Accurate Recommendation of EV Charging Stations Driven by Availability Status Prediction

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Abstract: The electric vehicle (EV) market is experiencing substantial growth, and it is anticipated to play a major role as a replacement for fossil fuel-powered vehicles in transportation automation systems. Nevertheless, as a rule of thumb, EVs depend on electric charges, where appropriate usage, charging, and energy management are vital requirements. Examining the work that was done before gave us a reason and a basis for making a system that forecasts the real-time availability of electric vehicle charging stations that uses a scalable prediction engine built into a server-side software application that can be used by many people. The implementation process involved scraping data from various sources, creating datasets, and applying feature engineering to the data model. We then applied fundamental models of machine learning to the pre-processed dataset, and subsequently, we proceeded to construct and train an artificial neural network model as the prediction engine. Notably, the results of our research demonstrate that, in terms of precision, recall, and F1-scores, our approach surpasses existing solutions in the literature. These findings underscore the significance of our approach in enhancing the efficiency and usability of EVs, thereby significantly contributing to the acceleration of their adoption in the transportation sector.

1 INTRODUCTION

Amidst growing concerns regarding environmental issues and the detrimental impacts of fossil fuels, the global adoption of electric vehicles (EVs) is witnessing a significant surge (El Halim, A. et al., 2022). Despite challenges posed by the COVID-19 pandemic, the EV industry has demonstrated remarkable resilience, with global sales exceeding 10 million units in 2022 (Intekin, 2022). China leads this trend, holding over 50% of the global EV market share and showcasing a strong commitment to sustainable mobility (International Energy Agency, 2023). However, the widespread adoption of EVs heavily relies on a robust and accessible charging infrastructure (Tambunan et al., 2023). Research indicates that the availability and quality of charging stations significantly influence EV adoption rates, with inadequate infrastructure posing a barrier even in countries with high home charging prevalence (El-Fedany et al., 2023; Karike et al., 2023; Schulz and Rode, 2022; Giansoldati et al., 2020; Engel et al., 2018). There is a link between the number of public charging points and the number of EVs that are bought, especially in cities (Hennlock and WP4 Shift, 2020). This shows how important it is to have a widespread and standardized charging infrastructure to help EVs grow and become more popular (George et al., 2022; Balakrishnan and Pillai, 2023).

Applying machine learning and deep learning techniques has become increasingly prevalent in optimizing various aspects of electric vehicle (EV) charging infrastructure. Soldan et al. (Soldan, 2021) employed data stream analysis and logistic regression to predict short-term EV charging station occupancy, utilizing both batch and real-time data. Sao et al.(Sao et al., 2021) introduced the Deep Fusion of Dynamic and Static Information Models (DFDS), integrating static and dynamic data patterns to enhance the accuracy of charging station occupancy forecasting. Hecht et al. (Hecht et al., 2021) explored ensemble machine learning methods, specifically Gradient Boosting De-

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cision Trees (GBDTs) and Random Forest Classifiers, to predict EV charging station accessibility. Meanwhile, Ma and Faye (Ma and Faye, 2022) utilized LSTM neural networks for intraday predictions of public charging station occupancy, incorporating diverse data sources to improve accuracy. These studies demonstrate the potential of advanced algorithms in optimizing EV charging infrastructure and predicting station availability, while also highlighting the need for further research to address real-world complexities and diverse charging scenarios.

In comparing these studies, Soldan et al.'s (Soldan, 2021) data streaming approach offers real-time updates, which could be advantageous for dynamic charging environments. Still, their model's performance might differ with varying data quality and size. Sao et al.'s (Sao et al., 2021) DFDS model demonstrated the potential of combining static and dynamic information, but its application in diverse geographical regions remains to be tested. Hecht et al.'s (Hecht et al., 2021) ensemble approach showcased promising accuracy, but the effectiveness might vary with different datasets and charging station types. Finally, the LSTM model proposed by Ma et al. (Ma and Faye, 2022) showed promise in intraday forecasts, but its generalizability to more extensive and diverse datasets warrants further investigation. These studies provide valuable insights into EV charging station occupancy forecasting, but additional research is necessary to validate and refine their methodologies under various real-world scenarios.

