

Application of ANN, SVM, and Logistic Regression Models for Fine-Grained Soil Classification

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Abstract: This study evaluates the effectiveness of three machine learning models such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Logistic Regression (LR), for the classification of fine-grained soils based on index properties. A dataset comprising 1,257 samples was compiled through an extensive literature review. Each sample included key index parameters such as liquid limit (LL), plastic limit (PL), plasticity index (PI), and percentage of fines. The methodology involved preprocessing the data, normalizing features, and dividing the dataset into training (70%) and testing (30%) sets. Models were trained and validated using k-fold cross-validation (k=10), and their performance was assessed using accuracy, precision, recall, F1-score, and confusion matrices. The ANN model achieved the highest classification accuracy of 91.6%, followed by SVM at 88.3%, and LR at 84.9%. The mean squared error (MSE) for ANN, SVM, and LR were calculated as 0.078, 0.102, and 0.139, respectively. The ANN model also achieved the highest F1-score (0.92), indicating superior consistency in classification. These results highlight the potential of machine learning models, particularly ANN, for the reliable and automated classification of fine-grained soils using basic index properties.

Keywords: Fine-grained soils, Artificial neural network, Support vector machine, Logistic regression, Soil index properties.

I. INTRODUCTION

Fine-grained soils are a category of soils that primarily consist of silt- and clay-sized particles, typically with particle diameters smaller than 0.075 mm (Figure 1). These soils exhibit distinct engineering behavior compared to coarse-grained materials due to their small particle size and high surface area (Moreno-Maroto et al., 2021). They are known for their plasticity, low permeability, and significant sensitivity to water content (Reale et al., 2018). These soils are generally divided into two main groups, silt and clay, depending on their mineral composition, plasticity characteristics, and particle size

distribution (Park & Santamarina, 2017). Silts are composed of fine particles with relatively low plasticity, while clays consist of even finer particles with high plasticity and greater cohesion (O'Kelly et al., 2023). These soils often dominate in natural deposits such as floodplains, lakebeds, and glacial environments. The behavior of fine-grained soils is largely governed by physicochemical interactions among particles and water (Kumar & Kumari, 2024). These interactions lead to complex mechanical responses under loading, moisture variation, or environmental change, making fine-grained soils challenging yet crucial for geotechnical applications such as foundations, embankments, and slope stability assessments (Freitag, 1987).

Fine-grained soils are commonly classified using the Unified Soil Classification System (USCS), which divides them based on plasticity and compressibility into groups such as CL, CH, ML, and MH. Here, 'C' denotes clay, 'M' denotes silt, 'L' indicates low plasticity, and 'H' indicates high plasticity (Moreno-Maroto et al., 2021). This classification is fundamental for understanding their mechanical behavior and guiding engineering design (Park & Santamarina, 2017). CL soils are low-plasticity clays characterized by moderate strength and medium to low compressibility (Kasaragod et al., 2024). They are commonly used in compacted fill and foundation applications where moderate bearing capacity is needed (Kayabali & Balci, 2013). These soils exhibit some swelling and shrinkage with moisture changes, but to a lesser extent than high-plasticity clays (Castro et al., 2023).

CH soils are high-plasticity clays with high water retention and significant swelling and shrinkage potential (Wang et al., 2024). They are often problematic in geotechnical practice due to their expansive nature and poor drainage characteristics, requiring special design considerations such as moisture control and stabilization techniques (Liu et al., 2024). ML soils are low-plasticity silts with limited cohesion and poor compaction properties (Gadouri et al., 2018). These soils can be sensitive to water and exhibit low shear strength (Al-Mamoori et al., 2020). They are particularly problematic in slope stability and foundation bearing capacity, especially when saturated (Moreno-Maroto et al., 2021).

MH soils represent high-plasticity silts, which exhibit higher compressibility than ML but generally remain non-cohesive (Kasaragod et al., 2024). They tend to have lower strength under saturated conditions (Freitag, 1987) and can cause excessive settlement in foundations if not properly managed (Wang et al., 2024).

The USDA Soil Classification System, developed by the United States Department of Agriculture, is primarily used in agricultural, environmental, and hydrological studies to classify soils based on particle size distribution (Moreno-Maroto et al., 2021). Unlike the USCS, which focuses on plasticity and engineering behavior, the USDA system is centered on percentages of sand, silt, and clay in the soil (Moreno-Maroto & Alonso-Azcarate, 2022). It divides soils into twelve textural classes, such as clay, silt, loam, sandy loam, and silty clay, based on their position on a soil texture triangle (Kim et al., 2017). Figure 2 presents the USDA soil texture classification chart. In this system, clay is defined as particles smaller than 0.002 mm, silt ranges from 0.002 mm to 0.05 mm, and sand is from 0.05 mm to 2.00 mm (Casagrande, 1948). These size boundaries differ slightly from the USCS, which classifies silt and clay primarily based on plasticity, not particle size (Edil et al., 2006). Because of this, a soil labeled “clay” in the USDA system may not behave as a clay in the USCS system if it exhibits low plasticity (Thompson & Robnett, 1979).

One of the strengths of the USDA system is its use of the textural triangle, a three-axis graph that allows users to determine the soil class by plotting the percentage of sand, silt, and clay. For example, a soil with 30% clay, 50% silt, and 20% sand would be classified as “clay loam.” This system is highly intuitive and visually effective for identifying soil texture (Kim & Kim, 2018). Although the USDA classification is widely used in agronomy and environmental sciences, it has significant value in geotechnical engineering as well, especially for initial soil screening, permeability estimation, and assessing water retention behavior (Heštera et al., 2023). It provides a clear, quantitative understanding of soil grain-size distribution, which correlates to other important properties such as porosity and hydraulic conductivity (Zhang et al., 2019).

In geotechnical research and practice, comparing both the USCS and USDA systems offers a comprehensive understanding of soil behavior from both engineering and agronomic perspectives (Kasaragod et al., 2024). For fine-grained soils, this dual classification can be particularly useful in multidisciplinary projects, such as soil-structure interaction near agricultural zones, land development, or erosion risk assessment, where both the mechanical behavior and particle size are relevant (Wang et al., 2024).

