Smart Strategies for Enhanced Electric Vehicle Battery Performance and Efficiency

Major Project Report

Submitted by

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BACHELOR OF COMPUTER APPLICATIONS
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CERTIFICATE

This is to certify that the project synopsis titled **Smart Strategies for Enhanced Electric Vehicle Battery Performance and Efficiency** is a record of the bonafide work done by **AAYUSH UJJWAL** (*Roll. No. 2201062040*) submitted in partial fulfilment of the requirements for the award of the Degree of Bachelor of Computer Applications (BCA) in **AI AND DATA SCIENCE** of K.R Mangalam University, Gurugram – 122101
during the academic year 2023-2024.

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DECLARATION

We declare that this written submission represents our ideas in our own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all the principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will cause disciplinary action by the Institute and canal so evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed. We further declare that if there is any violation of the intellectual property right or copyright, my supervisor and university should not be held responsible for the same.

Aayush Ujjwal (2201062040)

Place: K.R. MANGALAM UNIVERSITY

Date: 30/05/2024

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ABSTRACT

In the contemporary landscape of transportation, the proliferation of electric vehicles (EVs) stands as a pivotal stride towards sustainable mobility. However, optimizing the performance and efficiency of EVs, particularly in terms of range estimation and driving dynamics, remains a paramount concern. This project endeavours to address this challenge by employing a multifaceted approach encompassing the development and integration of advanced battery management systems (BMS) and predictive modelling techniques. With the surge in EV adoption and the imperative to enhance their range and operational efficiency, the project assumes significance in the current context of environmental sustainability and energy transition. The primary objective is to devise an intelligent system capable of accurately estimating range, predicting optimum driving conditions, and optimizing energy management in EVs, thereby fostering their widespread acceptance and viability.

Methodologically, the project involves the amalgamation of diverse methodologies, including data gathering, pre-processing and model training, to facilitate the development of robust predictive models. Various machine learning algorithms, such as Random Forest Regressor, Extra Trees Regressor, long short-term memory (LSTM), and Linear Regression, are employed to predict range, optimum acceleration, and velocity. The ensemble of these models allows for comprehensive analysis and comparison, yielding insights into the most effective predictive approaches. Furthermore, the project entails the design and implementation of a real-time web application, leveraging Python-based tools and frameworks, to provide users with intuitive interfaces for estimating range and optimizing driving parameters. The conclusions drawn from this project underscore the efficacy of predictive modelling techniques in enhancing the performance and efficiency of EVs, paving the way for their seamless integration into the mainstream automotive landscape.

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence
EV: Electric Vehicle
IC: Internal Combustion
CSV: Comma-Separated Values
MAE: Mean Absolute Error
MSE: Mean Squared Error
RNN: Recurrent Neural Network
LSTM: Long Short-Term Memory
HVAC: Heating, Ventilation, and Air Conditioning
MAE: Mean Absolute Error
MSE: Mean Squared Error
R^2: R-squared
RF: Random Forest
LR: Linear Regression
DL: Deep Learning
ML: Machine Learning
CNN: Convolutional Neural Network
GPU: Graphics Processing Unit
CPU: Central Processing Unit
RAM: Random Access Memory
PDF: Portable Document Format
IEEE: Institute of Electrical and Electronics Engineers
SVM: Support Vector Machine
API: Application Programming Interface
PID: Proportional-Integral-Derivative
FCC: Federal Communications Commission
MAE: Mean Absolute Error
MSE: Mean Squared Error
R^2: R-squared
AI: Artificial Intelligence
EVs: Electric Vehicles
BMS: Battery Management System
SOC: State of Charge
ISOCC: International SoC Design Conference

CHAPTER 1
INTRODUCTION

1.1. Area of Work and Present Scenario

The automotive industry is undergoing a shift towards sustainable alternatives to traditional IC engine vehicles. One such category is electric vehicles, which are widely spreading in the market. The core part of this revolution is the battery of electric vehicles, which decides the performance and acceptance of EVs in the current market. To boost this transition further and overcome existing challenges, our project titled "Smart Strategies for Enhanced Electric Vehicle Performance and Efficiency." attempts to explore innovative methods to optimize the functionality of EV batteries.

As the demand for clean and efficient transportation increases, the efficiency and longevity of EV batteries become the main factors for consideration. This project focuses on smart strategies for shaping the future of EVs. By engaging in range estimation through predictive analysis, energy-efficient driving assistance systems and advanced battery management techniques, our project aims to contribute substantially to the advancement of EVs. Range estimation currently is achieved through estimation equations and doesn't factor in a lot of variables from outside world. With the help of the new emerging technology of Machine Learning we can train the model based on the data available and use it in real time application. The accuracy of the predictions can be increased by proper training of the algorithms and optimization.

1.2. Motivation and Relevance

Contributing to this new age technology and merging its application with the electrical and electronics aspect is an interesting aspect of this project. Electrical Engineering in itself is a very vast and complex field. With the introduction of Electric Vehicles, the need of new breakthroughs is more important than ever. With the help of this new age technology, we want to make extensive research easier and development faster. Running multiple iterations in software is much easier and faster. It also helps in saving economical resources and minimizes the risk of damage if possible.

This project is most relevant to the currently advancing world with the introduction of powerful AI tools in everyday life. This project aims to integrate some aspects of both and provide with better research methods.

1.3. Impact on the environment

Electric vehicles are at the forefront of the battle against global warming and depletion of natural resources faster than ever before. Development of Electric vehicle pose a lot of challenges. One of which is the range estimation. General people still lack proper understanding of EVs and confuse the performance with that of IC engines. We have to understand that both of the technologies are different and need to be treated differently.

To achieve an understanding of what are the best practices for the EV, this project first tries to develop a new method of estimating range and optimum velocity and acceleration. Once we get a satisfactory result, we can implement our learning on an app interface to mimick the real time interactions of driver and the dashboard.

This can help massively in the research and development of the EVs and also educate more people about how to treat their EVs. In this way we are aiming to enhance the life of EVs and also the quality of newly developed EVs. With these goals achieved, it will have a great impact on the complete shift of IC engine vehicles to EVs.

CHAPTER 2
LITERATURE REVIEW AND OBJECTIVES

2.1. Literature Review

In recent years, significant advancements have been made in battery management systems (BMS) for electric vehicles (EVs), driven by the increasing demand for sustainable transportation solutions. Rahimi-Eichi et al. [1] provide an overview of BMS applications in smart grids and EVs, emphasizing the importance of efficient energy management to optimize battery performance and lifespan. Brandl et al. [2] delve into batteries and BMS for EVs, discussing key considerations such as battery chemistry, cell balancing, and thermal management to ensure safe and reliable operation.

Accurate range estimation is crucial for EVs, considering changing environmental conditions and traction system efficiency. A study published in the IET Electrical Systems in Transportation journal [3] focuses on developing precise range estimation methods to address these challenges, enhancing EV usability and reliability. Chakraborty and Nandi [4] explore optimal driving regions for EVs during acceleration, aiming to improve energy efficiency and performance through intelligent driving strategies.

Battery technologies play a pivotal role in the advancement of EVs, with ongoing efforts to enhance battery packs' energy density, efficiency, and reliability. Mohseni et al. [5] discuss recent improvements in battery technologies and their implications for EVs, highlighting advancements in lithium-ion batteries and emerging battery chemistries. Additionally, Kim et al. [6] propose an adaptive battery state-of-charge estimation method for EV BMS, leveraging adaptive filtering techniques to enhance estimation accuracy and robustness.

Various state-of-charge (SOC) estimation methods have been proposed to accurately assess battery status and performance. Chang [7] provides a comprehensive review of SOC estimating methods, covering techniques such as Kalman filtering, neural networks, and model-based approaches. These methods play a crucial role in optimizing battery utilization and prolonging battery lifespan in EVs.

Moreover, handbooks such as "Electric Powertrain Energy Systems, Power Electronics and Drives for Hybrid, Electric and Fuel Cell Vehicles" by Hayes and Goodarzi [1] offer valuable insights into the design and implementation of electric powertrains, highlighting key components, control strategies, and integration challenges in electrified vehicles.

Web resources, such as the design of the Tata Nexon electric vehicle [8], provide practical insights into real-world EV design and development, offering valuable case studies and project examples for reference and inspiration.

Overall, the literature review highlights the multifaceted nature of EV technology, encompassing battery management, range estimation, energy efficiency, and SOC estimation. By synthesizing insights from academic papers, handbooks, and web resources, we gain a comprehensive understanding of the current state and recent developments in the field, guiding the objectives and methodology of our project.

With our research, we understand that there is no justified method of range estimation in EVs. We can use AI and create a method to estimate range and check its accuracy. Introduction of AI can be revolutionary in this field as AI and ML programs try to incorporate all the factors in the results. We have to analyse our results based on metrics and comparisons with our data. Using the same model, we can predict optimum driving conditions for an EV at real time so that the user can have a better experience of driving the EV and the life of EV is also increased. After a justified model is created and tested, we may use the learnings and apply it to a real-time app, which will take input from the EV and predict the range and optimum driving nature. We have formulated the following Objectives to reach our goals.

