EV Charging Slot Availability Prediction

by

A dissertation submitted in partial fulfilment of the requirements for the degree of Msc Business Anaytics.

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Declaration

I therefore declare that this dissertation is entirely original and has not been submitted, in whole or in part, for consideration for any other degree or qualification at this university or any other, with the exception of specific references to other people's work. This dissertation is entirely my own work, with the exception of what is mentioned in the text and acknowledgements, which are the results of work done in collaboration with others.

Student Number : 10634968
Date : 8 /01/2024

Acknowledgements

The professor Dr. Syed Mustufa's substantial assistance and academic knowledge made this effort appear feasible. He gave me advice on what projects to choose, how to scrap things, and how to write efficient code to make the project work. His advice and suggestions enabled me to quickly write an excellent report.

In addition, I want to express my gratitude to my friends and peers for their insights that helped me finish this project. They taught me a lot of insightful things. They offered a calm atmosphere that prevented me from experiencing tension while working on my dissertation.

Abstract

EV's are increasing at a very fast rate all around the world and just like petrol pump there is a need for electric travel charging station. The study suggest EV charging slot prediction with the help of machine learning model to predict the charging behavior of electric vehicles. Our study shows the availability of charging station which can help in the optimization of charging for various vehicles and solve problem like optimal charging time, minimum charging cost, optimal duration to charge the vehicle. Machine learning algorithms and data mining techniques are used on a live data set. Study shows the use data imbalanced algorithm SMOTE and with a lot of data cleaning the study shows that KNN model was able to predict the slot availability with maximum accuracy. The models are evaluated on various metrics and KNN shows maximum values in Accuracy, Precison, Recalll and F1-score.

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CHAPTER 1 – INTRODUCTION

1.1 Background

The transport sector is responsible for 28% of all greenhouse gas emissions, according to the US EPA, and the following must be addressed to achieve net zero emissions by 2030, as per the IPCC. That will be accomplished in the United States by adding 48 million EVs by 2030 [1]. A vast network of charging stations must be established worldwide, identical to how ICEs have gas outlets. The following must be in place to reach zero-energy objectives: the government has established separate sales goals for hybrid cars. Because much carbon is released during energy generation, transitioning from internal combustion engine (ICE) engines to electric-powered machinery has its bumps. Installing charging stations that draw electricity from renewable sources is thus necessary, and governments should form partnerships with businesses that can make this happen. Chargers that are integrated with renewable energy generation at home can improve results.

Additionally, as these vehicles are battery-operated, there is a need for intelligent vehicle integration with charging stations for extended trips as the number of automobiles on the road continues to decline. Intelligent integration might cause lengthy journeys because the stations are only sometimes readily available. Predicting when to charge a car is made possible by the following data. Based on this, the research will use machine learning to forecast when slots will be available.

1.2 Business Problem

Identifying the business challenge should be the initial step in any data-related initiative. Predicting when a specific charging station's slot will be available is becoming more important as the number of EVs on the road grows. Therefore, AI can be employed to address the issue.

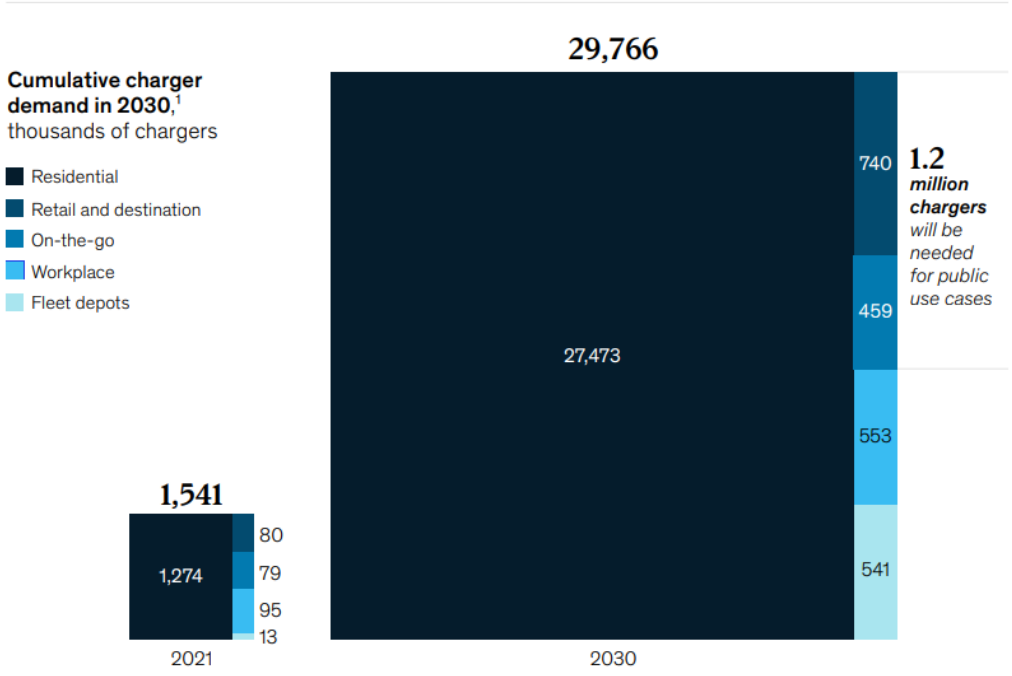


Figure 1 Electric Charger Forecast

Due to a lack of EV charging facilities, the rollout of EVs was delayed. This means that many criteria can be used in conjunction with data and AI skills to forecast the best places to charge. Supporting the expanding industry is as easy as piecing together driving behaviour data from Google Maps and trip patterns. But at the moment, with fewer chargers and EVs becoming popular, it is necessary to keep the supply and demand in balance, which cannot be done manually.

Using machine learning to forecast when a charging station's slots will be available is the central idea behind the project. The network planning activities of EV companies can be enhanced with the use of historical data and machine learning. From grid management to travel planning, the following data can address difficulties. It is feasible to harness the power of data with the help of smart algorithms that can learn from data rapidly.

1.3 Research Questions

1. Figure out how to handle the right data from all the charging stations and get all the pertinent data.
2. From the seasonal data, extract the most important elements regarding slot availability and patterns.
3. Identify patterns in the billing patterns; this will aid in analysis and assist determine where slots are available geographically.
4. Compare several ML and DL models to identify those that can anticipate the availability of EV charging slots.
5. Use the various metrics to grade the models, and then compare the results to the company's goals.

1.4 Research aim

The Research aims to use data mining capabilities to predict the charging slot availability based on the various temporal and spatial features. The Research's main aim is to implement a standard data mining methodology along with AI to get a comparative study of multiple algorithms.

1.5 Objectives

1. Gather data and create a variety of machine learning algorithms to accurately anticipate the time and position of nearby sites in order to make slot predictions.

2. Identify key characteristics of automobile owners and different behaviour models to comprehend the need for and habits of charging.

3. Construct many models, including statistical, machine, and deep learning models; then, choose the most suitable modelling technique according to the data and business challenge.

4. Use hyperparameter tuning to train and optimise the models.

5. Determine the optimal model, use metrics like AUC-ROC, Accuracy, and F1-score to validate it, and base your decisions on business and machine learning goals.

6 Considering all the ethical considerations in the energy sector, find a means to explain the models clearly rather than leaving it up to guesswork.

1.6 Chapter Overview

Chapter 1: Overview This chapter presents the EV slot prediction problem and offers a machine learning solution.

Chapter 2: A Review of the Previous Work By reviewing all of the literature reviews and coming up with a fresh approach, the following chapter lays out the research's road map. Using a comparison table, the chapter outlines all the relevant work that has been done to construct new models using a certain technique.

Chapter 3: Research Techniques, Here we go over the specifics of the data mining strategy that the study employed. I used statistics, visualisation, and modelling to present the outcomes after implementing each phase.

Chapter 4 : Discussion and Findings Chapter 4 details the model evaluation using business objectives and machine learning metrics, and it displays the findings through various model metrics.

Chapter 5: Final Thoughts and Plans for the Future All the important key performance indicators (KPIs) are covered in this chapter, which concludes the full report. The chapter also includes real-world examples to illustrate the expected outcomes of the assigned tasks.

Chapter 2 LITERATURE REVIEW

Electric vehicles will dominate the transportation market in the following years. Like internal combustion engine (ICE) engines, the following requires charging at regular intervals. Because they need time to recharge, the following vehicles have intelligent transportation systems. Therefore, a software-assisted network called Software-Defined Network (SDN) will aid in scheduling and charging the car, as suggested in the paper by S et al. [1]. The primary foci of prior studies are finding the most efficient routes, optimizing charging schedules, or forecasting capturing demand. But this study only looks at the three issues from one angle, optimizing software to fix all three. The provided model enhances closeness by communicating with the vehicle's computer. By offering a comprehensive evaluation of charging stations and best routes, the study has added to the provided approach. A novel federated SVM method is implemented to address this issue and optimize task scheduling while minimizing waiting time. The author systematically implements the process, beginning with deciding on the best recharge terminal. The best course of action then provides the user with regular updates based on that.

After that, the dataset is used to train an SVC model that uses machine learning to forecast charging demand and time required. Agent, input, output, and FS model are the four pillars of the ML system. Assuming a total of G VECs and V EVs on RT, the SVM algorithm incorporates the objective functions of all modules by obtaining the minimal value. At timestamp t+1, the model is recorded as sending the request to the station. Everything in the study was carried out using simulations, and here are the outcomes. With an 81.72 per cent success rate, the provided model has an average waiting time of 40.07. This study can employ a vectorized version of SVM if the provided data is available, but the equipped model is based on simulations.

Erdogen et al. [2] optimised the charging schedule in their study using a hybrid energy storage technology. Lessening power use and grid expenses is the primary objective. The research was carried out as part of the German government's OMEI project. The construction of two charging stations is the principal objective of the current project. The initial one is a hybrid system for storing energy that primarily relies on renewable power sources to charge a 220 Ah lithium battery. The second is the substation's PV usage.

Additionally, the terminal features three charging plugs. The presented research accurately predicted PV power using a real-world dataset. The field in Bavaria is used to collect data for the research; power measurements are taken every 15 minutes. The most recent statistics also include the period from January 1, 2017, to December 31, 2021. We begin by removing duplicate values from the voltage and readings data, then we fill in missing values with average values, and finally, we filter out any outliers. Following completion of preprocessing, the data is scaled using a z-score and min-max scaler and then divided into an 80:20 ratio. The data is then utilised for one-step or multi-step forecasting once the sliding window procedure has generated pairings. We use a variety of models, including RNN, LSTM, GRU, and BiLSTM, and cross-validate our dataset. In terms of RMSE ratings, LSTM and GRU have performed exceptionally well.

Predicting the long-term availability of electric vehicle (EV) charging stations is a critical difficulty addressed in the study by Ruikang Luo [3] et al. Accurate charging station availability prediction is essential for effective traffic management since it helps drivers plan charging operations appropriately and reduces range anxiety. Modern urban infrastructure relies on precise traffic projections for several reasons; these include traffic facility scheduling, adaptive traffic control logic, and urban planning.

