MACHINE LEARNING CLASSIFICATION OF BEARING CAPACITY IN OVERHEAD TRANSMISSION LINE TOWER FOUNDATIONS

ENERJİ İLETİM HATTI KULE TEMELLERİNDE TAŞIMA GÜCÜNÜN MAKİNE ÖĞRENMESİ İLE SINIFLANDIRILMASI

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ABSTRACT

In geotechnical engineering, the high spatial variability of soil behavior makes it difficult to make reliable engineering decisions in wide corridors with limited borehole data. Since traditional empirical approaches are insufficient in capturing nonlinear relationships between soil parameters, machine learning (ML) algorithms offer a powerful alternative to overcome these limitations. Determining the allowable bearing capacity (Q_{all}) in transmission line corridors extending for hundreds of kilometers is one of the most critical problems in geotechnical engineering. Although regression-based approaches have become widespread for continuous Q_{all} estimation, fundamental design decisions in corridor-type infrastructure projects are inherently discrete and threshold-dependent. In this study, a comparative ML classification framework for tower spread foundations is proposed using a geotechnical dataset consisting of physical, mechanical, and seismic soil parameters from 89 boreholes drilled in a transmission line corridor. Q_{all} values are divided into four engineering capacity classes based on quartile thresholds. Ten algorithms, including Logistic Regression, Decision Tree, Random Forest, XGBoost, and LightGBM, were evaluated with stratified five-fold cross-validation. Shapley additive explanations (SHAP) analysis shows that the average SPT-N, shear strength angle, and groundwater depth are important factors in geotechnical parameters. Based on the classification outputs, soil transition zones along the corridor, risk prioritization, and foundation type classification for non-drilling rig locations were carried out.

Keywords: *Allowable bearing capacity classification · Machine learning, Borehole database*

ÖZET

Geoteknik mühendisliğinde zemin davranışının yüksek uzamsal değişkenliği, sınırlı sondaj verisiyle geniş koridorlarda güvenilir mühendislik kararları alınmasını zorlaştırmaktadır. Geleneksel ampirik yaklaşımlar zemin parametreleri arasındaki doğrusal olmayan ilişkileri yakalamada yetersiz kaldığından, makine öğrenmesi algoritmaları bu kısıtları aşmada güçlü bir alternatif sunmaktadır. Yüzlerce kilometre boyunca uzanan iletim hattı koridorlarında izin verilebilir taşıma kapasitesinin (Q_{all}) belirlenmesi ise geoteknik mühendisliğinin en kritik problemlerinden biridir. Regresyon tabanlı yaklaşımlar sürekli Q_{all} tahmini için yaygınlaşmış olsa da koridor tipi altyapı projelerinde temel tasarım kararları doğası gereği kesikli ve eşik-bağımlıdır. Bu çalışmada, bir iletim hattı koridorunda açılmış 89 sondaja ait fiziksel, mekanik ve sismik zemin parametrelerinden oluşan jeoteknik veri seti kullanılarak kule yayılma temelleri için karşılaştırmalı bir makine öğrenmesi (ML) sınıflandırma çerçevesi önerilmektedir. Q_{all} değerleri çeyreklik eşiklere dayalı olarak dört mühendislik kapasitesi sınıfına ayrılmıştır. Lojistik Regresyon, Karar Ağacı, Rastgele Orman, XGBoost ve LightGBM dahil on algoritma, tabakalı beş katlı çapraz doğrulama ile değerlendirilmiştir. SHAP analizi, ortalama SPT-N, kayma mukavemeti açısı ve yeraltı suyu derinliğinin geoteknik parametrelerde kritik unsurlar olduğunu ortaya koymaktadır. Sınıflandırma çıktıları doğrultusunda koridor boyunca zemin geçiş bölgeleri, risk önceliklendirmesi ve sondajsız kule lokasyonları için temel tipi sınıflandırması gerçekleştirilmiştir.

Anahtar Kelimeler: *İzin verilebilir taşıma gücü sınıflandırması· Makine öğrenmesi, Sondaj veri tabanı*

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1. INTRODUCTION

Overhead transmission line (OHTL) corridors extend for hundreds of kilometres and comprise hundreds of tower foundations that transfer loads to the ground independently of one another. In building projects, the soil profile investigated at a single footprint can be treated as representative of the entire structure. A transmission line corridor, by contrast, crosses geologically unrelated units ranging from alluvial plains to rock outcrops and from shallow-groundwater flats to drained slopes, so the concept of a representative soil profile loses its validity, and each tower location constitutes a separate design problem. Johnson (2009) accordingly argued that geotechnical investigation along a transmission line must be evaluated holistically rather than being reduced to point-wise drilling. This variability is not merely a qualitative observation but a quantified source of uncertainty: the inherent variability of soil produces considerable scatter in shear strength and deformation parameters (Phoon and Kulhawy, 1999a, 1999b). Since lattice tower foundations carry uplift loads in addition to compressive loads, this uncertainty translates directly into a structural reliability problem (Mozer et al., 1984; Phoon et al., 2003). Reliability-based and simplified investigation and design frameworks have therefore been proposed for transmission line projects (Heim et al., 2011), and comparable spatial characterisation needs have been addressed through GIS-based approaches in other corridor-type infrastructure (Schwarz et al., 2015). This structure imposes three constraints. First, soil properties change discontinuously at geological unit boundaries rather than gradually along the route. Second, economic and logistical limitations preclude drilling at every tower location, making inference for uninvestigated positions unavoidable. Third, the corridor requires hundreds of independent foundation decisions rather than a single design. Taken together, these constraints indicate that corridor geotechnics requires a framework capable of producing consistent and repeatable decisions along the entire route rather than point-wise precision.