Beyond predicting EV charging station availability, research has also focused on understanding charging behaviors and forecasting future charging demand using machine learning and deep learning methodologies. Qiao and Lin (Qiao and Lin, 2021) developed predictive models to anticipate upcoming charging demand, capturing the behavior patterns of both long-term and short-term users. Their study employed XGBoost, SVR, and GBDT algorithms on real-world charging data, with XGBoost demonstrating superior performance. Shahriar et al. (Shahriar et al., 2021) investigated EV charging behavior, session duration, and energy consumption, addressing concerns about power grid strain from high-power charging. Their research utilized various machine learning algorithms, including DANN, Random Forest, and XGBoost, on the ACN dataset (Lee et al., 2019). These studies provide valuable insights into EV charging behavior and demand patterns, contributing to developing efficient charging strategies and infrastructure planning.

Research on EV charging behavior and demand forecasting by Qiao and Lin (Qiao and Lin, 2021) and Shahriar et al. (Shahriar et al., 2021) reveals valuable insights into user patterns and potential grid impacts. While XGBoost proves to be a robust prediction tool in both studies, further research is needed to develop comprehensive models that consider diverse user behaviors, charging patterns, and regional variations, ensuring applicability across different contexts and addressing potential power grid challenges.

The studies conducted by Almaghrebi et al. (Almaghrebi et al., 2020), Kim et al. (Kim and Kim, 2021), Zhao et al. (Zhao et al., 2021), and Zhu et al. (Zhu et al., 2019b; Zhu et al., 2019a) contributed to the research on EV charging demand forecasting.

Almaghrebi et al. constructed a model to forecast the charging demand using various machine-learning methods and evaluated its performance on a real-world dataset (Almaghrebi et al., 2020). In their study, Kim et al. compared different modeling approaches to predict charging demand, using both historical data and outside factors (Kim and Kim, 2021). Zhao et al. proposed a data-driven framework addressing overfitting issues with limited data in complex environments. The model was evaluated using real-world EV data and compared to high-performance models (Zhao et al., 2021). Zhu et al. developed an EV charging demand prediction algorithm using deep learning techniques and found that LSTM outperformed traditional time-series forecasters (Zhu et al., 2019b; Zhu et al., 2019a).

The research by Zhao et al. (Zhao et al., 2021), Almaghrebi et al. (Almaghrebi et al., 2020), Kim et al. (Kim and Kim, 2021), and Zhu et al. (Zhu et al., 2019b; Zhu et al., 2019a) helps us predict how much EV charging will be needed, but there are some problems with the models they use, how easy they are to understand, how stable they are, and how they can be used for long-term planning. Further research is necessary to refine these approaches and ensure their effectiveness across diverse scenarios.

In conclusion, the studies collectively contribute to advancing EV charging demand prediction. But making models easier to understand, testing how well they work in different environments, and thinking about both short-term and long-term prediction horizons would make these approaches more useful and effective(Intekin, 2022).

Despite the availability of various machine learning and deep learning models for analyzing EV charging infrastructure, a research gap exists in accurately predicting real-time charging station availability. This gap, coupled with challenges related to model accuracy and scalability, hinders effective charging planning for EV drivers. As the number of EVs and charging stations increases, accurate forecasting becomes increasingly crucial to ensure drivers can conveniently locate available stations that meet their immediate charging needs.

Forecasting electric vehicle charging stations is crucial for planning power systems and transportation networks. Existing research has made progress in sustainable transportation infrastructure using statistical models (Gruosso et al., 2020; Kim and Kim, 2021) and machine learning algorithms (Hecht et al., 2022; Yi et al., 2022; Koohfar et al., 2023) to predict demand and optimal station placement. However, a research gap still needs to be filled in forecasting station availability, facing challenges of accuracy and scalability due to limited data and complex user behavior and charging patterns.

