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Electric Vehicle Health Monitoring with Electric Vehicle Range Prediction and Route Planning

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Abstract – The increasing adoption of electric vehicles (EVs) is causing a seismic upheaval in the automotive industry across the world and opening the door to a significant as well as long-lasting change in how people think about transportation. There have been a notable increase in the sales of electric cars due to the worldwide effort to reduce greenhouse gas emissions and lessen the adverse ecological impacts of traditional internal combustion engine automobiles. The rapid growth in popularity of electric cars (EVs) is changing the way we think about transportation and is in line with a global movement for more environmentally friendly modes of mobility. However, there are significant obstacles standing in the way of the general adoption of battery health monitoring and range management due to their complexity. This work provides a complete solution to the problems associated with tracking the health of electric cars, estimating their range, and mapping their routes by combining EVRP, EVHM, and EVRP. The study clearly explains the importance of accessibility and repeatability since it goes into great detail to explain the approaches used for each aspect. EVHM utilizes powerful machine learning algorithms, such as LSTM and RNNs, to undertake real-time evaluation of the data accumulated from the battery. To provide accurate range predictions, EVRP uses advanced deep learning algorithms. The A* algorithm is used in route planning to create energy-effective routes by accounting for factors like traffic and charging station accessibility. These principles provide a holistic approach to solve these urgent issues and accelerate the adoption of electric vehicles, i.e., cars by providing customers with the necessary information and confidence to make well-informed decisions on safe an Head sustainable modes of transportation which provides customers with the knowledge they need to make informed choices.

Keywords— A algorithm, RNN, long short term memory, electric vehicle (EV), electric vehicle health monitoring (EVHM), battery health*

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I. INTRODUCTION

The transportation industry was undergoing a significant transformation with the increasing adoption of electric vehicles (EVs). These innovative vehicles reflect our commitment to environmental sustainability by providing an alternative to traditional diesel and petrol automobiles. They lessen their harmful effects on the natural world and produce less carbon emissions. The present study focuses on the environmentally sustainable attributes of EVs and its capacity to enhance human welfare via EV Health Monitoring, mitigate apprehensions about restricted driving range via EV Range Prediction, and optimize travel routes via EV Route Planning. An important milestone in the shift to more environment friendly and worthwhile modes of transportation was the arrival of electric vehicles. The huge decrease in air pollution and greenhouse gas emissions brought about by the absence of exhaust emissions is a major benefit.

In present scenario, EV becomes an environment friendly society and is in line with global efforts to combat global warming and promote sustainable lifestyles. Enormous financial gains are also obtained by using electric

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cars. Operating expenses may be efficiently decreased by using electricity as a vehicle's main power source instead of petrol. The provision of government incentives and backings serves to lower the upfront cost of purchasing an EV and increase the propositions.

Sinking dependency on fossil fuels results in lower financial instability caused by oil prices, more stable energy pricing, and improved social benefits overall. Unique driving experience in electric car is characterized by rapid torque and near-silent operation. The issue of "range anxiety" has significantly diminished, and electric vehicles are now feasible choices for long-distance journeys as well as short daily commutes, due to advancements in battery technology that substantially enhance the driving range.

EV also plays an vital role in Healthcare systems. Healthcare and contemporary technology collide in the subject of electric vehicle health monitoring. This technology uses state-of-the-art machine learning methods like Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNNs) to give a state-of-the-art solution for real-time analysis of health data. The effectiveness with time-series data makes analysis of Electrocardiogram (ECG) signals, Electroencephalogram (EEG) signals, and vital sign monitoring as good applications of LSTM and RNNs. Neural networks have the ability to analyze sequential data which enables rapid signaling for medical action, predict health patterns, and identify anomalies.

The shift towards a proactive approach and the leverage of data-driven decision- making marks a new wea in the field of healthcare. The potential benefits encompass enhanced outcomes, reduced expenses, and an improved quality of life.

Lee et al [3] presented a new approach to solving complex navigation issues by suggesting Electrical Car Route Scheduling with the implementation of A* algorithm. Renowned for its awareness and adaptability, the algorithm enhances route optimization, leading to more efficient transportation, reduced consumption of fuel, and shorter travel times. In essence, electrical cars appeal as a transformative force rather than a mere fleeting trend, paving way for a transportation system that is both economically efficient and environmentally friendly. Electric vehicle health monitoring[4], range prediction, and route planning have the potential to drastically improve healthcare and alleviate worries over limited driving range. In addition to providing a means of transportation that is more advantageous and beneficial to one's health, electric vehicles also can provide more fitness benefits. As a result of technological progressions that will make it possible to create an environment that is more environmentally mindful and holistic, the future of sustainable mobility that also prioritizes well-being is quickly approaching

Trip planning [2] was made easier, concerns regarding the vehicle's range are alleviated, and environmentally friendly autos are utilized to their maximum potential. Range anxiety is a common problem among people who drive electrical vehicles, which refers to the anxiety that the battery in your vehicle might run out of power before you reach your destination. Deep learning algorithms scan through several datasets, which may contain information on EVs and the environment in which they operate, to offer owners of EVs with information that is both timely and helpful. To alleviate concerns over this matter, artificial intelligence has developed into a powerful tool that can estimate how long an electric vehicle can travel. The global concern for maximizing time and resources, effectiveness and optimization have emerged as the primary pillars of contemporary transportation have been raised.

