Development of a Streamlit-Based Deep Learning Tool for Instant Soil Classification from Borehole Grain Size Data

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Abstract:

Soil classification is an important part of geology in geotechnical engineering, because it affects the design of foundations, slope stability, and the safety of the construction site. This study presents an easy, dependable, and intelligent soil classification framework using a Multilayer Perceptron (MLP) deep learning model. Data used to train the MLP model included both real borehole grain size distributions and synthetic granular soil data, with synthetically generated data used due to the limitations of previously small datasets in terms of size. Inputs included percentages of gravel, sand, and fines, metrics for grain size such as D10, D30, D50, and D60, and Gs. The MLP model was developed to classify soil according to the Unified Soil Classification System (USCS).MLP model training was monitored using a loss curve, while performance evaluation utilized a confusion matrix, with precision, recall, and F1-score metrics being evaluated on a class-by-class basis so the assessments of classification accuracy can be robust. The proposed classification method showed high performance in soil classification during the entire USCS, thus offering geotechnical engineers an alternative to the slow, manual soil classification techniques that may be fallible due to human error.To improve ease of access and use, a website based platform through Streamlit was developed to allow geotechnical engineers to input grain size data, obtain soil types, and visualize performance in real time. This tool is designed to eliminate mistakes, allow for fast analysis, and advance data-driven decisions in geotechnical investigations.

Keywords*: Soil Classification, Deep Learning, Streamlit Application, Grain Size Distribution,USCS system.*

INTRODUCTION

Soil classification is vital within geotechnical engineering and it has significant implications on the design, safety and viability of construction (Coduto et al., 2011). Past soil classification systems like the Unified Soil Classification System (USCS) involve manual calculations and laboratory testing with significant time requirements and often an element of inconsistency (*Standard Practice for Classification of Soils for Engineering Purposes (Unified Soil Classification System)*, n.d.). Artificial intelligence has evolved, and in recent years deep learning has emerged as a promising area of development which might help automate soil classification using borehole grain size distribution and specific gravity data (Shahin et al., 2001). This study will train a Multilayer Perceptron (MLP) neural network utilizing both actual data and synthetically generated data to improve accuracy and robustness(Kim, 2016) .The model will be utilized within a Streamlit based web app where engineers can enter soil parameters and receive USCS classification immediately (*Streamlit Documentation*, n.d.). Specific research questions of interest are: the potential of deep learning with limited geotechnical data, how synthetic data does influence the model, and relevant soil parameters in terms of classification (Basheer & Hajmeer, 2001).The research tool seeks to address the problems described above and improve on using soil classification processes by improving the speed, consistency, and accessibility of soil classification. This has been shown to provide significant advantages for engineers, especially in regional areas with limited testing laboratories or limited time (Liu et al., 2024).

LITERATURE REVIEW

Soil classification remains an essential component of geotechnical engineering, but traditional systems of classification such as the USCS requires manual tests and professional judgement, making the processes timely and potentially inconsistent. With the advancement of deep learning and AI, more studies are being published demonstrating how neural networks can classify soils in an automated fashions by utilizing grain size and geotechnical data. Additionally, the development of platforms such as Streamlit provide engineers with a means to deploy these models as interactive web applications, making the tools for soil classification increasingly available and user friendly for engineers in the field and laboratory. This article reviews select items of recent progress on AI based soil classification and its deployment onto a real-time web platform.

One the prior research integrates borehole data with Cone Penetration Test with pore pressure (CPTU) measurements to enhance the accuracy of soil classification. It also tackles the issue of noisy and inconsistent data, enabling more reliable and robust soil characterization across varied geotechnical contexts.("Machine Learning-Enhanced Soil Classification by Integrating Borehole and CPTU Data with Noise Filtering," 2021) Advanced deep learning algorithms are implemented to automate the classification of soil types, and their performance is evaluated using detailed metrics that measure how well the models can distinguish between different soil categories.(*A Study on Deep Learning Based Soil Classification*, 2022) A comprehensive review of computer-based approaches highlights the evolution of soil classification techniques. Special attention is given to image processing and machine learning strategies, which contribute significantly to automated and scalable classification methods.("Soil Identification and Classification Using Machine Learning," 2022) While traditional rule-based methods can interpret simpler borehole images effectively, deep learning models show superior performance in analyzing and understanding complex subsurface image data, offering improved classification accuracy.("Soil Identification and Classification Using Machine Learning," 2022) Machine learning models like neural networks have achieved up to 75% accuracy in identifying sand particles, whereas convolutional neural networks (CNNs) in deep learning frameworks have demonstrated 64% accuracy in the same task, indicating different strengths of each model.(*Deep Learning Algorithms Based Approach for AI Derived Borehole Images Automatic Interpretation*, 2023) Grain recognition can be performed using either conventional physical measuring tools or modern computational approaches. A newly developed and balanced dataset also addresses the scarcity of mineral classification data, aiding in more accurate predictions.("Classification of Sand Using Deep Learning," 2023) Soil grain sizes are broadly categorized into four groups—gravel, sand, silt, and clay. In addition, past geological investigations, such as those conducted in the Baikouquan Formation, have successfully identified different types of rocks using such classification systems.("Deep-Learning-Based Automatic Mineral Grain Segmentation and Recognition," 2022) In a study by Xu et al., machine learning techniques were used to predict Tunnel Boring Machine (TBM) penetration rates. The research compared models like gradient boosting, decision trees, and support vector machines (SVM) to determine the most effective predictor.("A Grain Size Auto-Classification of Baikouquan Formation, Mahu Depression, Junggar Basin, China," 2020) Soil classification has also been explored through a combination of deep learning and spectroscopy, with results compared against traditional SVM classifiers. These studies aim to assess improvements in speed, accuracy, and applicability of advanced methods.("Soil Classification by Machine Learning Using a Tunnel Boring Machine's Operating Parameters," 2022) Earlier works focused on applying standard machine learning algorithms to classify soil types, while recent studies have tested gradient boosting techniques that demonstrated notably high classification accuracies.("Soil Classification Based on Deep Learning Algorithm and Visible Near-Infrared Spectroscopy," 2021) Conventional soil classification methods often involve time-consuming laboratory procedures and limited sampling. In contrast, remote sensing and automated data collection systems are being developed to increase efficiency and accuracy in large-scale observations.("Use of Machine Learning Techniques in Soil Classification," 2023) Although few in number, studies comparing different machine learning models for soil texture classification have shown promising results. Techniques like log-ratio transformations have also been used to correct skewness in soil particle size distribution data.(*Automated and Flexible Measuring of Grain Size and Shape in Images of Sediment with Deep Learning*, 2024) Digital soil mapping has utilized models like Multinomial Logistic Regression (MNLR) and Random Forest (RF), with classification accuracy assessed through indices such as the confusion matrix to ensure model reliability.(*Digital Mapping of WRB Soil Classes Using Linear and Non-Linear Classification-Based Machine Learning Algorithms and Integration of Confusion Index in Knowledge Discovery*, 2023) Some research has focused on identifying soil variables that directly impact crop productivity, using tools such as machine learning, deep learning, and computer vision to support agricultural decision-making through soil classification.(*Soil Classification Using Machine Learning, Deep Learning, and Computer Vision*, 2023) Machine learning and deep learning models have been applied to classify soil fertility levels. These models, when combined with IoT sensors and cloud technologies, help facilitate precise and timely decision-making in modern agriculture.(*Machine Learning and Deep Learning for Soil Analysis and Classification of Micro and Macro Nutrient Using IOT*, 2024) Various machine learning algorithms such as Decision Trees, k-Nearest Neighbors (k-NN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) have been analyzed for their effectiveness in soil classification, with results offering insights for future applications.(*Innovative Deep Learning Methods for Soil Classification and Crop Yield Prediction*, 2024) A review of twelve key research papers explored the role of deep learning models in soil classification. These works evaluate the accuracy and potential of different architectures to recommend the most effective tools for future model development.(*Advancements in Soil Classification: An In-Depth Analysis of Current Deep Learning Techniques and Emerging Trends (2023) | P. Swarnalatha | 1 Citations*, n.d.) Deep learning techniques are increasingly used for automatic classification tasks across various domains. In the context of soil classification, these methods have demonstrated strong performance and are now integral to modern data mining pipelines.("A Comprehensive Review on Soil Classification Using Deep Learning and Computer Vision Techniques," 2021) Support Vector Machine (SVM) classifiers continue to be effective with high accuracy rates in soil classification. Studies comparing traditional and advanced models offer valuable comparisons that guide future improvements in this field.("Soil Color as a Measurement for Estimation of Fertility Using Deep Learning Techniques," 2022) For borehole image analysis, several methods have been proposed to detect relevant geological features, with Hough and Radon transforms being among the most widely adopted for structural feature extraction.("Improving Accuracy of Automatic Fracture Detection in Borehole Images with Deep Learning and GPUs," 2017) A range of studies has focused on the prediction and classification of soil using both machine learning and deep learning models, allowing for a comprehensive comparison between the two approaches in terms of performance, scalability, and adaptability.("A Novel Hybrid AI Federated ML/DL Models for Classification of Soil Components," 2022)

While there have been strides in the level of soil classification using AI, there are still several shortcomings in the studies that use AI and soil classification. The shortcomings include: the inconsistency between - CPTu and borehole log data sources, noise and subjectivity in the grain size data, and the use of smaller, imbalanced datasets that impede the generalization. Many deep learning models - even more than other models - place an immense amount of stress on the required spatial preprocessing and the complexity of feature engineering to allow for upscaling. Other problems like limited model interpretability, little reproducibility, and no real-time or applicable user-interface deployment solutions for engineers make the models less useful! There is a clear divide between the models that are being developed, and the models that are developed to be used in the field.