2.2. Objectives

1. **Objective: Develop a methodology using available resources to predict electric vehicle range and optimize driving conditions.**
2. **Objective: Develop a predictive analytics model for electric vehicle range estimation.**
3. **Objective: Develop a predictive model for recommendations of optimum driving practices and real time feedback to the driver.**
4. **Objective: Design an intelligent driving assistance system for energy-efficient driving and integrate all the findings in the project**

CHAPTER 3
METHODOLOGY

3.1. Methodology

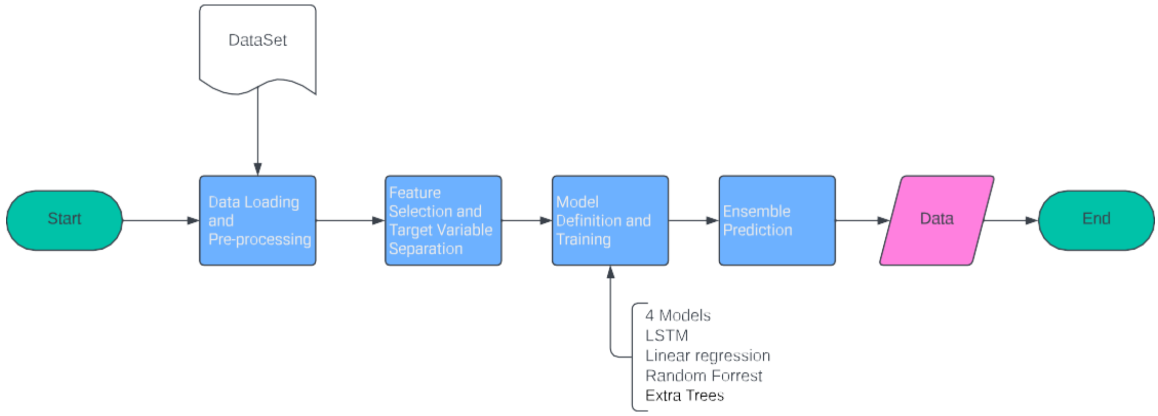

Figure 1: General Methodology of project

The methodology involves a systematic approach to use different models to predict range and optimum driving condition (acceleration and velocity). As shown in figure, we start with dataset gathering and pre-processing of dataset to fit the models and to be used in the training and testing of the models. The dataset has been created using Python to mimick real EV working situations. This step ensures that the data is in a suitable format for subsequent analysis and model training.

Following the data processing, we define the feature and targets to the models in the python code so that the model knows to calculate what on based of what. The features include speed, acceleration, elevation change, temperature, weather conditions, HVAC usage, battery health, state of charge, and driving mode. While training for different models, namely for range, optimum acceleration and velocity, we create the prescribed value using calculation ranging from complex equations to basic Newton's models to get the target values. Based on these target values in different models, the model is adapted.

Four different models are chosen to train and test the data namely Random Forest Regressor, Extra Trees Regressor, LSTM (Long short-term memory), and Linear Regression. These models are taken for their good proximity with the results involving linear results. Having the training done in four different models gives us a chance to compare the results of each model individually and provides us with the opportunity to ensemble results in all combinations possible and compare which is most relevant and helps in choosing optimal results. The performance of these models is evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2).

Linear Regression (LR):

Mathematical Equation: Linear regression fits a linear equation to the input features and the target variable. For a simple linear regression with one input feature, the equation is:

$$y = \beta_0 + \beta_1 \times x$$

Equation 1: Linear Regression Formula

where y is the predicted target variable, x is the input feature, and β_0 and β_1 are the intercept and slope coefficients, respectively. In multiple linear regression with multiple input features, the equation extends to include multiple coefficients.

Algorithmic Approach: Linear regression minimizes the sum of the squared differences between the observed and predicted target values by adjusting the coefficients $\beta_0, \beta_1, \ldots, \beta_n$ using techniques like Ordinary Least Squares (OLS) or gradient descent.

Random Forest (RF) and Extra Trees (ET):

Algorithmic Approach: Both Random Forest and Extra Trees are ensemble learning methods based on decision trees.
Decision trees recursively split the feature space into regions based on feature values, creating a tree-like structure. Each leaf node in the tree represents a prediction.
Random Forest builds multiple decision trees by bootstrapping the training data and using a random subset of features at each split. It then aggregates the predictions of individual trees to make the final prediction.
The random forest technique helps overcome some drawbacks of bare decision trees. It accomplishes this by obtaining multiple estimates and averaging them collectively, lowering each estimate's variation. This allows for training N distinct trees on various randomly selected subsets of the data set with replacement. The random forest notion is based on this idea [12]. This allows us to acquire the function.

$$f(y) = \frac{1}{N} \sum_{n\%1}^{N} f_M(y)$$

Equation 2: Random Forest equation

Where f_M is a tree with M training examples, and N is the number of trees. The projected value at the data point y for the i-th tree in the family is represented as $f_M(y; X_i, D_M)$, where X_i.............. X_N are independent random variables, distributed independently of D_M and in the same manner as the generic random variable X
Extra Trees (or Extremely Randomized Trees) is similar to Random Forest but introduces additional randomness by selecting random thresholds for each feature at each split, rather than searching for the best threshold.
Mathematical Expression: Decision trees themselves do not have a single mathematical expression like linear regression. Instead, they make binary decisions based on feature thresholds at each split to partition the feature space.

Long Short-Term Memory (LSTM):

Algorithmic Approach: LSTM is a type of recurrent neural network (RNN) designed to capture long-term dependencies in sequential data.
LSTMs contain memory cells and gates (input gate, forget gate, and output gate) that regulate the flow of information through the network, allowing them to retain information over long sequences.
LSTMs use sequential learning mechanisms to process input sequences and update internal states over time, enabling them to model complex temporal patterns.
Mathematical Expression: LSTMs involve a series of mathematical operations to compute activations, update internal states, and produce output predictions. These operations include matrix multiplications, element-wise operations, and activation functions like sigmoid and tanh, but they do not have a single mathematical equation like linear regression.

$$
\begin{aligned}
i_t &= \sigma(W_{x)} x_t + W_{*)} h_{t+1} + W_{c)} c_{t+1} + b_{)}) \\
f_t &= \sigma 7 W_{xf} x_t + W_{*f} h_{t+1} + W_{cf} c_{t+1} + b_{f} 8 \\
g_t &= \tanh 7 W_{x.} x_t + W_{*-} h_{t+1} + b_{-} 8 \\
c_t &= f_t \odot c_{t+1} + i_t \odot g_t \\
o_t &= \sigma(W_{xo} x_t + W_{*o} h_{t+1} + W_{co} c_t + b_o) \\
h_t &= o_t \odot \tanh(c_t)
\end{aligned}
$$

Equation 3: LSTM functions and equations

i_t, f_t, o_t are the input, forget, and output gates' activations at time step t respectively.
g_t is the cell's candidate value at time step t.
c_t is the cell state at time step t.
h_t is the hidden state at time step t.
x_t is the input at time step t.
$W_{..}$ are weight matrices, $b_{..}$ are bias vectors.
σ is the sigmoid function, tanh is the hyperbolic tangent function.
$\odot$ denotes element-wise multiplication.

MAE is calculated by taking average of the absolute differences between the predicted values and the actual values. measures the average magnitude of errors between predicted values and actual values. We aim to get as low MAE as possible to make the predictions as precise as possible. MSE measures the average of the squares of the errors between predicted values and actual values. It is calculated by taking the average of the squared differences between the predicted values and the actual values. Squaring the errors penalizes larger errors more heavily than smaller errors, making MSE sensitive to outliers. MSE is commonly used in optimization algorithms as it provides a smooth, differentiable loss function. R-squared quantifies the proportion of the variance in the dependent variable (target) that is predictable from the independent variables (features) in a regression model. It ranges from 0 to 1, where 0 indicates that the model does not explain any variance in the target variable, and 1 indicates that the model perfectly explains the variance.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y_i}\right|$$

Equation 4:Mean Absolute Error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2$$

Equation 5:Mean Squared Error

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \widehat{y_i}\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}$$

Equation 6: R-Squared Score

n *is the number of observations*
fi *is the actual value*
$\widehat{fi}$ *is the predicted value*
$\bar{f}$ *is the mean of the actual values*

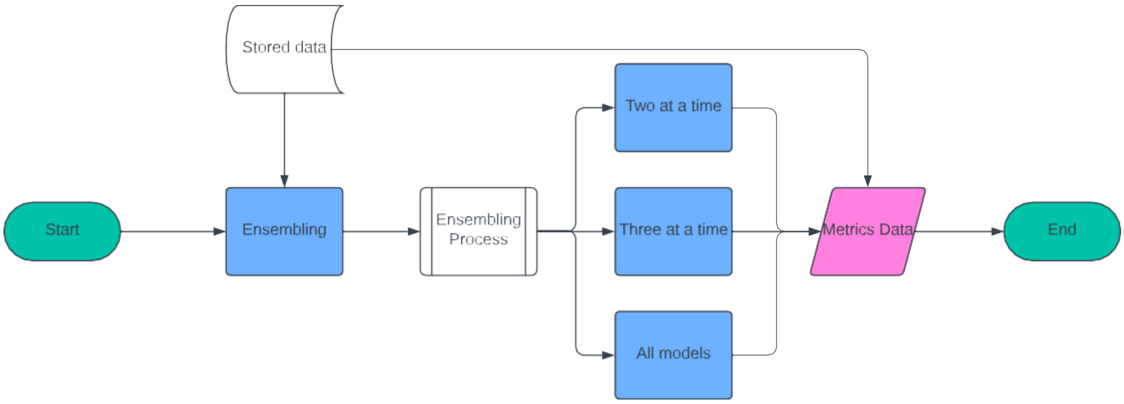

Figure 2:Ensembling process

We use all the possible combinations of ensembled data to understand the effectiveness of each of the models individually and in all possible combinations to take out the best method possible. The ensembled results are extracted from the stored data of models and their adjusted weight (based on their performance) is taken into account. The different combinations of models also allow us to understand which model is most relevant and which is least relevant. We have chosen to check all the possible combinations for their error and their relevance.

