iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 Issue: IV Month of publication: April 2024

DOI: https://doi.org/10.22214/ijraset.2024.60176

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue IV Apr 2024- Available at www.ijraset.com

Estimation of Electric Vehicle Range Using Artificial Neural Networks

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Abstract: This paper presents a project that addresses the transportation sector's rapid growth contributes to pollution through conventional fossil fuel vehicles emitting harmful gases, leading to global warming. Electric vehicles (EVs) offer a cleaner alternative, but range anxiety hinders widespread adoption. Range prediction, crucial for EV practicality, estimates travel distance on a single charge, considering factors like battery capacity, driving conditions, and weather. Accurate models, rooted in deep knowledge of EV technology and real-world driving, are essential. Our proposed solution employs a machine learning approach, integrating physical and environmental variables to minimize range anxiety, empower informed decision-making, and enhance the overall electric vehicle experience, promoting sustainable transportation

I. INTRODUCTION

Transport is a fundamental requirement of modern life, conventional combustion engines that use petrol and diesel are highly polluting and contribute to global warming. These conventional vehicles can be replaced with electric vehicles that have zero tailpipe emissions and are much better for the environment. They have relatively lower running costs, maintenance cost, convenience of charging at home, and are easy to drive and quiet. There is an increase in usage of electrical vehicles lately. It is expected that 145 million electric vehicles will be on the road by 2030. Range prediction is a critical factor for EV users to plan their trips effectively and alleviate range anxiety. Calculating the range of electric vehicles (EVs) using Machine Learning (ML) techniques has gained significant attention in recent years. ML algorithms leverage historical data from EVs, such as driving patterns, battery characteristics, and external factors like weather and road conditions. By analyzing this data, ML models can learn complex relationships and patterns that impact the vehicle's range. These models can then predict the remaining range based on real-time data inputs. ML-based range prediction systems can continuously adapt and improve their accuracy by learning from a large amount of data collected from various EVs and diverse driving scenarios. These models can account for factors like battery degradation, traffic conditions, driving behavior, and energy consumption patterns, providing more reliable and personalized range estimations. The integration of ML in range prediction for EVs has the potential to enhance the driving experience, optimize route planning, and increase confidence in electric vehicle technology. As research and development in this area advance, ML algorithms can contribute to maximizing the efficiency and usability of EVs, promoting their widespread adoption and contributing to a sustainable transportation future.

II. LITERATURE REVIEW

1) Zhigang He, Xiaoyu Shen, Yanyan Sun, Shichao Zhao, Bin Fan, Chaofeng Pan[1] have developed a variant long short term memory neural network (AST-LSTM NN) for state-of-health estimation and remaining useful life prediction of lithium-ion batteries. The model actively tracks cell states and utilizes the element-wise product of new inputs and historical cell states to accurately predict multi-step RUL.
2) Bohan Zheng, Peter He, Lian Zhao, Hongwei Li [2] introduced a Hybrid Machine Learning Model for Range Estimation of Electric Vehicles, which combines Self-Organizing Maps (SOM) with Regression Trees (RT) to predict power consumption during EV trips. The model demonstrates improved accuracy for both short and long trips based on cross-validation and mathematical criteria.
3) Prabhakar Sharma and Bhaskor J. Bora[3] conducted a review of modern machine learning techniques in predicting the remaining useful life (RUL) of lithium-ion batteries. Techniques explored include adaptive neuro-fuzzy inference systems (ANFIS), regression trees (RTs), artificial neural networks (ANN), response surface methodology (RSM), and gene expression programming (GEP). The review provides insights into the strengths and limitations of each method for real-world battery management systems.