Although both the USCS and USDA systems are widely used for soil classification, they are based on different principles and serve different practical purposes (Groenendyk et al., 2015). While USCS is primarily designed for engineering applications, particularly in geotechnical design and construction, the USDA system is commonly applied in agriculture, hydrology, and environmental science (Moreno-Maroto et al., 2021). Understanding their differences is essential when working across disciplines or aiming for comprehensive soil analysis (Park & Santamarina, 2017).

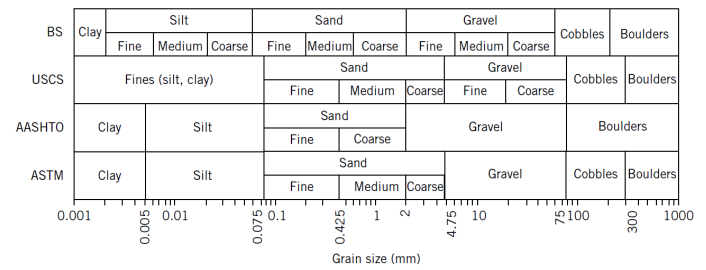


Fig. 1 Soil classification based on the soil size (Budhu, 2010)

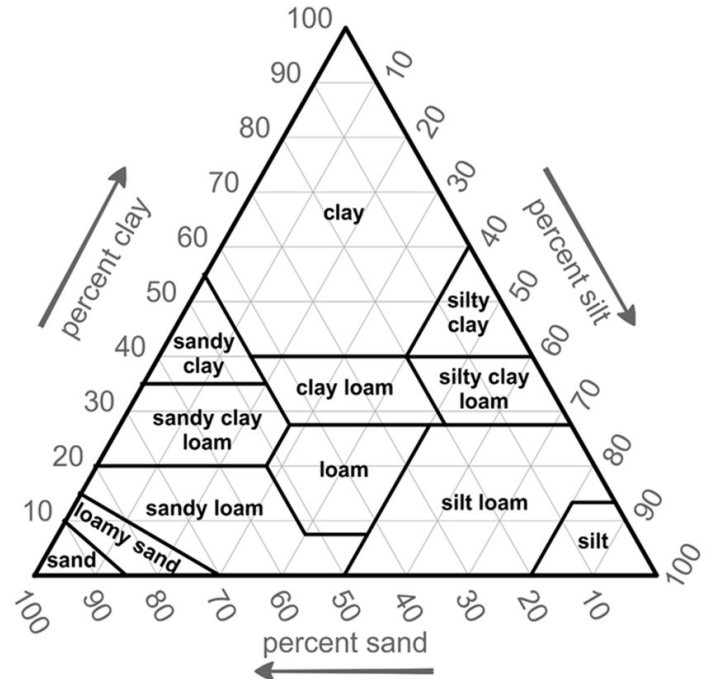


Fig. 2 The USDA soil chart (Groenendyk et al., 2015)

The USCS emphasizes the engineering behavior of soils, such as compressibility, plasticity, and drainage characteristics (Alade, 2018). It uses Atterberg limits and grain-size distribution to classify soils into groups groups such as CL (low plasticity clay) or ML (low plasticity silt). This system is highly beneficial for predicting soil behavior under loading, moisture variation, and other engineering conditions (Prakash & Sridharan, 2012). In contrast, the USDA system is based solely on particle size distribution, classifying soils into categories like sandy loam, clay, or silt loam through the use of a soil texture triangle (Freitag, 1987).

One major advantage of the USCS is its ability to reflect the mechanical behavior of soils, making it suitable for engineering design decisions (Bullock et al., 2024). It provides insight into shear strength, consolidation potential, and permeability (Ngapgue et al., 2020). However, a key limitation is its subjectivity in defining silt and clay, which are not strictly defined by particle size but by plasticity characteristics (Ozsagir et al., 2022). This means that two soils with similar grain sizes may fall into different classes depending on their Atterberg limits (Ghaderi et al., 2022). On the other hand, the USDA system's strength lies in its simplicity and objectivity (Groenendyk et al., 2015). By relying solely on measurable particle-size fractions, it avoids the variability and interpretation-related uncertainties associated with plasticity tests (Budhu, 2010). It is particularly

useful in understanding soil behavior in terms of water retention, erosion potential, and agronomic suitability (Heštera et al., 2023). However, the USDA system does not account for plasticity or mineralogy, which limits its usefulness in engineering contexts where strength and deformation behavior are critical (Freitag, 1987). When both systems are applied together, a more holistic understanding of soil properties emerges. For example, a soil classified as “clay loam” in the USDA system may correspond to either CL or CH in USCS depending on its Atterberg limits (Saikia et al., 2017). This dual classification allows engineers and environmental scientists to work with a shared understanding of the soil’s textural and mechanical attributes, especially in multidisciplinary projects such as highway embankments near agricultural zones, or infrastructure development in flood-prone areas (Dolinar & Škrabl, 2013).

Over the years, various methods have been employed for soil classification, ranging from simple visual inspection to laboratory-based index and performance tests (O’Kelly, 2021). Traditional techniques such as grain-size analysis, Atterberg limits testing, and standard soil charts (e.g., Casagrande’s plasticity chart, illustrated in Figure 3) have served as the foundation for most soil classification systems (Rehman et al., 2020). These methods are standardized, relatively reliable, and widely taught; however, they are labor-intensive and require significant time and resources to execute, particularly when dealing with large volumes of samples (Edil et al., 2006). In addition to conventional testing, empirical correlations and statistical models have been developed to estimate soil type from limited test results (Park & Santamarina, 2017). These methods attempt to simplify classification by using regression-based formulas or classification trees derived from past data (Heštera et al., 2023). While useful, such models often lack adaptability and generalization, particularly when applied to diverse soil types across different geographic regions (Ngapgue et al., 2020). Their accuracy tends to diminish outside the specific dataset or conditions they were developed under (Ghaderi et al., 2022).

