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Enhancement of Energy Management in Smart Buildings by using AI Powered Deep Learning

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ABSTRACT: The exponential growth in energy demand has led to a pressing need for intelligent and efficient energy management systems. This project focuses on developing a Smart Energy Management System (SEMS) that leverages Deep Learning and Machine Learning models to accurately predict energy consumption and optimize usage patterns. By integrating machine learning models like Random Forest and Decision Tree, the proposed system provides real-time energy forecasting with high accuracy. The project is initiated with data preprocessing and feature engineering to eliminate inconsistencies and enhance data quality. Advanced feature scaling techniques, such as Min-Max Scaling, are employed to normalize the data, making it suitable for model training. The system then implements model, which is particularly adept at capturing temporal dependencies in energy consumption patterns. Additionally, Random Forest and Decision Tree models are employed as benchmarks to compare performance. The proposed system is evaluated using metrics like the R^2 Score, which quantifies the model's ability to predict energy usage accurately. Visualizations are provided to present model performance and feature correlations effectively. The results indicate that the models are offering more accurate energy predictions. By implementing these models, we achieve a 3.94% energy savings and a monthly cost reduction of ₹702.4. This approach enhances energy efficiency, minimizes waste, and supports sustainable smart building initiatives.

KEYWORDS: Energy Optimization, Smart Buildings, Machine Learning, Random Forest, Energy Forecasting, Cost Savings.

I. INTRODUCTION

Energy consumption forecasting has been an essential component of energy management and planning for decades. The ability to accurately predict future energy consumption enables businesses, governments, and utility companies to optimize energy production, minimize waste, and ensure reliable power distribution. As the demand for electricity continues to grow globally, driven by industrialization, population increase, and technological advancements, energy forecasting has become even more crucial in shaping sustainable energy policies. Traditional energy forecasting methods, such as regression models and statistical approaches like ARIMA (AutoRegressive Integrated Moving Average), have been widely used in the past. However, these models struggle to capture the complex, non linear relationships present in energy consumption data, which is influenced by multiple factors such as weather conditions, time of day, seasonality, and human behavior. With the rise of Artificial Intelligence (AI) and Machine Learning (ML), data-driven forecasting techniques have significantly improved predictive accuracy. Among these, Recurrent Neural Networks (RNNs) and their advanced variant have demonstrated superior performance in handling time series forecasting problems. In recent years, smart grid technologies and the integration of renewable energy sources have further complicated energy consumption patterns. The growing penetration of distributed energy resources, such as solar and wind power, adds variability to energy supply, necessitating more accurate forecasting methods to balance demand and supply efficiently. Consequently, developing robust forecasting models using deep learning has become an active area of research, paving the way for intelligent energy management solutions.

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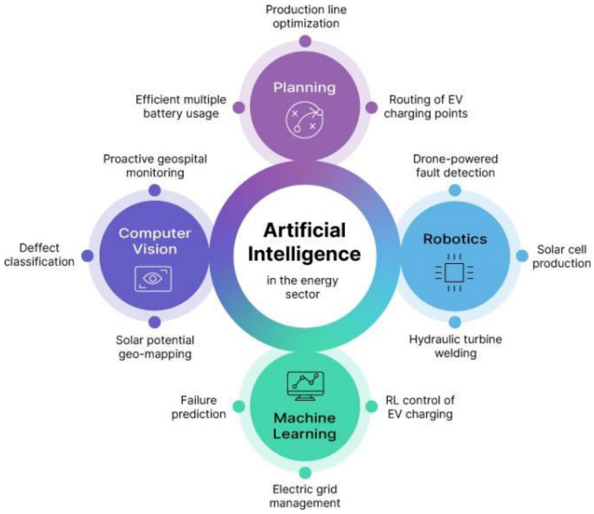

Fig 1 – Artificial Intelligence in Energy Sector

II. METHODOLOGY

a. Data Acquisition and Pre processing

The first step in developing an energy forecasting model involves gathering historical energy consumption data. The dataset includes time-series data on energy usage, weather conditions, occupancy levels, and other relevant parameters. Data is collected from various sources, such as smart meters, energy management systems, and public datasets. The dataset contains 5000 rows and 12 columns. This dataset includes the data of Month, Hour, Day Of Week, Holiday, Temperature, Humidity, Square Footage, Occupancy, HVAC Usage, Lighting Usage, Renewable Energy, Energy Consumption. Handling missing values using interpolation or mean imputation. Converting categorical variables into numerical format using label encoding. Normalizing continuous variables to ensure uniform scaling. Creating new features such as time-based attributes (hour, day, month) for better model performance.

- Missing values were addressed using mean or median imputation techniques.
- Outlier detection and removal were performed to maintain data integrity.
- Feature scaling was applied using Min-Max Normalization to ensure numerical stability across models.
- Feature engineering was conducted to extract meaningful insights from the temporal and categorical data, such as creating "Peak Hour" and "Weekend" features.

b. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed to gain a deeper understanding of the dataset and uncover hidden patterns and relationships between variables prior to model development. Descriptive statistical measures such as mean, median, standard deviation, and distribution plots were used to analyze the central tendencies and spread of the variables. Correlation analysis was conducted to identify the strength of relationships between input features and the target variable, helping to prioritize the most relevant predictors for model training. Visual tools such as heatmaps, boxplots, histograms, and time-series plots were employed to observe trends, detect seasonality, and highlight anomalies in the data. The insights gained during this phase not only guided feature engineering decisions but also provided a strong foundation for improving the accuracy and robustness of the predictive models.