As a result, this paper tackles the challenge of accurately predicting EV charging station availability by developing a system that utilizes web scraping, machine learning, and deep learning models. The resulting prediction system, integrated into a distributed software system, provides real-time availability information to EV drivers, addressing the limitations of existing research and enhancing the overall charging experience. These activities are carried out among those of the Horizon Europe ENERGETIC project https://energeticproject.eu/the-project/, where we design a three-layer resilient framework for BMS advanced analytics. The prediction service for EV charging station availability is among the ones deployed in the fog layer.

The rest of the paper is structured as follows: Section 2 presents our proposed methodology. The outcomes of our experimental evaluation are discussed in Section 3. Finally, Section 4 summarizes our take-away messages and alludes to future issues.

2 METHODOLOGY

In this section, we introduce our methodology for predicting the status of electric vehicle (EV) charging stations using an artificial neural network (ANN) model. The model uses Python code with the Keras deep learning library, employing a sequential architecture. The rationale behind using an ANN lies in its ability to effectively capture complex non-linear relationships between input features and charging station status categories. The ANN's versatility as a universal function approximator allows it to handle diverse and intricate patterns in the charging station data, making it well-suited for the multiclass classification task. The dataset used for training and evaluation is sourced from a CSV file containing comprehensive information about various charging stations that was provided in (Intekin, 2022). The model's performance is assessed using several evaluation metrics, including F1-score, precision, and recall. Additionally, visualization functions are employed to depict the prediction results in an interpretable manner.

This research aims to develop a robust system for predicting EV charging station availability by utilizing web scraping, machine learning, and deep learning techniques. By analyzing historical data and identifying patterns, the system accurately forecasts the availability of charging spots, providing EV drivers with real-time information through a user-friendly interface. This approach empowers drivers and enhances their overall charging experience.

In the following, we will provide a detailed account of each step mentioned above, including data scraping, dataset generation, ML/DL models for prediction, and EV charging spot availability prediction.

Figure 1 illustrates the key stages of the proposed EV charging station forecasting model. To extract meaningful information for precise predictions, the process starts with data scraping from various sources. Machine learning algorithms, including KNN, logistic regression, random forest, and support vector machines, are then employed to train robust predictive models. This iterative training process enables the model to identify patterns and relationships within the data, ultimately leading to reliable real-time predictions of charging station availability. This model highlights the intricate interplay between data scraping, feature engineering, and model training and underscores their collective contribution to the ultimate goal of providing reliable predictions for EV charging station accessibility. To put the issue in

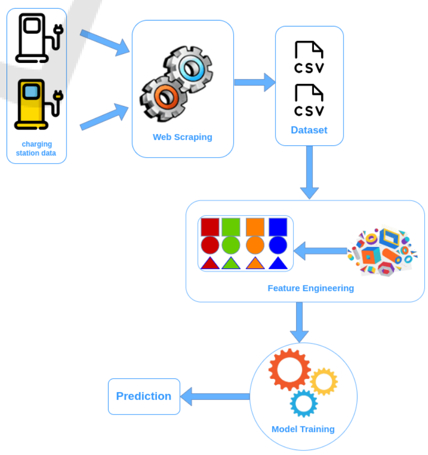


Figure 1: The overall architecture of the proposed approach.

simpler terms, Figure 2 illustrates how the model is designed to forecast the availability rate for charging stations along the driver's route and present this information to the driver. Notably, the third station stands out with the highest availability rate, making it the top recommendation for the driver.

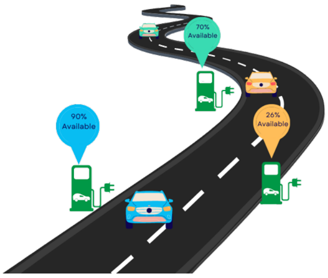


Figure 2: Model simplification.