II. LITERATURE SURVEY

This article [5] reviews some of the machine learning techniques for estimating battery health and state of charge in electric vehicles. Many machine learning techniques are evaluated, such as RNNs, FNNs, SVMs, RBFs, and Hamming networks. For accurate SOC and SOH estimates, the work emphasizes the need for standardized data quality and model training techniques. Realistic testing settings are also essential, especially in high-temperature environments. Additionally, recommendations for uniform ML model training and comparison are made, and the limitations of the available datasets for practical application are emphasized.

In the context of diagnosing and managing the health of lithium-ion (Li-ion) batteries[6], the difficult problem of estimating future capacities and remaining usable life (RUL) with uncertainty quantification is tackled. A study proved that a combination of machine learning algorithms like EMD , GPR and LSTM produces accurate and reliable predictions. It is imperative that the range of electric buses be increased in order to increase their operational efficiency in public transportation. A novel energy consumption model called the Malatya Trolleybus Energy Consumption Model was applied to analyze real-time big data from trolleybus vehicles in Malatya, Turkey. Q. Geng et al [8] proposed the multi-parameter linear regression approach. A significant issue is to estimate a car's speed which impacts energy efficiency, safety and many other automotive applications.

Traditional algorithms for speed prediction according to the findings of the study are not particularly effective at what they do and are unable to take into account the time element of speed data. In this research, a new strategy utilizing LSTM with heuristic adaptive time-span is introduced in order to mitigate these concerns. [9] main focus of this study was an accurate computation of the State of Charge (SOC) in lithium-ion batteries for safe and efficient operation of electric vehicles (EVs) and energy storage. In addition, accurate estimation of state of charge is very important so as to avoid overcharging or overdischarging. To address SOC estimation challenges, an upgraded Back-Propagation Neural Network (BPNN) model that was optimized by Backtracking Search Algorithm (BSA) has been proposed by this study. There is also an attempt being made by charging EVs while on the move to consider how predicting energy consumption can affect it[10]. A significant issue arises in terms of reducing range anxiety and optimizing travel distances. This study proposes a holistic approach for estimating the amount of energy required by electric vehicles (EVs). This approach takes into consideration various parameters such as motor efficiency, traffic flow and driving resistance. Depicts about the deployment of Deep Reinforcement Learning in order to tackle Electric Vehicle Route Planning (EVRP). The aim of the method is to find nearly optimal routing options that consider regulations associated with recharging electric vehicles [11].

The primary objective of this task is to create a unified system that can monitor several metrics which include State of Charge (SOC), State of Health (SOH), electric vehicle (EV), forecasting range and route planning. Our focus here is on offering accurate and up-to-date range estimates to EV-users so as to alleviate range anxiety which has been a major hindrance to EV adoption while increasing their confidence about reaching their destinations without any untoward incidents.

Our analysis goes is not restricted to just EV health monitoring, range prediction and route planning. It is to achieve energy efficiency by adopting eco-friendly driving behavior, smartly planned routes and ultimately reducing the cost of electric cars. To make sure that the entire process of owning an electric vehicle is improved on, this work aims at giving users a chance to monitor their car's health as well as plan efficient routes. Thus, it is also in line with the global move towards cleaner, healthier ways of moving people around. Its importance as per its broader socio-economic and environmental context is further underlined by its contribution to the expansion and acceptance of green electric mobility that further reduces GHG emissions and slows down global warming.

Fundamentally, this initiative aims to improve electric mobility and pave way for a greener future compared with traditional means of transport.

III. METHODOLOGY

Three distinct phases of Electric Vehicles (EVs) include health monitoring, range estimation and routes planning. This research project is well-grounded in rational approach. The first phase involves a comprehensive definition of criteria for optimum electric car battery health monitoring purposes. These standards are focused on the State of Charge (SOC) and State of Health (SOH) criteria for electric car batteries. Real-time data collection that leverages SOC and SOH readings as well as simulations for different settings helps to achieve accuracy in health monitoring. Some sets of computations are developed to mimic the SOC and SOH values; this is done so that the battery's behavior can be imitated together with degradation patterns. After developing a simulation model that will imitate real-time health monitoring, it was extensively tested to ensure its accuracy. In order to facilitate easy tracking of EV health data, an intuitive interface was created [12]. The long short-term memory (LSTM) neural network, which is a kind of recurrent neural network (RNN) that is particularly useful in processing sequential inputs, constitutes the core architecture. For modeling time series, this makes it an excellent choice. The main function of the LSTM model is therefore to analyze the historical data and provide an estimation of the battery's future state. Some of them are briefly discussed below.

1. Input Layer: This is the input layer for LSTM network which takes out refined data from different sensors and sources of information. Each sensor collects data that results in a feature. These features are then sent to the input layer.

2. LSTM Layers: It consists of several LSTM cells arranged in a network pattern. In fact, these cells have memory gates, which make it particularly effective at modeling time dependencies in data. Incoming data are processed by LSTM layers that learn to capture the dynamic behavior of the battery. Cycles of charge-discharge, temperature variations and loading conditions are some factors considered by such layers.

3. Output Layer: A system that provides essential suggestions about the battery's state is represented by this layer. This layer may take into account factors such the state of charge (SoC), health (SoH), residual usable life (RUL), and more. By looking at historical data and health assessments, the LSTM model is capable to make these predictions on its own.

