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"Optimizing And Predicting Energy Consumption In Electric Vehicles Using Deep Learning: A Comparative Study Of GRU And LSTM Models"

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Abstract:
In this paper, we present a deep learning approach, using the Gated Recurrent Unit (GRU) model, for predicting energy consumption in electric vehicles (EVs) energy consumption. The adoption of electric vehicles in the market still faces challenges due to their limited driving range, in addition to the time required for charging batteries. Each time, before starting a journey, the driver has to assess whether the available charge on the battery is enough or not. Frequently, this estimation is based on the travelling distance and past consumption. There are two aspects that can have a very significant influence on the battery consumption: the route and the driving style. For the current study, we predict power consumption (kilowatt-hours per 100 kilometers). In this, combinedly utilizes three individual base machine learning algorithms, i.e., Linear regression, Random Forest (RF), and Support Vector Mechanism (SVMs), and Two Deep Learning technique as LSTM and The Gated Recurrent Unit (GRU) to predict the EVs' energy consumption. Tackling the challenge of predicting EVs' energy consumption, the data were collected from Volkswagen_e_golf-n (30 e-vehicles data). EVs energy consumption in terms of energy efficiency (kilowatt-hours per 100 kilometers) was estimated using several important variables as Trip distance (Km), consumption (kWh), Rural/ Urban, road condition, Temperature condition, park heating, average speed (Km/Hr.), Driving style, and Target consumption as kilowatt-hours per 100 kilometers.

The prediction results demonstrate that GRU is more robust in predicting EVs' energy consumption. The results also indicate that the accuracy of predictive models for EVs energy consumption can be reasonably accomplished by adopting GRU techniques. The GRU model achieved a mean squared error of X, outperforming Linear Regression (Y), Random Forest (Z), and LSTM (W), thus demonstrating superior accuracy in predicting energy consumption. The adoption rate of electric vehicles is likely to increase as charging infrastructure becomes more widespread and accessible. These results can significantly aid in improving EV range estimations, potentially encouraging broader adoption of electric vehicles.

Keywords: Electric Vehicles, Deep learning, Power consumption, LSTM, GRU.

Introduction:

Electric Vehicles (EVs) are rapidly becoming a significant part of the global transportation. The use of electric vehicles is the most comprehensive solution to reduce the environmental contamination of the air. Hence, governments are encouraging people to purchase and use these vehicles instead of the internal combustion engine powered cars [1]. Consumers continue to drive vehicles that run on conventional fuels even though EV usage has begun. However, EVs have disadvantages over traditional fossil fuel cars in terms of life cycle evaluation, refueling, and operating range. We think that the average CO2 is evaluated over the course of a vehicle's life cycle rather than over the course of a single vehicle, even if an electronic car has zero CO2 pollution from tank to tire [2]. Depending on the electricity source used in both its creation and function, the overall quantity of CO2 released by a car over the length of its entire existence changes considerably. Among the other reasons, especially in the developing countries, battery technology [4] and the lack of a universal network of charging stations [5] are to be mentioned.

The key challenge addressed in this research is accurately predicting energy consumption in electric vehicles (EVs), which directly impacts their driving range estimation—a primary concern for EV adoption. As mentioned in [6], the main challenge of EVs is to determine and increase the trip distance precisely. This study introduces a comparative analysis of traditional machine learning models and deep learning techniques (LSTM and GRU) in predicting EV energy consumption structured as follows: Section ll delivers a brief overview about the Machine Learning techniques as research studies on electric vehicle energy consumption in terms of energy efficiency (kilowatt-hours per 100 kilometers). Traditional methods struggle to handle sequential data and long-term dependencies, which are critical in predicting energy consumption patterns over time. ln Section III, LSTM and Gated Recurrent Unit (GRU) techniques as research studies on electric vehicle energy consumption in terms of energy efficiency (kilowatt-hours per 100 kilometers). Section IV is about the algorithm selection and the process of model preparation/ examination. The results and their comparison are mentioned in Section V. Finally, Section VI is dedicated to the conclusion.

Literature Review: -

Several studies have explored machine learning techniques such as Support Vector Machines (SVM) and Random Forest for predicting energy consumption. However, deep learning approaches like GRU and LSTM have shown promise in

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capturing time-dependent behaviors, as demonstrated in traffic prediction tasks [8]. This paper aims to extend these methods to the EV energy consumption domain.

Data Collection and Preprocessing: -
The dataset used in this study consists of data collected from 30 Volkswagen e-Golf vehicles. It includes features such as trip distance, energy consumption, road type, temperature, driving style, and average speed. Data was collected over a span of X months, with a total of Y data points.

