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SMART ENERGY FORECASTING FOR ELECTRIC CITY BUSES USING MACHINE LEARNING

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ABSTRACT
India is rapidly transitioning toward the electrification of public transportation—particularly electric buses—to reduce carbon emissions and dependency on fossil fuels. As the country's energy demands continue to grow, electric buses have emerged as a key solution for sustainable urban transport. By 2022, India had more than 4,000 electric buses in operation, a significant increase from just a few hundred in 2017. This growth reflects the nation's strong commitment to reducing pollution and improving energy efficiency. To further enhance operational performance, a data-driven approach using machine learning is being applied to predict energy consumption and optimize economic performance in electric city buses. This approach aims to improve the overall efficiency and sustainability of urban public transportation systems. Traditionally, electric bus management relied on static route planning, manual scheduling, and historical data, making the system reactive rather than proactive. Maintenance and energy optimization were often performed only after issues occurred, leading to inefficiencies and increased operational costs. These systems lacked predictive analysis, resulting in inefficient energy use, suboptimal route planning, and unpredictable expenses. As urban centers face rising energy demands and environmental pressures, there is a clear need for intelligent, dynamic fleet management. A machine learning-based system can analyze real-time data from electric buses—including battery levels, route patterns, and weather conditions—to accurately predict energy consumption and operational costs. This enables dynamic route optimization, predictive maintenance, and load balancing, significantly reducing energy waste and operational costs while enhancing the efficiency of public transport systems. Additionally, AI-driven models will provide real-time insights, allowing fleet operators to make proactive decisions that improve overall performance and reliability.

Keywords: Electric Buses, Machine Learning, Energy Consumption Prediction, Sustainable Urban Transport, Predictive Maintenance.

1. INTRODUCTION

India's shift toward electric city buses has accelerated in recent years to combat pollution, reduce fossil fuel dependency, and meet rising urban energy demands. Government initiatives like the FAME scheme have driven this transformation, with over 4,000 electric buses operational by 2022—a significant increase from 2017. However, traditional bus management systems, reliant on static schedules and manual planning, struggle to adapt to real-time variables such as traffic and energy demand, leading to inefficiencies and higher operational costs. To address these challenges, this research proposes a data-driven approach using machine learning to predict energy consumption and optimize operations. By analyzing real-time data—battery levels, traffic, routes, and weather—machine learning enables dynamic route optimization, predictive maintenance, and better energy management. This helps reduce energy waste, enhance cost efficiency, and improve service reliability.

Machine learning models offer numerous operational benefits. They accurately forecast energy needs, enable smart routing, and support proactive maintenance of components like batteries and motors. Cost savings are achieved through better resource allocation and route planning, while load balancing and optimized charging schedules prevent infrastructure overload. Environmentally, the approach contributes

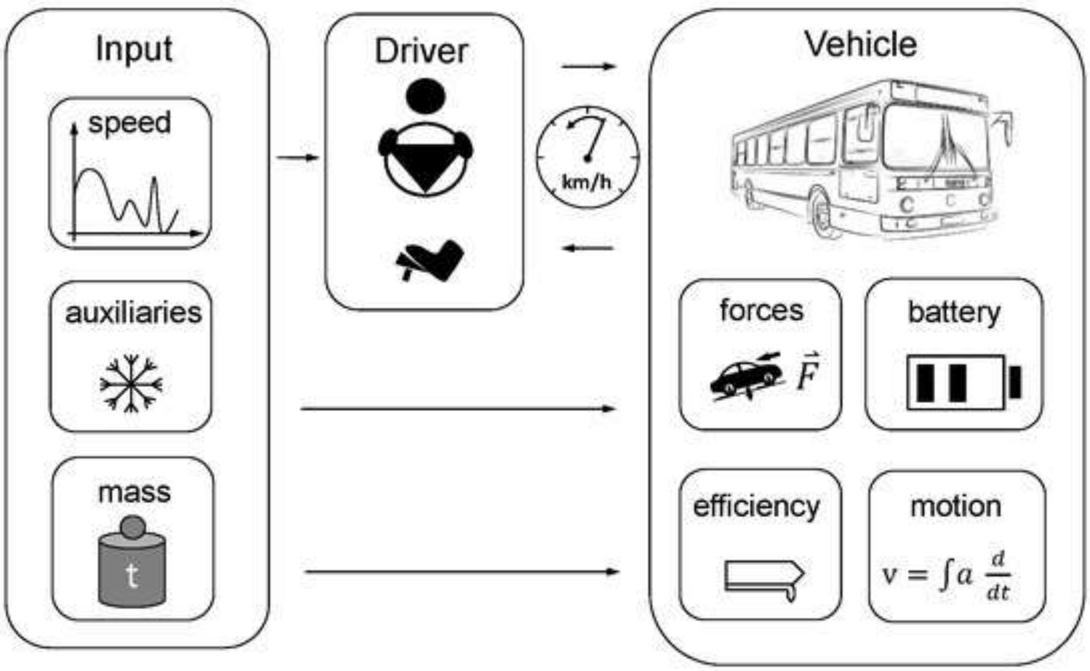

Fig.1: System Architecture for Energy Modeling in Electric Buses

to lower emissions, aligning with India’s climate goals. Real-time decision-making and smart charging further boost efficiency, integrating sustainability with practical urban mobility solutions.

