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Energy Economy Prediction for Electric Buses Using Machine Learning

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Abstract - In recent years, the transition to electric city buses has emerged as a pivotal component of sustainable urban transportation. This paper presents a data-driven approach to predicting the energy consumption and operational efficiency of electric city buses using advanced machine learning techniques. Our analysis employs algorithms such as Random Forest, Support Vector Machines, and Neural Networks, to capture the complexities of urban dynamics and enhance the reliability of energy forecasts. By integrating these predictive models into energy management systems, cities can enhance the performance of their electric bus fleets, reduce operational costs, and contribute to a greener urban environment. This research highlights the potential of machine learning as a transformation tool in the development of a data-driven energy economy for public transportation. This project aims at increased transparency of battery electric buses (BEB) energy economy. Achieving a prediction accuracy of more than 94%, our models performed excellent in combination with the sophisticated selection of features.

Key Words: Electric buses, Machine learning, Energy prediction, Neural networks, Sustainable transport, BEB

1.INTRODUCTION

The global shift towards sustainable transportation has gained momentum in recent years, driven by the urgent need to reduce greenhouse gas emissions and combat climate change. Among the various solutions being explored, electric city buses have emerged as a promising alternative to traditional diesel-powered vehicles, offering significant environmental benefits and operational efficiencies. However, the successful integration of electric buses into urban transit systems requires a comprehensive understanding of their energy consumption patterns and operational dynamics.

As cities continue to expand and evolve, the complexity of urban transportation systems increases, necessitating innovative approaches to energy management. Traditional methods of estimating energy needs often fall short in capturing the multifaceted interactions between various factors such as route characteristics, passenger demand, and environmental conditions. This is where machine learning (ML) comes into play, providing powerful tools to analyze large datasets and uncover hidden patterns that can inform decision-making.

In this context, we will explore various machine learning algorithms, assessing their effectiveness in predicting energy consumption and identifying key factors that influence operational performance. Additionally, we will evaluate the role of real-time data analytics in optimizing scheduling, battery usage, and overall fleet efficiency. The insights gained from this research will contribute to the development of a data-driven energy economy, ultimately supporting the transition to cleaner, more efficient public transportation systems.

Through this work, we aim to provide a valuable resource for policymakers, transit agencies, and researchers committed to advancing sustainable urban mobility while ensuring cost-effective and reliable transit solutions.

2.RELATED WORK

Various methods have been explored for predicting the energy economy of electric buses. [1] Wang and Li applied deep learning models for energy consumption forecasting, achieving high accuracy but requiring extensive computational resources. [2]Zhang et al. implemented Support Vector Machines (SVM), which performed well for small datasets but struggled with large-scale urban transit data. [3] Chen and Rao used Random Forest models, which reduced computational costs but faced challenges in handling dynamic route variations. [4] Patel and Singh employed regression-based approaches for real-time prediction, offering a lightweight solution but remaining sensitive to traffic and weather conditions. [5] Das et al. attempted deep learning-based optimization for large transit fleets, but it demanded significantly more resources than traditional methods.[6] Sharma and Gupta proposed a neural network-based energy forecasting model, improving accuracy at the cost of higher processing power.

In contrast to these approaches, our Energy Economy Prediction System prioritizes efficiency, scalability, and computational feasibility. It utilizes Random Forest, SVM, and Neural Networks for robust energy prediction, ensuring high accuracy without excessive computational overhead. This makes it practical for real-world urban transit applications..

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3. DATA PROCESSING AND ENERGY PREDICTION MECHANISM

Section 3.1 discusses the data collection and preprocessing techniques used in this system. Section 3.2 provides details on the model training process using machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and Neural Networks. Section 3.3 describes the energy consumption prediction mechanism, while Section 3.4 explains the energy management system and integration with real-time data for optimization.

3.1 Data Collection and Preprocessing:

The energy economy prediction system relies on various real-world datasets, including historical bus routes, passenger counts, traffic density, weather conditions, and battery usage patterns. These datasets are collected from GPS logs, smart sensors, and historical transit records.

- Data Filtering: Outliers such as abnormal energy consumption spikes are removed to improve model accuracy.
- Feature Selection: Key attributes such as speed, acceleration, temperature, and charging cycles are selected to enhance prediction accuracy.
- Data Normalization: All numeric features are standardized to ensure uniformity in model training.

