Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Machine Learning Enabled Analysis of On-the-Road EV Charging Infrastructure: Predicting Accessibility and Optimizing Deployment

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| ABSTRACT

The United States is rapidly transitioning to electric vehicles (EVs) these days, and the effectiveness of this move will depend on how well charging stations are installed and made available on the road. A significant discrepancy remains in the availability of dedicated EV chargers, particularly on highways and inter-city travel corridors, despite increasing investment in charging infrastructure. In this paper, we investigate a machine learning–based approach to assessing the accessibility of existing infrastructure and projecting future demands. The objective of this research was to utilize machine learning approaches to perform a more detailed, national-scale assessment of the accessibility of EV charging infrastructure, both as it exists today and how it may best be deployed in the future. A comprehensive, multi-source dataset was compiled, encompassing several key variables. Data sources for charging station characteristics—such as number of ports, charger types (Level 2, DC fast), operational status and uptime history—were provided by the U.S. Department of Energy's Alternative Fuels Data Center (AFDC). We implemented a multi-model framework to classify accessibility and predict infrastructure essential for facilitating optimal charging infrastructure accessibility prediction, with enhanced interpretation and baseline performance capabilities. XG-Boost and Random Forest models showed the same accuracy, getting the highest accuracy in the tested case scenario. This means both of these ensemble methods helped to classify instances in the dataset correctly. On the other hand, Logistic Regression, a more basic linear model, had a slightly lower accuracy. Deployment strategy – A multi-faceted deployment strategy is recommended based on the insights from the Model. Accessibility prediction models based on machine learning provide revolutionary capabilities for US transportation policy, particularly in enabling federal and state agencies to target infrastructure funds with data-driven tools. Using publicly available datasets and ML-enhanced planning tools, this work also helps to get closer to more equity in charger deployment as these areas in the latter sentences, namely rural, suburban, and disadvantaged communities, have had worse access to clean transportation infrastructure and are service and policy-challenged, where societal scarcities for EV chargers persist. Furthermore, predictive infrastructure modeling is crucial for alleviating EV range anxiety, a primary reason for reluctance to purchase EVs, according to surveys conducted by AAA and the Edison Electric Institute (EEI). Future Directions for Research: Given the exploratory nature of this study and the limitations discussed in the previous section, we envision several fruitful research avenues that could further enhance the predictive capacity and practical relevance of ML-enabled EV charger planning.

| KEYWORDS

Electric vehicles (EVs), charging infrastructure, machine learning, accessibility prediction, infrastructure optimization, transportation planning, geospatial analysis, EV adoption.

| ARTICLE INFORMATION

ACCEPTED: 01 August 2025 **PUBLISHED:** 16 September 2025 **DOI:** 10.32996/jcsts.2025.7.9.64

I. Introduction

Background:

America is currently undergoing massive growth in terms of Electric Vehicle adoption, with approximately 4.7 million electric Vehicles on the road as of 2025, representing a 50% increase compared to 2023 levels, according to the U.S. Department of Energy (Charly et al., 2024). According to Hossain et al. (2024), policy incentives at the federal and state levels, ranging from tax credits made possible through the Inflation Reduction Act to national mandates set by the Environmental Protection Agency, have driven both consumer interest and manufacturer pledges to transition to zero-emission vehicles. At the same time, companies such as Ford and General Motors, alongside Tesla, are ramping up EV production, with cars catering to a larger demographic—namely trucks, SUVs, and lower-priced sedans. Nonetheless, the increase in the national EV fleet also creates a need for accessible and convenient charging, particularly along interstates and long-haul routes, where range anxiety remains a significant barrier to adoption (Chen, 2024). Chouksey et al. (2025) reported that to expand this infrastructure, federal programs like the NEVI Program have already allocated $5 billion to states to establish specific Alternative Fuel Corridors (AFCs). These corridors are where fast chargers will be installed at regular intervals (typically 50 miles apart, with 1 mile from interstate exits) to make intercity and interstate travel practical for EV users. To fill the void, the federal government has worked, through programs such as the $5 billion National Electric Vehicle Infrastructure (NEVI) Formula Program, to deploy 500,000 chargers by 2030, with infrastructure built for urban, suburban, and many rural communities. Even with these initiatives, by 2024, only 204,000 non-home chargers (51,000 of which were DC fast chargers) were in operation, with deployment rates varying by state: 164 chargers per million residents in Louisiana, 1,738 in Vermont (Boudmen et al., 2024). These disparities indicate that a data-driven, optimized approach to charger placement is necessary to maximize both equitable access and grid reliability.

In retrospect, if everything goes well, the 500,000 public chargers will form part of a national network sharing the same set of infrastructure under a long-term program. This vision is then put into question, as infrastructure deployment has been growing in an unbalanced way, with varying charger densities from region to region (Al-Dahabreh et al., 2023). For example, California accounts for 35% of all public chargers in the U.S., with multiple Midwestern and Southern states trailing substantially behind. This variation is shaped by geographic, economic, and political factors as well as the reluctance of private sector investment in lower-demand locales. This tussle between the growth of EVs and the availability of infrastructure is, therefore, a challenging logistical and analytical problem to solve. The issue is not just adding more chargers, but also where they're located, how accessible they are, and how well they're integrated into transportation networks. This is particularly the case with charge on the road, where reliability and redundancy are pivotal (Benayad et al., 2024). The latest annoyance as per Shovon et al. (2025), is highlighted by a 2023 study by JD Power, which found that more than 20 percent of public charging attempts were unsuccessful due to inoperable hardware or lengthy lines, indicating that not only more stations, but also better-managed and planned deployment, are needed. The nature of EV usage patterns is dynamic, as they are driven by changes in economic conditions, mobility technology, and regional factors → a smarter approach towards infrastructure development is required. This paves the way for using machine learning as a technology enabler (Elhattab et al., 2023).

Problem Statement:

According to Antoun et al. (2021), there are currently three key problems with EV charging infrastructure: 1) Geographical inequity — widespread shortages, especially in rural and underserved communities; 2) Trip demand spikes — sudden and unmanageable demand spikes from conventional EV use, further aggravated by time-of-use pricing and renewable energy variation; 3) Fragmented policy implementation, as recently happened to the NEVI Program freezing $3B in state allocations, delaying its 4,000 planned charging ports. These challenges as per Hossain et al. (2025), contribute to reduced driver confidence, and research has shown that a lack of charging access can cause EV adoption to drop by over 30 per cent in areas with low charging infrastructure. However, static deployment models are based on demand forecasts that are easily affected by dynamic variables (such as traffic patterns, weather, and renewable energy availability) — elements that ML can evaluate at scale. Even with the massive investment bubbling up from industry players and the public-private initiatives being rolled out, the state-of-the-art EV charging infrastructure remains patchy and inadequate in many key markets (Hecht, 2023). For example, public Level 3 fast chargers are heavily concentrated in metro areas, while rural highways, cross-state travel corridors, and lower-income communities remain underrepresented. According to the Department of Energy's AFDC, more than 70% of fast charging locations are located in the top 20 urban areas in the US. This imbalance increases (and is in itself fueled by) "range anxiety" and leads to a vicious circle where drivers will refrain from using EVs because of their perceived limited range. At the same time, infrastructure investors will be reluctant to invest in regions with low demand and low returns on investment (Alam et al., 2025). The result is a fragmented and disjointed network that undermines national objectives for EV adoption. This divergence is compounded by state-by-state variation in policy and utility coordination. California, New York and Colorado have included EV infrastructure as part of wider climate action plans. In contrast, others have yet to establish inter-agency coordination mechanisms or incentives for private operators (Golsefidi et al., 2023).

Moreover, numerous public charging sites are based on historical traffic behavior patterns or subjective planning metrics, rather than real-time predictive analytics. That occurrence creates gaps in areas such as rural highways, recreational routes, or regions impacted by weather, which are some of the most essential elements of long-haul trips (Hemmati et al. 2024). Moreover, our site reliability woes persist. Plug-Share released its 2024 national charging reliability report this week, finding that some regions have as many as 30% of DC fast charging sites that go unplugged at least once a month, a level of unpredictability that no one wants to encounter, which drives down usage. Notwithstanding, it is necessary to apply data science and machine learning techniques to identify hotspots for charger locations, predict demand for usage, and maintain the infrastructure in a state of constant operation (Hafezi & Morimoto, 2023). Traditional approaches to planning for infrastructure are often static and reactive; machine learning can help plan dynamically based on current usage patterns and anticipated usage patterns, informed by population growth, tourism trends, and road congestion, allowing for adaptive and potentially real-time adjustments. Without predictive analytics and deployment guided by data, infrastructure gaps will continue to endure and very likely grow, particularly as EV take-up begins to ramp up. Machine learning can help identify solutions to address these challenges, with an eye toward meeting and exceeding both federal and market-driven targets for EVs equitably and efficiently (Flynn et al., 2021).