This research addresses these limitations by using actual borehole data and synthetically produced data to whittle down and enhance the dataset to provide a stronger data for learning. In this project, a simple Multilayer Perceptron (MLP) model was employed to produce predictions of grain size characteristics as it classifies soils, which reduces the burden of preprocessing. The model was evaluated using class-based metrics, including confusion matrices, to determine its level of classification accuracy in the validation. Ultimately, the model was implemented in a streamlined web-based application that engineers can utilize to input their own data and receive real-time predictions immediately. By utilizing this integrated platform, which connects research and practice, engineers now have a tool to quickly, consistently, and accessibly provide soil classification under the Unified Soil Classification System (USCS).

Research Objectives

The aim of this study is to build a deep learning-based soil classification tool that categorizes borehole grain size distribution and specific gravity data into Unified Soil Classification System (USCS) soil types. The main objectives of the study are: (i) obtain and preprocess actual borehole data, (ii) create synthetic soil samples to improve model balance and generalization, (iii) train and validate a Multilayer Perceptron (MLP) model and evaluate it using accuracy, precision, recall, and F1-score as performance metrics, and (iv) deliver a trained model deployed via a real-time Streamlit web app that is easy for users to operate.

The study targets the reduced level of manual effort, subjectivity, and time needed to classify soils using conventional techniques. While this model is focused on granular soils, these soils are still classified within USCS. A limitation is that this model seeks only to categorize soils using non-plastic parameters. This means only focusing on particle size distribution and specific gravity (and not using Atterberg limits or plasticity-based indices). Ultimately, this study hopes to create a high-accuracy classification model that is consistent, produce some insights into feature importance, and develop an accessible decision-support tool for geotechnical engineers.

Materials and Methods Used

Methodology

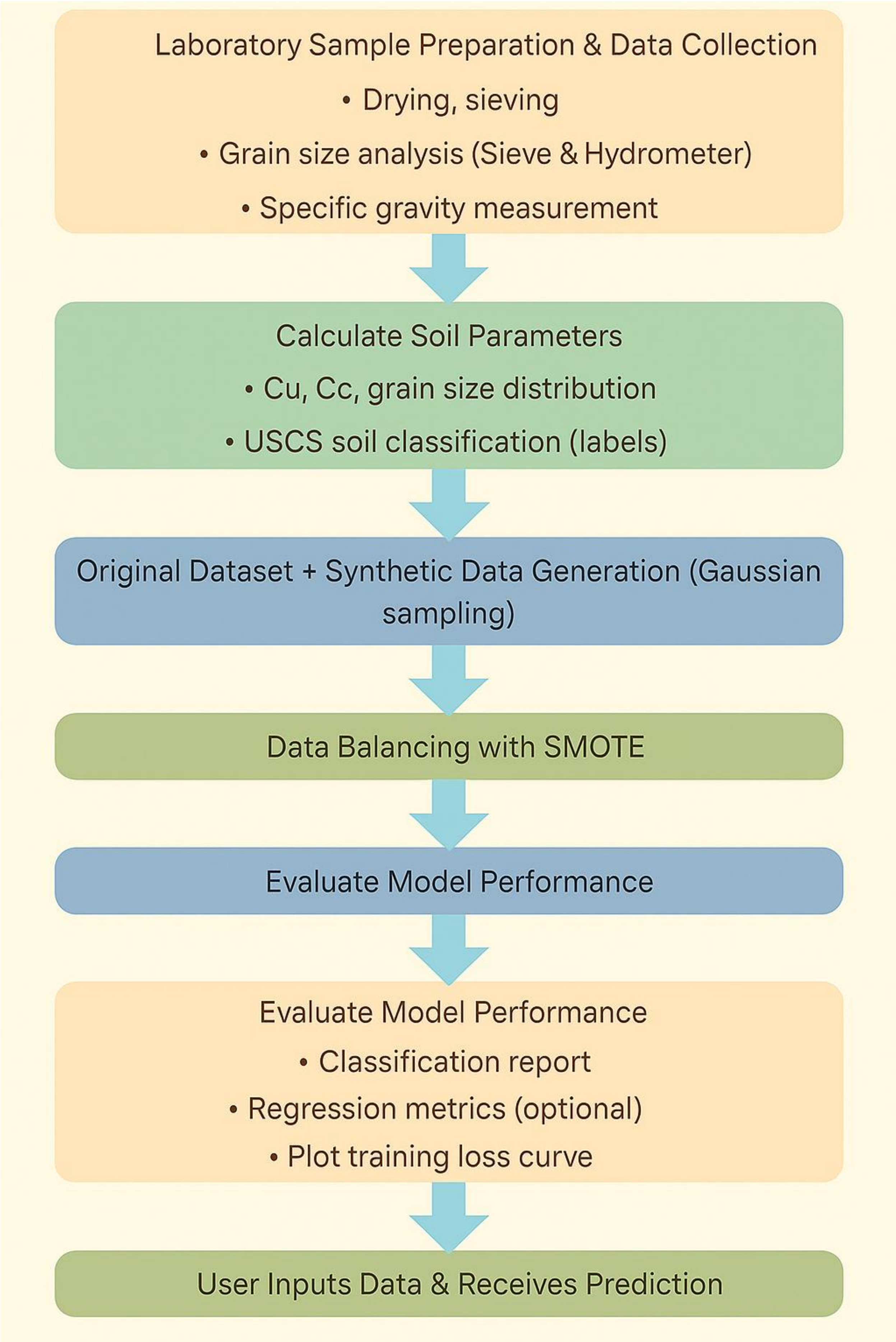


Figure 1 Methodology Flowchart

Research Design

This study utilizes a quantitative experimental research design to develop and evaluate a deep learning model for soil classification. As shown in Figure 1, the model predicts soil types based on grain size distribution and specific gravity data collected from boreholes in Arjundhara, Jhapa. To supplement limited field data, synthetic soil samples were generated. The final model was integrated into a user-friendly Streamlit web application for real-time classification, enabling practical field use.

Study Area and Human Participation

Soil samples were collected from boreholes drilled in Arjundhara, Jhapa, an area known for granular soils. Experienced field engineers and technicians conducted the drilling and sampling processes according to standard geotechnical protocols. Human involvement ensured accurate collection, labeling, and transportation of samples to the laboratory.

Data Collection Methods

1. Soil Sampling and Sample Preparation

- Soil samples were extracted at various depths from boreholes.
- Samples were carefully sealed and transported to the laboratory to prevent contamination.
- In the lab, samples were air-dried to remove moisture and then sieved to remove large debris and organic matter.
- Sieving was conducted using a standard sieve stack ranging from 4.75 mm to 0.075 mm mesh sizes, to separate particle fractions by size.

2. Grain Size Distribution Analysis

- *Sieve Analysis (ASTM D422)*: This test measures the distribution of coarser particles. Soil is passed through sieves of decreasing mesh sizes. The mass retained on each sieve is recorded and used to calculate the cumulative percent passing, generating the soil gradation curve.
- *Hydrometer Analysis (ASTM D7928)*: For particles finer than 0.075 mm, the hydrometer test was conducted. Soil suspension sedimentation rates were measured over time to quantify the percentage of silt and clay-sized particles.

3. Specific Gravity Measurement

- The **pycnometer method (ASTM D854)** was used to determine the specific gravity of soil solids. This involved weighing a known volume of soil and comparing it to an equal volume of water, helping assess soil density and behavior under loading.

4. Calculated Parameters

- *Coefficient of Uniformity (Cu):* Calculated as D90/D10, indicating particle size range.
- *Coefficient of Curvature (Cc):* Calculated as $(D30)^2 / (D10 * D60)$, reflecting particle size distribution shape.

Soil Classification

- The Unified Soil Classification System (USCS) was employed to classify soil samples using grain size distribution and fines content data.
- Most soils were classified as well-graded sands (SW), showing good gradation and minimal fines, suitable for construction applications.

