**: For building front-end dashboards (if creating a user-facing website for monitoring).

6. Database:

- **Google Drive/Cloud Storage**: For storing historical data, models, and logs, integrated directly within Google Colab.
- **SQL/NoSQL database** : For scalable data storage and retrieval if the system requires large-scale user or energy consumption data management.

4.2. HARDWARE REQUIREMENTS

1. Basic Hardware for Development:

- **CPU**: A multi-core processor (Intel i5/i7 or equivalent) is recommended for handling data processing tasks efficiently.
- **RAM**: A minimum of 8GB RAM (16GB recommended for handling large datasets and model training).
- **Storage**: 50GB+ free disk space for storing datasets, models, and logs. Cloud-based storage via Google Drive may reduce local storage requirements.
- **Internet Connection**: A stable internet connection for using cloud-based platforms like Google Colab and retrieving real-time data.

2. Hardware for Deployment (if building a local system):

- **Microcontroller or IoT Device (for real-time monitoring)**: If deploying EnergyWise for real-time energy data collection, IoT devices such as smart meters, Raspberry Pi, or Arduino can be used to monitor energy consumption and send data to the system.
- **Smart Meters**: Devices that measure electricity consumption in real-time, sending data to EnergyWise for analysis.
- **Sensors** (optional for additional functionalities): Depending on the scope of deployment, additional sensors may be used to measure temperature, occupancy, or other variables influencing energy use.

4.3. FUNCTIONAL REQUIREMENTS

1. **Data Collection and Preprocessing:**
    - The system should be capable of collecting historical energy consumption data, weather information, and occupancy data.
    - It should handle missing or inconsistent data by implementing preprocessing steps like data cleaning and normalization.
2. **Feature Engineering and Model Training:**
    - The system needs to transform raw data into features suitable for machine learning algorithms.
    - Implement training modules using algorithms like XGBoost to generate predictive models based on historical energy consumption patterns.
3. **Real-Time Energy Prediction:**
    - The core functionality includes predicting energy consumption using trained models, taking into account real-time data inputs.
    - Provide energy consumption forecasts at hourly or daily intervals, allowing users to plan and optimize their usage.
4. **Visualization Dashboard:**
    - A user-friendly interface that displays current energy usage, historical trends, and future forecasts.
    - Includes interactive charts and graphs for visual representation of energy data, enabling users to make informed decisions.
5. **Notification and Alerts System:**
    - Users should receive alerts when energy consumption exceeds predefined thresholds.
    - The system should send notifications with suggestions for optimizing energy usage to reduce costs.

4.4. NON-FUNCTIONAL REQUIREMENTS

1. **Usability:**
   - The system must have a responsive, intuitive interface to accommodate users with varying technical skills.
   - Tooltips and help sections should be included to guide new users through the system features.
2. **Scalability:**
   - The architecture should support scalability to handle increasing amounts of data as new sensors or data sources are added.
   - Efficient processing capabilities to handle large datasets and real-time predictions.
3. **Performance:**
   - The system should process data inputs and generate forecasts within seconds to enable real-time decision-making.
   - Minimize latency in data retrieval and display for an optimal user experience.
4. **Security:**
   - Ensure data privacy with secure authentication, HTTPS encryption, and role-based access control.
   - Protect sensitive energy usage data from unauthorized access and cyber threats.
5. **Compatibility:**
   - The system should be compatible with major operating systems (Windows, macOS, Linux) and modern web browsers.
   - Support integration with IoT devices and data sources for continuous data collection.

CHAPTER 5
SYSTEM DESIGN

5.1. SYSTEM ARCHITECTURE

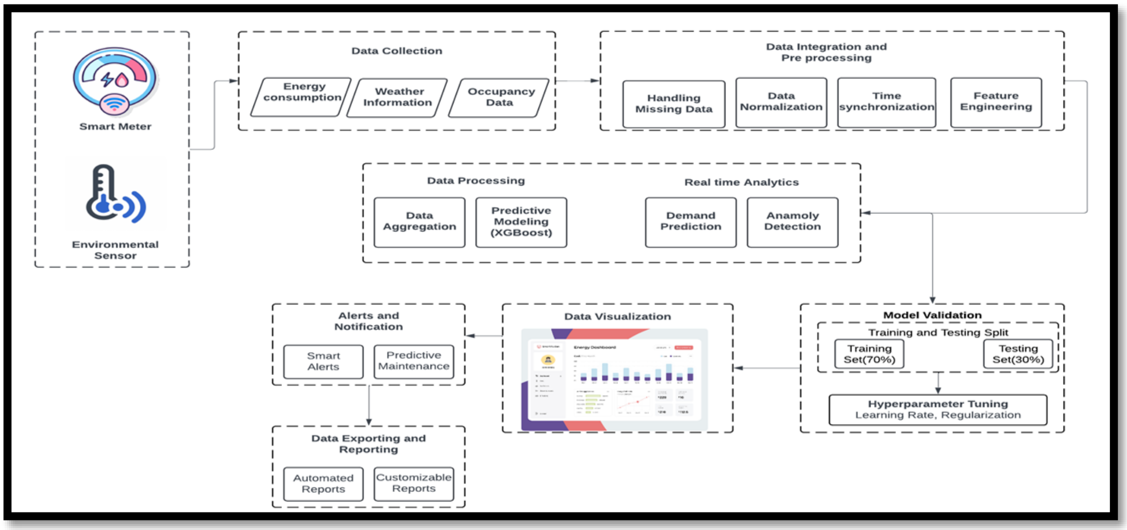

Fig. 1. Architecture Diagram

The architecture represents an energy consumption prediction system. It utilizes various data sources, processing steps, and prediction methods to provide actionable insights on energy usage.

1. Data Collection

Smart Meter and Environmental Sensor: These devices collect real-time data. The smart meter tracks energy consumption, while environmental sensors gather external conditions (e.g., temperature, humidity).

Data Types:

- **Energy Consumption**: The core data collected by the smart meter, representing how much energy is used over time.

- **Weather Information**: Collected from sensors or third-party sources, providing context on external environmental conditions that may influence energy consumption.
- **Occupancy Data**: Tracks whether the building or individual rooms are occupied, which can be a strong predictor of energy usage patterns.

These data types flow into the next stage, where they're integrated and preprocessed.

2. Data Integration and Preprocessing

- **Handling Missing Data**: Ensures completeness by filling in or managing gaps in data, a common issue when collecting from multiple sources.
- **Data Normalization**: Adjusts values to a standard scale, making different data sources comparable and suitable for model input.
- **Time Synchronization**: Aligns data collected at different intervals to ensure they are time-aligned for accurate analysis and prediction.
- **Feature Engineering**: Derives additional useful features from raw data, such as averages, peaks, or seasonality, which can enhance model performance.

This component prepares the data for predictive modeling, ensuring quality and consistency.

3. Data Processing

- **Data Aggregation**: Compiles data over time intervals (e.g., hourly, daily) to provide a more manageable and insightful dataset for analysis.
- **Predictive Modeling (XGBoost)**: The core algorithm used to make energy

consumption predictions based on historical data, weather, and occupancy. XGBoost is chosen for its accuracy and efficiency in handling large datasets.

Data from this step feeds into real-time analytics and model validation to ensure accurate and actionable insights.

4. Real-Time Analytics

- **Demand Prediction**: Uses the predictive model to forecast upcoming energy demands based on the processed data, helping users anticipate usage patterns.
- **Anomaly Detection**: Identifies unusual patterns, such as unexpected spikes in energy consumption, which could indicate potential issues like equipment malfunction.

