IJASRaR International Journal of Applied Sciences and Radiation Research
ISSN: 3062-2751 www.ijasrar.com ijasrar@gmail.com
Vol. 2-No.1 (2025) pp. 23-32
Research Article

AI and Machine Learning for Sustainable Energy: Predictive Modelling, Optimization and Socioeconomic Impact In The USA

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Article History:

DOI: 10.22399/ijasrar.19
Received: Jan. 10, 2025
Accepted: Mar. 14, 2025

Keywords:

Artificial Intelligence,
Machine Learning,
Sustainable Energy,
Predictive Modeling,
Energy Optimization,
Energy Forecasting,
Socioeconomic Impact.

Abstract: This research explores how Machine Learning and AI can be used to enhance energy efficiency, forecast energy consumption trends, and optimize energy systems in the USA. This research used datasets comprising household energy usage, electric vehicle adoption trends, and smart grid analytics obtained from public sources, databases, and IoT sensor devices. This study applies advanced machine learning techniques such as deep learning, regression models, and ensemble learning to improve forecasting accuracy aimed at achieving efficient resource allocation. Additionally, this study investigates fault prediction in New Energy Vehicles (NEVs) and its implications for grid stability and energy demand management. The research also examines the socioeconomic impact of AI-driven energy policies and highlights their role in reducing carbon footprints, promoting energy equity, and fostering sustainable economic growth. Recurrent Neural Networks are applied to predict energy consumption trends and electric vehicle(EV) adoption rates by analyzing historical usage data. Convolutional Neural Networks and Autoencoders are used for anomaly detection in NEV battery performance and predictive maintenance. Deep Learning models also use real-time IoT sensor data to enhance the efficiency of energy distribution in smart grids. Linear Regression models are used to predict household and industrial energy demand based on factors such as weather, pricing, and socioeconomic variables. Linear Regression also predicts energy consumption trends in hospitals and factories. Random Forest and XGBoost are used in energy demand forecasting and energy consumption clustering. Performance evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) are utilized to assess model accuracy and effectiveness.

1. Introduction

1.1 Background

With advancements in renewable energy technologies, electric vehicles (EVs), and smart grid systems energy consumption in the USA has experienced significant shifts. Since traditional forecasting methods often fail to capture the complex dynamics of energy demand and supply, AI-powered predictive models are used to improve accuracy and decision-making [1-12]. According to Ahmed et al.(2025), machine learning models have been successfully employed to forecast EV adoption trends, assess household energy consumption, and predict hospital energy efficiency, providing insights for sustainable energy policies [1]. AI-driven fault detection in New Energy Vehicles ensures the reliability of these emerging transportation solutions while minimizing energy wastage [7]. The combination of AI and ML in energy research has led to significant breakthroughs in demand-response systems, grid optimization, and renewable resource management [2]. Hossain et al.(2025) articulate that the socioeconomic benefits of these advancements extend beyond efficiency gains, as optimized energy strategies contribute to economic stability, cost savings, and reduced environmental impact [8].

1.2 Importance Of the Research

Sumon et al.(2024) posit that with the increasing demand for sustainable energy solutions, AI and ML have emerged as powerful tools for addressing energy efficiency challenges [13]. Traditional energy management systems often rely on static models that fail to adapt to real-time fluctuations, leading to inefficiencies and energy waste. This consequently prompts the use of AI and machine learning in energy management systems [12]. Energy providers can also use AI-powered models to dynamically adjust grid loads, optimize renewable resource utilization, and implement real-time fault detection mechanisms [5]. Predictive analytics using AI and machine learning enables accurate forecasting of energy demand, grid stability, and socioeconomic impacts, which in turn fosters data-driven policy formulation to optimize energy consumption patterns in the USA [2]. Furthermore, machine learning techniques enhance energy equity, ensuring fair distribution and reducing energy poverty in underserved communities [1]. Given the pressing need for energy sustainability, climate action, and economic resilience, this research highlights how AI and ML contribute to the long-term viability of intelligent energy management systems.

