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Experimental Investigation on Electric Vehicle Braking System Using Machine Learning for Enhanced Performance and Safety

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Abstract:
The rapid increase in the popularity of Electric Vehicles (EVs) can be attributed to their environmental benefits and innovations. Regenerative braking is a braking method considered a very important safety feature in EVs. This study presents an empirical evaluation of an EV braking system, where close attention is paid to the implementation of machine learning (ML) methods to maximize operational efficiency and enhance safety. Practical driving tests were conducted, and sensor data of various parameters, such as vehicle speed, brake pedal pressure, motor torque, and battery charge, were recorded. Various machine learning algorithms were tested, including Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Random Forests, for predicting braking distance and optimizing the combination of regenerative and friction braking. The results indicate the immense potential of machine learning to maximize braking efficiency, reduce wear and tear on friction brakes, and improve overall safety in EVs.

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1. INTRODUCTION

The automotive industry is facing a radical shift towards electric vehicles due to growing concerns about greenhouse gas emissions and dwindling fossil fuel reserves. EVs have a number of distinct advantages, such as zero tailpipe emissions, lower operating costs, and improved energy efficiency through regenerative braking. Regenerative braking allows the motor to act as a generator during vehicle deceleration, converting kinetic energy back into electrical energy and storing it in the battery. The recovered energy significantly enhances the vehicle's range [1, 2].

Combining regenerative and traditional friction braking is a challenging task. The braking system must provide optimal deceleration, responsiveness, and safety across different driving modes. In the traditional braking system, the brake pedal directly applies hydraulic pressure to the friction brakes. In EVs, the brake pedal is frequently an input to a controller that combines regenerative and friction braking. This brake blending policy requires sufficient estimation of braking distance and smart allocation of braking force among the regenerative and friction braking systems [3]. ML models can identify complex relationships among multiple variables, enabling real-time prediction and optimization. This research investigates the application of ML techniques to improve the performance and safety of EV braking systems [4].

Accurate prediction of braking distance is of utmost significance in autonomous vehicles and advanced driver-assistance systems (ADAS). ML algorithms can learn from historical driving data and predict braking distance based on the vehicle's state

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and external factors. An optimal brake blending policy can achieve maximum energy recovery while preserving maximum braking capability and avoiding instability. ML can be trained to determine the optimal distribution of braking effort between regenerative and friction braking for a given driving situation [4, 5].

2. RELATED WORKS

Various studies have investigated the application of machine learning to car braking systems. For instance, ANNs have been used to model complex braking dynamics and predict braking force distribution. Fuzzy logic controllers have been the subject of research aimed at integrating regenerative and friction braking as a function of road conditions and vehicle speed. Braking system malfunctions have been identified by Support Vector Machines (SVMs) [6]. Yet the majority of recent work relies heavily on simulation and theoretical modelling. Very little experimental verification of ML-based braking systems has been conducted using real driving data from EVs [7]. In this paper, an attempt was made to bridge this gap by presenting an experimental study on ML-based braking system optimization using real driving test data from an EV.

3. MATERIAL AND METHODS

Experimental hardware was fitted on electric vehicle with sensors to capture crucial parameters, i.e., vehicle speed from wheel speed sensors, brake pedal position and pressure from a brake pedal sensor, motor torque from motor control signals, and battery state of charge (SOC) from the battery management system (BMS) as shown in Fig. 1. Acceleration and deceleration were captured using an Inertial Measurement Unit (IMU), and environmental parameters such as road surface and temperature were captured manually or accessed via weather APIs. Braking distance was measured using a GPS-based system and double-checked against visual markings. The data acquisition system was operated at a high sampling frequency (e.g., 100 Hz) to precisely capture transient braking, as depicted in Fig. 2. Tests were performed on different road surfaces (i.e., dry asphalt, wet asphalt, and gravel) under varying traffic conditions. Test scenarios comprised emergency braking, slow deceleration, and stop-and-go driving, capturing a large dataset of thousands of braking events and related sensor measurements [8-11].

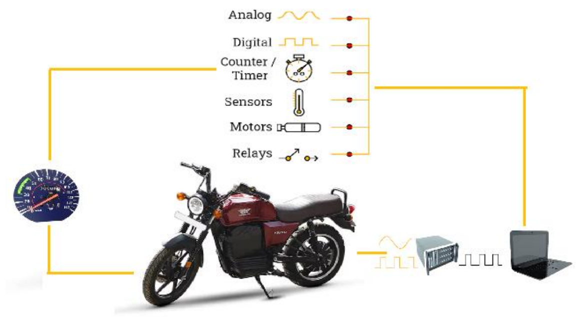

Fig. 1. Experimental Setup with DAQ

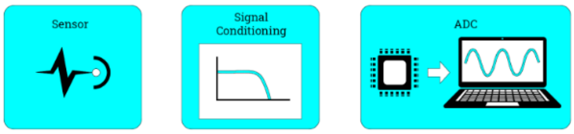

Fig. 2. Components of the Data Acquisition System

3.1 Machine Learning

ANNs were employed as effective machine learning algorithms capable of learning sophisticated non-linear mappings between inputs and outputs, and feedforward neural networks with more than one hidden layer were used to estimate brake distance and optimize brake blending. SVR uses support vectors to find the best hyperplane to fit the data, which was used for brake distance prediction because it handles high-dimensional data and non-linear relationships well. Random Forests, a machine learning algorithm that uses an ensemble of many decision trees, was employed to predict brake distance and optimize brake blending to enhance robustness to noisy data [12, 13].