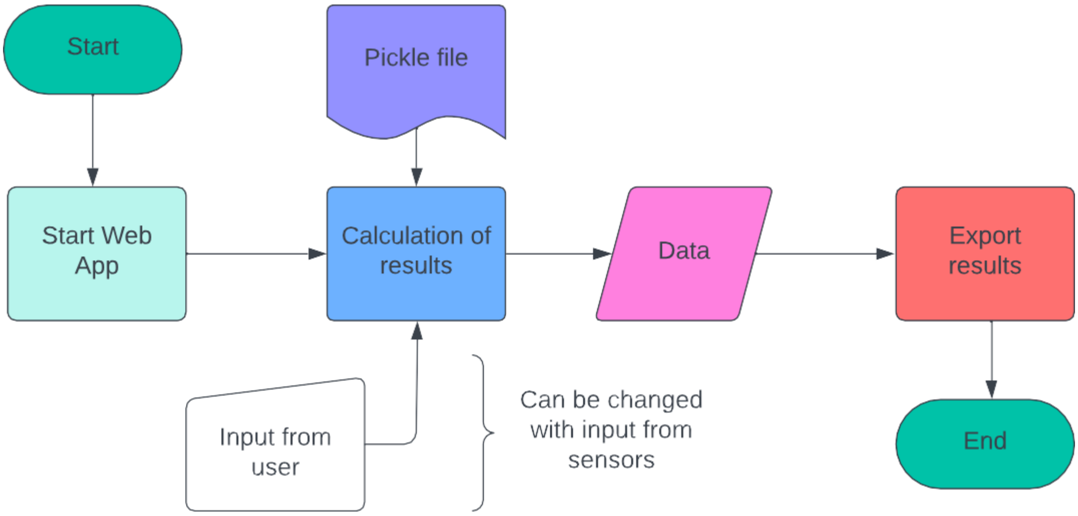

Figure 3: Real-Time Web app development

After the results are analysed, the trained model is then exported in a pickle file using python. This python file is used to approximate results in a real-time based simulation scenario. The real-time app is developed as a webpage and takes user input to approximate the results, namely range, optimum velocity and optimum acceleration. This model is a reference and the user input is expected to be replaced with sensor data available in an EV to estimate the results and display it to the user.

3.2. Assumptions

To achieve our results, we have had to make a few assumptions in the process. As development of EV technologies and battery technologies is a very competitive sector, no dataset could be found that would help us with what we had in mind for the project. To compensate for this shortcoming, we have had to make our dataset on our own using just software. To achieve real life like results, we have incorporated results from existing researches and books published on EVs. We assume the actual values calculated from these are true to real life implications and can thus be used in our project to train and develop the AI models. For range estimations, we have taken the characteristics and parameters of Tata Nexon into consideration and calculated the range from the given data available (See Annexure). For Optimum drive conditions, we have assumed the characteristics of the motor used in Tata Nexon, i.e., 3-phase permanent magnet synchronous motor, which has a constant torque vs speed relation. We have characterised the optimum velocity with keeping safety and drive conditions (Elevation, uphill or downhill, speed of the vehicle, battery remaining). With these in place, we aim to optimise the drive conditions to be most efficient in term of energy consumption.

3.3. Type and Nature of Project

This project focusses on the implement of new age technology of artificial intelligence with the present-day problems in development of Electric Vehicles. We have aimed to create a method which can be implemented in hardware usage. Our main aim was to overcome the software-based challenges and hence this project is software based.

With the use of this project, it lays a foundation for the work that can be done in hardware with proper tools available. This required a good understanding of electrical aspects of EV and development sense of python libraries to make use of AI models. We train our models and test them on software. This gives us an advantage in the development process of EV as it reduces the costing drastically for any new technology to be implemented. The results can further be verified in hardware settings and the new data will help AI to predict the values better.

3.4. Software Requirements

In recent times, advancements in technology have granted us the ability to do a lot of work by using software simulation and predicting very precisely. To achieve our goals, we have used different software to help us. Every step of the process is unique and needs an understanding of the tools that are used. The list of software used is:

1. Python
2. Google Colab
3. Neural Editor
4. Visual Studio Code

Python is a powerful tool that can be used to manage data and do the modelling, training, and evaluation of the AI model. We have used Python to create and store datasets for the training using simplified calculations. We then used Google Colab to model and keep our trained data in one place. Colab gives us a chance to keep different parts of our project in one place and run the desired part of the project one at a time so that we can better debug and interpret the results.

CHAPTER 4
RESULT ANALYSIS

4.1. Range Estimation

The methodology gave out good results after some adjusting of the data and the processes involved. Two different sets of models used, namely for Range estimation and optimum acceleration and velocity prediction. Four different models have been used to estimate range individually, namely Extra Trees Regression, Random Forrest, LSTM and Linear Regression. These models individually have a good output when compared to the actual range as shown in *Figure 4.*

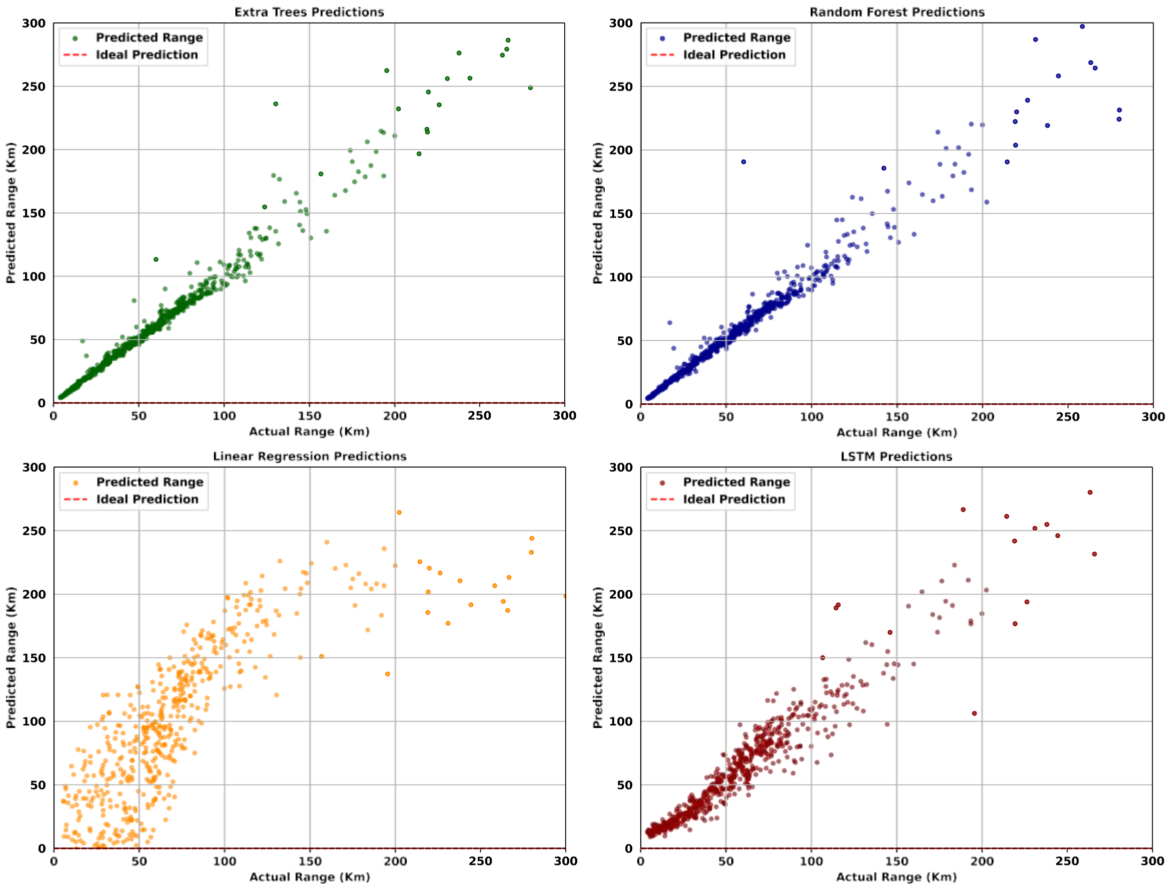

Figure 4: Range estimations for individual graphs

To validate our results we use error metrics, MAE, MSE and R-Squared score. The error values of Range estimations for individual models are listed in *table 1*. MAE indicates the mean error in the value of targeted item and MSE indicates how high these extremities are. R-squared is a method to evaluate the relevance of the inputs in the outputs achieved. The results for individual models indicate high error in prediction of the range value (indicated by MAE). Also paired with high MSE values and very low or negative R-squared value, this indicates that no model individually gives out the best preferred results. Individually comparing, Random forests and Extra Trees give best results as evident by their lower error and high R^2 values.

Table 1: Range Estimation individual model error metrics

	MAE	MSE	R^2
Random Forest	48.9601	5789.1816	0.3240
Extra Trees	56.9212	7474.4622	0.12726
LSTM	64.8427	9654.0162	-0.1272
LR	74.2692	13296.4647	-0.55253

Ensembling two models at a time showed a visible deflection of predicted values as compared to actual values as seen in *Figure 5.* It was observed that all the combination was under-estimating the range. Every combination showed a shift downward in the predictions.