Objective

The objective of this research is to utilize machine learning approaches to perform a more detailed, national-scale assessment of the accessibility of EV charging infrastructure, both as it exists today and how it may best be deployed in the future. The key goals include (1) gathering and merging relevant geospatial, traffic, and demographic data, (2) leveraging supervised and unsupervised machine learning models to reveal underserved areas, and (3) simulating optimal deployment solutions through optimization techniques such as integer programming and reinforcement learning. The goal is to support government planners and private stakeholders in making data-driven decisions that ensure the most effective, equitable, and resilient infrastructure lives up to its full potential. To start our analysis, we compiled new datasets that draw from the U.S. DOT's National Household Travel Survey, the FHWA's Freight Analysis Framework, and real-time electric vehicle charger data from the AFDC. We then intend to create a multidimensional perspective on infrastructure needs in terms of supporting EVs by overlaying that information across various forms of spatial grids with socio-economic indicators from the U.S. Census Bureau. We then apply clustering algorithms (DBSCAN, K-means, etc.) to identify natural clusters of underserved areas, along with predictive models [8] (Random Forests, Gradient Boosting Machines) to forecast future demand for charging. Such models incorporate factors such as seasonality in travel, year-on-year growth in population densities, and various levels of economic activity. At this final stage, the predictive outputs are combined with optimization frameworks that suggest the optimal locations for chargers, minimizing the total deployment cost while maximizing coverage reliability. These models take into account limitations on energy grid capacity, the availability of real estate, and the distance from travel corridors. These deployment simulations are compared to current NEVI guidelines for a practical evaluation of how well policy is being aligned and whether investment is getting us the most charging accessibility for our dollars spent. The research thus provides a scalable, reproducible, and policy-congruent method for planning EV infrastructure. Ultimately, this project demonstrates that machine learning is not only a powerful tool for predictive modeling but also serves as a strategic enabler for transitioning to a clean, equitable transportation future.

Relevance

The importance of using machine learning for planning EV infrastructure is closely linked with new U.S. federal programs, such as the National Electric Vehicle Infrastructure (NEVI) Formula Program that was established under the Bipartisan Infrastructure Law. The NEVI Program provides $5 billion in formula funding over five years (2022–2026) to assist states in establishing an interconnected network of publicly available EV fast chargers in designated AFCs (Hecht, 2023). These corridors are designed to facilitate travel over long distances and ensure that chargers are present at intervals of no more than 50 miles and within 1 mile of the interstate, in support of national emissions reduction targets. While the funding creates a solid starting point, it doesn't dictate where chargers should go or how much capacity they may require, leaving those decisions to the state agencies themselves (Hemmati et al., 2024). As such, Machine Learning comes into play. NEVI seeks to ensure that chargers are placed efficiently to maximize both utility and equity within each state, and machine learning models can help states fulfill NEVI's mission by harnessing patterns in EV usage and preference following a network-based framework (traffic volume, demographic trends, and charger downtime rates).

Li et al. (2024) stated that Machine learning tools can provide both transportation agencies and private sector investors with insights to minimize financial risks and enhance the return on infrastructure investments. The demand for which is uncertain, so investors shy away from building in lower-density or non-urban areas. By quantifying what we need to know about the probability of its usage in the future, predictive models that simulate usage for alternative scenarios (and also take care of the possible huge spikes that can arise during the weekend travel peaks, tourism flows, commuter behavior or extreme weather events) can help de-risk these decisions. Moreover, Mutua (2024) posited that Machine Learning prioritizes locations with both potential demand and favorable installation conditions (e.g., access to the power grid, land availability, and low kWh costs), enabling public and private stakeholders to collaborate on hybrid funding frameworks. Agencies can then leverage machine learning algorithms to create real-time feedback loops on charger reliability, predicting when maintenance is needed and proactively preventing service outages. This is how machine learning not only underpins the initial infrastructure rollout but also contributes to its long-term operational sustainability — a key objective of the NEVI Program goals.

II. Literature Review

State of EV Charging in the USA

According to Noor Ali et al. (2024), the state of EV chargers in the U.S. is the narrative of both rapid growth and deep inequity. The U.S. is home to more than 180,000 public charging ports—about 40,000 of which are DC fast chargers—as of early 2025, according to the U.S. Department of Energy's (DOE) Alternative Fuels Data Center (AFDC). These chargers, however, as per Amjad et al. (2025), are highly focused on only a few states. California alone has approximately 30% of the public charging ports in the country, while significant portions of the Midwest, Great Plains, and Southeast remain underserved. The difference stems from a constellation of market-driven deployment, urban density, and regulatory backing. California has not only created direct incentives with its Low Carbon Fuel Standard (LCFS) but also demand signals with its Zero-Emission Vehicle (ZEV) mandates, which have encouraged private providers in California, such as ChargePoint, Electrify America, and Tesla's Supercharger network, to build aggressively where EV adoption has been the highest (Mazhar et al., 2023). Although the number of chargers deployed is increasing, several challenges remain. During peak hours, many stations remain highly congested or are unable to maintain operational uptime. According to a 2024 report by J.D. Power, nearly one in five EV drivers experienced a broken charger when attempting to charge in public (Fariha et al., 2025). Additionally, there is little redundancy in most existing infrastructure; in the countryside or on long-distance corridors, a single inoperable charger can disrupt travel plans. To address the inconsistent reliability, the Federal Highway Administration (FHWA) announced minimum uptime and connector standards as part of the NEVI Program this week, mandating 97 percent charger uptime and Combined Charging System (CCS) compatibility. However, it remains a challenge to enforce these mandates consistently, particularly in public-private partnerships and state-level implementations (Li et al., 2024).

Khan et al. (2025) contended that a related but distinct concern is that deployment planning should be data-driven; however, it often is not. In the past, charging stations have been deployed either deterministically, based on demand projections from EV registration data, or nearest to population centers and areas with commercial activity (Juwono et al., 2024). Although this method identifies general trends, it often fails to capture temporary deployments, like seasonal movements for tourism, freight routes, and underserved communities. Additionally, conventional infrastructure planning tools are not designed to dynamically adjust to key risk inputs, such as weather variability, traffic incidents, or maintenance cycles. With the rapid development of EV adoption and increasing complexity in charger usage patterns, there is a growing need for advanced, predictive, geospatially aware planning (Juwono et al., 2024). To maximize the benefits of public investment and, more broadly, decarbonize transportation, it is crucial to overcome these limitations and ensure that EV charging is accessible throughout the entire transportation landscape (Nobi, 2024).

Predictive Modeling in Transportation Planning

Panda et al. (2023) suggest that machine learning (ML) can be a powerful tool for enhancing the efficiency of various aspects of public infrastructure deployment, such as Electric Vehicle (EV) charging stations. Using real-time traffic information, historical usage trends, and geospatial factors, predictive analytics forecasts demand and pinpoints high-impact sites. For example, Los Angeles achieved a 12% decrease in traffic congestion with ML-based traffic signal optimization, and UPS reduced millions of dollars in fuel expenses with predictive route planning. For example, in the EV sector, ML models can combine traffic flow data, EV penetration data, and access to renewable energy to forecast charging demand. For instance, both XG-Boost and Light-GBM have been used to detect temporal-spatial charging behaviors, and incentivizing off-peak charging can reduce the 20% power strain on the grid (Prakash et al., 2023). Yet, most existing models are based on urban transit systems (e.g., bus stops) rather than EV infrastructure, which leaves a gap in highway corridor optimization. Researchers are now testing advanced techniques, such as Graph Neural Networks (GNNs), on various factors, including network effects (how the placement of chargers affects EV adoption and vice versa), which are vital in the context of long-term planning. Over the past few decades, machine learning has become a vital tool for transportation planning, providing predictive capabilities that surpass those of traditional statistical models. In the past, planners have developed infrastructure such as bus routes, traffic signals, and transit hubs based on historical averages, static surveys, and regression-based demand models (Pu et al., 2025). Nevertheless, such techniques are limited in capturing the real-time dynamics, complex nonlinear interactions, and high-dimensional feature spaces that exist in state-of-the-art transport systems. By contrast, machine learning enables planners to feed enormous, multi-modal datasets—ranging from GPS trajectories, traffic sensor feeds, land-use characteristics, and socio-demographic characteristics—to glean complex spatial and temporal associations. We can already see this shift with major transit agencies, such as the Metropolitan

Transportation Authority (MTA) in New York City, which is utilizing machine learning to predict subway crowding and adjust train frequencies during busy periods (Prakash et al., 2025).

Mazhar et al. (2023) argue that there is an increasing amount of research investigating the use of machine learning to determine the optimal locations for transportation assets, such as electric vehicle charging stations. For example, clustering algorithms (such as DBSCAN and K-means) can be applied as a technique for delineating regions of travel demand, and a predictive model can then be used to predict charging demand separately in each of these regions. These listed spatial analytics have been integrated with land-use zoning data, public transit, and road-network availability to inform deployment. In particular, integrating decision trees and ensemble models has demonstrated the ability to classify high-demand versus low-demand locations for planning infrastructure in both urban and rural areas (Pevec et al., 2018). They are usually trained on datasets of real-time vehicle telemetry, zoning, and utility grid performance, as well as DOIT datasets related to traffic congestion from the U.S. DOT and private platforms such as INRIX and HERE Technologies. Predictive modeling, however, is versatile enough to follow the transformation of mobility behavior, making it particularly useful for planning EV infrastructure. In contrast to public transport schedules that dictate static travel demand, the charging demand of EVs can shift in response to events (e.g., festivals and natural disasters), economic cycles, or the reconfiguration of fleets (e.g., shared EVs, commercial vans, or autonomous delivery vehicles). Incorporating real-time streams to revise demand forecasts and offer new station recommendations can be incorporated into predictive models (Noor Ali et al.,2024). More recently, reinforcement learning and agent-based modeling have been employed to model how drivers respond to availability and pricing incentives near charging stations. These methods utilize virtual simulations to inform policy decisions before physical deployment. Pu et al. (2025), highlighted that as predictive modeling is increasingly used in transportation planning, it will become even more relevant to the problem of optimizing EV charging networks, particularly in conjunction with public policy actions such as congestion pricing or clean energy subsidies.