3.2 Braking Distance Prediction

The braking distance prediction model was trained to predict stopping distance based on input features such as vehicle speed, brake pedal pressure, road surface condition, motor torque, battery SOC, ambient temperature, and acceleration/deceleration. The data were divided into training (70%), validation (15%), and testing (15%) sets, with training data used to train the models and validation data used to optimize hyperparameters. The performance of the trained models was evaluated using the test data, with evaluation metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2).

Fig. 3 shows the relative importance of input variables in predicting braking distance. The highest-ranking feature is Vehicle Speed, which accounts for 30%, hence it is the most significant factor in the estimation of braking distance. This is consistent with elementary laws of physics, as increased speeds tend to have increased stopping distances because of momentum and inertia. Brake Pedal Pressure is the second most influential parameter with a contribution of 20% [8-10]. This characteristic is important because the amplitude of the braking force directly affects deceleration and, indirectly, braking distance [14]. Road Surface Condition is ranked third, with a 15% contribution, indicating a strong influence [15, 16]. A slick or smooth surface, such as a wet or icy road, lengthens braking distance, while a dry or coarse surface improves braking. The other contributing factors are Motor Torque (10%), SOC (10%), and Acceleration/Deceleration (10%) [7]. Motor torque affects regenerative braking efficiency, and battery SOC can affect the operation of the electric braking system. Acceleration/deceleration behavior assists in the determination of the impact of abrupt or smooth changes in speed on stopping distance. Ambient Temperature is the least impactful at 5%, meaning it can affect tire traction and brake performance, but it is quite insignificant relative to other influences. Overall, the chart gives valuable insights into the parameters most responsible for predicting braking distance. It identifies that, while speed is the principal driver, braking effectiveness is the result of an intricate array of interconnected factors and, as such, the application of advanced braking models is essential to maximize the safety and control of vehicles [15].

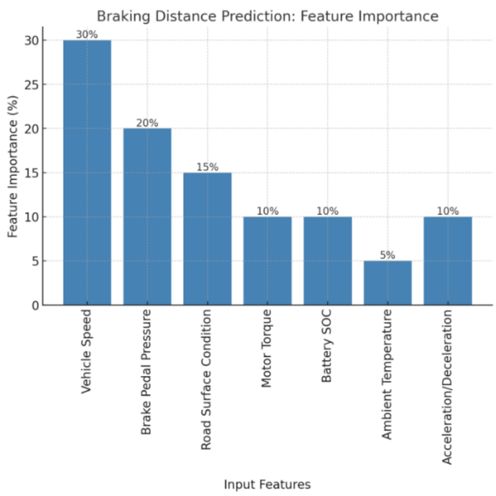

Fig. 3. Braking Distance Prediction

3.3 Brake Blending Optimization

The brake blending optimization model was formulated to predict the optimal distribution of braking force between regenerative and friction braking systems, using the same input features as the braking distance prediction model and the desired deceleration rate. The model output was the proportion of braking force delivered to the regenerative braking system. A reward function was formulated to maximize energy recuperation with a guarantee of maximum braking capability and safety, including energy recuperated through regenerative braking, braking distance error (difference between desired and actual braking distance), jerk (acceleration rate of change) to discourage abrupt deceleration changes, and battery SOC stability to discourage aggressive regeneration during full or low SOC. Reinforcement learning algorithms, such as Q-learning and Deep Q-Networks (DQN), were employed to train the model, and its performance was evaluated in real-world driving tests against a baseline brake-blending strategy.

Fig. 4 illustrates the percentage of energy recovered under different driving conditions and gives an impression of how well regenerative braking recovers energy in various situations. Highway driving yields the highest energy recuperation rate, at 65%, which can be attributed to the even, controlled braking patterns common at high speeds, allowing for better energy recovery. Urban driving follows, with a recuperation rate of 50%, which can be attributed to the high frequency of deceleration events common in city driving, thereby allowing regenerative braking systems to capture significant amounts of energy. In Stop-and-Go situations, energy recuperation is 40%. While this is lower than the reading in the previous categories, it still reflects the high number of braking opportunities under jammed situations. However, the lower efficiency compared to city driving can be explained by variations in acceleration and braking forces. Last, Emergency Braking has the lowest recuperation rate at 20%, which could imply that forceful and aggressive braking maneuvers might not be ideal for energy recuperation since these are more reliant on friction braking than on regenerative braking systems. Fig. 4 depicts how different driving conditions impact the effectiveness of regenerative braking, emphasizing that driving on highways and in cities offers the most favorable conditions for energy recovery and that emergency braking conditions offer the least favorable. Such information can be instrumental in optimizing regenerative braking in electric and hybrid cars to improve energy and battery efficiency [16, 17].