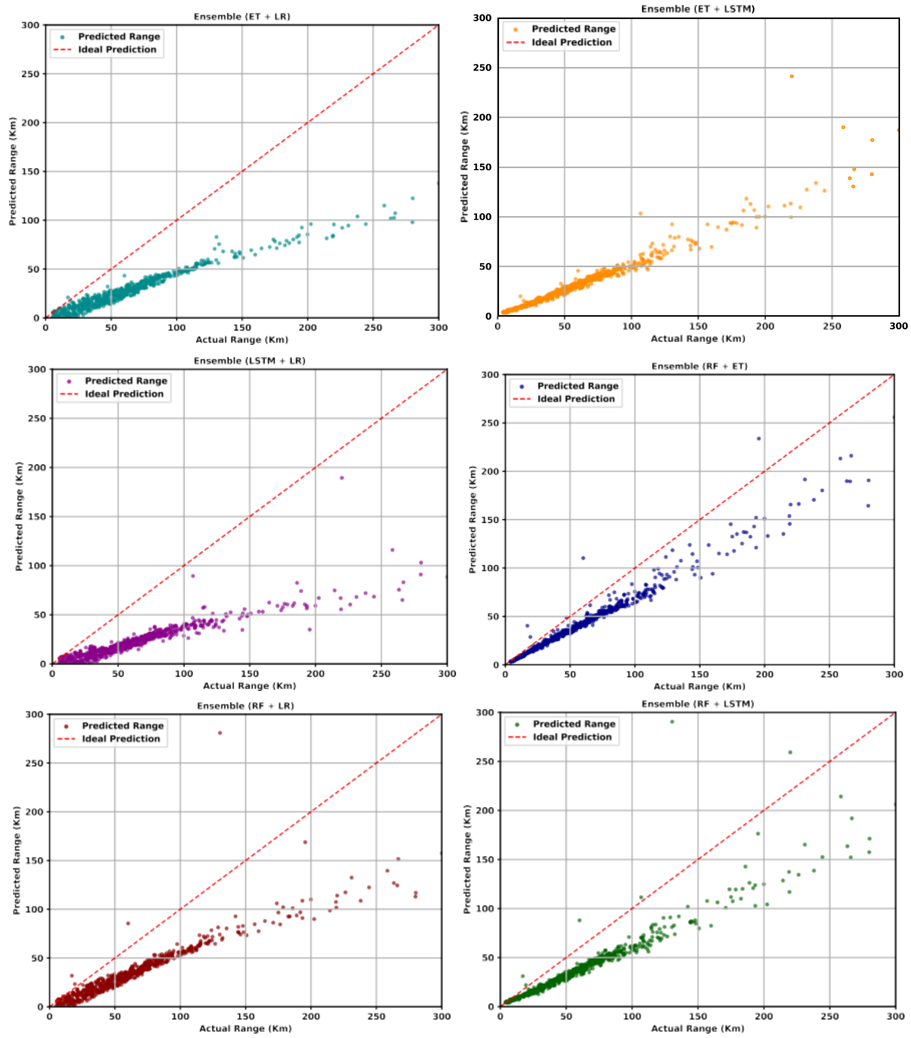

Figure 5: Range estimations for two models ensembled at a time

But Ensembling two models at a time showed improvement in the error metrics as seen in *Table 2.* but it is visible in the graphs that the trend is not visibly followed. The error metrics consistently indicate that the error margins have reduced and the ensembling has a better effect on the dependency of the results. Ensembling two models at a time further improved the results with MAE further decreasing and R-squared score increasing for all the models and none showed negative values. A significant development is R-squared score was seen and the best result was with the combination giving the best results in single models, i.e., RF and ET. The least error in MAE was 23.9957KM and highest R-squared score was 80.34% with RF + ET ensembling.

Table 2: Range estimation error metrics for two models ensembled at a time

	MAE	**MSE**	**R^2**
RF + ET	23.9957	1683.4930	0.8034
RF + LSTM	32.1282	2757.3992	0.6780
RF + LR	40.6688	4592.0880	0.4638
ET + LSTM	39.5757	3808.5576	0.5553
ET + LR	48.5913	6067.7023	0.2915
LSTM + LR	56.5151	8034.6238	0.0618

Inclusion of third model in the ensembling results in better predictions as seen in *Figure 6*. With all other models still under reporting, RF + ET + LSTM gives the best results. Even though the results are better but still long-range estimates are flaring up and deviating much more than in low range.

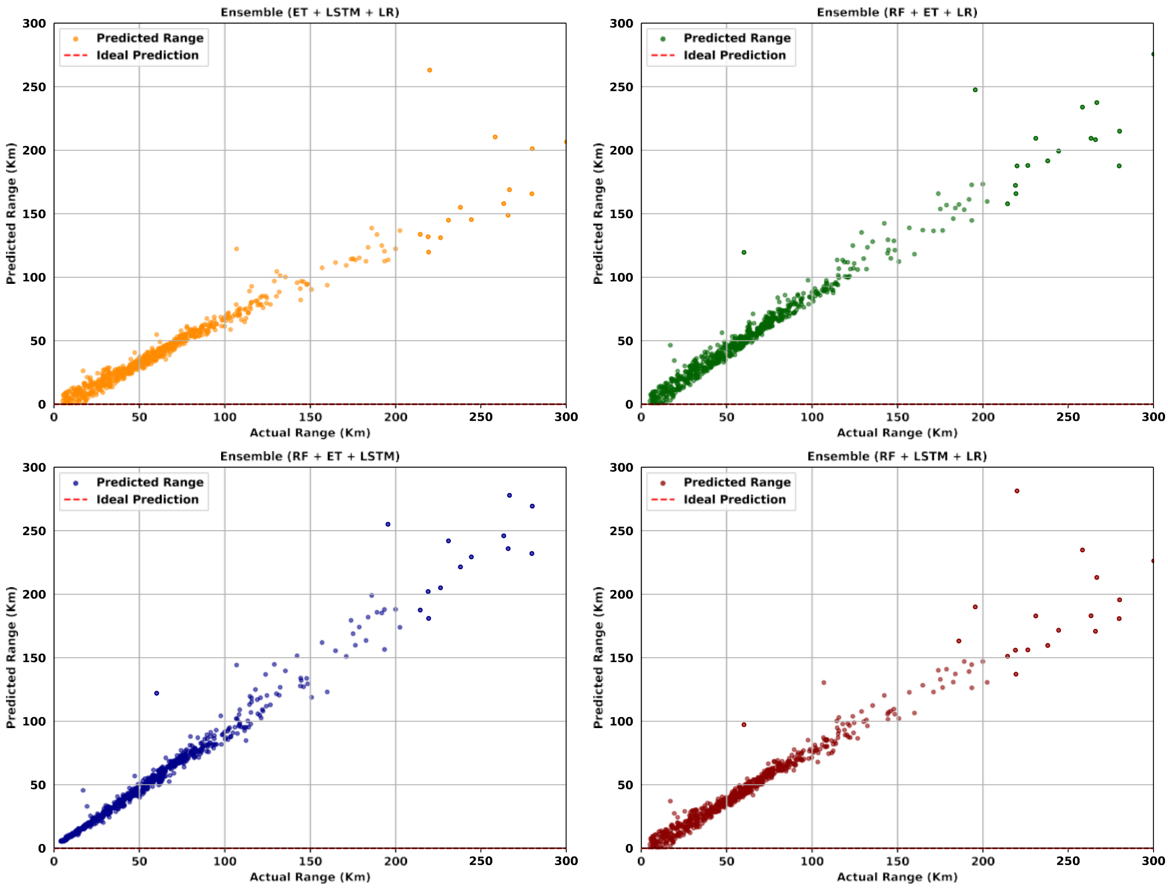

Figure 6: Range estimations for three models ensembled together

Following the trend and ensembling three models at a time, we see significant improvement in the metrics (*Table 3*). The MAE and MSE dropping significantly with R-squared value increasing drastically and reaching 60% + figures for all combinations. RF + ET + LSTM had the best results with 91% R-squared score and error a meagre 9KM.

Table 3: Range estimation error metrics for three models ensembled at a time

	MAE	**MSE**	**R^2**
RF + ET + LSTM	9.5055	718.7624	0.9160
RF + ET + LR	16.2524	1170.1474	0.8633
RF + LSTM + LR	24.1087	2031.4211	0.7628
ET + LSTM + LR	31.4100	2872.9132	0.6645

Finally, ensembling all of the models together, we get the best results with least deviation in both low range and high range visible in *Figure 7*. The results are consistent throughout and comparatively best in consideration with all the previous models

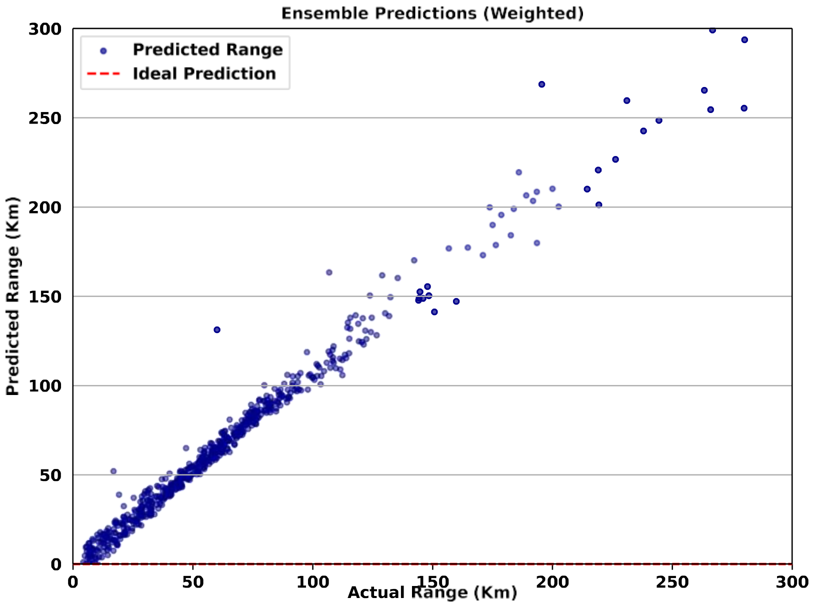

Figure 7: Range estimations for all models ensembled together

. Comparing metrics in *Table 4*, we can see the results are in comparison with RF + ET + LSTM results, which is true but the minor change in metrics is significantly visible in the range graph.