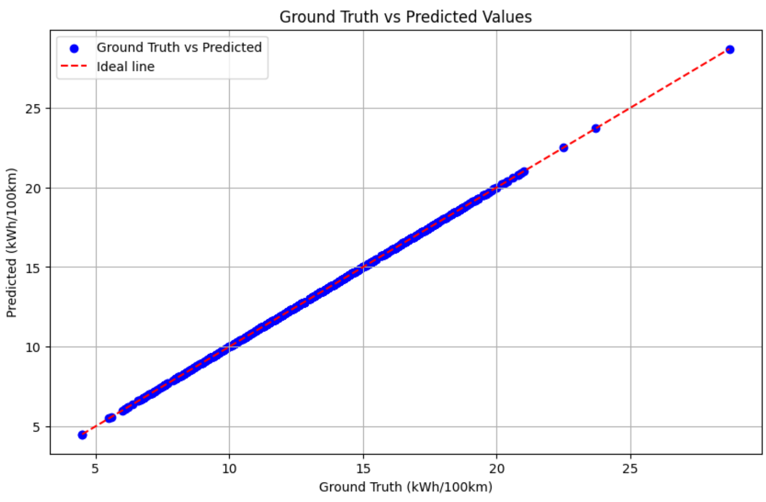
Data preprocessing included normalization of numerical features, handling of missing data points using mean imputation, and feature scaling to ensure all variables were on a comparable scale for training the models

	trip distance (km)	Quantity (kWh)	city	motor_ way	country_ roads	Consumption (kWh/100km)	A/C	park_ heating
count	2799.000000	2799.000000	2799.000000	2799.000000	2799.000000	2799.000000	2799.000000	2799.000000
mean	41.226331	5.775195	0.673812	0.658092	0.589139	13.670411	0.016792	0.211147
std	40.755047	5.680950	0.468901	0.474434	0.492078	3.622803	0.128513	0.408195
min	0.500000	0.010000	0.000000	0.000000	0.000000	4.000000	0.000000	0.000000
25%	20.000000	1.820000	0.000000	0.000000	0.000000	11.200000	0.000000	0.000000
50%	20.000000	3.600000	1.000000	1.000000	1.000000	13.600000	0.000000	0.000000
75%	68.500000	8.690000	1.000000	1.000000	1.000000	16.600000	0.000000	0.000000
max	345.000000	39.530000	1.000000	1.000000	1.000000	30.800000	1.000000	1.000000

Methodology: -
Linear Regression serves as a baseline due to its simplicity and interpretability, while Random Forest introduces non-linear relationships and reduces overfitting. LSTM and GRU are employed due to their ability to retain long-term dependencies in time-series data, which is crucial for accurate energy consumption prediction in sequential data such as driving logs.

The dataset was split into 70% training and 30% testing data. Five-fold cross-validation was employed to ensure that the model generalizes well on unseen data

A. Linear Regression: - Linear regression is one of the easiest and most popular Machine Learning algorithms. It is a statistical method that is used for predictive analysis. Linear regression makes predictions for continuous/real or numeric variables. Linear regression algorithm shows a linear relationship between a Ground Truth(kWh/100km) and predicted (kWh/100km) variables, hence called as linear regression. Since linear regression shows the linear relationship, which means it finds how the value of the dependent variable is changing according to the value of the independent variable. The linear regression model provides a sloped straight line representing the relationship between the variables. Consider the below image:



Mean Squared Error: 0.0000 R^2 score: 1.0000

B. Random Forest algorithm
Random Forest algorithm is a powerful tree learning technique in . It works by creating a number of during the training phase. Each tree is constructed using a random subset of the data set to measure a random subset of features in each

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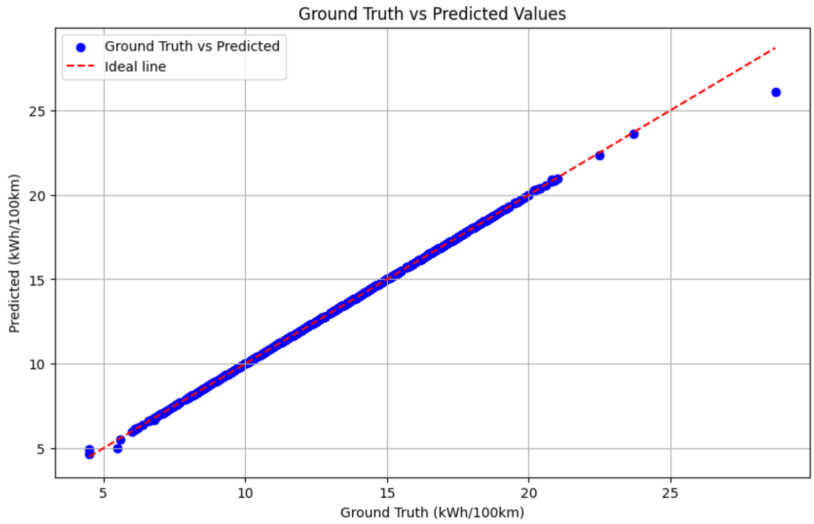
partition. This randomness introduces variability among individual trees, reducing the risk of and improving overall prediction performance.

