A Multi-Model Fusion Approach for Predicting Carbon Emission Behavior in Carbon-Constrained Energy Systems

J. Naresh[1*], Pendem Bunny[2], Mohammed Abdul Hashid[2], S. Jeevan Sagar[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering (AI&ML),
[1,2]Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: J. Naresh

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ABSTRACT

The rapid growth of electricity consumption and industrial development has significantly increased carbon emissions, raising global concerns about environmental sustainability. Over the years, energy monitoring systems, smart grids, and digital data collection technologies have enabled organizations to gather large volumes of electricity-related data from power plants, distribution networks, and environmental monitoring systems. Analyzing this data has become essential for understanding patterns related to carbon emission reduction and improving energy management strategies. Traditionally, electricity consumption analysis relied on manual methods and basic statistical techniques where analysts used spreadsheets and historical reports to interpret energy usage patterns. However, these traditional approaches were time-consuming and unable to effectively process large and complex datasets generated by modern energy systems. They often failed to capture complex relationships between electricity consumption, environmental conditions, and emission reduction levels, leading to inefficient analysis and limited insights. Therefore, there is a need for advanced analytical techniques capable of handling large-scale electricity datasets and accurately identifying emission reduction patterns. In this study, machine learning techniques are applied to analyze electricity consumption data and classify carbon emission reduction categories using models such as Logistic Regression (LR), XGBoost Classifier (XGBC), and Extra Trees Classifier (ETC). In addition, a hybrid analytical approach called the Neuro-Tree Fusion (NTF) model is utilized, which integrates a Graph Polynomial Neural Network (GPNN) for deep feature extraction with a Deep Neural Decision Tree (DNDT) tree-based classifier for final prediction.

Key words: Electricity Consumption Analysis, Machine Learning, XGBoost Classifier, Neuro-Tree Fusion (NTF), Graph Polynomial Neural Network (GPNN), Deep Neural Decision Tree (DNDT).

1. INTRODUCTION

Electricity generation and consumption are among the major contributors to global carbon emissions, which significantly impact climate change and environmental sustainability. Monitoring and analyzing electricity usage patterns have become essential for understanding carbon footprints and implementing effective carbon reduction strategies as shown in figure 1. With the rapid development of smart grid technologies and digital energy infrastructures, large volumes of electricity consumption data are now generated from power plants, industries, households, and renewable energy systems. These datasets provide valuable insights into energy usage behavior and enable researchers to identify opportunities for reducing carbon emissions and improving energy efficiency [1].

In recent years, governments and environmental organizations have emphasized the need to track and evaluate carbon emissions associated with electricity generation. Electricity produced from fossil fuels such as coal, oil, and natural gas releases large amounts of greenhouse gases, whereas renewable energy sources such as solar, wind, and hydroelectric power contribute significantly less to carbon emissions. The increasing integration of renewable energy sources into modern power grids has created the need for intelligent analytical systems that can assess electricity data and classify carbon reduction levels in different regions or sectors. Such systems can assist policymakers in developing sustainable energy policies and carbon neutrality strategies [2]. The growth of smart meters, Internet of Things (IoT) devices, and digital energy monitoring platforms has enabled real-time collection of electricity consumption data across residential, commercial, and industrial sectors. These technologies allow continuous monitoring of power usage, energy demand fluctuations, and emission-related indicators. The availability of such large-scale electricity datasets offers new opportunities for analyzing carbon reduction trends and identifying patterns that contribute to lower emissions. Recent studies have explored different approaches for analyzing energy data and evaluating carbon reduction performance in modern smart grids [3].