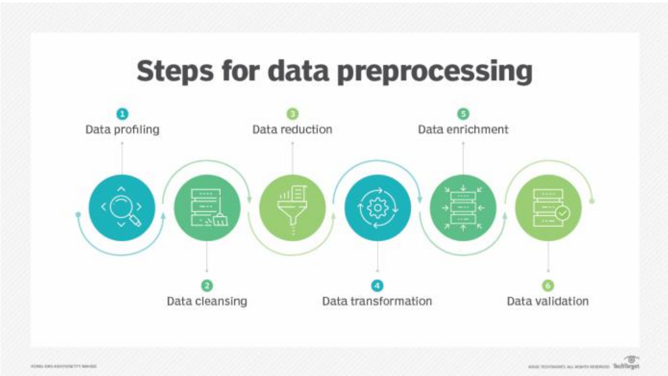

Fig-1: Data Preprocessing Workflow

3.2 Model Training with Machine Learning Algorithms:

The system employs Random Forest, Support Vector Machines (SVM), and Neural Networks for energy consumption prediction.

Random Forest: An ensemble learning method that builds multiple decision trees to improve prediction reliability.
SVM: A classification-based approach that identifies optimal decision boundaries between different energy consumption levels.
Neural Networks: A deep learning method capable of capturing complex nonlinear relationships in urban transit data.
The training process involves:
Feature Extraction: The preprocessed dataset is divided into training and testing sets.
Model Training: Algorithms are trained on historical bus energy data to learn patterns.
Performance Evaluation: Metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score are used to measure prediction accuracy.
The trained model is stored and optimized for real-time predictions.

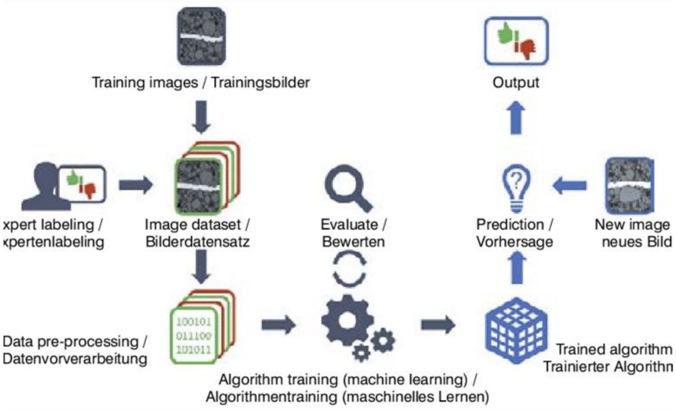

Fig-2: Machine Learning Training and Prediction Workflow

3.3 Energy Consumption Prediction Mechanism:

The Energy Prediction Model uses real-time inputs from buses, such as speed, route congestion, and temperature, to forecast energy usage.
Live Sensor Data: Integrated IoT devices collect and transmit data to the cloud.
Real-Time Inference: The trained model analyzes incoming data to estimate remaining battery levels and expected energy consumption.
Automated Alerts: If predicted energy usage exceeds expected limits, alerts are sent to fleet operators for corrective actions..

3.4 Energy Management System and Real-Time Integration:

The Energy Management System (EMS) systematically stores and organizes energy consumption data, allowing transit agencies to monitor trends and optimize bus operations.
Dashboard Visualization: A web-based interface displays route-wise energy usage trends and real-time vehicle statuses.
Predictive Analytics: Data-driven insights help optimize charging schedules and improve fleet efficiency.

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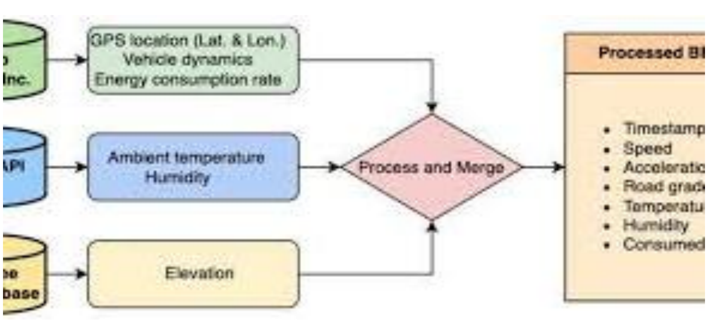

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Fig-3: Sample Excel Attendance Report