Table 4: Range estimation error metrics for all models ensembled together

	MAE	MSE	R^2
ENSEMBLED **(RF + ET + LSTM + LR)**	8.3972	676.5323	0.9210

The evaluation of all the metrics with all models can be seen in the *figure 8*. Both MAE and MSE, is lowest for Ensembled result of all the models together.

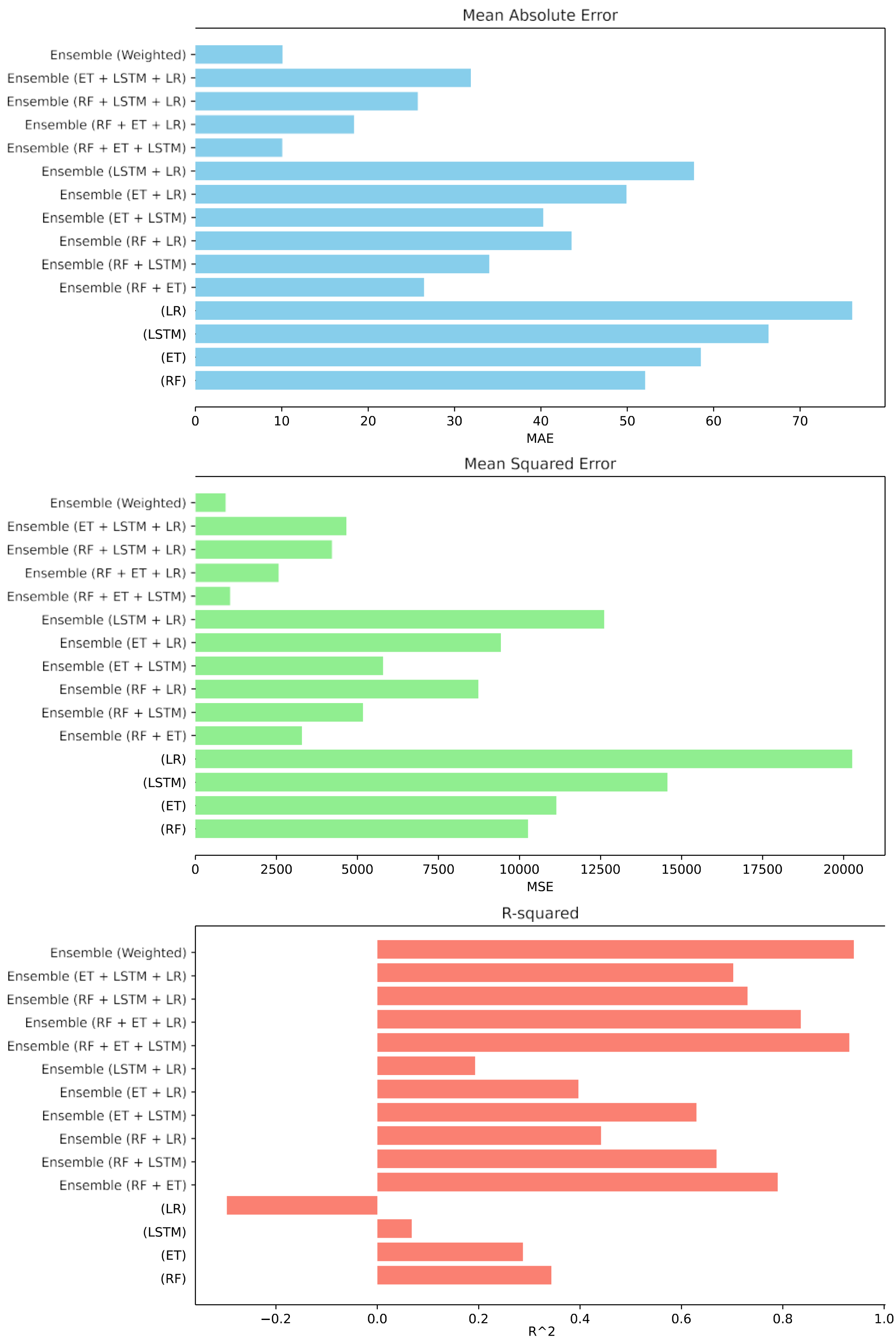

Figure 8: Range estimation error metrics visualized in graph

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4.2. Optimum Velocity and Acceleration

Same models were used with adjusted datasets, and results followed the trends seen in the range estimation models. As seen in *Figure 9,* the predicted values are in-line with optimum values but from the error metrics in *table* 5 it is evident that these results are not trust worthy.

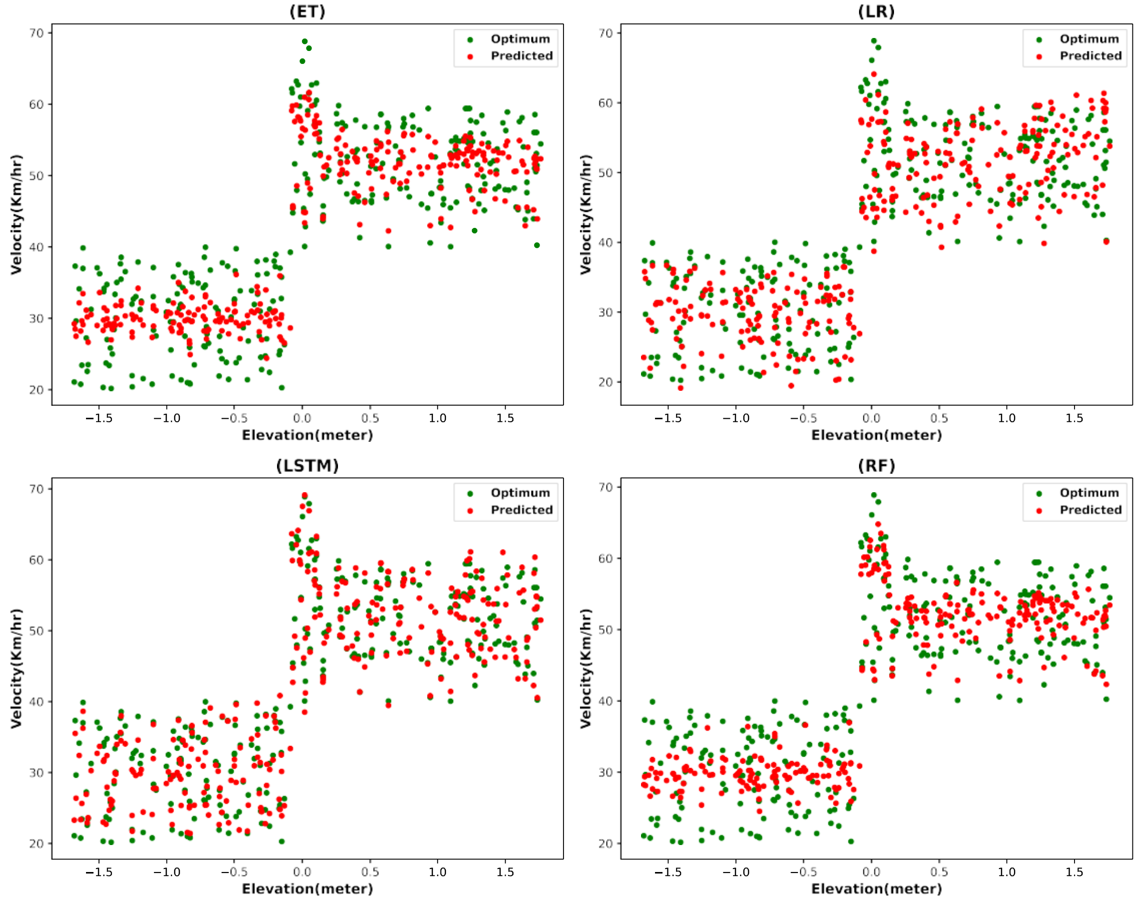

Figure 9: Optimum Velocity predictions for all the models

As seen in the *table 5*, we can see single models are very much off and the velocity errors are significantly high and the R-squared score is in negative. It is seen that even though the error metrics were not adequate and had a significant error, the optimum and predicted are pretty similar for all the models individually. But the negative R-Squared score indicates that this data is not reliable, so we have to consider ensembling of models as well.

Table 5: Optimum velocity error metrics for individual models

	MAE	**MSE**	**R^2**
Random Forrest	25.77450	737.04878	-3.6092
Extra Trees	30.07243	996.01807	-5.2288
LSTM	34.2942	1278.6985	-6.9966
LR	38.4952	1616.7553	-9.11070

We can see that these negative R-squared scores are varying and LR scores the least with RF being the best. It is still consistent with the range estimation results and we move further with ensembling all the combinations of these models.

All the ensembled results with two models were found to be majorly deviated and under reported the predicted velocity visible in *Figure 10*.