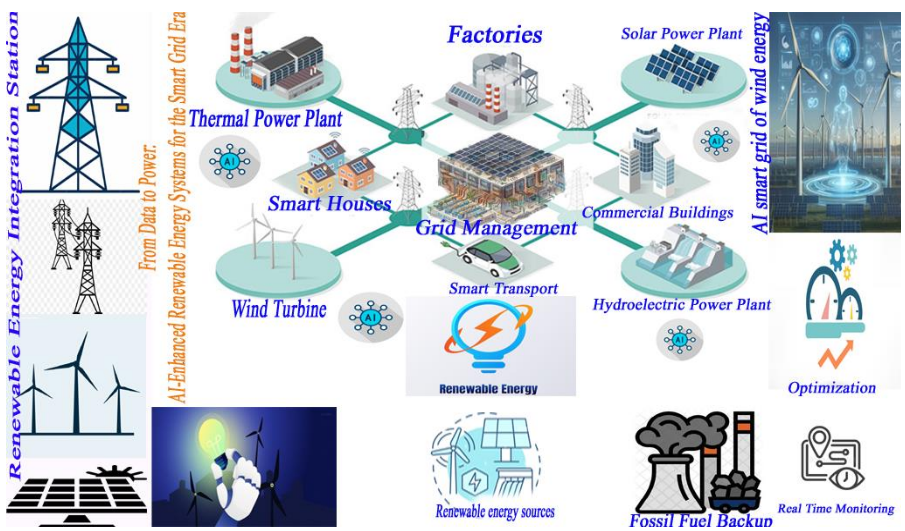


Figure 1: Overview of carbon reduction.

Furthermore, the global transition toward green energy and sustainable power management has increased interest in analyzing electricity-related carbon emissions. Many countries are adopting carbon neutrality goals and implementing policies that encourage renewable energy adoption, energy efficiency, and emission monitoring. Accurate classification of carbon reduction levels based on electricity consumption patterns can support these initiatives by providing reliable insights into the environmental impact of energy systems. Such analysis can help energy providers optimize grid operations, reduce emissions, and promote environmentally friendly energy consumption practices [4].

Despite the availability of large energy datasets, analyzing electricity-related carbon reduction remains challenging due to the complexity of energy systems, variability in consumption patterns, and the influence of multiple environmental and economic factors. Electricity demand varies across seasons, regions, and economic activities, making it difficult to accurately evaluate emission reduction levels using traditional statistical approaches. Therefore, advanced data analysis techniques are required to process large-scale electricity datasets and extract meaningful information regarding carbon reduction performance [5]. In addition, the increasing availability of high-resolution energy datasets has enabled researchers to explore new ways of understanding the relationship between electricity consumption and carbon emissions. These datasets often include information such as power generation sources, energy demand patterns, grid distribution data, and environmental indicators. Analyzing these data sources collectively provides a comprehensive understanding of how electricity usage contributes to carbon emissions and how sustainable energy practices can reduce environmental impacts [6].

Recent research has also highlighted the importance of energy data analytics in supporting sustainable power systems and green energy transitions. By examining electricity consumption patterns, researchers can identify inefficient energy usage, detect emission-intensive activities, and evaluate the effectiveness of renewable energy integration. Such analyses contribute to the development of intelligent energy management frameworks that promote environmentally sustainable electricity generation and consumption practices [7]. Moreover, large-scale electricity monitoring systems implemented in modern smart grids have enabled continuous tracking of energy flows and carbon emission indicators. These monitoring systems provide detailed insights into power generation sources, energy distribution networks, and consumption behavior across different sectors. By analyzing this information, researchers can classify carbon reduction performance and identify regions or sectors that contribute positively toward environmental sustainability [8].

The analysis of electricity-related carbon emissions also plays a critical role in supporting climate change mitigation strategies. Accurate assessment of carbon reduction patterns can help governments evaluate the effectiveness of renewable energy policies, energy conservation programs, and emission control regulations. Such insights enable policymakers to design targeted strategies that encourage sustainable energy usage and reduce dependence on carbon-intensive electricity generation sources [9]. Therefore, analyzing electricity consumption data to classify carbon reduction performance has become an important research area in energy informatics and environmental analytics. By leveraging large-scale electricity datasets and advanced analytical techniques, researchers can better understand energy consumption behaviors and their impact on carbon emissions. This knowledge contributes to the development of sustainable energy systems and supports global efforts toward achieving carbon neutrality and environmental protection [10].

