***Weather Forecasting for Power Prediction***

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***ABSTRACT:*** Weather forecasting is an essential task in the prediction of availability and efficiency of renewable energy resources like wind and sunlight. With accurate weather prediction, we can forecast power generation levels and make the best use of energy systems. Machine learning techniques like XGBoost, LSTM, and GRU models have been discussed here for weather parameter-based power consumption prediction. The models are compared on parameters like Mean Absolute Error (MAE), F1 Score, Accuracy, Precision, Recall, and Confusion Matrix. Additionally, a Graphical User Interface (GUI) is used to give real-time prediction based on user input. The outcome reveals that deep learning models outperform conventional regression-based models in terms of giving more accurate predictions and facilitating effective energy management.

***Keywords:***XGBoost, LSTM, GRU, energy optimization, time-series forecasting, power consumption

**INTRODUCTION:**

Use of renewable energy sources like solar and wind power has been a major component of power systems today. The variability of these sources, though, is a hindrance to having a stable and reliable power supply grid. Atmospheric conditions such as temperature, wind speed, humidity, and atmospheric pressure regulate the accessibility and effectiveness of renewable power output. Accurate weather forecasting can be a valuable input to energy management because it can precisely forecast the output of power and enable smooth resource distribution.

Forecasting of power has traditionally been achieved through physics-based and statistical models that would be incapable of determining non-linear and dynamic energy generation patterns as a result of fluctuations in the weather. That has changed, however, with newer developments in artificial intelligence (AI) and machine learning (ML) wherein newer approaches have been developed which tap into large quantities of data so that it may learn better patterns and trends.

The objective of this project is to create an artificial intelligence system that predicts weather and power demand using machine learning methods. The core concept here is to create forecast models with the help of historical weather patterns and electricity consumption to accurately forecast power demand. Applying the integration of the deployment of XGBoost, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) networks, this research applies a number of methods in high-level accuracy prediction.

Also, a Graphical User Interface (GUI) is planned for delivering an intuitive interface for real-time forecasting. The weather parameters can be entered by the users or future dates can be chosen in order to forecast power usage, and the system can be of tremendous value to power grid companies and energy companies.

The importance of this study is that it has the potential to enhance grid stability, reduce energy loss, and optimize the efficiency of power supply networks. The project is applicable in the development of smart energy systems with the ability to respond to real-time climatic conditions through the integration of weather forecasting and power forecasting.

This paper provides the problem statement, methodology, implementation of various machine learning models, evaluation metrics, and outcomes obtained. At last, future directions are elaborated to further enhance and generalize the proposed method.

**LITERATURE SURVEY:**

The field of weather-forebased power prediction has seen great progress with the development of machine learning and deep learning approaches. Traditional approaches were physics-based and statistical modeling, but existing literature demonstrates the usefulness of AI-based approaches in optimizing prediction quality. This part consolidates main literature related to weather forecasting, power consumption forecasting, and AI approaches used for energy management.

Weather Forecasting and Power Prediction

It is essential for predicting power generation due to renewable sources such as wind and solar energy. [1] has highlighted the importance of meteorological factors such as temperature, humidity, and wind speed in estimating electricity supply and demand. Statistical approaches like AutoRegressive Integrated Moving Average (ARIMA) have been widely used but have inferior performance with complex temporal relationships.

Machine Learning for Power Prediction

Past work has examined the use of machine learning algorithms such as Decision Trees, Random Forest, and XGBoost to predict power consumption. Ensemble-based learning models such as XGBoost have been found to give high prediction accuracy of electricity demand based on weather factors by [2]. Feature engineering with temporal trends and lagged variables has been found to significantly improve the prediction performance through the study.

Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have been extensively employed for time series forecasting purposes. Research conducted by [3] demonstrates that LSTM networks can learn long-term dependencies of electricity usage patterns and outperform traditional regression models. GRU networks also confer computational advantages through the reduction of parameters without sacrificing prediction accuracy.

AI-Based Forecasting Systems with GUI Integration

Different research works have provided simple-to-use AI-based forecasting tools to enable enhanced decision-making in energy management. In [4], an interactive interface was provided for users to input weather information and receive power forecasts. Based on the research, the decision-making and accessibility of energy operators can be enhanced and made real-time by integrating machine learning models with interactive GUI systems.

**METHODOLOGY:**

This study follows a structured approach to predict power consumption using AI techniques. The methodology includes data preprocessing, training machine learning models, evaluating their performance using key metrics, and implementing a GUI for real-time predictions. The models used include XGBoost, LSTM, and GRU, each optimized for handling weather-based power consumption forecasting.

**Data Preprocessing**

* Load the dataset and parse the date column for time series analysis.
* Normalize power consumption values using MinMaxScaler.
* Create sequences of past observations for deep learning models.
* Split data into training (80%) and testing (20%) sets.

**Model Implementation**

**XGBoost Model**

* Extract weather features and lagged power consumption values.
* Train the model using hyperparameter tuning.
* Evaluate performance using MAE, Accuracy, and F1 Score.

**LSTM Model**

* Use sequential input of power consumption and weather features.
* Implement LSTM layers with dropout to prevent overfitting.
* Train using Adam optimizer and mean squared error loss function.

**GRU Model**

* Similar to LSTM but utilizes Gated Recurrent Units for faster training.
* Reduces memory consumption while maintaining prediction accuracy.
* Evaluated using standard performance metrics.

**GUI Implementation**

* Built using Tkinter to provide an interactive prediction tool.
* Users enter a future date for power consumption prediction.
* Displays predicted power usage and categorizes it as "High" or "Low".
* Ensures validation of input data and user-friendly experience.

This structured methodology ensures that the models provide accurate and reliable predictions while allowing users to interact with the system for real-time forecasting.

**RESULT:**

The models were evaluated using MAE, Accuracy, Precision, Recall, F1 Score, and Confusion Matrix.

(i) LSTM:

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(ii) XGBOOST:

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(iii) GRU:

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GUI:

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A screenshot of a computer

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FLOWCHART:

A diagram of a flowchart

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