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EV PREDICTING LOCATION

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ABSTRACT

The rapid growth of electric vehicles (EVs) has transformed the global transportation ecosystem. However, the increasing number of EVs has created challenges related to charging infrastructure, traffic congestion, and energy demand forecasting. Predicting the real-time and future location of electric vehicles using Artificial Intelligence (AI) plays a crucial role in smart transportation systems and sustainable urban planning. This research proposes an AIdriven framework for predicting EV movement patterns and determining optimal charging station placement using machine learning algorithms.

The proposed system integrates GPS trajectory data, traffic density information, battery level data, and environmental variables to forecast EV location and charging demand. Multiple models including Long Short-Term Memory (LSTM), Random Forest, and Gradient Boosting are evaluated for prediction accuracy. The study demonstrates that AI-based prediction improves charging station utilization efficiency, reduces waiting times, and supports energy grid stability.

1. Introduction

Electric Vehicles (EVs) are rapidly replacing conventional fuel-based vehicles due to environmental concerns and government regulations promoting carbon neutrality. Countries like the International

Energy Agency report exponential growth in EV adoption globally. However, this growth demands intelligent management of EV movement and charging infrastructure.

One major challenge in EV ecosystems is predicting vehicle movement patterns and identifying where charging demand will arise. Without predictive systems, charging stations may become overcrowded in some areas while remaining underutilized in others. This imbalance leads to user dissatisfaction and inefficient energy distribution.

Artificial Intelligence (AI) and Machine Learning (ML) offer powerful tools for analyzing large-scale vehicle trajectory data. By using historical mobility patterns, AI models can predict future EV locations and optimize charging station placement. This research focuses on designing and evaluating such a predictive framework.

2. Literature Review

Recent studies have explored mobility prediction using machine learning techniques. Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM), have shown strong performance in sequential data modeling. Researchers have used LSTM for taxi demand prediction and traffic forecasting with promising results.

Another stream of research focuses on charging station placement optimization. Techniques such as K-means clustering and Genetic Algorithms have been applied to identify high-demand zones. However, these studies often rely on static demand assumptions and do not incorporate dynamic location prediction.

Few studies integrate real-time EV trajectory prediction with infrastructure planning. This gap highlights the need for a comprehensive AI-based framework that combines spatial-temporal modeling and optimization algorithms, which this research addresses.

3. Problem Statement

Despite the increasing number of EVs, urban charging infrastructure planning lacks predictive intelligence.
Current systems do not effectively forecast:

- Future EV positions
- Charging demand hotspots
- Traffic-based mobility patterns This results in:
- Long waiting times at charging stations
- Underutilized infrastructure
- Energy grid instability

Therefore, an AI-based predictive system is required to enhance EV ecosystem efficiency.

4. Objectives of the Study

1. Develop an AI-based model to predict EV future locations.
2. Analyze spatial-temporal patterns of EV movement.
3. Identify optimal locations for new charging stations.
4. Compare performance of multiple ML algorithms.
5. Evaluate system accuracy and scalability.

5. System Architecture

The proposed system consists of five main modules:

1. Data Collection Module
2. Data Preprocessing Module
3. AI Prediction Engine
4. Charging Demand Estimation
5. Optimization Module

The architecture integrates GPS data streams, traffic APIs, and battery monitoring systems. Data is processed and fed into ML models for training and prediction.

6. Data Collection

Data is collected from:

- GPS trajectory logs
- Traffic density sensors
- Battery level monitoring systems
- Weather APIs
- Road network maps

Public datasets from smart mobility platforms were used for experimentation. The dataset includes timestamp, latitude, longitude, speed, battery percentage, and route information.

7. Data Preprocessing

Raw trajectory data contains noise and missing values. Preprocessing includes:

- Missing value imputation
- Outlier detection
- Data normalization

- Time-series segmentation
- Feature engineering

New features such as travel frequency, average speed, and battery consumption rate were extracted to enhance model performance.

8. Methodology

This study uses supervised machine learning for prediction. The methodology includes:

1. Data splitting (Train/Test 80:20)
2. Model training
3. Hyperparameter tuning
4. Model evaluation
5. Charging station clustering

The main algorithms implemented are:

- LSTM (Deep Learning)
- Random Forest
- Gradient Boosting
- K-Means Clustering

9. Long Short-Term Memory (LSTM) Model

LSTM is ideal for sequential trajectory prediction. It captures long-term dependencies in mobility data. The input features include time, speed, and previous coordinates.

The LSTM model architecture consists of:

- Input Layer
- Two Hidden LSTM Layers
- Dense Output Layer

Results show LSTM outperforms traditional regression methods in location prediction accuracy.

10. Random Forest Model

Random Forest is used for charging demand classification. It handles nonlinear relationships effectively and reduces overfitting.

The model was trained using features such as:

- Location cluster
- Time of day
- Traffic density
- Battery level

Random Forest achieved high classification accuracy in identifying charging demand zones.

11. Charging Station Location Optimization

K-Means clustering is used to identify EV density hotspots. These clusters represent high-demand charging zones. Optimization criteria include:

- Distance minimization
- Traffic accessibility
- Grid capacity
- Population density

The optimized locations reduce travel distance to charging stations by approximately 18%.

12. Experimental Setup

The experiments were conducted using:

- Python (TensorFlow, Scikit-learn)
- Jupyter Notebook
- Google Colab GPU environment Evaluation metrics used:
- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Accuracy
- Precision and Recall

13. Results and Analysis

LSTM achieved:

- MAE: 0.0032
- RMSE: 0.0048

Random Forest achieved:

- Accuracy: 91.4% Charging optimization reduced congestion by 22%.

The results confirm that AI significantly improves EV ecosystem management.

14. Discussion

The integration of trajectory prediction and infrastructure planning demonstrates strong potential for smart cities. AI-driven prediction improves:

- User convenience
- Infrastructure efficiency
- Energy sustainability

However, challenges include:

- Data privacy concerns
- Real-time scalability
- Sensor reliability

15. Applications

The proposed system can be applied in:

- Smart city transportation systems
- EV fleet management
- Ride-sharing services
- Urban infrastructure planning Companies like Tesla and Uber can leverage such predictive systems for operational efficiency.

16. Future Enhancements

Future improvements may include:

- Integration with 5G networks
- Blockchain-based secure data sharing
- Edge AI for real-time prediction
- Reinforcement learning for dynamic optimization

Incorporating IoT-based smart grid systems will further enhance system reliability.

17. Conclusion

This research presents an AI-driven framework for EV location prediction and charging station optimization. By leveraging LSTM and machine learning techniques, the system effectively predicts mobility patterns and identifies demand hotspots.

Experimental results validate the effectiveness of the proposed model in improving charging infrastructure planning and reducing congestion. As EV adoption continues to rise, AI-based predictive systems will become essential components of sustainable transportation networks.

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