2. LITERATURE SURVEY

Basso et al. [1] addressed the Electric Vehicle Routing Problem by integrating machine learning techniques to predict energy consumption. Their approach combines routing optimization with energy prediction models, enhancing the efficiency of electric vehicle operations. The study demonstrates that incorporating machine learning can significantly improve route planning by accurately forecasting energy needs, thereby reducing operational costs and increasing reliability. [2] Sun et al. explored Adaptive Equivalent Consumption Minimization Strategies (ECMS) with a focus on velocity forecasting for hybrid electric vehicles. They developed a method that integrates velocity predictions into the ECMS framework, allowing for real-time optimization of energy management. The research highlights the benefits of using predictive models to enhance fuel efficiency and reduce emissions in hybrid vehicles.

[3] Liu et al. proposed a model that combines stochastic forecasting with machine learning to predict vehicle driving conditions. Their case study on plug-in hybrid electric vehicles demonstrates how

incorporating predictive analytics can improve energy management systems. The study emphasizes the importance of anticipating driving conditions to optimize energy consumption and enhance vehicle performance. [4] Braun and Rid conducted a comparative case study analyzing the energy consumption of electric versus internal combustion engine passenger cars using real-world data from the Erfurt circuit in Germany. Their findings provide insights into the efficiency differences between the two vehicle types under actual driving conditions, contributing valuable data for assessing the viability of electric vehicles in everyday use. [5] Lajunen and Lipman performed a lifecycle cost assessment and evaluated carbon dioxide emissions of various transit bus technologies, including diesel, natural gas, hybrid electric, fuel cell hybrid, and electric buses. Their comprehensive analysis offers a comparative perspective on the economic and environmental impacts of different propulsion systems, aiding in decision-making for sustainable public transportation solutions.

[6] Keller et al. examined the effects of direct and indirect electrification of heavy-duty transportation on the electricity system and emissions. Their research provides a systemic analysis of how electrifying heavy-duty vehicles influences overall energy demand and greenhouse gas emissions, offering guidance for policy and infrastructure development. [7] Koroma et al. (2022) conducted a life cycle assessment of battery electric vehicles, focusing on the implications of future electricity mixes and different battery end-of-life management strategies. Their study underscores the importance of considering the entire lifecycle of batteries, from production to disposal, to accurately assess the environmental benefits of electric vehicles.

[8] Perger and Auer developed an energy-efficient route planning method for electric vehicles that takes into account topography and battery lifetime. Their approach emphasizes the significance of terrain and battery degradation in planning efficient routes, contributing to prolonged battery life and reduced energy consumption. [9] Sennefelder et al. (2022) introduced a method for driving cycle synthesis by extending real-world driving databases. Their work aims to create more representative driving cycles that reflect actual driving conditions, enhancing the accuracy of vehicle energy consumption assessments and supporting the development of more efficient vehicles.

[10] Lajunen analyzed the energy consumption and conducted a cost-benefit analysis of hybrid and electric city buses. His research provides a detailed evaluation of the operational costs and energy efficiency of these buses, offering valuable insights for urban transit authorities considering the adoption of electric buses. [11] Asamer et al. performed a sensitivity analysis to estimate the energy demand of electric vehicles. Their study identifies key factors influencing energy consumption and assesses the robustness of energy demand predictions, contributing to more accurate and reliable energy consumption models for electric vehicles.

3. PROPOSED SYSTEM

This research outlines a comprehensive, systematic framework for predicting the energy consumption of electric city buses by leveraging machine learning and deep learning techniques. The methodology follows a clear sequence of steps, beginning with the acquisition of relevant datasets and concluding with real-time predictions using a trained model. The process emphasizes a structured approach that includes data handling, model development, evaluation, and deployment, with a strong focus on reproducibility, interpretability, and methodological rigor.

