Stasiun Pengisian Kendaraan Listrik Umum (SPKLU) Model Using GIS and Machine Learning

Febryansyah Hans Arieyantho[1], Luqman[2], Herman Bedi Agtriadi[3]
Ilmu Komputer, Institut Teknologi PLN, Indonesia, 11750
febryansyah2430501@itpln.ac.id

Accepted on December 11th, 2025
Approved on December 23rd, 2025

***Abstract*—The adoption of electric vehicles in Indonesia is a key strategy supporting the national "Go Green" agenda and the Net Zero Emission target by 2060. As electric vehicle usage rises, especially in West Java, strategically distributed Stasiun Pengisian Kendaraan Listrik Umum (SPKLU) locations are needed to ensure service accessibility and operational efficiency. Previous studies on SPKLU planning generally relied on buffer analysis focused on demographic variables, resulting in uneven infrastructure distribution. However, socio-economic factors also influence purchasing power and charging demand, indicating the need for a more comprehensive analytical approach. This study aims to develop a reliable prediction model for identifying potential SPKLU locations by integrating spatial and socio-economic variables. Geographic Information System (GIS) techniques are combined with machine learning algorithms, namely Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM). Spatial datasets from OSM, Geofabric, and Open Data West Java are collected and processed through proximity analysis to classify locations into Shared-Residential, Enroute, and Destination categories. These outputs are merged with socio-economic variables such as population density, income level, vehicle ownership, household characteristics, education level, and age distribution. The results show that the MLP model performs best, achieving an accuracy of 92.8%. The most influential variable is the number of productive-age residents, minority population, unemployment, and total population. The study concludes that demographic and socio-economic factors significantly influence SPKLU suitability.**

Keywords: SPKLU, GIS, Multi-Layer Perceptron, Support Vector Machine, Socio-Economic

I. INTRODUCTION

The use of electric vehicles in Indonesia is one of the Government's efforts to realize the "Go Green and Net Zero Emission" program in 2060. To realize this challenge, proactive steps and strict management implementation are needed to control and minimize emissions produced by vehicles[1].

The Head of the Energy and Mineral Resources Agency revealed that the number of electric vehicle users in West Java as the research, reached 29,465 in 2024[2]. This shows that interest in using electric vehicles is increasing every year. This growth indicates an urgent need for supporting infrastructure to ensure the convenience and sustainability of electric vehicle use, particularly Stasiun Pengisian Kendaraan Listrik Umum (SPKLU) as the primary charging facilities.

Previous studies on SPKLU planning have predominantly relied on spatial buffer analysis and demographic indicators to identify suitable charging locations, which often led to infrastructure recommendations that were uneven and spatially biased [3]. Although demographic variables such as population density and vehicle ownership provide useful baseline insights, they do not fully capture the complex behavioral and economic dimensions that influence EV adoption [4]. Recent literature highlights that socioeconomic attributes including income level, household expenditure, employment status, and poverty distribution play a critical role in determining purchasing power, charging affordability, and long-term EV market demand [5] . However, these variables were frequently simplified or excluded in earlier suitability models, resulting in limited predictive accuracy and reduced planning relevance at local scales [6]. For instance, several location-allocation studies prioritized proximity and mobility factors without incorporating income inequality or economic segmentation, which led to planning outcomes that favored high-density urban areas while neglecting suburban and lower-income communities [7].

Addressing this gap, the present study introduces a more comprehensive predictive framework by integrating both spatial and socioeconomic variables to access SPKLU feasibility. By incorporating indicators such as income distribution, employment ratios, household composition, and socio-demographic structure, the proposed model improves the contextual relevance of suitability results and enhances sensitivity to real-world EV adoption potential. This expanded variable set supports a more accurate, equitable, and demand-responsive understanding of charging needs, representing a significant methodological advancement beyond previous approaches. Addressing this gap, the present research introduces a more comprehensive predictive by integrating both spatial and socioeconomic variables to assess SPKLU feasibility.