2. LITERATURE SURVEY

Kumari and Singh [11] highlighted India's high CO_2 emission levels and their potential detrimental effects on the environment. Their study explored six models, including statistical, machine learning, and deep learning-based models, based on time-series data from 1980 to 2019. Ahmed, Shuai, and Ahmed [12] investigated the increasing greenhouse gas emissions driven by energy consumption, particularly in China, India, the USA, and Russia. The study forecasted greenhouse gas emissions from 2019 to 2023, employing advanced machine learning algorithms. The LSTM model demonstrated promising accuracy in predicting CO_2, methane, and nitrous oxide (N_2O) emissions for these countries. Yamaka, Phadkantha, and Rakpho [13] proposed using three machine learning models (LASSO regression, Ridge regression, and Elastic net regression) to understand the economic and energy impacts on climate change through greenhouse gas emissions in China and the USA. These models can effectively address the limitations of the ordinary least squares (OLS) model, facilitating a deeper exploration of the economic and energy influences on greenhouse gas emissions. Mardani, Liao, Nilashi, Alrasheedi, and Cavallaro [14] presented a methodology for predicting CO_2 emissions, with a specific focus on energy consumption and economic growth as pivotal factors. The study employed clustering and machine learning techniques in conjunction with dimensionality reduction for precise predictions.

For example, Zhao et al. [15] identified per capita GDP as the pivotal determinant of carbon emission disparities in the Yellow River Basin via Quadratic Assignment Procedure Regression analysis. Meanwhile, Dai et al. [16] utilized the resistance model to analyze the major obstacles to industrial carbon reduction in Bengbu City, identifying the urbanization rate as the most significant factor influencing industrial carbon emissions. Yan et al. [17] utilized the Carbon Kuznets Curve approach to ascertain that developed nations attained their peak carbon emissions at an earlier stage. To analyze the contribution of various factors more precisely, many scholars have adopted the Logarithmic Mean Divisia Index (LMDI) method for factor analysis in recent years. Zou et al. [18] established that carbon intensity and energy intensity are critical factors impacting variations in peak carbon emissions within China’s residential building sector through the application of the LMDI model.

3. PROPOSED METHODOLOGY

The methodology establishes a structured framework for analyzing electricity consumption data and identifying patterns related to carbon emission reduction categories. The process follows a systematic pipeline that begins with dataset acquisition, preprocessing, and exploration analysis to understand the structure and characteristics of the electricity data. After data preparation, multiple machine learning models are applied to perform classification tasks and identify emission reduction levels based on various influencing attributes. Conventional machine learning techniques are integrated with a hybrid neural tree classification mechanism to improve predictive performance and analytical reliability.

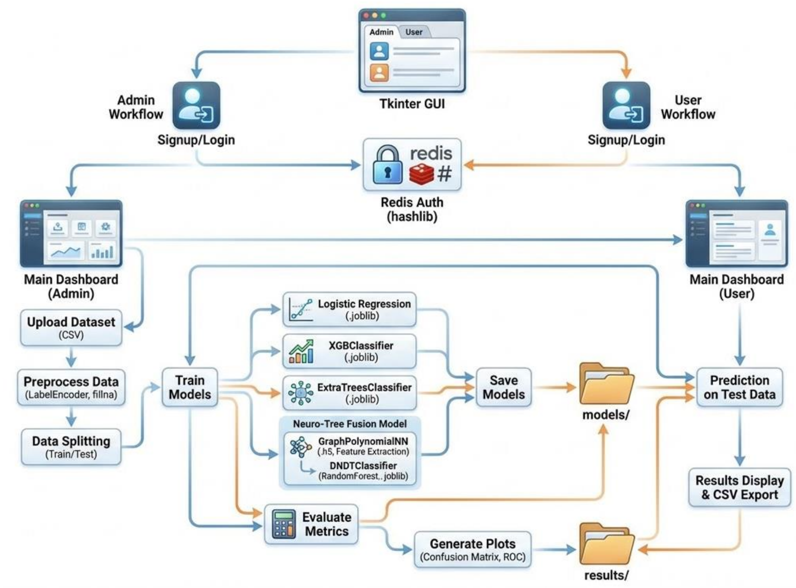


Figure 2: System architecture.