Data on EV charging stations was collected through web scraping from two sources: OpenData Paris "Belib" (bel, a), providing information on 1,822 stations in Paris, France, and Enefit Volt, covering over 185 stations across Estonia. Belib's public API [1] (bel, b) facilitated real-time data retrieval, while Enefit Volt required a different approach due to the lack of a public API. The collected data, stored in CSV files, included station status, location, timestamps, and additional attributes. This comprehensive dataset served as the foundation for model development and training (scr,).

The second data source examined in this study pertains to a privately owned Estonian company known as Enefit Volt. The company asserts that it operates the largest network of EV charging stations in Estonia, with over 185 stations spread throughout the country. The company offers an array of chargers tailored to various requirements and is continuously expanding its network (ene,). Nonetheless, as Enefit Volt does not provide a public API, scraping this data source involved a somewhat distinct approach compared to the previous source. As with the script used for the first data source, the response from Enefit Volt contains details of multiple charging sites, which are then processed one by one to retrieve comprehensive data for each particular charging station. The collected data for each charging station is then stored in a CSV file, resulting in over 370,000 rows of data, each representing a single EV charging point with the charging points information (Intekin, 2022).

The data collection timestamp is also recorded using datetime.now() for each entry. Once the data is scraped from both sources, the rows are added to a CSV file to create the final dataset for constructing the model.

To apply the generated datasets in machine learning algorithms, it is crucial to perform both feature engineering and pre-processing on the datasets. Feature engineering encompasses transforming raw data into useful features for the model, including selecting the most pertinent predictor variables. The model comprises both outcome and predictor variables (Fea,). Due to two distinct datasets with various data types and columns, two separate preprocessors were developed for each of them. Our second step is preprocessing the obtained data to prepare it for ANN model training. The charging station information is sourced from the CSV file," and relevant data manipulations are performed using the Pandas library. The charging station status labels are encoded into numerical values, ensuring compatibility with the ANN's numerical computations. Subsequently, the encoded output variable is one-hot encoded, transforming it into a categorical form suitable for multiclass classification tasks. Feature extraction is accomplished by separating the "Status" column from the dataset. Lastly, the dataset is divided into training and testing sets using the train_test_split function, ensuring proper separation for model evaluation.

The core of our methodology lies in designing the model architecture to effectively capture the intricate relationships between the input features and the output charging station status. The sequential model architecture offered by Keras is adopted to design the ANN. The model comprises two essential layers: a dense hidden layer with 256 neurons and a dense output layer with eight neurons. The hidden layer employs the Rectified Linear Activation (ReLU) function, enabling the model to extract meaningful features from the input data. The ReLU activation introduces non-linearity, allowing the ANN to handle complex patterns that may exist in the charging station data. The output layer utilizes the softmax activation function, providing class probabilities for each charging station status category. The softmax activation is particularly advantageous for multiclass classification, as it allows the model to express its confidence in predicting different status labels.

Once the model architecture is established, the next step is to train the model on the prepared training dataset. The training is performed over 20 epochs with a batch size of 10 to optimize model parameters and ensure convergence. The choice of 20 epochs for training provides ample iterations for the model to learn from the data and adjust its internal weights. The Stochastic Gradient Descent (SGD) optimizer achieves efficient optimization during training with a learning rate of 0.3. We finally reached the prediction needed to obtain predicted values for the testing dataset, enabling further analysis and comparison

[1] https://opendata.paris.fr/explore/dataset/belib-points-de-recharge-pour-vehicules-electriques-disponibilite-temps/api/?disjunctive.statut_pdc\&disjunctive.arrondissement\&disjunctive.arrondissement

with actual charging station statuses.

In conclusion, the methodology revolves around using an Artificial Neural Network model to predict the status of electric vehicle charging stations. The ANN's capability to capture non-linear patterns and its adaptability as a universal function approximator make it suitable for the multiclass classification task.