Spatial analysis in this research is conducted using Geographic Information System (GIS), to integrate diverse geospatial layers such as proximity to infrastructure, land use, and accessibility criteria into a unified suitability model that captures spatial patterns which cannot be captured by simple buffer or demographic techniques alone, as demonstrated in recent EV charging station studies that combine GIS with advanced analytical methods [8]. The spatial outputs generated through GIS are then combined with socio-economic variables and processed using machine learning algorithms such as Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM) to capture complex nonlinear relationships and classification boundaries within the data, resulting in a robust predictive model for optimal SPKLU location identification [9].

A similar approach was also found in the multistage model [10], which incorporated MLP within a spatio-temporal demand prediction framework to produce more precise infrastructure needs estimates. MLP, as a multilayer neural network, is capable of learning intricate and nonlinear variable interactions, which strengthens its ability to identify spatial and socio-economic patterns associated with charging demand. Prior studies have reported that MLP achieved high prediction accuracy often exceeding 90% in EV charging usage modelling and demand forecasting scenarios, outperforming basic neural structures and decision-tree-based approaches [11]. On the other hand, the SVM algorithm is widely used for classification tasks related to the feasibility of charging station locations, [12] which utilized SVM to assess potential locations based on demographic criteria, accessibility, and traffic density. Furthermore, the [13] showed that SVM excels in predicting the availability and success of charging slot reservations at stations, thereby helping operators identify points at risk of over and under-utilization. Recent comparative evaluations have shown that SVM models achieved accuracy levels between 85% and 92% in EV infrastructure feasibility classification tasks, surpassing several baseline models such as logistic regression and random forest in smaller sample settings [11]. Overall, MLP provides strong demand prediction capabilities, while SVM plays an important role in classification and determining location feasibility, making it a relevant combination in SPKLU analysis and planning.

Building upon these previous findings, the present research expands the application of MLP and SVM by focusing the analysis on the integration of spatial data and geolocation parameters such as road networks, housing, apartment, parking and amenities (university, school and hospital) by GIS technology to form indicators of the feasibility of SPKLU locations in West Java Province. The purpose of this research is to assess the feasibility of locations based on the type of charging usage and compare the effectiveness of MLP and SVM algorithms in classifying SPKLU feasibility using features obtained from spatial data extraction. In addition, this research also visualizes the distribution of feasible SPKLU locations based on the best-performing model into a thematic map, thereby providing spatial information support for future infrastructure planning.

II. METHODOLOGY

The research methodology was carried out using two phases, namely data preparation for the analysis process with GIS and the analysis stage using the MLP and SVM algorithms.

A. Studi Area

The study area in this research is the administrative area of West Java province, as presented in Fig. 1. West Java is located in the western part of Java Island, bordering the DKI Jakarta province to the north, Banten Province to the west, and Central Java Province to the east. To the south, West Java borders the Indian Ocean. The total area of West Java is approximately ± 35,378 km², making it one of the largest provinces in Indonesia[14]. West Java Province has high geological complexity, consisting of various rock formations that are divided into three main zones, namely, the geology of the North zone (Bekasi, Karawang, Subang) which has the characteristics of young alluvial lowlands, dominated by clay and sand deposits, fertile and relatively stable soil suitable for housing and industry, then the central zone (Bandung, Sumedang, Cianjur) which has the characteristics of volcanic plateaus, dominated by andesite rocks, breccias, tuffs, traces of ancient volcanic activity, has the risk of earthquakes and landslides. This region is very densely populated, especially Greater Bandung and the southern zone (Garut, Tasikmalaya, and Sukabumi). It features folded mountains and igneous/plutonic rocks, numerous active faults, relatively unstable, steep, and landslide-prone soils, but is fertile for agriculture, and the population is more sparsely distributed. West Java Province has a total of 27 administrative regions, divided into nine cities: Bandung, Banjar, Bekasi, Bogor, Cimahi, Cirebon, Depok, Sukabumi, and Tasikmalaya. It also comprises 18 administrative districts: Bandung, West Bandung, Bekasi, Bogor, Ciamis, Cianjur, Cirebon, Garut, Indramayu, Karawang, Kuningan, Majalengka, Pangandaran, Purwakarta, Subang, Sukabumi, Sumedang, and Tasikmalaya.