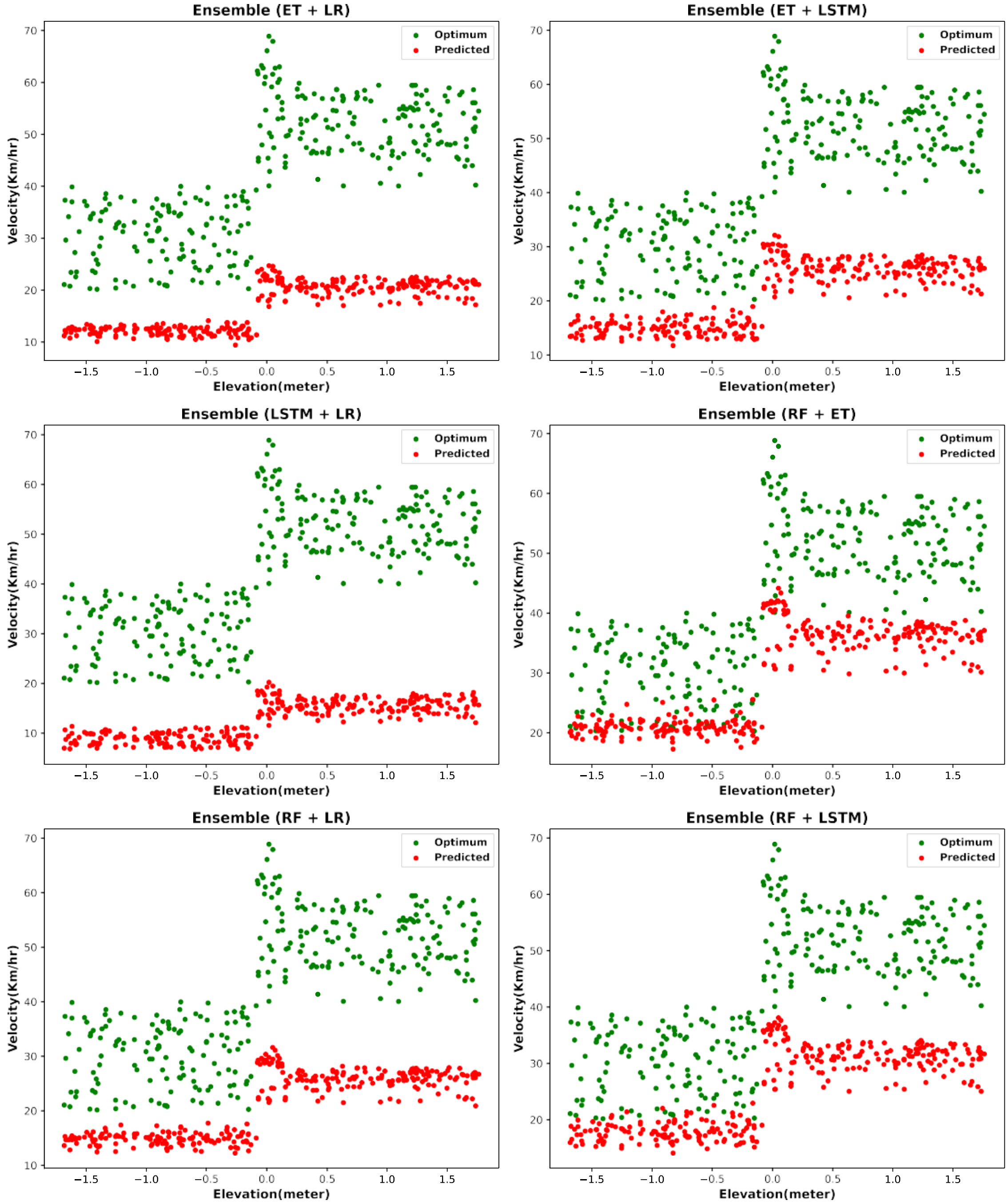

Figure 10: Optimum Velocity predictions for two models ensembled at a time

After ensembling all two combinations, we see significant improvement in the Error metrics in *Table 6* as MAE decreases for all of the models and the R-squared score has also improved significantly. This is consistent with the previous model for range estimations.

Table 6: Optimum velocity error metrics for two models ensembled at a time

	MAE	MSE	R^2
RF + ET	13.0648	204.9211	-0.2815
RF + LSTM	17.2603	335.2375	-1.0964
RF + LR	21.4613	517.8597	-2.2385
ET + LSTM	21.5583	515.4414	-2.2234
ET + LR	25.7592	737.3835	-3.6113
LSTM + LR	29.9810	981.7578	-5.1396

Ensembling three models together further increased the accuracy of the model, this is confirmed by the graphs in *figure 11*. The predictions are less deviated and show better results. The best results with least deviation in RF + ET + LSTM model. This is also consistent with the previous model of range estimation.

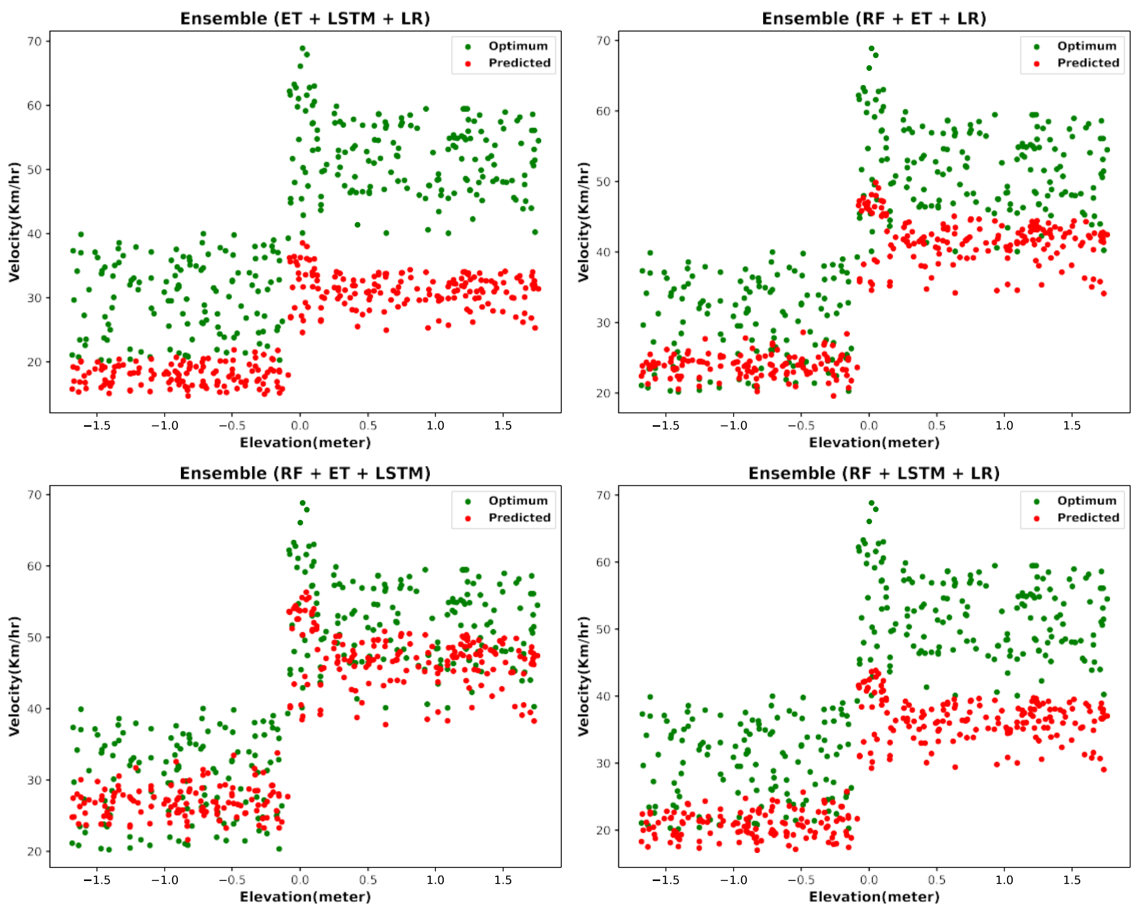

Figure 11: Optimum Velocity predictions for three models ensembled at a time

With the three models being ensembled together, we see major jump in performance in *Table 7.* RF + ET + LSTM score around 77% significance and the error has also come down to 5. All of the combinations show better results. This confirms our improvement in the predictions seen above.

Table 7: Optimum velocity error metrics for three models ensembled at a time

	MAE	MSE	R^2
RF + ET + LSTM	5.1705	36.296	0.7730
RF + ET + LR	8.9953	102.8037	0.3570
RF + LSTM + LR	12.9472	194.81398	-0.21830
ET + LSTM + LR	17.2451	335.5723	-1.09857

For final ensembled results of all models together, we see significantly improved graph of optimum and predicted graphs in *Figure 12.* These results have satisfactory predictions with least deviations.

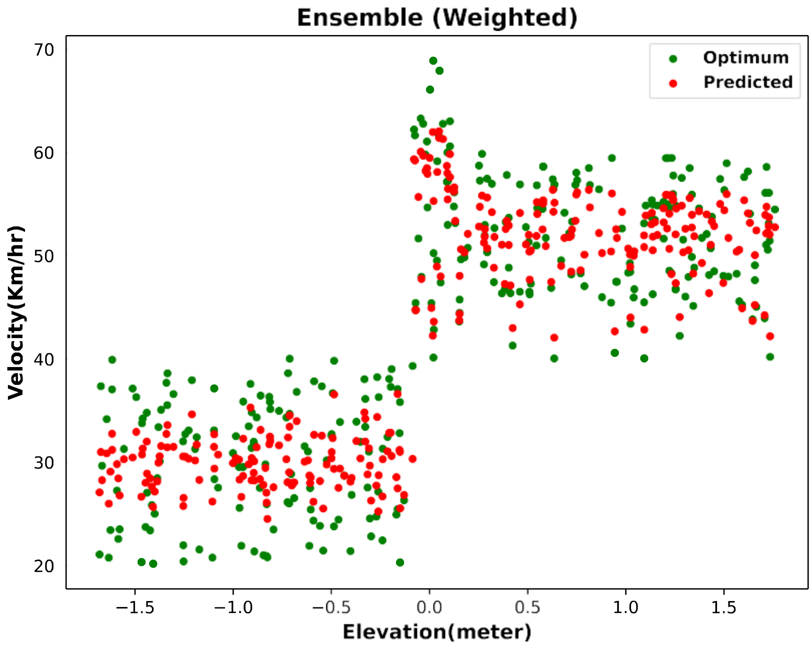

Figure 12: Optimum Velocity predictions for all models ensembled together

The error metrics for four models ensembled together is also very significant as seen in *Table 8.* These low errors and high R-squared scores confirm that all four models ensembled together gives the best results.