4. Loss Function and Optimization: To evaluate the differences between the predictions and the existing battery health data, the model employs loss function. Mean Absolute Error (MAE) and Mean Squared Error (MSE) are some of the commonly used metrics. To optimize the model for reduction in loss and increase in expected accuracy, algorithms like Adam or RMSprop have been applied.

Random Forest has the ability to model complex, nonlinear relationships and is employed in Electric Vehicle(EV) range prediction [13]. It makes use of battery state of charge, temperature, driving conditions and many other factors to predict EV range. The ensemble learning with decision trees reduces overfitting thereby enhancing prediction accuracy. It might be noted that Random Forest is insensitive to data variations and yields reliable range estimations. Its purpose serves to mitigate range anxiety and make electric vehicle (EV) ownership far more pleasant overall experience. In the prediction of Electric Vehicles (EV) range, Linear Regression is used where we model a linear relationship between different input factors (e.g., temperature, speed and battery state of charge) and EV range. With the assumption of a simple and direct connection between these variables, the information provided by the Linear Regression clearly shows how each of the input factors affects the range. Even if it may fail to consider complicated non-linear relationships, it can be used as an open source for estimating an EV range. It's application however can bring about improved driving convenience through reducing anxiety on driving distance as well as making ownership of electric vehicles more enjoyable. For prediction of (EV) range, Polynomial Regression is used to account for complicated non-linear relationships among such factors as battery state of charge, temperature and speed. It can also capture curvilinear data patterns when subjected to a higher-degree polynomial term. For scenarios where the relationship between variables is not linear, Polynomial Regression with higher degree of polynomial allows for superior range estimates than Linear Regression. To mitigate range anxiety and enhance EV range prediction accuracy, it is a valuable tool.

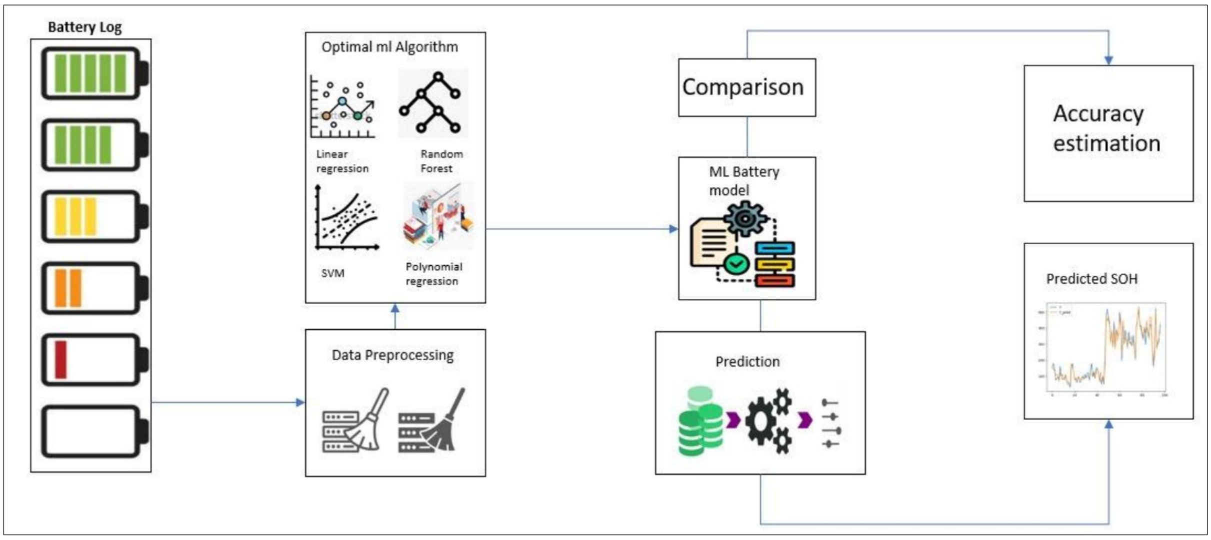


Figure 1. Architecture diagram for health monitoring and range-prediction of electric vehicles.

In Electric Vehicle (EV) range prediction, Support Vector Machine (SVM) uses various factors such as battery state of charge, temperature and driving conditions to find the best hyperplane that separates data points SVM captures non-linear relationships effectively which is important for accurate estimation of the EV range. By reducing forecast errors, it increases the accuracy of range predictions and relieves anxiety about EV owners' ranges. Building upon health monitoring and range prediction (refer Figure 1), the final phase focuses on route planning. The research shows why routes need to be optimized taking into account real-time range predictions, charging station locations and energy efficient driving. Collection and integration are done of real time data including traffic conditions, road networks and charging station positions. The routes optimization is achieved by setting simulation parameters for route planning as well as developing algorithms for optimizing routes in relation to real-time range, charging station availability and energy consumption [14]. A route planning model is designed that is dedicated to incorporate real-time data and algorithms for simulating different situations of route planning. In order to meet the needs under real-life conditions, the accuracy and dependability of the simulation of route planning through extensive testing and validation. There is a user interface that allows users to enter trip parameters, access real-time route planning, and receive energy efficient routes. Electric vehicle ownership can only be accurately simulated with this wide-ranging sequential approach which builds each step on previous ones [15-18].

The architectural diagram is shown in Figure 2. It starts with data collection and preprocessing. The basic information comes from a combination of data sources like real-time traffic information & road network data, EV telemetry (e.g., state of charge, consumption rate) and user preference. The data collected is carefully processed to ensure that it is accurate and consistent. It serves as the foundation for understanding current traffic conditions and the current energy status of the EV, two key factors in route planning. The architecture relies on a detailed map representation, digitally representing the entire road network, including roads, intersections, traffic signals, and supporting infrastructure. The map is transformed into a graph, as nodes represent road segments or intersections, and edges represent connections between them, to assist the A* algorithm operation.