When standard penetration tests, grain distribution, consistency limits, strength parameters, and groundwater measurements are recorded for each borehole along the route, a dataset consisting of thousands of values is obtained. Experts must first evaluate this raw data on a location basis before it can be used directly as project input. However, interpreting a dataset of this scale entirely manually is quite time-consuming and carries the potential for error. Even if geospatial analysis yields efficient results, the proper selection of the interpolation method and the properties of the geodatabase can significantly impact the reliability of the results (Yildiz et al., 2024). Thanks to rapidly developing computational technologies, algorithms can now be reliably used in classification, change detection, and data scaling studies. Indeed, Baghbani et al. (2022), in their review covering 1235 publications, indicated that artificial intelligence (AI) applications in geotechnical engineering are rapidly spreading in nine different areas. Firoozi and Firoozi (2023) stated that machine learning (ML) plays a transformative role in geotechnical risk assessment, but the interpretability problem in black-box models needs to be solved. In class estimation studies, the relationship between soil parameters and the output must be understandable so that the developed model is interpretable and can be validated. So, the engineering accuracy of the results is verified using the SHapley Additive exPlanations (SHAP) method (Lundberg and Lee, 2017). Studies in the literature indicate that the SHAP importance rankings are consistent with soil mechanics expectations (Díaz and Spagnoli, 2024; Nguyen et al., 2024). In these and similar situations, using AI-based algorithms to eliminate the natural variability of the ground or reduce the number of boreholes is not possible with any data processing method; these methods, which take into account a large dataset, can systematically identify where the

variability is concentrated. This provides alternatives in determining the construction method, project duration and cost, and preventive measures and action plans that can be taken in advance in terms of structural safety before construction begins. This developed framework does not replace expert opinion; instead, it allows experts to focus their attention on critical segments and makes the distribution visible, rather than reducing uncertainty in the ground environment.

Bearing capacity estimation with ML has been developed predominantly within a regression framework (Ahmad et al., 2021; Millán et al., 2021), with ensemble methods proving particularly effective for limited datasets (Liu and Liang, 2024; Yaghoubi et al., 2024; Zeini et al., 2025). Regression, however, distributes learning capacity uniformly across the value range, whereas classification directs it towards the decision thresholds themselves. On a bimodal and skewed target this distinction is decisive: regression is dominated by the two density clusters, while quartile-threshold discretization yields a balanced learning problem. Threshold-based categorization is well established in geotechnical engineering, having been applied to liquefaction potential (Fadliansyah et al., 2024) and slope stability (Nanehkaran et al., 2023). Uray and Yıldız (2026) developed ten regression-based ML models for bearing capacity prediction using the same 89-borehole dataset, but the conversion of these predictions into a classification framework for pre-construction decision-making remained outside the scope of that study. The present study addresses this gap by establishing a decision framework on the same dataset. Its original contributions are: (i) bearing capacity was reformulated as a discrete decision problem through four threshold-defined classes; (ii) ten ML classification algorithms were compared under a common random-search hyperparameter optimization framework (Bergstra and Bengio, 2012); and (iii) the black-box structure of the model was interpreted through SHAP analysis, and the consistency of the resulting feature rankings with classical bearing capacity theory was verified (Lundberg and Lee, 2017; Meyerhof, 1963; Terzaghi, 1943). The classification outputs enable low-capacity sections to be identified before construction, providing a directly applicable input for preliminary foundation-type assignment, prioritization of additional investigation, and allocation of field resources to high-risk sections.

2. MATERIAL AND METHOD

2.1 Study Area and Geotechnical Database

In the study, a geotechnical database compiled from 89 boreholes along an energy corridor for transmission lines was used. The dataset is the borehole dataset introduced in the authors' previous work (Uray and Yildiz, 2026), compiled from the geotechnical investigation campaign of a 500 kV OHTL in Uzbekistan whose corridor extends 343 km; the 89 records used here cover the first lot of the alignment (Towers 1–89). Eight of the 89 records (9%) were incomplete. These were completed with a parameter-based imputation rule: parameters satisfying both Moran's $I > 0.20$ and a composite spatial score > 0.45 (sand content, fine content, average SPT-N and groundwater table depth) were interpolated by inverse distance weighting (Shepard, 1968), while the remaining parameters were imputed with a distance-weighted k-nearest-neighbour imputer ($k = 5$) (Troyanskaya et al., 2001). Distributional equivalence before and after imputation was verified by two-sample Kolmogorov–Smirnov tests ($p = 0.997$–1.000). At these eight locations Q_{all} itself was not statistically imputed; it was re-derived deterministically from the completed parameter set Each record includes water content (WC), grain size distribution fractions (gravel, sand, fine grain, and Clay),