Deep Learning

1. Model Architecture

- A fully connected feedforward neural network was built using scikit-learn's MLPClassifier.
- The network consists of:
    - Input layer with 11 input features (soil grain size and index parameters).
    - Two hidden layers with 100 and 50 neurons respectively, using ReLU activation.
    - Output layer with a neuron per soil class (3 classes) using softmax internally for multi-class classification.

2. Training Configuration

- The network was trained using the Adam optimizer with:
    - A maximum of 500 iterations (epochs).
    - Early stopping enabled to prevent overfitting, monitoring validation loss.
    - A validation fraction of 20% from the training data.
    - ReLU activation for hidden layers.
- The training loss curve was monitored and used to ensure adequate convergence without overfitting.

3. Data Preparation

- The original soil dataset was augmented by generating synthetic samples using Gaussian sampling per soil class to enlarge training data.
- Features were standardized (scaled) using StandardScaler for improved neural network training.
- SMOTE (Synthetic Minority Oversampling Technique) was applied on the scaled data to balance the class distribution further.
- The combined dataset was then split into 80% training and 20% validation sets with stratified sampling.

4. Model Training and Validation

- The model was trained on the augmented, scaled, and balanced dataset.

- Validation data was used during training for early stopping.
- Training loss per iteration was recorded and plotted to verify proper training behavior.

5. Model Evaluation

- The model's predictions on the validation set were evaluated using:
    - Classification report including precision, recall, F1-score, and support for each soil class.
    - Regression metrics (R^2, MAE, MSE) were optionally calculated by treating class labels as numeric values to quantify prediction errors.
- The training loss curve was visualized to monitor convergence and detect possible overfitting.

Streamlit Web Application Development

1. Application Purpose

- To translate the trained deep learning model into a practical tool for engineers and technicians, enabling quick soil classification in field or office settings.

2. User Interface Design

- Interactive numeric input fields were created for each soil parameter (Gravel %, Sand %, Fines %, D10, D30, D50, D60, Cu, Cc, Gs).
- A 'Predict' button triggers model inference.

3. Backend Processing

- Input data from the UI is processed with the same StandardScaler instance used in model training to maintain consistency.
- The processed inputs are fed into the pre-trained neural network model to predict the USCS soil class.

4. Output

- Predicted soil classification is displayed clearly on the web page.
- Users can input different soil parameters to test multiple samples in real-time.

5. Deployment

- The app is run locally using the command streamlit run app.py within a Conda environment.
- Necessary packages include Streamlit, TensorFlow, scikit-learn, pandas, and numpy.

RESULTS AND DISCUSSION

Table 1 consolidated comparison of the Seven boreholes (BH01–BH07) over the 1.5–4.5 m depth interval

Borehole	**Gravel (%)**	**Sand (%)**	**Fines (%)**	**D10 (mm)**	**D30 (mm)**	**D50 (mm)**	**D60 (mm)**	**Cu**	**Cc**	**Gs**	**USCS**
BH-1	24.1	74.8	1.2	0.22	0.48	0.90	2.00	9.09	0.52	2.50	SW
BH-2	9.8	89.1	1.0	0.30	0.50	0.70	1.00	3.33	0.83	2.70	SW
BH-3	14.0	85.4	0.6	0.20	0.32	0.60	0.80	4.00	0.64	2.50	SW
BH-4	7.5	91.6	0.9	0.20	0.40	0.60	0.90	4.50	0.89	2.50	SW
BH-5	30.0	65.0	5.0	0.15	0.35	0.50	1.50	10.00	1.00	2.60	SP
BH-6	15.0	80.0	4.5	0.25	0.45	0.60	1.80	7.20	1.10	2.65	SP
BH-7	40.0	55.0	5.0	0.10	0.25	0.40	0.70	7.00	1.20	2.55	GP

The soils Table 1 consolidated comparison of the Seven boreholes (BH01–BH07) over the 1.5–4.5 m depth interval from BH01 to BH04 are predominantly classified as well-graded sands (SW) with high sand content and minimal fines, indicating good gradation and favorable engineering behavior. BH01 and BH02 exhibit strong gradation characteristics, while BH03 suggests minor silt/clay presence. BH05 and BH06 fall under poorly graded sands (SP), with higher fines content and moderate gradation. BH07, with the highest gravel content, is classified as poorly graded gravel (GP), suggesting good drainage but low cohesion.

Model Performance Evaluation

- **Training and Validation Results:** The MLP model was trained on a balanced dataset (154 samples per class) and converged after 27 iterations. The highest validation accuracy reached was 98.65%, after which early stopping was triggered.
- **Classification Results**: On the validation set, the model achieved perfect classification performance with precision, recall, and F1-score of **1.00** for all three classes (GP, SP, SW).
- **Regression Evaluation**: Treating class labels as numeric values, the model yielded **R^2 = 1.000**, **MAE = 0.000**, and **MSE = 0.000**, indicating strong predictive reliability and no observed error.

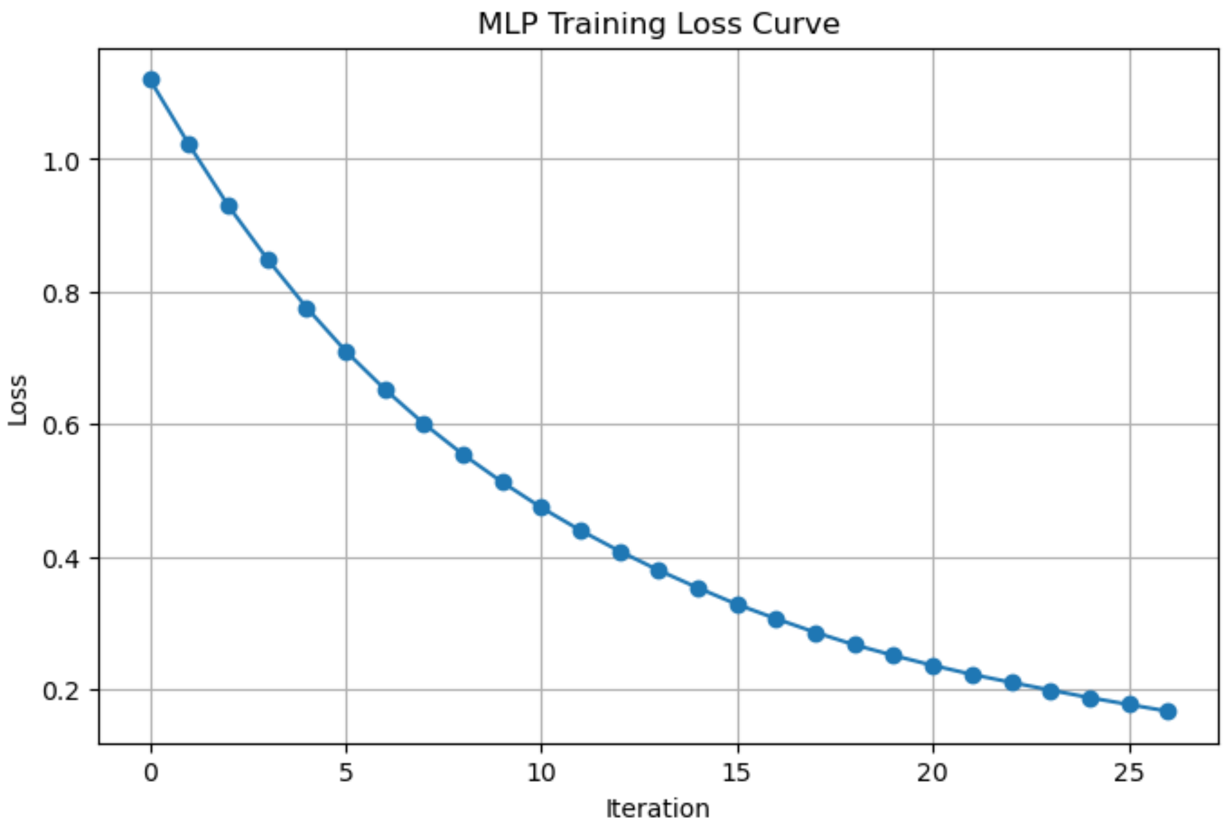


Figure 2 MLP T raining loss curve

The training progression of the MLP model is illustrated in Figure 2, which shows a steadily decreasing loss over successive iterations. This consistent decline indicates effective learning and convergence of the model. The training was halted after 27 iterations through early stopping, as no significant improvement in the validation score was observed beyond that point.

Table 2 Cross-Validation Performance

Fold	Accuracy	Precision	Recall	F1-score
1	0.9892	0.9896	0.9892	0.9892
2	0.9892	0.9896	0.9892	0.9892
3	0.9891	0.9896	0.9892	0.9892

4	0.9783	0.9792	0.9785	0.9783
5	0.9891	0.9896	0.9889	0.9891
Mean ± SD	**0.9870 ± 0.0044**	**0.9875 ± 0.0042**	**0.9870 ± 0.0043**	**0.9870 ± 0.0044**

To ensure the robustness and generalizability of the MLP model, 5-fold cross-validation was conducted. As shown in Table 2**,** the model consistently achieved high accuracy, precision, recall, and F1-score across all folds.