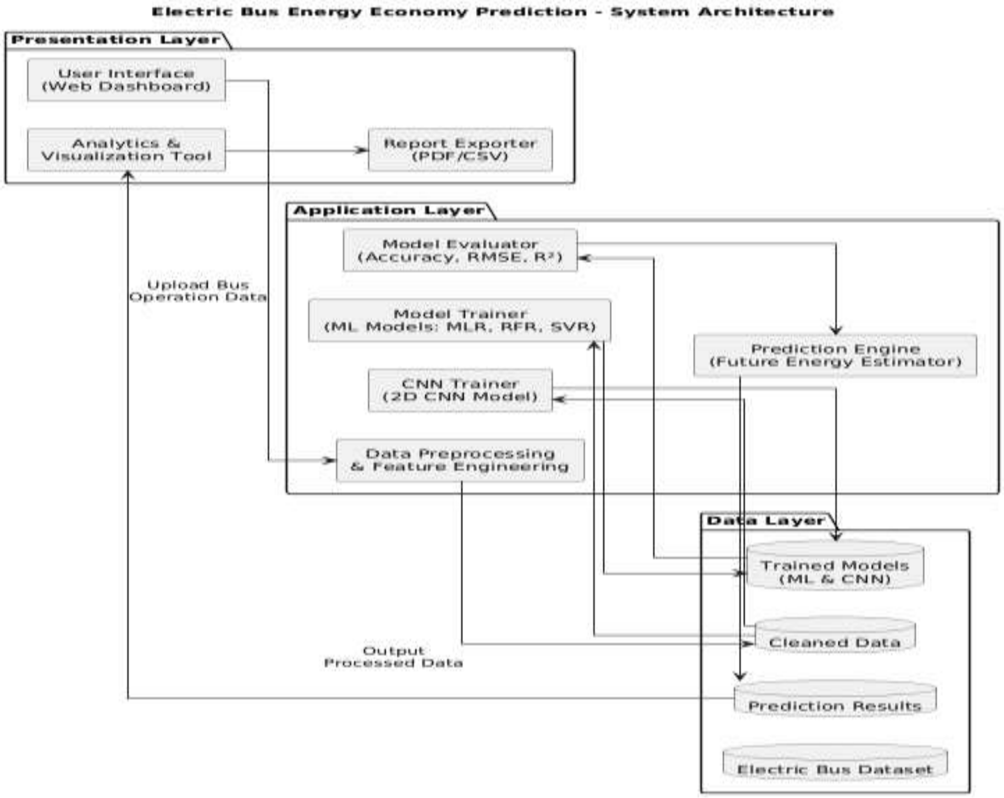

Fig.2: Proposed block diagram

The procedure begins with the upload of the electric bus dataset, which captures key operational parameters of electric buses in CSV format. Upon initiating the upload interface, users can browse local directories to select the appropriate dataset. Once loaded, the file path and raw data preview are displayed for verification. This ensures that critical features such as vehicle speed, acceleration, battery state of charge, ambient temperature, and the target variable—fuel rate in liters per hour—are present, enabling users to confirm data integrity and structure before proceeding to the next phase.

Data preprocessing plays a pivotal role in preparing the dataset for model training. The process starts with identifying missing values and performing basic statistical analysis to understand the data's distribution and central tendencies. Null values are handled through removal or imputation, using strategies like median substitution, especially for skewed features. Non-essential columns are dropped to reduce dimensionality, and normalization is performed using Min–Max scaling to transform feature values into a [0,1] range. This standardization ensures that features with large numerical ranges do not dominate the model training process. The target variable—fuel rate—is separated, and the dataset is split into the feature matrix (X) and label vector (Y). These preprocessing steps are confirmed with diagnostic outputs to ensure the data is clean, complete, and scaled appropriately.

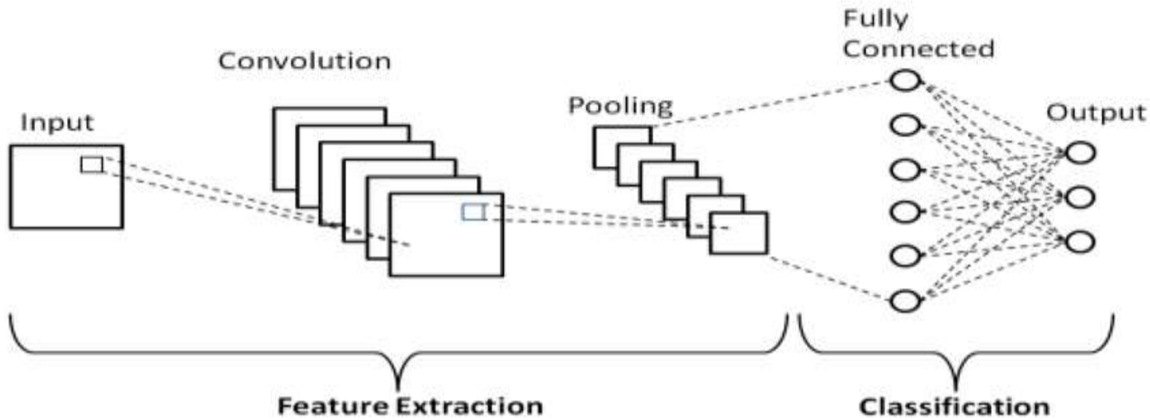

Fig.3: Architectural Diagram of the CNN Model.