1. Heatmap of Feature Correlation

The heatmap visualizes the strength of correlation between all the features and the target variable, helping identify which features have the most predictive potential. Understanding the impact of different features on the model's prediction helps in refining the forecasting approach. A correlation heatmap is generated to visualize feature dependencies:

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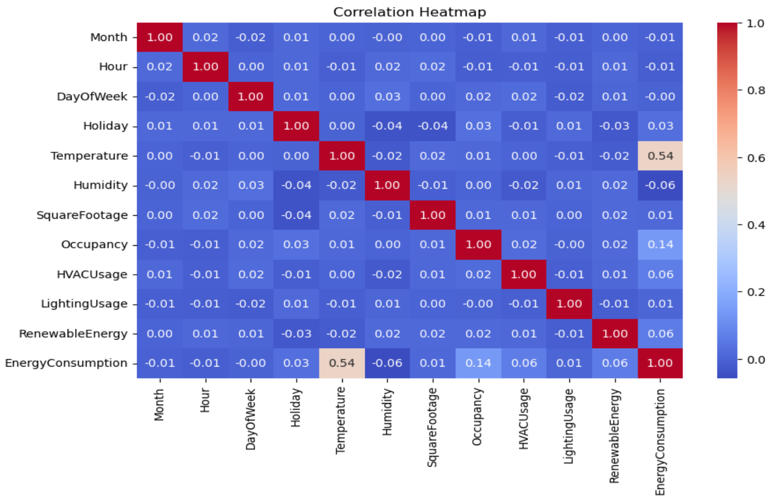

Fig 2 – Correlation Heatmap

2. Time Series Plots

Monthly energy consumption analysis provides a broader view of usage trends over time. It helps detect seasonal variations, such as higher energy consumption during summer months due to increased air conditioning or in winter for heating. Hourly analysis of energy consumption helps in identifying peak and off-peak usage times throughout the day. From the visualization and data trends, it is observed that the energy demand is typically higher during business hours, especially between 9 AM to 6 PM, when HVAC systems, lighting, and electronic equipment are in heavy use. Weekly energy consumption trends reveal how energy usage fluctuates across different days. In most cases, energy usage is higher on weekdays, especially from Monday to Friday.

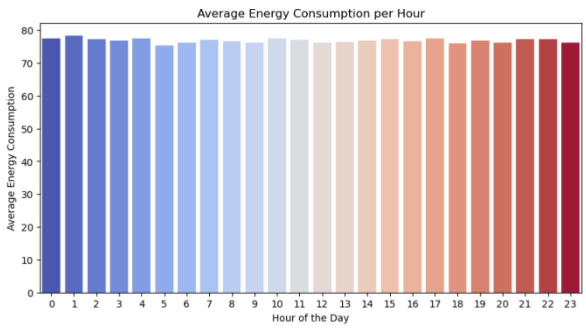

Fig 3 - Average Energy Consumption per Hour

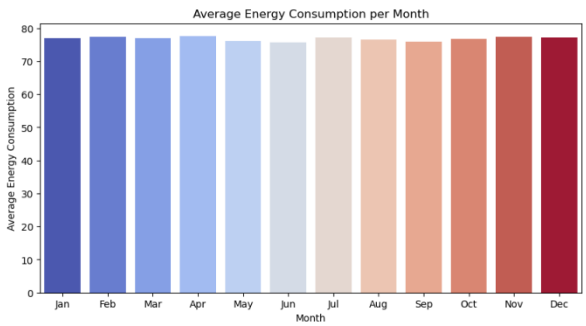

Fig 4 - Average Energy Consumption per Month

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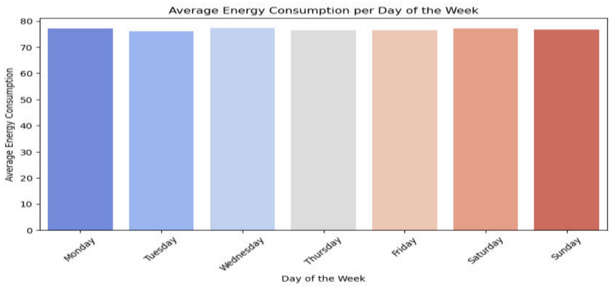

Fig 5 - Average Energy Consumption per Day of the Week

3. Environmental Factor Trends

Energy consumption has a strong correlation with ambient temperature, especially in smart buildings equipped with HVAC systems. As the temperature rises, the demand for cooling increases, leading to a surge in electricity usage. Similarly, lower temperatures result in increased heating requirements. Our analysis shows that energy consumption peaks during extreme temperature conditions, confirming that temperature regulation systems are a major contributor to overall energy usage. Understanding this relationship helps in planning demand response strategies and optimizing HVAC usage based on temperature forecasts.