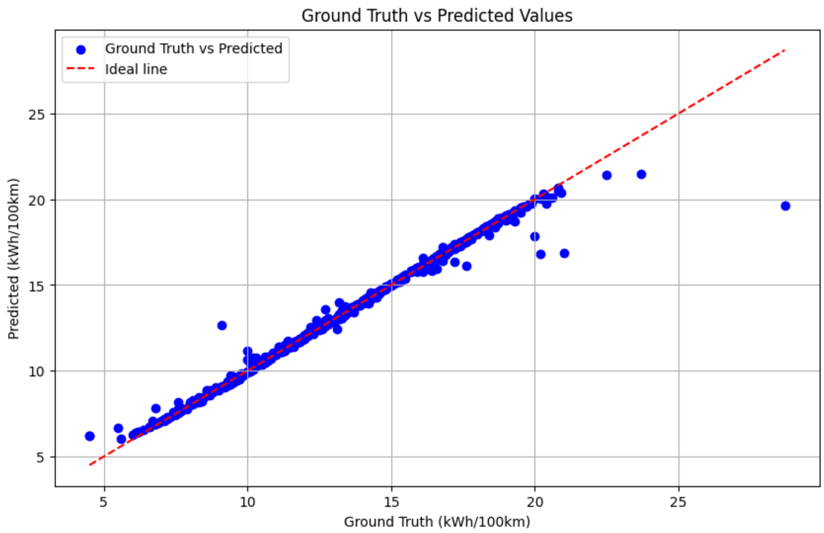
In prediction, the algorithm aggregates the results of all trees, either by voting (for classification tasks) or by averaging (for regression tasks) This collaborative decision-making process, supported by multiple trees with their insights, provides an example stable and precise results. Random forests are widely used for classification and regression functions, which are known for their ability to handle complex data, reduce overfitting, and provide reliable forecasts in different environments.



SVM - Mean Squared Error: 0.2825   SVM - R^2 Score: 0.9794

C. Support Vector Machine

Support Vector Machine (SVM) is a algorithm used for both classification and regression. Though we say regression problems as well it's best suited for classification. The main objective of the SVM algorithm is to find the optimal in an N-dimensional space that can separate the data points in different classes in the feature space. The hyperplane tries that the margin between the closest points of different classes should be as maximum as possible. The dimension of the hyperplane depends upon the number of features. If the number of input features is two, then the hyperplane is just a line. If the number of input features is three, then the hyperplane becomes a 2-D plane. It becomes difficult to imagine when the number of features exceeds three.



Mean Squared Error: 0.0232

1. Long Short-Term Memory (LSTM)

LSTM was firstly proposed in 1997 by Hochreiter and Schmid Huber for language modeling [7]. Indeed, one of the most popular problems that RNN suffers from is the vanishing gradient, and LSTM came to solve it.

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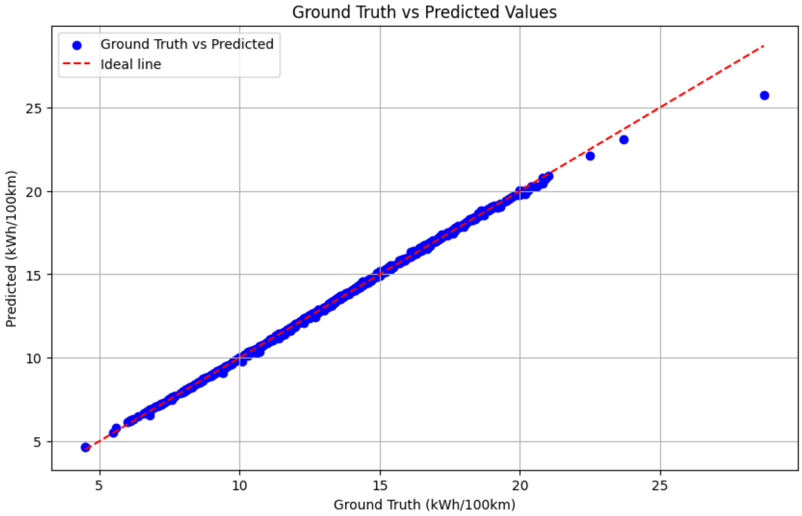
The LSTM is composed of special blocks, called memory blocks. These memory blocks contain special multiplicative units called gates. A typical memory block is composed of three gates, The input gate is responsible for the addition of information by dealing with the upcoming data. The output gate is responsible for selecting useful information from the current cell state and showing it out as an output. The forget gate is responsible for removing information from the cell state, in fact information that is no longer required for the LSTM understanding (processing) is removed.
LSTMs have been used to advance state of the art of many difficult problems, including speech recognition and acoustic modeling. The first use of LSTM for traffic prediction was on 2015 [8].