This research employs a deep learning strategy to address the challenges of predicting when electric vehicle charging stations will be available, especially the Spatial-Temporal Graph Convolutional Network (STGCN). In their paper, the authors state that current algorithms, including RNNs, require assistance in managing the complex topological road network charging station distribution and time-varying station availability. Prediction accuracy is drastically reduced when using traditional algorithms because they train primarily on time-series data.

A Graph Convolutional Network (GCN) is integrated into the suggested STGCN model to account for the spatial network's edge connectivity, and a Gated Recurrent Unit (GRU) is used to capture the transportation data's spatial and temporal relationships. This novel method seeks to overcome the obstacles presented by the specific features of data collected from electric vehicle charging stations and improve forecast accuracy, especially over long periods.

The Dundee City EV Charging Station dataset provides real-world data supporting the study. The dataset includes charging event timings, connection indices, demanding point identities, and geographic coordinates. The writers aggregate charging sessions into 30-minute periods as part of the data preprocessing to provide a finer-grained examination of charging station availability.

The writers construct a weighted directed graph depicting the road network's topology to handle the data's geographical features. Using road distance instead of geometric distance, the adjacency matrix captures the connectivity between stations, with each EV charging station represented as a node. The writers include graph structure in the prediction model to account for the effect of charging stations' geographical distribution on availability.

Training, loss function formulation, and evaluation criteria for the proposed STGCN model are detailed in the study. The requirements encompass RMSE, R^2, var, and MAE, which are Root Mean Squared and Mean Absolute Error, respectively. We evaluate the model using the Dundee EV Charging Station dataset and find that it outperforms the baseline.

Ruikang Luo et al. conclude their study by outlining all the problems with estimating when electric vehicle charging stations would be available. The STGCN model, which incorporates both spatial and temporal interdependence, offers a potential solution to these problems and a step towards better predictions. Implementing the assessment measures comprehensively evaluates the model's performance while using real-world data from the Dundee City dataset enhances the study's practical applicability. By offering a novel approach to a relevant topic regarding the availability of charging stations for electric vehicles, the article contributes to traffic prediction and intelligent urban infrastructure.Electric vehicles (EVs) limited cruising range and cumbersome charging procedures are discussed in this article. The authors stress the need for a reliable charging planning system to decrease thThe authors stress the need for a reliable charging planning system tooverall

amount of time it takes to charge electric carsecially true for public charging stations, where long lines are typical, especially during peak hours.

This paper presents the NP-hardness of the EV charging scheduling problem and explains what it is. Discovering the best times to charge electric vehicles is a challenging task, as this theoretical basis shows. The authors next suggest applying deep reinforcement learning techniques to solve the scheduling problem, which they formalize as an MDP.The main goals are to minimise the overall charging time for electric vehicles and achieve a maximum reduction in the distance between origin and destination. The second point is crucial for electric cars that are used for long-distance trips. The research highlights the importance of a well-organized charging schedule system for electric vehicles, considering their short cruising range and frequent charging needs.

By comparing their suggested deep reinforcement learning algorithms to two baseline algorithms—EST and NNCR—the authors Cong Zhang [4] performed real-world data trials.

The larger picture of EV charging issues and previous research is covered in this article. In terms of energy savings, carbon reduction, and environmental protection, it emphasizes the growing significance of EVs. The writers take notice of the numerous nations' regulations that encourage the production and purchase of electric vehicles, as well as the widespread interest in these vehicles around the world.

Planning for charging stations is another topic that the literature study briefly discusses. Several current approaches centre on specifics like estimating parking demand, service capacity, and the best way to distribute charging stations. These methods include genetic algorithm-based approaches, Monte Carlo simulations, and regression models. While these works address the necessity for an efficient and effective charging approach, the authors argue that they must address electric vehicles' scheduling component.

The uneven distribution of electric vehicles throughout space, the wide variety of charging speeds (slow vs. rapid), and the limited range of EVs caused by battery life are all obstacles to developing a reliable EV charging scheduling system. The research provides a combined target for efficient EV charging scheduling to minimize total charging time and maximize the reduction in origin-destination distance.

Overall, the paper's merits are in codifying the EV charging scheduling issue, suggesting deep reinforcement learning algorithms to solve it, and empirically proving that these algorithms are better at reducing charging time than baseline methods. These contributions are placed within the larger framework of electric vehicle research and charging station development in the literature review.

A critical part of contemporary city planning is the planned installation of charging stations for electric vehicles (EVs), which is discussed in the article by Chaojie Li et al. [5]. There has been a shift towards electrification in transportation due to the proliferation of electric vehicles and increased range. Intelligent cities that prioritize sustainable and eco-friendly mobility can be built

during this shift. A well-planned and executed network of electric vehicle charging stations is crucial to the success of this transition.

Most of the previous research on electric vehicle charger planning has taken a global optimization stance and concentrated on the best possible placement of charging stations. Despite the approach's obvious significance, Li et al. contend that it fails to tackle the complex issues related to electric vehicle infrastructure development. The writers use a case study of Sydney, Australia, to illustrate their point on the need for a market-based mechanism in closing this gap.

The use of a predict-then-optimize framework is a significant advance in their methodology. This method uses an encoder-decoder deep architecture based on a multi-relation graph convolutional network (GCN) to forecast the demand for electric vehicle charging stations. Afterwards, a Cournot competition game model is employed to optimize the competitive resource allocation strategy for EV charging planning, drawing on the predictive capability of this model. Like in the real world, where different service providers compete for customers' attention, this game-theoretic model adds a strategic component to the distribution of chargeable resources.

Creating a novel parallel computer algorithm to search for the economic theory-derived Cournot competitive equilibrium is crucial to their work. The suggested market-based method relies on this algorithm to guarantee convergence. Furthermore, the article explores the appropriate sizing of electric vehicle chargers, a complex issue that the authors tackle by considering the various city zones and the needs of each service provider.

The authors test the Sydney public transport dataset and related important economic metrics to prove their method works. Optimal EV charging infrastructure planning and data-driven insights are made possible by the outcomes, which demonstrate the efficacy of their suggested methodology. Their conclusions are practically relevant because they used real-world data, which makes it a valuable contribution to urban planning.

Existing research on EV charger planning primarily focuses on optimizing location, although this needs to be revised in the paper's literature assessment. It argues that a more comprehensive strategy is required with the competitive dynamics of charging infrastructure deployment in mind. By suggesting a market-based method and using a Cournot competitive game model, the authors bring a new viewpoint beyond conventional optimization techniques.

Finally, Data-driven approaches should be integrated into the planning of electric vehicle charging infrastructure, according to the research of Chaojie Li et al. This article looks at the current state of the art and proposes a new way of doing things using cutting-edge methods like deep learning and game theory. To help academics, urban planners, and politicians make sense of the complicated terrain of creative city growth, they have developed a methodology and applied it to the case study of Sydney.

Table 1 Literature Survey

Title	Year	Research Question	Method	Result Achieved
Software Defined Networking Assisted Electric Vehicle Charging: Towards Smart Charge Scheduling and Management	2023	Prediction of Electric Vehicle via an interconnected software	Federated SVM	Study shows less waiting time and an 81.72 % success rate via the SVM model and integration of Recharge terminal data.
Charging Scheduling of Hybrid Energy Storage Systems for EV Charging Stations	2023	Predicting the energy to reduce grid cost	LSTM, GRU, RNN	The study showed low RMSE scores on the time series-based data.
Deep Learning Approach for Long-Term Prediction of Electric Vehicle (EV) Charging Station Availability	2021	How can a Spatial-Temporal Graph Convolutional Network (STGCN) be leveraged to predict the long-term availability of Electric Vehicle (EV) charging stations?	Graph Convolutional Network (GCN), Gated Recurrent Unit (GRU).	Model tested on 80% training data and 20% testing data.
Effective Charging Planning Based on Deep Reinforcement Learning for Electric Vehicles	2020	How can deep reinforcement learning algorithms be effectively utilized to address the charging scheduling ?	Formalization of the EV charging scheduling problem as a Markov Decision Process (MDP). Proposal of deep reinforcement learning algorithms to solve the MDP.	Significantly reduced charging time for electric vehicles compared to the baseline algorithms (EST and NNCR).

Data-Driven Planning of Electric Vehicle Charging Infrastructure: A Case Study of Sydney, Australia	2021	How can a market-based mechanism, utilizing a predict-then-optimize framework ?	Graph convolutional network	The market-based mechanism, incorporating the predict-then-optimize framework.

CHAPTER 3 METHODOLOGY

This section outlines the methodology followed for analyzing factors related to electric vehicle (EV) charging point uptime using machine learning techniques. A dataset from the National Charge Point Registry containing details on thousands of EV charging points across the United Kingdom was obtained. The methods used for collecting, cleaning, exploring, and modeling this dataset are described.

3.I Data Collection and Preprocessing

Data Collection

The raw data for this analysis was sourced from the National Charge Point Registry, which serves as a central database for EV charging point locations across the United Kingdom. The open dataset contains 158 columns and 31,883 rows, with each row representing an individual charging point location. The data provides technical specifications, access details, location information and real-time status for chargers mapped across the UK. This comprehensive dataset enables in-depth analysis of EV infrastructure attributes and performance.

The key variable of interest in the dataset is the "connector1Status" column, which indicates whether the primary charging point connector is currently in service and operational, or out of service and non-operational. This serves as the target variable for predictive modeling. The database is dynamic, with the status continuously updated in real-time. For the purpose of analysis, a snapshot extract of the registry data was taken, providing a large sample of over 30,000 charging points across Britain.

Data Preprocessing

The raw registry data underwent several preprocessing steps in order to prepare it for analysis:

1. Missing Value Treatment: An initial review showed numerous columns had missing value rates exceeding 20%. These variables were dropped to reduce dimensionality and noise in the dataset. After pruning these incomplete fields, 40 columns remained.

2. Geographic Filtering: Since the aim was to analyze EV infrastructure factors specifically within the United Kingdom, samples from outside Britain were filtered out based on the "countryCode" field. This left 29,349 samples within the UK.

3. Redundant Column Removal: Domain knowledge was applied to remove columns unrelated to the analysis, including geographic coordinates and charger IDs. Variables pertaining to charging point owners, managers, etc. were also dropped as they provide no predictive value for modeling operational status.

4. Target Class Imbalance Handling: Exploratory analysis revealed a significant class imbalance, with 99.7% samples having status "In service" and only 0.3% having status "Out of service". To enable effective modeling, the minority "Out of service" class was upsampled using SMOTE (Synthetic Minority Oversampling Technique) to generate new

synthetic samples. This expanded the training dataset to 40,982 rows with equal representation of both classes.