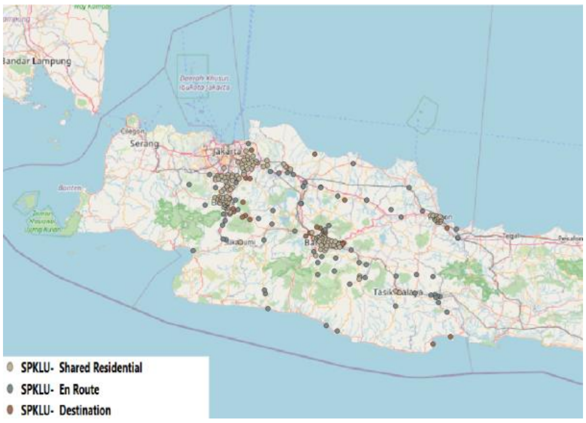

Fig. 1. Study area of research West Java with SPKLU point

B. Methodology

Research methodology process begins by determining the location parameters for SPKLU based on spatial analysis using QGIS software, then modeling classifying SPKLU location types using a comparison of the MLP and SVM algorithms

1. Preparation Data
   - Gather spatial datasets from the three sources shown: OpenStreetMap (OSM) for road networks, housing, apartments, parking, and public amenities (schools, hospitals, universities); Geofabrik for administrative boundary shapefiles (West Java); and OpenData Jabar for existing SPKLU point locations.
   - Data sample preparation to inspect the SPKLU point dataset for duplicates, missing coordinates, incorrect attributes, or outliers.
   - Boundary clipping using Administrative Boundaries
   - Use the West Java administrative polygon to clip all OSM-derived layers and other datasets so the analysis extent is constrained to the study area. This ensures consistency and reduces processing load.
   - Convert each thematic vector layer to raster at a defined spatial resolution (cell size).
   - For each raster layer, compute proximity (distance-to-feature) raster’s using GIS proximity/distance tools.
   - Optionally compute Kernel Density Raster’s (KDE) for point datasets to capture concentration.
   - Convert raw distance raster’s to suitability indicators with reclassify distances into suitability scores or continuous normalized values.
   - Normalization of data values
   - Overlay Data
   - From the composite suitability map, segment areas into the three target categories:
     - Shared Residential SPKLU: locations of housing
     - Road Route SPKLU: Enroute locations
     - Destination Type SPKLU: Malls, University, Office.
2. Kernel Density Estimation (KDE), compute KDE for relevant point data (e.g., existing SPKLU, population centers, amenities) to produce continuous density surfaces. Extract KDE values at sample locations and add them as features to the dataset.
3. Input parameter of socio-economic as variable predictor such as population, median household income, total household, vehicles mode, minority population, population below poverty level, population density, population with college education, household size, vehicle ownership, and median age
4. Data Analysis, the extracted data was analyzed and divided into two parts such as testing and training data
5. Architecture Model, two types of machine learning algorithms were used as the model architecture such as Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM)
6. Evaluation Model, the two models were compared using the following evaluation metrics such as Precision, Accuracy, Recall, and F1 Score
7. Best Model, the model with the best performance based on the evaluation was selected as the final model for classifying SPKLU locations.
8. Map Layout, the classification results were visualized as a map of SPKLU locations classified according to their types.