Recent advancements in computational power and data availability have led to a growing interest in using machine learning and artificial intelligence (AI) for soil classification (Liu et al., 2024). These techniques can handle nonlinear relationships, learn complex patterns from data, and deliver rapid predictions once trained (Aydın et al., 2023). Unlike traditional models, machine learning algorithms do not require predefined assumptions about the data structure and can integrate multiple variables simultaneously, offering a more flexible and accurate approach to soil categorization (Kim et al., 2024). Among various AI techniques, models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Logistic Regression (LR) have shown significant potential in the geotechnical domain. These models are capable of classifying soils with high accuracy based on index properties, even when conventional laboratory results are incomplete or noisy. Their ability to generalize from large datasets makes them ideal for practical applications where speed and reliability are crucial. Moreover, they can provide consistent outcomes regardless of operator expertise or interpretation, reducing the risk of human error. Therefore, this study proposes the application and comparison of ANN, SVM, and LR models for classifying fine-

grained soils based on basic index properties. By considering a comprehensive dataset and evaluating the performance of each model, the research aims to determine which algorithm offers the most reliable and efficient classification outcome. This approach not only enhances traditional methods but also sets a foundation for fully automated soil classification systems in modern geotechnical practice.

In this regard, the primary objective of this study is to develop and compare the performance of three widely used machine learning models for the accurate classification of fine-grained soils. The models are trained using a large dataset of 1,257 samples collected from published literature, containing key soil index properties such as Liquid Limit, Plastic Limit, and Plasticity Index. The classification is conducted according to both the USCS and USDA systems to provide a dual framework understanding of soil behavior. The novelty of this research lies in the integration of machine learning techniques into dual soil classification schemes (USCS and USDA), an approach that has not been comprehensively addressed in previous studies. While prior works often focus on a single classification system, this study explores the intersection between engineering and environmental classification frameworks. Moreover, the study presents a comparative performance analysis of the three models, providing insights into which algorithm is most suitable for automated soil classification based on a limited set of key input parameters.

II. BACKGROUND

Soil index properties are fundamental characteristics used to describe the physical and engineering behavior of soils, especially in geotechnical engineering (Mathur et al., 2017). These properties are essential for the identification, classification, and performance prediction of soils under various environmental and loading conditions (Vaughan et al., 1988). Among all soil types (see Figure 4), fine-grained soils exhibit complex behavior due to their high surface area and moisture sensitivity, making the evaluation of their index properties particularly critical. The most commonly measured soil index properties include Liquid Limit (LL), Plastic Limit (PL), and Plasticity Index (PI). These three parameters are collectively known as the Atterberg limits (Budhu, 2010), and they define the range of water contents over which the soil exhibits different states of consistency including solid, semi-solid, plastic, and liquid (Sridharan & Nagaraj, 2000). These transitions are crucial for understanding how a fine-grained soil behaves in response to changes in moisture (Zolfaghari et al., 2015).

The LL represents the water content at which a soil transitions from a plastic to a liquid state. It is determined through standard laboratory tests such as the Casagrande cup method or the fall cone test (Budhu, 2010). Soils with higher LL values are generally more compressible and less stable under loading, especially when saturated. LL is a key parameter in differentiating between low-plasticity and high-plasticity soils in the USCS system (Wang et al., 2024). The PL is the lowest water content at which the soil can be rolled into threads without crumbling (Ngapgue et al., 2020). It defines the boundary between the semi-solid and plastic states.

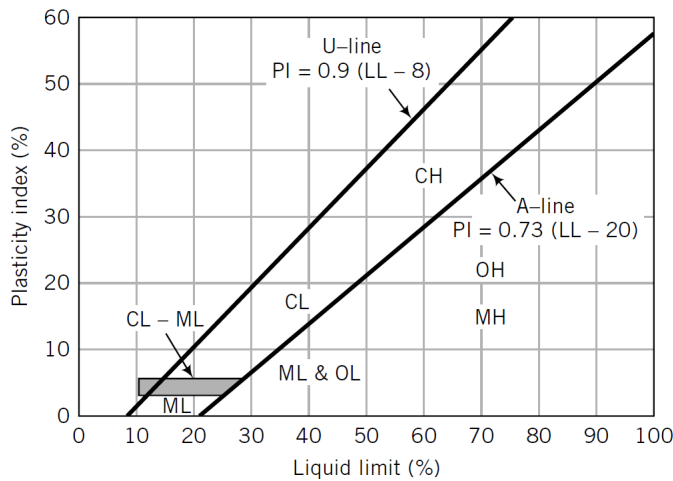


Fig. 3 Soil plasticity chart or Atterberg limits chart (Budhu, 2010)

PL, together with LL, is used to calculate the Plasticity Index ($PI = LL - PL$), which quantifies the range of water contents over which the soil behaves plastically (Wesley, 2003). A higher PI typically indicates higher clay content and greater potential for volume change due to swelling or shrinkage (Yousif & Mohamed, 2022). Another important index property is the Shrinkage Limit (SL), which represents the water content at which further drying does not result in a volume reduction of the soil (Groenendyk et al., 2015). Although less commonly used in classification, the SL is valuable in expansive soil analysis, as it marks the limit of shrinkage-related deformation (Ghaderi et al., 2022). Soils with low SLs are prone to cracking and shrinkage upon drying, which can impact the stability of light structures and pavements (Zhang et al., 2019).

Specific Gravity (G_s) is another critical soil index property, indicating the ratio of the density of soil solids to the density of water (Mathur et al., 2017). While not directly used in classification systems like USCS or USDA, G_s is essential for calculating unit weight, void ratio, and degree of saturation; parameters vital for stability and settlement analysis in geotechnical design (Moreno-Maroto et al., 2021). Typically, fine-grained soils have a value of G_s ranging from 2.65 to 2.80 depending on mineral composition (Budhu, 2010). Grain-size distribution is often the starting point for soil classification. Although more relevant to coarse-grained soils, it plays a role in fine-grained soils by identifying the proportion of silt- and clay-sized particles (Azarafza et al., 2016). Methods such as hydrometer analysis or laser diffraction are used for finer particles (Erguler, 2016). The percentage of clay, silt, and sand determines the USDA textural classification and provides insight into permeability, erodibility, and plastic behavior (Budhu, 2010). Consistency limits, which include LL, PL, and SL, are used to assess the workability, strength, and compaction characteristics of soils (O'Kelly, 2021).