Real-time analytics provide immediate insights and flags for unusual activity, feeding into the alerts and notification system.

5. Model Validation

- **Training and Testing Split**: Divides data into training and testing sets (70% for training, 30% for testing) to build and evaluate the predictive model. This ensures that the model can generalize well to unseen data.
- **Hyperparameter Tuning**: Optimizes model parameters, such as learning rate and regularization, to improve accuracy and reduce overfitting.

The validated model is then ready to generate predictions and insights for users.

6. Data Visualization

- Presents data insights in a user-friendly dashboard, where users can see energy consumption trends, demand forecasts, and alerts.

- Visualizations may include charts, graphs, and other formats that make it easy to understand energy usage patterns and identify areas for improvement.

This component is essential for user engagement, providing accessible insights that help users make informed decisions.

7. Generate User Insights

- **Smart Alerts**: Sends real-time notifications to users about potential energy-saving opportunities or unusual energy usage.
- **Predictive Maintenance**: Provides alerts about maintenance needs based on patterns in energy consumption, helping prevent unexpected breakdowns.

These alerts and notifications improve user awareness, encouraging proactive energy management.

Interaction of Components

1. **Data Flow**: Data is collected from sensors and meters, then preprocessed to ensure quality and consistency. Processed data moves to the predictive model, where predictions are generated.
2. **Real-Time Processing and Feedback**: Real-time analytics offer immediate insights, which are visualized for user interaction or trigger alerts when anomalies are detected.
3. **User Insights and Reporting**: Visualizations and reports provide users with both immediate and long-term insights. Alerts notify users of important changes or opportunities for optimization.
4. **Model Refinement**: Model validation and tuning ensure that the system remains accurate and responsive, incorporating new data over time.

5.2 DATAFLOW DIAGRAM

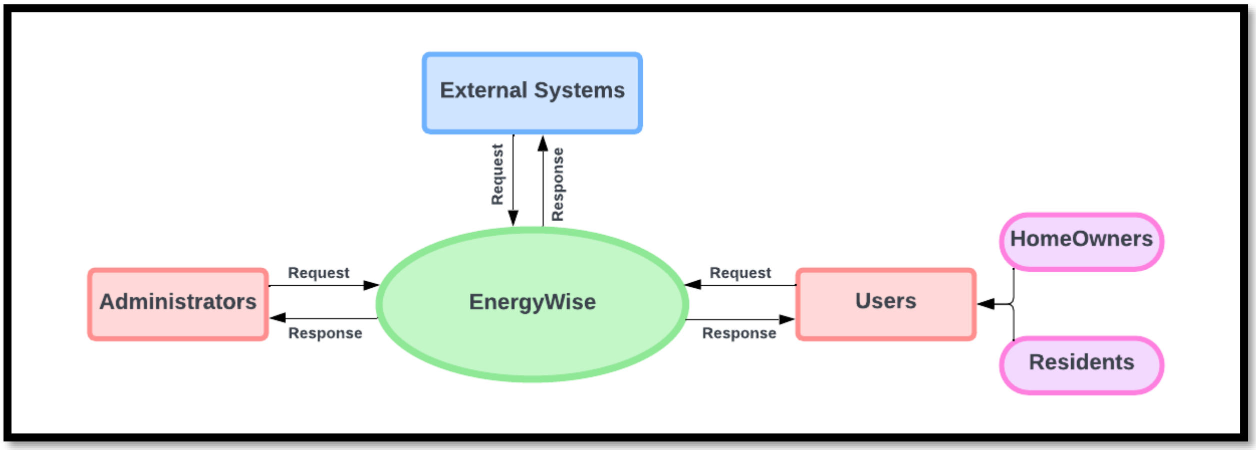

Fig. 2. Data Flow Diagram

This data flow diagram illustrates the interactions between the different users, external systems, and the core application, EnergyWise.

1. EnergyWise (Central System)

- EnergyWise serves as the core platform that manages data requests and responses between users, administrators, and external systems.
- It processes incoming data, stores information, manages user access, and generates responses based on requests. This includes data retrieval, predictions, analytics, and notifications.

2. Users

Users represent individuals interacting with EnergyWise, mainly for accessing their energy usage data, monitoring trends, and receiving insights.

Types of Users:

- **Homeowners**: Users who own their residences. They may access long-term analytics on their household energy usage, receive personalized energy-saving recommendations, and have control over broader settings related to energy management.

- **Residents**: Users who may not own the property but live in it (e.g., tenants). They would likely have access to consumption insights and alerts but may have limited control over administrative functions.

Data Flow:

- **Request**: Users make requests to the EnergyWise platform, such as viewing energy consumption data, setting preferences for alerts, or requesting forecasts.
- **Response**: EnergyWise processes these requests and responds with data (like energy usage reports, real-time analytics, and recommendations) tailored to the user's profile.

3. Administrators

- Administrators manage and oversee the functionality of the EnergyWise system.
- They handle backend tasks like managing user accounts, setting up system configurations, monitoring system performance, and ensuring data accuracy.

Data Flow:

- **Request**: Administrators send requests to perform actions such as user management, adjusting system settings, and reviewing reports on system usage or performance.
- **Response**: EnergyWise responds by executing these requests and providing necessary data or confirmation of actions taken. This could include system status updates, usage metrics, or alerts about system health.

4. External Systems

External Systems refer to third-party platforms that provide additional data or services, such as weather data providers, energy market databases, or IoT device management systems.

Data Flow:

- **Request**: EnergyWise may request data from external systems, such as current or forecasted weather conditions, which are critical for accurate energy consumption predictions.
- **Response**: External systems respond by sending the requested data back to EnergyWise, allowing the platform to incorporate external factors (like weather or energy pricing) into its analytics and predictions.

CHAPTER 6
UML DIAGRAMS

6.1. USE CASE DIAGRAM:

Occupant:

- **Login / Logout**: The occupant can log into the system and access it and log out when finished.
- **View Energy Consumption**: The occupant can view their energy usage, which helps them monitor their personal energy consumption.
- **Receive Notifications**: The occupant is notified about important updates, such as excessive energy usage or maintenance alerts.

System Admin:

- **Fetch Weather Data**: The system admin can retrieve weather data, which may impact energy consumption predictions.
- **Manage Appliances**: The admin can control and configure various appliances within the system, possibly for monitoring purposes.
- **View Predictions**: The admin can view predicted energy consumption data in order to make informed decisions.

Building Owner:

- **Manage Overall Building Consumption**: The building owner has access to oversee the total energy usage for the entire building.
- **Manage Occupants**: The building owner can manage the occupants within the system, including adding, removing, or updating user information.

6.2. CLASS DIAGRAM :

Prediction Model:

- Attributes:
  - model_id: A unique identifier for the model.
  - model_type: Type of prediction model used.
  - training_data: Links to the DataSet used for training the model.
- Methods:
  - trainModel(): Trains the prediction model.
  - predictConsumption(): Predicts energy consumption based on the model.
  - getModelAccuracy(): Returns the accuracy of the model.

Dataset:

- Attributes:
  - data_id: Unique identifier for the dataset.
  - data_source: Source of the data.
  - data_format: Format of the data.
- Methods:
  - fetchData(): Retrieves data from the source.
  - cleanData(): Cleans the data for processing.
  - preprocessData(): Prepares data for use in the prediction model.