Table 8: Optimum velocity error metrics for all models ensembled together

	MAE	MSE	R^2
ENSEMBLED **(RF + ET + LSTM + LR)**	2.8336	12.9442	0.91905

The error metrics are compared in *Figure13* and it is seen again that all four models ensembled together gives the best results with second best results being RF + ET + LSTM. This ensembling method has therefore proved itself to be very efficient and has had good results

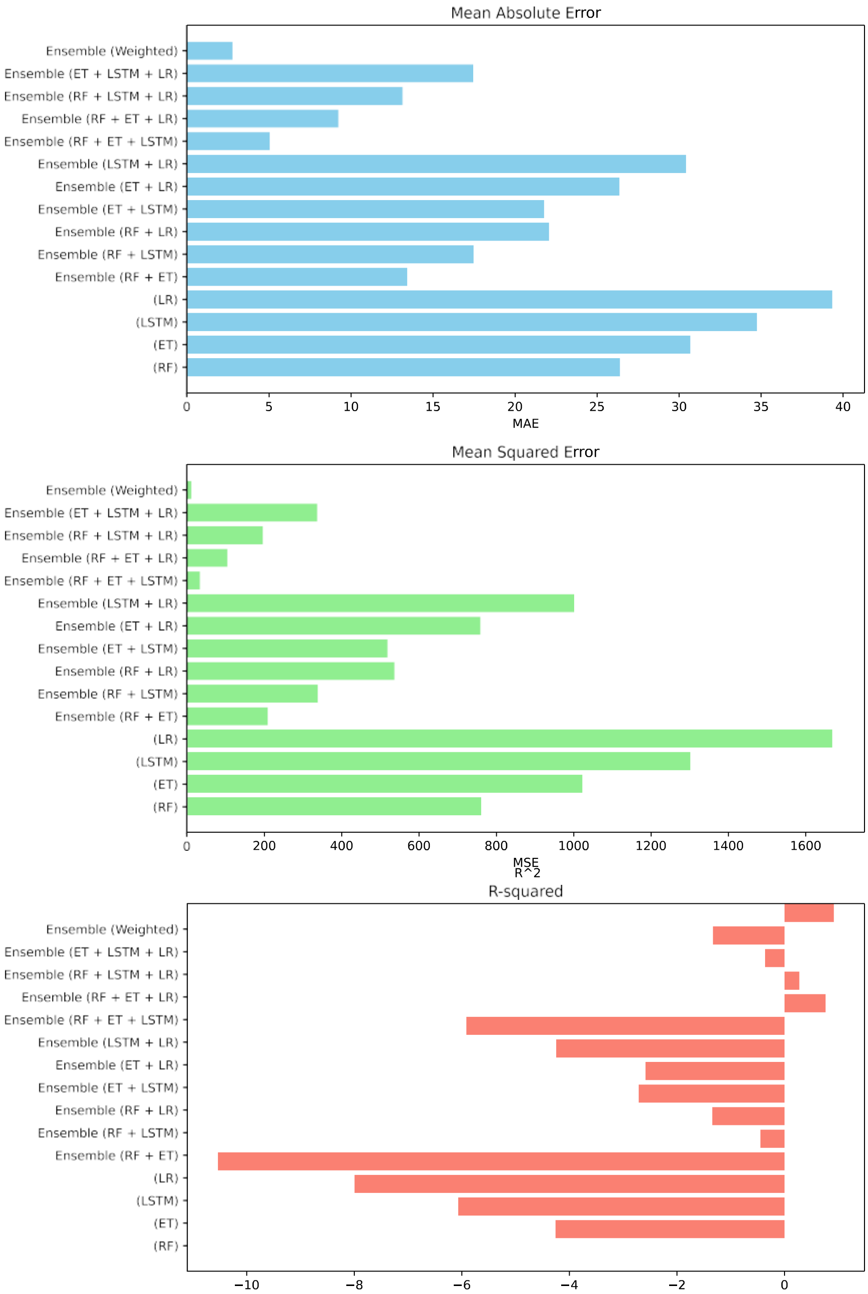

Figure 13: Optimum velocity error metrics visualized in graph

After evaluation of all the results, the trained models are exported and used to run the web app which gives out expected results based on the input of user. Input of user can be replaced with sensor inputs and data in a hardware setting. This sums up all of the processes and gives out a graphical interface for users to understand the workings and aim of our project. These results when paired up with appropriate hardware can be used in a real time system to assist driving for a better drive experience for both the driver and the vehicle. This will also promote healthy driving habits for the user to maximise the life of their EV. Snapshot of the web page is seen in *Figure 14.*

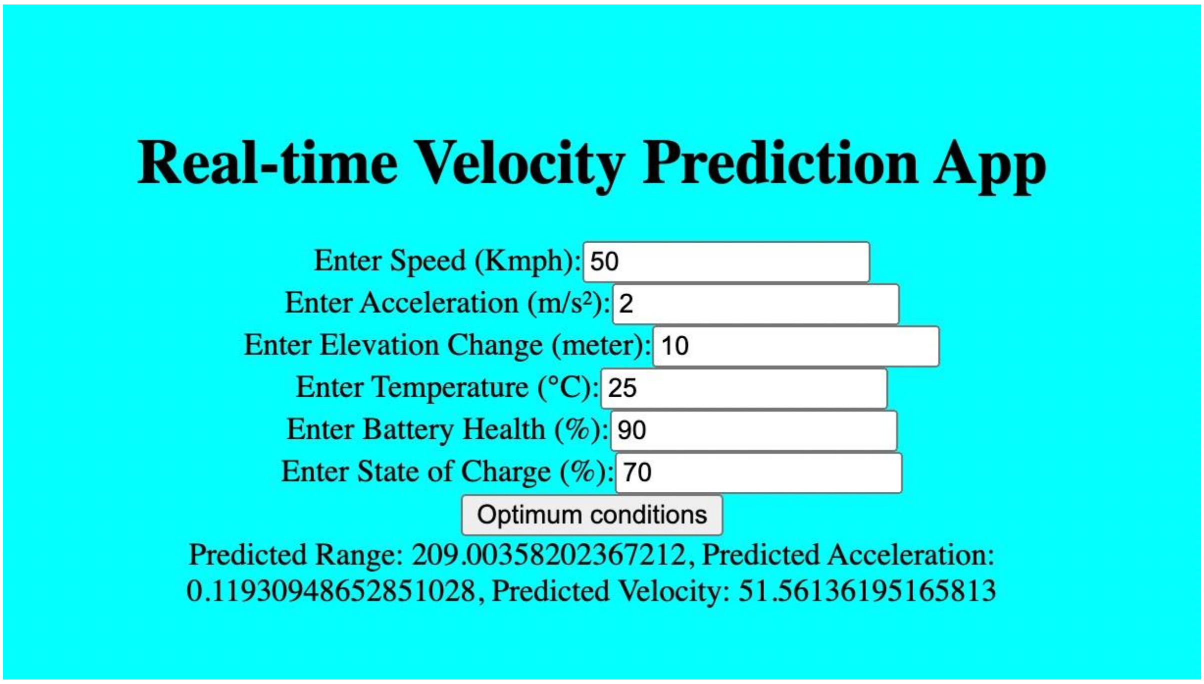

Figure 14: Real time web app

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1. Conclusion

In conclusion, this project tries to formulate a systematic approach to utilizing different ML models for estimating range, optimum velocity and acceleration in EVs. The methodology constituted of gathering and pre-processing of dataset, defining features and targets for the different models. These datasets were then used to train and test four different models including Random Forest Regressor, Extra Trees Regressor, LSTM, and Linear Regression. The performance of these models was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2) score.

The results strongly indicated that single models run individually have limitations in predicting the target values required. It was observed that ensembling models together reduces the errors and increases the credibility of the predictions both in error metrics and in graphs. By combining the models, we were able to achieve lower MAE, MSE and R-squared (R^2) score.

.

The real-time web app developed as part of this project aims provides a user-friendly interface for users to input their parameters and obtain predicted range, optimum acceleration, and velocity. This tool can be further enhanced by integrating it with sensor data from EVs, allowing for real-time monitoring and optimization of driving conditions.

5.1.Major Contributions:

- Development of a methodology for predicting range, optimum acceleration, and velocity in EVs using machine learning models.
- Evaluation of various machine learning models and ensembling techniques to improve prediction accuracy.
- Implementation of a real-time web app for user interaction and visualization of predicted results.

5.2.Limitations:

5.2.1. The project relies on simulated datasets created using software, which may not fullycapture real-world scenarios.
5.2.2. The accuracy of predictions may be influenced by the quality and quantity of dataavailable for training the models.
5.2.3. The performance of the models may vary depending on factors such as environmentalconditions, driving behaviour, and vehicle specifications.

5.3. Future Scope

5.3.1. Integration with real-time sensor data from EVs to enhance the accuracy and reliabilityof predictions.
5.3.2. Exploration of additional machine learning models and ensembling techniques tofurther improve predictive performance.

5.3.3. Implementation of adaptive learning algorithms to continuously update and refine the models based on new data.
5.3.4. Extension of the web app to include features such as personalized recommendations fordriving optimization and feedback on driving habits.
5.3.5. Collaboration with EV manufacturers and stakeholders to validate the effectiveness of the predictive models in real-world scenarios and integrate them into existing EV systems.