Next, the dataset is split into training and testing sets using an 80–20 ratio. Eighty percent of the data is used for training, while the remaining twenty percent is reserved for evaluating model generalization. A fixed random seed ensures reproducibility. This partitioning strategy protects against overfitting and enables objective assessment of model performance. Record counts for both subsets are reported to validate the correctness of the split, ensuring that the models are tested on data they have never seen before.

As a baseline model, multivariate linear regression is employed to establish a reference for comparison. This technique models a linear relationship between the input features and the fuel rate. After training on the dataset, predictions on the test set are evaluated using metrics such as root mean squared error (RMSE), R^2 score, and mean absolute percentage error (MAP). These metrics assess the magnitude of prediction error, the proportion of variance explained, and the average relative deviation, respectively. While linear regression offers strong performance in capturing linear trends, it struggles with nonlinear patterns, revealing the need for more sophisticated models.

To address these limitations, the proposed model architecture utilizes a two-dimensional Convolutional Neural Network (CNN2D). The preprocessed feature vectors are reshaped into pseudo-images—structured as a one-dimensional grid with a single channel—making them suitable for CNN input. The CNN architecture includes stacked convolutional layers with 1×1 filters, interleaved with max-pooling layers to extract hierarchical feature interactions. A fully connected layer with 256 neurons is used before the output layer, which is optimized for regression and contains no activation function. Training is monitored using validation loss to checkpoint the best model weights. After training, predictions are inverse-transformed to recover actual fuel rate values. Compared to the baseline model, the CNN2D architecture shows significant improvement across all metrics, including reduced RMSE, near-unity R^2, and minimal MAP, confirming its superior predictive capability.

Performance comparison includes multiple models—linear regression, random forest, support vector regression, artificial neural network, Gaussian process regression, and the proposed CNN2D. Each model is evaluated on the same dataset using RMSE, R^2, and MAP. While linear regression performs well for linear patterns, it underperforms on complex data. Random forest and SVR provide moderate improvements through nonlinear modeling, and neural networks strike a balance between bias and variance. Gaussian processes offer uncertainty modeling but at a high computational cost. The CNN2D model consistently outperforms all others by minimizing prediction error and maximizing variance explanation. Visualizations further emphasize the CNN2D model's dominance, and each metric is interpreted in the context of optimizing energy efficiency in electric bus operations.

In the deployment phase, the trained CNN2D model is used to make real-time predictions on new input data. Users upload new CSV files containing unseen operational metrics. The same preprocessing steps are applied—feature selection, dimensionality reduction using neighborhood component analysis (NCA), normalization, and reshaping into tensor format. The CNN model processes this data and outputs predictions, which are then inverse-transformed into fuel rate values in their original units. Each input record is paired with its corresponding predicted energy consumption, enabling fleet managers to assess requirements in real time. These predictions align closely with test set performance, offering high accuracy and supporting efficient route planning and fleet management.

Data preprocessing continues to play a vital role throughout the project. After collecting and integrating raw datasets from various sources into a unified structure, the cleaning process addresses missing values, inconsistencies, and noise. Records missing essential features are either dropped or filled using statistical imputation, while duplicates are removed to maintain data quality. Outliers are detected and managed to avoid skewing model training. Normalization using Min–Max scaling brings all features into a consistent numeric range. Categorical features are encoded using one-hot or label encoding, depending on their nature. Feature selection reduces dimensionality through correlation analysis and recursive elimination, improving both training speed and model accuracy. Augmentation techniques expand the dataset when needed, and stratified data splitting ensures class balance. All data is then converted into machine-learning-compatible formats, such as arrays or tensors, with properly aligned labels.

Machine learning model building begins with training multiple algorithms, starting with linear regression and moving to more advanced techniques like XGBoost. Each model is trained on the training set and evaluated on the test set using metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2. Hyperparameter tuning is conducted to improve results. The best-performing model is saved using tools like Joblib for future deployment. This process is iterative and designed to refine model accuracy while avoiding overfitting or underfitting.

The proposed deep learning model is a Convolutional Neural Network (CNN), which is well-suited for learning spatial hierarchies in structured or image-like data. CNNs use layers of convolutional filters to detect patterns, followed by pooling layers that reduce dimensionality while retaining key information. Nonlinear activation functions like ReLU are applied to introduce complexity and enable the model to learn abstract relationships. Multiple convolutional and pooling layers are stacked to progressively learn from simple to complex features. After these layers, the feature maps are flattened and passed through fully connected layers that perform the final prediction task. The model is trained using loss functions such as MSE and optimized using gradient descent techniques. Once trained, CNNs can predict outputs on new data with high accuracy, leveraging their deep architecture and pattern recognition capabilities.