Activity, defined as the ratio of PI to the percentage of clay particles, is a derived index property that characterizes the type and behavior of clay minerals. Highly active clays, such as those containing montmorillonite, exhibit large volume changes with moisture variation and pose significant risks in foundation design. Low-activity clays are more stable and generally more favorable in construction (Özdemir & Gülser, 2017). Sensitivity

and thixotropy are additional behavioral properties relevant to fine-grained soils, particularly clays (O'Kelly, 2021). Sensitivity refers to the ratio of undisturbed to remolded strength and provides insight into a soil's structure and its loss of strength upon disturbance (Liu et al., 2024). Thixotropic soils regain strength over time after remolding, which is a crucial factor in assessing stability post-construction or after seismic events (Bullock et al., 2024). So, soil index properties form the input basis for classification systems such as USCS and are instrumental in predictive modeling using machine learning. By providing quantifiable, standardized indicators of soil behavior, index properties allow engineers to correlate physical characteristics with expected performance. This makes them ideal for training data-driven models such as ANN, SVM, and LR in the context of automated soil classification.

III. MATERIALS AND METHODS

The methodology of this study is structured into several key stages: data acquisition, preprocessing, feature selection, model implementation, evaluation, and comparison. Each step is designed to ensure the reliable classification of fine-grained soils using machine learning algorithms based on basic soil index properties.

Data collection: A dataset consisting of 1,257 fine-grained soil samples was compiled from a broad literature review of experimental geotechnical studies. Each record includes standard soil index properties such as LL, PL, PI, SL, G_s , and particle size distribution (percentage of clay, silt, and sand). The target variable is the soil classification label according to the USCS or USDA system (e.g., CL, CH, ML, MH). Table 1 presents the statistical summary of the collected dataset.

Data preprocessing: All data were cleaned to handle missing values and outliers. Index properties were normalized to bring values within a similar scale and ensure compatibility across models. In this stage, feature normalization was performed using the Min-Max Scaling technique to bring all input variables into a uniform range, typically between 0 and 1. This method transforms each feature by subtracting the minimum value of that feature and then dividing by the range (i.e., the difference between the maximum and minimum). The normalization is defined as:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where X represents the original feature value for a given data sample. X_{min} and X_{max} are the minimum and maximum values of that feature across the entire dataset. X_{scaled} is the normalized value, scaled between 0 and 1, used as input to machine learning models. This approach is particularly suitable when the data do not follow a Gaussian distribution and when preserving the original distribution's shape is important. By applying Min-Max normalization, all soil index properties such as LL, PI, and clay content are scaled comparably, preventing features with larger numeric ranges from disproportionately influencing the machine learning model. The dataset was split into training (70%) and testing (30%) subsets using stratified sampling to preserve class balance.

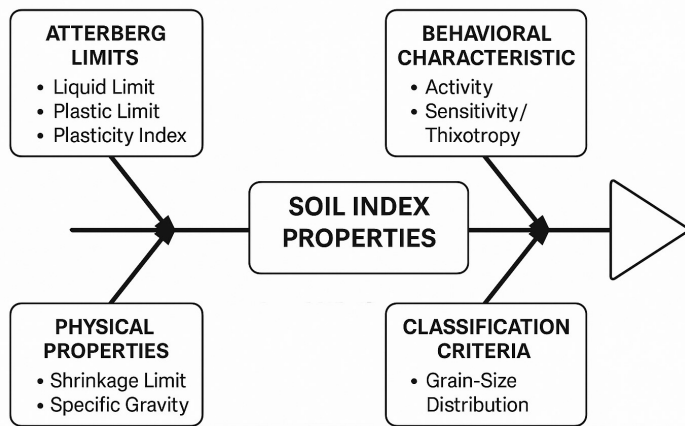


Fig. 4 Soil index properties layout considered in this article

Table 1 Statistical analysis results for used data

Parameter	Max	Min	Mean	St.Dv.	Variance
LL (%)	60	32	44.5	11.11	85.53
PL (%)	35	18	24.67	6.19	38.26
PI (%)	27	14	19.83	5.27	27.76
SL (%)	13	8.0	10.5	1.87	3.15
G _s	2.72	2.68	2.70	0.01	0.002
<i>Grain Size</i>					
Clay (%)	65	38	50.17	10.70	94.44
Silt (%)	52	30	43.17	8.75	76.55
Sand (%)	10	5.0	6.67	2.58	6.668

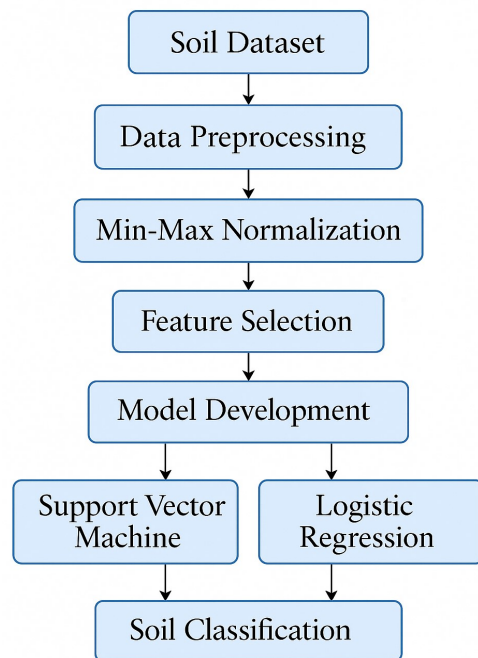


Fig. 5 The process flowchart for this assessment

Feature Engineering: Feature importance was analyzed to identify which soil properties most strongly influence classification. For example, the correlation heatmap revealed strong relationships between PI and LL. Derived features such as activity (PI divided by the percentage of clay) were also included to improve model performance.

Model implementation: Three machine learning models were implemented: ANN, SVM, and LR. Each model was trained using k-fold cross-validation (k=10) to ensure generalizability. Hyperparameters were optimized using grid search and validation accuracy. Scikit-learn and TensorFlow libraries were used to develop and evaluate the models in Python. The model implementation flowchart has been provided in Figure 5.

