Detection and Classification of Land Mines

Course Project

AAI-500: Probability and Statistics for AI

MS Program in Applied Artificial Intelligence

Submitted To:

Dr Rakesh Das

University of San Diego

Team 10:

Team Members:

1. Nitin Kumar Mishra
2. Nikhilesh Begur Mallapa
3. Rishabh Pathak

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1. Introduction:

The dataset selected for this project is taken from [Land Mines - UCI Machine Learning Repository](). The data base was generated as part of the paper "Passive Mine Detection and Classification Method Based on Hybrid Model" by Yilmaz .et. all [1]. In this paper, the authors, as part of their doctoral work, have tried to develop passive techniques to detect and classify landmines of various types.

1.1. Summary of the work carried out in the paper

The paper "Passive Mine Detection and Classification Method Based on Hybrid Model" by Cemal Yilmaz, Hamdi Tolga Kahraman, and Salih Söyler introduces an innovative way to detect and classify land mines using passive detectors, which are safer than active detectors that might trigger explosions. Traditionally, passive detectors have been less effective, but this research enhances their performance using artificial intelligence (AI).

1) Background:

Land mine detection is crucial for safety. Active detectors are accurate but risky, while passive detectors are safer but less reliable. This study uses AI to improve passive detectors.

2) Method:

The new method relies on three parameters: magnetic anomaly, measurement height, and soil type. These are analyzed with AI techniques like artificial neural networks (ANNs) and meta-heuristic algorithms. The researchers conducted experiments with various mines and soil conditions to collect data for training their models.

3) AI Models:

Several models were developed to detect and classify mines:

1. Detection models (Msense): Combined parameters like magnetic anomaly, height, and soil type in different ways.
2. Classification models (Mclass): Used the same combinations to identify mine types.

4) Results:

The most effective detection model (Msense_1) used all three parameters and achieved 98.2% accuracy. The best classification model (Mclass_1) also used all three parameters and reached 71.3% accuracy.

5) Importance

The study shows the value of using comprehensive parameters for mine detection. The combination of magnetic anomaly, height, and soil type significantly improved the models' accuracy. The use of a meta-heuristic k-NN algorithm with a fuzzy distance metric was particularly effective.

6) Conclusion

This research advances passive mine detection technology by integrating AI, enhancing safety and accuracy. With high detection success and promising classification performance, this method offers a safer, more effective alternative for making mine-affected areas safer worldwide.

In this project, we will apply the learnings of the course and carry out data cleaning, exploratory data analysis, statistical model selection, model analysis, and draw inferences from this selected data. Our aim will be to asses whether we are able to arrive at a simpler model with acceptable accuracy, based on the learning of AAI-500.

2. Description of proposed Project work:
   As part of the final project for the course, AAI – 500 Probability and statistics for AI, a relevant dataset has to be selected to apply the learnings of the course and carry out data cleaning, exploratory data analysis, statistical model selections model analysis, and draw inferences from the selected data set.

2.1 Dataset: The dataset available has 3 independent variables (Voltage (magnetic anomaly), measurement height, and soil type. The dependent variable is the Mine Type (1 – Null, 2 - Anti-Tank, 3 - Anti-personnel, 4 - Booby Trapped Anti-personnel and 5 – M14 antipersonal). The Following table shows the variables present in the data set.

<table>
<tr><td></td><td colspan="6">Parameters</td></tr>
<tr><td></td><td colspan="4">Independent variables – Inputs</td><td colspan="2">Dependent Variable - output</td></tr>
<tr><td></td><td>Voltage (V)</td><td>Height (H)</td><td colspan="2">Soil Type (S)</td><td colspan="2">Mine Type (M)</td></tr>
<tr><td>Definition</td><td>Output voltage of sensor due to magnetic distortion</td><td>Height of sensor from ground</td><td colspan="2">6 different soil types depending on moisture condition</td><td colspan="2">Mine types encountered commonly on land. 5 different classes</td></tr>
<tr><td rowspan="6">Boundary values/ Class</td><td rowspan="6">[0V,10.6V] Normalised in the dataset to [0V, 1V]</td><td rowspan="6">[0 cm,20cm] Normalised in the dataset to [0, 1]</td><td>1</td><td>Dry and sandy</td><td>1</td><td>Null</td></tr>
<tr><td>2</td><td>Dry and Humus</td><td>2</td><td>Anti-Tank</td></tr>
<tr><td>3</td><td>Dry and Limy</td><td>3</td><td>Anti-personnel</td></tr>
<tr><td>4</td><td>Dry and sandy</td><td>4</td><td>Booby Trapped Anti-personnel</td></tr>
<tr><td>5</td><td>Dry and Humus</td><td rowspan="2">5</td><td rowspan="2">M14 anti - personal</td></tr>
<tr><td>6</td><td>Dry and Limy</td></tr>
</table>