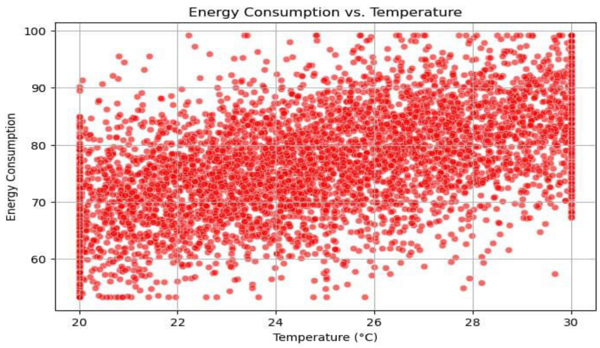

Fig 6 - Energy Consumption vs Temperature

Humidity also plays a crucial role in influencing energy consumption. High humidity levels often lead to discomfort, causing increased reliance on air conditioning systems, which in turn raises electricity usage. The analysis reveals that energy consumption tends to rise with increased humidity levels, particularly in regions or seasons with naturally humid climates. By integrating humidity sensors and predictive models, smart buildings can automate HVAC systems to balance comfort and energy efficiency. This proactive approach not only enhances indoor environmental quality but also contributes to energy conservation.

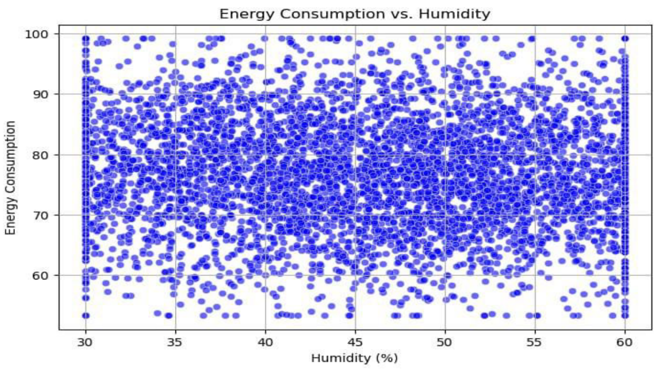

Fig 7 - Energy Consumption vs Humidity

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The relationship between energy consumption and renewable energy contribution is a vital indicator of sustainability in smart buildings. As renewable sources like solar and wind are integrated into the energy system, the dependency on non-renewable power grids decreases significantly. Our analysis shows that during peak sunlight or wind availability, a substantial portion of energy demand can be met using renewable energy, effectively lowering the net energy consumption from external sources. This not only reduces overall electricity costs but also minimizes the carbon footprint of the building.

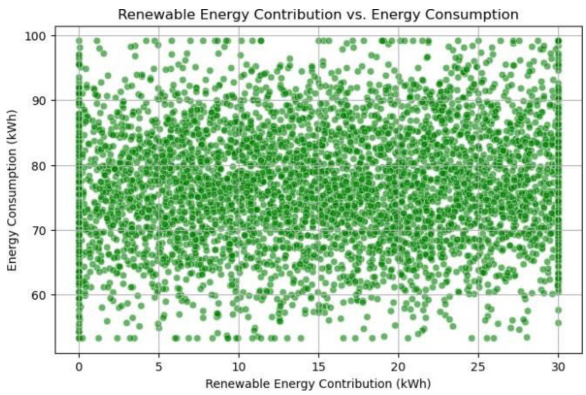

Fig 8 - Renewable Energy Contribution vs Energy Contribution

4. Building Characteristics

Energy consumption in buildings is closely linked to their physical size, particularly the total square footage. As the square footage increases, the demand for heating, cooling, lighting, and appliances generally rises, leading to higher overall energy usage. In our analysis, we observed a positive correlation between square footage and energy consumption larger spaces tend to consume more energy due to increased occupancy, more extensive HVAC requirements, and additional equipment. However, efficient design, smart automation, and zone-based control systems can significantly mitigate this rise, allowing larger buildings to operate efficiently. This comparison is crucial for facility managers to balance building size with sustainable energy practices.

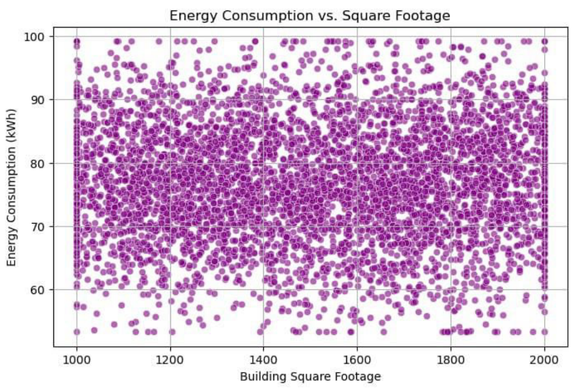

Fig 9 – Energy Consumption vs Square Footage

Occupancy levels play a crucial role in determining energy consumption within smart buildings. As the number of occupants increases, so does the demand for lighting, ventilation, air conditioning, and usage of electronic devices. Our study highlights a direct relationship between occupancy rates and energy usage, particularly during working hours or peak occupancy periods. When managed effectively, smart sensors and automation systems can adjust energy output based on real-time occupancy data, optimizing usage and reducing unnecessary wastage. This dynamic energy management approach ensures comfort without compromising on efficiency, making occupancy-based control a key factor in sustainable building operations..