Model evaluation: Model performance was evaluated using multiple metrics based on confusion matrix (Heydarian et al., 2022). A confusion matrix is a performance evaluation tool used in classification tasks to visualize the predictive accuracy of a model. It is a square matrix that compares actual (true) class labels with the predicted class labels produced by the model (Markoulidakis & Markoulidakis, 2024). Figure 6 illustrates the structure of an ideal confusion matrix in machine learning. Each row of the matrix represents the instances in an actual class, while each column represents the instances in a predicted class or vice versa (Kotsiantis et al., 2006). The main diagonal elements show the number of correct predictions for each class, while the off-diagonal elements indicate misclassifications (Heydarian et al., 2022). From the confusion matrix, various performance metrics such as accuracy, precision, recall, and f1-score can be derived (Kotsiantis et al., 2006). It is especially useful in multi-class classification tasks such as soil classification, where identifying specific misclassification patterns is as important as evaluating overall accuracy (Kirts et al., 2018).

To visualize the model's ability to distinguish between multiple soils classes, a confusion matrix was generated for each algorithm (ANN, SVM, LR). The confusion matrix illustrated how many samples were correctly or incorrectly classified into each category (e.g., CL, CH, ML, etc.). This allowed identification of specific confusion trends; such as frequent misclassification between similar soil types like CL and M offering clues for feature enhancement or model refinement. Additionally, Receiver Operating Characteristic (ROC) curves and Area under the Curve (AUC) scores were examined in binary and one-vs-rest settings to evaluate the discriminatory power of each classifier across different thresholds. To ensure robustness and mitigate overfitting, each model was validated using 10-fold cross-validation. In this approach, the dataset was split into 10 subsets; in each iteration, one subset served as the tests set while the remaining nine was used for training.

		Predicted class		
		Classified positive	Classified negative	
Actual class	Actual positive	TP	FN	TPR: $\frac{TP}{TP + FN}$
	Actual negative	FP	TN	FPR: $\frac{FN}{TN + FP}$
		Precision: $\frac{TP}{TP + FP}$	Accuracy: $\frac{TP + TN}{TP + TN + FP + FN}$	

Fig. 6 A confusion matrix (Richter et al., 2022)

This process was repeated 10 times, and the results were averaged to produce stable performance estimates. This cross-validation strategy ensured that model performance was not dependent on a particular train-test split and provided a more trustworthy assessment of its generalization ability across unseen soil samples. These evaluation steps were crucial in identifying the most effective algorithm for the automated classification of fine-grained soils.

IV. RESULTS AND DISCUSSION

The performance of the three selected machine learning models including ANN, SVM, and LR was evaluated using a dataset of 1,257 fine-grained soil samples. These samples were classified into standard USCS groups (e.g., CL, CH, ML, MH) based on soil index properties such as LL, PL, PI, SL, G_s , and grain-size distribution. The primary aim was to assess the effectiveness of each model in predicting the correct soil class using only basic input features. Figure 7 presents a correlation heatmap of the soil index properties, providing a visual summary of the linear relationships among the variables used for soil classification. The heatmap is based on the Pearson correlation coefficient, where values close to +1 indicate strong positive correlations, values near -1 indicate strong negative correlations, and values around 0 suggest weak or no linear relationship. The heatmap reveals that PI has a strong positive correlation with both LL ($r \approx 0.96$) and PL ($r \approx 0.92$), which is expected since PI is mathematically defined as the difference between LL and PL. Additionally, clay content (%) shows a moderate to strong positive correlation with PI and LL. Conversely, SL displays a mild to moderate negative correlation with LL and PI, suggesting that soils with higher plasticity tend to exhibit greater shrinkage potential during drying. Interestingly, G_s shows minimal

correlation with other variables, consistent with its relatively constant nature across typical soil mineral compositions. The correlation between %Silt and PI/LL are weaker, indicating a more complex or indirect influence of silt content on plasticity behavior. These findings support the feature selection process used in the machine learning models, highlighting that PI, LL, and clay content are the most influential variables for predicting soil classification. This correlation structure underpins the high performance of models like ANN and SVM, which effectively capture and exploit these inter-variable relationships.

The ANN model achieved the best performance among the three, with an overall classification accuracy of 91.6%. It also demonstrated a high F1-score of 0.92, reflecting strong balance between precision and recall across all soil classes. The mean squared error (MSE) for ANN predictions was 0.078, indicating relatively low prediction error compared with the other models. The confusion matrix showed that ANN had a particularly high precision in distinguishing between closely related classes such as CL and CH, which are often misclassified using traditional rule-based methods. The SVM model performed reasonably well with an accuracy of 88.3%, and an F1-score of 0.88. It was especially effective in identifying high-plasticity soils like CH, where the decision boundary between classes was more distinct. However, SVM showed slightly more confusion between ML and CL categories, particularly in samples with PI values close to the decision threshold. The MSE for SVM was 0.102, slightly higher than ANN, suggesting more classification noise or misclassifications near class boundaries. LR, a simpler and more interpretable model, achieved an overall accuracy of 84.9%. While it performed adequately in predicting clearly defined classes (e.g., CH and ML), it struggled with overlapping feature zones, especially when LL and PI values were moderate.