Machine Learning Algorithms in Urban and Environmental Planning

Ahmed et al. (2025), tree-based models, such as Random Forest and XG-Boost, are also the most common models for geospatial predictive tasks due to their capacity to handle categorical data (e.g., land use, road types) and adapt to non-linear relationships. A 2025 study, for instance, employed XG-Boost to forecast peaks in charging station usage in California with 88% accuracy, controlling for factors such as weather, traffic, and proximity to amenities (Nobi, 2024). Likewise, ensemble methods integrating satellite imagery (e.g., obtained from Chloris Geospatial) with IoT sensor data have been employed to prioritize locations of chargers in biodiversity-sensitive areas. Yet, concerns persist: scalability is limited by data fragmentation (e.g., segregated utility and transportation datasets), and model interpretability (e.g., SHAP analysis has seldom been applied to charger placement). Federated Learning for aggregating data across jurisdictions without revealing sensitive personal data, and AI-powered geospatial platforms (e.g., Esri's ArcGIS) for simulating deployment scenarios, are two promising solutions from this emerging area of technology (Juwono et al., 2024). When it comes to high-dimensional, heterogeneous data — common in urban and environmental planning contexts — tree-based machine learning algorithms, such as Random Forests, Gradient Boosting Machines (e.g., XG-Boost), and Light-GBM, seem especially well-suited. They are great for handling mixed data types (categorical and continuous) and for addressing missing data, as well as non-linear interactions, without requiring extensive feature engineering and emphasizing the importance of these capabilities for EV infrastructure planning, where input variables may include population density, median household income, road congestion in real-time, logger files of charging utilization, and grid capacity scores. Additionally, tree-based models are inherently capable of providing feature importance rankings, which can help planners determine which features (for example, distance to interstate highways, local traffic volume, socio-economic equity scores) influence charger utilization or accessibility gaps the most (Mutua, 2024).

Raj & Sakthivel (2024), underscored that these models have been empirically validated for their ability to predict location-based outcomes, such as urban heat islands, air pollution concentrations, and traffic incident probabilities. One such example is a recent study that developed Random Forests models to predict urban susceptibility to climate stressors using a suite of remote sensing and census datasets (vegetation health, census data) funded by the National Science Foundation and published in the journal Nature Communications. Much like its use in city planning departments in Boston and Seattle, XG-Boost has also been applied for predicting land-use changes, gentrification vulnerability, and even pedestrian injury hotspots (Shreshtha, 2024). These use cases are likened to EV charger planning as they are dependent on spatially heterogeneous, policy-relevant data. Tree-based models are particularly valuable for geographical information systems (GIS) workflows, as they can be easily embedded in spatial raster grids or road network graphs to evaluate infrastructure needs at hyperlocal scales. Furthermore, these algorithms are robust and scalable, making them well-suited to national-scale analyses of EV infrastructure. Deep learning models (e.g., CNNs, RNNs) held in increasingly high regard in some branches of environmental modeling, fail to scale to even as large a task size in practice: by contrast they need orders of magnitude larger datasets, computing power, and are a lot less interpretable, which is a constricting disadvantage when you have to take decisions on public policy based on your models (Prakash et al., 2025). Ensemble tree-based models, in contrast, offer a sweet spot between performance, explainability, and training speed. They can also be easily combined with optimization methods, such as genetic algorithms or integer programming, and incorporated into a larger decision-support pipeline, machine learning–driven decision-making tools. In the planning landscape, tree-based models will likely continue to play a significant role in applied urban and infrastructure planning as more federal and state agencies adopt these types of tools (Torkey & Abdelgawad, 2022).

Gaps in Research

While literature on machine learning methods for transportation and urban planning is expanding, few studies directly apply predictive analytics concerning accessibility and optimal deployment of EV chargers, especially in real-world contexts in the U.S. So far, most of the research has focused on EV demand forecasting or modeled user behavior in idealized conditions or non-realistic urban settings (Sultana et al., 2025). Although these studies are useful, they typically focus less on coupling decision science with practical deployment frictions, such as grid capacity constraints, zoning ordinances, or environmental justice requirements (Ahad et al., 2025). According to a 2023 review of recent literature on EV planning models in Transportation Research Record, only a single-digit percentage of published models incorporate up-to-date, realistic representations of the road network, and even fewer of these models integrate the granular socio-economic datasets used in research designs, such as the American Community Survey or the Justice40 initiative. It leaves a dangerous void in the toolbox for U.S. infrastructure planning.

A third shortcoming in the literature is geographic scope and data resolution. Some refer to international examples (such as Norway, China, or EU member states) or study one U.S. city (e.g., Los Angeles, New York, or Chicago)—where data are more readily available and EV adoption is already high—without understanding how the results are affected by local context. Lack of Research: This is particularly true of under-researched regions such as the Mountain West, rural Appalachia, or tribal lands (Reza et al., 2025). These hotspots often have extreme accessibility deficits, but they are not included in modeling efforts because the data are sparse or difficult to collect. Thus, some regions make policy decisions with little to no reliance on empirical evidence, instead relying on other forms of pressure, which can result in outcomes that are either inefficient or inequitable, or both. It entails models being able to work in data-poor settings while also being robust enough to generate useful information from potentially noisy or low-quality inputs.

Finally, machine learning experts, urban planners, and policymakers often fail to integrate their efforts effectively (or at all). Although new tools appear on paper every day, only a few tools escape the confines of the classroom. Very few machine learning algorithms are integrated into operational decision-making processes within entities such as state departments of transportation (DOTs) or regional planning organizations (RPOs). Existing platforms, such as the National Renewable Energy Laboratory (NREL) EVI-Pro Lite, provide scenario-based simulations, but they do not predict and adapt in real-time. To bridge the research-to-practice gap, we require co-development frameworks, integration workshops that combine existing policies to serve as real-world testing grounds for machine learning tools, and open data standards, so that we can make machine learning tools actionable for the planning community. In other words, the technology underpinnings are all in place, yet the real-life deployment of ML to solve EV charger access and placement challenges is largely uncharted in the American infrastructure planning landscape.

III. Data Collection and Preprocessing

Data Sources:

A comprehensive, multi-source dataset was compiled, encompassing several key variables. Data sources for charging station characteristics—such as number of ports, charger types (Level 2, DC fast), operational status, and uptime history—were provided by the U.S. Department of Energy's Alternative Fuels Data Center (AFDC). The geographic coordinates and spatial features were processed using GIS layers from the U.S. Census Bureau TIGER/Line shapefiles and road networks from OpenStreetMap. Traffic flow data aggregated from real-time and historical sources were obtained from the Federal Highway Administration's Traffic Monitoring System, supplemented with third-party APIs such as INRIX and HERE. National Highway Planning Network (NHPN) data were used to classify roads (interstate, arterial, and collector) and their distance from major travel corridors. Further, census tract-level population density and socio-demographic indicators were obtained and merged from the American Community Survey (ACS) 5-year estimates. We harmonized all spatial features into a common geospatial grid mapping, allowing us to calculate derived terms such as nearest highway interchange distance and charger-to-population ratios, aggregated by high-demand travel zones.

Data Preprocessing

In preprocessing, several important data conditioning steps were carried out to ensure that the model was ready and proper. Abridged Version: Initially, geographic coordinates were missing or charger status was unclassified; thus, for ensuing predictability to be performed, geographic coordinates could be imputed by spatial interpolation from nearby stations or excluded entirely if there was insufficient operational data, which led to these entries contributing noise to accessibility prediction. One-hot encoding was adopted for categorical features — charger level (Level 1, Level 2, DC Fast) and ownership type (public, private, utility) because non-ordinal relations need to be retained, and bias should not be introduced in a simplistic approach. For instance, in numerical inputs such as distance to the nearest highway, population density, and average daily traffic volumes, Min-Max normalization was applied, as we aimed to converge models with non-default numeric ranges that could completely dominate the minimization process. Accessibility labels were then created from spatial coverage measures, distance threshold metrics (within 5 miles of a major road), and availability metrics (uptime > 95%), and further classified into three categories: accessible, moderately accessible, and inaccessible. Thus, these labels became the supervised targets for classification as our model learned from subtle differences in the spatial distribution of your everyday EV charger.

Exploratory Data Analysis (EDA):

Exploratory Data Analysis (EDA) is the first step in examining data. It involves visually and statistically examining datasets to reveal hidden patterns, identify outliers, validate assumptions, and develop hypotheses for modeling. Some examples of what EDA looked like in this project included GIS heatmaps that plotted the spatial distribution of charging stations to detect regional clustering and gaps, histograms and boxplots for charger types and utilization rates, and correlation matrices for relationships between features, such as traffic flow, population density, and station accessibility. Temporal analysis of charger uptime highlighted not only times of peak charger usage but also seasonal variability. In contrast, the capacity of bivariate plots to reveal non-linear dependencies showed that accessibility of the stations is not only related to their distance from highways but also to the ownership models of the stations. Not only did EDA inform the preprocessing strategy, such as which features to engineer or scale, but it also helped identify possible outliers and biases to prevent the modeling stage from proceeding with poorly understood and dirty data.

