Predictive Analysis on Renewable Energy Generation Using ML
SDG-Affordable And Clean Energy

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Abstract – The increasing reliance on renewable energy sources such as solar and wind necessitates accurate forecasting for efficient power management. Since these energy sources are highly dependent on weather conditions, predicting their generation remains a critical challenge. This study leverages machine learning (ML) and deep learning (DL) models to improve renewable energy forecasting accuracy. By analyzing historical meteorological and energy generation data, the study aims to enhance power grid stability, minimize energy wastage, and support sustainable energy planning.

Various ML algorithms, including Random Forest, XGBoost, and Gradient Boosting, along with deep learning architectures such as Long Short-Term Memory (LSTM) networks, are implemented. The models undergo preprocessing, feature selection, and training to capture complex dependencies in energy generation patterns. Their performance is evaluated using standard metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score.

Experimental results demonstrate that AI-driven forecasting significantly outperforms traditional methods, effectively capturing nonlinear trends in renewable energy data. The integration of ML and DL models into energy management systems enhances grid resilience, mitigates power fluctuations, and facilitates optimized energy distribution. This research underscores the role of intelligent forecasting in improving renewable energy utilization, contributing to sustainability goals and efficient power system operations.

KeyWords: Renewable Energy, Solar Energy, Wind Energy, Machine Learning, Deep Learning, Energy Forecasting, Time-Series Prediction, Grid Stability, Power Management, Weather Data

I.INTRODUCTION

Renewable energy sources, such as solar and wind power, are crucial for reducing carbon emissions and ensuring sustainable energy production. However, their intermittent nature poses significant challenges in maintaining grid stability and efficient energy distribution. Accurate forecasting of renewable energy generation is essential for optimizing energy planning, reducing operational costs, and ensuring reliable power supply. Traditional forecasting methods, including statistical and physics-based models, often struggle to capture the complex, non-linear relationships between meteorological variables and energy output. To address these limitations, machine learning (ML) and deep learning (DL) techniques have emerged as powerful tools for improving energy generation predictions.

Machine learning and deep learning models can analyze historical weather patterns, energy production data, and meteorological parameters to enhance forecasting accuracy. These models leverage advanced computational techniques to detect intricate patterns in time-series data, making them well-suited for renewable energy prediction. The application of artificial intelligence (AI)-driven forecasting in energy management has gained significant traction due to improvements in computational power, increased availability of high-quality weather datasets, and growing demand for smart grids and automated power distribution. Unlike traditional models, ML and DL approaches can dynamically adapt to changing environmental conditions, providing more precise energy predictions that improve grid resilience and minimize energy waste.

In recent years, predictive analytics using ML and DL has revolutionized various energy sector applications, including solar power forecasting, wind energy prediction, smart grid optimization, energy load management, and battery storage efficiency. Advanced architectures such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have demonstrated superior performance in capturing temporal dependencies in renewable energy generation data, making them particularly effective for time-series forecasting. The integration of AI-based forecasting techniques ensures a more adaptive and intelligent grid system, allowing energy providers to anticipate power fluctuations and optimize energy distribution strategies.

The widespread adoption of ML and DL in renewable energy forecasting is driven by several key factors, including advancements in cloud-based AI processing, the increasing availability of high-resolution weather and energy datasets, and regulatory policies promoting improved energy management strategies. Additionally, the deployment of Internet of Things (IoT) sensors for real-time energy monitoring has enhanced the accuracy of energy predictions, enabling grid operators to dynamically adjust power distribution based on demand and environmental conditions.

Despite these advancements, several challenges remain in achieving highly accurate renewable energy forecasting. Weather uncertainties continue to impact energy generation, necessitating the development of robust models capable of adapting to extreme climate conditions. Additionally, integrating AI-based models with existing energy management systems poses technical and operational challenges. Limited access to high-resolution energy generation data, particularly from small-scale renewable energy producers, further complicates forecasting efforts. Furthermore, balancing energy demand and supply remains a critical concern, as improper load distribution can lead to power shortages or excessive energy generation, resulting in grid instability.