Atterberg limits (LL, PL, and IP), effective shear strength parameters (c′, Ø′), unit weight (γ), peak ground acceleration (PGA), seismic zone, average SPT-N, groundwater table depth (GWT), and the target variable allowable bearing capacity (Q_{all}, kPa). Since the Q_{all} value is obtained analytically, the true value represents the analytical result rather than the capacity measured in the field. Q_{all} was not measured in load tests but calculated for each tower, as detailed in Uray and Yildiz (2026), for a 2.1 m × 2.1 m square footing with $D_f = 3.05$ m. For fine-grained soils with an observed groundwater level, Terzaghi's (1943) undrained equation ($\varphi = 0$, $N_c = 5.14$) with cu = $6xN_{60}$ (Stroud, 1974) and FS = 3.0 yields $Q_{all} \approx 13.4N_{60}$. For coarse-grained soils, the settlement-based equation of Peck et al. (1974) for 25 mm yields $Q_{all} = 11x(N1)_{55}$. Both were checked against settlement using Rocscience Settle3. Ø′ and c′ were also derived from SPT-N correlations. A horizontal ground surface and vertical, centric loading were assumed; ground inclination and tower uplift loads were not considered. The ML models therefore act as surrogate learners of these closed-form equations rather than predictors of measured capacity. There are no missing values in the dataset. The descriptive statistics of the parameters are presented in Table 1.

Table 1. Descriptive statistics of the parameters

	Average	Std. Deviation	Min	Q1	Median	Q3	Max	CV (%)	Skewness	Kurtosis
Depth	4.64	1.53	1.5	3.75	4.5	5.79	9	32.9	-0.05	0.41
WC	15.52	5.85	3.53	11.2	16.47	19.75	26.83	37.71	-0.26	-0.65
Gravel	0.73	1.68	0	0	0.09	0.69	12.92	231.42	4.94	31.87
Sand	17.79	15.92	0.35	2.25	16.46	31.92	50.25	89.5	0.45	-1.19
Fine	80.73	17	36.83	66.54	82.51	97.46	99.56	21.06	-0.43	-1.1
Cl	4.29	1.89	0	3.03	4.3	5.53	9.4	44.09	0.2	0
LL	24.9	2.22	17.39	23.89	24.98	26.35	32.27	8.9	-0.43	2.1
PL	18.1	1.63	11.17	17.31	18.36	19.16	20.84	9.02	-1.11	2.67
IP	6.8	1.43	3.49	6	6.58	7.46	11.82	20.99	1.01	2.1
Ø (°)	29.28	3.32	26	26	28	32	36	11.34	0.59	-1.16
c' (kPa)	3.35	0.94	2	2	4	4	4	28.15	-0.76	-1.46
γ(kN/m^3)	18.35	0.55	18	18	18	19	20	2.97	1.28	0.7
PGA	0.21	0.02	0.2	0.2	0.2	0.25	0.25	10.34	1.12	-0.76
Seismic Zone	7.26	0.44	7	7	7	8	8	6.07	1.12	-0.76
Ave SPT-N	13.51	7.96	3	6.84	11	19	39	58.95	1.03	0.82
GWT	8.1	5.29	1.5	3.5	6	15	15	65.25	0.36	-1.61

2.2 Exploratory Data Analysis and Class Definition

The distribution of the Q_{all} value determined according to different parameter values in the dataset is shown in Figure 1. According to the given graph, the Q_{all} variable, with a mean of 195.7 kPa and a median value of 132 kPa, exhibits a right-skewed and bimodal distribution. It is seen that the bearing capacity values are concentrated between 100 and 160 kPa for a low-capacity cluster and 300 and 480 kPa for a high-capacity second cluster.