3 RESULTS AND DISCUSSION

This section presents the results of evaluating the performance of multi-class classification machine learning and deep learning models. The performance of these models is assessed using precision, recall, and F1 score metrics to measure and compare their effectiveness in predicting charging station availability. Table 1 displays the outcomes obtained through the machine learning/deep learning (ML/DL) methodology applied to the Paris dataset. The results demonstrate that among the ML baseline models, Random Forest (RF) achieved the highest performance across all metrics, with an accuracy rate exceeding 95%. K-Nearest Neighbors (KNN) followed closely with a rate of 94% in all metrics. Regarding the F1 Score, the Support Vector Machine (SVM) yielded the lowest rate at 59.54%, with Logistic Regression closely behind at 60.73%.
However, the artificial neural network (ANN) model, despite slightly trailing behind the K-nearest neighbors (KNN) and random forest (RF) models in performance scores, managed to attain a precision of 89.46%, a recall of 87.94%, and an F1 score of 88.69%.

Based on the results presented in Table 1 and Figure 3, the Random Forest and K-Nearest Neighbors models are the top performers on this dataset, as they consistently achieve high precision, recall, and F1 scores. The Logistic Regression and Support Vector Machine models show weaker performance. At the same time, the Artificial Neural Network model also performs well, falling in between the top-performing models and the weaker ones. While it's noteworthy that ANN forecasts rates for all potential outcomes and offers real-time predictions, the instance-based learning of KNN constrains its ability to provide real-time predictions. Additionally, RF doesn't furnish rates for output classes, presenting results solely.

Figure 4 illustrates the initial five prediction outcomes produced by the artificial neural network (ANN) prediction engine using the Paris dataset. The values displayed in the figure indicate the proportions of status outputs, with each percentage corresponding to a particular interpretation. This interpretation is further demonstrated in Figure 4, which showcases the prediction outcomes of the model utilizing ANN for the Belib dataset. In Figure 4a, the charging spot is predicted to be 93.89% Available ("*Disponible*"). In Figure 4b, the charging spot is predicted to be 95.26% in maintenance ("*En maintenance*") and 0.326% Available ("*Disponible*"). In Figure 4c, the charging spot is predicted to be 79.79% Available ("*Disponible*") and 0.842% in the process of commissioning ("*En cours de mise en service*"). In Figure 4d, the charging spot is predicted to be 64.62% Available ("*Disponible*") and 16.53% Busy ("*En charge*"). In Figure 4e, the charging spot is predicted to be 99.92% Available ("*Disponible*").

Table 1: Performance results (%) per model for the Belib Dataset.

APPROACH	RECALL	PRECISION	F1-SCORE
ARTIFICIAL NEURAL NETWORK	87.94	89.46	88.69
K-NEAREST NEIGHBOURS	94.13	94.10	94.11
LOGISTIC REGRESSION	72.16	66.65	60.44
RANDOM FOREST	95.56	95.54	95.41
SUPPORT VECTOR MACHINE	71.90	66.41	59.54

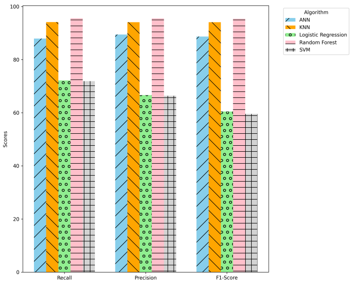
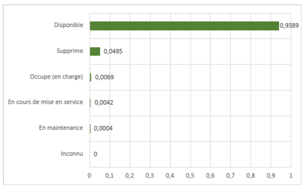


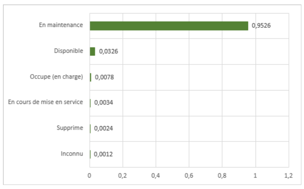
Figure 3: Performance results (%) per model for the Belib Dataset.