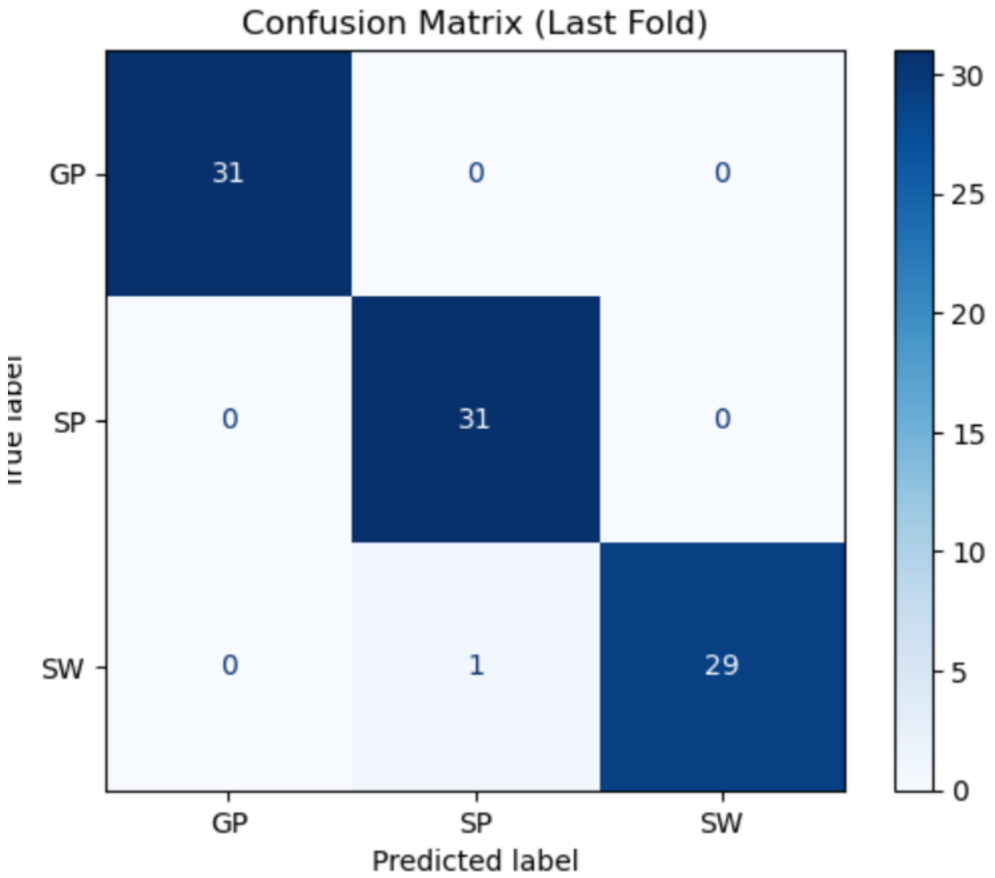


Figure 3 Confusion Matrix Last Fold

The confusion matrix for the final validation fold is presented in Figure 3, providing a clear view of the model's classification performance across all classes. The matrix shows that the MLP model correctly classified nearly all instances with minimal or no misclassifications. This further confirms the model's high accuracy and balanced performance across the soil categories.

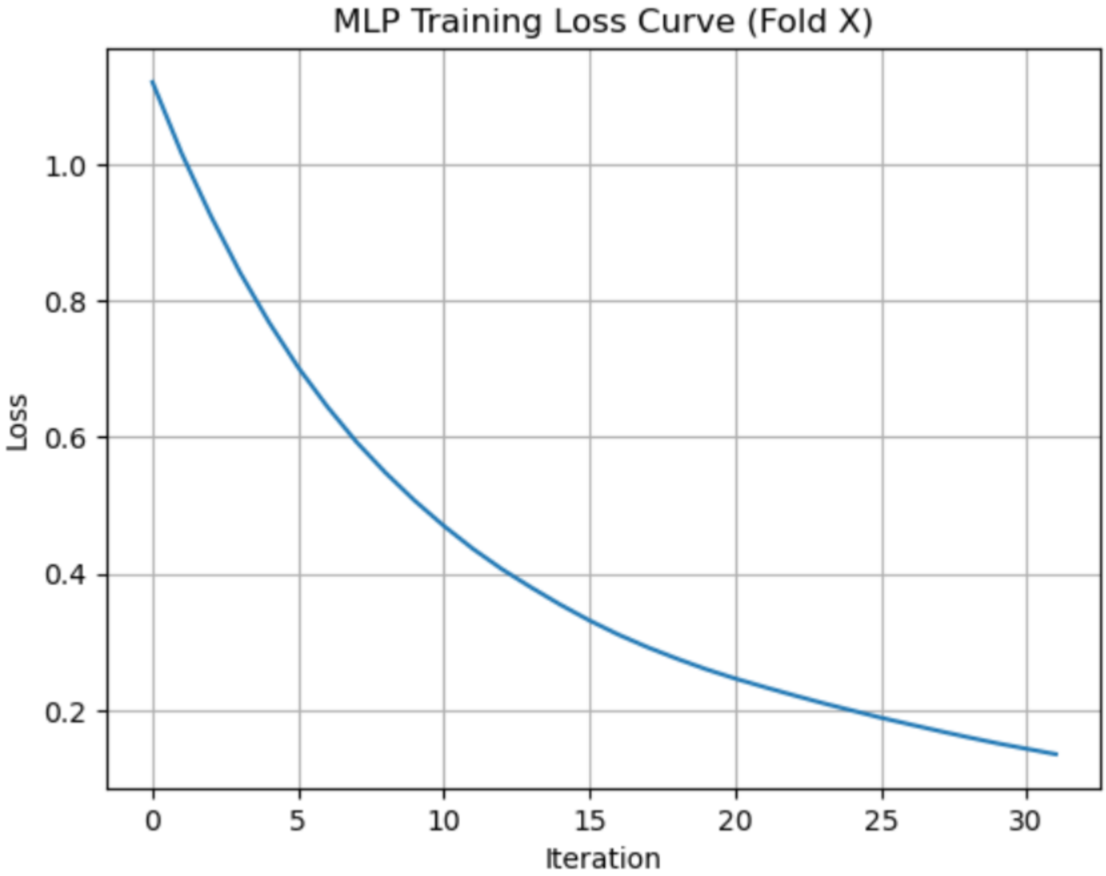


Figure 4 MLP Training Loss curve(X fold)

The training loss curve for Fold X is illustrated in Figure 4, showing a consistent decrease in loss over iterations. This trend confirms stable convergence of the MLP model during cross-validation. The smooth reduction in loss suggests effective learning without signs of overfitting.