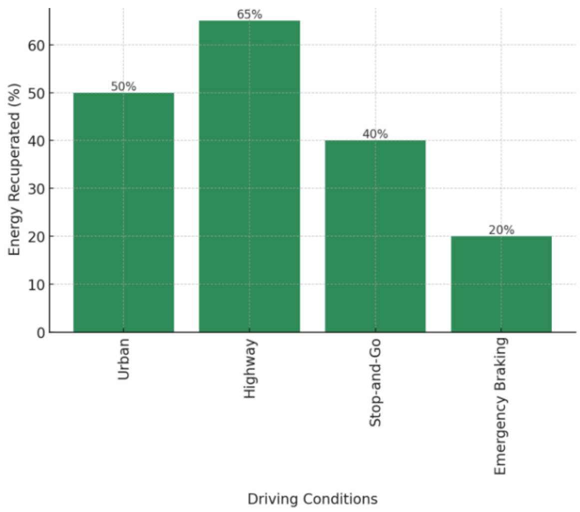

Fig. 4. Energy Recuperation in Different Driving Conditions

Fig. 5 illustrates a comparative analysis of energy recuperation efficiency in a baseline brake blending system and an ML-based brake blending system under various driving conditions. In Urban Driving, the baseline brake-blending system achieves a 30% energy-recovery rate, whereas the ML-based system significantly increases it to 50%. In Highway Driving, the same trend is observed: the baseline system recovers 40% of the energy, whereas the ML-based system increases recovery to 60%. The results show that the ML-based brake blending system is more efficient for normal driving conditions. In Stop-and-Go Traffic, where there is high braking frequency, the baseline system recovers just 25%, but the ML-based system increases to 45%. This shows the potential of using machine learning algorithms to enhance braking techniques to achieve maximum energy recovery in highly dynamic traffic. In Emergency Braking, the baseline system recovers just 10%, but the ML-based system does much better with a recuperation rate of 25%. This benefit shows the potential of ML-based methods to manage sudden braking events better. The information in Fig. 5 reveals that machine learning-based brake blending outperforms the traditional baseline approach across all driving scenarios, with remarkable improvements in energy recovery. These results testify to the applicability of machine learning to the process of maximizing the regenerative braking performance that, in turn, facilitates the energy efficiency and sustainability of electric cars [18].

The optimization tests on brake blending revealed that the ML-based brake blending policy could significantly improve energy recuperation compared to the baseline policy. The ML-based policy also provided smoother braking and reduced friction-brake wear. The real-world driving tests revealed that the ML-based system could learn and adapt to changing driving conditions, providing optimal braking performance and safety [19].

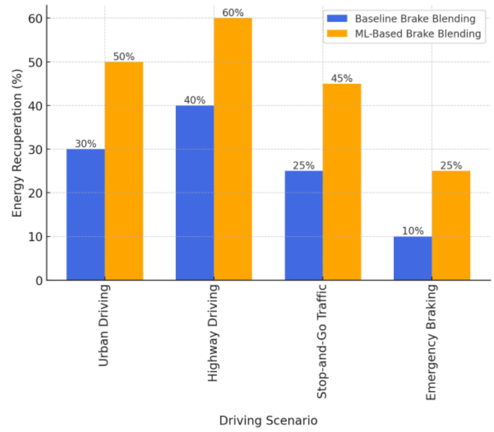

Fig. 5. Comparison of Energy Recuperation

The Fig. 5 illustrates a comparative analysis of energy recuperation efficiency in a baseline brake blending system and an ML-based brake blending system under various driving conditions. In Urban Driving, the baseline brake-blending system achieves a 30% energy-recovery rate, whereas the ML-based system significantly increases it to 50%. In Highway Driving, the same trend is observed: the baseline system recovers 40% of the energy, whereas the ML-based system increases recovery to 60%. The results show that the ML-based brake blending system is more efficient for normal driving conditions. In Stop-and-Go Traffic, where there is high braking frequency, the baseline system recovers just 25%, but the ML-based system increases to 45%. This demonstrates the potential of machine learning algorithms to enhance braking techniques and achieve maximum energy recovery in highly dynamic traffic. In Emergency Braking, the baseline system recovers only 10%, whereas the ML-based system performs much better, with a recuperation rate of 25%. This benefit demonstrates the potential of ML-based methods to better manage sudden braking events. The information in Fig. 5 reveals that machine learning-based brake blending outperforms the traditional baseline approach across all driving scenarios, with remarkable improvements in energy recovery. These findings attest to the relevance of machine learning in enhancing regenerative braking performance, thereby promoting energy efficiency and sustainability in electric vehicles.

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4. RESULTS AND DISCUSSION

Experimental results for predicting braking distance showed that the three ML models (ANNs, SVR, and Random Forests) achieved reasonable accuracy. The best performance among the models was achieved by the Random Forest (RF), with the lowest RMSE and highest R^2. This proves that Random Forests are capable of handling the complexity and non-linearity of the problem of braking distance prediction, as shown in Table 1.