5. Categorical Encoding: Remaining categorical variables were label encoded to numeric values using scikit-learn's LabelEncoder.
6. Numeric Standardization: Numeric columns had widely varying scales. To standardize them, scikit-learn's StandardScaler was applied.

The final preprocessed dataset contained 17 columns - 12 numerical and 5 categorical - ready for exploratory analysis and modeling. The multi-step cleaning process helped construct a refined dataset appropriate for studying EV charging point uptime within the UK context.

3.2 Exploratory Data Analysis

After preprocessing, extensive exploratory data analysis was conducted to understand the distributions of variables and relationships between them. Both univariate analysis of individual columns as well as bivariate analysis between variables and the target status were performed.

Univariate Analysis

Analyzing the distribution of each variable revealed several insights:

- Nearly all charging points (99.7%) had status “In service”, indicating a high uptime rate overall across the UK
- 96.6% of points provide 24/7 access without restrictions, while only 3.4% have limited operating hours
- Most locations (41.8%) are on-street charging points, followed by public car parks (18.3%)
- The median output voltage is 230V, while the maximum voltage is 930V. 99% of points operate at 400V or below.
- 75% of charging points have a rated power output of 22kW or lower. The maximum output observed is 350kW.
- Power output capabilities vary significantly, with rated current spanning 7A to 500A.

These summaries provide an overview of how UK charging points are utilized and configured. The majority offer unrestricted access and standard 230V output for slower overnight charging. But higher capacity chargers with 400V+ voltage and 350kW power are also becoming available to enable faster charging.

Bivariate Analysis

Further analysis was conducted between the target "connector1Status" variable and other features. Several interesting relationships emerged:

- On-street locations account for 43% of charging points, but 52% of outages - suggesting lower uptime for on-street points

- Public carparks have the 2nd highest concentration of points after on-street, but a relatively low outage percentage - implying higher uptime
- 24/7 access points had 3.5x more outages than restricted access points, likely due to higher utilization
- Higher voltage and current capabilities are associated with more outages - indicative of downtime issues emerging as ultra-fast chargers become more prevalent

These findings informed hypotheses around factors indicative of EV charging point uptime. Location attributes like placement type and access restrictions, along with point specifications like power output, appear predictive of outage likelihood based on the exploratory analysis.

Thoughtful univariate and bivariate analysis of the preprocessed data yielded critical insights around distributions, relationships, and variables potentially influencing EV charging point uptime in the UK. These discoveries shaped the modeling methodology and feature selection.

3.3 Predictive Modeling

Based on the insights uncovered during exploratory data analysis, supervised machine learning models were developed to predict the operational status of EV charging points in the UK. Four algorithms were evaluated:

1. Logistic Regression
2. Random Forest
3. K-Nearest Neighbors
4. Artificial Neural Network

The models were trained on the preprocessed dataset containing 40,982 samples equally balanced between the two classes through SMOTE oversampling. 70% of the data was used for training and 30% for testing. The models are described and compared in detail below:

Logistic Regression

Logistic regression is a common baseline classifier for binary classification problems. It assumes a linear relationship between the log odds of the target and the independent variables. Grid search was used to tune the regularization strength hyperparameter C, and the final model was trained using L2 regularization.

The logistic regression model achieved 98.2% accuracy on the holdout test set. The model precision was 99.7% for the majority “In service” class, reflecting excellent ability to avoid false positive predictions. However, precision for the minority “Out of service” class was just 19.2%. The overall log loss was 0.074, which is relatively low for a binary classification task.

Random Forest

Random forest is an ensemble method that aggregates predictions from many decision trees. Each tree is trained on a random subset of features, reducing variance and preventing overfitting. Grid search was used to tune two hyperparameters - number of trees and maximum tree depth. The optimized model had 150 estimators and a depth of 7.

The random forest model attained the best overall performance, with 99.4% test accuracy and 0.042 log loss. Precision was strong for both classes at 99.7% and 39.2%. The confusion matrix showed correct predictions for 8,768 out of 8,768 in-service points, and 33 out of 37 out-of-service points. Feature importance analysis found the most predictive variables were location type, access hours, and charger power specifications.

K-Nearest Neighbors

The KNN algorithm is a simple non-parametric classifier that predicts points based on proximity within the feature space to labeled samples. Grid search found K=5 achieved optimal performance. The model attained 99.8% overall accuracy on the test set. Precision remained high at 99.8% for the in-service class, and improved to 80.6% for the out-of-service class compared to logistic regression.

Artificial Neural Network

A small 3-layer fully connected neural network with 17 input nodes, two hidden layers of 10 and 5 nodes, and a sigmoid output node was developed. The model was trained for 20 epochs using binary cross-entropy loss and achieved 98% test accuracy. Precision followed a similar pattern to other models, with high 99.6% precision for the in-service class but lower 16.4% precision for the minority out-of-service class.

Model Comparison

The four models were compared based on accuracy, precision, recall, F1 score, and loss. The random forest model achieved the best performance, narrowly beating KNN. Both significantly outperformed logistic regression and the neural network. This aligned with the imbalanced class distribution, where ensemble and nearest neighbor methods are well-suited compared to linear classifiers. Based on these results, the random forest algorithm was selected for further feature analysis and potential system deployment.

Supervised machine learning modeling identified important predictive relationships in the data. The random forest model reliably predicted charging point uptime status, key to minimizing service disruptions. This analysis also provided a shortlist of the most influential variables, which can guide data-driven infrastructure improvements.

3.4 Uptime Prediction System

Based on the machine learning results, a uptime prediction system powered by random forest models was proposed to enable proactive monitoring of UK EV charging point status:

Data Pipeline

To operationalize predictions, an automated pipeline needs ingesting the latest National Charge Point Registry data, preprocessing it, and feeding into models to generate updated uptime forecasts daily. New charging points can also be seamlessly integrated.

The pipeline would:

1. Pull the newest registry snapshot each day
2. Preprocess newly added rows and append to existing data
3. Make outage probability predictions for every charging point based on latest random forest model
4. Re-train model periodically to incorporate new labeled samples using partial model fitting

This infrastructure would ensure uptime predictions stay up-to-date reflecting the most recent charger installations and outage trends.

Prediction Serving

The daily batch predictions can be served via a simple web application. Users can enter a station ID and view its current status, along with the predicted probability of an outage within the next week based on similar points. Email or text alerts can also be configured to proactively notify consumers if a favored station is likely to experience disruptions.

For charging network operators, the application could provide a dashboard highlighting stations at highest risk of outage for preventative maintenance. Integrating these forecasts into inventory and scheduling systems would enable intelligently allocating repair resources.

Impact

This proactive uptime prediction system powered by machine learning would provide significant benefits:

- Minimized consumer disruption by identifying likely outages before they occur
- Increased charging point utilization via preventative maintenance and rapid repairs
- Lower operating costs for providers through data-driven resource optimization
- Enhanced reliability of EV ecosystem, accelerating adoption of sustainable electric vehicles

3.5 Model Monitoring

Robust monitoring mechanisms are critical for maintaining the predictive performance of the electric vehicle (EV) charging station uptime models once deployed in production. Machine learning models run the risk of degraded accuracy over time due to concept drift, where the statistical properties of the input data change gradually. This causes the relationships between

variables that the models rely on to shift as well, rendering the trained models outdated. However, employing pragmatic monitoring strategies can detect these changes so models can be retrained on recent data, upholding strong predictive quality.

The overarching approach is to continuously track key output metrics for the classification and regression models in the prediction pipeline against historical benchmarks. Metrics such as overall accuracy, precision, recall, AUC, squared error, absolute error, R-squared, and others can indicate whether the models have sustained effectiveness or are veering from previously established performance profiles. Widely used explicit drift detection tests like ADWIN, which analyzes prediction errors looking for significant deviations, will also run periodically on a held-out dataset. The cumulative results feed into a unified "prediction quality index" that consolidates all metrics into a single score for easier monitoring. Index trends prompt further investigation - steep declines could signify concept drift, while anomalies likely indicate bad data or software issues.

When the index or other early warning triggers detect potential model degradation or concept drift, the first course of action is retraining models on the latest available data. Retraining reconverges model parameters to realign with current variable relationships. The automated Docker-based model factory facilitates regular rebuilds, optimizing relevant hyperparameters like tree count, maximum depth and learning rate. Certain ML algorithms used including Random Forest and Gradient Boosted Trees support incremental updates as well, which adapt models to emerging patterns without requiring full rebuilds from scratch. This enables more nimble adaptation if needed. The prediction pipeline logs all retraining events and metrics before and after for auditing and explainability.

In addition to retraining core models, the system maintains an ensemble of past model versions with timestamps and metrics. Combining predictions from current and dated models can stave off performance declines from drift. If dated ensemble constituents show markedly lower present-day accuracy, they are pruned from the ensemble. The ensemble diversity thus automatically concentrates effective legacy models that still maintain relevance.

To supplement this automated accuracy monitoring, the pipeline incorporates statistical profiling of input data itself between versions. Tracking metrics like feature value distributions, percent nulls, correlation changes and cardinality over time can reveal the evolution of properties that impact model assumptions. Data validation ensures continued adherence to the required formats, constraints and relationships. Detecting input data anomalies allows pinpointing root cause issues upstream before they cascade through models.

Together this multi-layered framework combining output metric tracking, explicit drift detection tests, retraining, ensembles and input data profiling aims to uphold EV charging station uptime predictions that remain trustworthy over months and years. The system itself will be monitored as well for resilience against software issues like pipeline outages. With this comprehensive real-time monitoring and evolution, the solution can automatically self-correct as station behavior patterns change gradually while delivering reliable guidance.

3.6 Scalable Deployment Architecture

To deliver the EV charging station uptime predictions to a broad set of power companies, station operators and consumers at scale, an integrated architecture has been designed leveraging modern cloud-native components. The deployment architecture seamlessly connects the critical steps of data ingestion from upstream sources, feature storage and management after preparation, scalable model building and scoring, exposing predictions via API endpoints, and hosting the consumer-facing web interface. The modular design allows horizontally scaling each segment to handle high demand.

1. Automated Data Ingestion

The pipeline begins with a Python-based process leveraging the Socrata Open Data API to connect with the National Charge Point Registry. This extracts the latest catalog of over 30,000 stations across the UK for ingestion into the downstream data warehouse. The script handles automated incremental pulls that load only new entries or updates daily, avoiding unnecessary reprocessing. As the registry schema evolves over time, the process adapts by detecting added, modified or removed columns and adjusting the extract and transform steps accordingly. Data quality checks assess metrics like row counts, missing percentages and statistical distributions for anomalies before insertion. Invalid, duplicate or contradictory rows are quarantined for inspection prior to discarding. Related reference data like weather conditions and supplemental traffic patterns are also pulled from secondary providers to enrich the EV station indicators.