4) Ran Li, Hui Sun, Xue Wei, Weiwen Ta, Haiying Wang [4] propose an integrated learning algorithm, AdaBoost.Rt-RNN, for state-of-charge (SOC) estimation of lithium batteries. The algorithm combines AdaBoost.Rt ensemble learning with a cyclical neural network model. The model aims to improve SOC estimation accuracy by addressing the low accuracy and poor generalization of neural network algorithms. It employs a chain-connected recurrent neural network (RNN) model to adapt to sample data correlation in the spatio-temporal dimension, enhancing SOC estimation accuracy under various operating conditions.
5) Ganesh Sankaran, S. Venkatesan, M. Prabhahar discuss the issue of range anxiety in electric vehicles (EVs) in India and its impact on customers. They explore technical factors contributing to range anxiety and strategies to address it, such as increasing battery capacity, improving charging infrastructure, implementing smart charging solutions, and providing real-time range information. The paper also considers the use of range extenders like fuel cells or internal combustion engines.
6) Llyès Miri, Abbas Fotouhi, Nathan Ewin propose an accurate modelling approach for estimating electric vehicle (EV) energy consumption. The goal is to model the target EV, including its powertrain system and longitudinal dynamics, and validate it using available data. The paper emphasizes the importance of accurate energy consumption models for EV range estimators, as current estimators often rely on historical data analysis and may lack accuracy.
7) Emilia M. Szumska and RafałS. Jurecki analyzed data from a real electric vehicle and utilized big data analysis to estimate the vehicle's range. They employed a mathematical model to examine large datasets and identify patterns affecting the assumed variable, focusing on parameters influencing electric vehicle range such as vehicle design, driver's behavior, and use conditions.
8) Jun Bi, Yongxing Wang, Qiuyue Sai, Cong Ding developed nonlinear estimation models based on real-world data to predict the remaining driving range of battery electric vehicles under various temperature conditions. Their study underscores the importance of considering practical travel situations, especially in developing countries like Beijing, to accurately estimate battery electric vehicle driving range.
9) Jun Bi, Jun Wang, Yongxing Zhang introduced a novel method for predicting the driving range of battery electric vehicles using the gradient boosting decision tree (GBDT) algorithm. This method incorporates numerous feature variables and real-world conditions to enhance prediction accuracy and applicability, potentially benefiting automotive manufacturers and policymakers in sustainable transportation planning.

III. PROBLEM STATEMENT

The current range prediction systems for electric vehicles (EVs) often oversimplify calculations, focusing primarily on battery capacity and neglecting crucial factors like driving conditions and weather. This limitation contributes to widespread range anxiety, as drivers cannot fully rely on the accuracy of estimated remaining range. The proposed project aims to rectify this by introducing a sophisticated machine learning based system that considers diverse variables, providing more accurate and reliable range predictions. This improvement is crucial for enhancing the overall user experience, encouraging informed decision-making, and addressing concerns hindering the widespread adoption of EVs.

IV. PROPOSED SYSTEM

The proposed system aims to transform the way electric vehicle (EV) range is predicted by leveraging sophisticated machine learning algorithms that incorporate a wide array of variables. Unlike current models, this system will overcome limitations by adjusting in real-time to actual driving conditions, user habits, and environmental influences. By constantly updating itself with the latest information, the system will seamlessly integrate with existing EV setups, providing drivers with precise predictions while on the road. This empowerment will enable drivers to make informed choices, enhancing their overall driving experience.

Through the integration of advanced machine learning techniques and a comprehensive range of factors, the proposed system promises to revolutionize EV range prediction. By addressing the shortcomings of existing models, it will dynamically adapt to the complexities of real-world driving scenarios, ensuring accuracy and reliability. The system's ability to deliver real-time updates will empower drivers with timely information, allowing them to optimize their journeys and make educated decisions. This seamless integration into existing EV systems will enhance user experience and contribute to the widespread adoption of electric vehicles.

V. METHODOLOGY

The methodology for the project "Estimation of Electric Vehicle Range Using Artificial Neural Networks" is a comprehensive and systematic approach aimed at developing a sophisticated predictive model for estimating electric vehicle (EV) range. At the outset, the project meticulously defines its objective: leveraging artificial neural networks (ANNs) to accurately predict EV range based on various input parameters.

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The journey begins with the thorough collection of pertinent data on electric vehicles, encompassing factors such as battery capacity, vehicle weight, driving conditions, weather, terrain, and driving patterns. This rich dataset forms the foundation upon which the predictive model will be built.