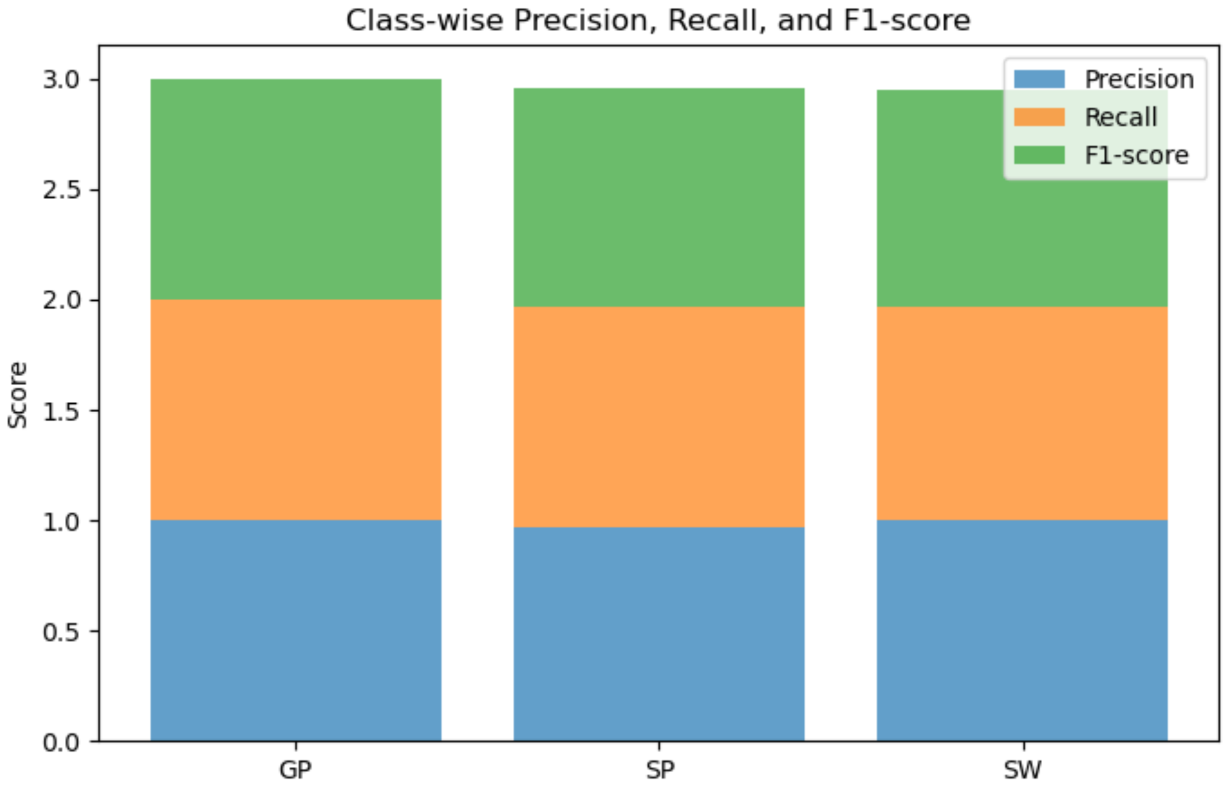


Figure 5 Classwise Precision,Recall,F-1 Score

The class-wise performance metrics are visualized in Figure 5, highlighting the precision, recall, and F1-score for each soil class. The consistently high scores across all classes reflect the model's balanced classification capability. No class shows significant performance degradation, affirming robustness and generalization.

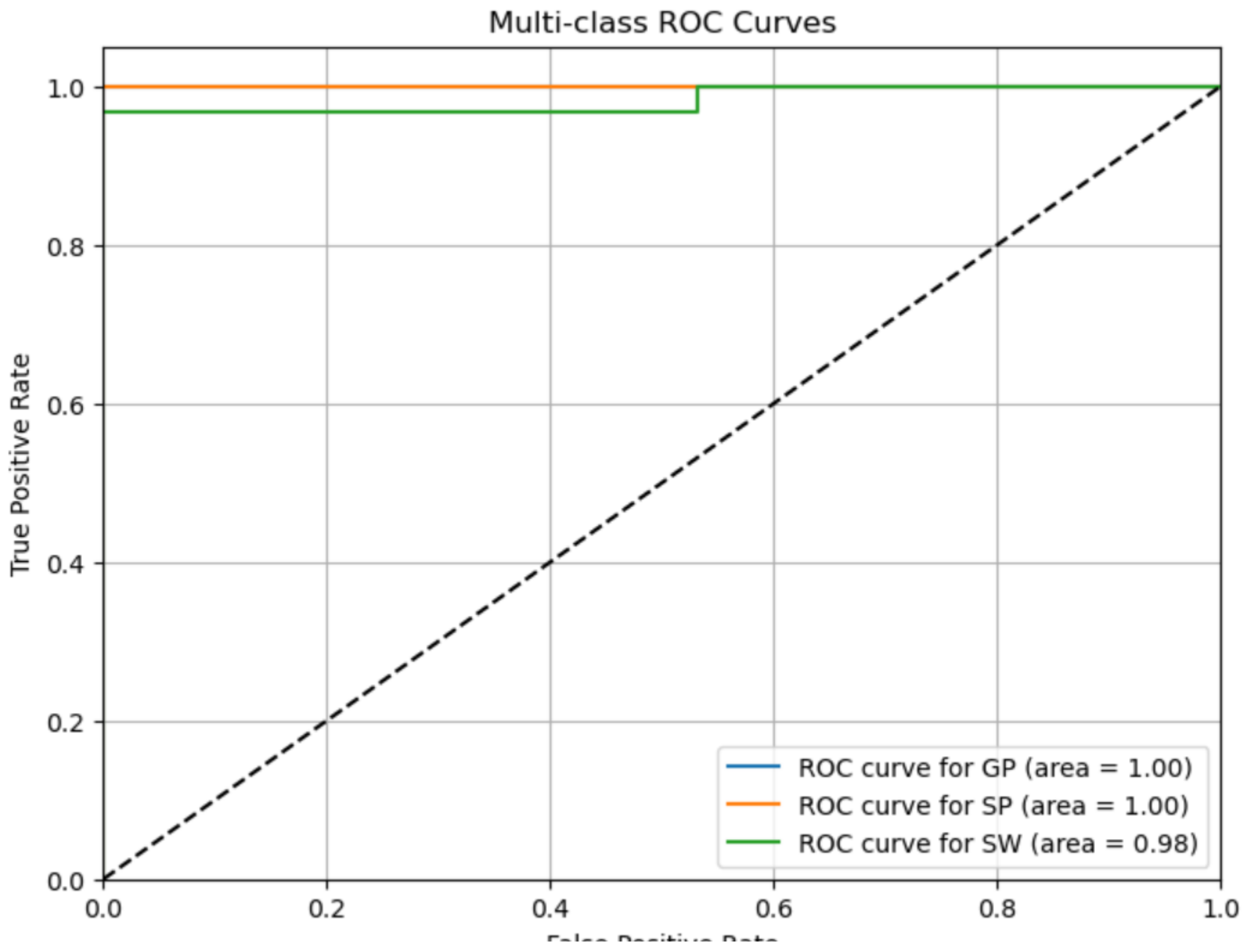


Figure 6 Multiclass ROC Curve

The multi-class ROC curves shown in Figure 6,illustrate the trade-off between true positive rate and false positive rate for each soil class. The area under the curve (AUC) values close to 1.0 indicate excellent discriminative ability of the MLP model across all categories. This confirms the model's strong predictive performance and robustness in class separation.

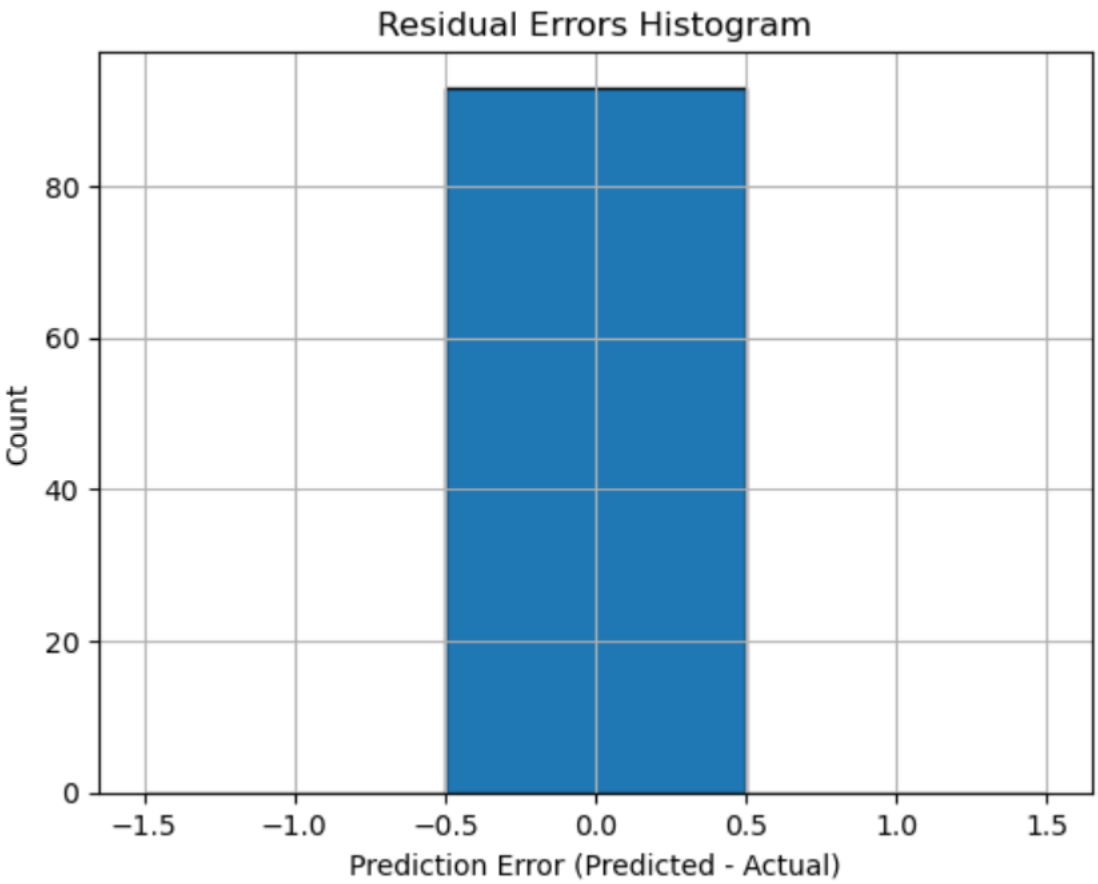


Figure 7 Residual Errors Histogram

Figure 7 displays the histogram of prediction errors, calculated as the difference between predicted and actual numeric labels. The concentration of errors near zero indicates that the model's predictions closely match true values. This low residual error distribution supports the model's high accuracy and reliability.