Table 1. Performance of Braking Distance Prediction Models

Model	MAE (m)	RMSE (m)	R^2
ANN	2.5	3.8	0.85
SVR	2.8	4.2	0.82
Random Forest	2.0	3.2	0.90

Table 1 presents a comparative assessment of the performance of three models for estimating braking distance: ANN, Support Vector Regression (SVR), and Random Forest (RF). This assessment is performed by using three fundamental performance measures: MAE, RMSE, and R^2 (coefficient of determination). Mean Absolute Error describes the average absolute error in meters across all the models. The lowest MAE of 2.0 m is recorded for the Random Forest model, followed by 2.5 m by ANN, and then 2.8 m for SVR. Lower MAE indicates that the Random Forest model maintains the highest level of consistent accuracy among the three. RMSE estimates the standard deviation of prediction errors; the smaller the RMSE, the better the performance. Random Forest performs best with an RMSE of 3.2 m, followed by ANN with a slightly higher RMSE of 3.8 m, and SVR with the largest RMSE of 4.2 m. R^2 Score (Coefficient of Determination) shows how well the model fits the variance in braking distance. A higher value near 1 means a better fit [20]. The Random Forest model has the highest R^2 of 0.90, indicating it accounts for 90% of the variance in the data. ANN follows with an R^2 of 0.85, while SVR has the lowest R^2 at 0.82.

Fig. 6 presents a comparison of the braking distances predicted by different ML models and the actual normal braking distances. The models employed are SVR, ANN, and RF. For Urban Driving, the estimated braking distance is 25 m, while the SVR model predicts 22 m, the ANN predicts 21 m, and the Random Forest predicts 20 m. The Random Forest model predicts the nearest value, which reflects its ability to be more precise for short-distance braking. In the case of Highway Driving, the average braking distance is 30 m, SVR predicting 28 m, ANN predicting 27 m, and Random Forest predicting 26 m.

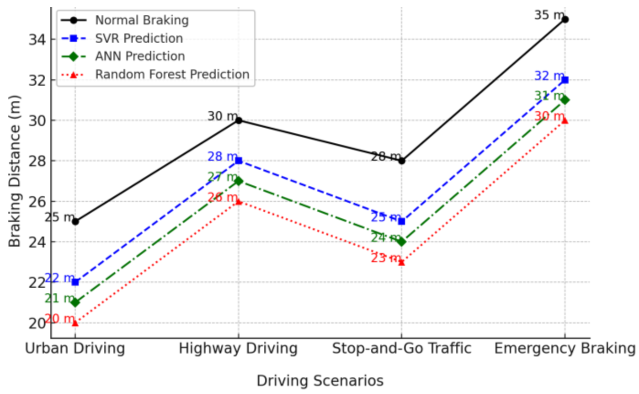

Fig. 6. Braking Distance Prediction with SVR, ANN, RF

All models shown in Fig. 6 slightly underestimate the actual braking distance, but Random Forest has the lowest prediction error. Furthermore, in the Stop-and-Go Traffic condition, the measured braking distance is 28 m, and SVR estimates 25 m, ANN estimates 24 m, and Random Forest estimates 23 m. Once again, all the ML models lower the braking distance, with Random Forest estimating the closest to it. Also, for Emergency Braking, the maximum braking distance is 35 m; SVR estimates 32 m, ANN estimates 31 m, and Random Forest estimates 30 m. This shows that the ML models slightly under-estimate the critical emergency braking distances. The Random Forest model always gives the best accuracy level in prediction as its predictions always align with the actual braking distances under various driving conditions. The SVR model has the largest prediction error, particularly for emergency braking, and therefore is the least reliable choice for high-speed braking. The ANN model shows fair performance with predictions more accurate than SVR but less accurate than Random Forest. Emergency braking shows the largest discrepancies between real and predicted values, suggesting that machine learning algorithms may need further tuning for unusual braking situations [17].

Fig. 7 illustrates normal braking and ML-based braking across four driving scenarios, indicating that ML-based predictions consistently yield shorter braking distances. Under Urban Driving, ML-based braking predicts 20 m, whereas normal braking predicts 25 m; under Highway Driving, ML-based predictions are at 25 m versus 30 m. Likewise, in Stop-and-Go Traffic, ML models predict 22 m versus 28 m, whereas Emergency Braking has them predict 30 m versus the actual 35 m. This trend indicates that ML-based braking systems could enhance stopping efficiency but also pose safety risks, particularly in emergency maneuvers, where underestimating braking distance could prove fatal. The largest deviation occurs in stop-and-go traffic, suggesting that ML models could benefit from additional tuning under dynamic conditions. Although the ML-based system has the potential to optimize braking performance, it needs to be thoroughly tested to ensure reliability and safety in real-world scenarios [21].

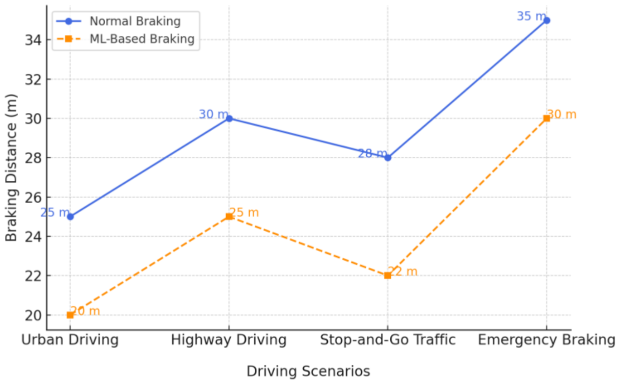

Fig. 7. Comparison of Normal Braking and ML-based Braking

The results of the three ML models—ANN, SVR, and Random Forest are compared in the Fig. 8. ANN gives the prediction for braking distance of 24 m with a blending efficiency of 80%, while SVR gives the highest braking distance of 26 m but the lowest brake blending efficiency of 75%. Random Forest, however, gives the lowest braking distance of 23 m and the highest brake blending efficiency of 85%.