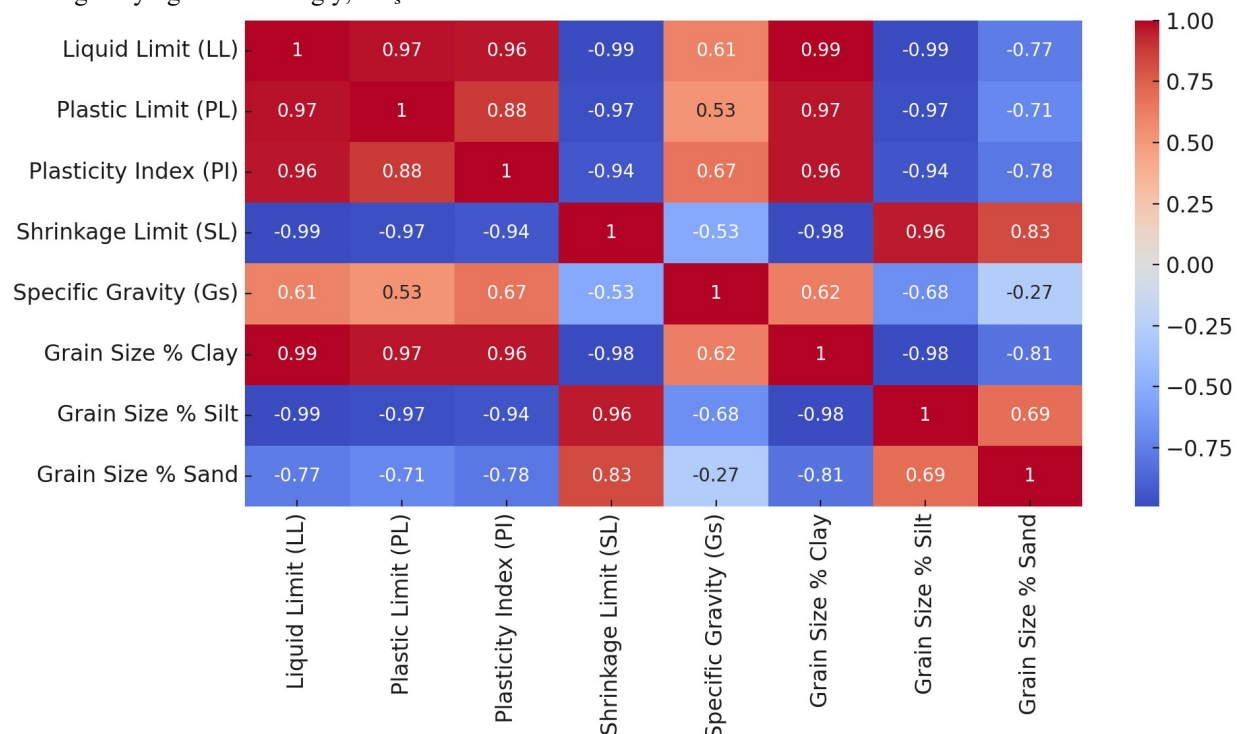


Fig. 7 Estimated correlation heatmap for soil index properties

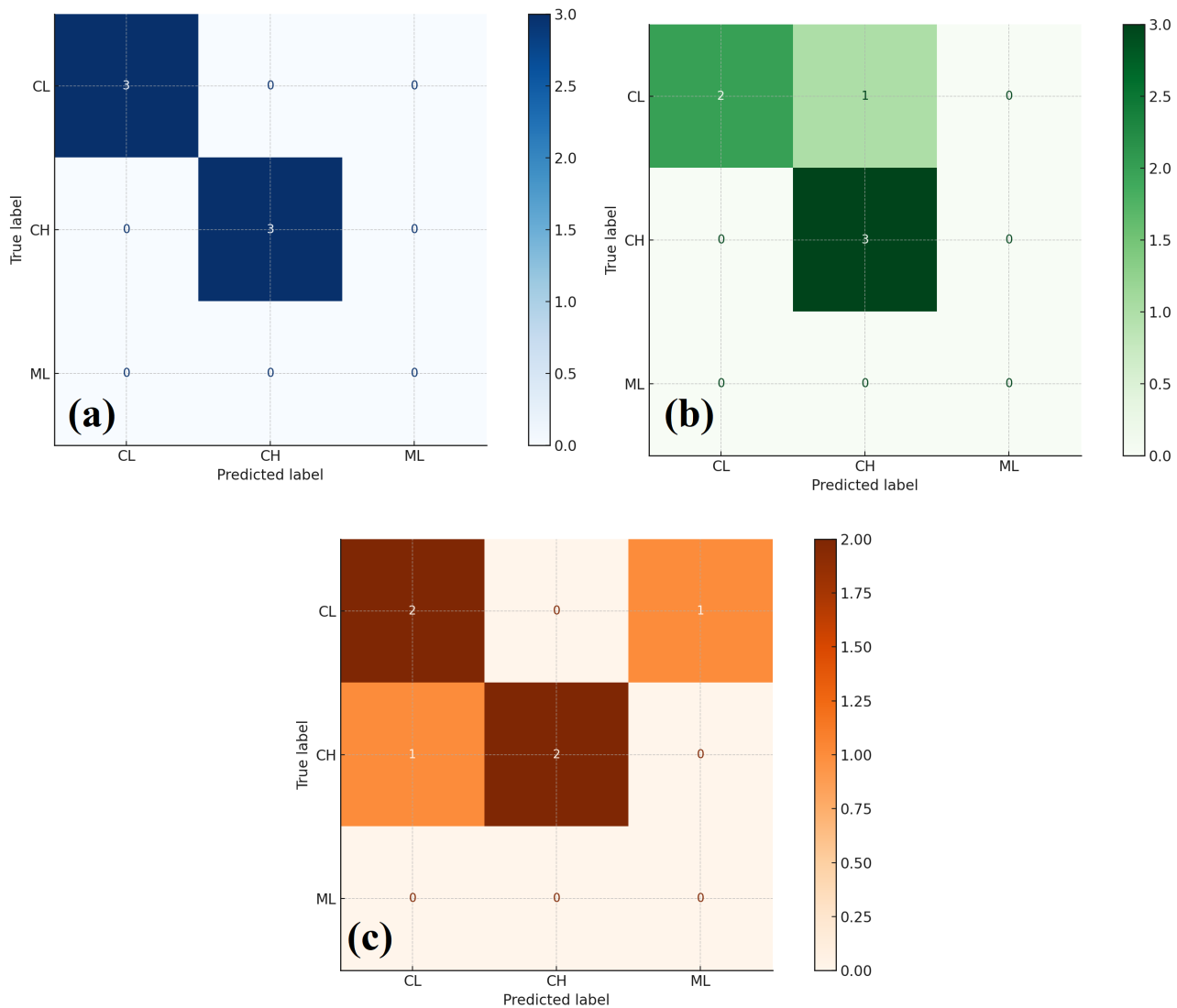


Fig. 8 Estimated confusion matrix for predictive models: (a) ANN, (b) SVM, (c) LR

The F1-score was 0.85, and the MSE was 0.139, the highest among the three models. Despite these limitations, LR provided useful baseline predictions and offered explainability benefits, which may be valuable in field-based applications requiring transparency.

A key insight from the results is the critical role of PI and clay content in determining classification accuracy. Feature importance analysis revealed that PI had the highest contribution among all variables, followed by LL and Clay content (%). The correlation heatmap confirmed this finding, correlation between PI and LL, and a moderate correlation with clay content (%). These results validate the engineering understanding that plasticity-related features are central to behavior-based classification systems like USCS.