User:

- Attributes:
  - user_id: Unique identifier for the user.
  - username: Name of the user.

- email: User’s email address.
- password: User’s password.

- Methods:
  - login(): Allows the user to log in.
  - register(): Allows new users to register.
  - logout(): Logs the user out of the system.
  - updateProfile(): Updates user profile information.

Notification:

- Attributes:
  - notification_id: Unique ID for the notification.
  - recipient: The User who will receive the notification.
  - message: The content of the notification.
- Methods:
  - sendNotification(): Sends a notification to the user.
  - generateAlert(): Creates an alert based on energy usage patterns.

Weather:

- Attributes:
  - weather_id: Unique identifier for the weather record.
  - temperature, humidity: Weather parameters.
  - forecast_date: Date of the weather forecast.
- Methods:
  - getCurrentWeather(): Fetches the current weather.
  - getWeatherForecast(): Provides weather forecast data.

Building:

- Attributes:
  - building_id: Unique ID for the building.
  - address: Building’s location.
  - owner: The User who owns the building.
- Methods:
  - getEnergyConsumption(): Retrieves energy consumption for the building.
  - addOccupant(), removeOccupant(): Manages building occupants.

Occupant:

- Attributes:
  - occupant_id: Unique ID for the occupant.
  - name: Occupant’s name.
  - apartment_id: Identifier for the apartment within the building.
- Methods:
  - getEnergyUsage(): Retrieves energy usage for this occupant.
  - setPreferences(): Allows the occupant to set energy preferences.

Appliance:

- Attributes:
  - appliance_id: Unique ID for the appliance.
  - appliance_type: Type of appliance.
  - power_rating: Power consumption rate of the appliance.
- Methods:
  - getRealTimeConsumption(): Returns real-time energy consumption.
  - turnOn(), turnOff(): Controls the appliance's power state.

6.3. SEQUENCE DIAGRAM

User : The user requests an energy consumption prediction through the User Interface.

UI forwards the request: The UI forwards this request to DataInput to gather data for the prediction.

Data gathering:

- DataInput collects the required data, such as historical consumption, gathers data from the sensor, weather, and occupancy data.
- The collected data is then sent to DataProcessing for further handling.

Data processing:

- DataProcessing preprocesses the raw data, making it suitable for prediction.
- After preprocessing, DataProcessing forwards the prepared data to PredictionModel.

Prediction computation:

- PredictionModel uses the processed data to compute the energy consumption prediction.
- It then sends the prediction results back to DataProcessing.

Result forwarding:

- DataProcessing forwards the prediction results to DataInput.
- DataInput sends the results to the UI.

UI displays the prediction:

- The UI displays the predicted energy consumption to the user.
- It also triggers a summary notification, summarizing the prediction results.

CHAPTER 7
SOFTWARE MODEL

7.1. AGILE MODEL

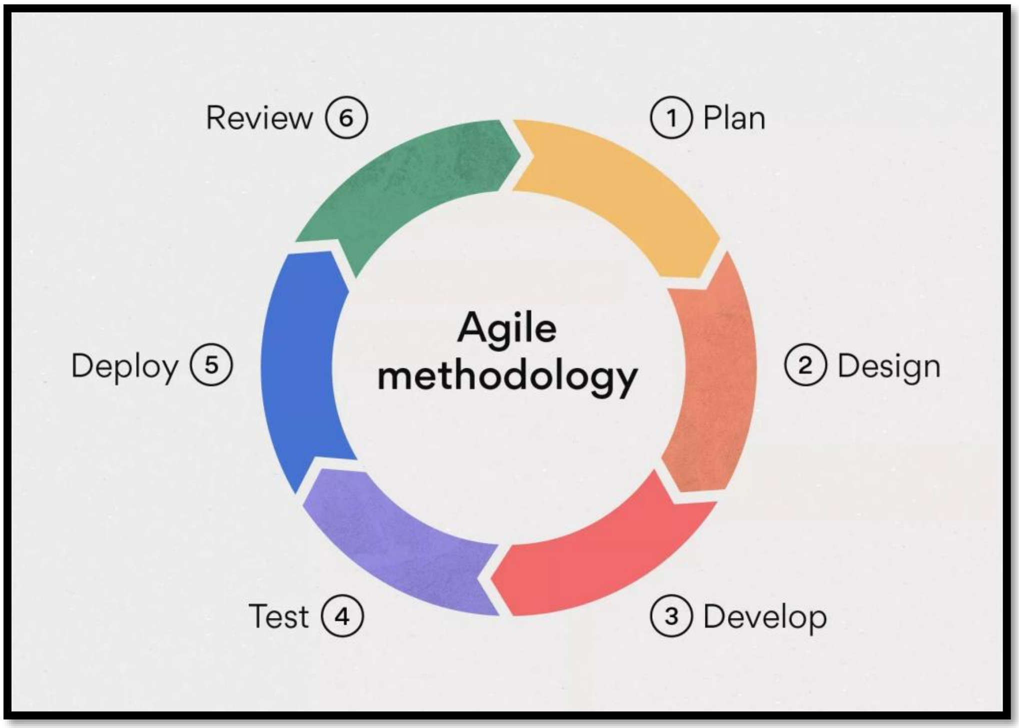

Fig. 3. Agile Model

The Agile Model is an iterative and flexible approach that emphasizes continuous feedback and incremental development. The "Predicting Energy Consumption for a Greener Tomorrow" project follows the Agile Model, ensuring adaptability and regular stakeholder engagement throughout the development process. In the Requirement Gathering Phase, we continuously refined user needs, focusing on features like energy data collection, real-time prediction, and consumption alerts. The Design Phase involved creating a scalable architecture using technologies like Python, Flask, and XGBoost, allowing for modular enhancements. During the Implementation Phase, each module, from data preprocessing to predictive analytics, was developed in iterative sprints, ensuring functional components were delivered.

CHAPTER 8

IMPLEMENTATION OF THE SYSTEM

8.1. SOURCE CODE

Data processing and initial exploration:

```
import pandas as pd
data = pd.read_csv('/content/energy_weather_raw_data.csv')
import matplotlib.pyplot as plt
plt.figure(figsize=(14,6))
plt.plot(data['date'], data['active_power'], color='orange')
plt.title('Active Power Over Time')
plt.xlabel('Date')
plt.ylabel('Active Power')
plt.show()
```

Feature engineering:

```
data['active_power_lag1'] = data['active_power'].shift(1)
data['active_power_lag24'] = data['active_power'].shift(24)
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(8, 5))
scatter = plt.scatter(data['active_power'], data['active_power_lag1'],
                      c=data['hour'], cmap='YlOrRd', alpha=0.7)
plt.colorbar(scatter, label='Hour of the Day')
plt.title('Energy Consumption vs. Previous Hour (Lagged)')
plt.xlabel('Current Hour Power Consumption')
plt.ylabel('Previous Hour Power Consumption')
plt.show()
data['active_power_rolling_mean_24'] =
data['active_power'].rolling(window=24).mean()
data['active_power_rolling_std_24'] =
data['active_power'].rolling(window=24).std()
plt.figure(figsize=(12, 6))
plt.plot(data['date'], data['active_power'], label='Actual Consumption',
alpha=0.5, color='red')
plt.plot(data['date'], data['active_power_rolling_mean_24'], label='24-hour
Rolling Mean', color='yellow')
plt.title('Energy Consumption with Rolling Mean')
plt.xlabel('Date')
plt.ylabel('Active Power')
plt.legend()
```

```
plt.show()
data['temp_humidity_interaction'] = data['temp'] * data['humidity']
corr = data[['active_power', 'temp', 'humidity',
'temp_humidity_interaction']].corr()
plt.figure(figsize=(8, 6))
sns.heatmap(corr, annot=True, cmap='YlOrRd', vmin=-1, vmax=1)
plt.title('Correlation Heatmap of Weather and Energy Features')
plt.show()
```