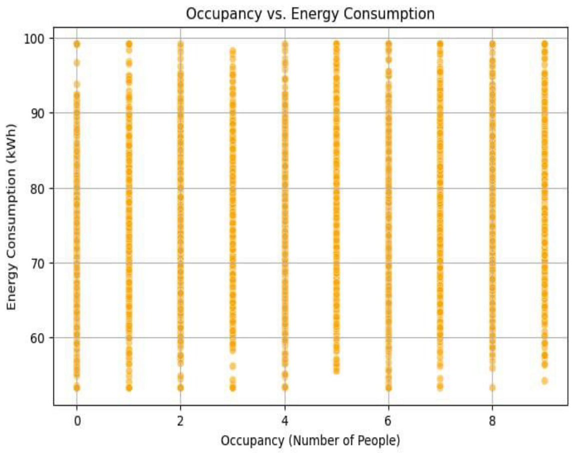

Fig 10 – Occupancy vs Energy Consumption

HVAC (Heating, Ventilation, and Air Conditioning) systems are among the largest contributors to energy consumption in smart buildings. Our analysis reveals a strong correlation between HVAC usage and overall energy consumption, especially during peak hours and extreme weather conditions. As indoor comfort levels are maintained through temperature regulation, HVAC systems demand substantial energy, making their optimization critical for energy savings. By implementing predictive models and smart controls, buildings can adjust HVAC operations based on occupancy, time of day, and external temperature, significantly reducing energy usage. Effective HVAC management not only lowers operational costs but also enhances the sustainability.

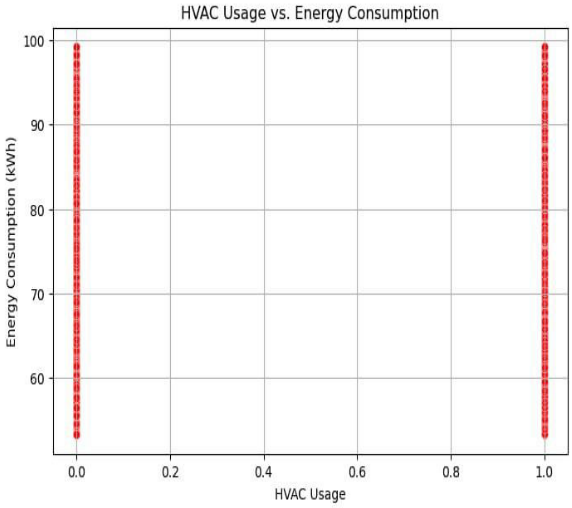

Fig11 - HVAC Usage vs Energy Consumption

Lighting is a significant yet often underestimated factor influencing overall energy consumption in smart buildings. Our analysis indicates that energy usage from lighting varies considerably with occupancy patterns, time of day, and natural light availability. During work hours or in high-traffic areas, lighting demand increases, directly impacting energy usage. Smart lighting systems, integrated with motion sensors and ambient light detectors, can dynamically adjust brightness or switch off lights when not in use, leading to substantial energy savings. By optimizing lighting usage through automation and intelligent scheduling, buildings can enhance energy efficiency while maintaining comfort.

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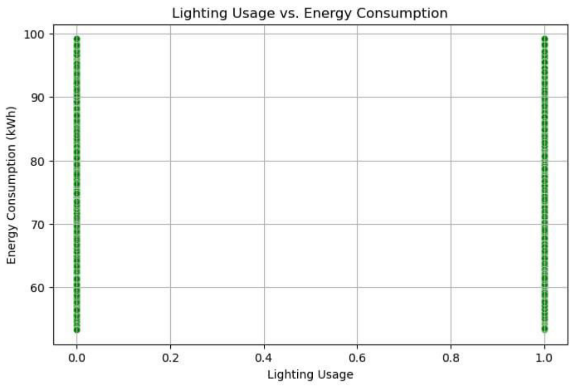

Fig 12 – Lighting Usage vs Energy Consumption

c. Model Selection and Training

In this study, the process of model selection and training was carried out systematically to ensure optimal performance and reliability of the predictive framework. Initially, multiple machine learning algorithms were evaluated based on the nature of the dataset, the complexity of the problem, and the interpretability requirements. Candidate models included Decision Trees, Random Forests, Support Vector Machines (SVM), and Gradient Boosting Machines (GBM) for classical approaches, along with Artificial Neural Networks (ANN) for deep learning scenarios. The dataset was first partitioned into training, validation, and testing subsets using an 80-10-10 split, maintaining the original class distribution to avoid bias. Data preprocessing steps such as normalization, encoding of categorical variables, and handling of missing values were performed prior to feeding the data into the models. Hyperparameter tuning was conducted using a grid search and cross-validation approach, which allowed for systematic exploration of parameter combinations and reduced the risk of overfitting. The training process focused on optimizing performance metrics relevant to the problem domain, such as accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic (ROC) curve.