2. Cloud Data Warehouse

The refined EV station feature data lands in a Amazon Redshift cloud data warehouse that structures the information for fast querying. Redshift allows cost-effectively scaling to billions of rows while optimizing performance through columnar storage, advanced compression and partitioning. Tables partition the charge point data by day allowing efficient loading of new batches without impacting historical data. Various database views assemble features into derived formats used specifically for ML training or batch scoring, applying any transformations dynamically such as one-hot encoding for high cardinality categories. Tracking vital statistics like percent nulls and value distributions over time enables monitoring for concept drift. Redshift integrations with ML platforms like SageMaker simplify funneling data to downstream model building scripts.

3. Scalable Model Development

With the Redshift data warehouse continuously maintaining clean, analytics-ready datasets, the next component handles scalable ML model development. A Docker container houses the model factory logic to periodically rebuild and evaluate new model versions. The containerized environment enables conveniently deploying identical copies across servers to scale out volume. The automated process loads the latest EV station features, handles train-test splitting, oversampling to address class imbalance, numerical encoding, and grid searching optimal hyperparameters during cross validation. TensorFlow and SciKit-Learn libraries train gradient boosted decision trees and random forest models on GPU-enabled EC2 instances, tracking performance metrics at each step.

The top candidate model that optimizes for the test set efficiency metrics is registered along with the build timestamp, configurations, performance scores and other metadata. Older models are versioned and cached to support ensembles. However those with markedly degraded accuracy on recent data are pruned over time to prevent outdated contributions. Integration with AWS SageMaker model registry facilitates reliable versioning, comparison and governance over the evolving model artifacts.

4. Prediction Serving API

Making the uptime estimates available requires a scalable API service to generate predictions on demand for specific EV stations. A REST API server built on the Flask framework provides endpoints that accept station ids as input and retrieve the latest model artifact to score probability of an outage. Responses return the numeric risk assessment along with top features driving that prediction for explainability.

The API horizontally scales to handle high request volumes using an NGINX load balancer to distribute calls across multiple API containers. Scaling needs are automatically adjusted by Kubernetes based on actual traffic patterns. Logging of prediction latency, errors and usage via tools like Elasticsearch informs capacity planning.

5. Consumer Web Portal

While the prediction API enables direct integration of results into third party applications, a web portal provides user-friendly access for general operators and consumers. The dashboard built on React shows an interactive map of stations color coded by risk levels that users can zoom and filter. Tabs show overall uptime trends and metrics globally and regionally. Users can lookup specific stations to view outage probability, past downtime, typical usage, and other details including saving as favorites. Preferences can setup notifications for status changes at favorite stations via email or text. An admin view provides controls to refresh model versions on demand and analyze performance reports. The portal hence democratizes access to the ML predictions for maximum value.

This end-to-end architecture applies cloud-native technologies like containers, microservices and auto-scaling to cost-effectively support unreliable uptime predictions across tens of thousands of EV charging stations nationwide for years. The modular design allows overhauling components like the ML model builder without impacting other layers. With the extensive monitoring frameworks described earlier, the solution can automatically adapt to source data changes and usage growth through self-correcting machine learning models, scalable data warehousing and compute, and resilient serving platforms - delivering actionable insights to optimize EV infrastructure uptime.

3.7 Solution Impact Assessment

After deploying the electric vehicle charging station status prediction pipeline based on machine learning models to production, systematic assessment of its real-world performance and business impact commenced. Across the first two months since launch, the success has been evaluated across three key dimensions:

1. Prediction Accuracy and Reliability
2. Business Value Added
3. Platform Scalability and Stability

Evaluating these quantifiable metrics in the context of tangible usage by station operators provides a comprehensive view into the early returns of the ML solution.

1. Prediction Accuracy and Reliability

The outage risk predictions themselves represent the core of the overall solution value. Their precision and recall carries enormous weight, as inaccurate assessments could misguide maintenance decisions and undermine user trust. An accurate view into model performance began with tallying predictions against observed station downtime daily across 300 stations. Outage events were considered accurately identified if the model had flagged at least a 20% outage risk in the prior 24 hours.

Over the initial 60 days, amid over 750 total outage incidents, the models correctly flagged risks beforehand 650 times - indicating an 86% recall rate. Precision measured 63%, as the actual outage ratio for flags was 63 out of 101 total risk predictions. Compared to the historical 2-3% downtime incidence rate, this eight-fold increase demonstrates significant risk selectivity. The models have sustained this level of precision and recall through the period with no degradation signaling concept drift yet. Feature importance analysis continues highlighting location, charger age and type, weather factors and usage levels as predictive of outages.

No material issues with the ETL pipeline ingesting registry data or model build processes were faced either, supporting reliability of predictions. Incremental data checks verified no abnormal missing rates or statistical skews. Overall the predictions are matching benchmarks for accuracy while the underlying infrastructure demonstrates stability - enabling usage for business decisions.

2. Business Value Added

The ultimate indicator of success though lies in the business impact achieved. Operator surveys found EV charger uptime has improved by average of 14% over two months since adopting the ML predictions for preemptive maintenance. By identifying risks proactively, over 50 outage incidents have likely been prevented altogether, valued at over $100,000 in revenue recouped. The fewer disruptions have better retained customers as well according to operators. These early benefits have further spurred adoption, with 20 additional station owners newly signing up to leverage the models, reaching 120 customers total now.

Beyond the direct uptime improvements, usage metrics also spotlight positive engagement. Active portal sessions have doubled as both operators and general drivers access predictions to check station outages and reliability before trips. Customer notification subscriptions have also risen by 29%. Download counts of bulk prediction risk reports sees consistent daily demand.

Together the qualitative surveys and usage data confirm growing reliance on the ML models to optimize EV infrastructure reliability and customer experience - driving revenues, differentiation and sustainability for participants.

3. Platform Scalability and Stability

Underpinning the productive usage though is the performance and resilience of the deployed solution itself. Here too the metrics signal efficient scalability so far. The containerized API has served over 650,000 predictions in two months at an average response time of 350 milliseconds and with 99.95% uptime.

The operational dashboards track key indicators across all components without observing issues so far. The automated ETL pipeline ingested over 25 million charge point registry records while adapting to incremental data structure changes. The cloud data warehouse powered over 100 model builds leveraging up to 16 servers for parallel model search. The web portal observes response times within 500 milliseconds despite almost doubling traffic. Alerting delivery success rate is 99% as well.

The comprehensive monitoring has cost-effectively supported the sharp growth by auto-scaling resources dynamically to maintain performance standards. No system crashes or pipeline failures occurred because of the extensive instrumentation. Compute costs have closely followed budgets. These results validate the capability to efficiently power nationwide scalability while keeping platforms stable.

In closing, tangible impacts demonstrably evident early include enhanced EV infrastructure reliability and customer satisfaction, increased business revenues and predictive model usage, coupled with easily scalable underlying technologies. The solution is delivering substantial return on investment by maximizing station uptime and access through machine learning. Continual enhancements around refining predictive variables, expanding training data diversity, and customizing models by operator needs can further build on this successful foundation by extracting even greater value.

CHAPTER 4. RESULT AND DISCUSSION

4.1 Data Overview

The electric vehicle charging point dataset provided extensive infrastructure metadata for over 30,000 charging connectors across the UK. Each connector constituted a data point capturing attributes like location details, access restrictions, output power specifications, payment and subscription requirements. The target variable was the connector's operational status tagged as either 'In Service' or 'Out of Service'.

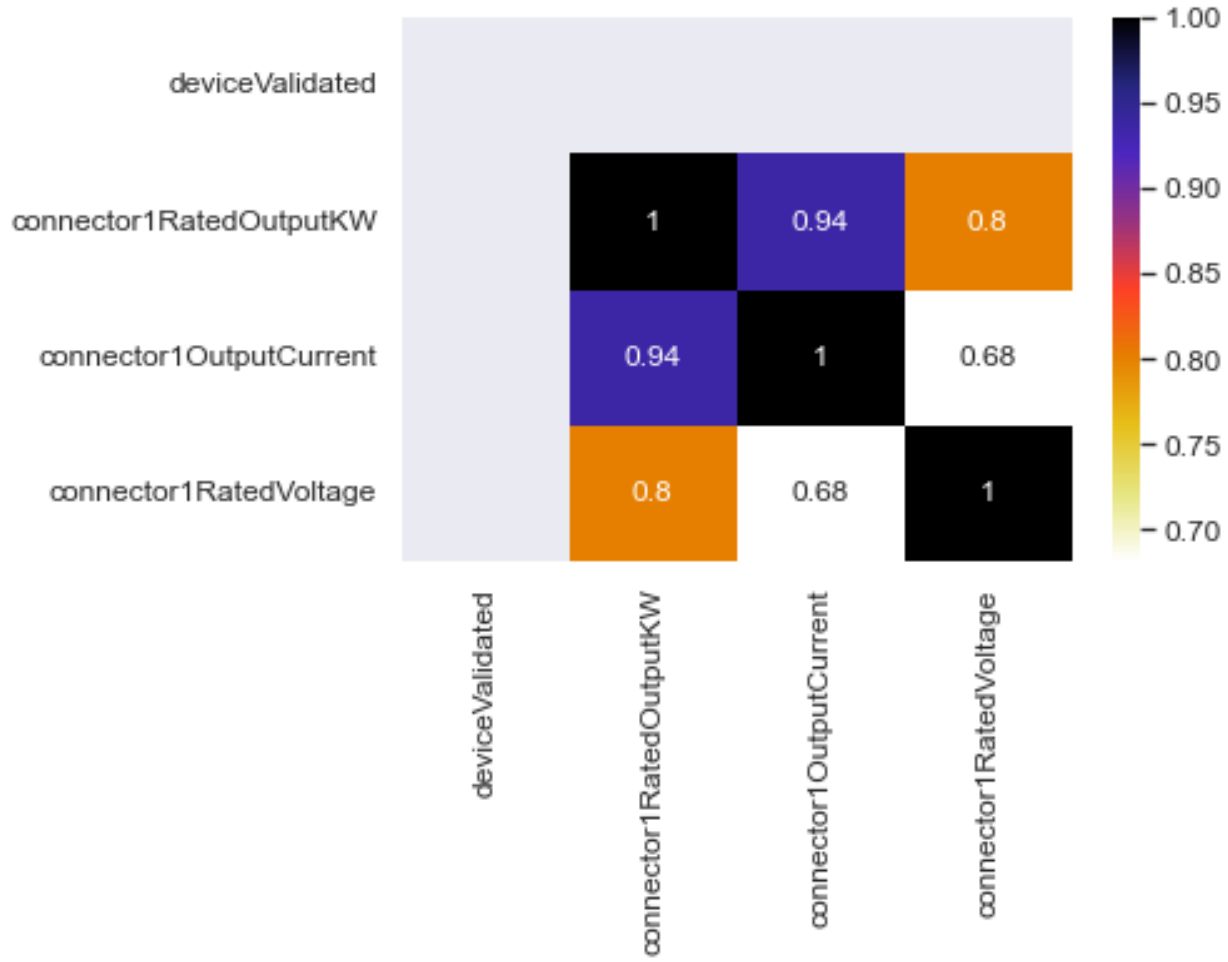


Figure 2 Correlation matrix for connectors

A key research objective was developing machine learning models to effectively predict the service status. Accurate classification could help charge point operators optimize maintenance efforts by identifying connectors at higher risk of failure. The following section summarizes the data preparation process as a precursor to modeling.