The findings from the application of machine learning (ML) and deep learning (DL) approaches to Estonian data are presented in Table 2. The K-Nearest Neighbours model performs consistently across all metrics. It achieves high precision, recall, and F1-score, indicating its strong ability to classify instances of different classes correctly. The Logistic Regression model shows competitive performance. It achieves high recall, indicating its effectiveness in identifying positive cases, and maintains a balanced F1 score. The Random Forest model demonstrates solid performance across all metrics. It achieves high recall and precision, resulting in a strong F1 score. The Support Vector Machine (SVM) model performs well, with high precision and recall values. The F1 score also reflects a good balance between the two metrics. The Artificial Neural Network (ANN) model achieves impressive results, particularly in precision. Its recall and F1-score are also high, indicating its effectiveness in classification tasks on this dataset.

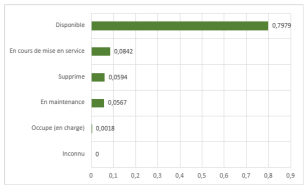
Based on the results presented in Table 2 and Fig-



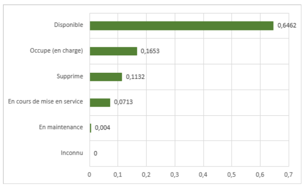
(a) First prediction outcome



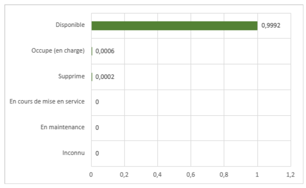
(b) Second prediction outcome



(c) Third prediction outcome



(d) Fourth prediction outcome



(e) Fifth prediction outcome

Figure 4: Results from the prediction model using ANN for the Belib database.

ure 5, all models exhibit strong performance on the ”Enefit Volt Dataset”. The ANN, Logistic Regression, and SVM models consistently achieve high precision, recall, and F1 scores. The K-Nearest Neighbours and Random Forest models also perform well but have slightly lower F1 scores than the others. Overall, these models appear to be well-suited for classifying instances in the ”Enefit Volt Dataset”.

Table 2: Enefit Volt Dataset Performance Results (%) by Model.

APPROACH	RECALL	PRECISION	F1-SCORE
ARTIFICIAL NEURAL NETWORK	95.74	96.04	95.89
K-NEAREST NEIGHBOURS	94.19	94.11	94.21
LOGISTIC REGRESSION	96.63	94.35	94.81
RANDOM FOREST	96.02	94.78	95.17
SUPPORT VECTOR MACHINE	96.32	95.15	95.75

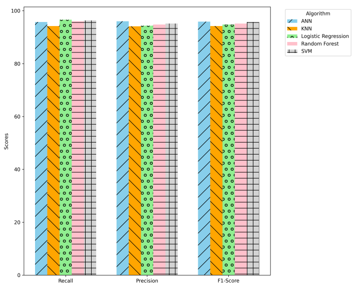
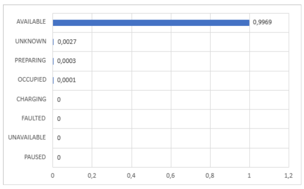


Figure 5: Enefit Volt Dataset Performance Results (%) by Model.

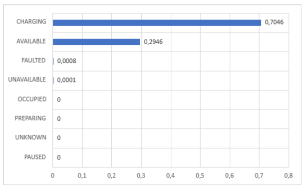
In Figure 6, there is a presentation of the initial five prediction outcomes derived from applying the artificial neural network (ANN) prediction engine to the dataset from Estonia. The figures represented in the visualization denote the percentages linked to different status outputs, as illustrated in Figure 6. This figure illustrates the prediction outcomes of the model utilizing ANN for the Enefit Volt dataset. In Figure 6a, the charging spot is 99.69% available and free to use. In Figure 6b, the charging spot is 70.46% in a charging session and 29.46% available. In figure 6c, the charging spot is 47.43% available; it is 35.7% in a charging session and 16.83% occupied by someone else. In Figure 6d, the charging spot is 99.56% available and free to use. In Figure 6e, the charging spot is 99.89% available and free to use.