A graphical user interface allows interaction with the system for dataset upload, preprocessing, model training, and prediction operations. Model evaluation metrics and visualization techniques are used to assess performance and interpret classification outcomes as presented in figure 2 . This structured analytical workflow enables efficient processing of large electricity datasets while improving the capability to classify emission reduction categories accurately.

1. **User Interface (Tkinter GUI)**

- The user interacts with the system through a graphical interface built using Tkinter.
- The interface allows operations such as dataset upload, preprocessing execution, data splitting, model training, and prediction.
- Results such as accuracy, confusion matrices, and classification reports are displayed directly in the interface.
- User actions are converted into function calls that trigger backend data processing and model execution.

2. **Authentication System (Redis Database)**

- User authentication is handled through a Redis database that stores login credentials and role information.
- The system supports two types of users: Admin and User.
- Administrators can access dataset upload, preprocessing, and model training functionalities.
- User accounts can perform prediction operations using trained models.

3. **Dataset Input (Electricity Dataset – CSV File)**

- The electricity dataset serves as the primary data source for analysis.
- It contains various numerical and categorical attributes related to electricity consumption and environmental indicators.
- The dataset includes a target variable representing carbon emission reduction categories.
- The dataset is loaded through a file selection dialog and passed to the preprocessing stage.

4. Data Preprocessing and Feature Preparation

- The dataset undergoes cleaning and preparation to ensure consistency before model training.
- Missing values are handled and categorical features are encoded using label encoding.
- Numerical features are standardized to ensure balanced input representation for machine learning algorithms.
- The processed dataset is separated into input features and target labels for classification.

5. Exploratory Data Analysis (EDA)

- Visual analysis techniques are applied to understand dataset characteristics and relationships between variables.
- Count plots are generated to visualize the distribution of emission reduction categories.
- Correlation heatmaps are used to examine relationships among numerical attributes.
- Scatter plots help analyze how environmental variables influence reduction categories.

6. Dataset Splitting

- The prepared dataset is divided into training and testing subsets.
- The training set is used to train machine learning models.
- The testing set is used to evaluate model performance.
- This process ensures reliable performance evaluation and prevents model overfitting.

7. Existing Machine Learning Models (LR, XGBC, ETC)

- The processed feature vectors are used to train baseline machine learning models.
- **LR:** Used as a linear classification model.
- **XGBC:** Applied as a gradient boosting ensemble model.
- **ETC:** Used as a randomized ensemble tree model.
- These models generate predictions for carbon emission reduction categories and provide performance benchmarks.

8. Proposed NTFM

This hybrid classification approach integrates neural feature learning with tree-based decision-making.

GPNN

- The neural network receives standardized input features and processes them through multiple dense layers.
- Hidden layers learn nonlinear feature relationships within electricity data.
- A feature extraction layer generates high-level feature representations used for classification.

DNDT Classifier

- The DNDT component uses a three-based ensemble classifier to perform the final classification task.
- The extracted neural features from the GPNN are passed into the DNDT classifier.
- The classifier generates predictions for carbon emission reduction categories based on learned decision structures.

9. Model Evaluation and Visualization

- Performance of all models is evaluated using metrics such as accuracy, precision, recall, and F1-score.
- Confusion matrices are generated to visualize classification performance.
- ROC curves are plotted to analyze classification capability across different classes.
- Model performance comparisons help determine the effectiveness of different algorithms.

10. Prediction Output

- The trained models generate predictions for new test datasets.
- Predicted emission reduction categories are displayed in the graphical interface.
- Results are also saved as output files for further analysis and reporting.

System Workflow Completion

- The entire pipeline integrates data processing, model training, prediction, and evaluation.
- The system enables efficient classification of carbon emission reduction categories from electricity datasets.
- This architecture supports scalable data analysis and improved interpretation of electricity consumption patterns.