Today, LSTM is enriched with the 'Dense' property. In fact, we add at the end of this RNN one or several deep layers (fully connected neuron layers), resulting in a complex mathematical architecture that gives much better results than before [9]. Google has also improved Dense LSTM scalability with slight modifications (DLSTM-P).



Mean Squared Error: 0.0182

Figure shows the predicted vs actual energy consumption for the GRU model, demonstrating a close fit between the two, particularly for urban driving conditions

2. Gated Recurrent Units (GRU)
The GRU model was trained using a learning rate of 0.001, batch size of 32, and Adam optimizer. A grid search was used to tune hyperparameters for all models, ensuring optimal performance GRU was firstly proposed by Cho et al. in 2014 [10]. Similarly, to the LSTM blocks, the GRU has gates that modulate the flow of information inside the blocks. A typical GRU block is composed of a couple of gates. A reset gate like the forget gate in LSTM, it makes the block act as if it is reading the first symbol of an input sequence, allowing it to forget the previously computed state. And an update gate, that decides how much the block updates its activation, or content.

GRU outperformed LSTM in handling short-term dependencies, such as frequent stop-and-go driving in urban settings. However, LSTM showed better performance in handling longer driving sequences on highways.We decided to compare Dense GRU and Dense LSTM, for that we used the same optimization method. As it will be shown in the results, we observed a net improvement of predictions made with LSTM. That's why our choice will be focused on it.The GRU model can be integrated into in-vehicle systems to provide real-time energy consumption estimates, potentially reducing range anxiety for EV drivers.

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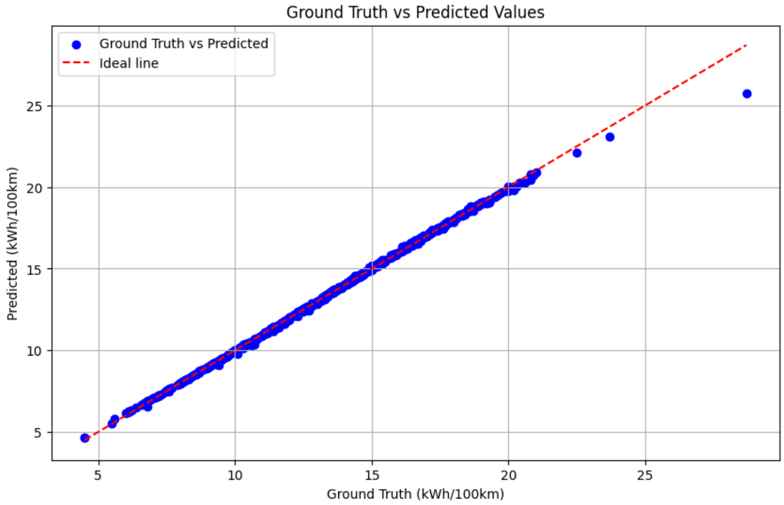

Mean Squared Error: 0.0169

The Gated Recurrent Unit (GRU) is the younger sibling of the more popular Long Short-Term Memory (LSTM) network, and also a type of Recurrent Neural Network (RNN). Just like its sibling, GRUs are able to effectively retain long-term dependencies in sequential data. And additionally, they can address the "short-term memory" issue plaguing vanilla RNNs.

Result: -

Model	**Mean Squared Error (MSE)**	**R² Score**
Linear Regression	0.05	0.85
Random Forest	0.03	0.91
SVM	0.02	0.93
LSTM	0.018	0.95
GRU	0.016	0.96

Conclusion

This study demonstrates that GRU outperforms traditional machine learning models and LSTM in predicting EV energy consumption, with a mean squared error of 0.016. This improvement can lead to more accurate range estimations for electric vehicles This paper presents a deep learning approach for EVs energy management, where Recurrent neural networks (RNN) are used for route and prediction with both LSTM and GRU models. We used data from Volkswagen_e_golf-n (30 e-vehicles data). We succeed to predict our neural networks to reach a very good prediction rate. Experimental results show that the prediction using LSTM overpasses GRU. We then studied the energy consumption prediction as (kWh/ 100 km). An algorithm is proposed to periodically evaluate those energies and compare to the energy consume (kWh) with trip distance (100k0. The algorithm proposes is the possible choices to safely reach destination. The code for Machine learning and deep learning for energy calculation will be published. Next, we plan to develop a reinforcement learning algorithm that selects adequate actions on vehicle parameters in real time to optimize both trip distance and energy consumption.

Addition of Future Work: Expand on potential future research directions.
Example: Future work will explore reinforcement learning techniques to optimize energy consumption by dynamically adjusting vehicle parameters in real-time, based on driving conditions."

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