The results of this paper demonstrate that the precision, recall, and F1 scores for all evaluation metrics surpass those of existing works in the literature review. These findings are particularly noteworthy given the differences in dataset features, which account for the varying evaluation scores of the models for the Paris and Estonia datasets. The performance results from both the ”Belib Dataset” and the ”Enefit Volt Dataset” demonstrate the effectiveness of various machine learning models in tackling classification tasks. Notably, the Estonia dataset is deemed more robust due to its inclusion of additional features such as price per kWh and outlet types, contributing to its higher overall scores than the Paris dataset.

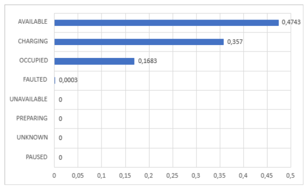
Although the evaluation metrics for the Paris dataset show that ANN has slightly lower scores than RF and KNN, it should be emphasized that ANN can provide real-time predictions, unlike KNN’s lazy-learning approach. Overall, the models’ performances indicate their capability to classify instances accurately on both datasets. The choice of the best-performing model would depend on the specific priorities of the task at hand. Furthermore, the artificial neural network (ANN) showcases outcomes in the form of a percentage for each distinct category, constituting a feature that is greatly favored. Furthermore, given the potential for including more complex features or a greater volume of records in future datasets, the ANN model is likely to perform even better with further improvements.



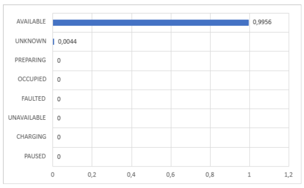
(a) First prediction outcome



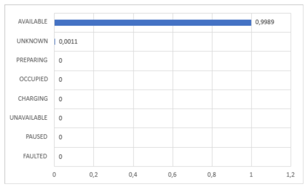
(b) Second prediction outcome



(c) Third prediction outcome



(d) Fourth prediction outcome



(e) Fifth prediction outcome

Figure 6: Results from the prediction model using ANN for Enefit Volt dataset.

4 CONCLUSION

This paper's initial focus was conducting a thorough literature review and analyzing state-of-the-art research on EV charging station availability prediction, including its strengths, weaknesses, models, methods, and datasets. By conducting a comprehensive review of existing literature, a foundation and rationale have been established to construct a scalable prediction engine for real-time availability forecasting in electric vehicle charging stations. The implementation process involved scraping data from various sources, creating datasets, and applying feature engineering to the data model. The paper then delved into using baseline machine learning models on the pre-processed dataset and subsequently building and training an artificial neural network model, which served as the prediction engine. In conclusion, the paper showcased the results visually, and the performance of different models was evaluated using standard metrics. The intended outcome was realized through the development of a prediction engine utilizing artificial neural networks. This engine furnishes probabilities of electric vehicle charging station availability, showcasing impressive evaluation scores that surpass the benchmarks set by existing literature. There are several potential avenues for future work to enhance the work presented in this paper while also addressing the challenges posed by controlling the uncertainty of the dynamic arrival of EV charging requests.

- The manual nature of the data scraping and feature engineering components suggests that automation could yield further improvements. Specifically, it may be possible to automatically identify which features are most important and which are less critical and to log differences that arise when a particular feature is excluded. Engaging in this process additionally improves the quality, precision, and dependability of the model.
- This study will also be extended to a larger scope, which is a better understanding of capacity fade, i.e., the battery's ability to hold a charge diminishes over time. Beyond intrinsic features like electrode degradation and solid-electrolyte interface growth, we would also be eager to explore the driving quality impact further.
- Last but not least, while the prediction engine is currently limited to Paris and Estonia, it could be readily adapted to other cities or countries.

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