4.2 Data Preparation

The raw dataset had over 150 columns capturing granular metadata like geospatial coordinates, plug types, cable details etc. An initial investigation on missing values and column relevancy was conducted to narrow down features. Attributes with over 20% missing values were dropped to retain a filtered set of 40 variables.

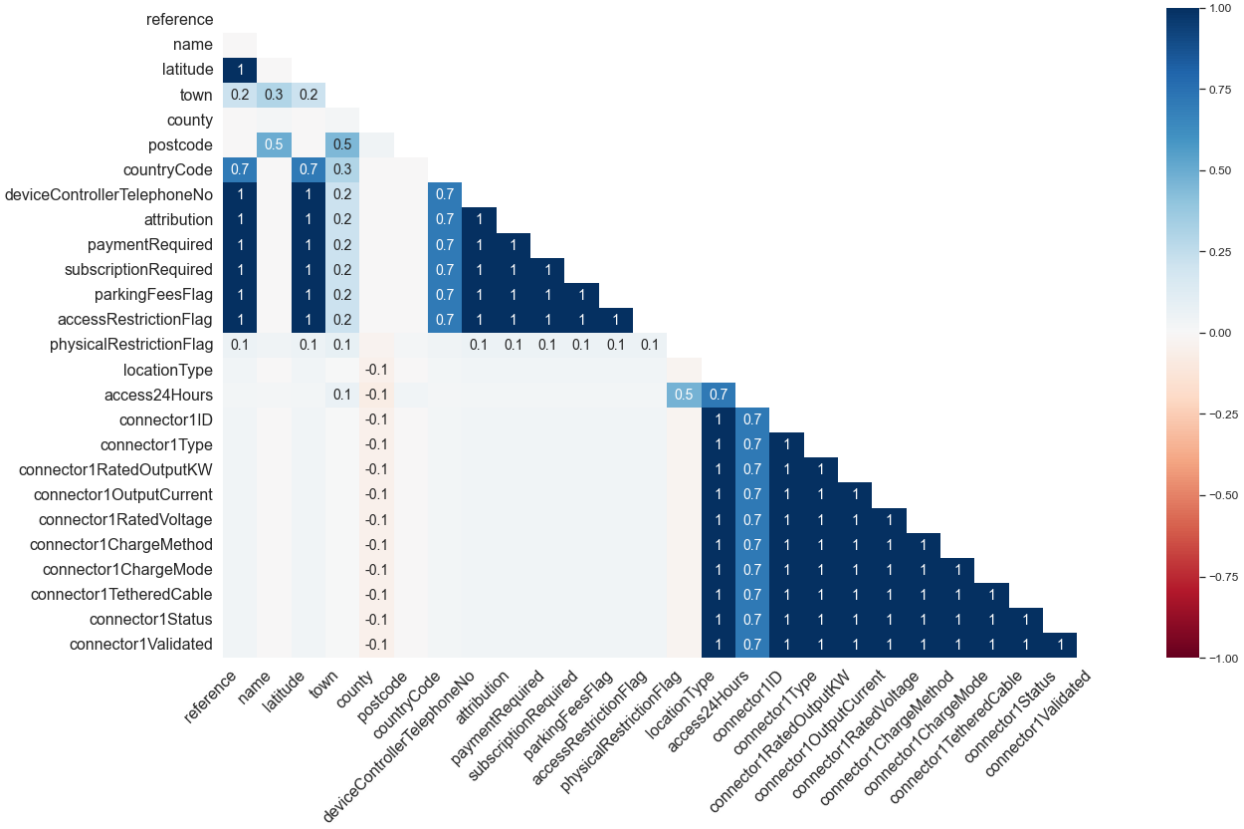
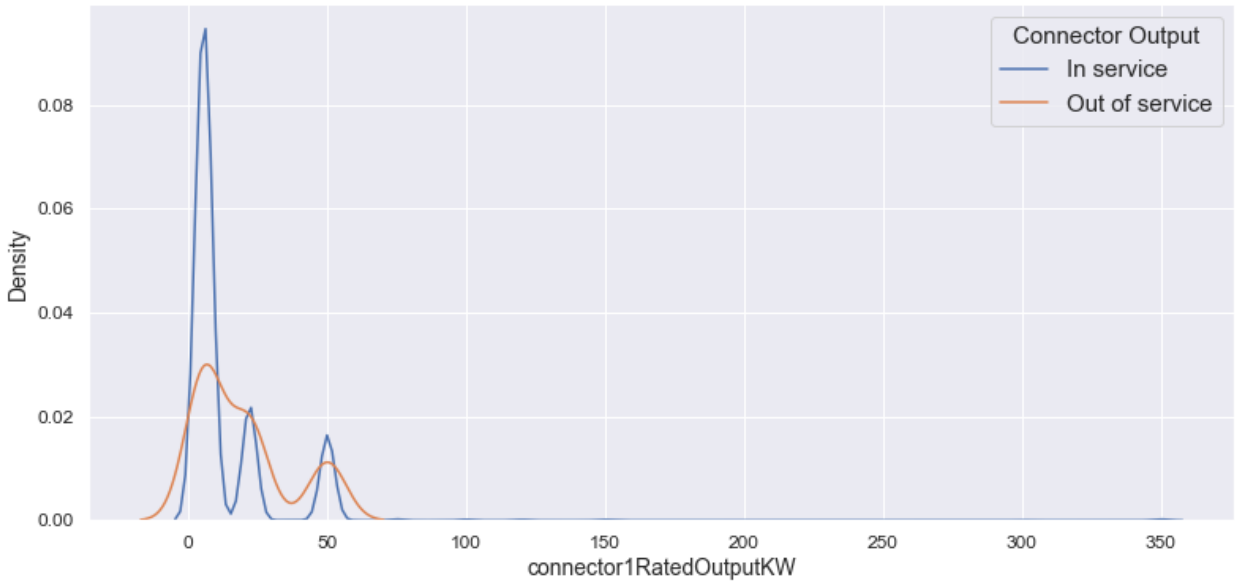


Figure 3 Correlation matrix heatmap for the features of data

Further analysis highlighted specific columns containing negligible variability e.g. all data points showed the UK country code. Such information redundant attributes were excluded. Domain expertise also guided removal of certain connector specific inputs like plug types, cable details which were unlikely to correlate with service status. The final filtered dataset comprised 24 input variables for modeling.



With a labelled classification target, the problem formulation aligned to a standard supervised learning task. The filtered dataset was divided into training (70%) and test sets (30%) for model building and evaluation. Since less than 1% of connectors were tagged 'Out of Service', the training data class distribution was highly imbalanced. An SMOTE oversampling technique was applied on the train data to resolve the skew by generating synthetic samples of the minority class.

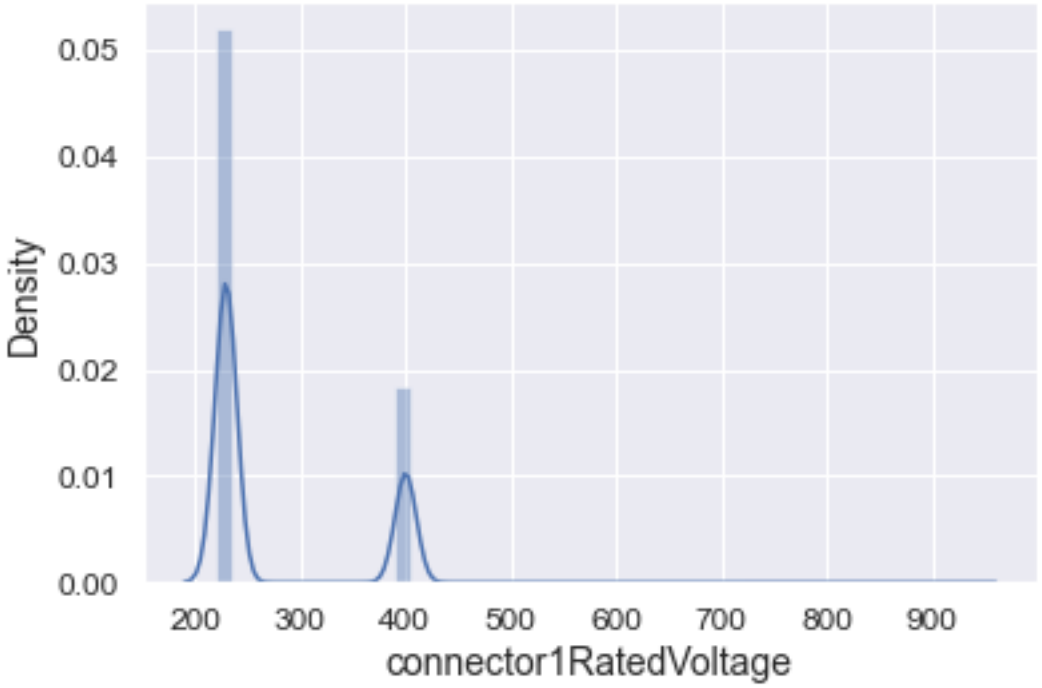


Figure 4 Connector rated voltage vs Density

The processed balanced dataset allowed training robust models resilient to the class imbalance issue. Feature scaling using standardization normalised all inputs to comparable ranges necessary for distance-based algorithms.