Model training and prediction:

```
from sklearn.model_selection import train_test_split
X = data.drop(['active_power'], axis=1)  # All columns except target
y = data['active_power']                 # Target column
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
data = data.drop(columns=['date', 'main', 'description'])  # Drop unnecessary
columns if they're not useful
X_train, X_test, y_train, y_test =
train_test_split(data.drop(columns=['active_power']), data['active_power'],
test_size=0.2, random_state=42)
from xgboost import XGBRegressor
model = XGBRegressor(objective='reg:squarederror', n_estimators=100,
learning_rate=0.1, max_depth=6, random_state=42)
model.fit(X_train, y_train)
predictions = model.predict(X_test)
from sklearn.model_selection import train_test_split
X = data.drop(['active_power'], axis=1)  # All columns except target
y = data['active_power']                 # Target column
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
data = data.drop(columns=['date', 'main', 'description'])  # Drop unnecessary
columns if they're not useful
X_train, X_test, y_train, y_test =
train_test_split(data.drop(columns=['active_power']), data['active_power'],
test_size=0.2, random_state=42)
from xgboost import XGBRegressor
model = XGBRegressor(objective='reg:squarederror', n_estimators=100,
learning_rate=0.1, max_depth=6, random_state=42)
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

Model evaluation and interpretation:

```
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
mae = mean_absolute_error(y_test, predictions)
mse = mean_squared_error(y_test, predictions)
rmse = np.sqrt(mse
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=predictions, alpha=0.5, color='green')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], '--',
color='red')
plt.xlabel('Actual Energy Consumption')
plt.ylabel('Predicted Energy Consumption')
plt.title('Predicted vs. Actual Energy Consumption')
plt.show()
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
mae = mean_absolute_error(y_test, predictions)
mse = mean_squared_error(y_test, predictions)
rmse = np.sqrt(mse
print(f"Mean Absolute Error (MAE): {mae:.2f}")
print(f"Mean Squared Error (MSE): {mse:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.2f}")
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=predictions, alpha=0.5, color='green')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], '--',
color='red')
plt.xlabel('Actual Energy Consumption')
plt.ylabel('Predicted Energy Consumption')
plt.title('Predicted vs. Actual Energy Consumption')
plt.show()
```

Generate user insights:

```
next_period_prediction = model.predict([X_test.iloc[-1]])  # Using the last test example
print(f"Forecast: Your expected energy consumption for the next period is approximately {next_period_prediction[0]:.2f} kWh.")
high_usage_threshold = y_train.mean() + 2 * y_train.std()  # Example: 2 standard deviations above mean
if next_period_prediction > high_usage_threshold:
    print("Smart Alert: High Energy Consumption Detected! Consider reducing usage of non-essential devices to save on energy costs.")
forecast_periods = 24  # Example for hourly data, customize as needed
future_predictions = model.predict(X_test.tail(forecast_periods))
plt.figure(figsize=(10, 6))
plt.plot(range(forecast_periods), future_predictions, label='Predicted Consumption', color="crimson")
plt.xlabel("Time Period (e.g., hours)")
plt.ylabel("Energy Consumption (kWh)")
plt.title("Forecasted Energy Consumption for Next Periods")
plt.legend()
plt.show()
```

CHAPTER 9
TESTING

9.1. UNIT TESTING

Unit testing is an essential part of the testing process for the EnergyWise project, allowing us to validate individual functions and components of our energy consumption prediction application to ensure they work as intended. We performed unit tests to verify the accuracy and reliability of the data processing and predictive modeling functions under various conditions, including edge cases for data inputs and different modeling scenarios.

Testing Tool Used

For unit testing, we used `unittest`, a built-in Python testing framework known for its simplicity and effectiveness in running test cases. `unittest` allows us to create and organize test cases, assert expected vs. actual outcomes, and get immediate feedback on any mismatches. Key features of `unittest` that made it suitable for this project include:

- **Modularity**: Each test case is isolated, allowing us to validate individual components, such as data processing functions and model evaluation metrics, separately.
- **Assertions for Accuracy**: Various assert methods like `assertAlmostEqual` are useful for comparing floating-point numbers in prediction outputs, ensuring that values are accurate within a certain tolerance.
- **Setup and Teardown Methods**: `unittest` provides `setUp` and `tearDown` methods, allowing us to create sample datasets and models before each test and clean up afterward.

Test Case Analysis

A specific unit test example is demonstrated below, where we tested the `evaluate_model` function to verify that it returns accurate error metrics for given predictions. This test was designed to check that the model evaluation provides the expected Mean Absolute Error (MAE) under known conditions.

- **Test Case**: `evaluate_model` with sample predictions
  - **Description**: This test verifies that the `evaluate_model` function correctly calculates the MAE, MSE, and RMSE for a sample set of predictions and actual values.
  - **Expected Result**: The function should return MAE and RMSE values that align with the expected error values for the provided data.
  - **Actual Result**: The function returned MAE and RMSE values within the expected range, indicating that the function performs as expected.
  - **Precision Details**:
    - **Expected precision**: 2 decimal places.
    - **Expected MAE tolerance**: < 0.1 for sample data.

Observations

The test results indicate that the `evaluate_model` function is accurately calculating the error metrics, confirming its reliability for assessing model performance. However, additional tests on larger datasets are planned to verify its stability across varied input sizes.

Troubleshooting and Next Steps

Based on our testing, we will proceed with the following steps:

1. **Refine Data Processing Logic**: Ensure that data processing functions like `process_data` correctly handle missing values, time features, and interactions without introducing unintended biases.