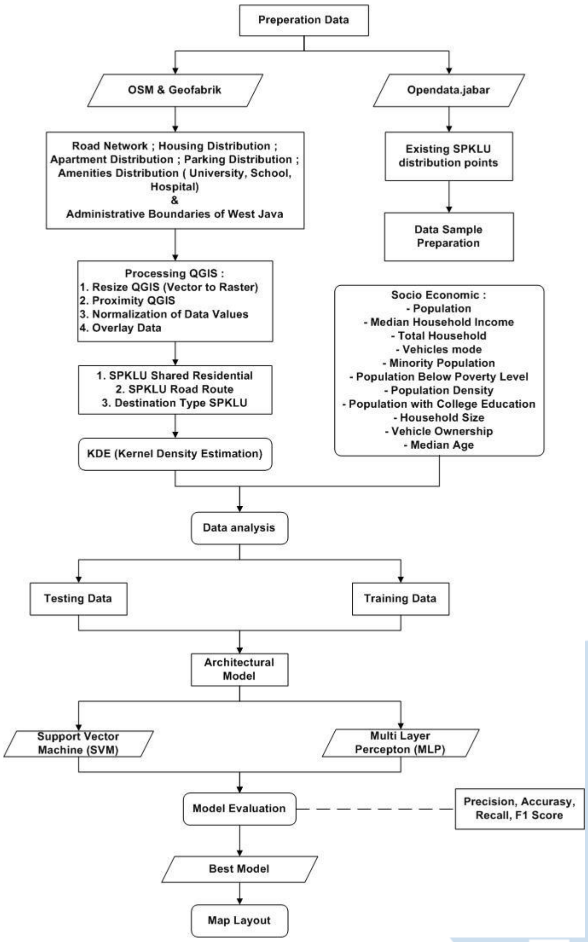

Fig. 2. Methodology

C. *Multi-Layer Perceptron (MLP)*

The Multi-Layer Perceptron (MLP) is a type of artificial neural network designed to learn complex, non-linear relationships between input variables and an output target. In the context of predicting potential SPKLU locations, MLP is used to determine whether a given location (represented as feature data) has high suitability for SPKLU placement[15]. The MLP architecture is as follows (Fig. 3.):

1. Input Layer: Feeding the SPKLU Predictors
   In this research, each sampled location is represented using many features derived from spatial and socio-economic data. These include:
   - Spatial suitability scores (Shared-Residential, Enroute, Destination)
   - KDE-based density scores
   - Population characteristics (productive-age population, minority population, total population)
   - Socio-economic indicators (income, poverty, unemployment)
   - Infrastructure-related variables (vehicle ownership, household distribution)
   - Educational and demographic variables (education index, median age)

2. Hidden Layers: Learning Non-Linear Relationships
   MLP contains one or more hidden layers with neurons that apply activation functions such as ReLU or sigmoid [16]. These layers learn:
   - Patterns between demographic variables and demand for charging stations
   - Spatial relationships (e.g., distance to roads or public facilities)
   - Interactions between socio-economic conditions and EV adoption potential
   - Non-linear combinations of variables that a simple statistical model cannot capture

3. Output Layer: Predicting SPKLU Suitability
   The output layer produces a binary prediction or probability score indicating whether the location is suitable for SPKLU development:
   - 1 or high probability → Suitable
   - 0 or low probability → Not suitable

4. Learning Process: Training With Existing SPKLU Locations
   The MLP learns by comparing its predictions with known existing SPKLU points:
   - Training samples with “SPKLU” (positive class)
   - Background or non-SPKLU samples (negative class)

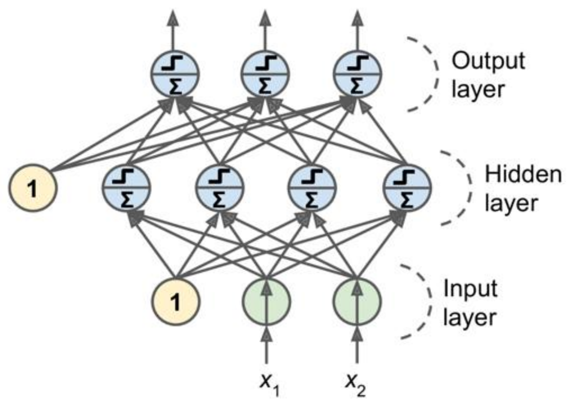

Fig. 3. Architecture of MLP

D. *Support Vector Machine (SVM)*

A Support Vector Machine (SVM) is a supervised classifier that learns to separate “suitable” vs. “unsuitable” locations for SPKLU by finding an optimal decision boundary (hyperplane) in a multi-dimensional feature space. Concretely, an SVM computes a function of the form

$$f(x) = sign(w \cdot x + b) \tag{1}$$

where x is the input feature vector (e.g. spatial coordinates and socio-demographic attributes of a candidate site), w is a learned weight vector, and b is a bias term. The algorithm chooses w and b to maximize the margin, the distance between the boundary and the nearest training points of each class[17].