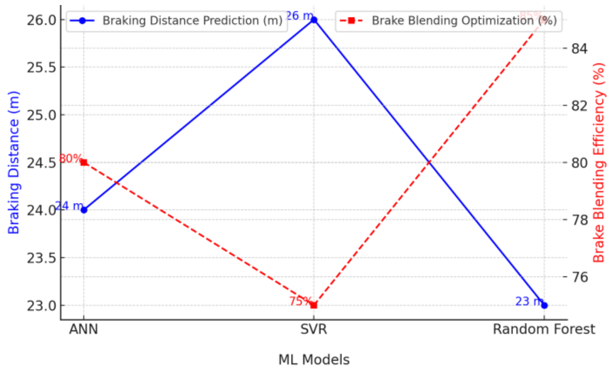

Fig. 8. Brake Blending Optimization

Results indicate a trade-off between the efficiency of brake blending and braking distance across models. While SVR has the highest estimated braking distance, it also has the lowest brake blending efficiency, indicating the need for overestimation in predictions. ANN falls in between in terms of balance in braking distance and efficiency, and therefore is a moderate performer. Random Forest is the top performer, with the shortest braking distance and the best brake blending efficiency, indicating optimal overall braking performance.

These findings show that Random Forest can be the optimal ML model for applications requiring optimal braking control, as it yields the shortest braking distance and the maximum energy recovered with the best combination of brakes. Improving these models or the implementation of a hybrid combination of strategies can be a future research area for maximizing prediction efficiency and accuracy.

Fig. 9 is a depiction of differences in braking distance under different driving conditions, expressed in meters. The driving conditions considered are Stop-and-Go Traffic, Emergency Braking, Urban Driving, and Highway Driving. The errors are noted in the bars for easier readability. The analysis shows that Emergency Braking has the highest error in braking distance, at 2.0 m. This is because the emergency braking involves quick and heavy braking force, thus having a high tendency to overestimate the stopping distance required. Stop-and-Go Traffic has an error of 1.5 m, which is most probably due to the repetitive stopping and starting, resulting in variability in stopping distance. Urban Driving has a moderate error in braking distance of 1.2 m, which reflects the haphazard nature of driving in urban settings where frequent halts are common. Highway Driving has the smallest braking distance error, at 0.8 m, reflecting the smoother, more controlled braking process under high-speed, low-congestion conditions. The inconsistencies seen in braking distance errors are crucial to understanding driving safety and vehicle dynamics management. Larger errors in braking distance can pose serious safety risks, especially during emergency stops, where precise stopping distances are critical to avoid accidents. This analysis can be useful for improving advanced braking support systems [22, 23], such as adaptive braking and autonomous emergency braking (AEB), with the overall goal of raising safety levels across different driving scenarios [24, 25].

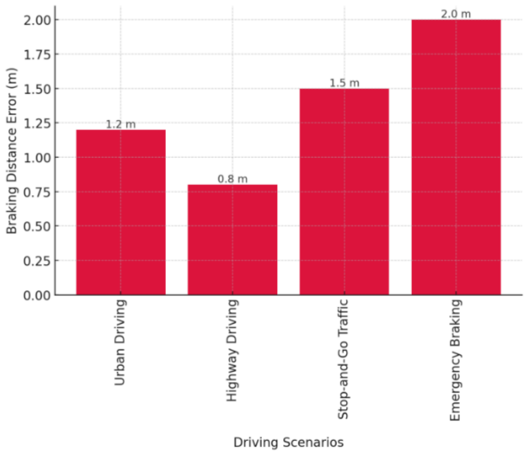

Fig. 9. Braking Distance Error

Fig. 10 shows the jerks, or the rates of change of acceleration, under different driving conditions. The four driving conditions considered are Urban Driving, Highway Driving, Stop-and-Go Traffic, and Emergency Braking. The Fig. 10 clearly indicates that Emergency Braking has the greatest jerk value of 3.0 m/s^3. This is as expected since emergency braking entails a rapid deceleration, which creates sudden acceleration changes. Stop-and-Go Traffic has a jerk of 2.3 m/s^3, most likely due to the repeated cycles of acceleration and deceleration typical of congested traffic sections. Urban Driving indicates a moderate jerk value of 1.5 m/s^3, consistent with the frequent interruptions and accelerations typical in urban driving. Highway Driving indicates the lowest jerk value of 0.9 m/s^3, indicating smoother acceleration and braking manoeuvres in this scenario. The differences seen in jerk values for various driving conditions are reflective of the various levels of driving comfort and vehicle response for various driving conditions. More abrupt motion changes are suggested by higher jerk values, which could make the passengers uncomfortable and impose more wear on vehicle parts. The differences must be understood to be able to design ADAS and optimize vehicle control strategies to enhance ride quality and safety.