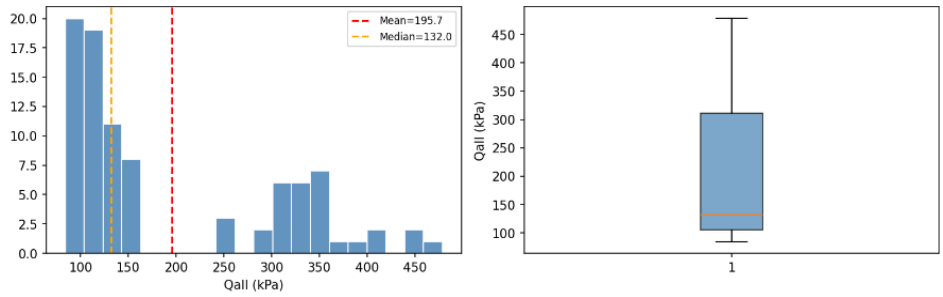

Figure 1. Distribution of Q_{all} (kPa), with histogram and boxplot

The suggested normality assumptions were not supported by the parameters' distribution characteristics, as shown by the Shapiro–Wilk test ($p < 0.05$) (1965). Furthermore, the exponential change in the angle of internal friction with the carrying capacity factors shows that the effects are non-linear. This is why a non-parametric Spearman rank view was chosen instead of the Pearson detail view, which relies on normality and linearity assumptions. According to this evaluation, the most robust relationships with Q_{all} have been determined for parameters of average SPT-N ($\rho = 0.96$), Ø′ ($\rho = 0.94$), c' ($\rho = -0.80$), and GWT ($\rho = 0.77$). Although regression models achieved high accuracy on this dataset (Uray and Yildiz, 2026), foundation design decisions along a corridor are threshold dependent. The bimodal distribution of Q_{all} largely reflects the undrained and drained calculation regimes described in Section 2.1. For this reason, balanced decomposition based on quartile thresholds (Q25, Q50, and Q75) was applied in the classification of the target values. It has been seen that, in the dataset considered, 25% of the Q_{all} values are below 106 kPa (Q1), 75% are below 311 kPa, and 50% are below 132 kPa (Table 2).

Table 2. Capacity classes, threshold values and recommended foundation solution

Capacity class	Q_{all} range	Recommended foundation solution
C1 — Low	< 106 kPa	Ground improvement / piled foundation
C2 — Moderate	106–132 kPa	Carefully proportioned spread footing
C3 — Good	132–311 kPa	Standard spread footing
C4 — High	≥ 311 kPa	Economic / minimal footing

Figure 2 presents the frequency and percentage distribution of the four capacity classes, which are almost equally represented in the dataset. The recommended foundation solution corresponding to capacity classes is given specifically for this project, and generalization for a final decision requires a detailed geotechnical evaluation specific to the location. Since the required foundation area increases as capacity decreases, making it less feasible and economical, this study's proposal is based on shallow foundation principles (Meyerhof, 1963; Terzaghi, 1943; Vesić, 1973). This is because in lattice tower foundations where tensile loads are decisive, deep foundation or soil improvement solutions are preferred in low-capacity soils (Heim et al., 2011; Phoon et al., 2000).

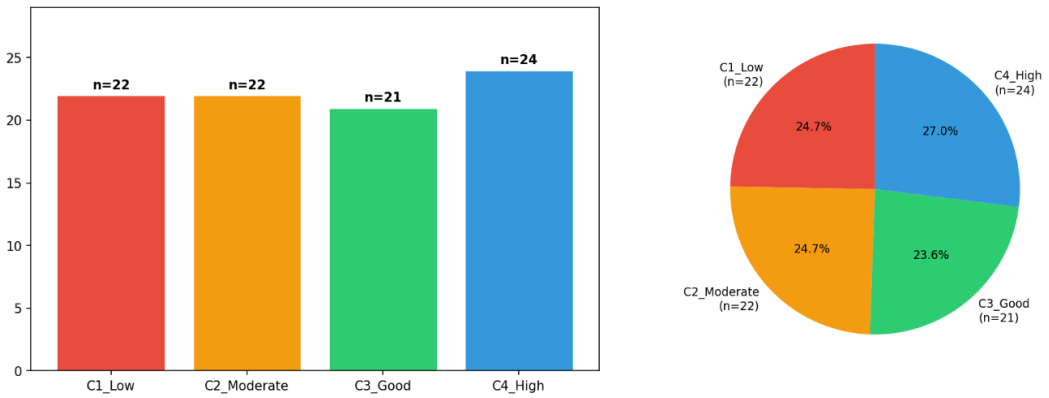

Figure 2. Frequency and percentage distribution of the four capacity classes

2.3 Machine Learning Approach

In ML analyses, the soil parameters given in Table 1 were considered as input, and the class labels (C1-C4) of Q_{all}, classified according to the threshold value given in Table 2 as the target variable, were coded with integer values. The dataset was split into 80% training (n =

71) and 20% testing (n = 18). A stratified approach was applied in the split so that the proportion of each capacity class was maintained in both the training and test sets. In a simple random split, it is possible for a class to be completely omitted due to the small size of the test set; for example, if no C1 sample falls into the test set, the model's performance in that class cannot be measured and is underestimated. Since the variables span very different scales (SPT-N in tens of blows against PGA below 0.4), large-scale variables dominate distance-based algorithms. Features were therefore standardized for the scale-sensitive models, with the scaling parameters derived solely from the training set and applied unchanged to the test set to prevent data leakage. This reflects the intended use of the framework, classifying undrilled tower locations within the same corridor, although the reported performance may be optimistic for locations without nearby boreholes and for other corridors, as neighboring boreholes may share similar conditions. A stratified random split was adopted to assess the model's ability to classify undrilled locations within the same corridor. Tree-based models were left unscaled, as threshold-based splitting is invariant to monotonic transformations. Ten classification algorithms were selected to evaluate the performance of different learning approaches. Linear and probabilistic models were Logistic Regression (Cox, 1958) and Gaussian Naïve Bayes (John and Langley, 2013); distance- and margin-based models were K-Nearest Neighbor (KNN) (Cover and Hart, 1967) and Support Vector Classifier (SVC) (Cortes et al., 1995); and tree-based models were Decision Tree (Breimann et al., 1984), Random Forest (Breiman, 2001), Extra Trees (Geurts et al., 2006), Gradient Boosting (Friedman, 2001), XGBoost (Chen and Guestrin, 2016), and LightGBM (Ke et al., 2017). A common framework for hyperparameter optimization, which plays a crucial role in the success of each algorithm and provides the highest-performing algorithm parameter combination, has been applied to all models. Thirty parameter combinations (number of iterations) were sampled from the parameter space of each algorithm using random search (Bergstra and Bengio, 2012), and each combination was evaluated using stratified five-fold cross-validation. The mean macro-F1 across the five rounds was taken as the performance measure of the respective hyperparameter combination. Due to the limited size of the dataset considered in the study, the performance of the trained models was examined using accuracy, macro-F1, Cohen kappa, RPC-AUC, and cross-validation F1 mean values. The algorithm with the best performance was evaluated using the SHAP method.