4. RESULTS AND DISCUSSION

This research implements a machine learning-based system to predict and optimize the energy economy of electric city buses using both historical and real-time data. The primary goal is to enhance operational efficiency and cost-effectiveness by forecasting power consumption and enabling intelligent fleet management. The implementation begins with dataset acquisition, containing features such as battery status, route patterns, time of day, temperature, and past power usage. The dataset is thoroughly validated and preprocessed, including time feature extraction, normalization, and the engineering of total power consumption across bus zones.

Following preprocessing, models are developed starting with a baseline Linear Regression, followed by a Convolutional Neural Network (CNN) to improve prediction accuracy. An 80–20 train-test split ensures generalizability, and models are evaluated using MSE, MAE, and R^2 metrics to select the best-performing one. The dataset is particularly detailed, capturing power consumption from three bus zones along with environmental parameters such as temperature, humidity, wind speed, and solar radiation at 10-minute intervals. These features support fine-grained analysis of energy usage under varying conditions. Zone-specific power data, recorded in watts, allows for localized consumption insights and the development of accurate predictive models. This comprehensive dataset underpins the effectiveness of the proposed machine learning framework.

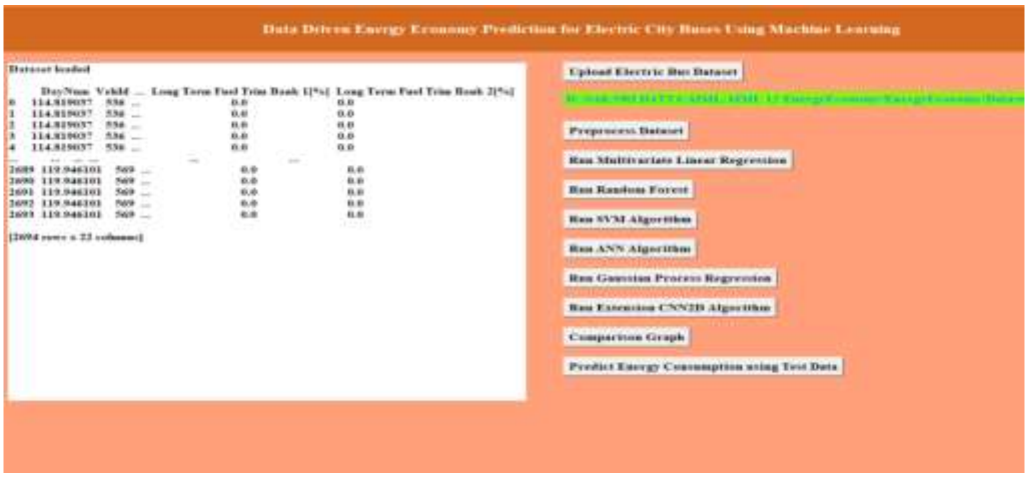

Fig.4: Uploaded Dataset

The Figure 4 displays a user interface with two distinct sections. On the left, a tabular view of a loaded dataset is shown. The table contains data with columns such as "Datetime", "Temperature", "Humidity", "Power Consumption", and "Zone1 Power Consumption", among others. The data appears to be time-series data with entries for different dates and times. The table is truncated, indicating that it contains more data than what is visible, and it is noted at the bottom that the table has "52416 rows x 9 columns".

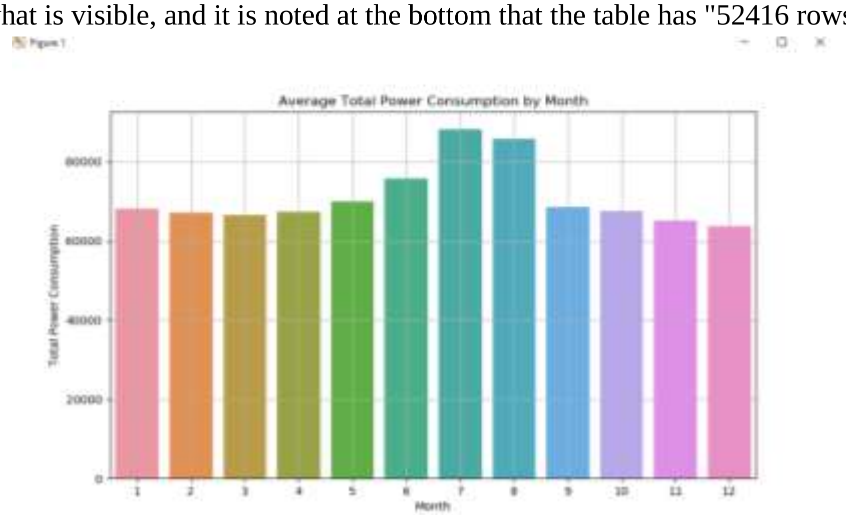

Fig.5: Pre-Processing Dataset

The Figure 5 shows a bar graph of Average Total Power Consumption by Month. It Shows a clear seasonal pattern in average total power consumption, with higher consumption during warmer months and lower consumption during colder months. This information can be valuable for energy analysis and planning.