2.1.2.1. Data Set Size: The dataset is available as a 338x4 matrix with 338 observations of V, H, S and corresponding M

2.1.2.2. Data Set Normalization: The entire data set is normalized and available on the UCI machine learning data set website as such.

2.1.2.3. Missing values: There are no missing values found in the data set.

2.2. Project Description: as part of this project work, the following work is proposed to be carried out on the data set selected:

1. Data Set Selection: This step involved exploring the UCI machine learning database to find possible datasets to which either regression or classification algorithms could be applied to draw inferences.
2. Exploratory Data Analysis: This will consist of understanding the data set, carrying out summary and descriptive statistics, scatter plots, histograms and sampling distributions of the variables.
3. Model Selection: Based on the problem type a statistical model will be selected for this data set. Since this appears to be a classification, possible classification approaches such as logistic regression, decision tree, Random Forest Classifier, Gradient Boosting Classifier and SVC will apply to the dataset to find out which model has a better accuracy, given the dataset
4. Model Analysis: All the above models will be compared based on accuracy, classification report and confusion matrix to evaluate which model perform better in predicting and classifying the Mines of various types
5. Conclusion and inferences: In these sections we will look at the inference derived out of out analysis. We will asses whether we could arrive at a model with sufficient accuracy. We will also look at whether overall our modelling attempt was successful or any more sophisticated modelling approaches may be needed for this dataset.

3. Exploratory Data Analysis:

3.1. Data Overview: The dataset consists of columns for magnetic anomaly (V), measurement height (H), soil type (S), and mine presence indicator (M)

3.2. Summary Statistics: The following table shows the summary statistics for the variables in the dataset.

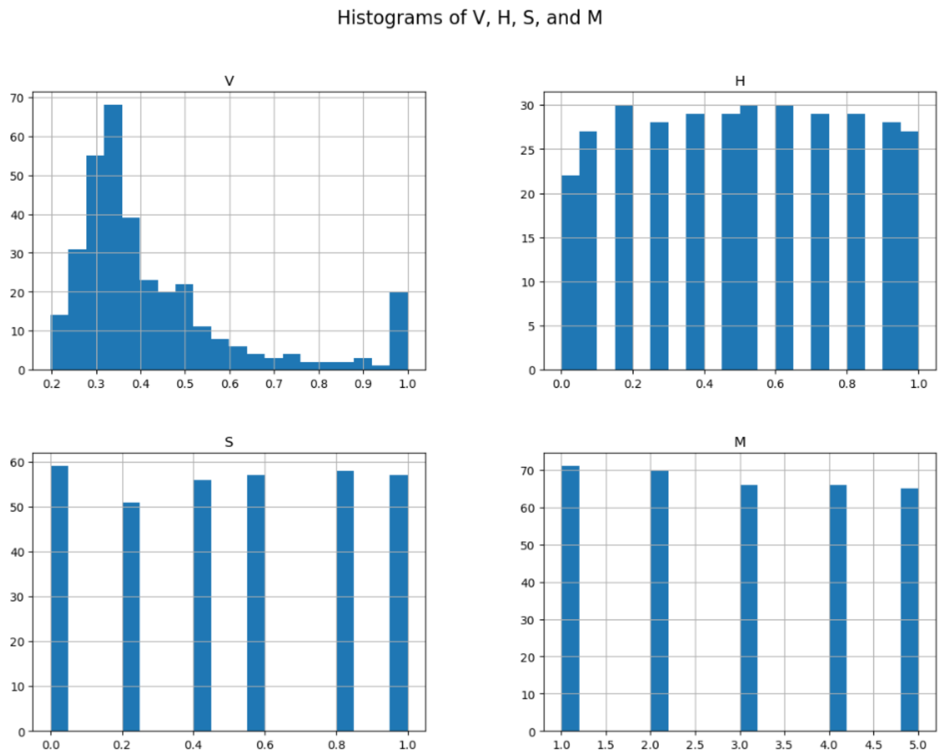
	V	H	S	M
count	338.000000	338.000000	338.000000	338.000000
mean	0.430634	0.508876	0.503550	2.952663
std	0.195819	0.306043	0.344244	1.419703
min	0.197734	0.000000	0.000000	2.000000
25%	0.309737	0.272727	0.200000	3.000000
50%	0.359516	0.545455	0.600000	4.000000