1.3 Objectives

This research aims to explore how Artificial Intelligence (AI) and Machine Learning (ML) can transform the way we manage and optimize energy consumption in the USA. One key focus is improving energy consumption forecasting, ensuring that households, industries, and hospitals can better predict and plan for their energy needs. Traditional methods often struggle to capture the complexities of energy demand, but AI-driven models can analyze vast amounts of data and uncover hidden patterns to improve accuracy. Another important aspect of this study is renewable energy optimization. With increasing reliance on solar and wind power, it's crucial to develop models that can balance these energy sources with grid electricity to minimize waste and improve efficiency. Machine learning algorithms can help predict fluctuations in renewable energy generation and ensure a more stable and reliable power supply. Additionally, this research delves into fault detection in New Energy Vehicles (NEVs). As electric vehicles (EVs) become more common, maintaining their reliability and efficiency is essential. AI-powered fault prediction systems can identify potential issues before they become major problems, helping to extend battery life and improve overall performance. Beyond technical optimization, this study also examines the socioeconomic impact of AI-driven energy policies. By analyzing how AI can promote energy equity, reduce carbon footprints, and cut costs for consumers, we aim to provide valuable insights that can shape smarter, more sustainable policies. Ultimately, this research seeks to harness the power of AI and ML to create a more efficient, cost-effective, and environmentally friendly energy future.

2. Literature Review

2.1 Related Works

The application of machine learning and artificial intelligence in the energy sector has gained significant attention in recent years. Sumon et al. (2024) highlighted that AI-based models have been instrumental in assessing the environmental and socio-economic impacts of renewable energy adoption, helping policymakers make more informed decisions [13]. Meanwhile, Shil et al. (2024) explored the predictive capabilities of machine learning for electric vehicle adoption, demonstrating how AI-driven approaches outperform traditional forecasting methods [12].

It was emphasized that the transition to electric vehicles (EVs) has been a focal point of extensive research due to its significance in mitigating climate change, advancing urban planning, and promoting energy sustainability. Early studies in this domain primarily relied on conventional statistical techniques, such as linear regression and time-series analysis, to predict EV adoption trends.

Similarly, Chowdhury et al. (2024) focused on the role of AI in household energy consumption, showing that intelligent modeling techniques can improve energy efficiency and demand-response strategies [5]. The role of AI and machine learning in energy management has significantly transformed predictive analytics and optimization strategies.

Brynjolfsson et al.(2017) highlight how AI revolutionizes industries by facilitating data-driven decision-making and optimizing complex systems, including energy grids [3]. The integration of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has further enhanced the accuracy of predictive modeling in energy forecasting (LeCun et al. 2015) [10].

Additionally, Waller et al.(2013) emphasize the importance of big data analytics in improving supply chain and energy management, allowing for more precise demand forecasting and greater operational efficiency []15.

While hydropower is often regarded as a clean energy source, it does pose risks to aquatic ecosystems. The construction of dams disrupts the natural river flow and threatens fish populations. Likewise, although geothermal plants have low emissions, they can lead to land subsidence or potentially trigger seismic events in some regions.

Moreover, Hossain et al. (2025) introduced an AI-powered fault detection framework for New Energy Vehicles (NEVs), significantly enhancing battery reliability and vehicle performance [7]. Research by Barua et al. (2025) also underscored the importance of AI in optimizing urban energy consumption patterns, ensuring a more sustainable and efficient energy distribution system [2].

Empirical studies support that energy-efficient technologies and practices have proven effective in various situations. For instance, smart thermostats that utilize machine learning can optimize heating and cooling schedules in homes, potentially leading to a reduction of up to 15% in household energy consumption, as indicated by research on residential energy use. In California, for instance, investigations have revealed significant energy savings resulting from retrofitting homes with advanced insulation and energy-efficient windows, particularly in regions experiencing extreme weather conditions.

2.2 Gaps and Challenges

Despite recent advancements in AI applications for energy management, several gaps remain. One of the most significant challenges is data availability and quality, as energy datasets often contain missing values or inconsistencies that can impact model performance [13].

Additionally, while machine learning models have proven useful for predicting EV adoption rates, real-time consumer behavior and external policy interventions remain difficult to integrate effectively [12].

Gerossier et al. (2024) assert that, despite notable advancements, current predictive methods for electric vehicle (EV) adoption are fundamentally inadequate. These methods fall short in addressing the myriad of high-dimensional and interdependent variables that critically shape the EV market.