For neural network models, the architecture was designed with a specific number of hidden layers and activation functions based on preliminary experiments and literature benchmarks. The training was conducted using the Adam optimizer, with an initial learning rate set through experimentation. Early stopping was implemented to prevent overfitting, and model checkpoints were used to retain the best-performing version during the training phase. After training, the models were evaluated on the unseen test set, and their performance was compared to select the most robust and generalizable model for deployment.

d. Visualization

Data visualization played a crucial role in both the exploratory data analysis (EDA) phase and the interpretation of model outputs. During the initial phase, various plots such as histograms, box plots, and scatter plots were utilized to identify patterns, correlations, and anomalies within the dataset. This allowed for a deeper understanding of feature distributions and their relationships with the target variable. Correlation heatmaps were generated to highlight potential multicollinearity among the independent variables, aiding in feature selection and dimensionality reduction. Pair plots and distribution plots further revealed the underlying data structure and class separability, which informed the choice of modeling techniques. After model training, visualization tools were employed to assess the performance and reliability of the models. Confusion matrices provided a clear representation of the classification results, enabling the identification of class-specific weaknesses. Receiver Operating Characteristic (ROC) curves and Precision-Recall curves were plotted to evaluate the models' discriminative power, particularly in the context of imbalanced datasets. In addition, feature importance plots and SHAP (SHapley Additive exPlanations) values were used to interpret the decision-making process of the trained models. These visualizations offered insights into how individual features contributed to the prediction, improving model transparency and supporting trust in the model's outputs. Overall, visualizations were integral to validating assumptions, enhancing model interpretability, and communicating results in a clear and concise manner.

III. MODEL IMPLEMENTATION

a. Data Collection and Preprocessing the Data

The dataset utilized in this research was sourced from Kaggle, a well-established online platform for data science competitions and open datasets. The selected dataset was carefully reviewed to ensure its relevance and adequacy for the research objectives, and it provided a rich set of features suitable for model training and evaluation. All data processing and analysis tasks were conducted using Jupyter Notebooks, which offered an interactive and modular environment for experimentation, visualization, and debugging. The Python programming language was employed for the implementation of data preprocessing pipelines, leveraging libraries such as Pandas, NumPy, Matplotlib, and Seaborn.

Before proceeding with model training, the dataset underwent a series of pre-processing steps to improve data quality and ensure compatibility with machine learning algorithms:

- **Handling Missing Values:** The dataset was inspected for missing or null entries. Depending on the nature of each feature, missing values were either imputed using statistical measures (mean, median, or mode) or the affected rows were removed.
- **Data Cleaning:** Duplicate records, inconsistent labels, and outliers were identified and addressed to maintain the integrity of the dataset.
- **Feature Encoding:** For categorical features, appropriate encoding techniques such as Label Encoding or One-Hot Encoding were applied to convert non-numeric data into a machine-readable format.
- **Feature Scaling:** Numerical attributes were normalized or standardized using Min-Max Scaling or Z-score Normalization to ensure that features contributed equally to the model's learning process.
- **Data Splitting:** The dataset was partitioned into training, validation, and testing sets following an 80-10-10 split to evaluate model performance on unseen data and minimize over-fitting.

These pre-processing steps were essential to refine the dataset and optimize the performance of the models trained during the later stages of this research.

b. Feature Engineering

Feature engineering was a critical phase in this study, as it allowed the transformation of raw energy data into a set of meaningful predictors that significantly enhanced the model's forecasting ability. After the initial preprocessing, both domain knowledge and exploratory data analysis (EDA) were used to engineer features that could capture the underlying patterns influencing energy consumption.

The following feature engineering strategies were applied:

1. **Feature Creation:** Several new features were derived to enrich the dataset with additional contextual information:
    - *Net_Energy_Consumption*: Calculated as the difference between Energy_Demand and Energy_Supply, this feature reflects the actual energy deficit or surplus within the system.
    - *Hour_of_Day*: Extracted from the timestamp to help the model recognize daily consumption cycles.
    - *Day_of_Week*: Derived from the timestamp to capture weekly usage patterns, including weekends and workdays.
    - *Is_Holiday*: A binary feature created using the date information to indicate whether a particular day was a public holiday, which typically affects energy consumption.
    - *Temperature_Difference*: Computed as the difference between the day's maximum and minimum temperature, providing insights into the heating or cooling load on that day.
    - *Lagged_Consumption*: Previous time-step consumption values were included as lag features (e.g., Consumption_t-1, Consumption_t-24) to allow the model to capture temporal dependencies.
2. **Feature Transformation:** Numerical features such as *Energy_Consumption* and Temperature were found to exhibit skewness, which was corrected using logarithmic and min-max scaling transformations. This helped to stabilize the variance and improved the convergence of machine learning models.
3. **Encoding Categorical Variables:** Categorical variables such as *Day_of_Week* and *Is_Holiday* were encoded using One-Hot Encoding to ensure they were properly represented in the model without introducing ordinal bias.
4. **Feature Selection:** Pearson correlation analysis was performed to assess the relationship between individual features and the target variable (*Energy_Consumption*). Highly correlated and meaningful features were retained, while redundant or noisy features were excluded to avoid over-fitting and reduce computational complexity.