3. RESULTS AND DISCUSSION

3.1 Model Performance Comparison

The performance metrics of the models obtained from the ML analyses are given in Figure 3 along with their values. Furthermore, a ranking system was used to determine the rank value and average rank value for each metric of the ten ML algorithms, with metric 1 being the best in terms of performance and the next best being 2 (Figure 4). Examination of the graphs provided indicates that the LightGBM model demonstrates superior performance. Distance and margin-based algorithms (KNN and SVC) exhibit the poorest performance, whereas Decision Tree and XGBoost algorithms together maintain the second position, and the Random Forest approach occupies the third place. A general assessment revealed that tree-based algorithms (LightGBM, Decision Tree, XGBoost, and Random Forest) rank in the first performance group, linear and probabilistic models in the second, and distance- and margin-based algorithms in the third and worst performance groups. The confusion matrix presented in Figure 5 for the three models indicates that in the LightGBM model, a borehole

designated as C2 is misclassified as C3, with just 1 out of 18 boreholes being incorrect (Accuracy 17/18 = 0.944).

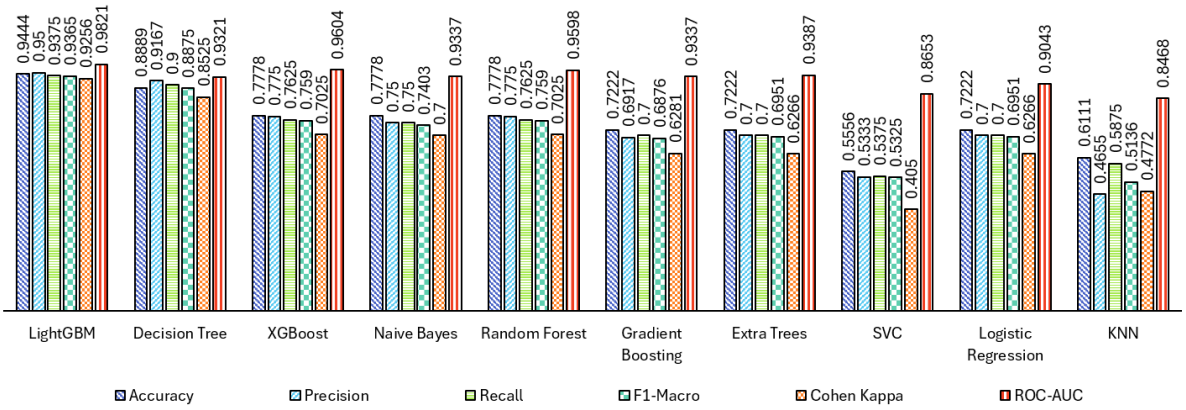

Figure 3. Comparison of ten ML algorithms' performance

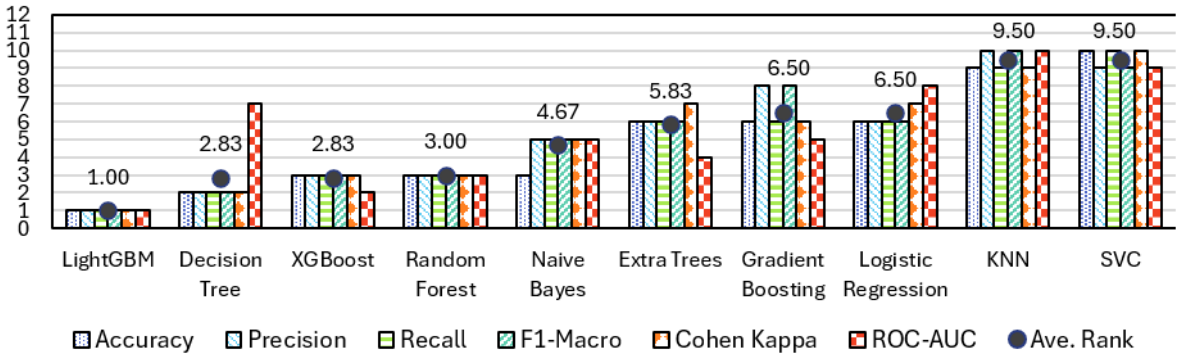

Figure 4 Rank values of ten ML algorithms' performance metrics

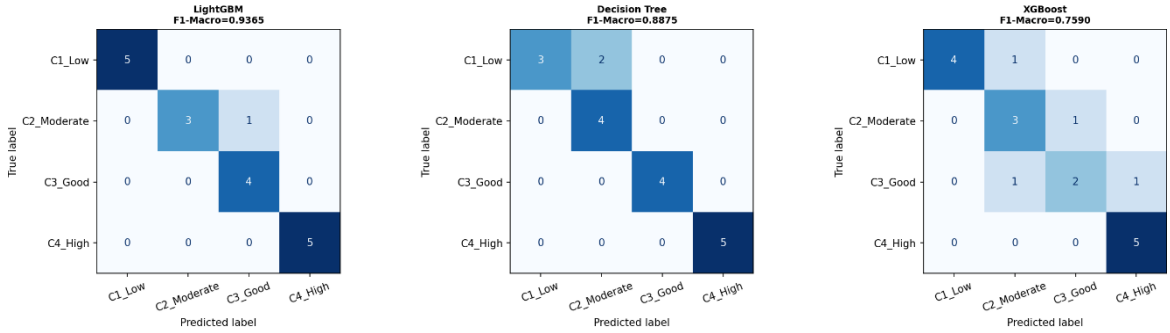

Figure 5. Confusion matrices for the best three models

Upon assessing alternative algorithm matrices, it was noted that the high-quality soil feature was misclassified as a medium-quality soil feature (two errors for Decision Tree, with accuracy of 16/18 = 0.889 and four errors for XGBoost, with accuracy of 14/18 = 0.778). An overall evaluation of the misclassifications shows that all errors are confined to neighboring classes and that the most critical error type, a distant-class error, does not occur in any of the models. A shift from C2 to C3 affects foundation dimensioning rather than foundation type and therefore represents a manageable deviation. In contrast, classifying a