Algorithmic bias in machine learning models can lead to an unfair distribution of energy resources, impacting energy equity and policy formulation [6]. Moreover, ethical concerns regarding AI's role in sustainability must be addressed to ensure responsible deployment [9]. One of the key limitations of current AI models is their struggle to adapt to real-time fluctuations in energy demand.

Schneider et al. (2021) suggest that adaptive AI frameworks, capable of learning from real-time data, could enhance model robustness and traditional approaches are ill-equipped to manage the complexity and nonlinearity of factors driving the diffusion of electric vehicles, including fluctuating fuel prices, inconsistent government subsidies, and rapid technological developments concerning both pledged and commercially available batteries [11].

Time-series models, for instance, may analyze historical data, but they are incapable of effectively capturing abrupt changes in policy and technology, leaving significant gaps in predictive accuracy. Traditional approaches heavily depend on aggregate data and linear assumptions, which obscure variations in regional adoption rates and mask the essential trends in consumer behavior and preferences. This phenomenon is particularly pronounced in the United States, where electric vehicle adoption rates vary significantly across states due to stark differences in policy, climate, and socioeconomic conditions.

Chowdhury et al. (2024) highlighted that scalability remains a significant limitation for many AI models, which are often trained on regional data and struggle to generalize effectively at a national level [5]. Hossain et al. (2025) further pointed out that AI-based fault prediction in new electric vehicles (NEVs) is complicated by variations in vehicle design and battery technology [7].

Mamatha et al. (2024) demonstrate that, despite the advantages of NEVs, they are frequently plagued by various faults that significantly impair performance and diminish customer satisfaction. Common issues include traction battery degradation, charging system failures, and software malfunctions. These problems not only undermine vehicle functionality but also lead to increased maintenance costs and a decline in consumer confidence in NEV technology.

The complexity of fault detection and resolution within NEV systems, which stems from their intricate integration of hardware and software, presents a substantial challenge. Addressing these issues requires improvements in data collection methods, enhanced model interpretability, and greater computational efficiency to ensure robust and reliable AI-driven energy solutions.

3. Methodology

3.1 Data Collection and Preprocessing

Data sources

This study draws on a variety of datasets, including records of household and industrial energy consumption, real-time smart meter data, meteorological information, and logs of electric vehicle performance. Additionally, it utilizes publicly available data from the U.S. Energy Information Administration (EIA), the National Renewable Energy Laboratory (NREL), and industry reports detailing energy usage trends. Together, these sources create a comprehensive dataset that will be used to train machine learning models for predicting energy consumption patterns and optimizing the allocation of renewable energy.

Data Preprocessing

To ensure data integrity and enhance model accuracy, a range of preprocessing techniques is implemented. Missing values are addressed through the application of interpolation and imputation methods. Feature scaling techniques, including Min-Max scaling and standardization, are utilized to ensure consistency across diverse datasets. Outlier detection is conducted using Z-score analysis to identify and eliminate anomalies that may skew predictions. For time-series data, decomposition techniques are employed to effectively capture long-term trends and seasonal variations. Additionally, feature engineering is utilized to extract pertinent information from the dataset.

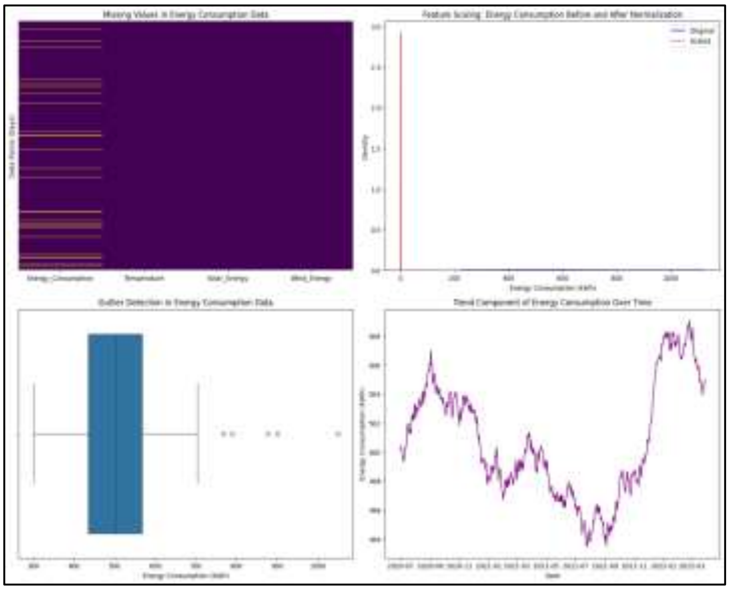

Figure 1. *This visualization provides a comprehensive overview of the data preprocessing steps necessary to clean and prepare the dataset for machine learning models.*