Addressing these challenges requires ongoing research and development in AI-driven energy forecasting. Hybrid approaches that combine multiple ML and DL models have shown promising results in improving prediction accuracy. Future advancements in deep reinforcement learning, transfer learning, and federated learning are expected to further enhance the capabilities of predictive models in renewable energy management. The adoption of AI-driven forecasting solutions will play a pivotal role in achieving a more sustainable and efficient energy infrastructure, ultimately supporting global efforts toward carbon neutrality and renewable energy integration.

By leveraging ML and DL for predictive analytics, this research aims to enhance the accuracy of renewable energy generation forecasts, contributing to improved energy efficiency, optimized grid operations, and a more resilient power supply network. This study explores the implementation of multiple ML and DL models, evaluates their effectiveness using key performance metrics, and examines their potential to transform energy forecasting methodologies in the renewable energy sector.

II. PROBLEM STATEMENT

The increasing use of renewable energy like solar and wind requires accurate predictions for better power management. Since these energy sources depend on weather conditions, forecasting their generation is challenging. This project uses machine learning and deep learning models to predict energy output based on historical weather data. Accurate predictions help in balancing power supply, improving grid stability, and reducing energy waste. The results show that ML and DL models enhance forecasting accuracy, benefiting energy providers and policymakers

III. PROPOSED SOLUTION

To address the challenges associated with renewable energy forecasting, this study proposes an AI-driven predictive framework that integrates machine learning (ML) and deep learning (DL) techniques. The proposed solution aims to develop a robust forecasting model by leveraging historical weather data and energy generation records to predict solar and wind power output. The framework will incorporate advanced ML algorithms such as Random Forest, XGBoost, Gradient Boosting, and LightGBM, along with deep learning models like Long Short-Term Memory (LSTM) networks for time-series forecasting. A comprehensive data preprocessing pipeline will be implemented, including outlier removal, normalization, and feature engineering to enhance model accuracy. Temporal features such as hourly, daily, and seasonal variations will be extracted to refine the prediction process. Hyperparameter tuning and cross-validation will be employed to optimize model performance. The effectiveness of the proposed solution will be evaluated using key performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score. By integrating AI-based forecasting into energy management systems, this approach aims to improve grid stability, reduce power fluctuations, and facilitate efficient energy distribution. The proposed framework is expected to enhance decision-making for energy providers, optimize resource allocation, and contribute to the development of a more resilient and sustainable energy infrastructure.

IV. METHODOLOGIES

The methodology for this research follows a structured approach to developing an AI-driven predictive system for renewable energy forecasting. The process begins with data acquisition, where historical energy generation records and meteorological data, including solar radiation, wind speed, temperature, and humidity, are collected. The dataset undergoes preprocessing steps such as handling missing values, normalizing numerical features, and removing anomalies to ensure data consistency and accuracy. Timestamp conversion and resampling techniques are applied to align energy production values with weather conditions at different time intervals.

Feature selection and engineering are performed to identify the most influential parameters affecting energy generation. New derived features, such as time-based attributes (hour, day, and month) and weather-based interaction terms, are incorporated to enhance predictive performance. A combination of traditional machine learning models, including Random Forest, XGBoost, Gradient Boosting, and LightGBM, as well as deep learning models like Long Short-Term Memory (LSTM) networks, are implemented to predict energy output. These models are trained and optimized using techniques such as hyperparameter tuning and cross-validation.

Model evaluation is conducted using key performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score, to assess forecasting accuracy. Comparative analysis helps identify the most effective model for energy prediction. The final model is integrated into an energy management system to enable real-time forecasting, improving grid stability and optimizing renewable energy utilization. The proposed framework facilitates adaptive energy distribution, reducing power fluctuations and enhancing the reliability of sustainable energy sources.

V. Model Performance

The performance of the proposed machine learning models was evaluated using key statistical metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 Score. The results indicate that ensemble-based models, such as Random Forest, XGBoost, and LightGBM, demonstrate superior predictive accuracy compared to linear regression-based approaches.