C1 location as C3 or C4 would imply that ground improvement is unnecessary and that a standard foundation is sufficient in weak soil. Such a misclassification would result in an inadequately designed foundation and would pose a structural safety risk. With only 18 test samples, a single misclassification changes the accuracy by 5.6 percentage points, and the 95% confidence interval of the LightGBM accuracy (17/18) is approximately 0.74–0.99 (Wilson interval). The difference between the top-ranked models (LightGBM 17/18, Decision Tree 16/18) corresponds to a single borehole and should not be interpreted as statistically significant.

3.2 SHAP-Based Interpretability Analysis

The SHAP analysis shown in Figure 6 examined how much each feature contributed to the model's decision; the highest contribution was found to be from the average number of standard penetration test blows (Ave SPT-N). This parameter is followed by groundwater depth (GWT), internal friction angle (Ø′), clay content (Cl), liquid limit (LL), and fine grain content (Fine), respectively.

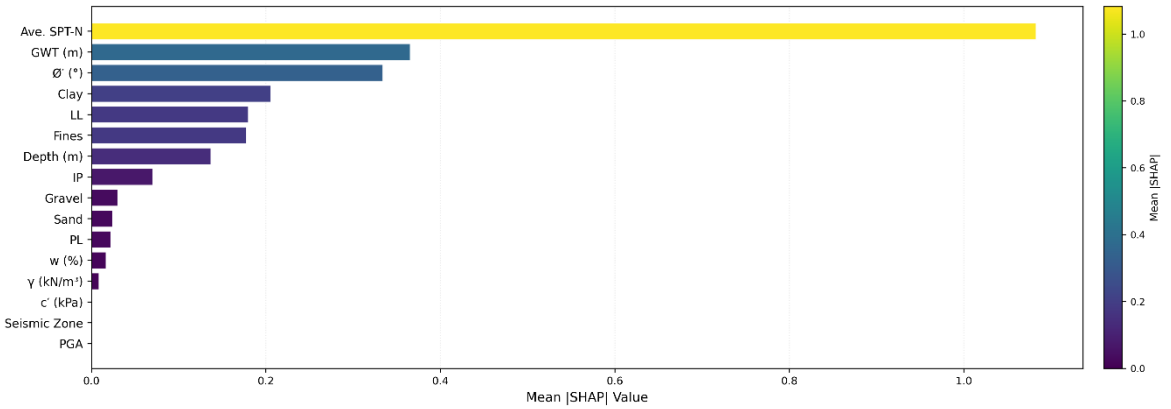

Figure 6. Global SHAP feature importance for the LightGBM model

This ranking reflects how Q_{all} was calculated (Section 2.1): Q_{all} depends linearly on SPT-N in both the undrained and drained regimes, and the presence of groundwater in fine-grained soils determines which regime applies. The prominence of Ø′ mainly results from its derivation from SPT-N ($\rho = 0.95$; Uray and Yildiz, 2026). In contrast, seismic parameters (PGA, seismic zone) and c' provided low contributions. The ineffectiveness of seismic parameters stems from the limited variation of these variables along the corridor; a variable that does not carry distinctive information cannot contribute to the classification even if it is physically significant. The low contribution of effective cohesion stems from the high correlation of this parameter with the internal friction angle ($\rho = -0.83$). When examining the SHAP feature importance graph for C1-Low (Figure 7), the contribution of Ave-SPT-N stands out significantly compared to the other three classes, demonstrating that it relies almost entirely on a single parameter for evaluating weak soil bearing capacity.