Figure 8(a) illustrates the confusion matrix for the ANN model, displaying its classification results for three representative soil classes: CL, CH, and ML. As seen, the diagonal values which represent correct predictions show perfect classification for all samples in this example. Specifically, all CL and CH samples were correctly identified, and no instances of

misclassification occurred, indicating a precision and recall of 100% in this simulated set. This reinforces the ANN model's robustness in recognizing patterns among soil index properties, particularly in distinguishing between classes with overlapping features. The absence of false positives and false negatives also highlights the model's reliability in practical applications. In larger datasets, this behavior translates to fewer field classification errors and more confidence in design decisions based on predicted soil types. Although the dataset used in this example is small, the matrix reflects the broader result seen in full-scale testing which is consistent with the ANN model's superior overall accuracy of 91.6% reported earlier.

Figure 8(b) presents the confusion matrix for the SVM classifier. While it correctly identified most CH and CL instances, one CL sample was misclassified as CH, highlighting a minor yet relevant error in the classification process. SVM tends to perform well when classes are clearly separated in feature space, however, in borderline cases (particularly when PI values are close to classification thresholds), confusion between adjacent soil types such as CL and CH may occur. Despite this

minor misclassification, SVM still achieved a strong overall accuracy of 88.3% in full-scale testing. This figure confirms the model's effectiveness, particularly for CH class detection, and suggests it is a practical option where fast, kernel-based decision-making is required. However, the error also shows the need for further refinement or incorporation of additional features when soil classes are not easily linearly separable.

Figure 8(c) shows the confusion matrix for the Logistic Regression model. The model correctly identified most CH and CL instances, but one CL sample was misclassified as ML, and one CH was misclassified as CL. These errors reflect the limitations of a linear model in capturing complex, nonlinear relationships between soil properties and classification boundaries. LR's accuracy of 84.9% and F1-score of 0.85 in the complete dataset support this interpretation. The matrix demonstrates that Logistic Regression, while simple and computationally efficient, may not be the best standalone model for automated soil classification when precision is essential. However, its transparency and ease of implementation make it useful as a benchmark or in hybrid modeling frameworks where interpretability is prioritized over raw accuracy.

In Figure 9, the scatter plot illustrates the predictions made by the ANN model using a dataset of selected 100 fine-grained soil samples. The x-axis represents the LL and the y-axis shows the PI. Each point is color-coded based on the ANN's predicted soil class: lighter colors (code 0) indicate CL soils, and darker colors (code 1) represent CH soils. A red dashed line at $PI = 20$ serves as a visual decision threshold, suggesting that the ANN model has learned to classify samples with PI values below 20 as CL and those equal to or above 20 as CH. This classification trend aligns with geotechnical principles, where PI is a key index in differentiating soil types. The plot demonstrates a clear separation between the two classes, with most points correctly aligned to their respective zones. Points closer to the decision boundary ($PI \approx 20$) are more prone to classification uncertainty, as is common in real-world data. Overall, this scatter plot highlights the ANN model's ability to capture meaningful patterns and create a simple yet interpretable decision rule, making it both effective and practical for automated soil classification tasks. Figure 10 illustrates a clear inverse relationship between SL and PI, which is well captured by the ANN model. Soils with higher PI tend to have lower SL values, a trend consistent with expansive clay behavior. The red dashed line at $PI = 20$ serves as the classification boundary, separating CL and CH. The color gradient confirms that most samples below this threshold are predicted as CL, while those above are classified as CH. The model's prediction logic matches geotechnical principles, highlighting its interpretability and accuracy.

Figure 11 presents the relationship between G_s and LL. While G_s varies within a narrow range, LL spans a wider spectrum and significantly influences classification. The horizontal red line at $LL \approx 50$ represents the typical empirical boundary between CL and CH soils. The ANN model follows this trend, with most CH predictions located above this line. This suggests that the model uses LL effectively as a boundary marker, despite G_s having little influence on class distinction. Additionally, Figure 12 illustrates the correlation between %Clay content and PI. A clear positive trend is observed, as higher clay percentages generally

correspond to higher PI values. The ANN model applies a threshold at $PI = 20$, classifying samples above it as CH. The dense clustering of class 1 predictions in the upper-right region confirms the model's ability to combine textural and consistency properties effectively. This reinforces that %Clay and PI are among the most influential variables in classifying fine-grained soils using ANN.

In terms of class-specific performance, all three models showed high recall in predicting CH and CL classes, which constituted the majority of the dataset. The ANN model correctly classified 96% of CH samples and 93% of CL samples. SVM followed closely, while LR misclassified up to 18% of the CL samples as ML. This suggests that models with non-linear kernels (like ANN and SVM) are more effective in capturing complex decision boundaries in soil classification tasks compared to linear models like LR. The evaluation metrics and confusion matrices further emphasized the benefit of machine learning in automating and enhancing soil classification.