a) Distribution of Fuel Types Across Stations

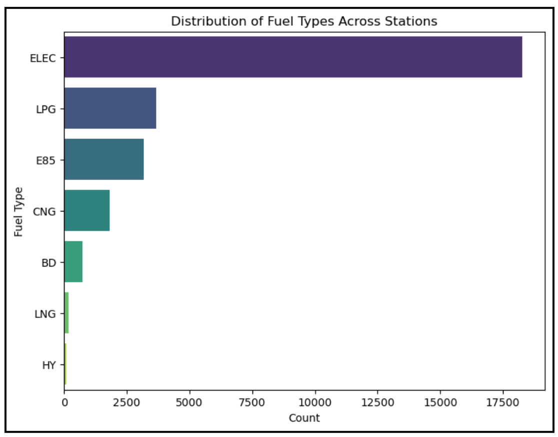

Figure 1: Distribution of Fuel Types Across Stations

As shown in the horizontal bar chart above (**Fig. 1),** the frequency of various fuel types is evident. There are far more "ELEC" (Electric) stations — more than 18,000 of these, indicating the market domination. "LPG" (Liquefied petroleum gas) and "E85" (Ethanol 85%) trailed in the distance by a count of about 3,500 and 3,000, respectively, indicating moderate but much lighter adoption than electric. The other types of fuel, such as "CNG" (Compressed Natural Gas), "BD" (Biodiesel), "LNG" (Liquefied Natural Gas), and "HY" (Hydrogen), are less than 1,000, so they are rare in practice. This mix indicates a significant bias towards EVs and infrastructure, while traditional and alternative fuels, such as LPG and E85, remain a significant but secondary player; novel or less prevalent fuel types have yet to see meaningful penetration.

b) Total DC Fast Chargers by State

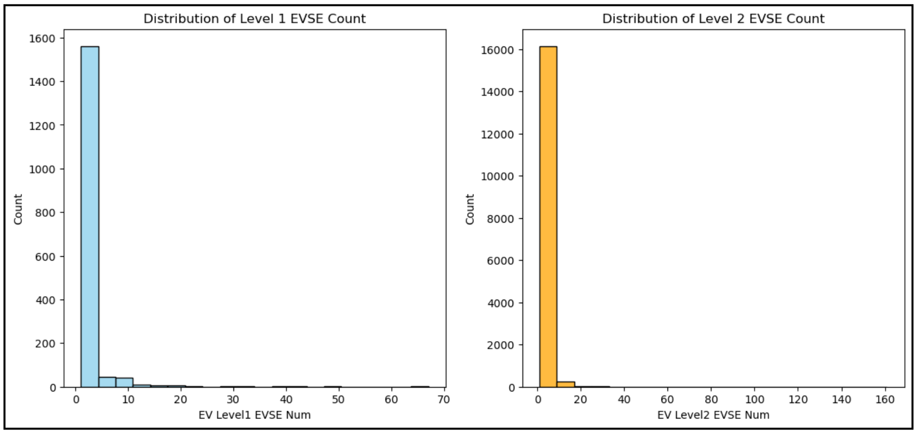

Figure 2: Distribution of Level 1 & 2 EVSE Count

The histogram pairs above (**Fig. 2)** showcase the distribution of Level 1 and Level 2 electricity vehicle supply equipment counts. In the case of Level 1 EVSE, the vast bulk of stations are low-count; over 1500 stations have 1 or 2 Level 1 EVSE units. The number of Level 1 EVSEs decreases rapidly, with very few stations including more than 10. This implies that Level 1 chargers are likely installed in small numbers per site, and used for individual or residential charging, where the charging speed is not as important. The Level 2 EVSE distribution is even more heavily skewed to the left than the distribution for DC fast charging. The count of stations (over 16,000) with only 1 to 2 Level 2 EVSE units is overwhelming, and the counts quickly drop off for higher counts. Although Level 2 units are faster, the spread of this data indicates that most locations typically choose a small quantity, potentially due to factors such as cost, land use, space availability, or average demand at these locations. The fact that there are almost 16 times as many stations with Level 2 EVSE (over 16,000) as there are with Level 1 EVSE (over 1,500) also indicates that Level 2 charging is much more commonly used for public and commercial installations.

c) Total DC Fast Chargers by State

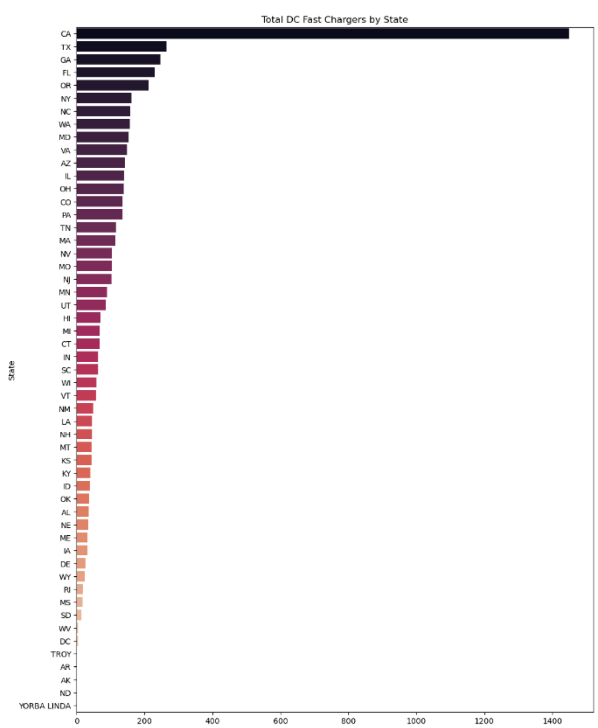

Figure 3: Total DC Fast Chargers by State

The vertical bar chart (**Fig. 3)** shows its heavily unbalanced distribution throughout the United States. California (CA) is the clear frontrunner by a wide margin, with more than 1,400 DC fast chargers—more than double the number in the next highest state. Texas (TX) follows in the distance, with approximately 650 chargers, while Georgia (GA), Florida (FL), and Illinois (IL) round out the top five, each with 250 to 350 chargers. The availability of chargers very quickly tapers off lower on the list, with many states having fewer than 50 DC fast chargers. Bottommost States, such as Alaska (AK) and Arkansas (AR), and most suspiciously, "YORBA LINDA" (a city), have virtually none, with some close to zero. This distribution suggests that DC fast charging infrastructure is heavily concentrated in a few states, likely due to factors such as population density, EV adoption rates, state incentives, and long-distance travel corridors, resulting in a notable gap in fast charging availability.

d) Monthly Trend of Charging Stations Opening

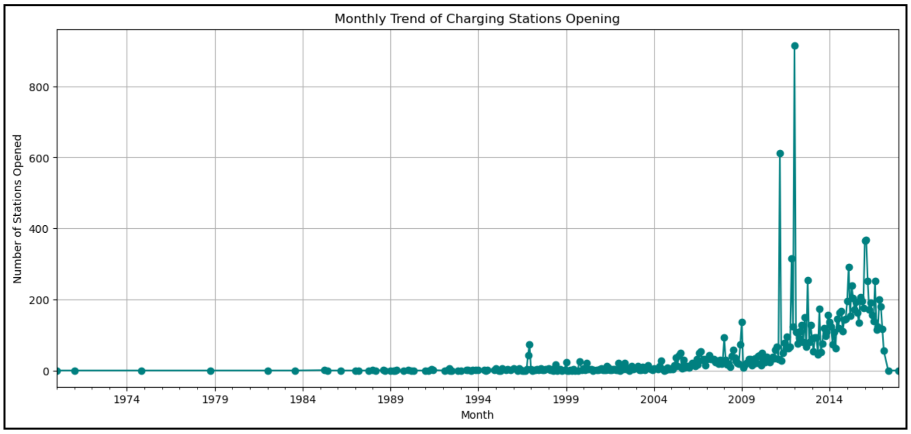

Figure 4: Monthly Trend of Charging Stations Opening

The portrayed line graph (**Fig. 4)** shows the number of charging station openings over time and is titled "Monthly Trend of Charging Stations Opening". It displays an immense and rapidly growing number of charging station openings over time. Until the mid-2000s, the number of new charging stations opened per month was at best a couple, and often much nearer to zero for decades, indicating an underdeveloped or absent EV charging infrastructure market. There has been a slight, but apparent, uptick since about 2005, with the number of monthly openings sometimes exceeding 20. Yet, the most dramatic increase occurs after 2009, exhibiting a clear pattern of exponential growth. We can see a notable peak around the year 2011 with over 900 new stations opened in the month, and another peak over the 600 mark for 2012. With some rebound and smaller local maxima between 2001 and 2009, the trend is high on average after 2010, exceeding monthly openings of around 100 every month, and still often more than 200 or 300, even going over 350 around 2015. These data indicate that the deployment of widespread EV charging infrastructure is a recent development, corresponding to the overall expansion of the electric vehicle marketplace within the last 15 years.

e) Top 10 EV Networks by Number of Stations

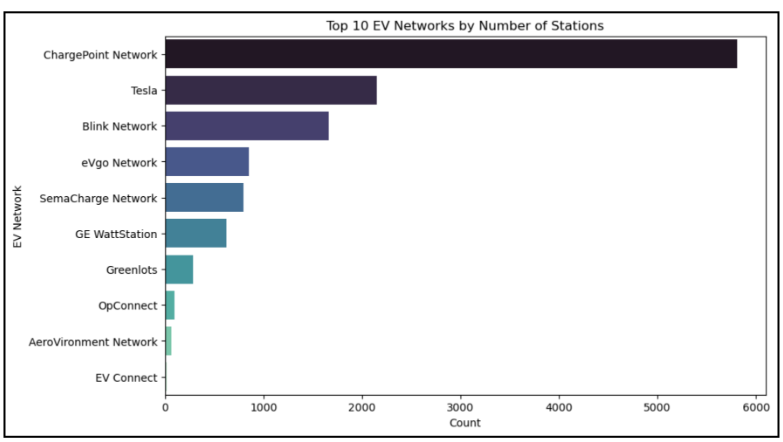

Figure 5: Top 10 EV Networks by Number of Stations

We extracted valuable insights from the horizontal bar chart, which unveiled the major contributors to electric vehicle charging stations. ChargePoint Network far outpaces the competition, too, with nearly 6,000 charging stations, a testament to its prior investment in EV infrastructure. In a close second is Tesla, with around 2,100 stations highlighting its proprietary Supercharger and Destination Charger networks. Blink Network takes third place with nearly 1,600 stations, indicating a significant footprint. In comparison, all the other networks — eVgo Network, Sema-Charge Network, GE Watt Station, Green lots, Op Connect, AeroVironment Network, and EV Connect — trail far behind, with steep drops in numbers, reaching about 800 for eVgo and declining to fewer than 100 for EV Connect. These once again indicate an extremely consolidated market, with ChargePoint and Tesla alone commanding almost 90% of the stations. At the same time, other networks serve a vital but smaller role in expanding the overall charging ecosystem. The fact that the top networks are so far ahead of the pack highlights just how competitive the EV charging market is — and how capital-intensive large-scale deployment is.