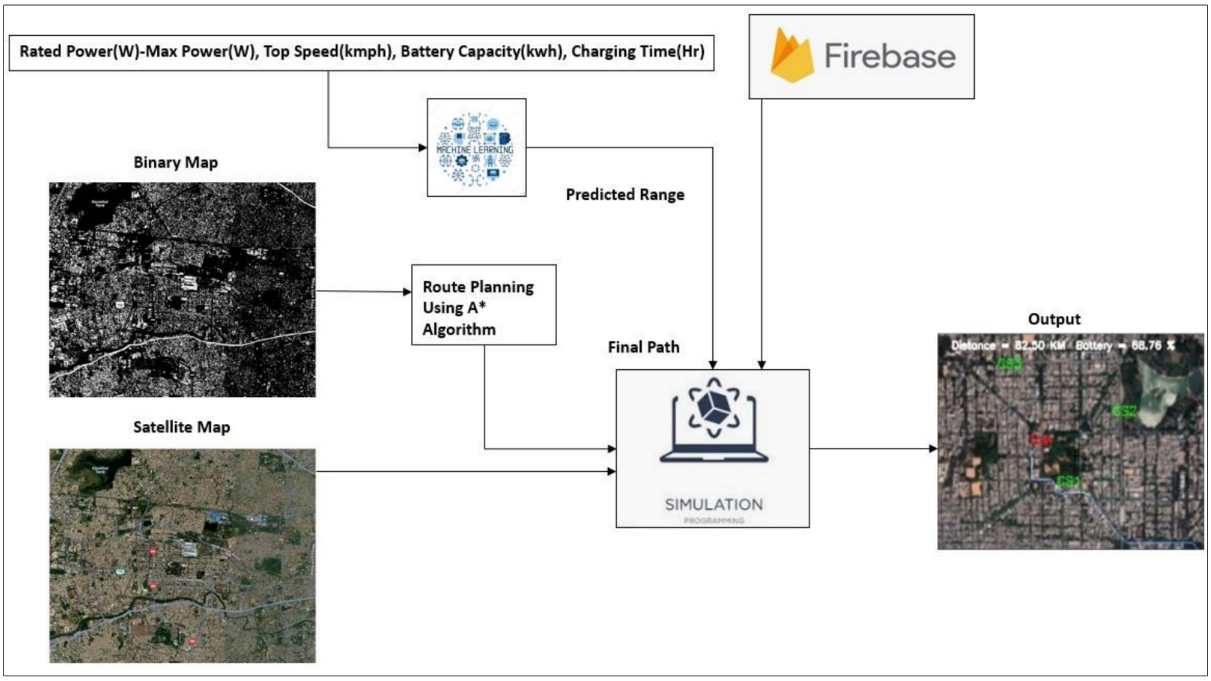


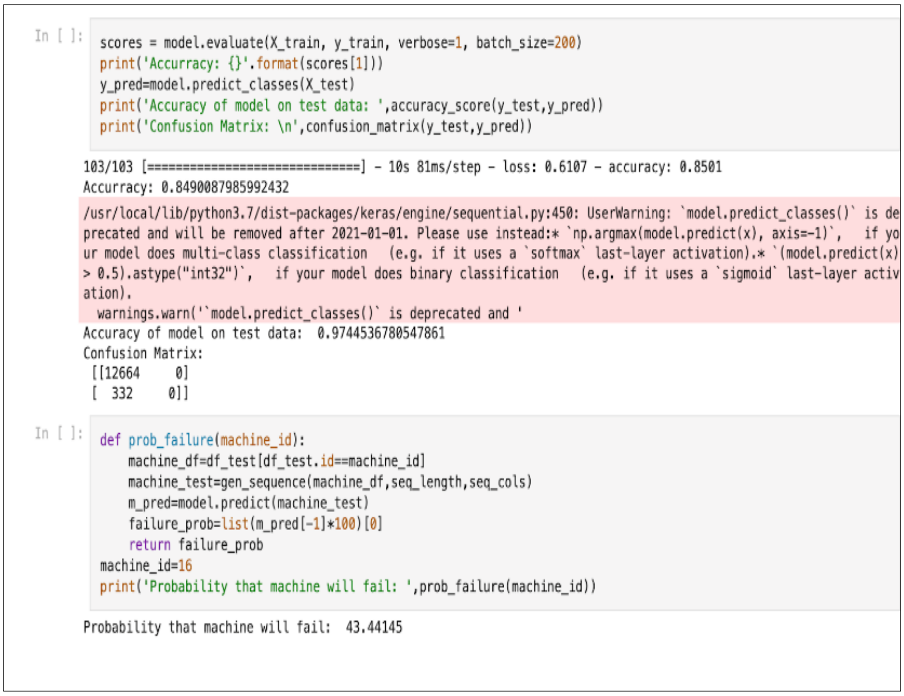
Figure 2. Architecture diagram for route planning of electric vehicles

