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**ENERGY CONSUMPTION PREDICTION USING MACHINE  
LEARNING TECHNIQUES**

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**ABSTRACT**

Forecasting energy consumption has emerged as a critical requirement for next-generation smart grid architectures and environmentally responsible energy governance frameworks. Reliable energy demand prediction empowers grid operators to optimize resource allocation, achieve balanced load distribution, and substantially lower operational expenditures. This research paper proposes a machine learning-based framework for predicting energy consumption using historical usage data and environmental parameters. The system utilizes supervised learning algorithms including Linear Regression, Random Forest Regressor, and Long Short-Term Memory (LSTM) neural networks to analyze patterns in energy usage. Data preprocessing techniques such as normalization, missing value handling, and feature engineering were applied to enhance model performance. The experimental results demonstrate that machine learning models can accurately forecast short-term and medium-term energy consumption with high prediction accuracy. Among the tested models, Random Forest achieved the best performance with high precision and minimal error. The proposed framework can be integrated into smart energy management systems to support intelligent decision-making and efficient power distribution.

**KEYWORDS:** *Energy Consumption Prediction, Machine Learning, Smart Grid, Random Forest, LSTM, Energy Forecasting.*

## I. INTRODUCTION

Global energy demand continues to escalate at an accelerating pace, driven by expanding industrial activity, rapid urban expansion, and sustained demographic growth worldwide. Efficient energy management is necessary to ensure sustainability and reduce energy waste. Traditional forecasting techniques often struggle to capture the complex, non-linear patterns present in contemporary energy usage data.

Modern machine learning methodologies offer sophisticated capabilities for uncovering latent structures and non-obvious correlations embedded within high-dimensional datasets. By learning from historical energy consumption records, machine learning models can accurately anticipate future usage trajectories, enabling energy providers to optimize electricity generation, reduce operational costs, and maintain grid stability.

This research focuses on developing a machine learning model that predicts energy consumption using historical electricity usage data, weather parameters, and time-based features. The goal is to improve forecasting accuracy and provide an efficient system that can assist in intelligent energy management.

## II. RELATED WORK

Several studies have explored the application of machine learning techniques for energy forecasting. Conventional statistical approaches, particularly the Autoregressive Integrated Moving Average (ARIMA) framework, have long served as the baseline for temporal sequence modelling, yet their inherent linearity assumptions constrain their capacity to represent the complex, non-stationary dynamics of real-world energy data.

Contemporary investigations have shifted attention toward data-driven paradigms encompassing Support Vector Regression (SVR), ensemble-based Random Forest architectures, multi-layer Artificial Neural Networks (ANNs), and sophisticated Deep Learning frameworks, each demonstrating measurable enhancements in predictive fidelity.

Despite these improvements, many existing systems suffer from limitations such as insufficient feature engineering, lack of real-time adaptability, and high computational cost. This research addresses these limitations by designing an optimized machine learning pipeline.

### III. MATERIALS AND METHODS

#### A. Dataset Description

The dataset used for this research consists of historical energy consumption records collected from smart meters. The dataset includes parameters such as date and time, temperature, humidity, day of the week, and electricity usage.

#### B. Data Preprocessing

Systematic data preprocessing constitutes a foundational component of the modelling pipeline. The following preprocessing techniques were applied:

- Handling Missing Values — Missing entries were imputed using interpolation techniques to maintain temporal continuity.
- Normalization — Feature scaling was applied to standardize numerical values and ensure uniformity across input dimensions.
- Feature Engineering — Time-based features such as hour, day, and month were extracted to expose cyclical consumption patterns.
- Data Splitting — The dataset was partitioned into training and testing subsets to enable unbiased model evaluation.

#### C. Machine Learning Models

Multiple machine learning algorithms were implemented and compared:

1. Linear Regression — A simple statistical model used as a baseline predictor to benchmark the performance of more sophisticated algorithms.
2. Random Forest Regression — An ensemble learning model that improves prediction accuracy by combining multiple decision trees through bootstrap aggregation.
3. Long Short-Term Memory (LSTM) — A recurrent deep learning architecture capable of learning long-range temporal dependencies inherent in time-series data.

#### D. Model Training

The models were trained using historical energy data. Performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and prediction accuracy were used to evaluate the models.

#### IV. RESULTS

The performance of the proposed system was evaluated using standard regression metrics. The results demonstrate that machine learning algorithms can effectively predict energy consumption patterns.

**TABLE I. Performance Comparison of Models.**

Model	MAE	RMSE	Accuracy
Linear Regression	0.21	0.31	85%
Random Forest	0.12	0.18	92%
LSTM	0.15	0.22	90%

The Random Forest model achieved the highest accuracy among the tested algorithms, indicating its ability to handle nonlinear relationships in the dataset effectively.

#### V. DISCUSSION

The experimental results highlight the effectiveness of machine learning in forecasting energy consumption. The Random Forest regressor exhibited superior predictive capability attributable to its bagging-based ensemble strategy.

Deep learning models such as LSTM also performed well because they can capture sequential dependencies in time-series data. However, they require higher computational resources and longer training times.

The proposed system can be applied to real-world smart grid systems for optimizing electricity distribution, reducing energy wastage, and improving energy planning strategies.

#### VI. CONCLUSION

This research presented a machine learning-based framework for predicting energy consumption using historical energy data and environmental factors. The system utilized multiple machine learning models to analyze energy usage patterns and forecast future demand.

Experimental results demonstrated that the Random Forest algorithm achieved the highest prediction accuracy. The proposed framework provides a reliable approach for energy demand forecasting and can assist power utilities in optimizing energy distribution and improving efficiency.

Embedding machine learning capabilities within energy management infrastructure represents a transformative step toward achieving sustainability targets and enabling intelligent, data-driven stewardship of energy resources.

## VII. FUTURE SCOPE

Future research can further improve the proposed system by integrating advanced deep learning architectures such as Transformer-based models. Real-time data streams from IoT-enabled smart meters can also be incorporated to enable dynamic energy forecasting.

Additionally, integrating renewable energy sources such as solar and wind power into the prediction model can enhance the accuracy of energy planning systems. Cloud-based deployment and distributed data processing can further scale the system for large-scale smart grid infrastructures.

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