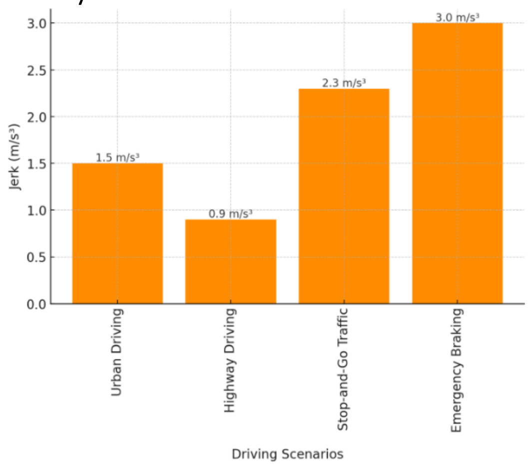

Fig. 10. Jerk in different driving conditions

5. DISCUSSIONS

Fig. 11 presents the results of the comparison between two machine learning algorithms, Random Forest and SVR, on three specified evaluation metrics: MAE, RMSE, and R^2 Score. The score values are displayed on the y-axis, and the evaluation metrics are listed on the x-axis. The bars are drawn in different colors to distinguish them, with blue and orange representing the Random Forest and SVR algorithms, respectively. In the case of MAE, the Random Forest model has a lower value of 0.80 than that of SVR with 1.00. Since MAE is the average absolute variation between the actual and predicted values, a lower value signifies greater predictive accuracy. For RMSE, the Random Forest model is also superior, with a value of 1.20, while the SVR model has a higher RMSE of 1.50. Since RMSE penalizes large errors more, this means that the Random Forest model has a more stable performance with fewer large errors of the actual values. For the R^2 Score, which measures the percentage of variance explained by the model, the Random Forest model achieves 0.95, slightly higher than SVR's 0.90. A greater R^2 score indicates that the model is more capable of extracting the underlying patterns in the data and explains more variance in the target variable. In general, the comparison indicates that the Random Forest model performs better than SVR on all three metrics of evaluation, implying that it produces more accurate and consistent predictions in this particular dataset. Such a finding could be useful while selecting an optimal model for regression problems where minimization of prediction errors and maximization of explained variance are the most important objectives.

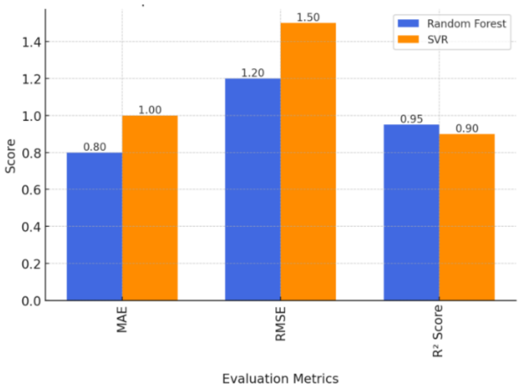

Fig. 11. Comparison of Random Forest and SVR Models

Fig. 12 illustrates the correlation between Battery SOC and Braking Distance. The x-axis is the Battery SOC percentage (%), and the y-axis is the Braking Distance in meters (m). The blue crosses represent the empirical values of the study. A red dashed trend line has also been added to indicate the general trend of the data.

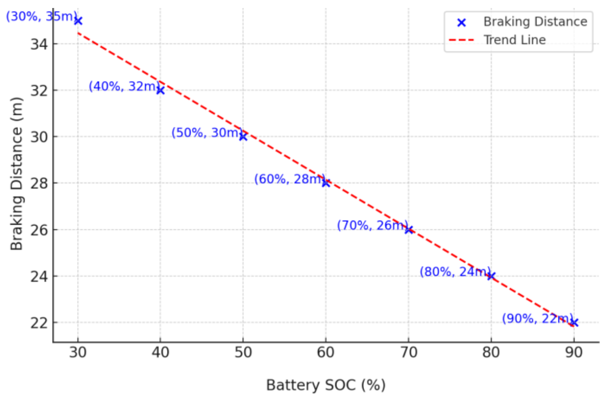

Fig. 12. Comparison of Battery SOC

From Fig. 12, it is clear negative correlation between Braking Distance and Battery SOC. The braking distance also decreases proportionally with battery SOC as SOC increases from 30% to 90%. An example is that the braking distance at SOC of 30 is approximately 35 m, whereas the braking distance at 90 of SOC is 22 m. This suggests that higher battery charging levels result in improved braking capability, perhaps due to greater availability of regenerative braking or greater braking effort. The trend line also shows a linear relationship between these variables, confirming that braking distance decreases proportionally with increasing battery charge. This is a significant finding for enhancing EV performance, particularly regarding safety factors and energy management [26, 27]. It highlights the importance of keeping track of battery levels, as lower SOC levels can lead to longer stopping distances, which can affect vehicle safety in emergency braking.