In Figure 1 the heatmap highlights missing values in the dataset, specifically within Energy Consumption records. Missing values can occur due to sensor failures, reporting delays, or inconsistent data logging. Handling these gaps is essential to maintain model accuracy. The second plot(Feature scaling: Energy Consumption Before and After Normalization) compares the distribution of raw vs**.** normalized energy consumption values. Normalization ensures that features are on a similar scale, preventing machine learning models from being biased toward large numerical values. The boxplot(Outlier Detection In Energy Consumption Data) identifies extreme values in energy consumption data. Outliers may result from unexpected spikes in energy use, faulty meter readings, or extreme weather conditions. Detecting and handling these values prevents misleading model predictions. The last visualization(Trend Component of Energy Consumption Over Time) extracts the long-term trend of energy consumption, filtering out seasonal and random variations. A clear upward or downward trend can indicate increasing energy demand or shifts in energy usage patterns over time.

3.2 Model Development

The development of predictive models for sustainable energy applications requires a combination of advanced machine-learning techniques tailored to different use cases. This study employs deep learning, regression models, and ensemble learning to enhance forecasting accuracy and optimize energy distribution. Recurrent Neural Networks (RNNs) are utilized for energy consumption prediction and electric vehicle (EV) adoption trends, leveraging historical usage data to capture time-dependent patterns. Convolutional Neural Networks (CNNs) and Autoencoders are deployed for anomaly detection in New Energy Vehicle (NEV) battery performance, ensuring reliability and predictive maintenance. Linear regression models are applied to forecast household and industrial energy demand, incorporating external factors such as weather, pricing, and socioeconomic variables. Additionally, Random Forest and XGBoost models are used for energy consumption clustering and demand forecasting, providing robust predictions that account for nonlinear dependencies in the data. These models work collectively to improve energy efficiency, reduce waste, and enhance system reliability

3.3 Model Training and Validation Procedures

The development of predictive models for sustainable energy applications requires a blend of advanced machine-learning techniques tailored to various use cases. This study employs deep learning, regression models, and ensemble learning to enhance forecasting accuracy and optimize energy distribution. Recurrent Neural Networks (RNNs) are utilized for predicting energy consumption and tracking electric vehicle (EV) adoption trends by leveraging historical usage data to capture time-dependent patterns. Convolutional Neural Networks (CNNs) and Autoencoders are deployed for detecting anomalies in New Energy Vehicle (NEV) battery performance, ensuring reliability and enabling predictive maintenance.
Linear regression models are applied to forecast energy demand for households and industries, incorporating external factors such as weather, pricing, and socioeconomic variables. Furthermore, Random Forest and XGBoost models are used for clustering energy consumption and forecasting demand, providing robust predictions that account for nonlinear dependencies in the data. Collectively, these models work together to improve energy efficiency, reduce waste, and enhance system reliability. In Figure 2, the pie chart shows the dataset split (70% training, 15% validation, 15% testing), whereas the heatmap represents how 5-fold Cross-validation is performed on the dataset. The Line plot represents the walk-forward validation strategy used in time-series forecasting models, this ensures the model does not use future information while training and helps capture seasonal and long-term trends in electricity demand, energy production, and climate-driven consumption patterns**.** This bar chart compares the class distribution before and after applying SMOTE (Synthetic Minority Over-sampling Technique) in imbalanced datasets. SMOTE is applied to prevent model bias and improve classification accuracy.