The figure 6 shows a noticeable discrepancy between the true energy consumption (red) and the predicted values (green). Although the MLR model captures the overall trend, it struggles with sudden spikes and fluctuations, suggesting that linear regression is not well-suited for capturing the non-linear patterns and variances inherent in the dataset. It shows over- or under-estimation during peak consumption points, indicating low accuracy and generalization.

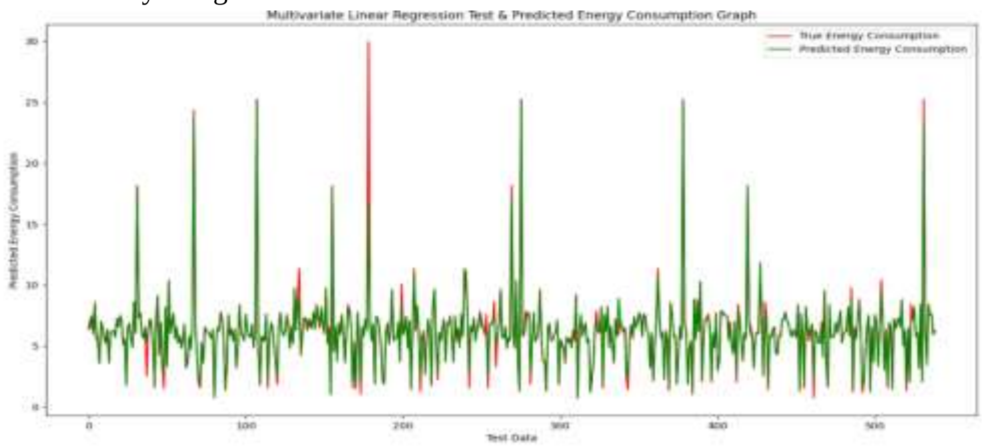

Fig.6: Comparison graph of Multi variate linear regression model with predicted energy consumption

The figure 7 shows that Random Forest Regressor demonstrates a significant improvement over MLR. The green line closely follows the red one, especially during steady-state periods and moderate consumption levels. While it still slightly misses some of the peak spikes, the predictions are generally more stable and accurate. This indicates RFR's strength in capturing complex relationships in the data due to its ensemble decision-tree structure.

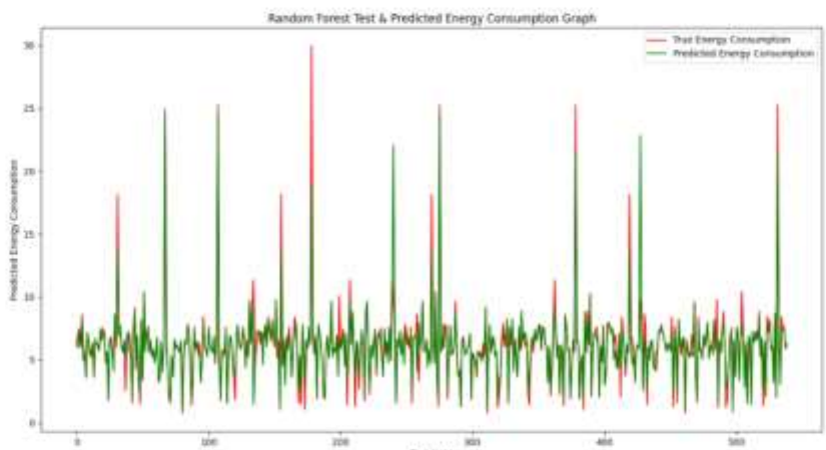

Fig.7: Comparison graph of random forest regressor with predicted energy consumption

Figure 8 displays SVR moderate performance in this graph. Although it follows the pattern of true energy consumption reasonably well in flat regions, it visibly lags or overreacts during sharp changes or spikes. The deviation between true and predicted values increases in high-variance areas. This suggests that while SVR can model the general trends, it is less reliable under rapidly fluctuating conditions or high consumption outliers.