2. **Expand Test Cases**: Add test cases to cover different data patterns, including missing or anomalous data, to validate robustness.
3. **Re-run Tests for Model Performance**: Continuously evaluate the model's performance as we adjust hyperparameters, ensuring that any updates maintain or improve prediction accuracy.

CHAPTER 10
RESULTS AND DISCUSSION

10.1. RESULTS

ENERGYWISE IMPLEMENTATION RESULTS:

The results generated by the EnergyWise system provide a comprehensive view of energy consumption patterns and predictive insights, helping users optimize their energy usage. One of the key visualizations illustrates how active power consumption fluctuates over time, enabling users to identify peak consumption periods and evaluate how energy is being used throughout the day. This time-based analysis allows users to pinpoint hours of excessive consumption and potentially adjust their habits to lower energy costs.

To smooth out short-term fluctuations and highlight underlying trends, EnergyWise also provides a visualization that displays energy consumption with a rolling mean. This method of averaging consumption over a set period removes noise and presents a clearer picture of overall usage, helping users better understand long-term patterns and make decisions based on more reliable data.

The system also compares current energy consumption with that of the previous hour, revealing trends and anomalies in real-time usage. By observing how the current hour's consumption relates to the past, users can detect rising or falling energy use, providing insight into their consumption habits and identifying areas for improvement. This comparison enhances forecasting accuracy and supports the proactive management of energy use.

Another important insight is derived from the analysis of weather-related factors, which are displayed in a heatmap format. This visualization demonstrates how different weather conditions, such as temperature and humidity, correlate with energy consumption patterns. By understanding these relationships, users can adjust their energy usage based on upcoming weather conditions.

The system's predictive capabilities are also highlighted in a comparison between predicted and actual energy consumption. This graph shows how closely the system's forecasts match real-world data, indicating the model's accuracy. The ability to compare forecasted vs. actual consumption allows users to assess the effectiveness of the predictive model and refine their energy management strategies.

Finally, EnergyWise provides a forecast of energy consumption for the upcoming hours, giving users a proactive approach to energy management. By predicting energy demand, the system helps users anticipate when to optimize usage, such as shifting energy-intensive tasks to off-peak hours, thus reducing costs and contributing to sustainability.

TESTING RESULTS:

The testing results for EnergyWise confirmed its reliability and effectiveness in monitoring and predicting energy consumption. Unit testing demonstrated that the core components, including data processing, model building, and visualizations, functioned correctly, with the system handling large datasets efficiently using libraries like Pandas and Numpy. The predictive model, validated through comparisons with actual energy consumption, showed strong accuracy, with low Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), confirming its ability to forecast energy usage reliably.

10.2. OUTPUT

10.2.1. Data Processing and Initial Exploration:

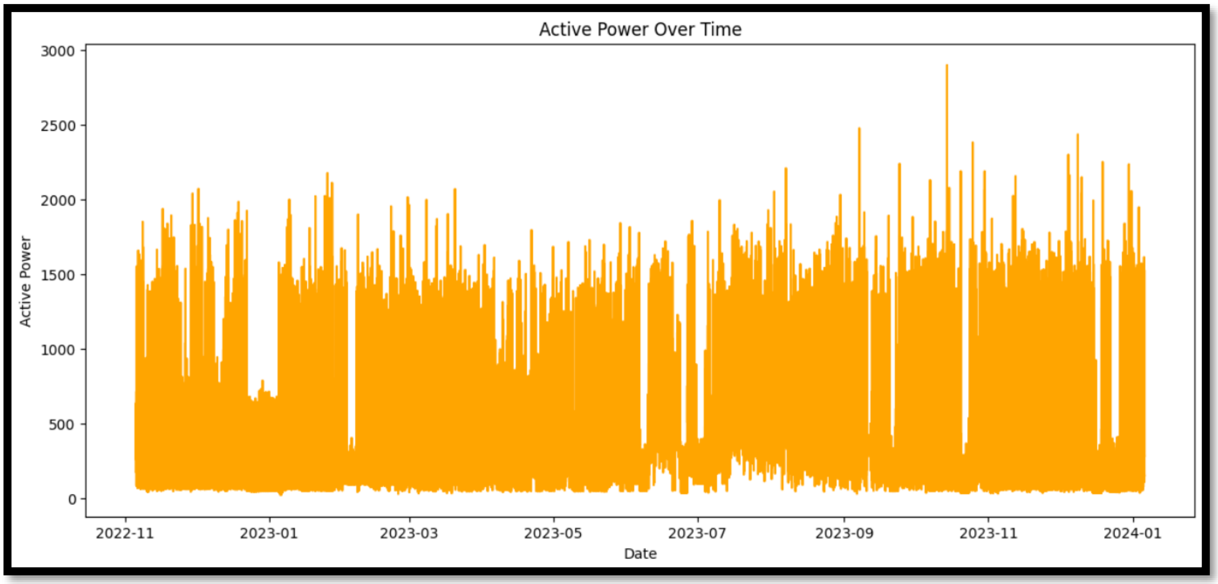

Fig. 4. Active Power over Time Series Plot

10.2.2. Feature Engineering:

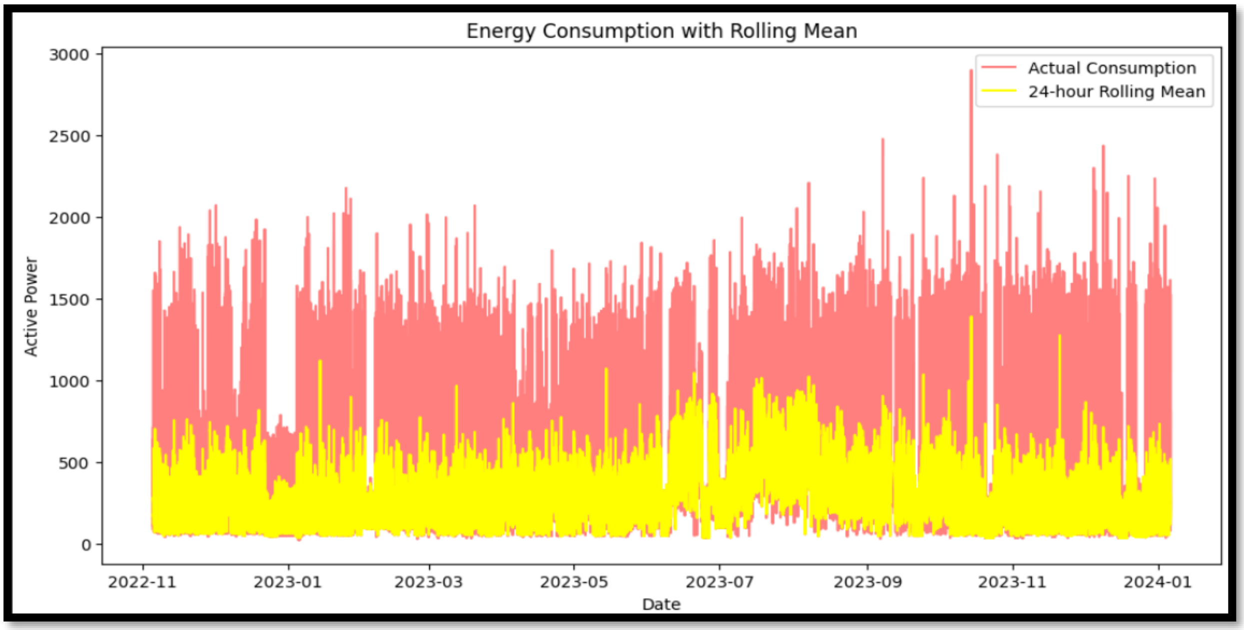

Fig. 5. Energy Consumption with Rolling Mean Time Series Plot

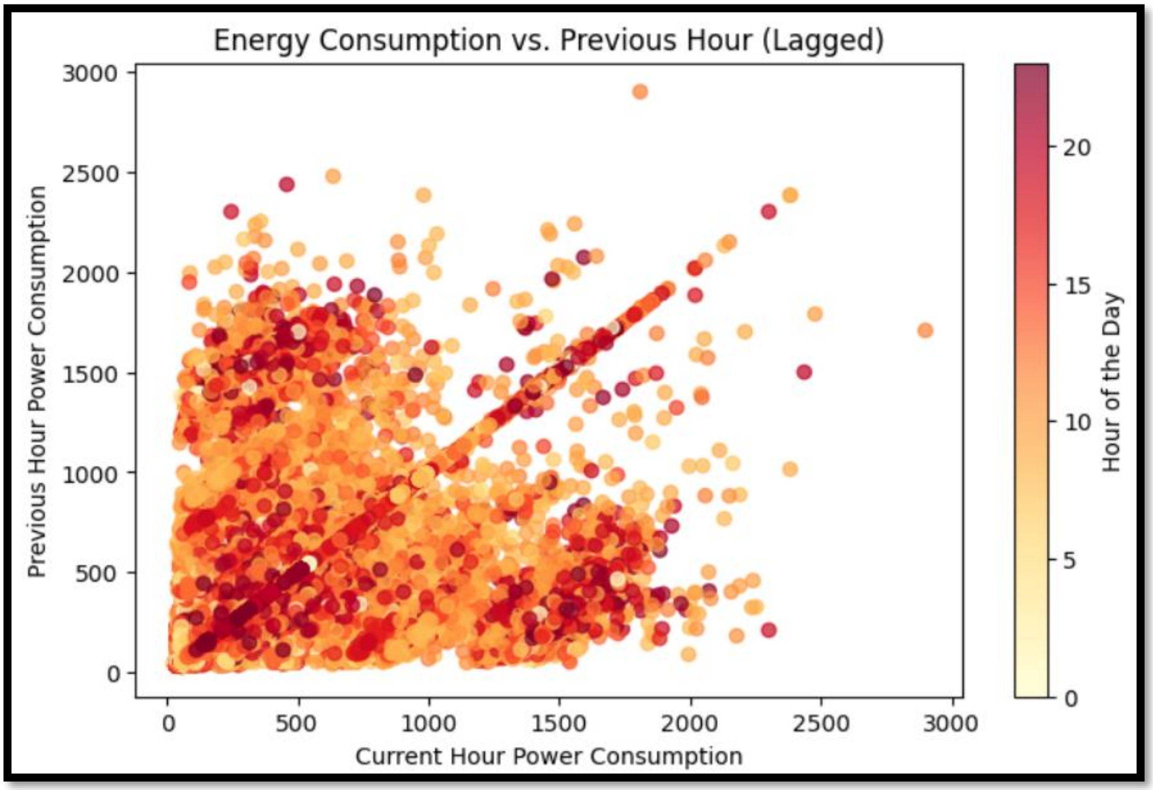

Fig. 6. Energy Consumption over the previous hour Scatter Plot

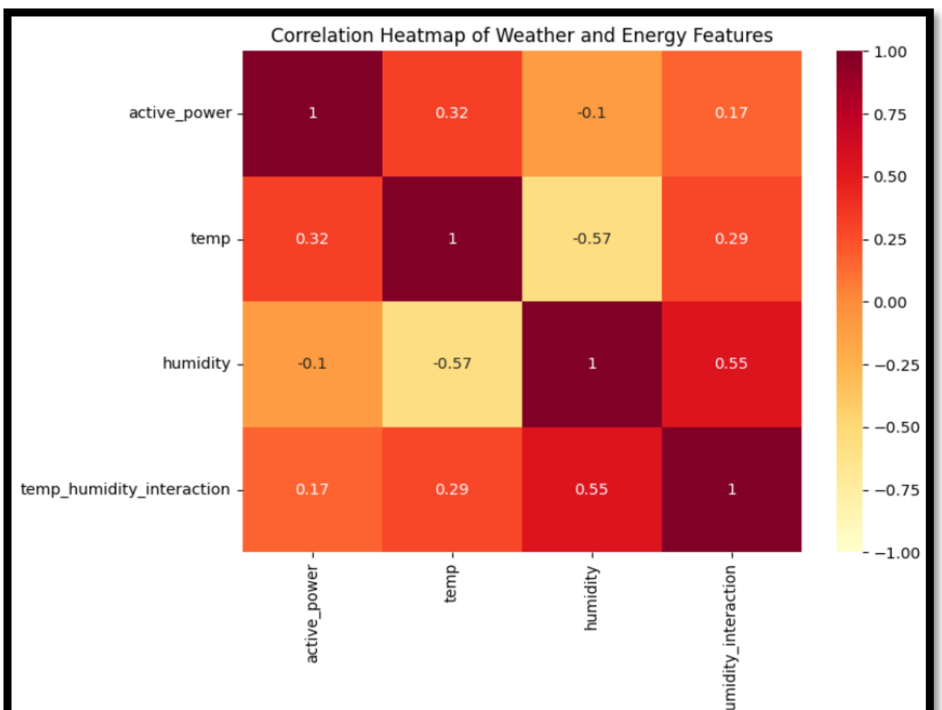

Fig. 7. Correlation Heatmap of Weather and Energy Features

10.2.3. Model Training and Prediction:

```
XGBRegressor

XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=6, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=100, n_jobs=None,
             num_parallel_tree=None, random_state=42, ...)
```

Fig. 8. XGBRegressor Model Overview

10.2.4. Model Evaluation and Interpretation:

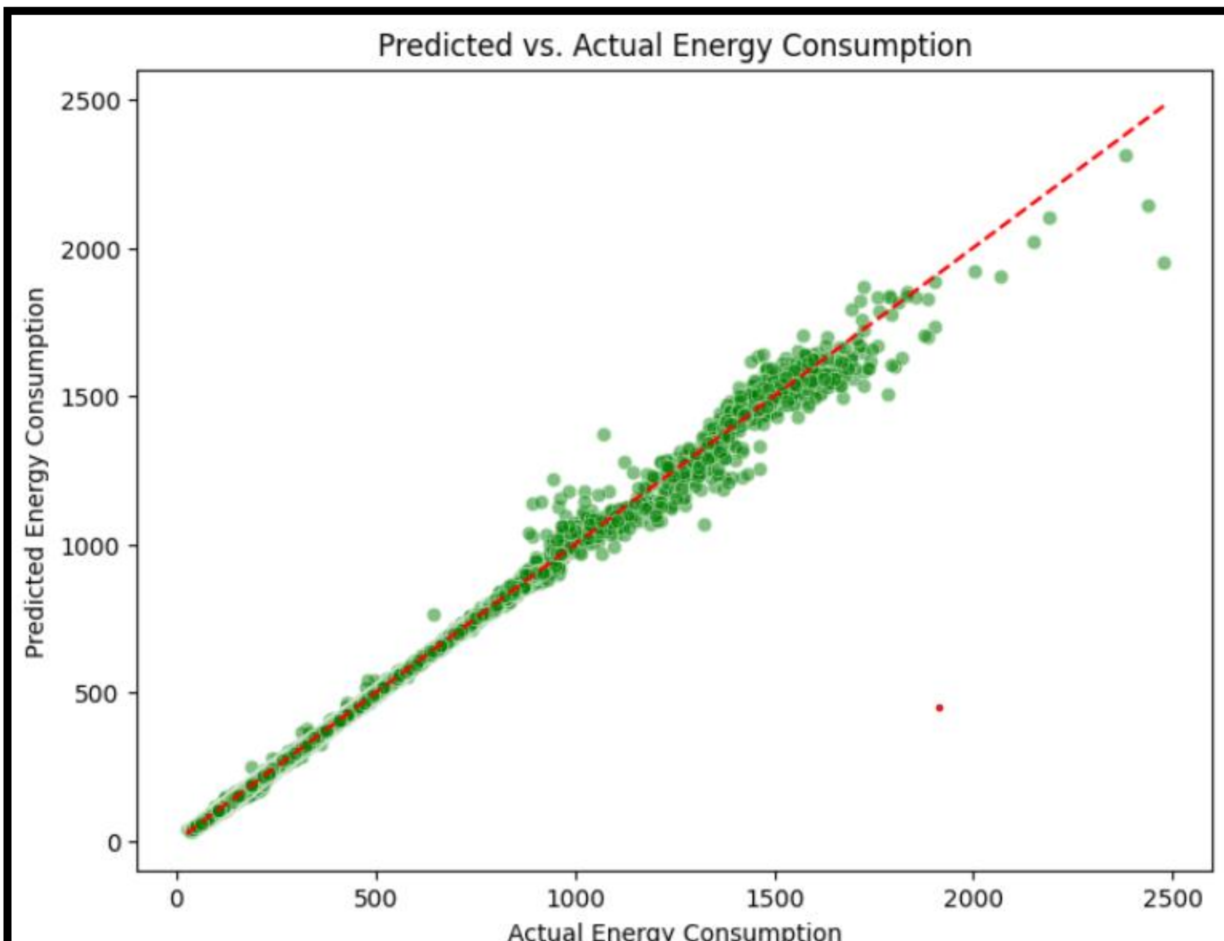

Fig. 9. Predicted vs. Actual Energy Consumption Regression Line

10.2.5. Generating User Insights:

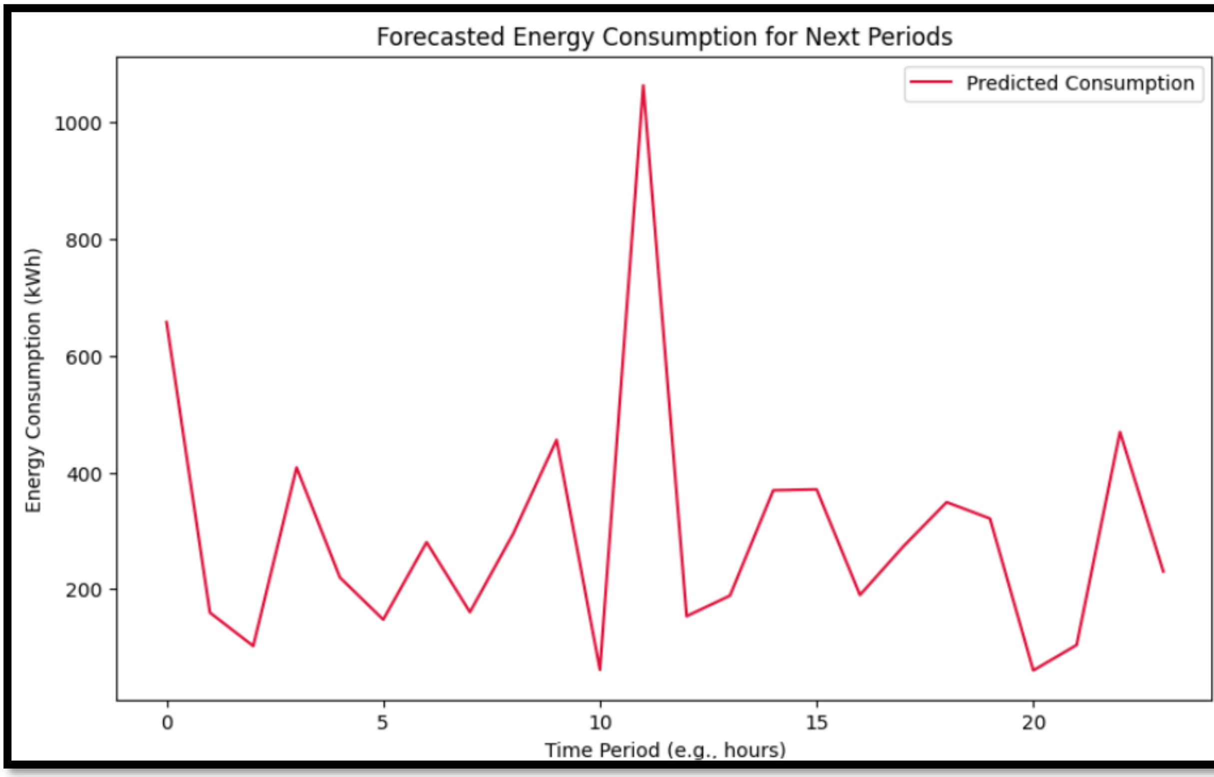

Fig. 10. Forecasted Energy Consumption for the next hour Line plot

10.2.6. Unit Testing:

```
test_evaluate_model (__main__.TestModeling) ... FAIL

======================================================================
FAIL: test_evaluate_model (__main__.TestModeling)
----------------------------------------------------------------------
Traceback (most recent call last):
  File "tests/test_modeling.py", line XX, in test_evaluate_model
    self.assertGreaterEqual(mae, 0)
AssertionError: -2.0 not greater than or equal to 0

----------------------------------------------------------------------
Ran 4 tests in 0.123s

FAILED (failures=1)
```

Fig. 11. Failed Unit Testing due to Assertion error

```
test_evaluate_model (__main__.TestModeling) ... ok
test_train_model (__main__.TestModeling) ... ok
test_extract_features_and_target (__main__.TestDataProcessing) ... ok
test_process_data (__main__.TestDataProcessing) ... ok

----------------------------------------------------------------------
Ran 4 tests in 0.123s