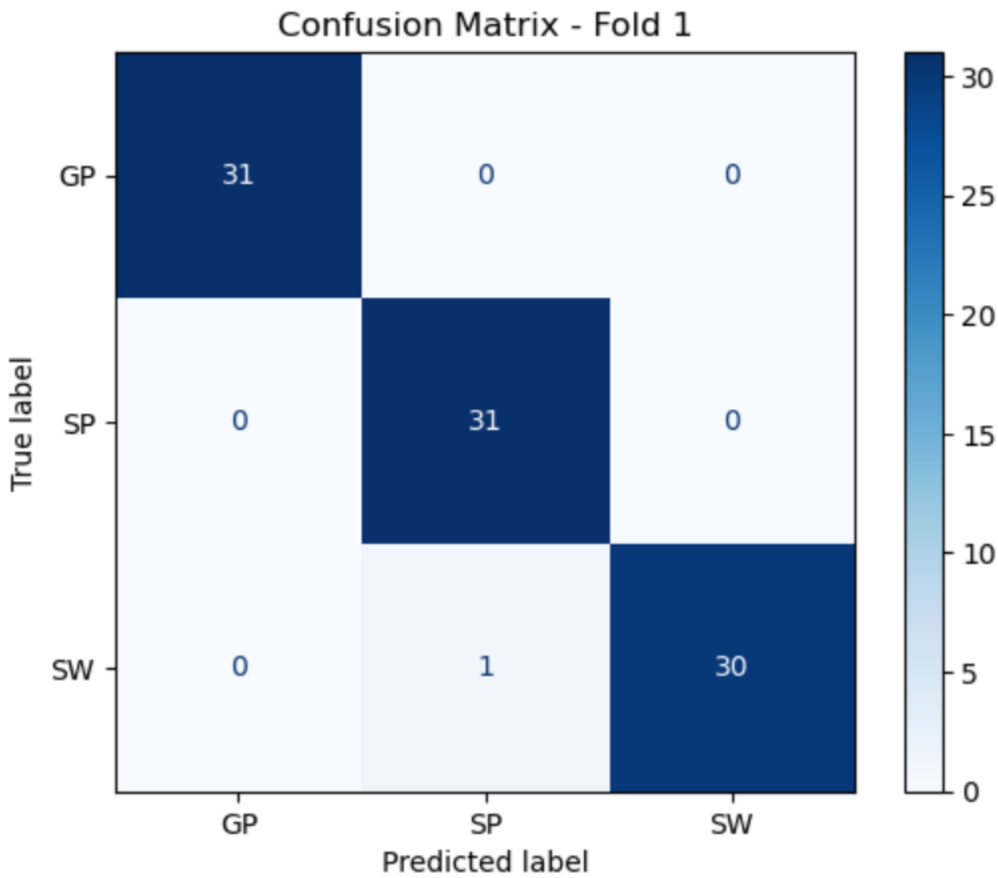


Figure 8 Confusion Matrix Fold 1

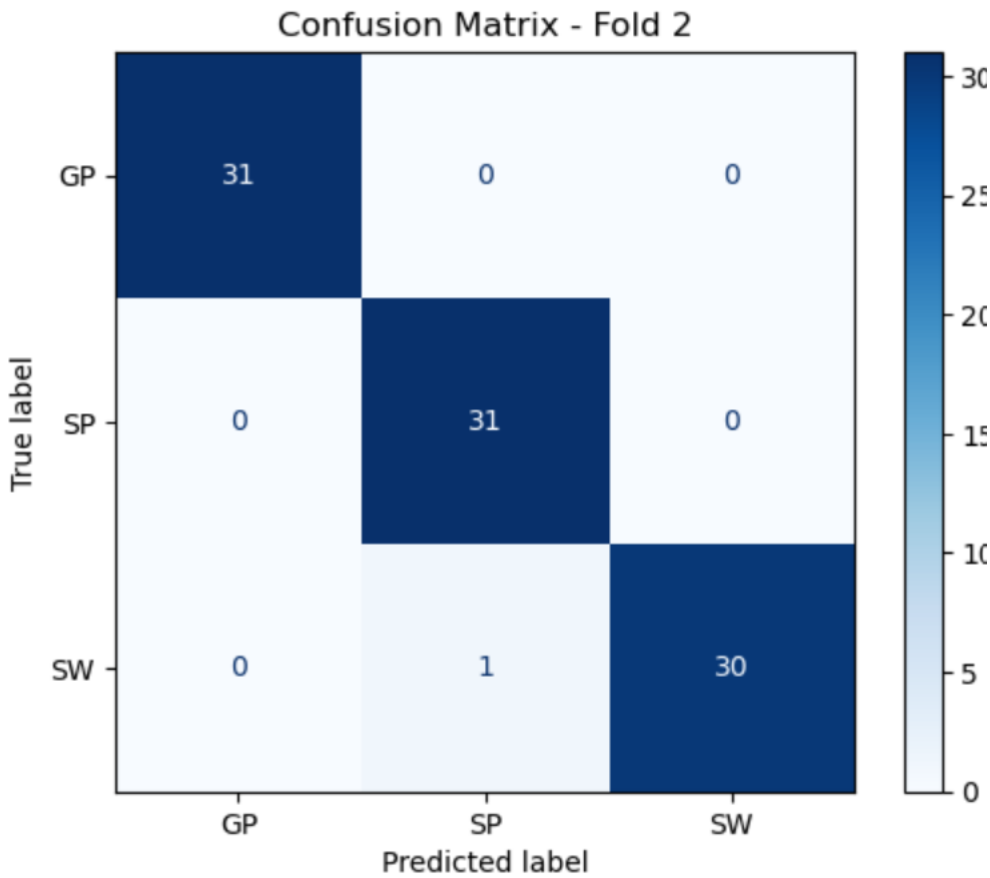


Figure 9 Confusion Matrix Fold 2

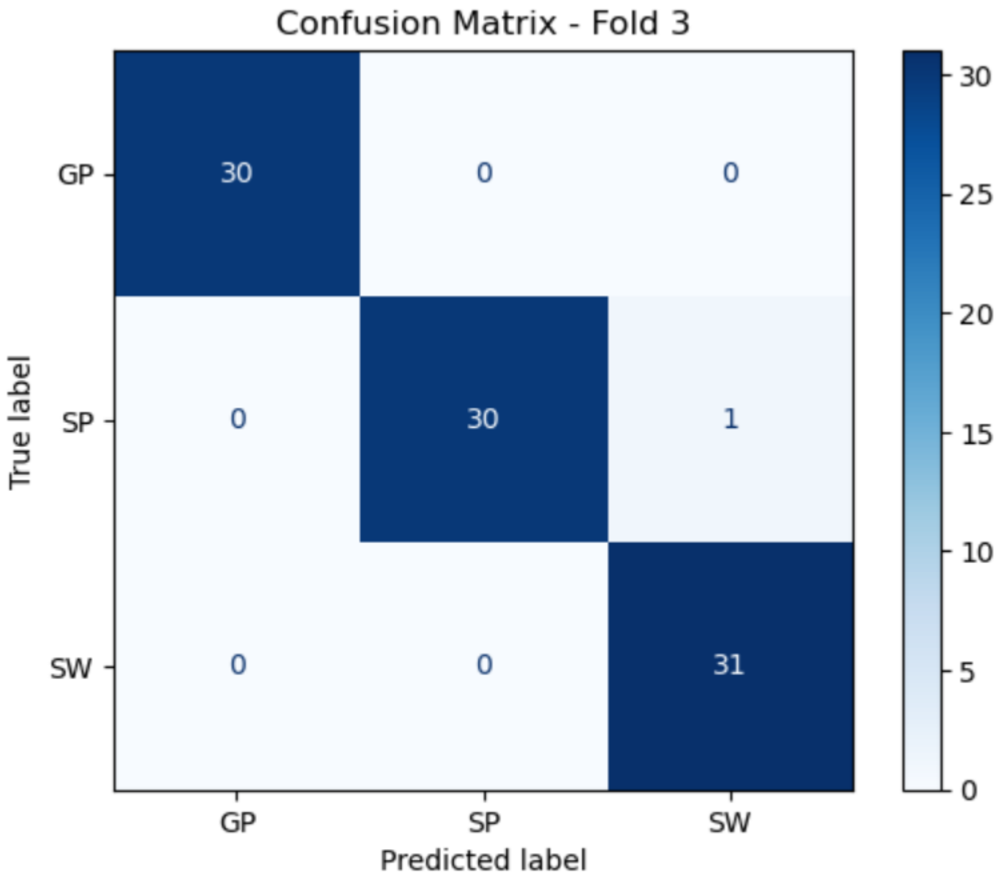


Figure 10 Confusion Matrix Fold 3

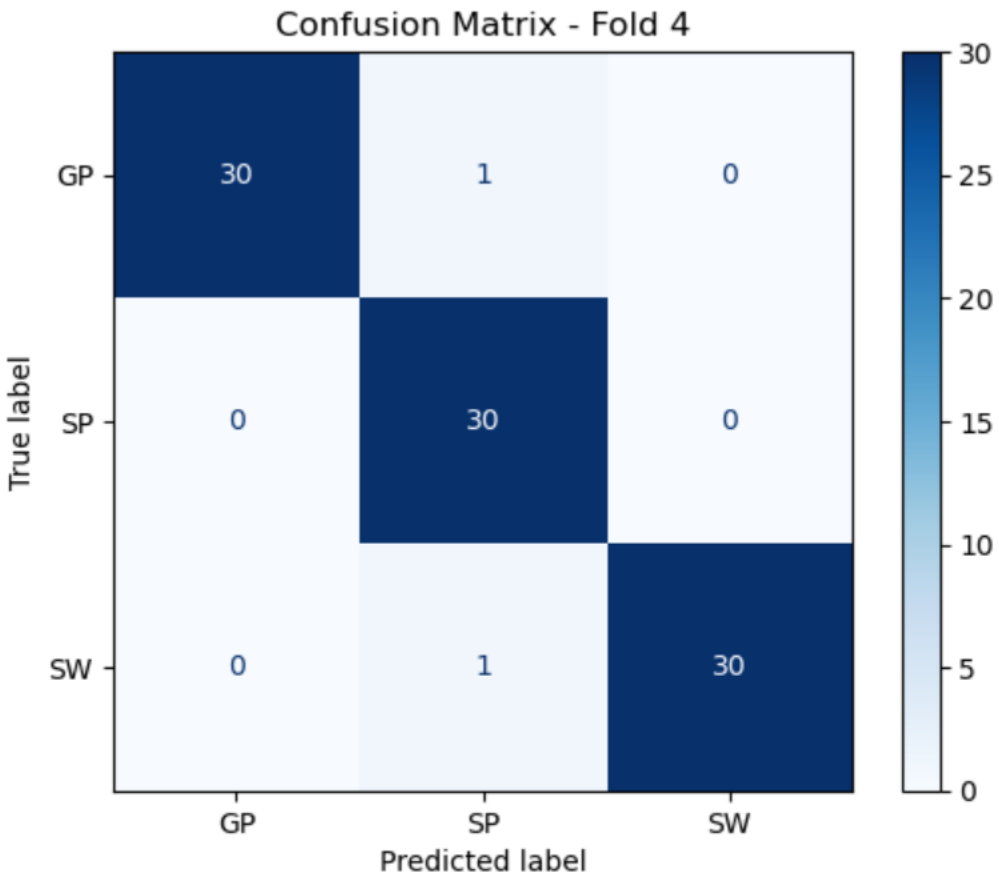


Figure 11 Confusion Matrix Fold 4

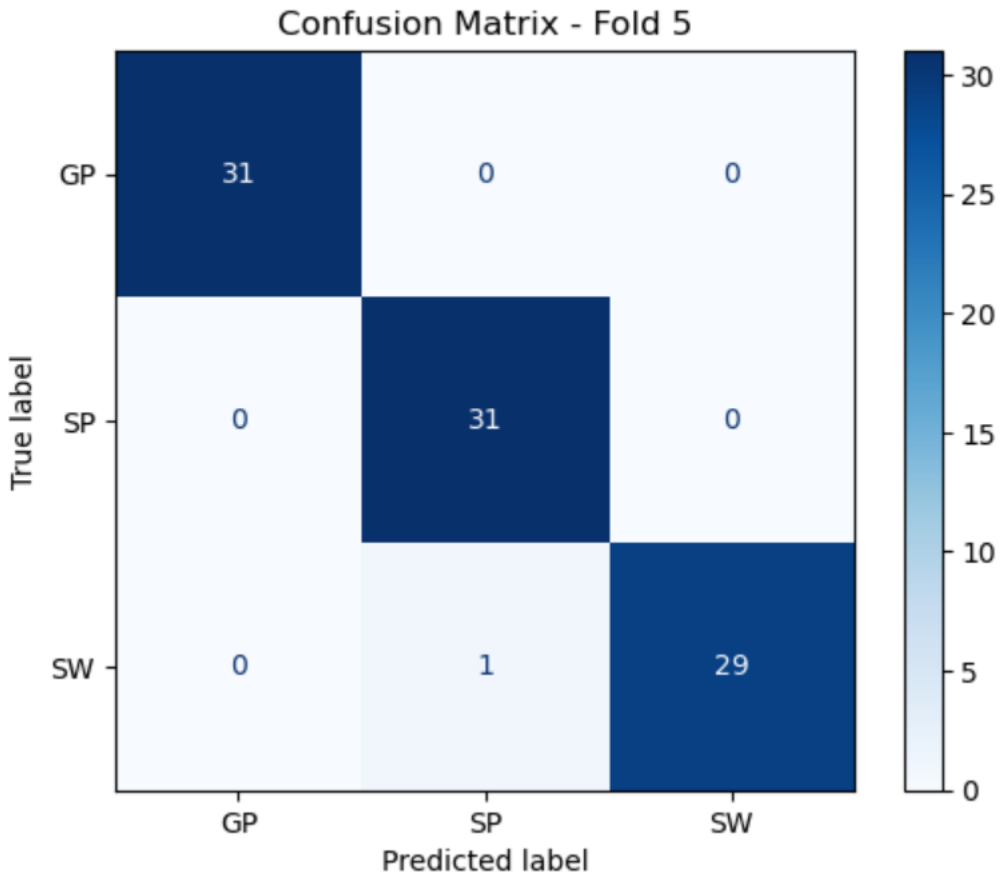


Figure 12 Confusion Matrix Fold 5

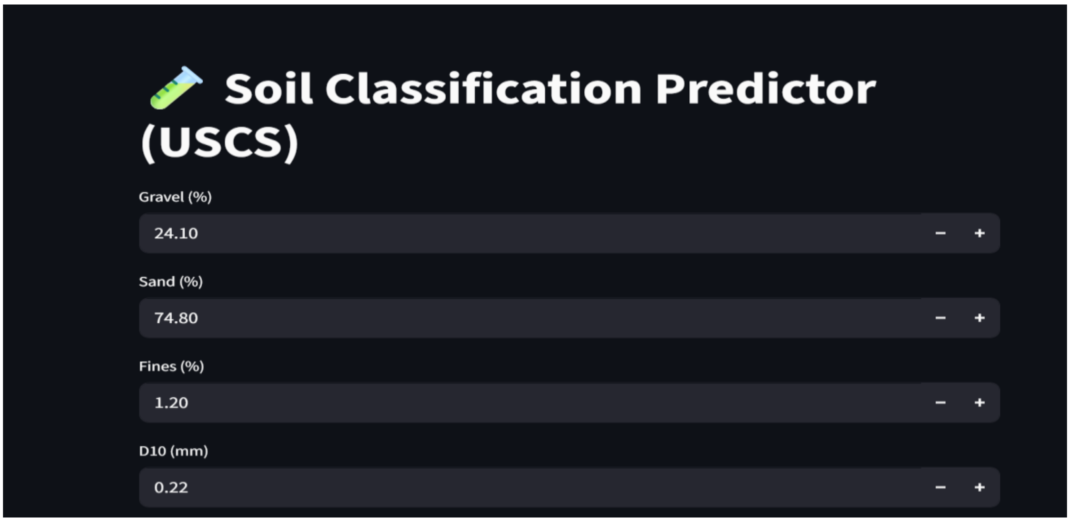
Confusion matrices for each fold of the 5-fold cross-validation are presented in Figure 8 **(Fold 1)** to Figure 12 **(Fold 5)**. These matrices consistently show strong classification performance with minimal misclassifications across all folds. This demonstrates the model's stable and reliable predictive ability throughout the validation process.

Model Training and Prediction

The MLP classifier was trained using standardized grain size parameters and USCS soil classes were encoded as categorical labels. A single hidden layer architecture was used and early stopping was used to minimize the rate of overfitting and help generalization. For the input data, feature scaling was performed on all inputs so the trained model was able to classify new samples from the appropriate USCS categories.

The model converged quickly during training, as it continuously decreased training loss throughout the 25 epochs. The validation accuracy was also improved consistent showing an increase from 0.50 to 1.00 by epoch 4….after which early stopping was conducted due to no improvement in performance being detected. The final model demonstrated a strong predictive capacity, successfully classifying unseen soil samples—such as correctly classifying one test sample as 'SP' (poorly graded sand)—demonstrating the model's robust capacity suited for practical soil classification purpose.