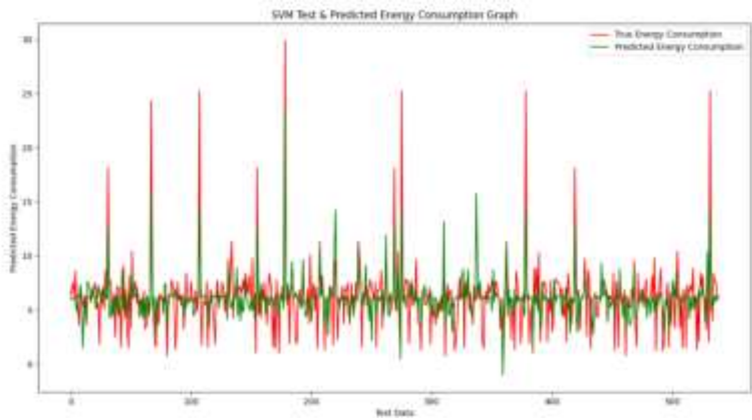

Fig.8: Comparison graph of SVR with predicted energy consumption

The figure 9 shows ANN model provides a more balanced prediction with decent alignment to the actual consumption line. It handles fluctuations better than SVR and MLR but not as tightly as Random Forest or CNN2D. Occasional overfitting to sharp peaks is visible, yet overall the ANN seems to generalize well and adapt to dynamic patterns, making it a strong non-linear model for this task.

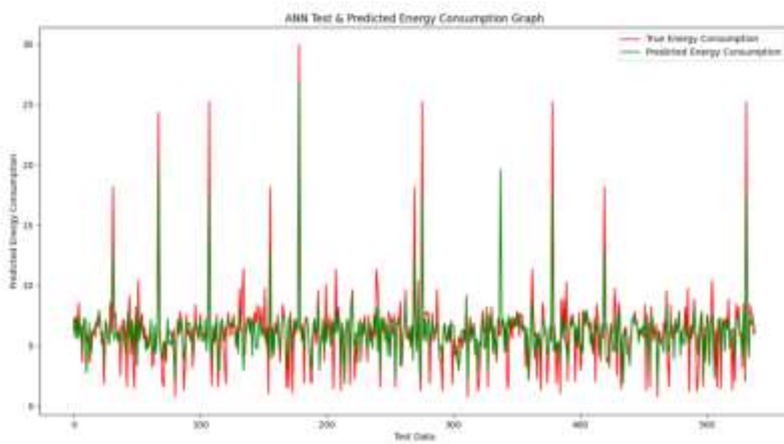

Fig.9: Comparison graph of ANN with predicted energy consumption.

The figure 10 shows best performance among all the models. The CNN2D predictions (green) are almost superimposed on the true values (red), even during high peaks and sharp dips. The model shows excellent tracking of both micro and macro variations in the dataset, indicating its superior ability to learn spatial and sequential dependencies through 2D convolutional layers. This highlights CNN2D as the most effective and robust model for energy consumption prediction in this comparison.