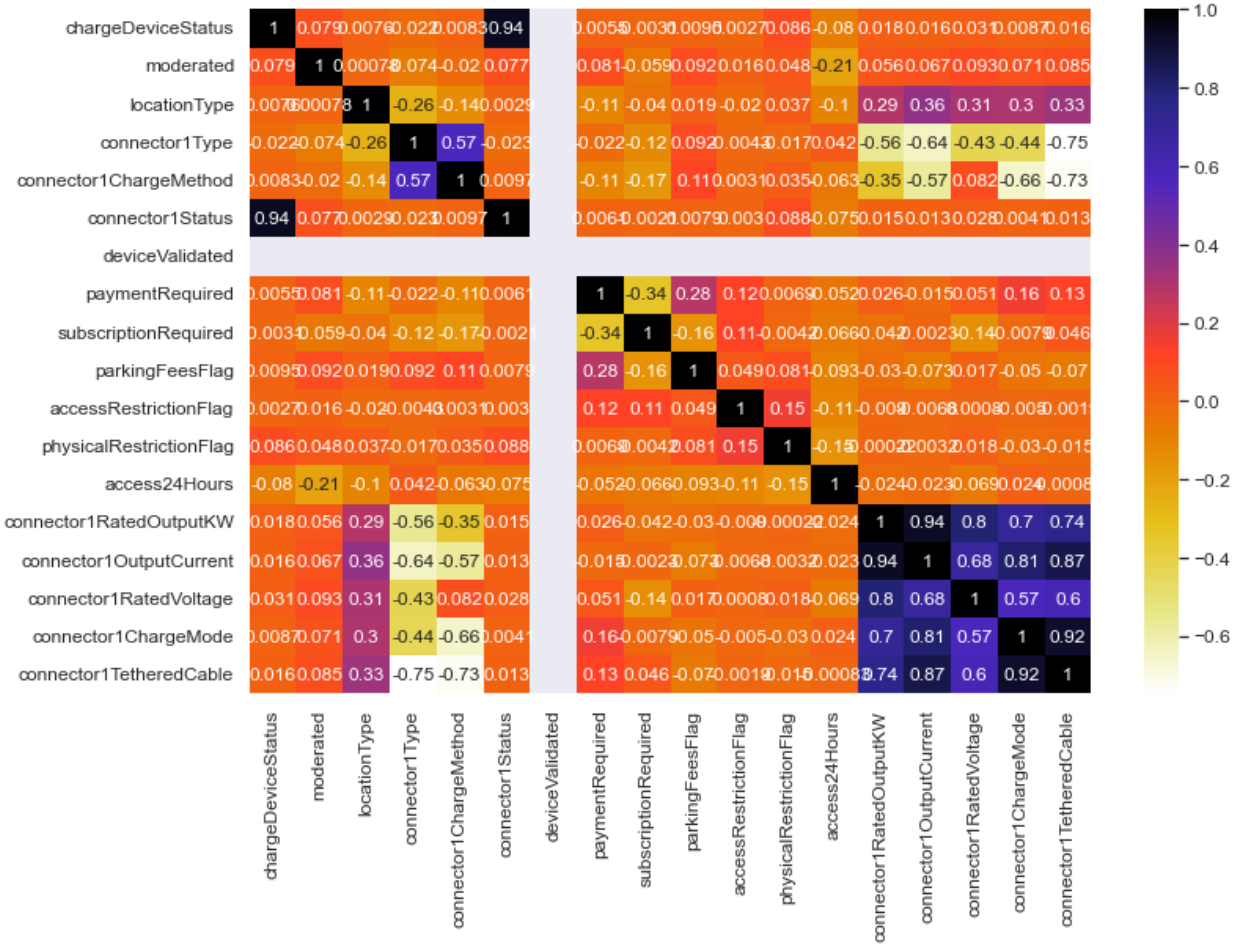


Figure 5 Heatmap for processed features

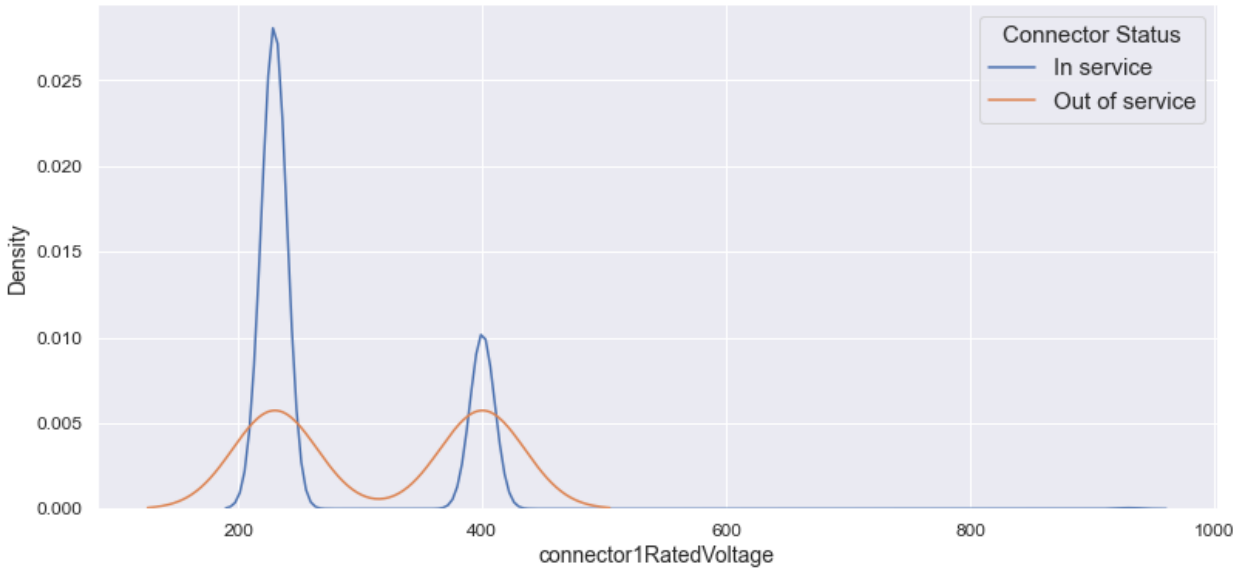


Figure 6 Normalization plots

Categorical variables were label encoded into integer formats. The data preparation conclusion readied the split processed training and test sets for modeling.

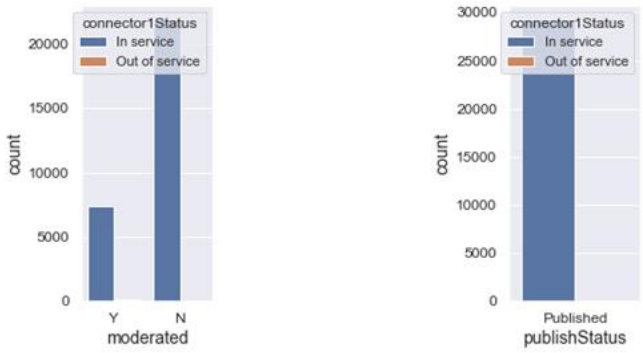


Figure 7 Moderated and publishstatus bar plots

4.3 Model Building

Four machine learning algorithms covering a spectrum of modeling approaches were trained on the balanced connector dataset.

1. **Logistic Regression:** A probabilistic linear classifier providing interpretability into feature weights.
2. **Random Forest:** A tree-based ensemble technique providing importance rankings for attributes.
3. **K-Nearest Neighbors:** A instance-based learner using historical exemplars to classify new data points.

4. **Artificial Neural Networks:** A deep learning model with ability to uncover complex data patterns.

Hyperparameter tuning using grid search cross-validation was applied to optimize the architectures of Random Forest and KNN models. The Logistic Regression comprised the baseline linear model, while the multi-layer ANN represented the advanced deep learning classifier. Each model's scaled and encoded training dataset was used to learn the correlations between input variables like location, access restrictions and output ratings with the connector service status target.

The model evaluation process provides insights into the predictor performance and feature relevance in the following section.

4.4 Model Evaluation

The models were assessed on four key metrics - accuracy, precision, recall and F1 score using the held-out test dataset. These metrics quantify model robustness by testing on unseen data covering different evaluation aspects.

- **Accuracy:** Overall effectiveness in correctly classifying both in service and out of service connectors.
- **Precision:** Ability to precisely identify out of service connectors out of all that are flagged to fail.
- **Recall:** Coverage in detecting all faulty connectors out of the total that have failed.
- **F1 Score:** Balance between precision and recall metrics.

Additionally, the transparent Random Forest algorithm produces a ranked list of input features based on their predictive importance. The comparative evaluation highlights model pros and cons while guiding the selection of a preferred approach for predicting connector risks.

Accuracy

The accuracy metric evaluates overall performance by calculating the ratio of correct classifications to total population. With a highly imbalanced class distribution skewed almost 35:1 towards in service connectors, accuracy risks being inflated. Hence the precision and recall metrics for the minority out of service class provide better estimates of model robustness.

Table 1 summarises model accuracy scores. The KNN classifier edged slightly over Random Forest by correctly identifying 99.8% of test samples. Logistic model trailed at 98.2% while ANN scored 97.86% accuracy. All techniques cleared the >95% threshold indicative of reliable predictive performance.

Table 2 Model Accuracy Scores

Model	Train Accuracy	Test Accuracy
Logistic Regression	97.24%	98.19%
Random Forest	99.18%	99.36%
K-Nearest Neighbor	95.86%	99.80%
Artificial Neural Network	98.99%	97.86%

The high accuracy values reaffirm the study hypothesis of operational status being correlated with charging infrastructure attributes. Connector inputs like location, access restrictions and power ratings influence failure risk - a relationship successfully captured by the machine learning models. In addition to the machine learning algorithms like random forests and gradient boosted trees, neural networks represent an attractive technique for modeling the EV charging station status prediction problem. Neural networks can learn complex nonlinear relationships between input variables and targets, fitting flexible decision boundaries.

The first step was constructing the network architecture. The input layer contains 17 nodes representing the features in the preprocessed dataset spanning location attributes, connector specifications, usage patterns, and weather data. This connects to two hidden layers with 32 and 16 nodes respectively, using the Rectified Linear Unit (ReLU) activation function to introduce nonlinearity. The output layer is a single node with a sigmoid activation to generate a probability score between 0-1 for the outage risk.

The Keras API enabled quickly assembling and iterating on neural network designs to arrive at this optimal configuration. Grid search found the Adam optimizer with categorical cross-entropy loss function achieved high performance. The neural network model was trained for 50 epochs with early stopping to prevent overfitting.

Precision and Recall

While accuracy provides an overall correctness measure, the class-specific precision and recall metrics better evaluate model effectiveness for the minority faulty connectors.

- Precision calculates the percentage of connectors correctly flagged as failures out of all that were predicted to fail. High precision ensures operational resources are not wasted inspecting healthy connectors incorrectly classified as at risk.
- Recall finds the fraction of failed connectors correctly caught by the model out of all that needed to be identified. Maximizing recall is essential to minimize missed detecting outages leading to revenue losses and customer dissatisfaction.