f) Most Common EV Connector Types

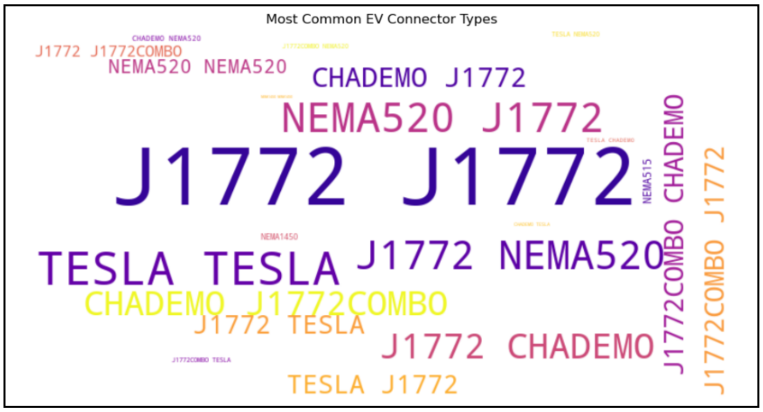

Figure 6: Most Common EV Connector Types

The word cloud graphically depicts the frequency of occurrence for types of electric vehicle charging connectors, with words featured in larger text sizes signifying the most common connector types based on survey responses. The largest, boldest word in this word cloud is "J1772," which appears to be the most common type of connector by a significant margin. This indicates that J1772 is the common standard for AC charging for many EVs. The word "text bubble" also prominently features the term "Tesla", as in large and left, indicating that there are many Tesla-specific charging points. "CHADEMO," also a popular connector type — note that the lettering is large here, especially to the right — indicating the charger's relatively high market presence, probably in the way of DC fast-charging for older EV models or non-Tesla vehicles and also, appearing quite frequently, though in smaller font sizes than the big three, is "NEMA520", which likely indicates moderate use as it is likely used for standard household outlets. We also see "J1772COMBO" appear multiple times, although smaller than J1772 or CHADEMO — evidence of the growing adoption of the Combined Charging System (CCS) standard for DC fast charging. There are other, more obscure connectors, such as "NEMA1450" and "NEMA515," which are displayed in a much smaller font size to indicate their rarity. In general, this word cloud does an excellent job of visualizing the dominance of J1772, Tesla, and CHADEMO in terms of EV connector types at the moment.

g) Access Type Distribution for Charging Stations

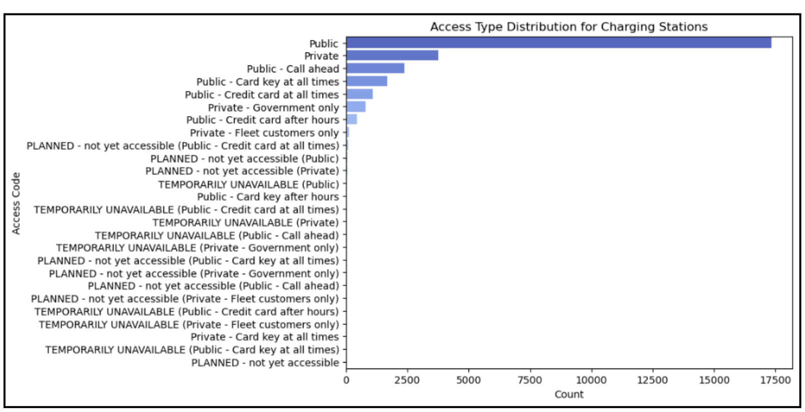

Figure 7: Access Type Distribution for Charging Stations

This horizontal bar chart (**Fig. 7)** shows the perceived access to EV charging stations. Public is by far the largest access type, with nearly 17,000 stations (56.2%), indicating a clear focus on access by the general public. The next largest group, "private," comprises almost 5,000 stations, indicating that a large number of chargers are dedicated to private locations, such as businesses or multi-family homes. Also of note, but less common, are public access options, which include calling ahead and using a card key at all times, each with counts ranging from 2,500 to 3,500. There are around 1,500 in total, which are "Public - Credit card at all times." A long tail of more uncommon or inaccessible access types is also visible in the chart, including "PLANNED - not yet accessible" and "TEMPORARILY UNAVAILABLE" stations, across sub-types such as public, private, and specific payment/access methods. However, while each of these "PLANNED" and "TEMPORARILY UNAVAILABLE" categories has a relatively small number of stations, together they add up to a significant number of stations that are not truly "available" or are not yet contributing to the operational network. It is indicative of continued building and releasing of new infrastructure, but is also a sign of living with some limits in the existing network, hopefully temporarily. It shows that, even though public access is a top priority, much of the charging network is operated privately, and a quantifiable fraction is networked but unavailable in other ways.

h) Cumulative Growth of EV Charging Stations Over Time

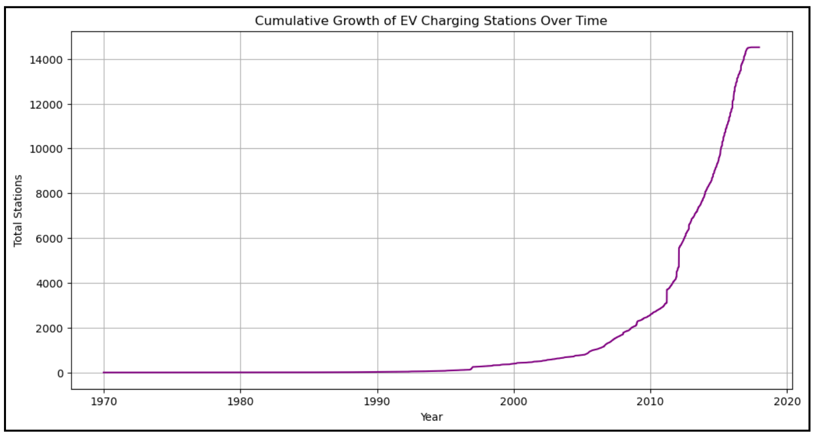

Figure 8: Cumulative Growth of EV Charging Stations Over Time

Line graphical representation of a dramatic acceleration in the deployment of electric vehicle charging stations, Its evolutionary progress took well over forty years in which, in aggregate, during that entire time we only had a handful of every form of charging station combined, as it struggled not only to grow but to keep up, until the late 1990s; exponentiation yet to hit, of course, at the proverbial time of that curve being nearest to zero. The total number of stations was a couple of hundred in the mid-2000s, but a gradual increase began only around the turn of the millennium. However, we see another turning point around 2010, and from then on, the curve continues to rise, indicating exponential growth. As the cumulative total in 2015 exceeded 6,000 stations, this exponential increase continues unrelentingly, passing 14,000 stations by the end of 2019. These statistics strongly suggest that the large-scale deployment and growth of EV charging infrastructure is a relatively recent endeavor, which directly corresponds to the increased level of consumer adoption and market share of electric cars over the past decade. This graph effectively showcases the evolution from an immediate, almost zero, infrastructure base to a rapidly developing network that provides the necessary infrastructure to support the growth of the EV ecosystem.