This indicates that the model can distinguish this class without needing additional information in soils where SPT-N <10. In the C2-Moderate graph, SPT-N values do not vary significantly within a narrow bandwidth of 106–132 kPa, indicating that this parameter has lost its distinguishing characteristic and that soil grain content has become more prominent. This indicates that the model captures the different behavior under varying loads caused by

differences in soil composition in clay or sandy soils with similar SPT-N values. Furthermore, this output demonstrates the difference in the classification algorithm, which evaluates each class individually, unlike the regression model. In the C3-Good classification, average SPT-N (Ave SPT-N) again stands out as the parameter providing the highest contribution, but it is not as dominant as in the C1 class. Liquid limit (LL) and fine grain ratio (Fines) also show significant contributions in this class. The C3 class covers a wide band of 179 kPa (132–311 kPa), indicating that both fine-grained and granular soils can be found within this range. The model's emphasis on consistency limits along with average SPT-N stems from the need to differentiate soil types. Class C4–High exhibits the most balanced distribution among the four classes due to the close contribution values of the three most influential parameters. This is because the high bearing capacity is achieved not by a single condition but by the simultaneous fulfillment of multiple conditions: a high average SPT-N indicates a tight profile, a high internal friction angle (Ø′) suggests a granular structure, and a deep groundwater level indicates that the effective stress is preserved. The resulting parameter combination is consistent with bearing capacity theory.

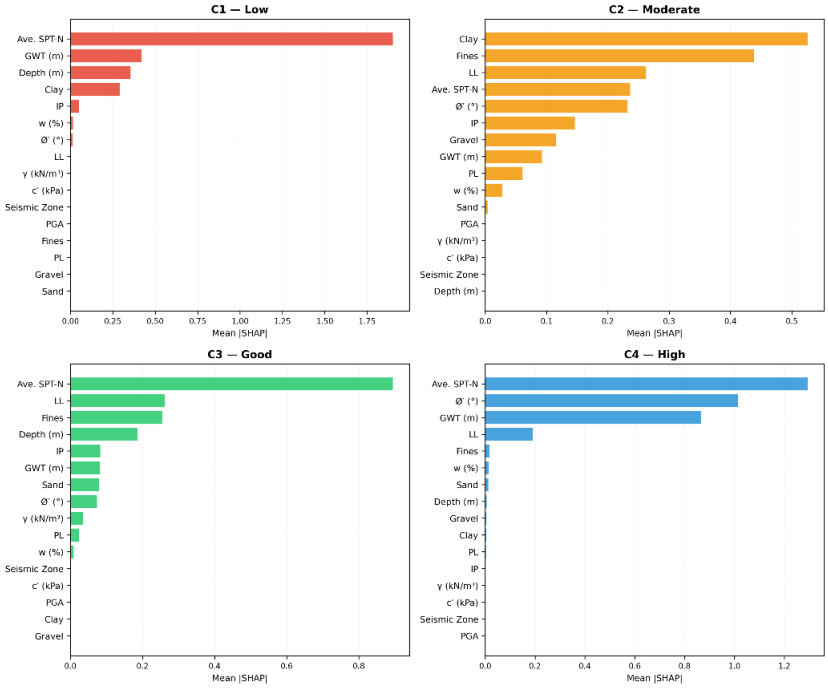

Figure 7. Class-wise SHAP feature importance for the LightGBM model

3.3 Corridor Zonation and Risk Prioritization

In projects involving large datasets and long corridors, interpreting soil parameters at each tower location individually is significantly time-consuming and creates bottlenecks between the research and design processes. Corridor zoning maps offer a practical alternative in this regard. The resulting map allows for the identification of risky sections along the corridor in terms of changes in groundwater level, soil type, and grain composition. Thus, it can be determined before construction which sections should receive priority funding for research and where safety measures should be implemented; time loss in preliminary studies is reduced. In this context, ML-based class estimations were arranged according to the drilling sequence to create a corridor zoning map, which is presented in Figure 8, with estimated load-carrying capacity classes along the corridor displayed along with threshold values of

the measured values, risk information, and soil transition zone provided according to color coding.