The SVM takes as input a vector of spatial and socio-economic features describing each candidate site. Spatial features might include the site's geographic coordinates or derived measures such as distance to the nearest road, proximity to city centres or public transit, or local land-use indicators. Socio-demographic features can include population density, average income, vehicle ownership levels, existing SPKLU adoption rates, or usage patterns in the area. SVM handles nonlinearity via kernel functions that implicitly map the input features into a higher-dimensional space. Instead of computing $\varphi(x)$ explicitly, the SVM uses a kernel function

$$K(x, x') = \varphi(x) \cdot \varphi(x') \quad (2)$$

that returns inner products in feature space. Common kernels include linear, polynomial, sigmoid, and the Radial Basis Function (RBF)[18]. The SVM architecture is as follows (Fig. 4.):

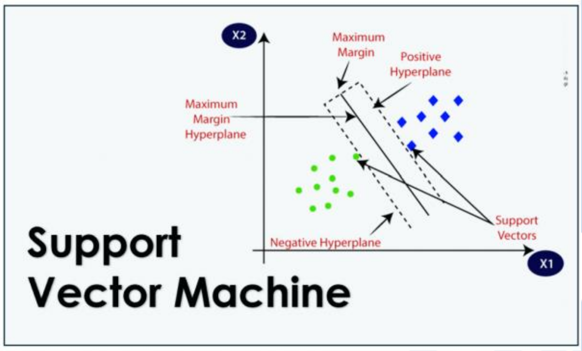

Fig. 4. Architecture of SVM

E. Evaluation Model

After developing the prediction models, we performed a validation test to assess their accuracy by comparing the predicted values with the actual values from the previously partitioned testing dataset. To evaluate model performance, a confusion matrix was employed, where accuracy is calculated as the percentage ratio between the sum of true negatives (TN) and true positives (TP) and the total number of testing samples, as shown in Table 1.

TABLE I. CONFUSION MATRIX OF MODEL VALIDATION

	Predicted: No SPKLU (0)	**Predicted: SPKLU exist (1)**
Actual: No SPKLU (0)	True Negative (RN)	False Positive (FP)
Actual: SPKLU exist (1)	False Negative (FN)	True Positive (TP)

III. PREVIOUS RESEARCH

Several previous researches have explored the spatial aspects of SPKLU. One such research, "Examining Spatial Disparities in Electric Vehicle Charging Station Placements Using Machine Learning," examined the spatial disparities in the distribution of Electric Vehicle Charging Stations (EVCS) in Orange County, California. Random Forest algorithm successfully identified areas with low access to charging facilities 11.04% of the county that required prioritizing investment. The model achieved 94.9% accuracy at a spatial resolution of 3 km, demonstrating that social, economic, and demographic factors have a significant influence on more equitable and equitable EVCS planning[19].

Another research in Indonesia highlighted the optimization of SPKLU locations through a geospatial approach. The research, titled "Optimizing SPKLU Development Locations Using Geographic Information Systems in Medan City with the Buffer Analysis Method," utilized buffer analysis to determine the most potential areas for providing SPKLU[20]. Through spatial data processing, the research produced a digital map depicting the adequacy of SPKLU coverage in Medan City. These findings underscore the importance of utilizing GIS to support equitable access and electric vehicle infrastructure planning in urban areas.

Furthermore, "Research of Electric Vehicle Charging Facility Development in the Greater Bandung Area," broadens the scope of the analysis by incorporating the perspectives of various stakeholders[21]. Conducted over three years through literature review, field surveys, and focus group discussions. The research emphasized the role of collaboration between the government, academics, and the electric vehicle user community. The research resulted in recommendations for infrastructure development aimed at reducing greenhouse gas emissions, minimizing dependence on fossil fuels, and strengthening the electric vehicle ecosystem in the Bandung metropolitan area.