Subsequently, the collected data undergoes a rigorous preprocessing phase, where it is meticulously cleaned and transformed to ensure uniformity and eliminate any anomalies or irrelevant information. Techniques such as normalization, scaling, and feature engineering are employed to optimize the dataset for input into the ANN. With the data primed and ready, the focus shifts to designing the architecture of the artificial neural network. Here, considerations are made regarding the number of layers, types of neurons, and activation functions to construct a model capable of capturing the intricate relationships between the input parameters and EV range.

Following architecture design, the ANN model undergoes intensive training using a portion of the collected data. Through iterative adjustments of its internal parameters, the model endeavors to minimize the disparity between predicted and actual EV range observed in the training data. Validation of the trained model follows, wherein a separate dataset, distinct from the training data, is employed to ensure the model's ability to generalize and accurately predict EV range under diverse conditions. Rigorous testing further scrutinizes the model's performance, either through additional datasets or real-world scenarios, to assess its reliability and accuracy.

In the pursuit of optimization, the performance of the ANN model is meticulously evaluated, identifying areas for refinement or enhancement. Fine-tuning of model parameters, adjustments to architecture, and the incorporation of supplementary features are explored to augment prediction accuracy. Upon achieving satisfactory performance benchmarks, the ANN model is poised for deployment, potentially integrating into EV dashboard systems or mobile applications. This deployment would empower EV owners with real-time estimates of their vehicle's range, predicated on prevailing conditions.

Throughout this methodology, meticulous documentation and reporting serve as indispensable companions, chronicling each step of the journey from data collection to model deployment. By adhering to this comprehensive approach, the project endeavors to deliver a robust and reliable predictive model, enriching the understanding of EV range dynamics and offering practical utility to both EV owners and manufacturers.

VI. ARCHITECTURE

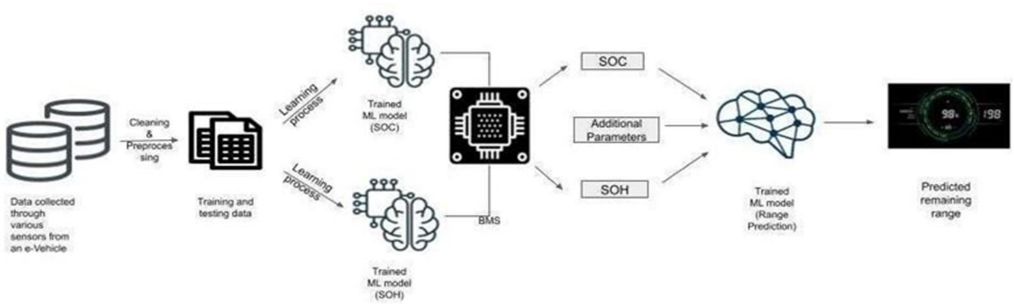

Fig 1: Architecture

This fig.1 presents a detailed diagram of a computer chip, specifically focusing on the conceptual design and functionality aspects of machine learning (ML) models within a System on Chip (SOC) architecture. The diagram is rendered in black and white, emphasizing the schematic nature of the illustration. It includes textual annotations that guide the viewer through various stages of machine learning processes, such as data collection, cleaning, preprocessing, learning parameters setting, training, and prediction phases. Notably, the diagram highlights the application of trained ML models in predicting the State of Health (SOH) from data collected through sensors from an electric vehicle (e-Vehicle), indicating a practical use case in the automotive industry. The design includes a mix of flowcharts and textual descriptions to explain the sequential steps involved in training and deploying ML models. The presence of terms like "Additional Learning process," "Training and testing data," and "Predicted range Prediction" suggests a comprehensive approach to understanding and optimizing machine learning workflows for predictive analytics. The diagram serves as an educational tool, offering insights into the complexities and considerations involved in developing and implementing machine learning models within electronic devices. Overall, the image is a fusion of technical design and instructional content, aimed at conveying the intricacies of machine learning integration in modern technology applications.