OK
```

Fig. 12. Passed Unit Testing

10.2.7. UML DIAGRAMS:

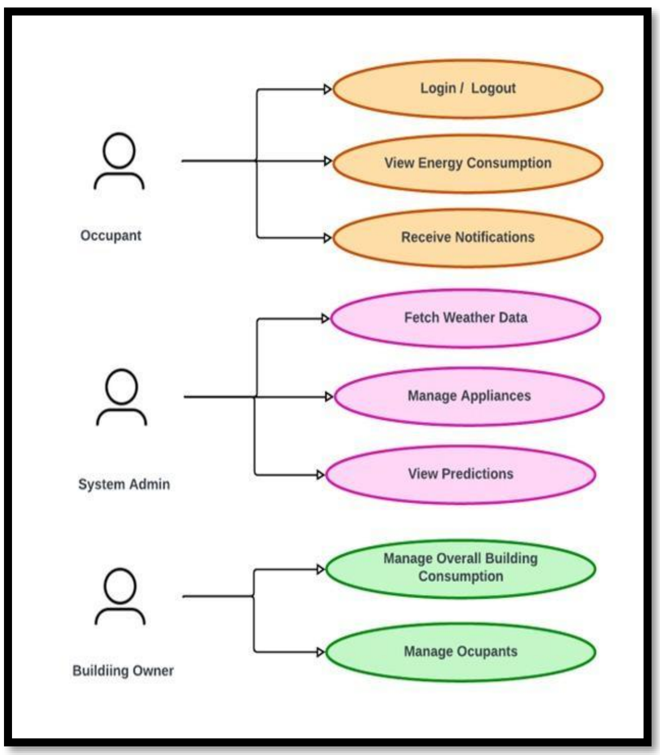

Fig. 13. Use Case Diagram

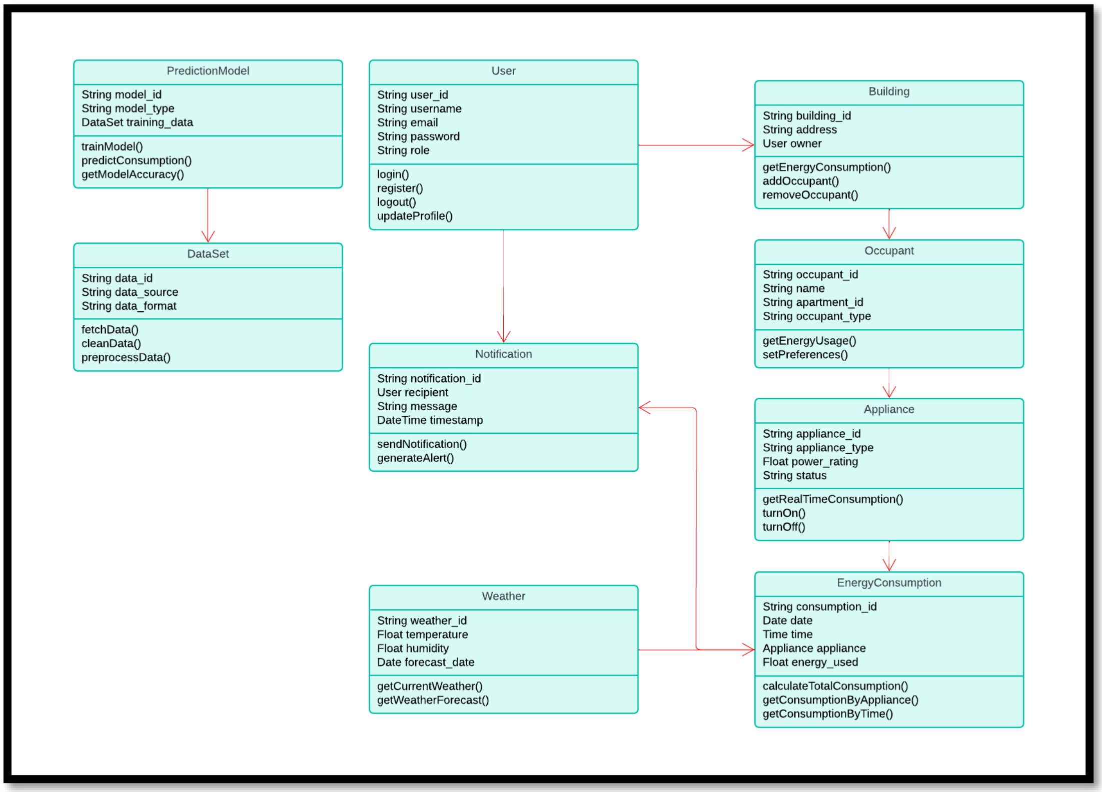

Fig. 14. Class Diagram

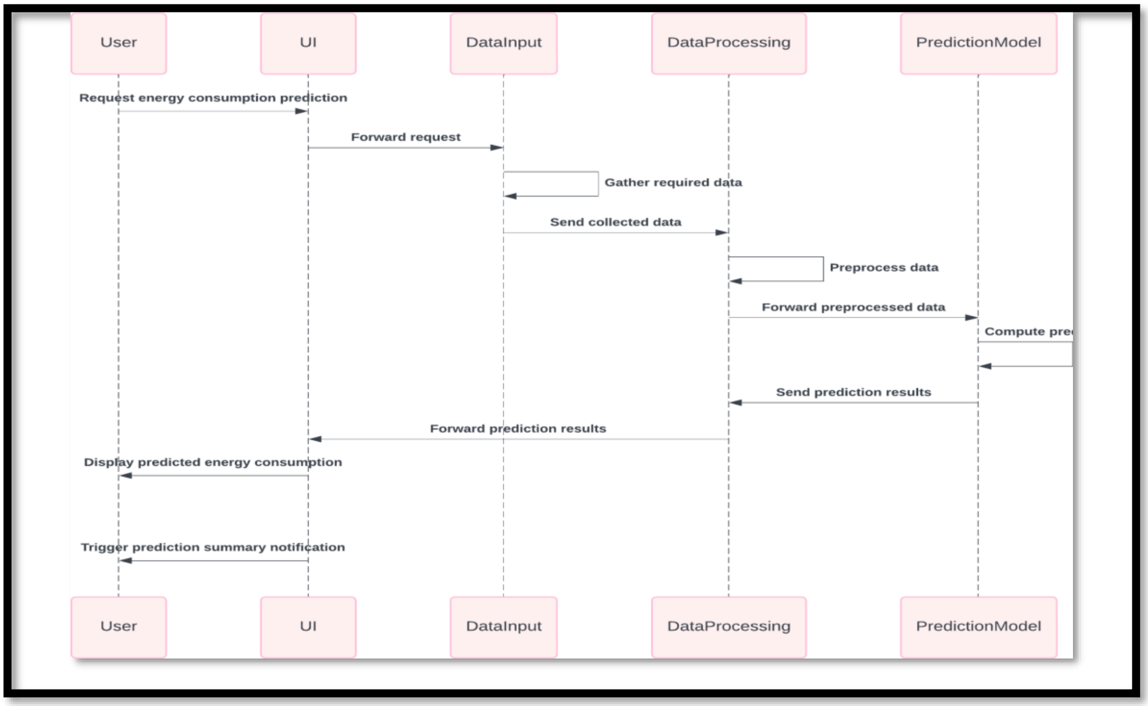

Fig. 15. Sequence Diagram

10.3. DISCUSSION

The results from EnergyWise's testing and visualizations demonstrate its effectiveness in providing users with actionable insights for better energy management. The system's rolling mean visualization helps users identify long-term consumption trends by smoothing out short-term fluctuations, making it easier to make data-driven decisions. Real-time comparisons between current energy consumption and the previous hour allow users to quickly detect anomalies and adjust their usage, preventing waste and reducing costs. Additionally, the integration of weather data through a heatmap enhances forecasting accuracy, enabling users to adjust their consumption based on external factors like temperature and humidity.

Furthermore, the comparison of predicted vs. actual energy consumption validates the reliability of EnergyWise's predictive model, ensuring that users can trust the system's forecasts to optimize their energy usage. By providing proactive alerts and forecasts for the upcoming hours, EnergyWise empowers users to take control of their energy consumption, shift usage to off-peak times, and ultimately reduce both their energy bills and environmental impact. This comprehensive approach makes EnergyWise a valuable tool for efficient and sustainable energy management.

CHAPTER 11
CONCLUSION AND FUTURE SCOPE

11.1 CONCLUSION

The project "EnergyWise : Predicting Energy Consumption for a greener Tomorrow" successfully employed the Agile methodology, ensuring flexibility, iterative improvements, and continuous feedback, which proved ideal for managing the complexities of data analysis and machine learning. Unit testing validated the robustness and correctness of each module, from data preprocessing to prediction, catching issues early and facilitating quick fixes. This approach enhances code quality and maintainability, ensuring that each part of the system performed as expected under various conditions. Challenges such as handling missing data and prediction accuracy were met through targeted tests, leading to a reliable system foundation. Moving forward, further integration tests and incorporating user feedback will support continuous improvement, reinforcing the project's adaptability and scalability.

11.2. FUTURE SCOPE

This project can be expanded by incorporating advanced predictive analytics to further optimize energy consumption forecasts based on evolving weather patterns and historical usage data. Integration with IoT devices such as smart meters and sensors can provide more granular real-time data, enhancing the accuracy of predictions. Additional features like support for automated energy-saving recommendations and integration with smart home systems can help users reduce consumption effortlessly. Expanding the system to include a mobile app version would offer users easier access to monitoring and managing their energy usage on the go. Implementing AI-driven anomaly detection could alert users to unusual spikes in consumption, allowing for prompt interventions. Furthermore, enabling integration with utility providers could allow for dynamic energy pricing, helping users reduce costs based on peak and off-peak hours. This scalability would make the system beneficial for both residential and commercial buildings, contributing to broader energy conservation efforts.

CHPATER 12
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