Fig. 13 indicates the efficiency of regenerative braking for several ML models employed for the purpose of performance improvement. It is observed that the efficiency of the Random Forest model in regenerative braking is the highest at 82%, which is the highest of the three compared models. This is followed by ANN with an efficiency of 78%, and SVR with the lowest efficiency of 74%. The significant drop in efficiency from ANN to SVR indicates that SVR is perhaps not as capable as predicting or optimizing regenerative braking performance in this instance. In contrast, the steep increase in efficiency from SVR to Random Forest indicates the latter's robust predictive ability, which is perhaps due to its capacity to model complex relationships within the data [28, 29].

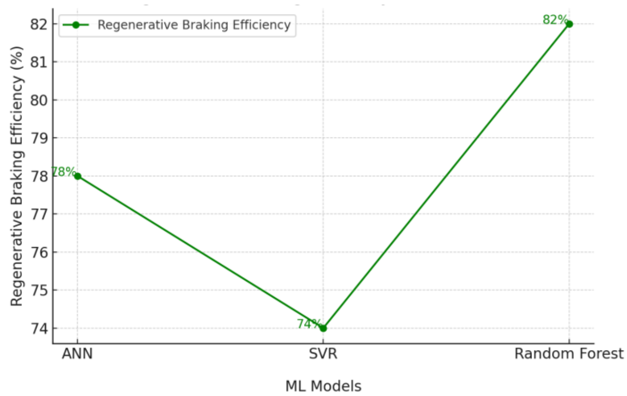

Fig. 13. Regenerative Braking Efficiency

The results of the analysis demonstrate that the selection of the machine learning model could be a critical difference in the process of regenerative braking systems optimization. The enhanced functionality of the Random Forest model indicates that it might be used as a credible means of maximizing the amount of energy that can be recaptured during braking, thereby improving the efficiency and sustainability of electric cars. This data may be a valuable resource for engineers and researchers seeking to improve energy recovery during braking through data-driven approaches.

Fig. 14 demonstrates the estimated braking distance against the various ML models, i.e., ANN, SVR, and Random Forest. The ML models are plotted against the x-axis, with the y-axis representing braking distance in meters. The difference between the braking distances predicted by the various models is shown by the blue line connecting the points.

It is seen that the maximum braking distance of 26 m is being predicted by the SVR model and 24 m by the ANN. The Random Forest model predicts a minimum braking distance of 23 m. This indicates that SVR can also overestimate the braking distance, whereas Random Forest will predict better stopping performance.

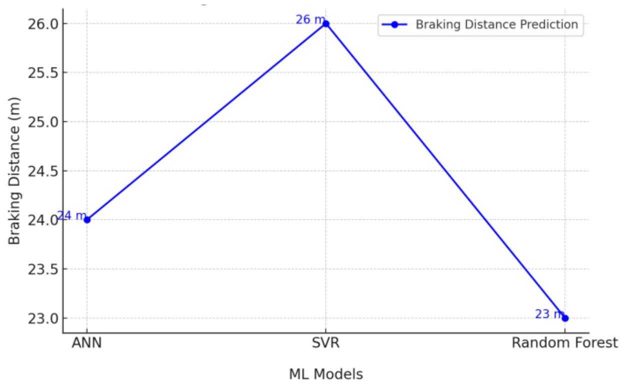

Fig. 14. Braking Distance Predictions with ML Models

The findings indicate that various machine learning models vary in their accuracy in estimating braking distance. The reason the predicted braking distance of Random Forest is lower is that this algorithm can identify complex patterns in the data and thus provides more accurate estimates. Conversely, the high predictions of SVR may also indicate a more conservative method, which may also have more uncertainties. These differences are essential to detect so that better braking behavior of the vehicle may be achieved, especially when using it in safety-critical conditions such as autonomous vehicle driving and ADAS.

It was observed from Fig. 15 that the SVR model is the model with the largest braking distance error of 2.5 m, and this shows that it is most likely to make less accurate predictions than the other models. ANN has a lower error of 1.8 m, showing that it is superior to SVR but with some variation from actual values. Random Forest model, however, has the lowest braking distance error of 1.2 m, and therefore it is the most dependable of the three models when it comes to avoiding prediction inaccuracies.

The SVR model estimates the maximum stopping distance of 26 m, while the ANN estimates 24 m, and the Random Forest estimates the minimum stopping distance of 23 m, as shown in Fig. 16. These differences indicate that the models are differently sensitive to the input parameters and thus affect their stopping distance estimations [30-32].

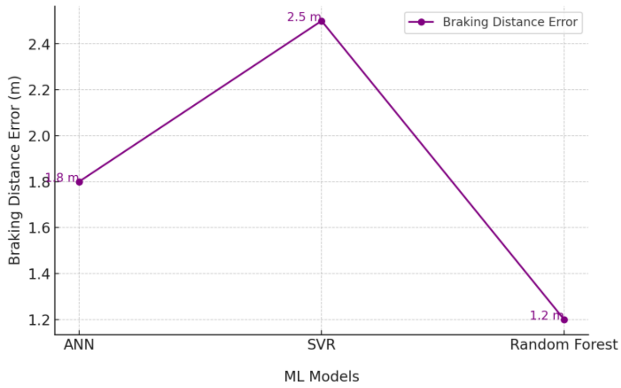

Fig. 15. Braking Distance Error with ML Models

The observed pattern is that the SVR model may be overestimating stopping distances, potentially leading to overly conservative braking predictions. Random Forest, however, gives the shortest stopping distance prediction, which could indicate a more aggressive braking response.