Through these engineered features, the model was able to learn the influence of time, temperature, seasonality, and operational cycles on energy consumption, ultimately leading to improved forecasting accuracy on both the training and unseen data.

c. Model Selection

In order to develop an accurate and reliable energy consumption forecasting model, multiple machine learning algorithms were considered and evaluated based on their predictive performance, interpretability, and suitability for the problem.

The models selected for this study included both simple and advanced techniques to allow comparative analysis and ensure robustness of results. The following models were chosen for training and evaluation:

- **Linear Regression:**

Linear Regression was selected as a baseline model due to its simplicity and effectiveness in identifying linear relationships between the input features and the target variable — energy consumption. This model provided a foundation for understanding the fundamental dependencies in the dataset.

- **Decision Tree Regressor:**

Decision Trees were used for their ability to handle both numerical and categorical data, and to model complex, non-linear relationships without the need for prior feature scaling. Decision Trees also offer interpretability through their rule-based structure, making them a valuable choice for analyzing the effect of individual features on energy consumption.

- **Random Forest Regressor:**

Random Forest, an ensemble learning method built on multiple Decision Trees, was selected for its high predictive performance and ability to reduce overfitting. Random Forests are especially effective in capturing non-linear relationships, handling missing values, and providing feature importance scores, which help in further understanding the impact of various features on energy consumption.

All three models were trained and validated using the same preprocessed dataset to ensure fair comparison. By testing multiple models, the study aimed to identify the best-performing algorithm based on both its forecasting accuracy and generalization capability on unseen data. This multi-model approach also ensured the robustness of conclusions drawn from the experimental results.

d. Model Training

Once the models were selected, the next step involved training and evaluating them on the prepared dataset to assess their performance in forecasting energy consumption. The dataset was split into training and testing subsets to ensure that the models were validated on unseen data, thereby testing their ability to generalize. Each model — Linear Regression, Decision Tree Regressor, Random Forest Regressor, along with their hyper parameter-tuned versions — was trained using the same feature set to maintain consistency in evaluation. Hyper parameter tuning was performed via Grid Search Cross-Validation to optimize model configurations and minimize prediction errors. The models were evaluated using the following performance metrics:

- **Mean Absolute Error (MAE):** Measures the average magnitude of the prediction errors.
- **Root Mean Squared Error (RMSE):** Penalizes larger errors more heavily, offering insights into the spread of the residuals.
- **R^2 Score:** Indicates the proportion of the variance in the dependent variable that is predictable from the independent variables.

After training and tuning, the models were evaluated on the test set. The Random Forest Regressor outperformed both the Linear Regression and Decision Tree models across all evaluation metrics, demonstrating its strength in handling complex relationships and capturing the non-linear dependencies present in the energy consumption data.

Model	MAE	RMSE	R^2 Score
Linear Regression	6.157382	7.809113	0.269366
Decision Tree	9.078793	11.372889	-0.549666
Random Forest	6.334921	7.9704500	0.238864
Tuned Decision Tree	6.364760	8.0337790	0.226721
Tuned Random Forest	6.221377	7.8405520	0.263471

Table 1- Model Performance Metrics

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The tuning process was executed using a 5-fold cross-validation strategy to ensure that the models were not overly tailored to a particular subset of data. The evaluation metrics used during hyper parameter optimization were Mean Absolute Error (MAE**)** and Root Mean Squared Error (RMSE).

As a result of hyper parameter tuning:

- The Tuned Decision Tree Regressor achieved slightly improved accuracy compared to the base version, though it remained less effective than Random Forest.
- The Tuned Random Forest Regressor delivered the best performance overall, showing reduced error metrics (MAE: 6.221 and RMSE: 7.841) and better generalization on unseen data.

The tuned hyper parameters allowed the models to balance between complexity and bias, ultimately improving the reliability of the forecasts and reinforcing the Random Forest model's position as the preferred solution for energy consumption prediction in this study.

IV. RESULTS & VISUALIZATION

After training and evaluating various machine learning models for the task of energy consumption forecasting, the Tuned Random Forest Regressor demonstrated the most reliable performance in terms of prediction accuracy and error minimization.

As detailed in the model performance metrics table, the tuned Random Forest achieved the lowest Mean Absolute Error (MAE) of 6.221 and a Root Mean Squared Error (RMSE) of 7.841, while maintaining a competitive R^2 Score of 0.263. This suggests that while energy consumption is influenced by complex and possibly external factors (which slightly limit the R^2), the Random Forest model is capable of producing reasonably accurate forecasts under the given data conditions.