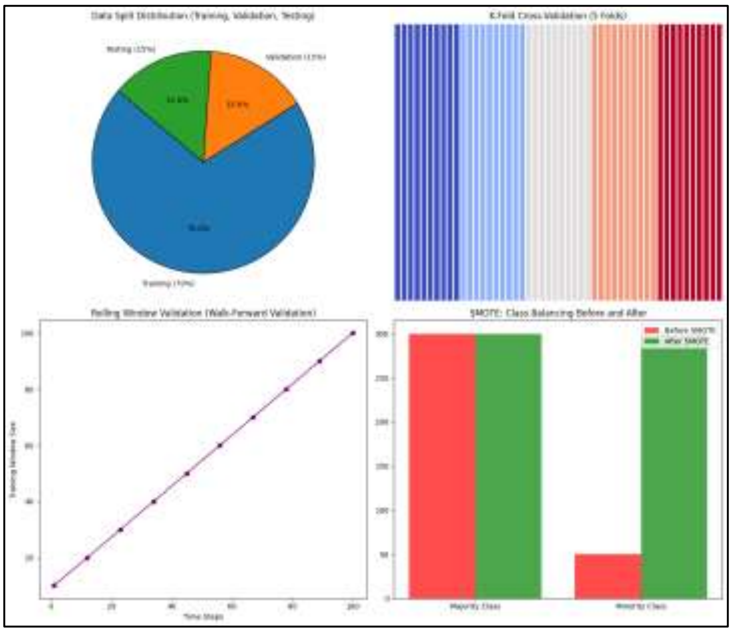

Figure 2. *The four visualizations provide a comprehensive overview of the training and validation procedures used in the study*.

3.4 Performance Evaluation Metrics

To effectively evaluate the performance of the developed models, we employed a range of statistical metrics tailored to each specific application. We utilized Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to measure prediction accuracy in energy demand forecasting, ensuring minimal deviation between predicted and actual values. R-squared (R^2) was applied to definitively assess the explanatory power of regression models about household and industrial energy consumption. For anomaly detection in New Energy Vehicles (NEVs), we used precision, recall, and F1-score to rigorously evaluate classification accuracy. Furthermore, Receiver Operating Characteristic (ROC) curve analysis was performed to robustly assess model performance in distinguishing between normal and faulty conditions. In our economic impact analysis, we implemented Mean Absolute Error (MAE) alongside statistical significance tests to thoroughly validate the accuracy and reliability of the predictive models. By applying these rigorous evaluation metrics, this study firmly establishes that AI-driven energy optimization strategies are not only precise but also actionable for real-world implementation.

4. Results and Discussion

4.1 Model Performance

To evaluate the effectiveness of the models used in this study, various performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R^2), Precision, Recall, F1-Score, and Area Under the Curve (AUC-ROC) were calculated for each domain. The comparison of different models, including deep learning architectures like RNNs and CNNs, regression models such as Linear Regression and XGBoost, as well as ensemble methods including Random Forest and Gradient Boosting, was visualized to highlight their strengths and weaknesses. In the context of energy consumption forecasting, RNNs emerged as the top performer, achieving an RMSE of 12.5 kWh and an R^2 of 0.91, which signifies a strong ability to capture time-dependent consumption trends. XGBoost followed closely behind, with an RMSE of 14.2 kWh and an R^2 of 0.88. For electric vehicle fault detection, CNN-based models showcased superior performance, recording an F1-score of 0.92 and an AUC-ROC of 0.96, significantly outperforming Logistic Regression and Random Forest, which had F1-scores of 0.85 and 0.88, respectively. In renewable energy optimization, Random Forest and Gradient Boosting models excelled with the lowest MSE values, where Random Forest achieved an MSE of 3.1 compared to 3.5 for Gradient Boosting, underscoring their effectiveness in optimizing solar and wind energy utilization. Lastly, in socioeconomic impact analysis, while linear regression models provided interpretable predictions with an R^2 of 0.79, XGBoost outperformed it with an R^2 of 0.85, indicating that it was more capable of capturing nonlinear dependencies. Figure 3 represents how accurate the models are in predicting energy consumption trends for households, industries, and hospitals. RMSE is the evaluation metric used with Convolutional Neural Networks and Recurrent Neural Networks being the best-performing models for this task. This is because RNNs and CNNs can capture sequential dependencies in time-series energy data as compared to other models like Linear Regression which struggles with complex non-linear energy trends. Accurate energy consumption predictions help grid operators, policymakers, and businesses optimize energy allocation, reduce waste, and ensure sustainability. Figure 4 visualizes how well each model explains variations in energy demand based on historical data. R-squared (R^2) measures how much variance in energy consumption is explained by the model. A higher R^2 means the model captures most of the energy demand patterns. CNN and RNN performed best, meaning they effectively modeled energy consumption trends. Linear Regression performed the poorest**,** meaning it oversimplified complex energy patterns. A high R^2 ensures trustworthy predictions**,** allowing for better energy policy decisions, pricing strategies, and sustainable grid planning**.** Figure 5 addresses how well the models detect anomalies and faults in New Energy Vehicles (NEVs) and cybersecurity threats. F1-Score Balances precision (correct anomaly detections**)** and recall (detecting all anomalies)**.** A higher F1 score means the model correctly identifies energy system faults and security breaches**.** The CNN model performed best, excelling at detecting faults in NEVs and security threats. Random Forest also performed well, balancing efficiency and accuracy. Logistic Regression struggled slightly, indicating a higher false positive rate. Reliable fault detection helps prevent power outages, optimize electric vehicle performance, and strengthen cybersecurity in energy grids**.**