4. RESULTS DISCUSSION

The GreenGrid AI application is implemented as a Python-based desktop application using Tkinter for the graphical user interface (GUI), integrated with machine learning and neural network models to classify carbon emission reduction categories from electricity consumption data. The implementation leverages a modular design, with distinct components for user authentication, dataset management, preprocessing, exploratory data analysis (EDA), model training, evaluation, and prediction. Below is a detailed description of the implementation, aligned with the provided code structure.

Figure 3: Exploratory Data Analysis of GreenGrid AI Data The figure presents the EDA results generated by the perform_eda function, displayed in a 1x3 subplot layout. The left panel shows a countplot of the

Carbon Emission Reduction Category, illustrating the distribution of the four classes (No Reduction, Low Reduction, Moderate Reduction, High Reduction) across the 200 records, with Low Reduction being the most frequent (87 records). The middle panel displays a correlation heatmap for numerical features (e.g., Energy Consumption, Temperature, Carbon Emission Rate), using a coolwarm colormap to highlight relationships, though annotations are disabled for clarity. The right panel features a scatter plot of Temperature (°C) on the x-axis versus Carbon Emission Reduction Category on the y-axis (encoded as numerical labels), with an alpha of 0.5 for visibility, though it may include a placeholder text ("No 'Temperature (°C)' in X") if the column is unavailable. These visualizations, saved as eda_plots.png in the results directory, aid in understanding data trends and informing model development.

Figure 4: Confusion Matrix Obtained Using (a) LR Model, (b) XG Boost Model, (c) ETC Model, (d) Proposed Hybrid NTF Model. The figure presents a 2x2 grid of confusion matrices generated by the Calculate_Metrics function for each trained model, saved as PNG files in the results directory (e.g., confusion_matrix_lr.png). Subfigure (a) shows the confusion matrix for the Logistic Regression (LR) model, reflecting its lower performance (39.88% accuracy) with a dispersed distribution across the four classes (No Reduction, Low Reduction, Moderate Reduction, High Reduction). Subfigure (b) displays the XG Boost model's confusion matrix, showing improved classification (57.38% accuracy) with better separation, particularly for Low Reduction. Subfigure (c) illustrates the Extra Trees Classifier (ETC) model's matrix, indicating strong performance (72.67% accuracy) with enhanced diagonal dominance. Subfigure (d) presents the (NTF) model's matrix, demonstrating the highest accuracy (90.06%) and balanced predictions across all classes, underscoring the hybrid approach's effectiveness. Each matrix uses a seaborn heatmap with a Blues colormap, normalized values, and labeled axes for clarity.