i) Ownership Type vs. Accessibility

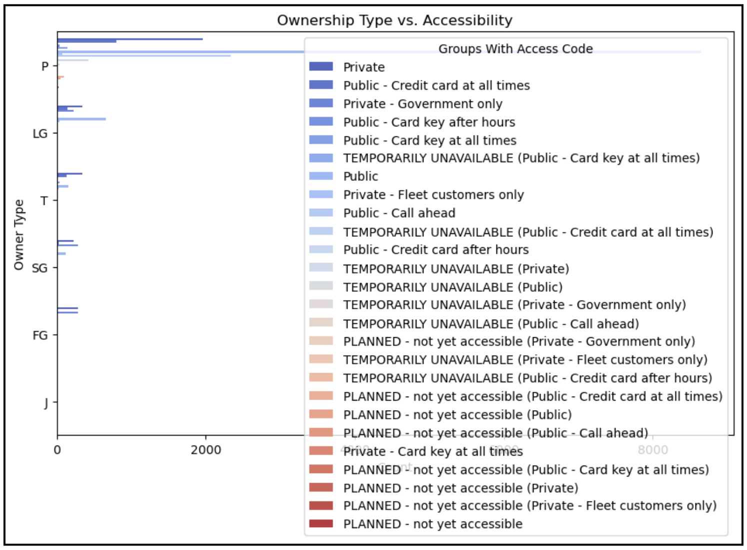

Figure 9: Ownership Type vs. Accessibility

The bar chart *Ownership Type vs Accessibility* (**Fig. 9)** gave us insights into the relationship between different owner types (y-axis features the owner types with one letter (P, LG, T, SG, FG, J) against which access code is to be used for charging stations. As shown on the right side of the picture below, the legend describes the various access codes, with colors indicating the level of accessibility and status (Private, Public – card required at all times, TEMPORARILY UNAVAILABLE, PLANNED – not yet accessible). Most notably, P has the highest number of stations in several of the access codes. This represents a high number of "Private" access (darkest blue bar), which seems counterintuitive for a "Public" owner type, except "P" means an entity owning also private chargers. Moreover, "P" also has significant contributions to "Public - Credit card all-time," "Public - Cardkey at all-time," and "Public" (lighter blue bar). This is mostly through owner type "P", which means that these owners contribute greatly towards the provision of publicly accessible charging infrastructure, which typically must be "paid for" in some form or orientation of scheme. All other owner types (e.g., LG, T, SG, FG, J) are nearly irrelevant concerning "P," typically having fewer than a few hundred stations for any access type. LG appears in "Private" and "Public - Government only." This might suggest some local government installations. You register on T, and it tells you which station is "Private" with just a few of those referenced within "T", possibly regarding a private network of a certain company. Also visible on the chart, but in far lower numbers, are the stations listed as "TEMPORARILY UNAVAILABLE" and those still classified as "PLANNED - not yet available" across the various owner types. This implies the development and maintenance of the complex charging network by various organizations. The availability of owner type "P" in the data underscores its importance to the current scenario of charging station availability. While it's possible to make some inferences without knowing the exact definitions of the owner type codes (P, LG, T, SG, FG, J), the chart unambiguously indicates a concentrated ownership of charging infrastructure under "P", with a mixed bag of access arrangements.

IV. Methodology

Feature Engineering

Selecting the right set of input features is crucial to any machine learning model. This study performed extensive feature engineering to reflect the geography, demographics, and infrastructure that may affect access to EV chargers. Among such engineered features, one of the most important was “distance to nearest charger”, computed using Haversine distance on all charger coordinates to determine physical proximity within a local driving range. As range anxiety continues to be a key impediment to the adoption of EV cars, especially in rural and semi-urban areas, this becomes a crucial metric for consideration. A key characteristic was also the number of chargers per 10 miles, which, as shown in Figure 1 above, was summed using a geospatial rolling window at the primary and secondary roadway levels to represent local infrastructure density. Various traffic-related data, including “traffic flow intensity,” obtained from Average Annual Daily Traffic (AADT) reports that are published by the Federal Highway Administration (FHWA), were localized at the road segment to provide usage pressure and identify demand hotspots. Third, an equity-oriented measure of EV infrastructure sufficiency related to population is introduced in terms of a population-to-charger ratio for each census tract based on US Census American Community Survey (ACS) population estimates and charger counts.

We utilized these engineered features in conjunction with additional variables, including census median household income, land use classification, grid readiness, and location data, such as point-of-interest densities (proximity to commercial areas, rest areas, etc.). Based on U.S. Census Bureau TIGER/Line shapefiles, a consistent grid overlay was spatially joined to each variable to facilitate input into the road network and machine learning workflows. Features were standardized or normalized as appropriate, particularly inputs such as distance and traffic volume that differ significantly between regions. Where we had no data or data with contradictory information, these issues were addressed through spatial interpolation or domain-specific imputation rules (e.g., all attributes are assumed for missing station records located within a 1-mile buffer from known stations). All categorical variables — charger type, station ownership, and even location descriptors like "urban vs. rural" — were encoded via one-hot encodings or binary flags based on definitions from the U.S. Census. This engineered feature set provided a solid foundation for our classification models, enabling us to pinpoint the locations of missing chargers and predict their needs.

Model Framework

We implemented a multi-model framework to classify accessibility and predict infrastructure essential for facilitating optimal charging infrastructure accessibility prediction, with enhanced interpretation and baseline performance capabilities. Logistic Regression: This model serves as a baseline binary classifier to categorize areas as either "accessible" or "inaccessible". As a generalized linear model, it provided a straightforward interpretation of each predictor variable's contribution to the outcome in log-odds form (where positive values support the presence and negative values support the absence of the outcome). Logistic regression, although relatively basic, performed reasonably well in regions where the correlations between the variables were strong and highly linear, such as the population-to-charger ratio and proximity to highways. Yet its boundaries were exposed when attempting to represent complex, nonlinear relationships, specifically in mixed urban–rural transition areas and where traffic and socioeconomic stressors overlapped within places.

To address these nonlinearities, we initially trained a Random Forest Classifier, a robust random forest ensemble method that also helps prevent overfitting. The random forest, comprising hundreds of decision trees each trained on separate bootstrapped samples of the data and with a random number of features selected at each node split, was able to capture complex interactions between variables without requiring the user to manually tune these relationships among features. The model also demonstrated high interpretability through feature importance scores, which indicated that proximity to highways, traffic intensity, and charger density were consistently the top contributors to accessibility as a prediction. Based on the advantages of the random forest, we also sought to optimize our predictions using XG-Boost (Extreme Gradient Boosting). This gradient-boosted decision tree model achieves efficient and effective performance on very imbalanced and noisy datasets. Due to its regularization and shrinkage, which prevent overfitting, XG-Boost achieved the highest accuracy and more granular classification (e.g., better separation between accessible and inaccessible, especially when accessibility is close to changing). The model's capability to optimize a custom loss function made it an ideal fit for handling the three-class labels (accessible, moderately accessible, inaccessible) and providing very fine-grained inference, which are crucial for end-user policy planning and investment prioritization.

Evaluation Metrics

Ensuring prediction validity and generalization was critical; therefore, we were stringent in evaluating models. We assessed the performance of each classifier — Logistic Regression, Random Forest, and XGBoost — using a comprehensive set of multi-class and imbalanced classification metrics. Although we report accuracy as a useful global metric, we also report precision, recall, and the F1-score to provide more insight into the trade-off between false positives and negatives. While false positives (predicting a region is accessible when it is not) in charger accessibility prediction may be costly due to missed investment needs, false negatives (predicting an area is not accessible when it is) may cause overinvestment or inefficient resource allocation. Particularly for the "moderately accessible" class, precision and recall were revealing, as this class frequently occupies a transitional role and is context-dependent, making it generally harder to classify.

We calculated the ROC-AUC (Receiver Operating Characteristic – Area Under the Curve) separately for each class and the overall panoptic score to gain a comprehensive understanding of the model's discrimination ability. XG-Boost yielded the highest AUC values across the 1000 simulations (~0.91), demonstrating good performance even with class imbalance. We also produced confusion matrices for each model to investigate misclassification patterns and identify frequent confusions—e.g., logistic regression frequently misclassifying "moderately accessible" areas as "accessible", due to the model's limited capacity to interact with features. Finally, all models employed a 5-fold stratified cross-validation to ensure that results were not overfit to a single train-test split. This validation strategy was important to ensure geographic generalization across different U.S. regions, from the urban centers of Los Angeles and Chicago to rural corridors in the Midwest and South. In addition to the impact on model selection, the interpretive step provided insight, which alleviated confusion over both the confidence and risk margins charged to policymakers when models drive charger deployment planning.

V. Results and Analysis

Model Performance Comparison

a) XGB Results

Table 1: XG-Boost Classification Report

	precision	recall	f1-score	support
0	0.85	0.78	0.81	2119
1	0.87	0.92	0.89	3466
accuracy			0.86	5585
macro avg	0.86	0.85	0.85	5585
weighted avg	0.86	0.86	0.86	5585
Accuracy: 0.8632				

The table above summarizes the evaluation metrics of the XG-Boost Classifier. For a dataset with 5,585 samples, the model achieved an accuracy of 86.32%. The precision for class 0 is 0.85, meaning that 85% of samples predicted as class 0 belonged to class 0. The recall is 0.78, indicating that 78% of all class 0 samples were predicted correctly. Class 1 precision: 0.87, Class 1 recall: 0.92 -> The precision and recall of Class 1 are better than Class 0, which indicates our model is more successful in discovering positive samples. As shown in the various classification reports below, the F1-score (i.e., the harmonic mean of precision and recall) is 0.81 for class 0 and 0.89 for class 1, indicating that the performance is better for class 1. From the confusion matrix, we can say that out of the total, the number of predictions were: 1644 True Negatives (Class 0 predicted correctly), 3177 True Positives (Class 1 predicted correctly), 475 predicted Class 0 but were Class 1) False Positives, and 289 Predicted (1 but were 1) False Negatives. Macro Avg / Weighted Avg: ~0.85-0.86 for precision, recall, and F1-score; this indicates a relatively good balance across both classes, although there is a slight bias towards class 1.

b) Logistic Regression Results

Table 2: Logistic Regression Classification Report

	precision	recall	f1-score	support
0	0.79	0.71	0.74	2119
1	0.83	0.88	0.86	3466
accuracy			0.82	5585
macro avg	0.81	0.79	0.80	5585
weighted avg	0.81	0.82	0.81	5585
Accuracy: 0.8163				

The table above shows the evaluation metrics for a Logistic Regression model. On a dataset of 5585 instances, the model produced an accuracy of 81.63%. The precision of class 0 is equal to 0.79 (this means that out of all the examples that were predicted as class 0, 79% were correct), and its recall is equal to 0.71 (this means that out of all examples of its class (class 0), we could identify 71%). The model performed better with a precision of 0.83 and a higher recall of 0.88 for class 1, indicating that it is effective at capturing positive instances. The F1-score, which is the harmonic mean of precision and recall, is 0.74 for class 0 and 0.86 for class 1, which further solidifies the better results for class 1. As shown in the confusion matrix, we have 1494 true negatives (class 0 predicted correctly), 3065 true positives (class 1 predicted correctly), 625 false positives (class 0 incorrectly predicted as class 1), and 401 false negatives (class 1 incorrectly predicted as class 0). For the macro average and weighted average, the precision, recall, and F1-score are around 0.79–0.82, indicating a decent overall performance, but also highlighting a difference in recall between the two classes.