A machine learning-based approach to determining SPKLU locations is also seen in the research "Decision Support System for Determining the Location of Stasiun Pengisian Kendaraan Listrik Umum (SPKLU) with Machine Learning." with combining the Analytic Hierarchy Process (AHP) method and geospatial data processing. This research assesses the feasibility of SPKLU locations in Ambon City based on criteria of accessibility, population density, and electricity infrastructure conditions. The model results recommend several strategic points, including Jalan Yos Sudarso, which is considered the most effective for SPKLU development and has a positive impact on economic growth and carbon footprint reduction.

In addition to location and spatial feasibility approaches, several studies have highlighted the technical aspects of electric vehicle charging. The research of, "Application of Deep Learning and Reinforcement Learning with Convolutional Neural Network Methods for Electric Vehicle Charging in Smart Grids," focuses on predicting charging load profiles in smart grids[22]. The study utilized various deep learning architectures such as ANN, LSTM, GRU, and ANFIS. The results showed that ANFIS provided the highest accuracy in predicting charging patterns influenced by seasonal factors. These findings provide an important basis for electric vehicle energy management to be more efficient and responsive to demand fluctuations[23].

IV. Result and Discussion

A. *Data Preparation*

Several predictor and respon variables used in the analysis process are converted into raster map. The response variables used in this research are proximity of Kernel Density Estimation (KDE) that obtained from phase 1 divided into three categories such as SPKLU Shared-Residential, SPKLU Enroute and SPKLU Destination [24] (Fig. 5.).

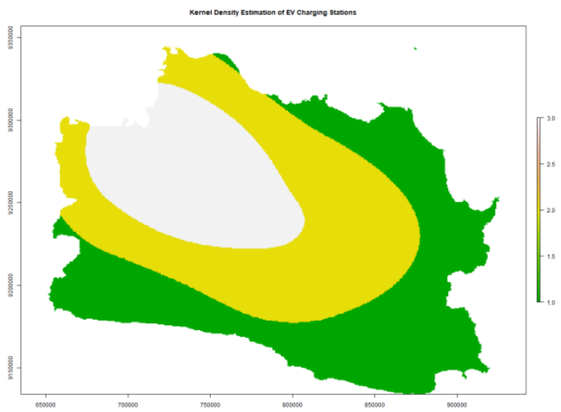

Fig. 5. Kernel Density Estimation (KDE)

Next, the predictor variables used in the analysis process are socio-economic. (Fig. 6.).

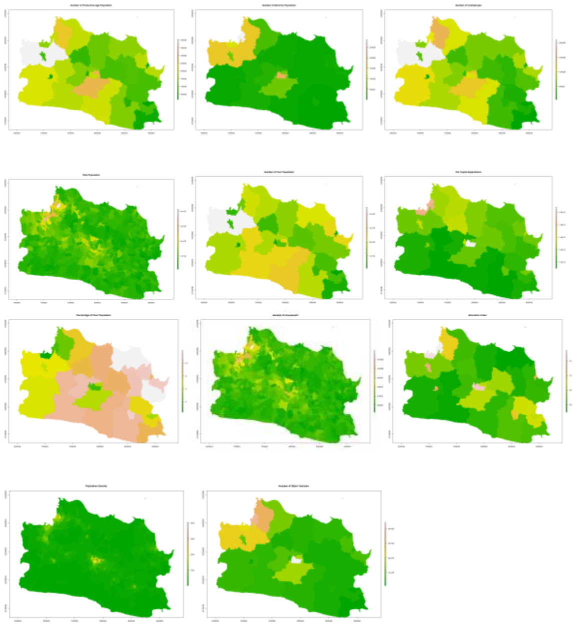

Fig. 6. Variabel predictor such as number of productive-age population, number of minority population, number of unemployed, total population, number of poor popuation, per capita expenditure, percentage of poor population, number of household, education index, population density, and number of motor vehicles

The data used in this research amounted to 147,911 with a total of 12 variables. As for the predictor variables encompass key socio-economic indicators, including the number of productive-age individuals, minority populations, unemployed persons, total population, poor populations, per capita expenditure, percentage of poverty, number of households, education index, population density, and the number of motor vehicles. These variables collectively represent demographic pressure, economic capacity, and mobility demand, making them essential determinants for spatial modeling and strategic planning of SPKLU infrastucture [25](Table II).

