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Enhancing Electric Vehicle Range Prediction Through Deep Learning: An Autoencoder and Neural Network Approach

Gregorius Airlangga
Information System Study Program, Atma Jaya Catholic University of Indonesia
Email: gregorius.airlangga@atmajaya.ac.id

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ABSTRACT

The burgeoning adoption of electric vehicles (EVs) signifies a pivotal shift towards sustainable transportation, necessitated by the global imperative to mitigate climate change impacts. Central to this transition is the resolution of range anxiety, a significant barrier impeding wider EV acceptance. This research introduces a novel deep learning framework combining autoencoders and deep neural networks (DNNs) to predict EV range more accurately and reliably. Leveraging a comprehensive dataset from the "Electric Vehicle Population Data," we embarked on a meticulous process of data cleaning, feature engineering, and preprocessing to prepare the dataset for analysis. The study innovatively applies an autoencoder for unsupervised feature learning, effectively reducing dimensionality and extracting salient features from high-dimensional EV data. Subsequently, a DNN model utilizes these features to predict the EV range, offering insights into the vehicle's performance across various conditions. Employing a 10-fold cross-validation approach, the model's efficacy is rigorously evaluated, ensuring robustness and generalizability of the predictions. Our methodology demonstrates a significant enhancement in prediction accuracy compared to conventional machine learning models, as evidenced by the Mean Squared Error (MSE) metric. This research not only contributes to the academic discourse on sustainable transportation and deep learning applications but also provides practical insights for manufacturers, policymakers, and consumers aiming to navigate the complexities of EV adoption and infrastructure development. By addressing the critical challenge of range prediction, this study paves the way for advancing EV analytics, ultimately supporting the transition to a more sustainable and efficient transportation ecosystem.

Corresponding Author:
Gregorius Airlangga,
Information System Study Program,
Atma Jaya Catholic University of Indonesia,
Jakarta, Indonesia
Email: gregorius.airlangga@atmajaya.ac.id

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1. INTRODUCTION

The transition towards sustainable transportation systems, epitomized by the increasing adoption of electric vehicles (EVs), is a cornerstone in global efforts to combat climate change [1]–[3]. Electric vehicles offer a promising solution to reduce greenhouse gas emissions, decrease fossil fuel dependency, and improve air quality [4]–[6]. However, the integration of EVs into the mainstream automotive market and the broader energy grid presents complex challenges [7]–[9]. These include optimizing charging infrastructure, enhancing battery technology, predicting vehicle performance, and understanding user behavior [10]–[12]. Addressing these challenges requires sophisticated analytical tools that can process and analyze the vast and complex datasets generated by EV ecosystems [13]–[15]. The body of literature on EV data analytics is extensive and diverse, reflecting the multifaceted challenges and opportunities that EVs present [16]–[18]. Early research focused on descriptive analytics, providing insights into EV adoption patterns and charging behavior [19]–[21]. As the field has matured, predictive models have become increasingly prominent, employing a range of statistical and machine learning techniques to forecast EV-related phenomena such as charging demand, vehicle range, and market growth [22]–[24]. Notably, studies such as [25] and [22] highlight the application of machine learning models in understanding factors influencing EV adoption and predicting battery health, respectively. Despite the advancements, the application of deep learning, particularly in unsupervised learning for feature extraction and enhancement of predictive models, remains underexplored in EV research [13], [26], [27]. This gap signifies an opportunity for leveraging complex neural network architectures, such as autoencoders, to uncover latent patterns in EV data, thus enhancing the predictive accuracy and providing deeper insights.

The urgency of optimizing EV technology and infrastructure is underscored by the imperative to mitigate climate change impacts and transition to sustainable energy systems [28]–[30]. The state-of-the-art in EV data analytics increasingly incorporates artificial intelligence (AI) and machine learning to address these challenges [31]–[33]. However, the potential of deep learning, especially autoencoders for unsupervised feature learning, has not been fully realized in this domain [34]–[36]. This underutilization points to a critical research gap, despite deep learning's proven capability in extracting meaningful patterns from complex datasets in other fields. This research aims to bridge this gap by investigating the application of deep learning techniques, specifically autoencoders followed by deep neural networks (DNNs), in enhancing the analysis of EV data. Our focus is on the prediction of EV range: a critical parameter influencing consumer acceptance and market penetration. By employing sophisticated feature extraction and prediction models, this study seeks to advance the state-of-the-art in EV data analytics, providing more accurate, reliable, and insightful predictive models to inform stakeholders across the EV ecosystem.