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The image under discussion provides a comprehensive overview of a computer chip, with a specific focus on the conceptual design and functionality aspects related to machine learning (ML) models within a System on Chip (SOC) architecture. Rendered in black and white, the schematic illustration prioritizes clarity and simplicity to effectively convey intricate details. The inclusion of textual annotations guides the viewer through various stages of the machine learning process, from initial data collection to the practical application of trained models in predicting the State of Health (SOH) in electric vehicles (e-Vehicles).

The diagram emphasizes the sequential nature of machine learning workflows, starting with data collection, cleaning, and preprocessing. This foundational stage ensures that the input data is appropriately formatted and devoid of inconsistencies, laying the groundwork for accurate model training. The annotations within this section likely detail specific techniques and considerations in preparing data for effective machine learning applications.

Moving forward, the illustration covers the learning parameter setting phase, a critical step where the model's hyperparameters are tuned for optimal performance. The inclusion of this component suggests a focus on the intricacies of configuring ML models, reflecting an understanding of the nuanced decisions involved in fine-tuning algorithms to achieve desired outcomes.

The subsequent phases in the diagram involve training the ML models, reflecting the process of exposing the model to labeled data to enable it to learn and adjust its internal parameters. The annotations likely elaborate on the methodologies employed in this stage, shedding light on the algorithms and techniques chosen for effective model training. Furthermore, the presence of terms like "Additional Learning process" hints at a nuanced understanding of continuous improvement and refinement beyond the initial training phase.

The image's thematic highlight is the practical application of trained ML models in predicting the State of Health (SOH) from sensor data in electric vehicles. This real-world use case emphasizes the relevance and applicability of machine learning in the automotive industry, underlining the potential benefits of predictive analytics in enhancing the performance and reliability of electric vehicles.

In summary, the diagram intricately weaves together various components of machine learning, from data preprocessing to model training and real-world applications, offering an educational tool that delves into the complexities and considerations involved in integrating machine learning models within the context of a System on Chip (SOC) architecture.

VII. ACKNOWLEDGMENT

The group express our gratitude most sincerely to our guide Mr. P. Hari Krishna who guided and motivated us in this course of time of understanding the concepts. We are grateful for the insightful comments offered by the peer reviewers.

VIII. RESULT

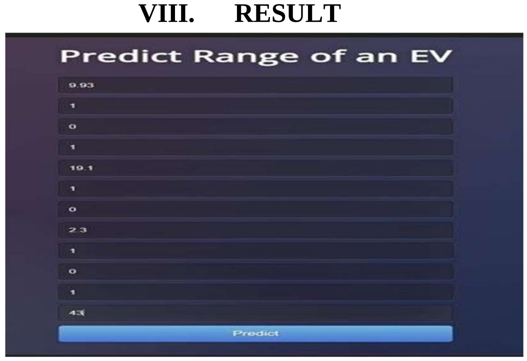

Fig 1: Web App UI

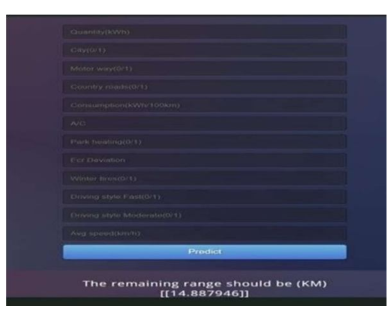

Fig 2: Final Result Page

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IX. CONCLUSION

The machine learning model's successful application in calculating State of Charge (SOC) has yielded highly promising results, demonstrating its efficacy in practical scenarios. Through the utilization of updated SOC values, the model not only accurately predicts the State of Energy (SOE) but also exhibits a remarkable closeness between its predictions and the actual outputs, as evidenced by the Mean Absolute Error (MAE) of 5.96 during the computation of remaining range. This low MAE signifies a tight match between the model's estimations and the true values, underscoring its precision in capturing complex relationships within the data. The observed accuracy in estimating the remaining range implies the model's robust ability to understand and generalize patterns, showcasing its reliability for predicting crucial parameters in real-world applications. This outcome is particularly noteworthy, as it enhances the model's practical usability in contexts where precise state-of-charge information is crucial, such as electric vehicle management systems. The consistent and close correspondence between predicted and actual values, coupled with the model's low MAE, establishes its trustworthiness and suitability for deployment in diverse settings, further validating its potential for optimizing decision-making processes based on accurate state-of-charge predictions. In conclusion, the machine learning model emerges as a valuable tool with tangible benefits for applications requiring dependable SOC estimations in practical, dynamic environments.