4.SYSTEM ARCHITECTURE

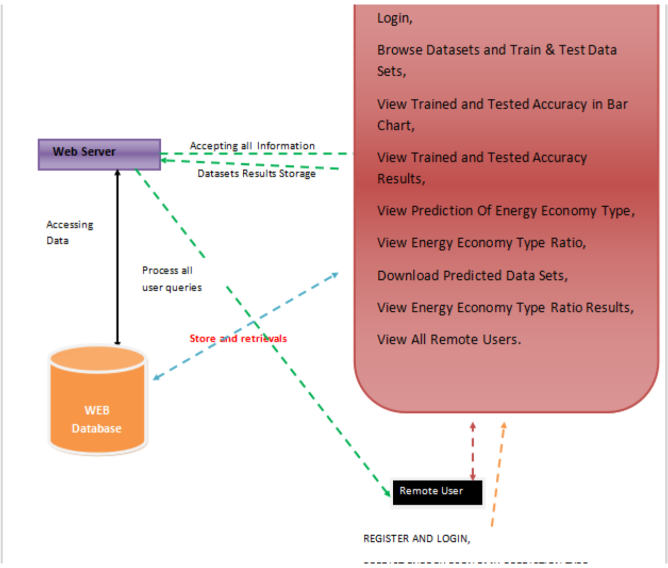

Fig-4: System Architecture

The Energy Economy Prediction System utilizes machine learning to analyze and optimize energy consumption in electric buses. By leveraging real-time and historical data, the system enhances efficiency, reduces operational costs, and improves fleet sustainability.

The Frontend is developed using HTML, CSS, and JavaScript, providing a user-friendly dashboard for monitoring energy trends. The Backend is built with Flask, ensuring smooth data processing and cloud integration for predictive analytics.

The Data Collection Module gathers information from IoT sensors, GPS trackers, and battery management systems, storing data for further analysis. Machine learning algorithms, such as Support Vector Machines (SVM), Random Forest, and Neural Networks, are employed to predict energy consumption based on route patterns, driving behavior, and battery usage.

The Predictive Analytics Engine uses these algorithms to identify optimal charging schedules, energy-efficient routes, and driving strategies. The system generates Excel-based reports, allowing transit agencies to track energy performance and refine operational strategies.

The Admin Dashboard provides an interface to monitor fleet-wide energy consumption, manage schedules, and access AI-driven recommendations. This system enhances sustainability, cost-effectiveness, and data-driven decision-making, making it a vital tool for efficient electric bus management.

5.RESULT:

Section 5.1 presents the web application interface, detailing the user login, admin page registration with dashboard. while Section 5.3 discusses the integration of attendance data storage and export functionalities.

5.1 Web Application Interface:

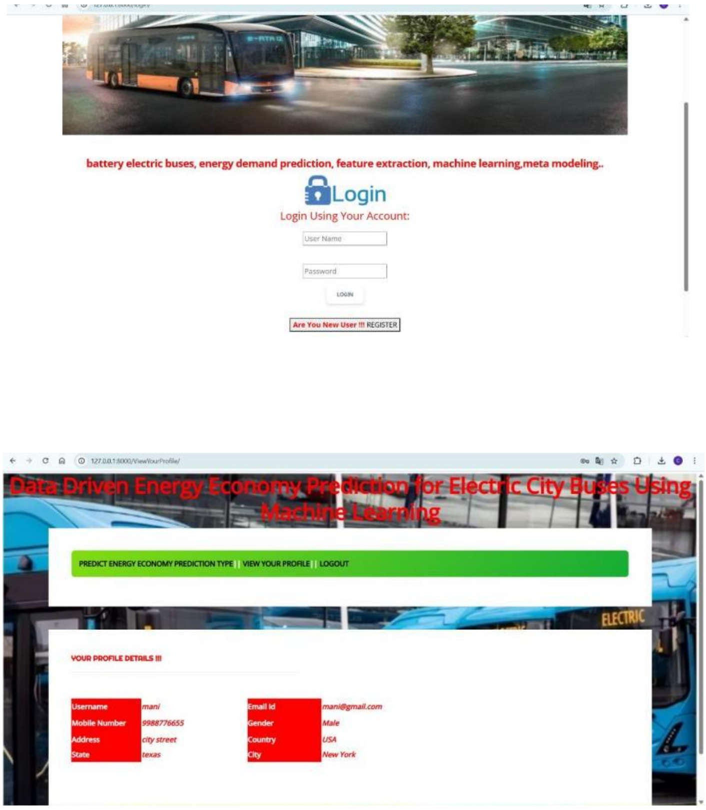

Fig-5: **User Login Page** (By providing the login and password the user can logged in) and **Dashboard** (Each individual user can see their input details).

Fig-6: Service Provider where the admin has the authority to view the test and trained datasets, algorithms used and the detailed analysis of the graphs.