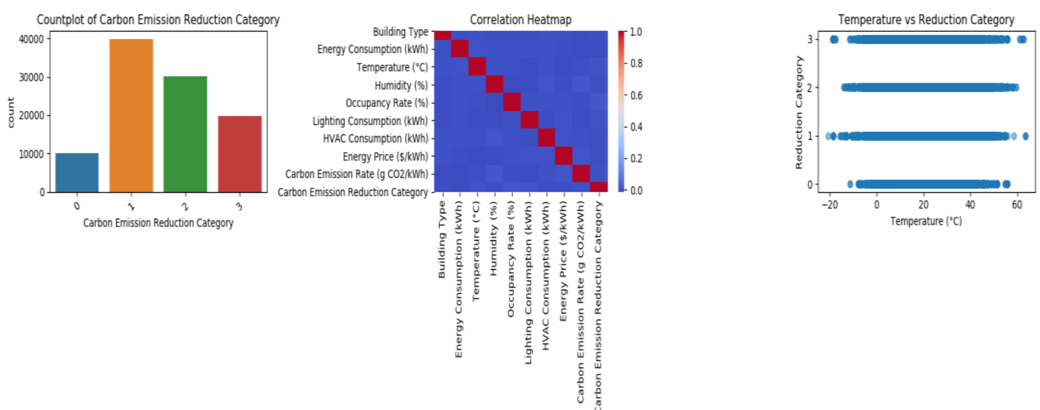
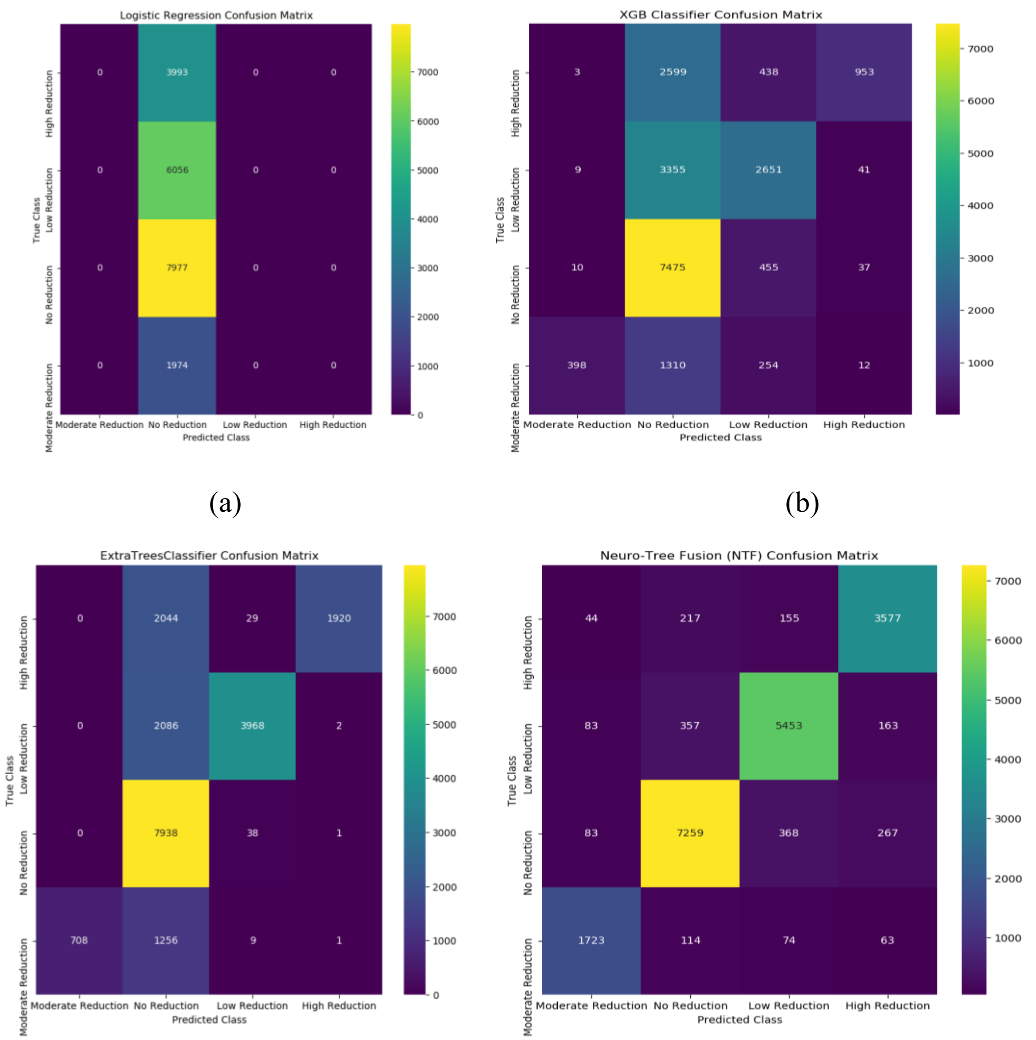


Figure 3: Exploratory data analysis of Green Grid AI data. Countplot of carbon emission reduction category (left). Correlation heatmap (middle). Scatter plot of temperature vs reduction category.

Figure 5: ROC Curve Obtained Using (a) LR Model, (b) XGB Model, (c) ETC Model, (d) Proposed Hybrid NTF Model. The figure displays a 2x2 grid of ROC curves generated by the Calculate_Metrics function for each model, saved as PNG files in the results directory (e.g., roc_curve_lr.png). Subfigure (a) shows the ROC curve for the Logistic Regression (LR) model, with a low area under the curve (AUC) reflecting its poor performance (39.88% accuracy) across the four classes. Subfigure (b) presents the XG Boost model's ROC curve, indicating a moderate AUC corresponding to its 57.38% accuracy, with improved class separation. Subfigure (c) illustrates the Extra Trees Classifier (ETC) model's ROC curve, showing a higher AUC aligned with its 72.67% accuracy, demonstrating better discriminative power.