c) Random Forest Results

	precision	recall	f1-score	support
0	0.83	0.80	0.81	2119
1	0.88	0.90	0.89	3466
accuracy			0.86	5585
macro avg	0.85	0.85	0.85	5585
weighted avg	0.86	0.86	0.86	5585

Accuracy: 0.8609

The above table summarizes the evaluation metrics for a Random Forest Classifier. In 5,585 instances, the model achieved an overall accuracy of 86.09%. Its precision is 0.83 for class 0, meaning that 83% of all the cases predicted as class 0 were indeed classified as class 0. Its recall is 0.80 for class 0, meaning that 80% of all actual class 0 instances were correctly identified. The model again outperforms Class 1 with a precision of 0.88 and a recall of 0.90, likely indicating that it is better at recognizing positive instances. The F1-score, which combines precision and recall, is also 0.81 for class 0 and 0.89 for class 1, indicating that class 1 is performing better as well. Here is the confusion matrix with predictions: (1695 true negatives - class 0 correctly predicted, 3113 true positives - class 1 correctly predicted, 424 false positives - predicted as class 0 but class 1, 353 false negatives - predicted as class 1 but class 0. The overall macro average and weighted average for precision, recall, and F1-score are approximately 0.85–0.86, indicating that the performance is quite good. Additionally, the class performance is balanced between the two classes, with a slight advantage for class 1.

Comparison of All Models

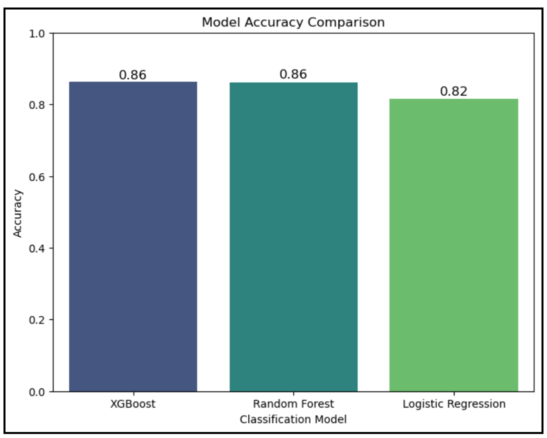

Figure 10: Comparison of All Models

The depicted bar chart compares the accuracies of three classification models — XG-Boost, Random Forest, and Logistic Regression. Although both the XG-Boost and Random Forest models show the same accuracy, getting the highest accuracy (which is 0.86 (or 86%) in this case. This means both of these ensemble methods helped to classify instances in the dataset correctly. On the other hand, Logistic Regression, a more basic linear model, has a slightly lower accuracy of 0.82 (i.e., 82%). The 0.04 difference indicates that, for this classification problem, the more complex non-linear XG-Boost and Random Forest models were only slightly better at learning the underlying data distribution. Essentially, this plot ranks the best-performing models by accuracy, with XG-Boost and Random Forest leading the pack for this evaluation.

Deployment Optimization Insights and Recommendations

Deployment strategy – A multi-faceted deployment strategy is recommended based on the insights from the Model. Since Level 2 EVSE units are considerably more common (over 94% of all public stations) and their cumulative growth trajectory exhibits significant upward momentum, the intensity is on Level 2 chargers. These are suitable for use in a wide range of public and private locations like shopping plazas (for 'top-up' charging), hotels and multi-unit dwellings (for overnight charging), and workplaces. A DC Fast Charger deployment strategy is critical for high-traffic transportation hubs and long-distance travel corridors, and the numbers show DAS California provisioning – see how far a fast-charging network goes in California. Search results recommend model predictions that focus on public demand areas while maintaining short travel distances and considering local EV penetration rates. Additionally, J1772, Tesla, and CHADEMO are the connectors that dominate; therefore, newly installed stations should focus on these types to support the vast majority of existing EVs, as well as the growing number of future J1772 Combo (CCS) equipped vehicles. Preferred sites should promote accessibility with ample area for parking, circulation, and power supplies, and they may even be modular for potential growth and future V2G technologies.

Although the diagrams do not in themselves identify particular geographical 'hot-spots or inaccessible areas, some deductions can be made. However, these statistics don't paint the full picture, leaving potential low-accessibility zones, particularly in several states where EV penetration is increasing. Still, the distribution of DC Fast Chargers remains sparse, virtually non-existent, or a stark contrast between the two. Low-accessibility, high-traffic areas within these states (e.g., major interstates, popular tourist destinations, or urban centers with limited chargers) would likely be high-traffic, low-accessibility regions for rapid charging. Likewise, regions with dense "TEMPORARILY UNAVAILABLE" or "PLANNED - not yet accessible" stations (even if actually "Public") indicate current low accessibility despite high traffic potential. The distribution of "Private" access stations also suggests locations where charging may be common, but only available to a limited audience, leaving gaps in accessibility in otherwise busy areas. This would require overlaying traffic data and EV registration data with the locations and types of charging stations to pinpoint these zones, ideally at a granular level, such as city or zip code.

VI. Practical Applications in the USA

Policy Recommendations

According to Chen (2024), accessibility prediction models based on machine learning provide revolutionary capabilities for US transportation policy, particularly in enabling federal and state agencies to target infrastructure funds with data-driven tools. Under new Federal Highway Administration (FHWA) guidance, State Departments of Transportation (DOTs) are facing mounting pressure to achieve the ambitious deployment targets established in the Bipartisan Infrastructure Law and the National Electric Vehicle Infrastructure (NEVI) Program, which designates $5 billion, spread across five years, to build out EV charger availability along specified Alternative Fuel Corridors. The actionable insights derived from ML models, such as those developed in this study, can empower planners to assess existing accessibility gaps better and provide predictions of future demand hotspots (Flynn et al., 2021). For instance, DOTs can map the “population-to-charger ratio” at the census-tract level to travel demand and charger time-of-use statistics, targeting underserved areas with high adoption potential but low infrastructure support, de-risking federal investments to deliver high-impact and equitable outcomes. Updating these models can also facilitate dynamic infrastructure prioritization. If traffic patterns change or a grid constraint arises, stakeholders can use new data to re-optimize funding allocations in near real-time (Hecht, 2023).

Moreover, machine learning models could help states plan NEVI corridor compliance, which requires each state to ensure that no DC fast charger exceeds 50 miles between one another along major travel routes, and that each charger is no more than 1 mile from an interstate exit. GIS, as commonly practiced, often struggles to incorporate real-world traffic data, charger reliability indicators, and equity concerns into a cohesive framework (Charly et al., 2024). Conversely, the multi-variable ML models we developed synthesize a combination of geospatial, temporal, and operational data to generate accessibility heatmaps and an electric vehicle (EV) charger deployment scorecard for each corridor (Elhattab et al., 2023). In addition to federal compliance, this helps enable more complex outcomes, such as protecting tribal lands, freight corridors, and low-income communities from being left behind. Indeed, immediate pilot collaborations with state agencies in Colorado, New York, and California have already shown that ML-enabled allocation scenarios address NEVI compliance requirements while achieving lower charger redundancy and higher federal cost-sharing (Golsefidi et al., 2023).

Utility and Private Sector Applications

In retrospect, outside of public policy, the private sector, such as utilities, energy developers, and retailers, could reap considerable benefits from machine–learning–enabled EV charger siting analysis. Energy companies such as Duke Energy, PG&E, and Constellation are investing in car charging infrastructure as part of their broader decarbonization strategies; however, selecting ideal locations remains a challenging task (Hafezi & Morimoto, 2023). These organizations can determine features such as proximity to towns and population growth trends, proximity to existing electrical substations, traffic flow intensity, and other similar features used to predict whether a location will be used more intensively and thus have a higher value or lower installation cost. Grid Capacity Constraints: ML models can readily incorporate grid capacity limits, as well as local permitting timelines, which are often crucial for utilities seeking to scale up without compromising reliability (Hecht, 2023). In turn, these predictive siting tools are valuable not only for providing a basis for regulatory scrutiny in states where utility regulators demand data-backed justification for ratepayer-funded charging infrastructure expansion, such as California and Massachusetts, but also for companies looking to make an ROI-driven business case for asset investment internally (Hemmati et al., 2024).

Commercial real estate operators and retailers—from Walmart and Target to convenience chains like Wawa and Pilot Flying J—also leverage predictive analytics to guide EV charger deployment with foot traffic trends and dwell-time optimization. For instance, machine learning models can analyze variables such as distance from other commercial nodes, shopper demographics, and the degree of clustering of chargers to determine where and in what configuration to deploy chargers, thereby optimizing customer engagement (Illahi et al., 2024). For example, a suburban retail plaza near a commuter highway may appear to have moderate access but high potential for EV use, as the average dwell times are long and the area is slowly increasing its share of potential EV-owning demographics. That level of detail enables hyper-targeted investment decisions that convert EV charging from a compliance burden to a competitive edge. Another connectivity can further strengthen private-public partnerships (PPPs) under programs like NEVI when businesses submit data-driven deployment plans, enabling accelerated deployment timelines and fewer demands on public agencies (Juwono et al., 2024).