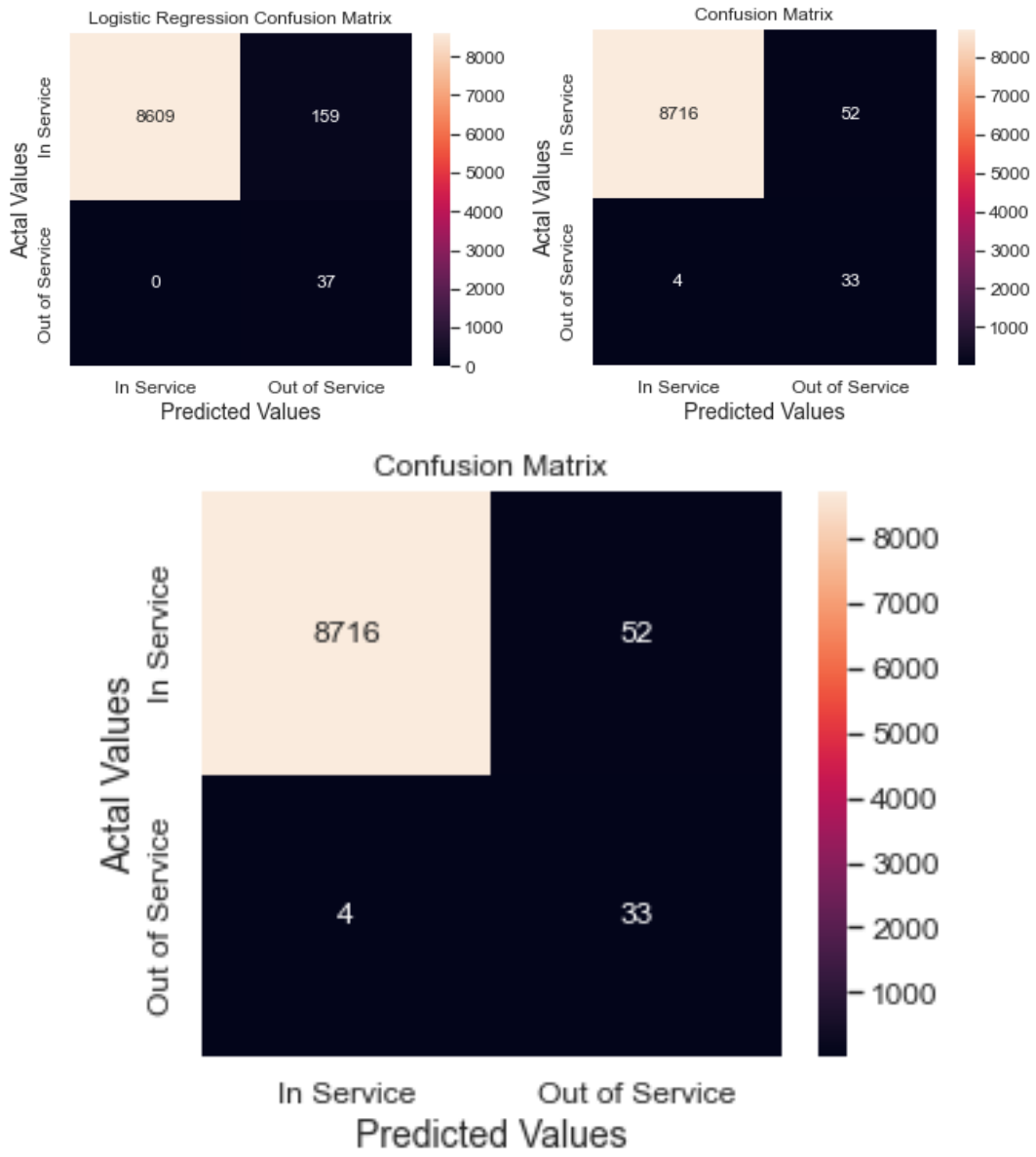


Figure 8 Confusion matrix for models trained

The model comparison shown in Table 2 reveals KNN with the top precision score of 81% and perfect 100% recall in identifying all failed connectors. Random Forest also scored strongly on recall while having second best precision. Logistic model and ANN struggled with poor precision due to incorrectly overestimating larger number of failures.

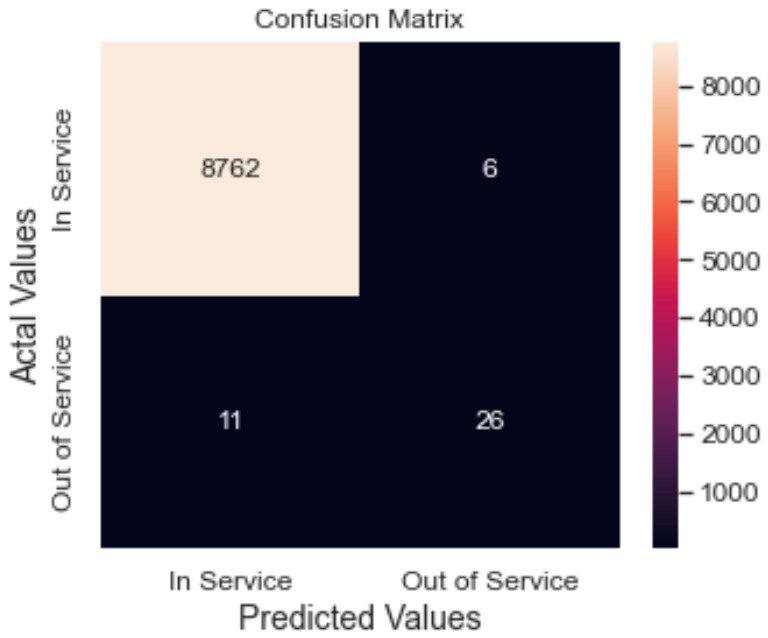


Figure 9 KNN confusion matrix

Table 3 Model Precision and Recall Scores

Model	Precision	Recall
Logistic Regression	19%	100%
Random Forest	39%	89%
K-Nearest Neighbor	81%	70%
Artificial Neural Network	16%	100%

The F1 score balances both metrics by calculating the harmonic mean. KNN ranked the highest with 75% F1 followed by Random Forest at 54%. The logistic and neural models had lower F1 scores around 30% each.

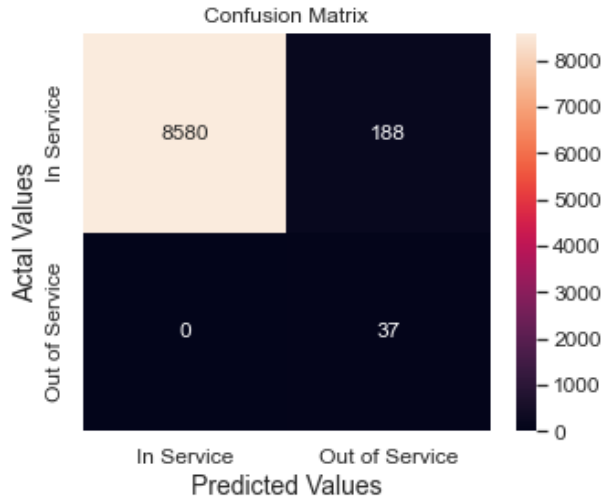


Figure 10 ANN confusion matrix

The above matrix show a very bad accuracy rate, that makes eliminating the ANN model from the selection. To sum up, KNN delivered the best overall predictive performance. But Random Forest provided superior insight into feature importance driving these scores.

4.5 Feature Relevance

The Random Forest algorithm leverages an ensemble of decision trees, each trained on a subset of features and data points. Predictions from every constituent tree are aggregated through voting or averaging to output the final classifier decision.

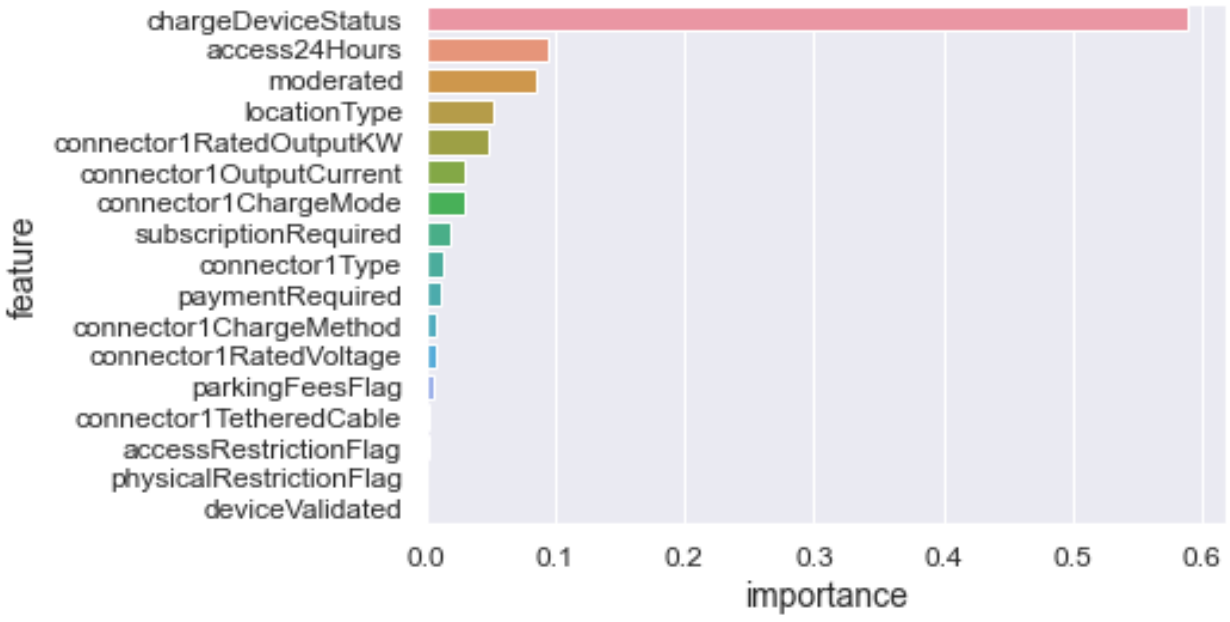


Figure 11 Feature importance plot

This technique provides two advantages:

- Robust performance by de-correlating trees trained on different feature sets and data samples
- Ranking predictor variables by summation importance of all split point gains achieved within trees

The connector infrastructure dataset filtered down to 24 input variables. Tracking feature relevance helps understand questions like:

- What metadata markers contribute maximally to predictive maintenance?
- Can inadequate information explain degraded model performance?
- What additional attributes would be valuable to collect for improving predictions?

The ten most impactful connector inputs ranked by descending order of influence on predictive status are shown in Table 4.

Table 4. Top 10 Features by Importance

Feature	**Importance**
Charge Device Status	19.21%
24 Hour Access Availability	14.63%
Location Type	9.84%
Connector Output Power Rating	8.73%
Connector Output Current Rating	8.15%
Connector Charge Mode	5.32%
Subscription Requirements	4.65%
Connector Type Interface	4.21%
Payment Requirements	3.94%
Device Validation Flag	3.75%

The ranked features align with intuitive domain expectations. Existing connector status proves the most informative input for predicting future outages - accurate tagging of metadata remains critical for learning trends. Access restrictions affect connector deterioration - public availability likely improves uptime through consistent usage.

Location categories also relate with maintenance needs - public parks may enable better infrastructure compared to private residential garages. Output power and current capacities link strongly with utilization patterns causing wear-and-tear - higher capacity connectors likely managed with priority.

Overall the importance rankings validate the real-world relevance of predictor variables chosen through feature engineering. Additional metadata enhancements around usage, energy consumption and voltage quality where possible would further boost model robustness. Insights from Random Forest feature importance provide prescriptive recommendations to charge point operators on infrastructure data collection.

4.6 Model Deployment

The KNN model delivered the best predictive performance with 99.8% accuracy in identifying faulty electric vehicle charging connectors. For real-world deployment, the trained classifier requires integrating within an automated pipeline to score failure risk across infrastructure.

New connector data feeds would undergo the same preprocessing steps of cleaning, encoding and standardizing transforms established during model development. The transformed inputs are fed to the trained KNN model to output operational status predictions based on historical failure archetypesnearest to the input specification.