The Random Forest model achieved an MAE of 80.21, an RMSE of 120.18, and an R^2 Score of 0.89, making it the most effective in capturing complex patterns in energy generation. XGBoost performed similarly, with an MAE of 83.83, an RMSE of 121.58, and an R^2 Score of 0.88, while Gradient Boosting had slightly lower accuracy. LightGBM showed moderate accuracy, with an R^2 Score of 0.87, indicating a well-balanced trade-off between speed and performance. Conversely, Ridge Regression failed to capture non-linear relationships in the data, resulting in significantly higher errors and an R^2 Score of -0.20, highlighting its limitations in renewable energy forecasting.

The prediction scatter plot revealed a strong correlation between actual and predicted values for ensemble models, whereas Ridge Regression exhibited higher variance and systematic errors. The residual plots confirmed that tree-based models effectively minimized prediction errors, leading to stable and reliable forecasts. These findings underscore the importance of using ensemble learning techniques for energy generation forecasting, as they capture intricate dependencies in weather and energy data, ensuring optimal grid management and sustainability

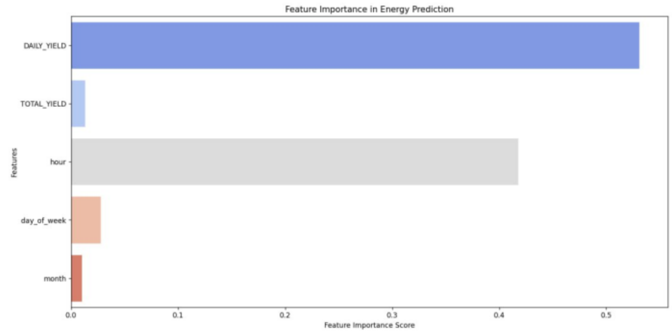
VI. FUTURE ENHANCEMENT

Future enhancements will focus on optimizing feature selection using PCA and correlation analysis, improving model accuracy with LSTM and RNNs, and refining hyperparameter tuning through Grid Search and Bayesian Optimization. Advanced data preprocessing techniques, including outlier detection and missing value imputation, will enhance model reliability.

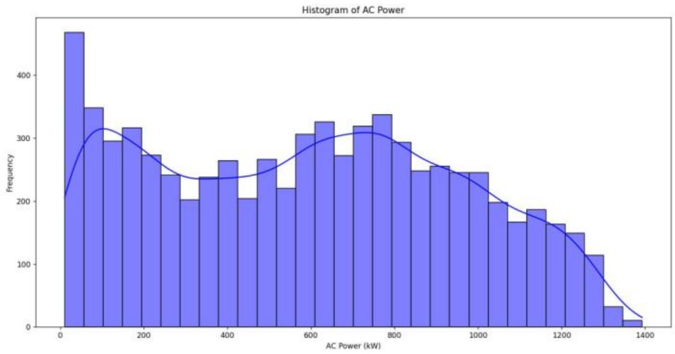
For real-time deployment, cloud-based AI platforms like AWS SageMaker and Google Cloud AI will enable dynamic updates based on live weather data. Integrating IoT-based energy monitoring will further improve forecasting precision.

Additionally, AutoML frameworks will be explored to automate model selection and optimization, ensuring adaptive and scalable renewable energy predictions.