TABLE II. Predictor and Respon Variable

No	KDE	number of poor popuation	number of motor vehicles	population density	number of household	number of minority population	education index	total population	number of unemployed	per capita expenditure	percentage of poor population	number of productive-age population
1	2	204500	307404	3.196	14296	164728	69.14	40845	142818	12500000	4.80	2354038
2	2	204500	307404	3.196	14296	164728	69.14	40845	142818	12500000	4.80	2354038
3	2	204500	307404	3.196	14296	164728	69.14	40845	142818	12500000	4.80	2354038
4	2	204500	307404	3.196	14296	164728	69.14	40845	142818	12500000	4.80	2354038
5	2	204500	307404	3.196	14296	164728	69.14	40845	142818	12500000	4.80	2354038
…	…	…	…	…	…	…	…	…	…	…	…	…

114	1	187800	135737	4.637	20516	51786	60.75	52050	100404	12942000	7.86	1810263
115	1	187800	135737	4.637	20516	51786	60.75	52050	100404	12942000	7.86	1810263
116	1	187800	135737	4.637	20516	51786	60.75	52050	100404	12942000	7.86	1810263
117	1	187800	135737	4.637	20516	51786	60.75	52050	100404	12942000	7.86	1810263
118	1	187800	135737	4.637	20516	51786	60.75	52050	100404	12942000	7.86	1810263
…	…	…	…	…	…	…	…	…	…	…	…	…
67187	3	175900	67146	12.656	32349	8980	58.88	87354	107550	9815000	6.87	1934988
67188	3	175900	67146	14.830	17838	8980	58.88	54697	107550	9815000	6.87	1934988
67189	3	175900	67146	14.830	17838	8980	58.88	54697	107550	9815000	6.87	1934988
67190	3	175900	67146	14.830	17838	8980	58.88	54697	107550	9815000	6.87	1934988
67191	3	175900	67146	14.830	17838	8980	58.88	54697	107550	9815000	6.87	1934988

B. Model of Multi-Layer Perceptron

The train:test dataset ratio in this research is 80:20. The variable importance results from the MLP analysis can be seen in Fig. 7.

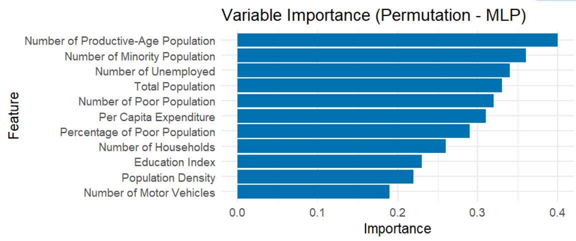

Fig. 7. Variable importance of MLP

Based on Fig. 8, the three variables that most influence the SPKLU prediction are the productive-age population (40%), the minority population (35%-40%), and the unemployed (30%-35%). The analysis results are then mapped to the West Java region. The map layout for the predicted SPKLU placement generated using the Multi-Layer Perceptron (MLP) method for the West Java region is shown in Fig. 8.

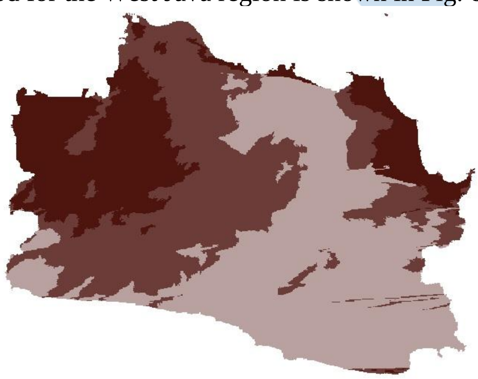

Fig. 8. Model MLP SPKLU

C. Model of Support Vector Machine

The variable importance results from the SVM analysis can be seen in Fig. 9.