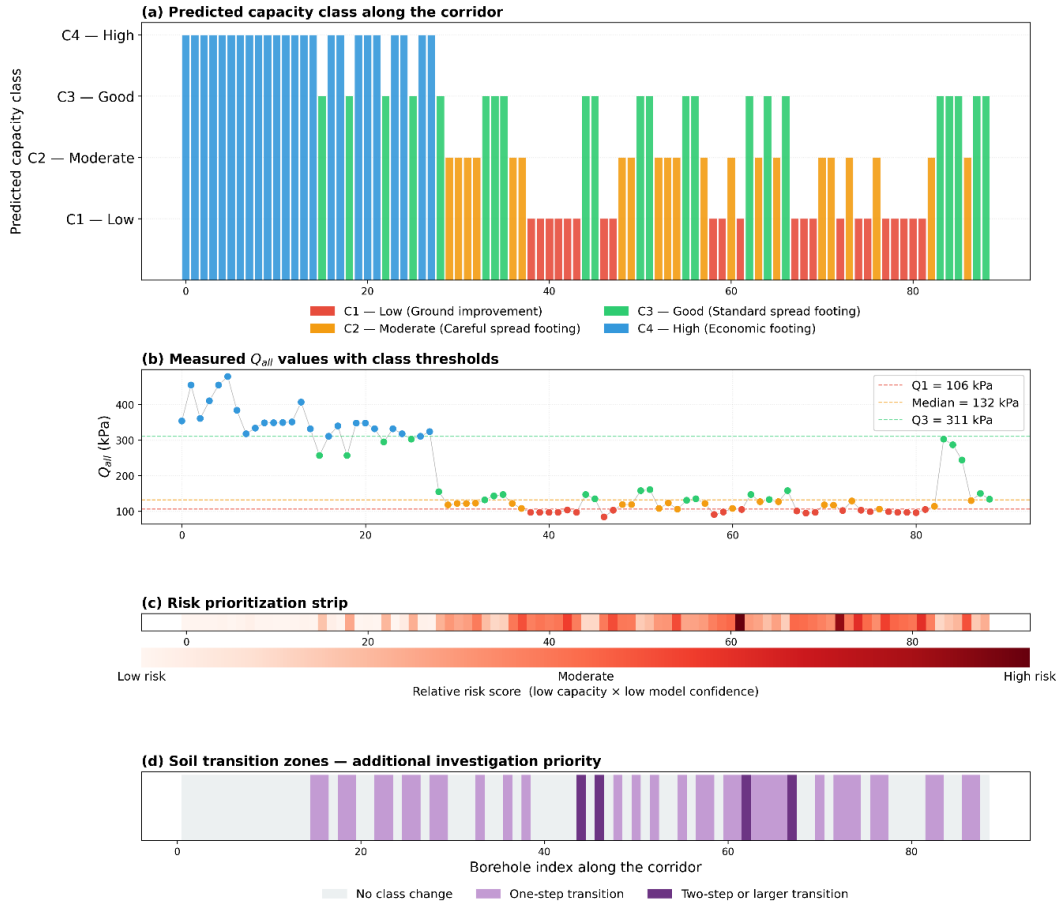

Figure 8. Geotechnical corridor zonation map based on LightGBM predictions

When the predicted values in Figure 8.a and the actual values in Figure 8.b are compared, it is seen that they match perfectly, indicating that the classification has yielded reliable results along the corridor. Upon examining Figures 8c and 8d together, it becomes evident that two-stage class transitions with elevated risk levels align between around the 43rd and 67th boreholes. This segment represents a zone characterized by the aggregation of low-capacity soils and abrupt variations in soil characteristics across subsequent sites. In light of this ambiguity, it is advisable to undertake further field research in this area and assess the necessity for soil enhancement based on the findings acquired.

4. CONCLUSIONS

In this study, the allowable bearing capacity (Q_{all}) of tower foundations was classified into four classes using a geotechnical dataset of 89 boreholes drilled along a long transmission line corridor, and ten different machine learning algorithms were compared. Q_{all} values were classified into four capacity classes using quartile thresholds, yielding a nearly balanced distribution that eliminated the need for the class imbalance corrections often required in small datasets. Among the ten algorithms, LightGBM achieved the highest test-set scores across all evaluation criteria (accuracy = 0.944; macro-F1 = 0.937; κ = 0.926; ROC-AUC = 0.982), although its margin over the next-best models corresponds to a single borehole. All

classification errors occurred between neighbouring classes, with no errors skipping two or more classes; the most critical error type for safe design — classifying weak soil as sound soil — did not occur at all. SHAP analysis showed that the model relies mainly on SPT-N, GWT and Ø′, reflecting the SPT-based equations used to calculate Qall; this agreement constitutes a consistency check rather than evidence of a new physical relationship. Finally, the classification outputs were converted into a corridor zonation map, which enables risky sections to be identified before construction, directs the investigation budget towards areas of highest uncertainty, and focuses expert evaluation on critical sections.The findings demonstrate that machine learning-based classification produces applicable outputs that can guide design and further soil investigations in corridor-type projects. This study has limitations: Q_{all} was calculated from SPT-based equations rather than measured, so the models act as their surrogates; ground inclination and tower uplift loads were not considered; and the small dataset (89 boreholes, 18 test samples) without spatially blocked validation may yield optimistic performance. Future work will extend the framework to other lots of the campaign (approximately 900 boreholes) with lot-to-lot validation and measured load test data.

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