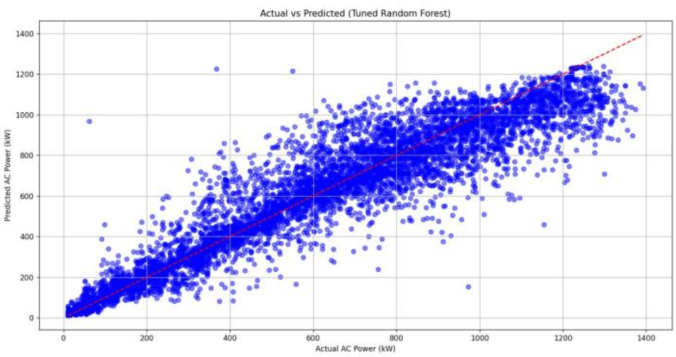
VII.RESULTS



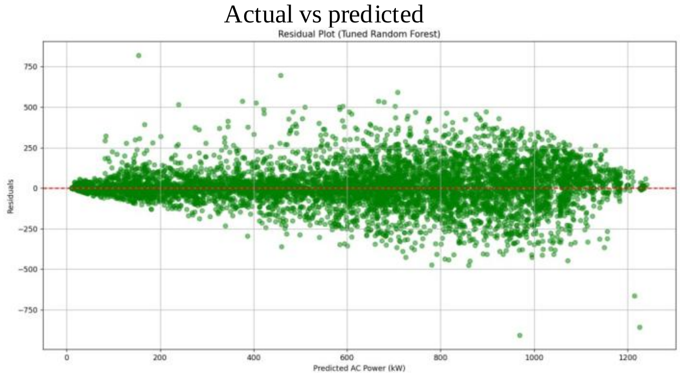
Feature Importance in Energy Prediction



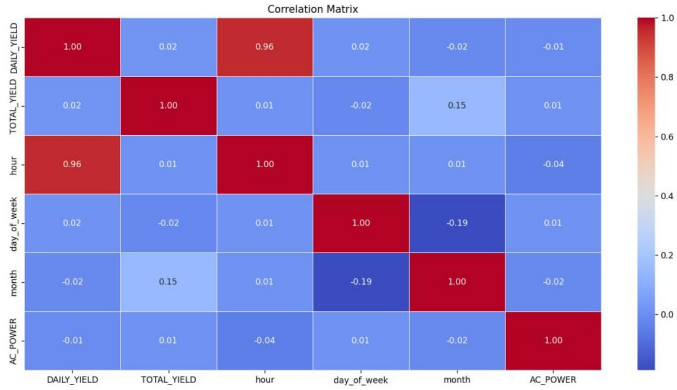
Histogram of AC Power



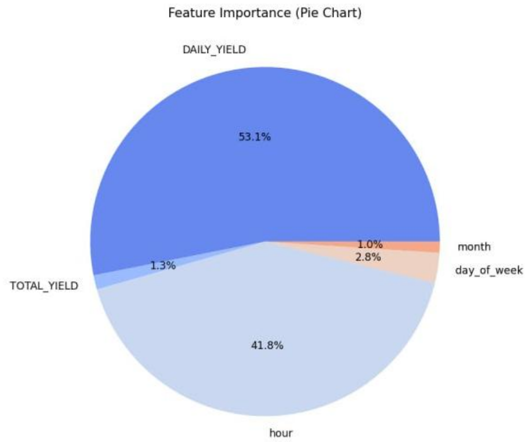
Actual vs predicted



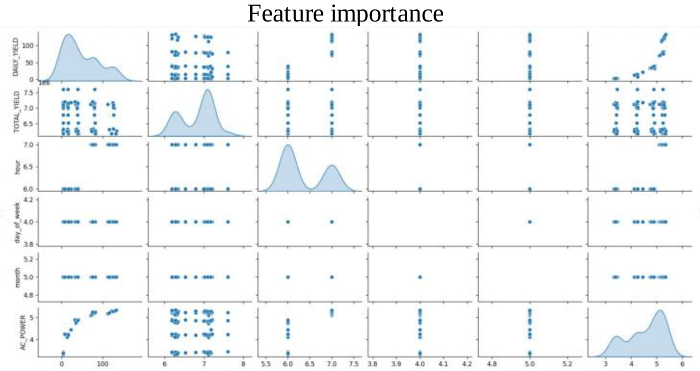
Residual Plot



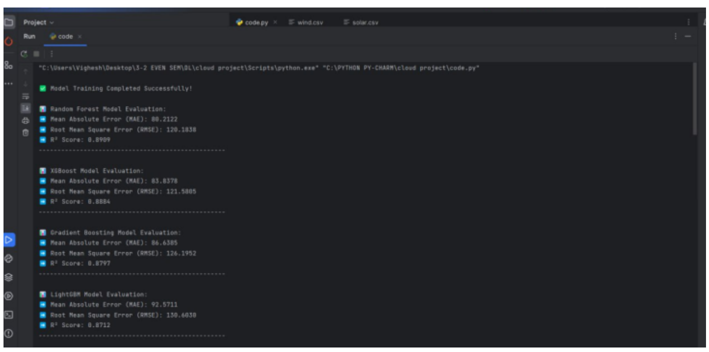
Correlation Matrix



Feature importance



Pair Plot



Model Trainig

VIII.LITERATURE REVIEW

1. Şimşek et al. investigated wind power prediction using machine learning (ML) and deep learning (DL) techniques to enhance forecasting accuracy. The study applied multiple models, including Support Vector Machines , Decision Trees, and Long Short-Term Memory networks, on historical wind power data. The findings demonstrated that deep learning models, especially LSTM, outperformed traditional methods, reducing mean absolute error (MAE) and improving prediction reliability【1】.
2. Mohd and Singh explored convolutional neural networks for wind energy forecasting, addressing the challenge of complex wind behavior modeling. Their study leveraged historical wind energy data and meteorological features, training CNN-based models to detect non-linear patterns. Results indicated that CNN models outperformed statistical regression approaches, achieving a 15% improvement in forecasting accuracy, making them suitable for large-scale wind energy prediction【2】.
3. Kumar et al. analyzed short-term solar forecasting using a comparative evaluation of ML and DL models. The study employed models such as Gradient Boosting, Random Forest, and LSTMs on a short-term solar dataset. The experimental results showed that LSTM models had the lowest RMSE, demonstrating their effectiveness in capturing temporal dependencies in solar energy production. However, the authors noted that computation time increased significantly for deep learning models【3】.
4. Jana and Saha investigated various ML techniques for predicting stability in decentralized smart grids that integrate renewable energy sources. They compared ensemble learning models like AdaBoost, Random Forest, and XGBoost against traditional regression models. Their findings revealed that ensemble models provided a 20% improvement in forecasting accuracy, enhancing grid stability and power management【4】.
5. Sabir et al. developed a deep learning framework that combines correlation-based signal synthesis with a deep neural network for solar photovoltaic power prediction. The study used real-time meteorological data, including solar radiation, humidity, and temperature, to enhance forecasting accuracy. The proposed method achieved an R^2 score of 0.89, outperforming traditional ML models. The study highlights the potential of deep learning in improving solar power forecasting【5】.