An existing studies reveals a significant gap in the application of deep learning techniques to EV data analytics. While conventional machine learning models have been employed to various degrees of success, the capacity of deep learning, particularly autoencoders, to improve model performance through efficient feature representation has not been adequately explored. This research gap is particularly pronounced in the context of predicting EV range, where the complexity and high-dimensionality of the data make it a prime candidate for the application of advanced neural network architectures. The contributions of this study are threefold: firstly, Innovative Methodology, it is Introducing an innovative methodology that combines autoencoders for feature extraction with DNNs for regression, this research pioneers a novel approach to analyzing EV data. By harnessing the power of deep learning, the study aims to unlock new insights into EV range prediction, setting a new benchmark for accuracy and reliability. Secondly, Comprehensive Evaluation, we employ a rigorous K-Fold cross-validation approach, the study not only ensures the robustness of the proposed models but also provides a comprehensive evaluation framework that can be adopted in future research endeavors within the EV analytics domain. Lastly, beyond theoretical contributions, the study offers practical implications for various stakeholders, including vehicle manufacturers, policymakers, and energy providers. By enhancing the accuracy of EV range predictions, the findings can help in optimizing charging infrastructure, shaping policy decisions, and guiding consumer education efforts.

The broader implications of this research are explored in the subsequent sections of the article, which is structured as follows: Section 2 delves into the methodology, detailing the data preprocessing steps, autoencoder and DNN model architectures, and the K-Fold cross-validation technique employed. Section 3 presents the study's findings, including model performance metrics and feature importance analysis, providing a comprehensive understanding of the models' predictive capabilities. Finally, Section 4 concludes the article, summarizing the key contributions and charting future research directions to further explore the potential of deep learning in advancing EV analytics and sustainable transportation. This expanded introduction and the detailed structure of the article set the stage for a substantive addition to the body of knowledge on EV analytics, highlighting the novelty, urgency, and transformative potential of this research in the field of sustainable transportation.

2. RESEARCH METHOD

2.1. Data Collection and Preprocessing

The dataset utilized in this study was sourced from the "Electric Vehicle Population Data," which contains detailed records of electric vehicles. Dataset can be downloaded in [37]. Key attributes include model year, make, model, base MSRP (Manufacturer's Suggested Retail Price), and electric range. Initial preprocessing involved cleaning the data by imputing missing values for the 'Base MSRP' (replacing 0 values with the median of the non-zero values) and creating a new feature, 'Age', calculated as the difference between the current year (2023) and the vehicle's model year. Subsequent steps involved the selection of predictors and the target variable. Unnecessary features such as 'VIN (1-10)', 'DOL Vehicle ID', 'Vehicle Location', and '2020 Census Tract' were dropped. The predictors included both numerical features ('Model Year', 'Legislative District', 'Base MSRP', 'Age') and categorical features ('County', 'State', 'Make', 'Electric Vehicle Type', 'Clean Alternative Fuel Vehicle (CAFV) Eligibility'). The target variable was 'Electric Range'. A ColumnTransformer was then employed to perform numerical and categorical preprocessing. Numerical data were standardized using StandardScaler to have mean 0 and variance 1, while categorical data were encoded using OneHotEncoder. This preprocessing step transformed the predictors into a format suitable for input into the autoencoder and DNN models, ensuring that the data was normalized and ready for analysis.