Streamlit-App



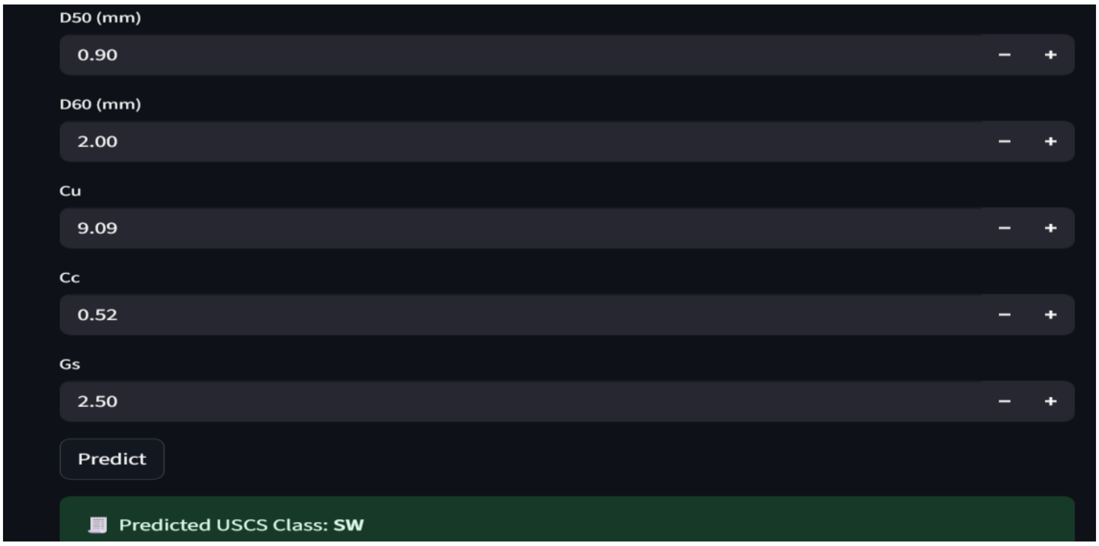


Figure 13 Screenshot of the Soil Classification Predictor app interface

The screenshot in Figure 13 shows input values confirming SW (well-graded sand) classification: high sand (74.8%), low fines (1.2%), and good gradation (Cu = 9.09). Despite low Cc (0.52), the soil meets USCS criteria for SW.

Conclusion

In this work, a deep learning-based soil classification model was successfully developed and deployed in a simple Streamlit web app for real-time USCS classification using borehole data (specifically, grain size distribution and specific gravity) from Arjundhara, Jhapa. Notably, the MLP model was able to attain a high classification accuracy, and this case study demonstrates that even with limited real-world data, synthetic data can improve model generalization and performance. The analysis confirmed that certain input features, particularly for particle size metrics and specific gravity, have substantial impact on classification.

The web app is a useful and convenient way to apply soil classification without reliance on labor-intensive methods for manual soil description. The web app allows for immediate prediction by inputting grain size data into an easy-to-use interface, thus providing an enhanced decision-making tool accessible to geotechnical engineers while aiding in more efficient site investigations. Even though the work was a success, the model performance is limited by the site-specific nature of the dataset and the omission of plasticity indices and other attributes of fine-grained soils. Potential future work will expand the original dataset to include cohesive soils, geotechnical parameters including plasticity indices, validating the trained model across different sites and geographical areas, and the exploration of other model architectures to enhance classifier usability and accuracy.

REFRENCES

1. A comprehensive review on soil classification using deep learning and computer vision techniques. (2021). *Multimedia Tools and Applications*, *80*(10), 14887–14914. https://doi.org/10.1007/S11042-021-10544-5

2. A grain size auto-classification of Baikouquan Formation, Mahu Depression, Junggar Basin, China. (2020). *Open Geosciences*, *12*(1), 275–289. https://doi.org/10.1515/GEO-2020-0106

3. A Novel Hybrid AI Federated ML/DL Models for Classification of Soil Components. (2022). *International Journal on Recent and Innovation Trends in Computing and Communication*, *10*(1s), 190–199. https://doi.org/10.17762/ijritcc.v10i1s.5823

4. *A study on Deep Learning based Soil Classification*. (2022, October 8). SciSpace - Paper. https://doi.org/10.1109/ICCCMLA56841.2022.9989293

5. *Advancements in Soil Classification: An In-Depth Analysis of Current Deep Learning Techniques and Emerging Trends (2023) | P. Swarnalatha | 1 Citations*. (n.d.). Retrieved July 21, 2025, from https://scispace.com/papers/advancements-in-soil-classification-an-in-depth-analysis-of-26g6t6pncl

6. *Automated and flexible measuring of grain size and shape in images of sediment with deep learning*. (2024, March 8). SciSpace - Paper. https://doi.org/10.5194/egusphere-egu24-8222

7. Basheer, I., & Hajmeer, M. N. (2001). Artificial Neural Networks: Fundamentals, Computing, Design, and Application. *Journal of Microbiological Methods*, *43*, 3–31. https://doi.org/10.1016/S0167-7012(00)00201-3

8. Classification of Sand Using Deep Learning. (2023). *Journal of Geotechnical and Geoenvironmental Engineering*. https://doi.org/10.1061/jggefk.gteng-11503

9. Coduto, D., Yeung, M., & Kitch, W. (2011). *Geotechnical Engineering: Principles and Practices*.

10. *Deep Learning Algorithms Based Approach for AI Derived Borehole Images Automatic Interpretation*. (2023, October 2). SciSpace - Paper. https://doi.org/10.2118/216488-ms

11. Deep-Learning-Based Automatic Mineral Grain Segmentation and Recognition. (2022). *Minerals*, *12*(4), 455–455. https://doi.org/10.3390/min12040455

12. *Digital mapping of WRB soil classes using linear and non-linear classification-based machine learning algorithms and integration of confusion index in knowledge discovery*. (2023, May 15). SciSpace - Paper. https://doi.org/10.5194/egusphere-egu23-510

13. Improving Accuracy of Automatic Fracture Detection in Borehole Images with Deep Learning and GPUs. (2017). *SciSpace - Paper*, 345–350. https://doi.org/10.1109/SIBGRAPI.2017.52

14. *Innovative Deep Learning Methods for Soil Classification and Crop Yield Prediction*. (2024, May 23). SciSpace - Paper. https://doi.org/10.1109/iccica60014.2024.10585003

15. Kim, K. G. (2016). Book Review: Deep Learning. *Healthcare Informatics Research*, *22*(4), 351. https://doi.org/10.4258/hir.2016.22.4.351

16. Liu, C.-Y., Ku, C.-Y., Wu, T.-Y., & Ku, Y.-C. (2024). An Advanced Soil Classification Method Employing the Random Forest Technique in Machine Learning. *Applied Sciences*, *14*(16), Article 16. https://doi.org/10.3390/app14167202

17. *Machine Learning and Deep Learning for Soil Analysis and Classification of Micro and Macro Nutrient Using IOT*. (2024, March 11). SciSpace - Paper; Research Square. https://doi.org/10.21203/rs.3.rs-4016181/v1

18. Machine learning-enhanced soil classification by integrating borehole and CPTU data with noise filtering. (2021). *Bulletin of Engineering Geology and the Environment*, *80*(12), 1–15. https://doi.org/10.1007/S10064-021-02478-X

19. Shahin, M., Jaksa, M., & Maier, H. (2001). Artificial Neural Network Applications in Geotechnical Engineering. *Australian Geomechanics*, *36*, 49–62.

20. Soil Classification Based on Deep Learning Algorithm and Visible Near-Infrared Spectroscopy. (2021). *Spectroscopy*, *2021*, 1–11. https://doi.org/10.1155/2021/1508267

21. Soil Classification by Machine Learning Using a Tunnel Boring Machine's Operating Parameters. (2022). *Applied Sciences*, *12*(22), 11480–11480. https://doi.org/10.3390/app122211480

22. *Soil Classification Using Machine Learning, Deep Learning, and Computer Vision: A Review*. (2023, January 1). SciSpace - Paper. https://doi.org/10.1007/978-981-19-9876-8_25

23. Soil Color as a Measurement for Estimation of Fertility using Deep Learning Techniques. (2022). *International Journal of Advanced Computer Science and Applications*, *13*(5). https://doi.org/10.14569/ijacsa.2022.0130536

24. Soil Identification and Classification using Machine Learning: A Review. (2022). *SciSpace - Paper*, 958–963. https://doi.org/10.1109/SMART55829.2022.10047446

25. *Standard Practice for Classification of Soils for Engineering Purposes (Unified Soil Classification System)*. (n.d.). Retrieved July 21, 2025, from https://store.astm.org/d2487-17.html

26. *Streamlit documentation*. (n.d.). Retrieved July 21, 2025, from https://docs.streamlit.io/

27. Use of Machine Learning Techniques in Soil Classification. (2023). *Sustainability*, *15*(3), 2374–2374. https://doi.org/10.3390/su15032374