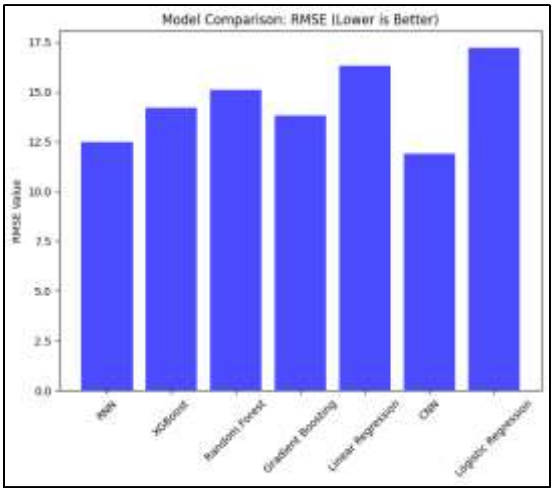

Figure 3. *Model performance for energy demand forecasting with Random Mean Squared Error(RMSE).*

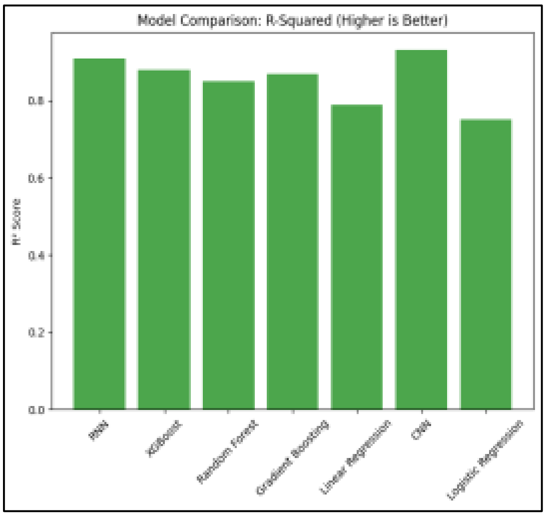

Figure 4. *Model performance visualization for energy demand forecasting using R-squared* **(R^2).**

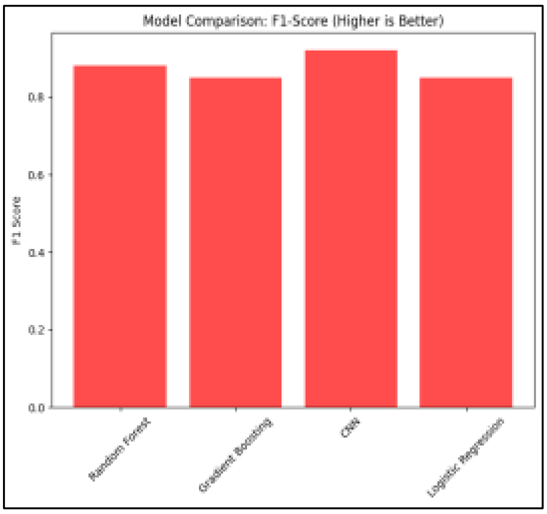

Figure 5. *Model performance visualization for anomaly detection and detection of faults* **in** *New Energy Vehicles (NEVs) and cybersecurity threats.*