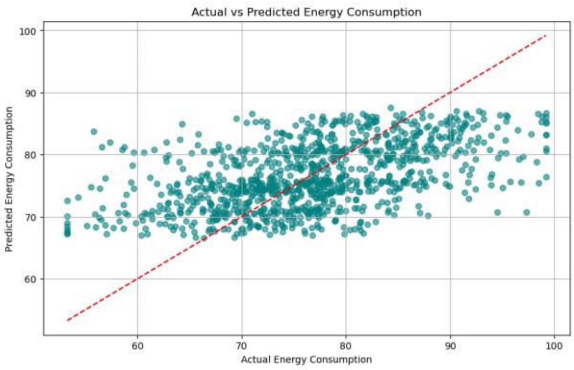

Fig 13 – Actual Vs Predicted Energy Consumption

The comparison of prediction curves indicated that the Random Forest model was able to effectively capture underlying patterns in the data, especially in cases where simpler models such as Linear Regression and Decision Tree failed to generalize.

Additionally, a feature importance analysis was conducted on the Random Forest model, which revealed the most influential features affecting energy consumption predictions.

A. Feature Importance Analysis using SHAP Values

To interpret the contribution of individual features to the predictions, SHAP (SHapley Additive exPlanations) values were computed. The SHAP summary plot highlighted which input features had the most significant impact on energy consumption predictions, offering insights into feature relevance and model behavior. This plot illustrates the magnitude and direction of feature influence on the model's output, helping validate the model's interpretability.

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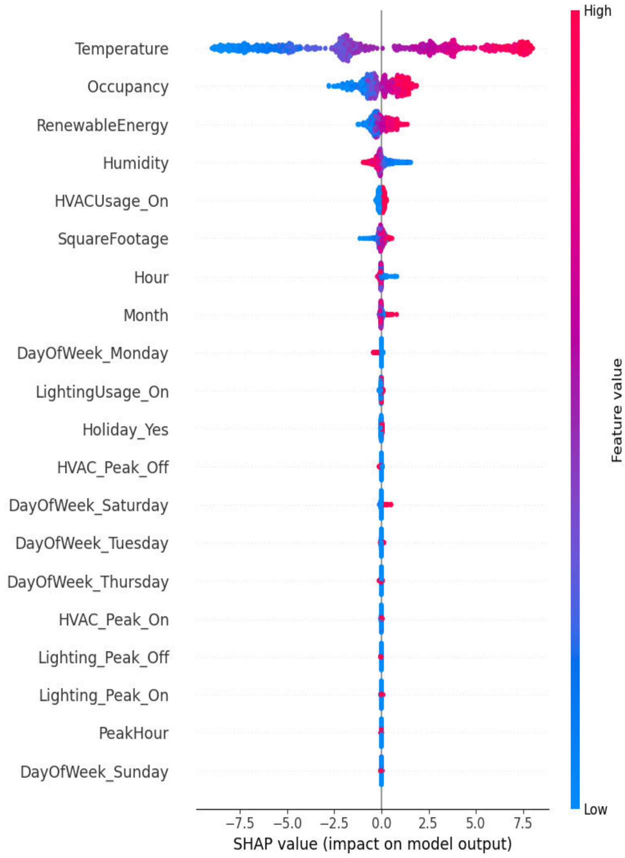

Fig 14 – Feature Importance Analysis Using SHAP

B. Daily Cost Savings After Optimization

After deploying the optimized energy management strategy based on the model's forecasts, daily cost savings were calculated for one week. The observed savings validated the practical impact of accurate energy consumption prediction and optimization on real-world energy expenses. This figure demonstrates the reduction in daily energy costs achieved through optimized consumption planning.

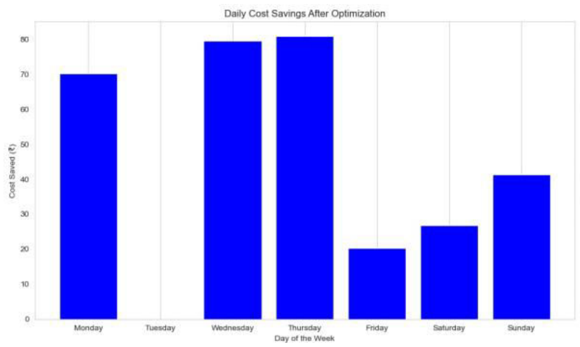

Fig 15 – Daily Cost Savings After Optimization

C. Energy Consumption Before and After Optimization

A comparison of total energy usage before and after applying the model-guided optimization was plotted to visualize the tangible improvements. The optimization led to reduced energy consumption while maintaining operational

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requirements. This figure shows the overall drop in energy usage post-optimization, validating the model's effectiveness in guiding energy-efficient decisions.