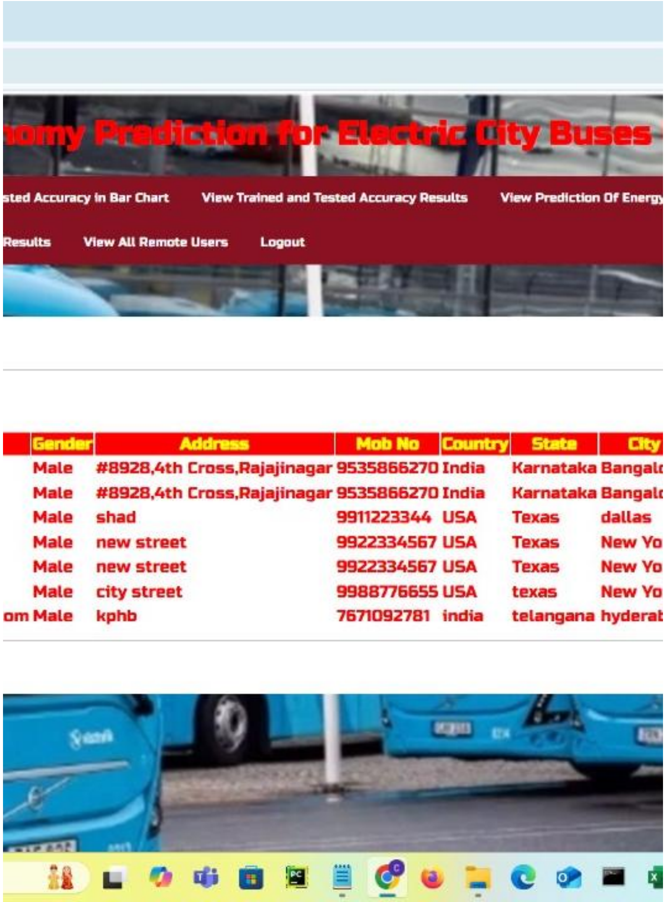

Fig-7: Admin Dashboard page where the admin can view all the user entries with their details like username, email,gender address, mobile no,country,state,city.

Fig-8: The **admin page** where the admin can view the predicted output efficiency percentage in the form of high or low..

5.2 Algorithms Efficiency Representation

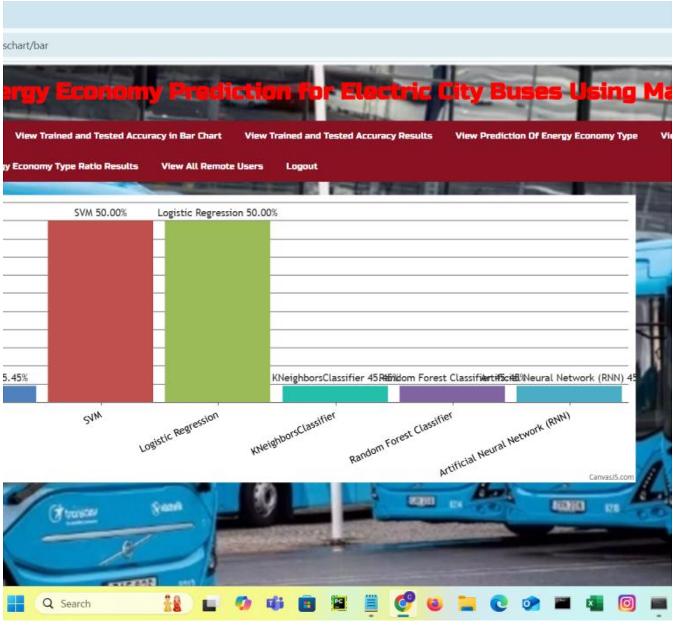

Fig-9: This image represents the accuraate efficiency of the algorithms used with their percentages.

6.CONCLUSION:

This research presents a data-driven approach using simulated and real-world data for public transport electrification. Feature selection and regression analysis effectively characterize battery electric bus (BEB) energy consumption under real driving conditions. Fleet operators can use this method to size batteries, optimize bus operations, and select charging strategies. The Vehicle Routing Problem is emphasized, requiring prior knowledge of energy demand for reliable service. A novel selection of explanatory variables, including spectral entropy of velocity profiles, improves energy prediction, ensuring efficient and scalable electrification planning

7.FUTURESCOPE:

Future research will extend this approach to various scenarios, aiding fleet operators in electrifying heavy-duty trucks, passenger vehicles, and rail transport. Further analysis of meteorological conditions, road types, and operational features will enhance predictive analytics for peak power, battery demand, and energy efficiency. Additionally, seasonally changing conditions will be examined, ensuring robust feature selection for different use cases. By refining predictive models, this methodology can support sustainable transportation planning, optimize fleet management, and improve decision-making in energy consumption.

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