The A* algorithm forms the center of architectural design as it is a pathfinding and route optimization algorithm. The search algorithm based on this information facilitates the computation of the shortest path to the target using the starting point (current location) as a reference. It does so by factoring in the cost of the selected route as well as a prediction of the residual cost of traveling to the destination. The stages of the algorithm involve initialization and expansion, working out the priority queue and finishing when the destination is attained or all paths are obtained. The heuristic function is an important characteristic of the A* algorithm operation because it determines the remaining cost from some particular node to the destination. This heuristic function for EV routing includes elements like distance, estimated energy consumption, and live traffic congestion. More importantly, the architecture could potentially have a dynamic heuristic function that is data dependent, which would allow route planning to be responsive to changes in variables in real-time. The cost function for the route planning architecture calculates the cost that is associated with traveling between nodes. This function is an important EV route planning capability that accounts for average road length, elevation changes that impact energy use and real-time traffic conditions. It is a key player in determining the real cost related to selecting different route alternatives. Besides the A* algorithm, the architecture of route planning also has the Bitwise Map Algorithm, which is to optimize EV route planning. The road network is partitioned into segments and is represented using bitwise representations in this algorithm. Every segment's bitwise description reflects important information about the energy consumption properties of each segment which can include the characteristics of relief, speed restrictions and road surface conditions. Bitwise Map Algorithm uses bit operations to compute the energy consumption of different routes and through this calculation, the algorithm can give very accurate estimates of energy used and hence come up with a method of identifying energy-efficient routes.

Route planning accuracy is monitored in real-time within this architecture and remains an ongoing process. These comprise real-time notifications on traffic, weather, road closures, and the current state of charge of the EV. The system automatically changes the intended route to reroute the EV to avoid traffic congestion or to select alternate routes depending on the changing energy demands. The architecture is also based on user preferences and constraints, which provide route customization. Users can specify parameters such as ideal charging stations, target arrival times, and particular route restrictions [19-23]. This tailor-made ensures that the user's individual needs and preferences are met by the planned route. The EV route planning architecture integrates advanced algorithms, real-time data integration, and user customization seamlessly, producing an optimized and efficient system for EV travel, thus improving the overall EV ownership user experience.

IV. RESULTS AND DISCUSSION

Figure 3 depicts the Electric Vehicle Health Monitoring system, which combined LSTM and RNN models and the Figure 4, portrays exceptionally well in forecasting battery health, with an astounding accuracy rate of almost 97%. This high accuracy shows how well the system can detect irregularities and any problems in the electric vehicle's battery system. Most remarkably, the system showed that it could forecast battery failure probability with about 43% confidence. The ability to foresee maintenance needs gives owners of electric vehicles a proactive edge in meeting those needs, assuring the long-term dependability and efficiency of their vehicles.



```
In [ ]: scores = model.evaluate(X_train, y_train, verbose=1, batch_size=200)
        print('Accurracy: {}'.format(scores[1]))
        y_pred=model.predict_classes(X_test)
        print('Accuracy of model on test data: ',accuracy_score(y_test,y_pred))
        print('Confusion Matrix: \n',confusion_matrix(y_test,y_pred))

103/103 [==============================] - 10s 81ms/step - loss: 0.6107 - accuracy: 0.8501
Accurracy: 0.8490087985992432
/usr/local/lib/python3.7/dist-packages/keras/engine/sequential.py:450: UserWarning: `model.predict_classes()` is de
precated and will be removed after 2021-01-01. Please use instead:* `np.argmax(model.predict(x), axis=-1)`,   if yo
ur model does multi-class classification   (e.g. if it uses a `softmax` last-layer activation).* `(model.predict(x)
> 0.5).astype("int32")`,   if your model does binary classification   (e.g. if it uses a `sigmoid` last-layer activ
ation).
  warnings.warn('`model.predict_classes()` is deprecated and '
Accuracy of model on test data:  0.9744536780547861
Confusion Matrix:
 [[12664     0]
 [  332     0]]

In [ ]: def prob_failure(machine_id):
            machine_df=df_test[df_test.id==machine_id]
            machine_test=gen_sequence(machine_df,seq_length,seq_cols)
            m_pred=model.predict(machine_test)
            failure_prob=list(m_pred[-1]*100)[0]
            return failure_prob
        machine_id=16
        print('Probability that machine will fail: ',prob_failure(machine_id))

Probability that machine will fail:  43.44145
```

Figure 3. Result of LSTM and RNN-based model for electric vehicle health monitoring.