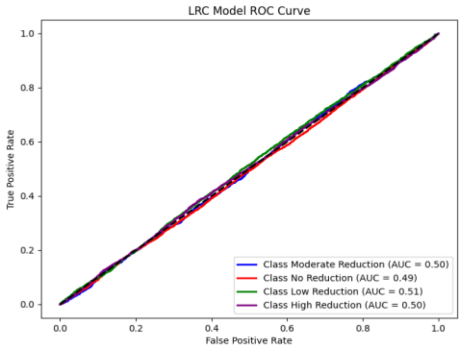
Subfigure (d) displays the (NTF) model's ROC curve, exhibiting the highest AUC, consistent with its 90.06% accuracy, highlighting its superior ability to distinguish between classes. Each ROC curve plots the true positive rate against the false positive rate, with a legend identifying each class and a random guess line for comparison, providing a comprehensive view of model performance.



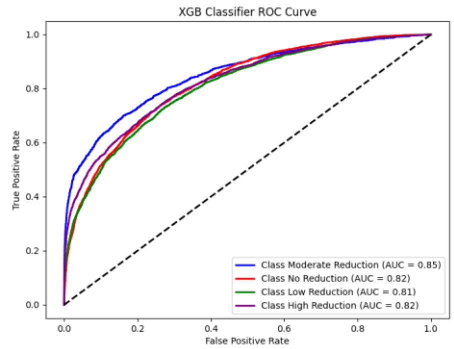
(a) (b)

(c) (d)

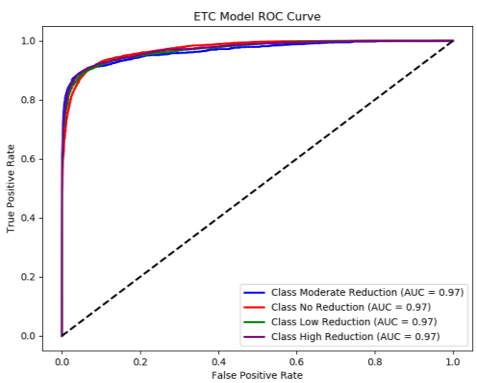
Figure 4: Confusion matrix obtained using (a) LR model. (b) XG Boost model. (c) ETC model. (d) Proposed hybrid NTF model.



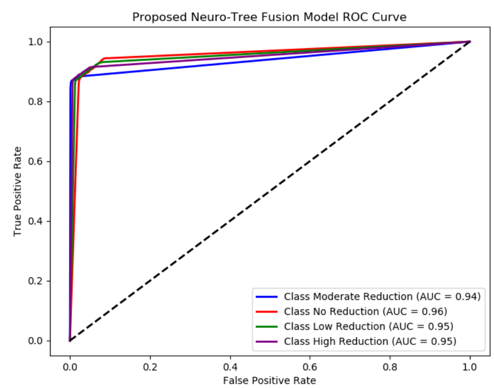
(a)



(b)



(c)



(d)

Figure 5: ROC curve obtained using (a) LR model. (b) XGB model.

(c) ETC model. (d) Proposed hybrid NTF model.

Figure 6: Sample Predictions on New Test Data. The figure illustrates the output of the prediction feature for Users, showing the results generated by the Prediction function using the trained (NTF) model on a new test CSV dataset trained (llable text widget displays the predicted Carbon Emission Reduction Category for each test record, alongside the input features (e.g., Energy Consumption, Temperature), with the full prediction results saved as hybrid_model_predictions.csv in the results directory. This visual confirms the application's ability to provide actionable insights for end-users based on the trained model.