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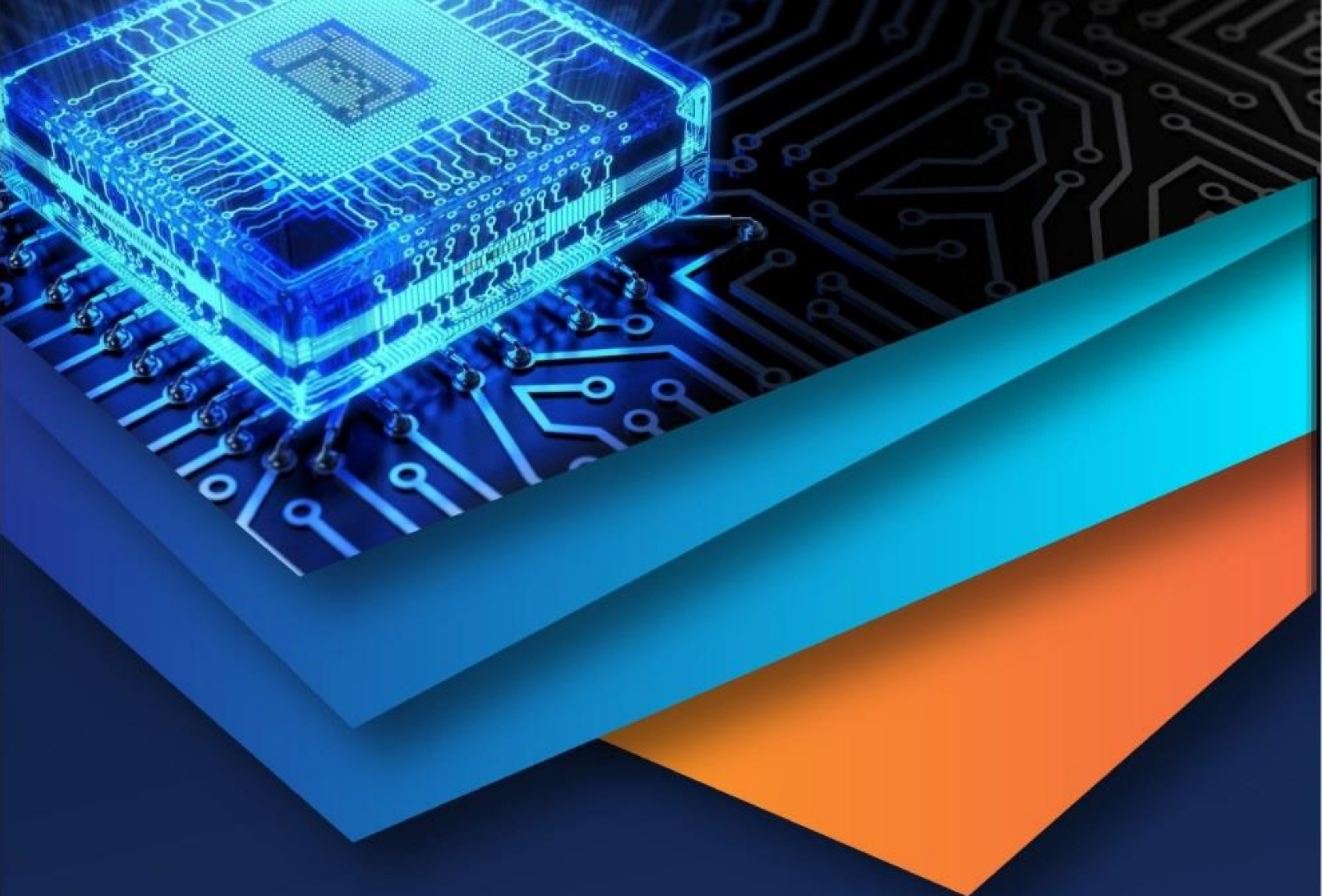

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