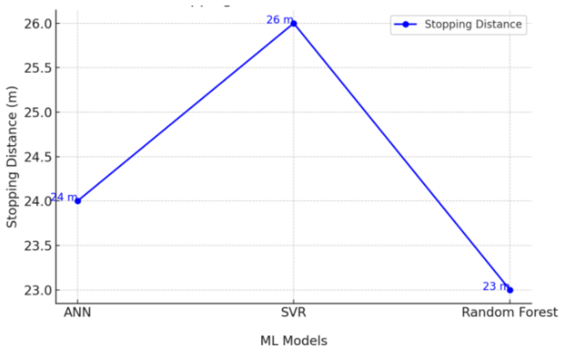

Fig. 16. Stopping Distance with ML models

Fig. 17 shows that the car speed, the blue line, has an upward trend, whereas the stopping distance varies from 20 m at Low to 40 m at High. The upward trend indicates that higher vehicle speeds lead to longer stopping distances, consistent with the fundamental principles of braking physics. The brake pedal pressure (red dashed line) shows a downward trend, indicating that higher brake pedal pressure reduces the stopping distance from 35 m at Low to 22m at High. This shows the significance of applying the brakes on time to decrease stopping distance. The motor torque, as indicated by the green dashed-dotted line, has a decreasing trend, with stopping distances reducing from 38 m for Low to 26 m for High. This means that an increase in motor torque can improve regenerative braking efficiency and, therefore, decrease stopping distance.

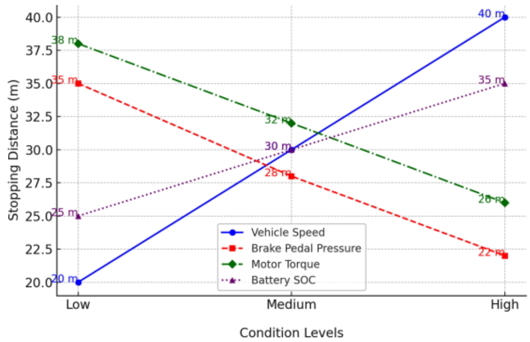

Fig. 17. Stopping distance based on Vehicle Speed, Brake Pedal Pressure, Motor Torque, and Battery SOC

The battery SOC, as indicated by the purple dotted line, shows an increase, which indicates that higher battery charge levels are associated with higher stopping distances. This is due to changes in regenerative braking performance with SOC levels. Lastly, Fig. 17 illustrates the effect of these parameters on stopping distance. An equilibrium among braking force, motor torque, and vehicle speed is essential for peak braking performance, particularly in electric and hybrid cars.

Fig. 18 shows the variation in regenerative braking efficiency (%) with four paramount influencing factors—vehicle speed, brake pedal pressure, motor torque, and SOC —evaluated at three different levels—Low, Medium, and High. Looking at the trends, all four variables show a positive trend, which implies that all four variables are positively correlated with regenerative braking efficiency. Vehicle speed (blue line) goes up from 70% at Low to 80% at High, which implies that the higher the speed, the more energy can be recovered through regenerative braking. Brake pedal pressure (red dashed line) also improves efficiency from 68% at Low to 79% at High, implying that controlled braking enhances energy regeneration.

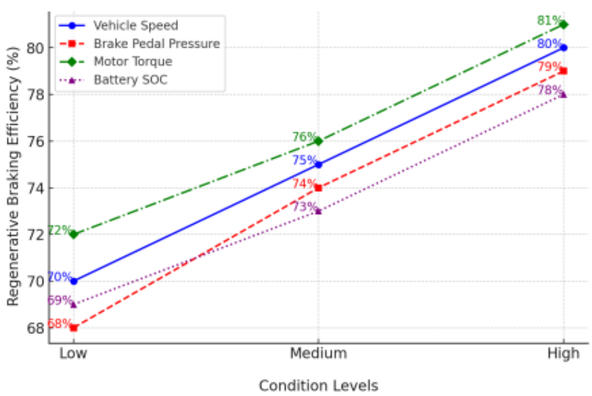

Fig. 18. Regenerative Braking Efficiency based on Vehicle Speed, Brake Pedal Pressure, Motor Torque and Battery SOC

Motor torque (green dashed-dotted line) has the most efficient values, increasing from 72% at Low to 81% at High. This indicates that higher torque values help recover more kinetic energy during deceleration. In addition, battery SOC (purple dotted line) also shows a consistent increasing trend, from 69% at Low to 78% at High. This indicates that a higher SOC may allow the system to store more regenerated energy more efficiently.

6. CONCLUSIONS

The paper provided an experimental study of an EV braking system using machine learning methods. The findings indicated that the ML algorithms had the capability to enhance the prediction of the braking distance, optimize the brake blending, and improve the overall braking of the EVs and their safety. The Random Forest model has provided the best estimate of braking distance and the brake blending strategy established by the ML enhanced energy recuperation and minimized friction brake wear.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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