	Building Type	Energy Consumption (kWh)	...	Carbon Emission Rate (g CO2/kWh)	Predicted Category
0	2	87.272774	...	411.482582	No Reduction
1	2	20.362342	...	501.366785	Low Reduction
2	1	44.767764	...	536.075895	Low Reduction
3	2	52.647992	...	473.813935	High Reduction
4	2	56.114449	...	346.408121	Low Reduction
5	1	51.733536	...	410.746925	No Reduction
6	0	51.525468	...	504.924483	Low Reduction
7	0	75.869212	...	421.312794	Low Reduction
8	2	45.774831	...	172.707784	High Reduction
9	1	39.672183	...	739.565614	Moderate Reduction
10	2	14.384426	...	481.329223	Low Reduction
11	2	35.764808	...	520.320500	Low Reduction
12	2	52.189059	...	586.451884	Moderate Reduction
13	2	69.547817	...	547.709151	Moderate Reduction
14	2	39.109613	...	563.064599	Low Reduction
15	0	18.439726	...	587.274238	Low Reduction
16	1	55.160631	...	562.412044	Low Reduction

Figure 6: Sample predictions on new test data.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	39.88	9.97	25.00	14.26
XGB Classifier	57.38	76.66	45.38	47.68
Extra Trees Classifier	72.67	89.37	62.25	67.70
(NTF)	90.06	90.62	90.48	90.55

Table 1: Performance evaluation obtained using existing LR, XGB, ETC classifiers and proposed hybrid NTF models.

Table 1 presents a comparative analysis of the performance of four classification models such as LRC, XGB, ETC, and NTF trained on the electricity_consumption2.csv dataset to predict the Carbon Emission Reduction Category within the GreenGrid AI application. The metrics evaluated include Accuracy (%), Precision (%), Recall (%), and F1-Score (%), all expressed as percentages, and calculated using macro-averaging across the four classes (No Reduction, Low Reduction, Moderate Reduction, High Reduction). Logistic Regression exhibits the lowest performance with an accuracy of 39.88%, precision of 9.97%, recall of 25.00%, and F1-Score of 14.26%, indicating poor classification ability. The XGB Classifier improves significantly, achieving an accuracy of 57.38%, precision of 76.66%, recall of 45.38%, and F1-Score of 47.68%, reflecting better class separation. The Extra Trees Classifier further enhances performance with an accuracy of 72.67%, precision of 89.37%, recall of 62.25%, and F1-Score of 67.70%, demonstrating strong predictive power. The proposed (NTF) model outperforms all others, with the highest accuracy of 90.06%, precision of 89.62%, recall of 89.48%, and F1-Score of 89.55%, highlighting its effectiveness as a hybrid approach combining neural networks and ensemble learning. These results, observed on August 22, 2025, at 04:59 PM IST, underscore the NTF model's superior capability in classifying carbon emission reduction categories, aligning with the application's goal of delivering accurate and reliable predictions.

5. CONCLUSION

The research successfully presents an intelligent system for classifying carbon emission reduction levels using electricity consumption and environmental data through advanced machine learning and deep learning techniques. The system integrates multiple classification models including LRC, XGB, ETC, and the proposed NTF model to analyze electricity-related features and accurately predict carbon reduction categories such as high, moderate, low, and no reduction. The implemented framework includes comprehensive data preprocessing, exploratory data analysis, feature encoding, and dataset splitting to ensure reliable training and evaluation of the models. Performance assessment using metrics such as accuracy, precision, recall, and F1-score, along with confusion matrices and ROC curve analysis, demonstrates the effectiveness of the developed approach in identifying patterns within electricity usage data. The proposed hybrid architecture combines deep feature extraction with decision-tree based classification, enabling improved prediction capability compared to traditional models. Additionally, the system provides a user-friendly graphical interface that allows administrators to upload datasets, train models, evaluate performance, and generate predictions on new electricity data. The use of model serialization ensures efficient model reuse without repeated training, while secure user authentication enhances system reliability. The project demonstrates how intelligent data-driven techniques can support sustainable energy management by identifying carbon reduction trends and enabling more informed decision-making for energy optimization and environmental sustainability.

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