2.2. Model Development

2.2.1. Autoencoder Architecture

The autoencoder was designed to perform unsupervised feature learning, with the aim of reducing dimensionality and extracting meaningful features from the EV data. The input layer matched the dimensionality of the preprocessed features. The encoder part of the autoencoder compressed the input into a lower-dimensional latent space representation (encoding_dim=32), using a dense layer with ReLU activation as presented in the equation (1) - (2). The decoder part aimed to reconstruct the input data from the latent space representation, using a dense layer with a sigmoid activation function matching the dimensionality of the input layer as presented in the equation (3) – (4). The autoencoder was compiled with the Adam optimizer and mean squared error (MSE) as the loss function as presented in the equation (5).

$$h = f(Wx + b) \tag{1}$$

$$f(x) = \max(0, x) \tag{2}$$

$$x' = g(W'h + b') \tag{3}$$

$$g(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

2.2.2. Deep Neural Network (DNN) Model

Following feature extraction via the autoencoder, a DNN was developed for regression to predict the EV range. The DNN comprised an input layer receiving the encoded features, followed by two dense layers with 64 neurons each and ReLU activation for non-linear transformation as presented in the equation (6) – (7). The output layer consisted of a single neuron with linear activation to predict the continuous target variable (EV range). This model was also compiled using the Adam optimizer and MSE as the loss function.

$$z_{l+1} = f(W_l h_l + b_l) \tag{6}$$

$$\hat{y} = W_o h_o + b_o \tag{7}$$

2.3. Model Training and Evaluation

The K-Fold cross-validation technique (with K=10) was employed to validate the model's performance. For each fold, the dataset was split into training and testing sets. The autoencoder was first trained on the training set to learn a compressed representation of the data, which was then used to transform both the training and testing sets as presented in the equation (8) – (10). The transformed data served as input to the network, which was trained to predict the EV range. Model performance was evaluated using MSE, providing insights into the accuracy and reliability of the predictions across different subsets of the data.

$$CV_K = \frac{1}{K}\sum_{k=1}^{K} MSE_k \tag{8}$$

$$\min_{W,b} \frac{1}{n_k} \sum_{i=1}^{n_k} \left| \left| x_i - g\left(f(x_i)\right) \right| \right|^2 \tag{9}$$

$$\min_{W_o, b_o} \frac{1}{n_k} \sum_{i=1}^{n_k} (y_i - \hat{y_i})^2 \tag{10}$$

2.4. Ethical Considerations

All data used in this study were anonymized and aggregated, ensuring that individual vehicle owners' privacy was maintained. The research was conducted with a commitment to ethical principles, ensuring that the findings contribute positively to the advancement of sustainable transportation research.

3. RESULTS AND ANALYSIS

In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results is presented in the table 1. The CNN model emerged as the most accurate in predicting urban happiness scores, with an RMSE of 0.5728. This superior performance can be attributed to the CNN's ability to extract and learn the most relevant features from the urban data, which likely contains spatial patterns that are pivotal in determining urban happiness. This finding underscores the potential of CNNs in handling complex, multi-dimensional data, a characteristic often found in urban datasets.

The RNN and Dense models also demonstrated commendable performance, with RMSEs of 0.7429 and 0.7829, respectively. The RNN model's success can be linked to its proficiency in capturing sequential dependencies within the data, suggesting that temporal factors play a significant role in urban happiness. Meanwhile, the Dense model's relatively low RMSE highlights the effectiveness of fully connected layers in understanding the relationships between different urban factors and happiness. Conversely, the LSTM model recorded the highest RMSE of 1.2038, indicating challenges in modeling urban happiness scores accurately. This outcome might reflect the LSTM's sensitivity to the quality of temporal sequences within the dataset or its complexity in capturing the dynamics of urban happiness. It suggests that not all sequential data models are equally suited for every dataset or problem type, emphasizing the need for model selection based on the specific characteristics of the data and task.

The Autoencoder and MLP Dropout models yielded RMSE values of 0.9179 and 0.9364, respectively. While not as accurate as the CNN or RNN models, these results highlight the utility of these models in understanding and predicting urban happiness to a certain extent. The Autoencoder's performance, in particular, suggests that dimensionality reduction and feature learning play a role in capturing the essence of urban happiness, albeit less effectively than direct prediction models like CNNs. The MLP Dropout model's performance, near that of the Autoencoder, indicates that addressing overfitting through dropout layers does not necessarily compensate for the model's inherent limitations in capturing the complex interplay of factors influencing urban happiness. The findings from this study offer several implications for urban studies and the application of deep learning in predicting urban happiness. The superior performance of the CNN model illuminates the critical role of spatial patterns in urban data, suggesting that models capable of extracting such patterns are more likely to succeed in predicting urban happiness. This insight can guide urban planners and policymakers in focusing on spatially relevant urban factors, such as green spaces, traffic congestion, and infrastructure layout, when aiming to enhance urban happiness.