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ANNEXURES

Annexure 1

PO & PSO Mapping

Note: use a tick mark if you have addressed that PO and PSO in your work

PO No	PO	✓ tick
PO1	**Engineering knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialisation to the solution of complex engineering problems.	✓
PO2	**Problem analysis:** Identify, formulate, research literature, and analyse complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.	✓
PO3	**Design/development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet t h e specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.	✓
PO4	**Conduct investigations of complex problems**: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.	✓
PO5	**Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modelling to complex engineering activities with an understanding of the limitations	✓
PO6	**The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.	✓
PO7	**Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.	✓
PO8	**Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.	✓
PO9	**Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings	✓
PO10	**Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions	✓
PO11	**Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.	✓

PO12	**Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.	✓
PSO1	Apply the engineering knowledge to analyze and evaluate the components of power system, its operation, control and protection	✓
PSO2	Model and Analyze linear and non-linear systems in both continuous and discrete domains.	✓
PSO3	Design and develop electronic circuits and systems for specified applications	✓
PSO4	Apply the programming skills to develop model and intelligent systems	✓

Expand the mapping with different level and give justifications:

PO and PSO number	Addressed in which chapter	Justification	Level: 0: Not related 1: Low 2: Medium 3: Strong
PO1	3	Create methodology	3
PO2	2	Literature review	3
PO3	3	Create methodology	3
PO4	5	Result analysis	3
PO5	3, 5	Methodology and result analysis	3
PO6	1	Need and relevance	3
PO7	1, 3	EV relevance, better research method	3
PO8	1	Need for the project	2
PO9	4	Worked individually for same goal	3
PO10	5, 6	Results and conclusions in easy language	3
PO11	2, 4	Distribute work evenly and understand finance plus points	3
PO12	6	Scope for improvement	3
PSO1	1, 2, 3	Electric drive system and management	3
PSO2	3	Methodology to train AI models	3
PSO3	3, 6	Method to integrate system with EV	2
PSO4	3, 5, 6	AI model trained and tested	3

Annexure 2

LO MAPPING

Note: use a tick mark if you have addressed that LO in your work

PLO No	LO	✓ tick
C1	Apply knowledge of mathematics, statistics, natural science and engineering principles to the solution of complex problems. Some of the knowledge will be at the forefront of the particular subject of study	✓
C2	Analyse complex problems to reach substantiated conclusions using first principles of mathematics, statistics, natural science and engineering principles	✓
C3	Select and apply appropriate computational and analytical techniques to model complex problems, recognising the limitations of the techniques employed	✓
C4	Select and evaluate technical literature and other sources of information to address complex problems	✓
C5	Design solutions for complex problems that meet a combination of societal, user, business and customer need as appropriate. This will involve consideration of applicable health & safety, diversity, inclusion, cultural, societal, environmental and commercial matters, codes of practice and industry standards	✓
C6	Apply an integrated or systems approach to the solution of complex problems	✓
C7	Evaluate the environmental and societal impact of solutions to complex problems and minimise adverse impacts	✓
C8	Identify and analyse ethical concerns and make reasoned ethical choices informed by professional codes of conduct	✓
C9	Use a risk management process to identify, evaluate and mitigate risks (the effects of uncertainty) associated with a particular project or activity	
C10	Adopt a holistic and proportionate approach to the mitigation of security risks	
C11	Adopt an inclusive approach to engineering practice and recognise the responsibilities, benefits and importance of supporting equality, diversity and inclusion	✓
C12	Use practical laboratory and workshop skills to investigate complex problems	
C13	Select and apply appropriate materials, equipment, engineering technologies and processes, recognising their limitations	
C14	Discuss the role of quality management systems and continuous improvement in the context of complex problems	
C15	Apply knowledge of engineering management principles, commercial context, project and change management, and relevant legal matters including intellectual property rights	
C16	Function effectively as an individual, and as a member or leader of a team	✓
C17	Communicate effectively on complex engineering matters with technical and non-technical audiences	✓
C18	Plan and record self-learning and development as the foundation for lifelong learning/CPD	✓

Expand the mapping with different levels and give justifications:

IET LO number	Addressed in which chapter	Justification	Level: 0: Not related 1: Low 2: Medium 3: Strong
C1	5, 6	Result analysis and conclusions	3
C2	3, 5, 6	Forming Methodology and analysing results	3
C3	3, 5	Methodology and result analysis	3
C4	1, 2	Literature review and need of project	2
C5	2, 3	Forming objectives and methodology	3
C6	3, 5	Methodology forming and results analysis	3
C7	2, 3, 6	EV range estimations and help in research	2
C8	1, 2	Explain why project needed	3
C9			
C10			
C11	2, 3	Creating methodology	3
C12			
C13			
C14			
C15			
C16			
C17	5, 6	Result explanation and conclusions	3
C18	6	Conclusion and further scope for the project	3

Annexure 3

Project/practice school work classification

Table 1: classification based on project domain classification

Type and Domain	✓ Tick
Product (Hardware/Software)	✓
Simulation	✓
Study	✓
Application	✓
Review	
Research	✓
Domain: Electrical	✓
Domain: Electronics	✓
Domain: Computer science	✓
Domain: Basic science (math/physics/chemistry)	
Domain: Management	

Table 2: classification based on societal consideration

Societal Impact	✓ Tick
ethics	✓
safety	
environmental	✓
commercial	✓
economic	✓
social	✓

Annexure 4

General data available/assumed for dataset:

"Speed (Kmph)", "Acceleration (m/s²)", "Elevation Change (meter)", "Temperature (°C)", "Weather Conditions", "HVAC Usage", "Battery Health (%)", "State of Charge(%)", "Driving Mode", "Range (Km)"

Calculations for dataset estimation:

```
Full_battery = 30.2 #kWh
# Data as per Tata Nexon
Area = 2.91 #m^2
Cd = 0.18 #Drag Coefficient
Rho = 1.2 #Air Density
mass=1295
g = 9.81
HVAC_load = 5

h=math.sqrt((elevation_change*elevation_change)+(50*50))
    sinA = elevation_change/h
    Fd = 0.5*Rho*Cd*Area*speed*speed
    Fc= mass*g*sinA
    Pd = (Fd+Fc)*speed
    Eb = SOC*battery_health*Full_battery

    range_estimate = (Eb*3.6*speed)/Pd
```

Dataset for Range estimations:

```
dataset.columns = ["Speed (Kmph)", "Acceleration (m/s²)", "Elevation
Change (meter)", "Temperature (°C)", "Weather Conditions", "HVAC
Usage", "Battery Health (%)", "State of Charge(%)", "Driving Mode",
"Range (Km)"]

# Split data into features and target variable
X = dataset[['Speed (Kmph)', 'Acceleration (m/s²)', 'Elevation Change
(meter)', 'Temperature (°C)', 'Weather Conditions', 'HVAC Usage',
'Battery Health (%)', 'State of Charge(%)', 'Driving Mode']]
#Target
y = dataset['Range (Km)']
```

Dataset for optimum velocity and acceleration estimation:

```
dataset.columns = ["Speed (Kmph)", "Acceleration (m/s²)", "Elevation
Change (meter)", "Temperature (°C)", "Weather Conditions", "HVAC
Usage", "Battery Health (%)", "State of Charge(%)", "Driving Mode",
"Range (Km)", "Optimum Velocity", "Optimum Acceleration"]
```

```
# Split data into features and target variables
X = dataset[['Speed (Kmph)', 'Acceleration (m/s²)', 'Elevation Change
(meter)', 'Temperature (°C)', 'Weather Conditions', 'HVAC Usage',
'Battery Health (%)', 'State of Charge(%)', 'Driving Mode']].values
y_velocity = dataset['Optimum Velocity'].values # Target variable for
optimum velocity prediction
y_acceleration = dataset['Optimum Acceleration'].values # Target
variable for optimum acceleration prediction
```

```
# Split data into features and target variable
X = dataset[['Speed (Kmph)', 'Acceleration (m/s²)', 'Elevation Change
(meter)', 'Temperature (°C)', 'Battery Health (%)', 'State of
Charge(%)', 'Range (Km)']].values
y = dataset['Optimum Velocity'].values
# Train models
rf_model.fit(X_train.reshape((X_train.shape[0], X_train.shape[1])),
y_train)
et_model.fit(X_train.reshape((X_train.shape[0], X_train.shape[1])),
y_train)
lstm_model.compile(optimizer='adam', loss='mse')
lstm_model.fit(X_train, y_train, epochs=1000, batch_size=32)
lr_model.fit(X_train.reshape((X_train.shape[0], X_train.shape[1])),
y_train)

# Predictions
rf_pred = rf_model.predict(X_test.reshape((X_test.shape[0],
X_test.shape[1])))
et_pred = et_model.predict(X_test.reshape((X_test.shape[0],
X_test.shape[1])))
lstm_pred = lstm_model.predict(X_test).flatten()
lr_pred = lr_model.predict(X_test.reshape((X_test.shape[0],
X_test.shape[1])))
# Initialize ensemble_metrics dictionary
ensemble_metrics = {}

# Combine predictions from all models using weighted averaging
ensemble_pred_weighted = (rf_weight * rf_pred + et_weight * et_pred +
                          lstm_weight * lstm_pred + lr_weight*lr_pred)
# Print ensemble metrics
for name, metrics in ensemble_metrics.items():
    print(f"{metrics['Name']} Metrics:")
    print(f"MAE: {metrics['MAE']}")
    print(f"MSE: {metrics['MSE']}")
    print(f"R^2: {metrics['R^2']}")
    print()
```

PROJECT DETAILS

Details of Student			
Name	AAYUSH UJJWAL		
Roll. No.	2201062040	SOET	BCA(AI & DS)
Mail ID	Jaayushujjwal@gmail.com	Mobile	7857907674
Project Details			
Project Title	Smart Strategies for Enhanced Electric Vehicle Battery Performance and Efficiency		
Project Duration	4 months		
Guide details			
Name of Guide1	Jyoti Kataria		
Designation, Dept., Institution	Associate Professor , (SOET)		

Signature of Student
Date:

Signature of Guide

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