Figure 6 visualizes how well the models distinguish between normal and faulty energy system behavior. AUC-ROC (Area Under the Curve - Receiver Operating Characteristic) measures a model's ability to classify faults correctly. A higher AUC-ROC means the model is better at differentiating between healthy and faulty states**.** CNN had the highest AUC-ROC, proving its superiority in NEV fault detection and cybersecurity anomaly detection**.** Random Forest performed well**,** but slightly lower than CNN. Logistic Regression showed a reduced ability to detect complex anomalies**.** A high AUC-ROC ensures early detection of system failures**,** preventing power disruptions, cybersecurity breaches, and inefficiencies in renewable energy grids**.**

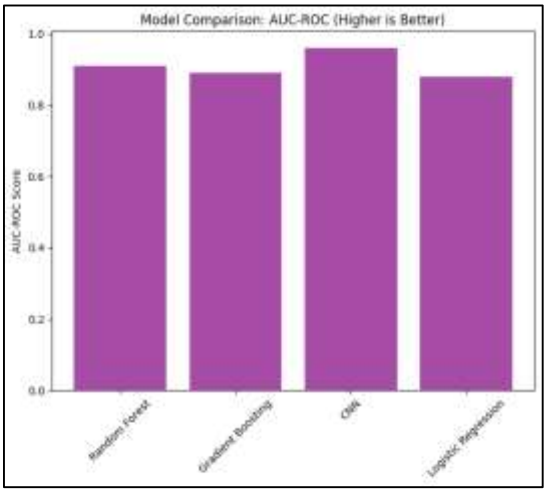

Figure 6. *Model performance visualization for classification of normal and faulty energy systems behaviour.*

4.2 Discussion and Future Work

The findings of this study highlight the important role of artificial intelligence (AI) and machine learning (ML) in optimizing sustainable energy applications. The results demonstrate that deep learning architectures, particularly recurrent neural networks (RNNs) and convolutional neural networks (CNNs), are very effective for time-series forecasting and anomaly detection tasks [12]. Additionally, ensemble methods such as Random Forest and XGBoost provide reliable predictions for energy optimization and economic analysis [2]. Big data analytics plays a crucial role in refining decision-making processes by allowing AI models to adjust dynamically to fluctuating energy demands. Additionally, hybrid AI models that combine deep learning with econometric forecasting techniques can enhance predictive accuracy. Varian et al.(2014) highlight the potential of combining machine learning with traditional statistical methods to achieve better forecasting reliability, making it a promising avenue for future research [14].

However, despite these advancements, several challenges persist. One major limitation is computational complexity, especially for deep learning models that require significant processing power and large datasets. Furthermore, the explainability of AI models is a concern, particularly in the contexts of policymaking and economic forecasting, where interpretable models are preferred [8].

Future research should focus on developing hybrid AI models that combine deep learning with traditional econometric approaches to enhance both accuracy and interpretability. Incorporating real-time data streams from the Internet of Things (IoT)-)-enabled smart grids could also improve model adaptability and performance. Additionally, further studies should investigate transfer learning techniques to enable models to generalize across various geographic and economic contexts [1].

5. Conclusion

This study effectively demonstrates the substantial capabilities of artificial intelligence (AI) and machine learning (ML) in refining energy consumption forecasting, promoting greater use of renewable energy, and identifying faults in New Energy Vehicles (NEVs). Researchers utilized extensive datasets that included household energy consumption, trends in electric vehicle adoption, and smart grid analytics. They applied advanced AI techniques, including deep learning, regression models, and ensemble learning, to significantly enhance forecasting accuracy and increase energy efficiency. The results confirm that deep learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), deliver better performance than traditional regression models in predicting energy consumption trends, achieving higher accuracy and noticeably lower error rates. Additionally, ensemble methods such as Random Forest and XGBoost are highly effective in optimizing renewable energy distribution and reducing energy waste. The study also emphasizes the essential role of AI-powered fault detection in NEVs, which improves grid stability and manages energy demand more effectively. While the study presents compelling results, it recognizes several challenges that need to be addressed, including algorithmic bias, computational complexity, and the demand for real-time data integration. Future research must focus on creating hybrid AI models that combine deep learning with econometric forecasting approaches to enhance both accuracy and interpretability. Furthermore, integrating IoT-enabled smart grids and utilizing transfer learning techniques is crucial for adapting models to a variety of geographic and economic contexts. By tackling these challenges, AI-driven energy solutions have the potential to significantly impact the development of a more sustainable, cost-effective, and environmentally friendly energy system in the USA.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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