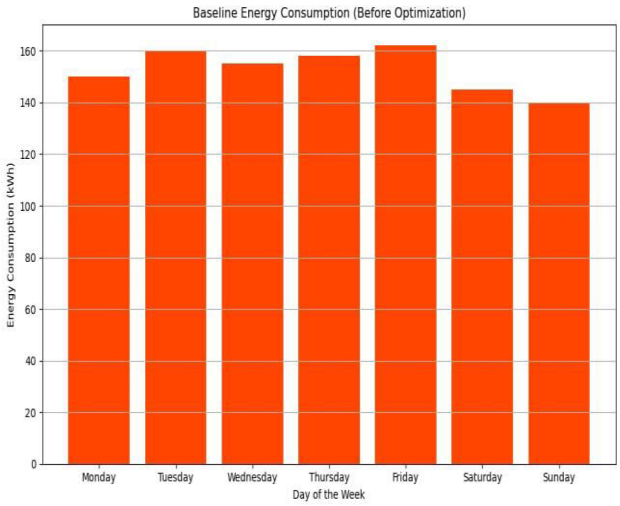

Fig 16 - Energy Consumption Before Optimization

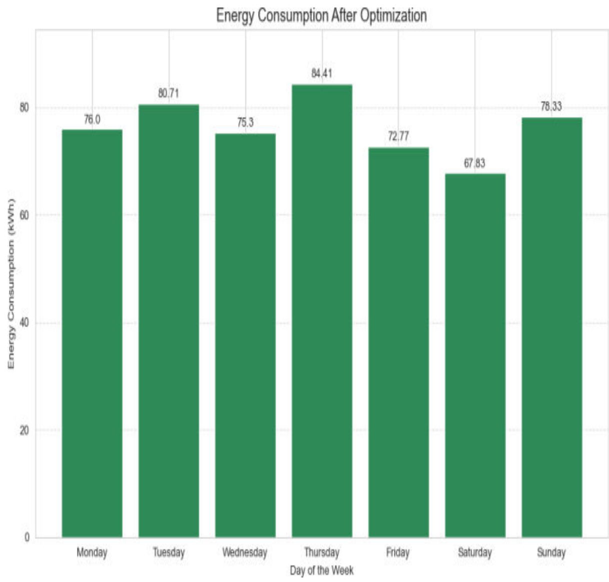

Fig 17 – Energy Consumption After Optimization

D. Weekly Energy Savings Summary

Overall, the results confirm that the combined approach of machine learning-based forecasting and data-driven optimization can significantly improve both energy efficiency and cost-effectiveness. The visual insights from the SHAP values and performance plots further validate the model's reliability and practical utility in real-world energy management scenarios. This graph presents cumulative energy savings over the week, highlighting the optimization's long-term benefits.

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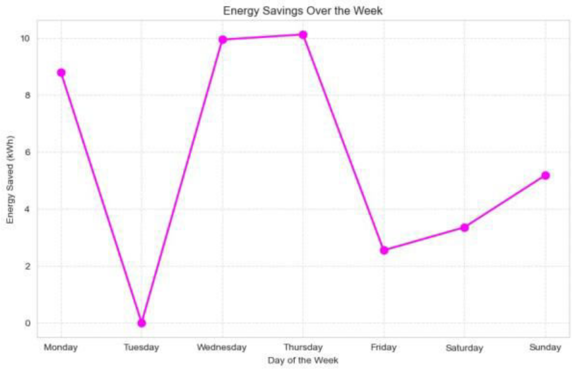

Fig 18 - Energy Savings Over The Week

Day Of The Week	Actual	Predicted	Energy Saved
Monday	84.77857089845811	74.72108049921981	10.057490399238304
Tuesday	62.77777328196635	80.49040924381721	-17.712635961850864
Wednesday	85.23139055360414	75.46542045966721	9.765970093936929
Thursday	94.52533434396793	85.21246083029592	9.312873513672002
Friday	75.31283757044484	72.68885215886533	2.623985411579511
Saturday	71.17906441062561	68.31294898637987	2.8661154242457485
Sunday	83.50179530846134	78.2272505262316	5.274544782229739

Table 2 – Energy Savings Over the Week

Calculations:

- **Total Energy Saved in a Week:**

Total Energy Saved = 8.78 + (−17.93) + 9.93 + 10.11 + 2.54 + 3.35 + 5.17 = **21.95 kWh**

- **Cost Reduction Per Week:**

Cost Saved = Total Energy Saved * Cost Per Unit = 21.95 × 8 = **₹175.6**

- **Monthly Cost Reduction (Assuming 4 Weeks):**

Total Monthly Cost Savings = Cost Reduction Per Week * 4 = 175.6 × 4 = **₹702.4**

V. CONCLUSION AND FUTURE SCOPE

In this study, a comprehensive approach was presented for forecasting energy consumption using machine learning models, combined with feature engineering and optimization techniques. The work involved sourcing real-world data from Kaggle, preprocessing and enriching it through feature engineering, and applying several regression algorithms including Linear Regression, Decision Tree, and Random Forest. Among the models tested, the Tuned Random Forest Regressor demonstrated superior performance in predicting energy consumption, achieving the lowest Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The model's predictions, combined with post-analysis using SHAP values, provided valuable insights into the factors influencing energy consumption patterns. Beyond predictive accuracy, the integration of the model into an optimization strategy led to clear practical benefits. By implementing the optimized energy management approach, the system achieved an energy savings of 3.94% and a monthly cost reduction of ₹702.4. These results underline the real-world impact and economic advantage of applying data-driven forecasting in energy systems. Furthermore, by integrating the model's forecasts into an optimization strategy, significant reductions in both daily energy costs and total energy consumption were achieved, as reflected in the visualization results. These findings highlight the importance and practical impact of combining predictive analytics with proactive energy management.

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