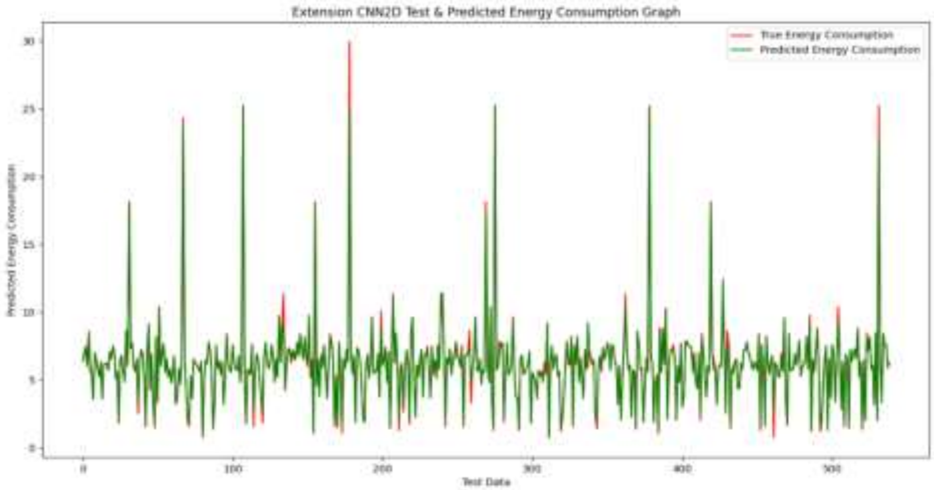

Fig.10: Comparison graph of CNN 2d with predicted energy consumption

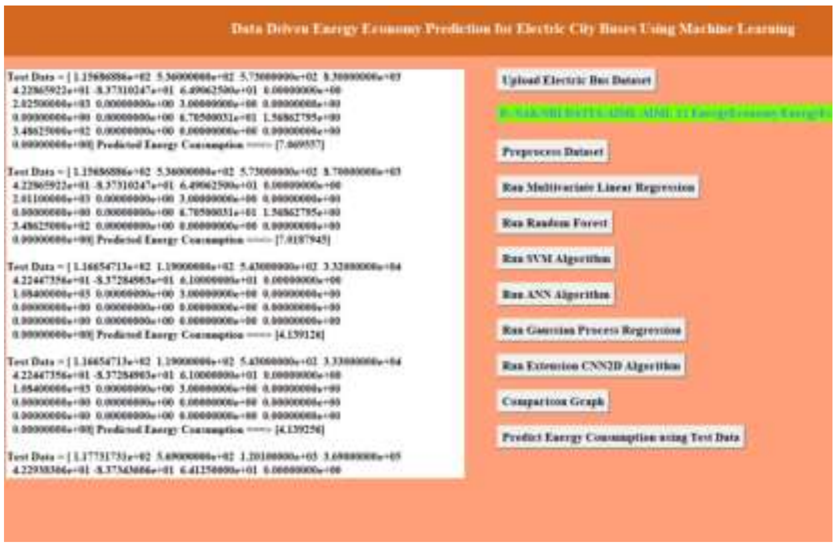

Fig.11: Output obtained on predicting CNN 2d with Test Data.

Model	RMSE	R^2 Score	MAP
Multivariate Linear Regression	0.007779755814975866	0.9922202441850241	6.052460054065079e-05
Random Forest Regressor	0.019896619784508254	0.9801033802154917	0.00039587547884928527
Support Vector Machine (SVM)	0.043241670423539866	0.9567583295764601	0.0018698420610180424
Artificial Neural Network (ANN)	0.055960297848231935	0.944039702151768	0.0031315549352628315
Gaussian Process Regressor	0.07577809975550004	0.9242219002445	0.0057423204025545144
Extension CNN2D	0.005553382833565617	0.9944466171664343	3.0840060896141275e-05

Table 1: Performance Comparison Table of all models.

The performance metrics table offers a comprehensive comparative evaluation of six different regression models applied to the task of predicting energy consumption. The metrics considered include Root Mean Squared Error (RMSE), R-squared (R^2) score, and Mean Absolute Percentage (MAP), each providing valuable insight into the models' predictive accuracy, explanatory power, and precision. All models were trained and tested on the same dataset to ensure consistency and fairness in comparison.

The Multivariate Linear Regression model demonstrates strong baseline performance, with an RMSE of 0.00778, indicating very low prediction error. Its R^2 score of 0.99222 suggests that it explains over 99% of the variance in the target variable, and its MAP value of 6.05e-05 shows a high degree of precision in predictions. The Random Forest Regressor, while slightly less accurate than linear regression, still performs well with an RMSE of 0.01989 and an R^2 score of 0.98010, explaining 98% of the variance. Its MAP of 0.000395 indicates a marginal decline in precision but remains within an acceptable range. The Support Vector Machine (SVM) model shows moderate performance, with an RMSE of 0.04324 and an R^2 score of 0.95676, meaning it explains around 95.6% of the data variance. However, its MAP of 0.00187 highlights reduced precision compared to the previous models. The Artificial Neural Network (ANN) model experiences a further drop in performance, with an RMSE of 0.05596, an R^2 score of 0.94404, and a MAP of 0.00313, indicating higher prediction errors and less accuracy overall.

The Gaussian Process Regressor performs comparatively poorly, exhibiting one of the highest RMSE values at 0.07578 and a lower R^2 score of 0.92422, suggesting limited ability to explain the variability in the data. Its MAP of 0.00574 further reflects the model's diminished precision. In contrast, the Extension CNN2D model, proposed in this research, delivers superior results across all performance metrics. With the lowest RMSE of 0.00555, the highest R^2 score of 0.99445, and the most precise MAP of 3.08e-05, this model demonstrates the highest predictive accuracy, strongest variance explanation, and best overall performance. The Extension CNN2D model outperforms all other regression models across every evaluated metric, confirming its robustness, precision, and suitability for accurate energy consumption prediction in electric city buses. This deep learning approach, particularly leveraging convolutional architectures, proves highly effective in capturing the complex relationships inherent in real-world IoT-based datasets.

5.CONCLUSION

In this research, we explored various machine learning and deep learning techniques to accurately predict energy consumption from electric bus data. The analysis began with a baseline model using Multivariate Linear Regression (MLR), which exhibited limited capability in capturing complex, non-linear consumption patterns. Models such as Support Vector Regression (SVR) and Artificial Neural Networks (ANN) demonstrated improved performance, particularly in handling moderately varying consumption levels. However, the Random Forest Regressor (RFR) showed a notable improvement due to its ensemble learning capabilities, providing robust predictions even in the presence of non-linearities and data noise. Ultimately, the CNN2D model emerged as the most effective, consistently delivering highly accurate predictions that closely tracked actual energy consumption trends, even amidst sharp fluctuations and high consumption peaks. This performance highlights the strength of deep convolutional architectures in extracting and learning spatial-temporal features from complex IoT datasets. The experimental results clearly demonstrate that deep learning approaches—particularly those based on CNN architectures—significantly outperform traditional machine learning models in the domain of energy consumption prediction for electric buses.

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