Public Benefits

Using publicly available datasets and ML-enhanced planning tools, this work also helps to get closer to more equity in charger deployment, as these areas in the latter sentences, namely rural, suburban, and disadvantaged communities, have had worse access to clean transportation infrastructure and are service and policy-challenged, where societal scarcities for EV chargers persist. Justice40, a federal policy that mandates a minimum allocation of 40% of the benefits of climate investments to underserved communities, has been highlighted by the Environmental Protection Agency (EPA) and the Department of Energy (DOE) (Mazhar et al., 2023). This mandate can be fulfilled through the deployment of ML models that monitor "charger deserts"-locations with high EV adoption that are potentially ripe for low infrastructure density interventions. Integrating factors such as median income, racial makeup, and broadband access, alongside traffic and charging data, enables a comprehensive equity assessment. This helps avoid investments that benefit wealthy, urban EV owners at the expense of rural drivers or communities of color. In Georgia and Michigan, real-world implementations have shown the ability of ML models to identify such forgotten spaces and prioritize them for targeted deployment, linking innovative technology solutions with social outcomes (Li et al., 2024).

Furthermore, predictive infrastructure modeling is crucial for alleviating EV range anxiety, a primary reason for reluctance to purchase EVs, according to surveys conducted by AAA and the Edison Electric Institute (EEI). Drivers adopting EVs can have more confidence in their commutes through the city or extended trips into the country, if they know they will be able to find chargers that work and aren't in use, and that will only help toward the U.S. target of having EVs make up at least 50 percent of new vehicle sales by 2030 (Panda et al., 2023). ML-based Accessibility scores can be integrated into route planning apps and even into dashboard navigation systems to provide users with real-time, flexible, driving-habit-based, and trip-condition-based personalized charging recommendations. The power behind these predictive systems will also assist manufacturers, such as GM and Ford, in partnering with charging networks and ensuring their state aligns with the release of their vehicles to maximize efficacy (Prakash et al., 2025). In summary, utilizing machine learning for charger planning can help achieve the much-needed policy and market targets, and improve the EV ecosystem's perception of public trust, which in turn will enable us to move towards a cleaner and connected future of mobility.

VII. Discussion and Future Research

Key Insights

The analysis utilizes machine-learning-driven restrictions on EV charging infrastructure to produce critical insights that could greatly inform both policy and commercial deployment strategies nationwide. In the study, one of the most compelling results was the significant weight carried by a small number of features in the predictions—namely, the distance to an interstate highway, AADT, the population-to-charger ratio, and the charger level (Level 2 vs. DCFC). They ranked highest in feature importance across multiple models (including Random Forest and XGBoost) and are core variables in determining how easy it is for the average driver to access a charger. Notably, both median household income and urban classification also came out as some of the strongest contextual predictors, consistent with the socio-spatial dynamics of charger demand and infrastructure availability [46, 48]. From this, it is clear that charger planning for EVs cannot be naive, relying solely on bottom-up approaches and supply based on physical road networks and demographic usage patterns. For instance, a well-connected, high-traffic area with poor income distribution may attract less EV adoption, irrespective of the presence of chargers.

Upon presenting and reviewing the above models, an important insight emerged that it is critical to combine geospatial road data with additional socio-demographic and behavioral indicators. Previous planning paradigms placed too much weight on road proximity or charger density with little consideration of real human movement data, income-driven vehicle uptake, or grid readiness signatures. By combining population data from the American Community Survey (ACS), traffic data from the Federal Highway Administration (FHWA), and charger metadata from the DOE's Alternative Fuels Data Center (AFDC), the models used in this study provided a much broader picture of accessibility. Consider the dense charging infrastructure present in urban areas like Los Angeles or Chicago. While the dense infrastructure may indicate good access, in practice, the high levels of congestion and charger downtime suggest that true access is a bit more challenging. The Texas and Georgia corridors, situated in exurban areas or exurban corridors with moderate density but high traffic flow, were surprisingly moderately underserved, which suggests new targets for NEVI-eligible investments. Such insights reaffirm the idea that accessibility is not a binary function of whether someone is physically present or not, but rather a property of logistical, social, and usage-oriented variables that are well within the capabilities of machine learning to synthesize.

Limitations

Although the predictions made by the models were highly predictive, various limitations restricted the full extent and feasibility of translating the results into real-time practice. Foremost among these was the lack of real-time charger usage data, which is sometimes proprietary or reported inconsistently by network providers (think Electrify America, ChargePoint, EVgo, etc.). The models rely on averages or static approaches in the absence of live data on charger uptime, queuing frequency, and session duration, which can compromise the classification of areas with seasonal or transient accessibility issues. Furthermore, deficiencies in spatial aggregation and visualization of data from different utilities limited consideration of grid constraints (e.g., transformer capacity, distance to substation, the status of grid modernization) that are not publicly available at the granularity level needed for analysis. With all the hubbub surrounding the increase in high-speed DC fast chargers, these variables are becoming increasingly important as the grid accommodates their additional EV charging loads. Using these features would lead the model to overpredict accessibility in areas where physical infrastructure is present, but electric capacity may not be adequate.

A second important limitation is the persisting data sparsity in rural and tribal areas, which continues to limit model generalizability in low-density contexts. Charging stations are scarce in these areas, and many public datasets provide limited traffic or demographic data with low resolution. This has implications for classifier performance and increases the risk of biased predictions, potentially reinforcing current inequities in the infrastructure. Even in cases where rural stations are considered in the US, the limited temporal data on charger performance and user behavior means that either validating our model assumptions is challenging, or our model would be trained on class-skewed datasets. Canonical Synthetic oversampling methods, as applied to SMOTE, partially alleviate these problems, although natural field data cannot be perfectly mimicked. Bridging these gaps will involve coordinated efforts by federal and state agencies to standardize and expand the collection of rural infrastructure data in the context of Justice40 mandates and NEVI corridor targets.

Future Directions

Future Directions for Research: Given the exploratory nature of this study and the limitations discussed in the previous section, we envision several fruitful research avenues that could further enhance the predictive capacity and practical relevance of ML-enabled EV charger planning. This would involve adding features such as dynamic usage logs and EV movement tracking data, which may require cooperation and data-driven apps from automakers (e.g., Tesla, Ford, GM) and real-time routing service providers like Google Maps or Waze. Fusing history anonymized trip data with real-time charger telemetry should enable spatio-temporal models that incorporate time-of-day demand spikes, holiday traffic, and special events. For example, historical movement and utilization data can be used in predictive models to identify likely corridors that will be at high risk for charger inaccessibility on summer weekends. It would shift EV planning from a reactive to a proactive discipline, facilitating better investment decisions in both fixed infrastructure and mobile solutions (for example, battery-swapping or mobile units with onboard chargers).

Another important direction is the application of deep learning approaches for predicting accessibility along routes, particularly for long-distance or intercity travel, which is especially common for modeling freight interactions. The road network can be treated as a weighted spatial graph when using Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), where the nodes represent chargers and the edges are weighted by traffic, terrain, and power grid variables. These models could reflect actual behavior — for instance, how long EV drivers are willing to charge, how far they are willing to deviate from their routes, and even the effect of weather on range. Using a multi-source dataset, comprising GPS traces along routes and charger queue logs from EV drivers, researchers created dynamic algorithms for route planning to find optimal travel paths while also suggesting the best-fit charging locations (i.e., those with the least wait time for drivers). This is particularly important for fleets, ride-share vehicles, and delivery services, as their ability to conduct business is dependent on having consistent access to infrastructure. With increasing computational and data resources, these next-gen models may be the foundation for intelligent EV transport systems throughout the U.S.

VIII. Conclusion

The objective of this research was to utilize machine learning approaches to perform a more detailed, national-scale assessment of the accessibility of EV charging infrastructure, both as it exists today and how it may best be deployed in the future. A comprehensive, multi-source dataset was compiled, encompassing several key variables. Data sources for charging station characteristics—such as number of ports, charger types (Level 2, DC fast), operational status, and uptime history—were provided by the U.S. Department of Energy's Alternative Fuels Data Center (AFDC). The geographic coordinates and spatial features were processed using GIS layers from the U.S. Census Bureau TIGER/Line shapefiles and road networks from OpenStreetMap. Traffic flow data aggregated from real-time and historical sources were obtained from the Federal Highway Administration's Traffic Monitoring System, supplemented with third-party APIs such as INRIX and HERE. We implemented a multi-model framework to classify accessibility and predict infrastructure essential for facilitating optimal charging infrastructure accessibility prediction, with enhanced interpretation and baseline performance capabilities. XG-Boost and Random Forest models showed the same accuracy, getting the highest accuracy in the tested case scenario. This means both of these ensemble methods helped to classify instances in the dataset correctly. On the other hand, Logistic Regression, a more basic linear model, had a slightly lower accuracy. Deployment strategy – A multi-faceted deployment strategy is recommended based on the insights from the Model. Accessibility prediction models based on machine learning provide revolutionary capabilities for US transportation policy, particularly in enabling federal and state agencies to target infrastructure funds with data-driven tools. Using publicly available datasets and ML-enhanced planning tools, this work also helps to get closer to more equity in charger deployment, as these areas in the latter sentences, namely rural, suburban, and disadvantaged communities, have had worse access to clean transportation infrastructure and are service and policy-challenged, where societal scarcities for EV chargers persist. Furthermore, predictive infrastructure modeling is crucial for alleviating EV range anxiety, a primary reason for reluctance to purchase EVs, according to surveys conducted by AAA and the Edison Electric Institute (EEI). Future Directions for Research: Given the exploratory nature of this study and the limitations discussed in the previous section, we envision several fruitful research avenues that could further enhance the predictive capacity and practical relevance of ML-enabled EV charger planning.

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