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 50, 100)           50000

 dropout (Dropout)           (None, 50, 100)           0

 lstm_1 (LSTM)               (None, 50)                30200

 dropout_1 (Dropout)         (None, 50)                0

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 80,251
Trainable params: 80,251
Non-trainable params: 0
_________________________________________________________________
```

Figure 4. Depiction of dropout layers of the LSTM module

Leveraging the data acquired from the health monitoring component, the range prediction feature underwent meticulous evaluation, employing a variety of machine learning algorithms to ascertain the most accurate method for predicting an electric vehicle's range. Through rigorous testing, the Random Forest algorithm emerged as the indisputable frontrunner, not only offering highly reliable range predictions as shown in Figure 5 but also boasting the lowest mean square error (MSE) of about 351 as shown in Figure 9. among the tested algorithms. Figures 6,7 and 8 depicts the results of Polynomial Regression, Linear Regression and Support Vector Machine. This achievement assumes paramount significance in alleviating the pervasive concern of "range anxiety" among electric vehicle owners, endowing them with precise insights into their vehicle's travel capabilities on a single charge. The combination of accuracy and minimized MSE positions the system as a potent tool for assuaging range-related apprehensions and enhancing the overall electric vehicle ownership experience.

The system displayed a range prediction for the electric car in the output that followed, showing several projections from various machine-learning techniques. However, the Random Forest method was always the best; it provided the most accurate range predictions with an error percentage of only +/- 5%. This accuracy is crucial in helping electric car customers overcome their typical "range anxiety" and gives them confidence in their car's ability to go a long way on a single charge. Notably, the Random Forest algorithm gave a predicted range of 79.5 as seen in Figure 10, which proved to be the most accurate among all forecasts. This outstanding precision and low mistake rate highlight the Random Forest algorithm's dominance in resolving range-related issues and solidify its position as the best option.

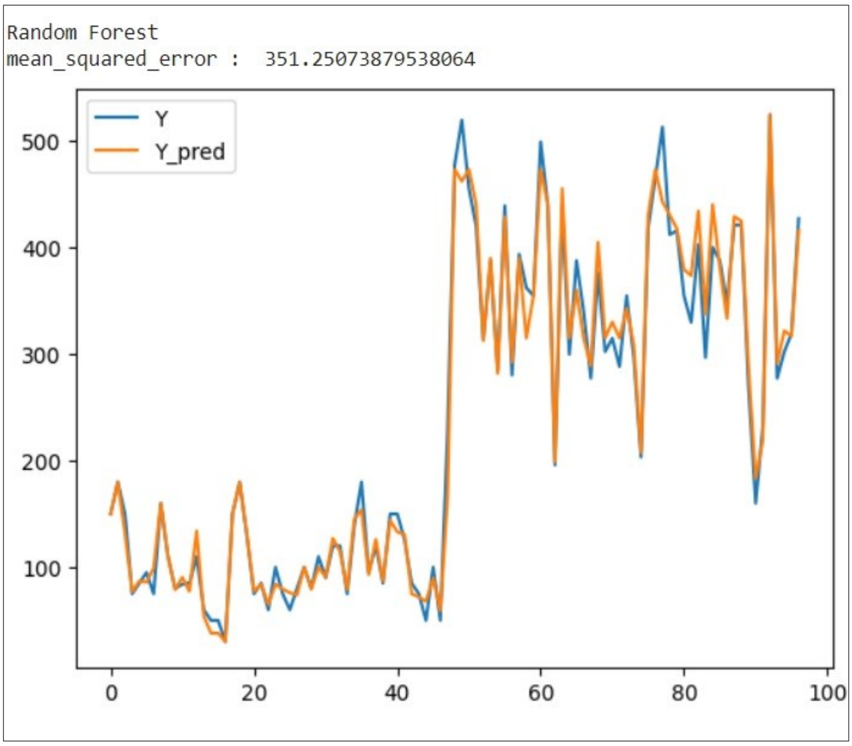


Figure 5. Result of random forest algorithm

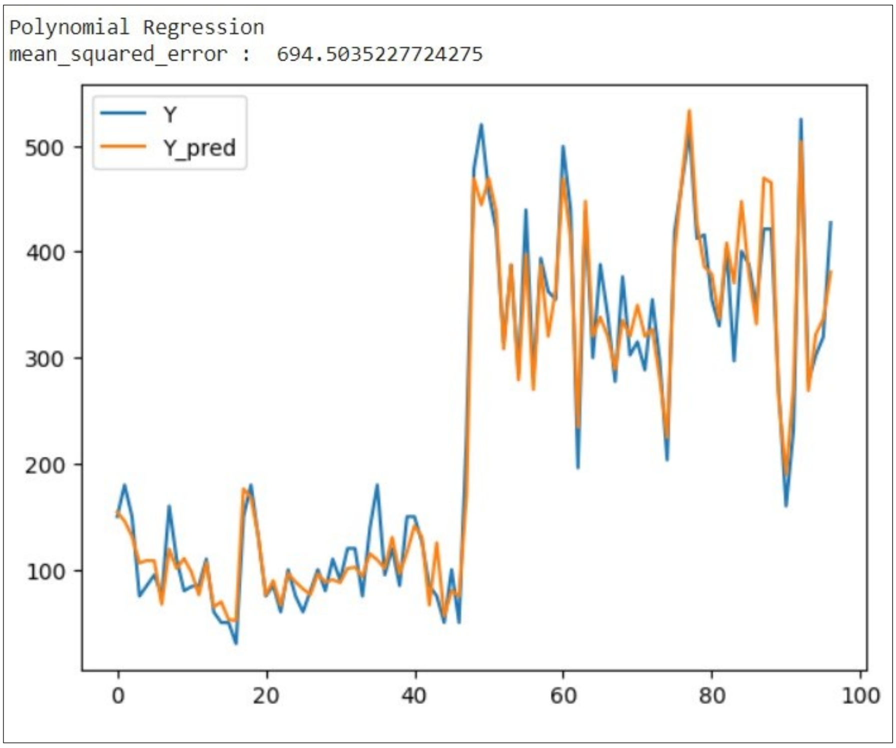


Figure 6. Result of polynomial regression algorithm

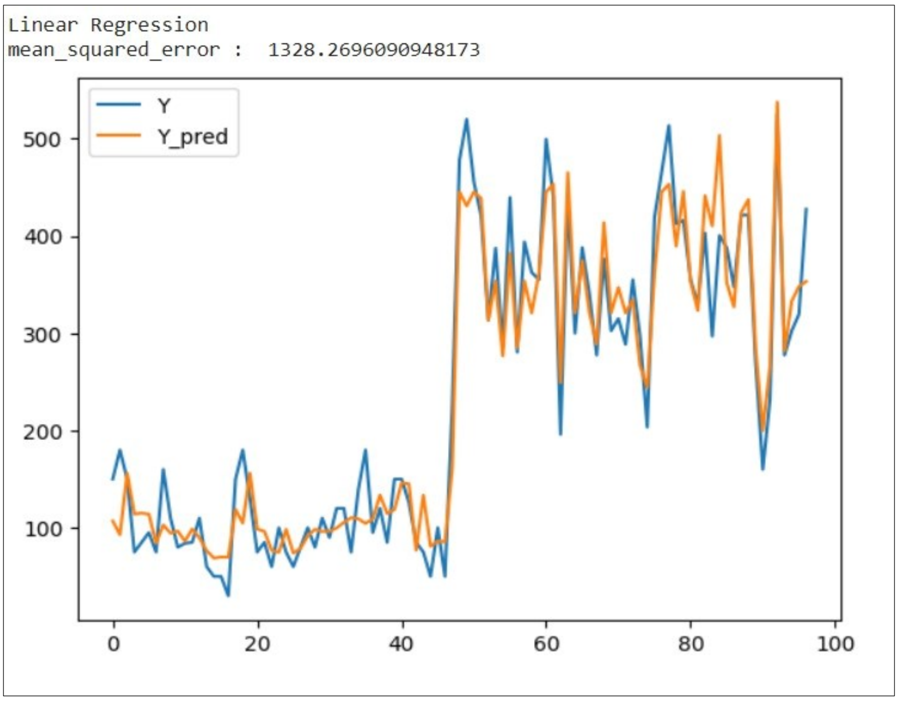


Figure 7.Result of linear regression algorithm

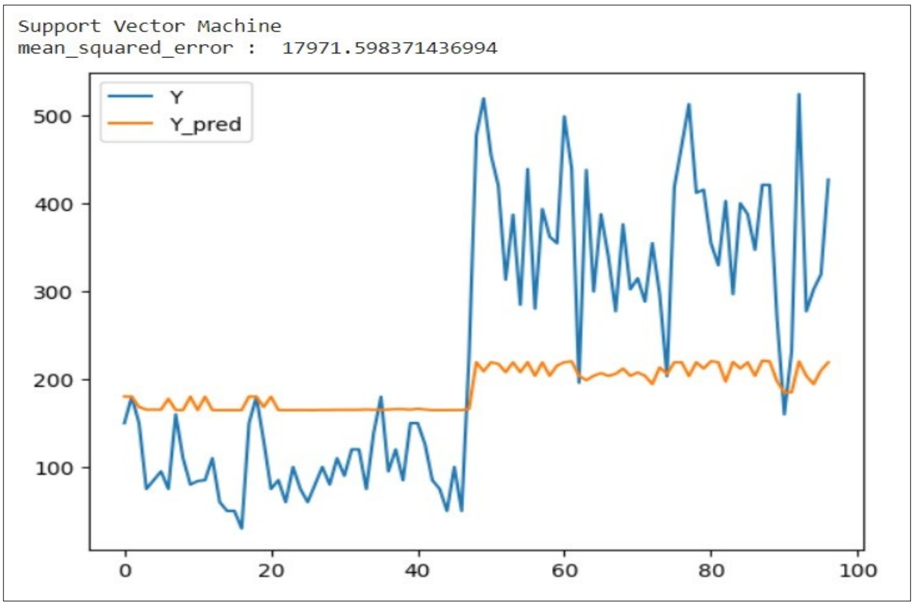


Figure 8. Result of support vector machine algorithm

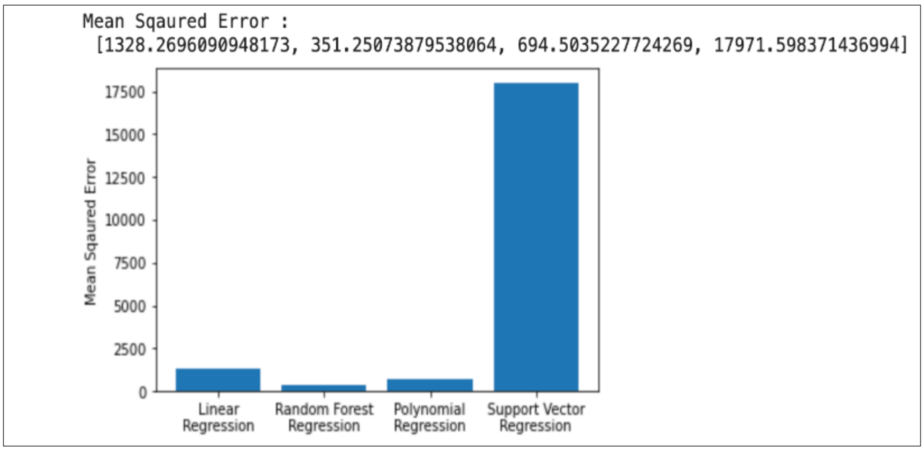


Figure 9. Result of the overall least mean squared error