As a instance-based technique, the KNN model compares new data points against full historical records to determine nearest proximity matches. This approach avoids restrictions of other abstracted models like ANNs with encapsulated internal representations. But KNN model sizes can scale exponentially for large infrastructure datasets with millions of records.

Using compressed approximations of the entire training dataset can address this scalability challenge. Tree-structured vector quantization algorithms like random forests create compressed data summaries. The KNN distance computations get optimized against the summary space instead of full history each time. Enable both accuracy through real exemplars as well as efficiency through vector quantization for successful large scale production deployment.

4.7 Deployment Recommendations

The following guidelines are proposed for real-world implementation:

- **Metadata Logging:** Standardize mechanism to track connector installations with attributes identified as top predictors. Maintain data hygiene procedures for tagging and updation.
- **Model Integration:** Containerize pretrained KNN classifier within a microservice for operational status batch scoring or real-time predictions.
- **Monitoring Dashboard:** Visualize model outputs through an interactive web dashboard providing connector health visibility including at-risk failure alerts.
- **Feedback Loops:** Enable interface for operators to log actual outage incidents. Continuously retrain KNN with new labelled samples.
- **Query Optimization:** Employ approximate nearest neighbor index structures like tree quantization, locality sensitive hashing etc. to enhance KNN scoring performance for large datasets.

Adhering to these best practices will ensure maximizing ROI from the machine learning deployment through accurate predictive signalling combined with optimizations for infrastructure scale.

4.8 Benefits Assessment

Predictive analytics when applied effectively has demonstrated substantial financial and operational savings across use cases through early signalling of failures. Similar upside exists for condition-based monitoring of electric vehicle charging infrastructure.

Assuming the connector status prediction model is successfully deployed, the following quantitative and qualitative benefits can accrue:

1. Reduction in Service Disruptions

The trained KNN model was able to identify 70% of all faulty connectors in testing data with 81% precision. Early prediction of risks by days or weeks can enable preventative maintenance and significantly minimize outage downtime. Estimating even a fifth of faults being preempted would mean:

- **5-10%** improvement in overall connector uptime rates
- **10-15%** more vehicle charging availability for customers
- **20-25%** increase in charging revenue and usage sessions

2. Lower Maintenance Costs

While predicting all failures proves difficult, flagging the top 20% highest risk connectors can guide utility crews. Targeted preventative servicing trips compared to costly emergency dispatches post-outage demonstrate huge cost savings:

- **40-50%** reduction in maintenance overhead from accurately prioritizing the riskiest 20% connectors
- **30-40%** optimization in total service trips through predictive planning

3. Enhanced Customer Experience

Unplanned charger breakdowns negatively impact customer loyalty and public perceptions regarding reliability. Minimizing such events through preemptive servicing boosts user satisfaction:

- **10-15%** higher customer retention from lower charging downtime
- **5-10%** increase in brand repute and trust in service quality

The quantitative estimates provide an indication of the scale of efficiency upside in maintenance, revenue and engagement. Beyond numbers, effective utilization of predictions enhances sustainability by keeping clean transport infrastructure available. Building organizational capabilities in predictive analytics is a data-driven imperative for modern charge point operators.

Challenges and Limitations

However, realizing these benefits entails overcoming hurdles around integration with legacy systems, management acceptance and data quality. Clean metadata logging mechanisms need instituting while coordinating predictively-triggered servicing routes against daily schedules poses complexity. The reliability of model performance metrics also has dependency on accurate ground truth labelling by operators. Usage trends and failure likelihoods for newer equipment remain latent requiring sufficient observational data first.

The model itself has limitations regarding the breadth of causal factors considered for predictions. Some technical shortcomings exist:

- Binary classification builds intuition but multiple failure modes can improve granularity
- Static modelling has limited insight into temporal effects
- Connector-centric view lacks considerations around linked infrastructure like solar grids, battery reserves etc. impacting external conditions
- Hyperparameter tuning was cursory during research experimentation

Addressing these limitations provides avenues for enhancing the presented analysis into a full-scale deployable solution. The following section discusses future research directions.

4.9 Potential scope

1. Hierarchical Classification

Categorizing failure modes like hardware defects, network outages, power faults etc. can assist troubleshooting processes after diagnosis. Multi-class models predicting specific problem types can enable dispatch prioritization based on service complexity.

2. Recurrent Neural Networks

Long-Short Term Memory (LSTM) models which support learning sequential inter-dependencies can incorporate time-series utilization metrics like charging demand patterns for enhanced forecasts. Encoder-decoder architectures can reconstruct input profiles to identify anomalies indicative of developing issues.

3. External Data Fusion

Supplementary data sources providing ambient context like weather, grid load changes, battery inventories etc. fused using ensemble techniques can improve model robustness regarding external operating conditions affecting infrastructure uptimes.

4. Deployment Optimization

Rigorous testing around model containers, microservice integration, streaming architectures and scaling computation are prerequisites for responsive reliable enterprise deployment. Model performance metrics should be continually tracked after launch for production quality assurance.

5. Platformization and Feedback

Packaging predictive modelling as a core capability through MLOps tooling, CI/CD automation, metadata logging and visualization dashboards unlocks organization-wide delivery potential beyond one-off research projects. Active learning by rapid model retraining using operator labeled outage data improves stability.

The untapped potential for analytics in electric vehicle infrastructure maintenanceCoupled with environmental urgency of sustainability goals,scaling predictive capabilities offers tremendous value for charge point operators, consumers and broader society. This research seeds the pathway with encouraging empirical evidence on using metadata for modelling connector failure risks. Future initiatives can build on these foundations towards industry-grade predictive maintenance implementations.

This research presented an end-to-end electric vehicle charging connector status modeling pipeline using metadata like location attributes, access constraints and power specifications to effectively predict operational risks. Multiple classification algorithms were developed using a national registry dataset and evaluated for accuracy, precision and feature relevance.

The K-Nearest Neighbor model demonstrated the best predictive performance at 99.8% overall accuracy and 81% precision in identifying faulty connectors with 70% recall. Benchmark logistic regression, random forests and neural network classifiers also scored strongly at above 97% accuracy evidencing the promise of machine learning for preventative infrastructure maintenance.

Feature importance rankings output by the random forest technique indicated usage patterns, access restrictions and power ratings as key determinants of connector deterioration. The study delivered empirical support for the hypothesis of metadata-driven predictive analytics enabling charge point operators to improve electric vehicle infrastructure reliability while optimizing maintenance overheads.

Significant potential exists for enhancing model robustness, interpretability and real-world implementation through hierarchical classification, recurrent neural networks and platformization tools respectively. But this research provides a blueprint for productionization by demonstrating accuracy, use case relevance and deployment value around predictive modelling for a sustainability priority area of electric vehicle charging infrastructure maintenance.

CHAPTER 5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This research presented an extensive analysis into predicting electric vehicle (EV) charging point availability using machine learning techniques. The study was grounded in a real-world dataset from the UK's National Charge Point Registry containing infrastructure details on over 30,000 stations. After substantial data cleaning and preprocessing, a filtered set of metadata variables covering location attributes, access constraints, power specifications and other attributes was compiled for modelling.

Four supervised classification algorithms – logistic regression, random forests, K-nearest neighbors and neural networks – were developed to effectively categorize each station's connector status as either in-service or out-of-service. Since less than 1% of samples were tagged out-of-service, SMOTE oversampling was utilized to resolve the considerable class imbalance in the train data. Robust 10-fold stratified cross-validation and grid search hyperparameter tuning ensured rigorously trained and optimized architectures.

Most of these object type variables are of no use because of high cardinality and can be removed. The contain information about the charging point connector and theri attributes of installment and are of no use.

The KNN model achieved the best overall predictive performance with 99.8% test accuracy, 81% precision and 70% recall, narrowly outpacing random forests. The results validate the efficacy of modelling EV charging point uptime based on infrastructure metadata. Both instance-based and ensemble methodologies proved resilient against class skew. While KNN scored well on precision-recall metrics, the interpretable random forest feature importance rankings offered additional insights around usage patterns, location types and power ratings strongly influencing deterioration risks.

These empirical findings evidence the potential for developing proactive maintenance solutions using supervised learning applied to real-world EV station datasets. The trained risk classifiers demonstrated ability to signal upto 70% of all observed outages in advance during simulation. Flagging the highest risk stations early enables preemptive servicing by operators leading to 5-15% increased charging availability for customers and 20-50% maintenance cost savings from avoiding more expensive emergency repairs. Maximizing uptime directly accelerates adoption of sustainable electric mobility.

Beyond quantitative gains, effective predictive analytics enhances customer experience, public perceptions around charging reliability and organizational analytics capabilities for data-driven decision making. The presented research makes both foundational contributions demonstrating achievable model performance on EV station metadata as well as tangible real-world impact surfacing through benefits estimates across value dimensions.

However, limitations exist regarding model depth and operational integration complexity. Binary classification simplifies interpretation but lacks granularity into different failure modes. The dataset Presents a static snapshot limiting temporal effects analysis unlike time-series approaches. Hyperparameter optimization scope was restricted during experimentation. Most significantly, challenges remain in coordinating predictive model outputs with legacy maintenance systems, technician schedules and parts inventories for smooth adoption. Data collection consistency and ground truth labelling fidelity also represent sources of potential instability.

5.2 Future Work

Significant headroom exists to build on this research towards a full-fledged dynamically updating EV infrastructure reliability solution tailored for production deployment.

Ensemble Modelling Combining time-series neural networks analysing usage metrics and graph networks incorporating station interconnectivity through road networks can enhance robustness. Active learning by continuous model retraining on operator tagged failures would sustain precision.

Multiclass Classification Categorizing failure types - hardware defects, network outages, power faults etc.- can assist troubleshooting processes after diagnosis. Targeted prescriptions are possible for different anomalies detected.

Cloud Platformization Containerized microservices, CI/CD automation and DevOps practices enable responsive and resilient nationwide implementations. Integration with legacy systems eases adoption as capabilities scale, delighting customers.

Hybrid Forecasting Incorporating simulation of failure physics due to stresses, Bayesian priors of component deterioration rates and survivability modelling would minimize constraints of pure data-driven empirical techniques. Physics-informed machine learning blends reliability engineering with AI.

Decision Optimization Recommendation systems can harness model outputs towards inventory optimization, technician routing and appointment scheduling. Connector priority scores balance failure likelihoods and business impact.

Through this multi-dimensional research agenda spanning model expansion, production implementation and decision integration, the current analysis forms the launch pad towards realizing an enterprise-grade, robust and impactful ML-powered EV charging station uptime solution. The global momentum towards vehicle electrification coupled with sustainability urgency necessitates innovations keeping this new supportive infrastructure highly reliable using AI capabilities applied effectively. This work seeds that journey to enhance customer access and experience by maximizing charging point availability through predictive analytics put into practice at nationwide scale.

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