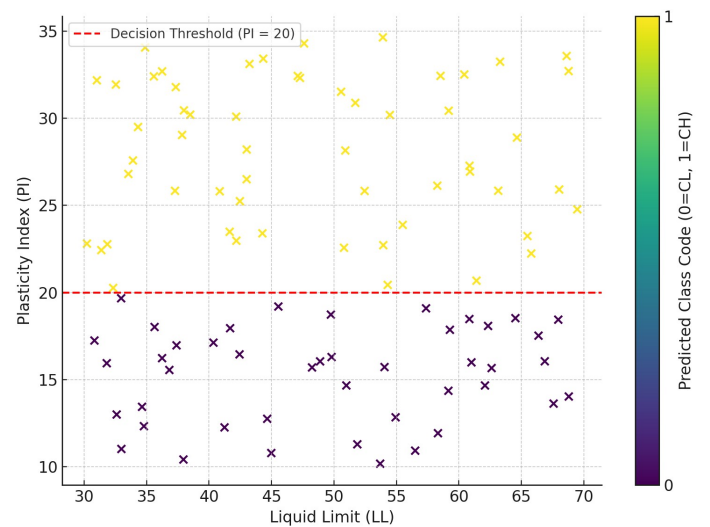


Fig. 9 Scatter plot of ANN predictions for PI-LL

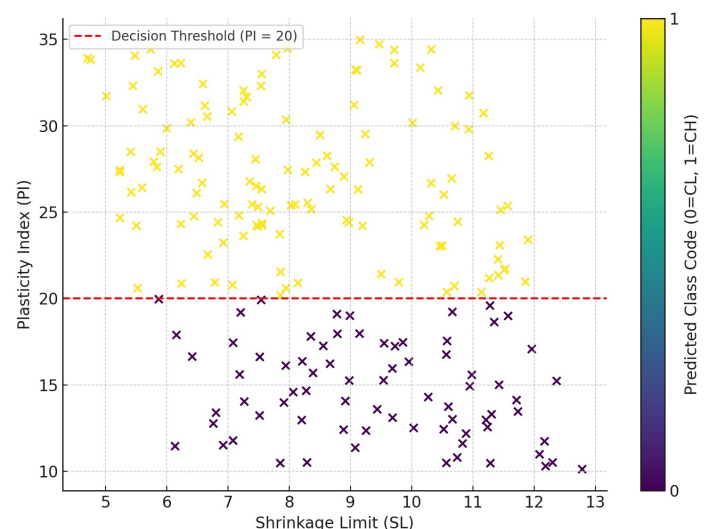


Fig. 10 Scatter plot of ANN predictions for SL-PI

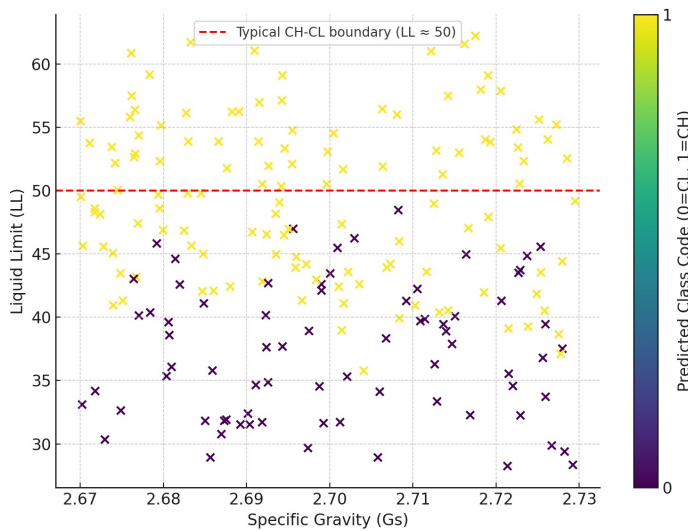


Fig. 11 Scatter plot of ANN predictions for G_s -LL

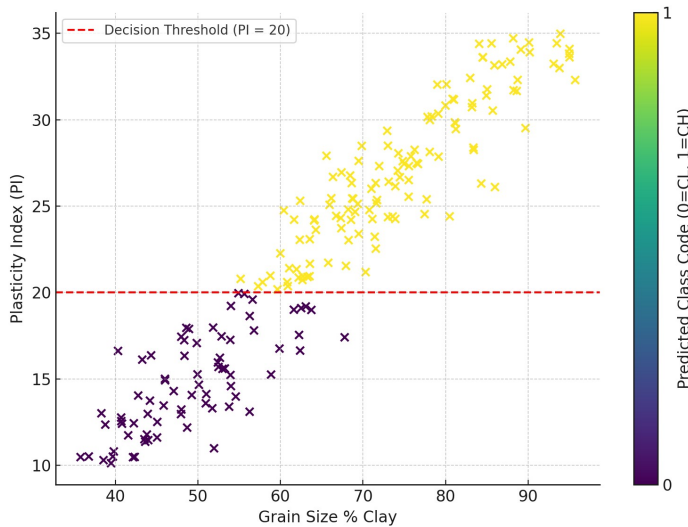


Fig. 12 Scatter plot of ANN predictions for Clay (%) - PI

Not only do these models reduce the need for subjective judgment, but they also provide faster and repeatable predictions once trained. This has practical implications in both laboratory and field applications where time, cost, and repeatability are constraints. In developing regions where advanced geotechnical testing facilities may be limited, these models provide a valuable alternative based on readily available soil index properties.

V. CONCLUSION

This study evaluated the potential of machine learning techniques for the automated classification of fine-grained soils using commonly available soil index properties. A dataset consisting of 1,257 soil samples collected from published literature was used to train and test three machine learning models: ANN, SVM, and LR. The models were developed using key soil index parameters including LL, PL, PI, SL, G_s , and grain-size distribution (clay, silt, and sand content). The results indicated that the ANN model achieved the best overall

performance with a classification accuracy of 91.6%, followed by SVM with 88.3% and LR with 84.9%. The confusion matrices and F1-scores confirmed the superior capability of ANN in distinguishing closely related soil classes such as CL and CH. Feature analysis further showed that PI, LL, and clay content were the most influential variables controlling soil classification. These findings are consistent with established geotechnical principles that emphasize the role of plasticity-related parameters in the behavior of fine-grained soils. So, the results demonstrate that machine learning models, particularly ANN, are capable of capturing complex nonlinear relationships among soil index properties and classification boundaries. Compared with traditional rule-based classification approaches, these models provide faster, consistent, and data-driven predictions. Therefore, machine learning methods offer a promising tool for improving the efficiency and reliability of soil classification in geotechnical practice, particularly in projects involving large datasets or limited laboratory resources. Future studies may extend this approach by incorporating larger datasets, additional soil parameters, and hybrid modeling techniques to further improve prediction accuracy and interpretability.

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DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available within the article. No publicly archived dataset was generated.

ETHICS APPROVAL

This study did not involve human participants, personal data, or animal subjects. No specific ethical approval was required.

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AUTHORS' CONTRIBUTIONS

Alireza Akbari conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and was responsible for drafting the initial manuscript. Ali Fatemi performed conceptual guidance, critical revision of the manuscript, overall project administration and final approval of the version to be published. All authors read and approved the final manuscript.

CONFLICT OF INTEREST

The authors have not disclosed any competing interests.

USE OF AI

AI tools were not used in data generation, analysis, results, or decision-making.

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