The varying performance of the models also highlights the importance of model selection in urban studies. It underscores that the choice of model should be informed by the data's nature and the specific urban phenomenon being studied. For instance, when dealing with data that has a strong temporal component, RNNs might be more appropriate, while CNNs could be better suited for data with pronounced spatial patterns. Furthermore, the relatively higher RMSE of the LSTM model suggests the need for further investigation into the model's configuration and the temporal dynamics of the data. It may also indicate the potential for combining models or using hybrid approaches to better capture the complexities of urban happiness. This study's exploration of deep learning models in predicting urban happiness scores reveals significant insights into the potential and limitations of various neural network architectures for urban studies. The CNN model's standout performance underscores the value of spatial feature extraction in understanding urban happiness. Meanwhile, the results collectively emphasize the necessity of careful model selection based on the specific attributes and challenges of urban data. These findings not only contribute to the academic discourse on urban happiness but also offer practical guidance for leveraging deep learning in urban planning and policy-making to foster happier urban environments.

Table 1. The performance of Deep Learning Algorithms

Method	RMSE
Dense Model	0.7828726742688900
LSTM	1.2037781813100201
MLP with Dropout	0.9363827225020532
Autoencoder	0.9178949422567036
RNN	0.7429113630776178
CNN	0.5727550578433185

4. CONCLUSION

This research embarked on an exploratory journey to harness the power of deep learning models for predicting urban happiness scores, driven by the premise that urban environments play a pivotal role in shaping the well-being of their inhabitants. Through a comparative analysis of six deep learning models—Recurrent Neural Network (RNN), Autoencoder, Multi-Layer Perceptron with Dropout (MLP Dropout), Dense Neural Network (DNN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM)—this study aimed to uncover the most effective model for understanding and predicting the complex dynamics of urban happiness. The findings revealed a notable variance in the performance of the models, with the CNN model demonstrating superior accuracy in predicting urban happiness scores, followed closely by the RNN and DNN models. This variance underscores the critical importance of model selection in urban studies, highlighting the need to match the model's capabilities with the specific characteristics and requirements of the urban data being analyzed.

The CNN model's standout performance can be attributed to its proficiency in extracting and learning spatial patterns from the urban data, suggesting that spatial factors play a crucial role in determining urban happiness. This insight has significant implications for urban planning and policy-making, emphasizing the need to prioritize spatially relevant urban factors, such as the layout of green spaces, traffic congestion, and infrastructure, to enhance urban well-being. Conversely, the higher RMSE of the LSTM model signals a potential mismatch between the model's strengths and the temporal dynamics of the urban happiness data, indicating that not all sequential data models are equally suited to every dataset or problem type. This finding points to the necessity of a nuanced approach to model selection, considering the data's temporal and spatial characteristics and the specific urban phenomena under study. The results of this research contribute to the burgeoning field of urban analytics, offering new insights into the application of deep learning models for predicting urban happiness. By highlighting the efficacy of specific models and the importance of model selection, this study provides valuable guidance for researchers, urban planners, and policymakers looking to leverage the capabilities of deep learning in understanding and enhancing urban environments. Future research could expand on this work by incorporating a broader range of urban factors, exploring hybrid models, and applying the findings to targeted urban planning and policy interventions.

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BIBLIOGRAPHY OF AUTHORS

Gregorius Airlangga, Received the B.S. degree in information system from the Yos Sudarso Higher School of Computer Science, Purwokerto, Indonesia, in 2014, and the M.Eng. degree in informatics from Atma Jaya Yogyakarta University, Yogyakarta, Indonesia, in 2016. He got Ph.D. degree with the Department of Electrical Engineering, National Chung Cheng University, Taiwan. He is also an Assistant Professor with the Department of Information System, Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia. His research interests include artificial intelligence and software engineering include path planning, machine learning, natural language processing, deep learning, software requirements, software design pattern and software architecture.