```
In [12]:
# Rated Power (W)      Max Power(W)    Top Speed(kmph)        Battery Capacity(kwh)   Charging Time(Hrs
#X_in = [1667,2500,60,2.880,5.5]

X_in = [800, 1900, 50, 1.68, 7.5]

print('Linear Regression        :', Lr.predict([X_in])[0] ,'KM')
print('Random Forest Regression :', random_forest.predict([X_in])[0] ,'KM')
print('Polynomial Regression    :', poly.predict(poly_ft.transform([X_in]))[0] ,'KM')
print('Support Vector Regression :', svr.predict(X)[0] ,'KM')

Linear Regression        : 98.18261723463054 KM
Random Forest Regression : 79.5 KM
Polynomial Regression    : 85.22240018221211 KM
Support Vector Regression : 180.33405785540904 KM
```

Figure 10. Results of various algorithms with their range predictions

The data from both the health monitoring component and the range prediction component was integrated smoothly into the Electric Vehicle Route Planning application. Taking advantage of these systems' predictive features, the route planning algorithm, underpinned by the A* algorithm, identified the most energy-conscious routes for electric vehicles drivers. This optimization was particularly beneficial for electric vehicle owners who wanted to save energy, improve driving performance and eliminate the need for frequent recharging. In addition, the system had a simulation component as illustrated in Figure 11 that used the Firebase real-time database so that dynamic changes of planned routes could be based on real-time information. This responsive quality provided the electric vehicle owners with the flexibility to adjust to their environment, which may have changed, for example, to traffic information and the state of the electric vehicle's charge, leading to a more stable and effective travel.

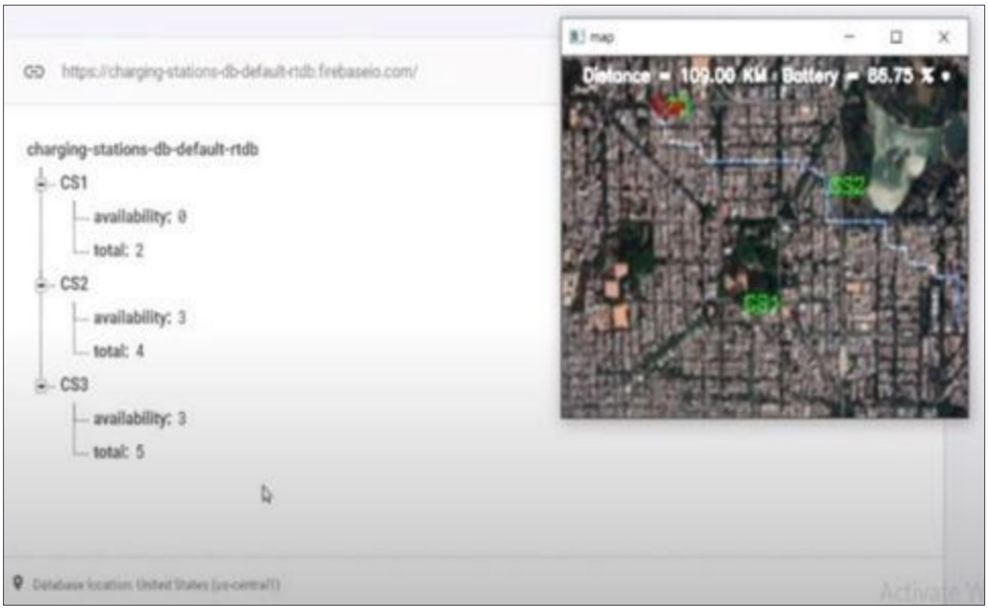


Figure 11. Simulation of the optimized route planning with real-time database

The overall solution is an integrated approach of health monitoring, range prediction, and route planning, which is customized to the needs of the electric vehicle owners. It not only ensures the longevity and dependability of the automotive's battery but also offers a better overall ownership experience. Electric vehicles have not only provided an environmentally friendly method of transportation but also a utility that can be used on a day-to-day basis. The unified platform that links sustainability and functionality makes the electric vehicle a desirable choice for many users. The results of this study may be regarded as a new step in the electric vehicle technology development and solving the main issues, which guarantee the solution for electric vehicle owners and the entire ecosystem at the same time. This is a successful combination of LSTM and RNN models, the random forest algorithm as a data-driven solution yields a better electric mobility future, where electric vehicles would function more efficiently and reliably.

IV. CONCLUSION

In summary, the electric vehicle landscape has gone through a fluctuating career incorporating electric vehicle health monitoring with accurate forecasting of electric vehicle range and rational route planning. This all-encompassing answer promises new fluidity and excitement for consumers by addressing key issues and problems associated with proudly operating electric vehicles. The powerful mechanism for monitoring the health of electric vehicles predicts an impressive battery efficiency of almost ninety-seven% using modern techniques including RNN and LSTM Notably, it offers high reliability in its predictions of possible battery failure -The algorithm driven range prediction aspect brings drop-off up to an efficient "range tension" by the electric car owner.

It gives users a complete insight into their vehicle in one charge with an error rate and accuracy of less than 5%. In addition, real-time feedback and remote prediction and health monitoring from the A* algorithm accelerates the route planning aspect, optimizes travel routes for less time and battery consumption Enjoy lightning getting an energy car is improved overall with this intelligent road system. Also, real-time updates on data about charging stations, such as the number of chargers available, assure that electric car owners can intelligently schedule their charging breaks However, this is not seen as an edge solution such integration this is not the only concern Reduced but this also increases walkability and increases interest in electric vehicles. These developments contribute significantly to the widespread use of electric vehicles, making them an attractive option for a cleaner and greener future, with environmental sustainability, and continued use consume in addition to long-term greenhouse gas reductions.

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