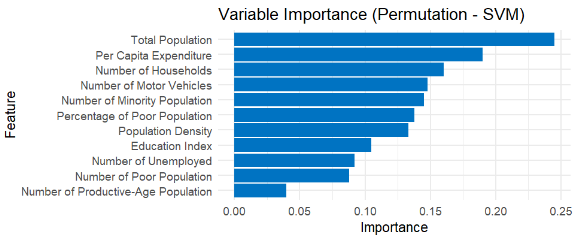

Fig. 9. Variable importance of MLP

The analysis in Fig. 10 indicates that the most influential predictors for SPKLU placement are total population (20%-25%), followed by per capita expenditure (17.5%–20%) and the number of household (15%–17.5%). These findings were subsequently visualized across the West Java area. The resulting spatial distribution of predicted SPKLU locations produced by the SVM model for West Java is presented in Fig. 10.

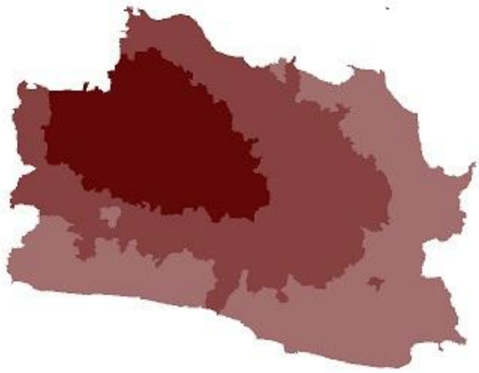

Fig. 10. Model MLP SPKLU

D. Model Evalution

The performance comparison between MLP and SVM shows (Table III) that both models achieve strong classification results across all three classes, with MLP demonstrating a slightly more balanced performance overall. For Class 1, MLP attains marginally higher precision, recall, and F1-score than SVM, indicating better consistency in identifying Shared-Residential locations. In Class 2, MLP again performs slightly better in all metrics, suggesting stronger reliability for Enroute category predictions. Although SVM achieves the highest precision for Class 3, MLP maintains superior recall, resulting in an equal or slightly higher F1-score, reflecting more stable performance for Destination class classification. Overall, MLP exhibits slightly stronger and more consistent predictive capability across all classes, reinforcing its suitability as the preferred model for SPKLU location prediction.

TABLE III. CLASS-WISE METRICS

Class	Precision		Recall		F1	
	MLP	SVM	MLP	SVM	MLP	SVM
1	0.938	0.934	0.931	0.919	0.935	0.926
2	0.903	0.891	0.910	0.912	0.906	0.901
3	0.955	0.963	0.955	0.954	0.955	0.958

Meanwhile, the accuracy results of the two models can be seen in the following table IV:

TABLE IV. ACCURACY MODEL

Model	Accuracy (%)	AUC
MLP	92.8	0.93
SVM	92.4	0.90

At Table IV, the accuracy comparison shows that both models between MLP and SVM perform very well in predicting SPKLU location classifications, with only a slight difference between the two. MLP achieves the highest accuracy at 92.8% and AUC 0.93, indicating its slightly superior ability to learn complex spatial–socio-economic patterns in the dataset. Meanwhile, SVM also demonstrates strong performance with an accuracy of 92.4% and AUC 0.90, suggesting that it remains a reliable alternative despite its marginally lower score. Overall, these results confirm that both machine learning models are highly effective, but MLP provides the best predictive capability for this study.

V. CONCLUSION

This study demonstrates that integrating GIS-based spatial analysis with machine learning provides an effective framework for predicting optimal SPKLU locations in West Java. By combining proximity features with socio-economic variables processed through KDE, the model particularly the MLP classifier with 92.8% accuracy successfully identifies areas with high potential demand. The dominance of demographic predictors, especially the productive-age population, underscores the importance of human-activity patterns in determining strategic SPKLU charging infrastructure placement. These findings highlight that data-driven spatial modeling can significantly support evidence-based decision-making for SPKLU infrastructure planning, ultimately enhancing the efficiency, accessibility, and sustainability of Indonesia's transition toward low-carbon mobility.

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