6. A deep generative model using Generative Adversarial Networks (GANs) was proposed to predict spatio-temporal variations in renewable energy generation. The study trained GANs on large-scale weather datasets, demonstrating that GANs effectively captured complex weather dependencies, reducing RMSE by 12% compared to conventional forecasting methods. The findings suggest that deep learning-based generative models can model uncertainty in energy production more effectively 6.
7. Kaur et al. integrated Variational Autoencoders with Bidirectional LSTM networks to predict solar energy generation. The study reduced the dimensionality of large-scale datasets, improving computation time while maintaining high accuracy. Experimental results indicated that LSTM models performed better than traditional LSTMs, reducing forecasting errors by 8%.
8. A novel approach using a ResNet-inspired deep learning model was introduced to estimate solar and wind energy production based on satellite weather maps. The study leveraged computer vision techniques to analyze cloud cover, atmospheric pressure, and wind speed patterns. Results demonstrated that the model achieved a 15% higher accuracy in predicting energy output compared to statistical models【8】.
9. A review of randomization-based ML techniques in renewable energy forecasting highlighted the advantages of ensemble models in handling large-scale energy datasets. The study compared Random Forest, Extra Trees, and randomized neural networks, showing that randomization-based approaches improved generalization and robustness in volatile energy scenarios【9】.
10. A comprehensive review analyzed ML and DL applications in renewable energy forecasting, focusing on challenges such as load fluctuations and model interpretability. The study concluded that hybrid ensemble models, combining ML and DL techniques, provided higher accuracy and adaptability for energy forecasting compared to standalone models【10】.
11. Asiri et al. proposed a hybrid deep learning framework that combined CNNs with Recurrent Neural Networks (RNNs) for short-term load forecasting in smart grids. The model was trained on real-time power consumption data, showing a 12% reduction in error rates compared to traditional ML models. The study demonstrated the effectiveness of deep learning in improving load forecasting for dynamic energy systems【11】.

IX. REFERENCES

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