75%	0.482628	0.727273	0.800000	4.000000
max	0.999999	1.000000	1.000000	5.000000

3.3. Missing Values: No missing values were found in the dataset.

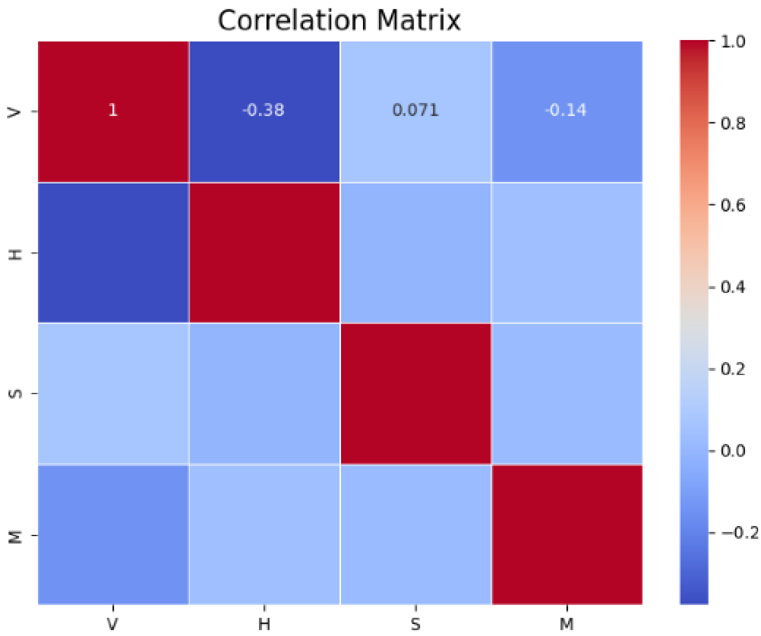
3.4. Data Visualization:

1. Histograms : The histograms show the distributions of each variable. For example, magnetic anomaly (V) and measurement height (H) have a roughly normal distribution, while soil type (S) and mine presence indicator (M) show bimodal and binary distributions respectively.

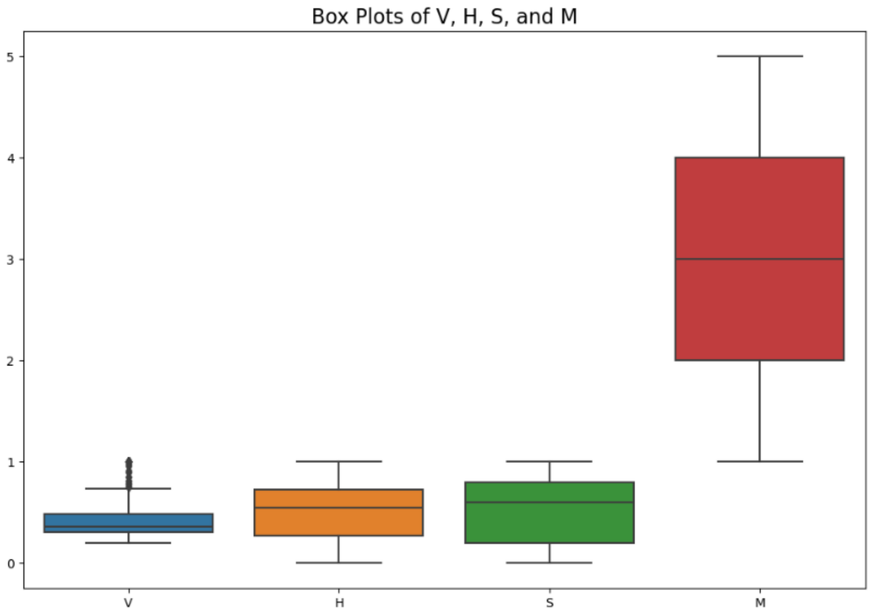


2. Correlation Matrix: The heatmap shows the correlation between the variables. There is a strong positive correlation between soil type (S) and mine presence (M), suggesting that soil type might be a significant factor in Mine detection.

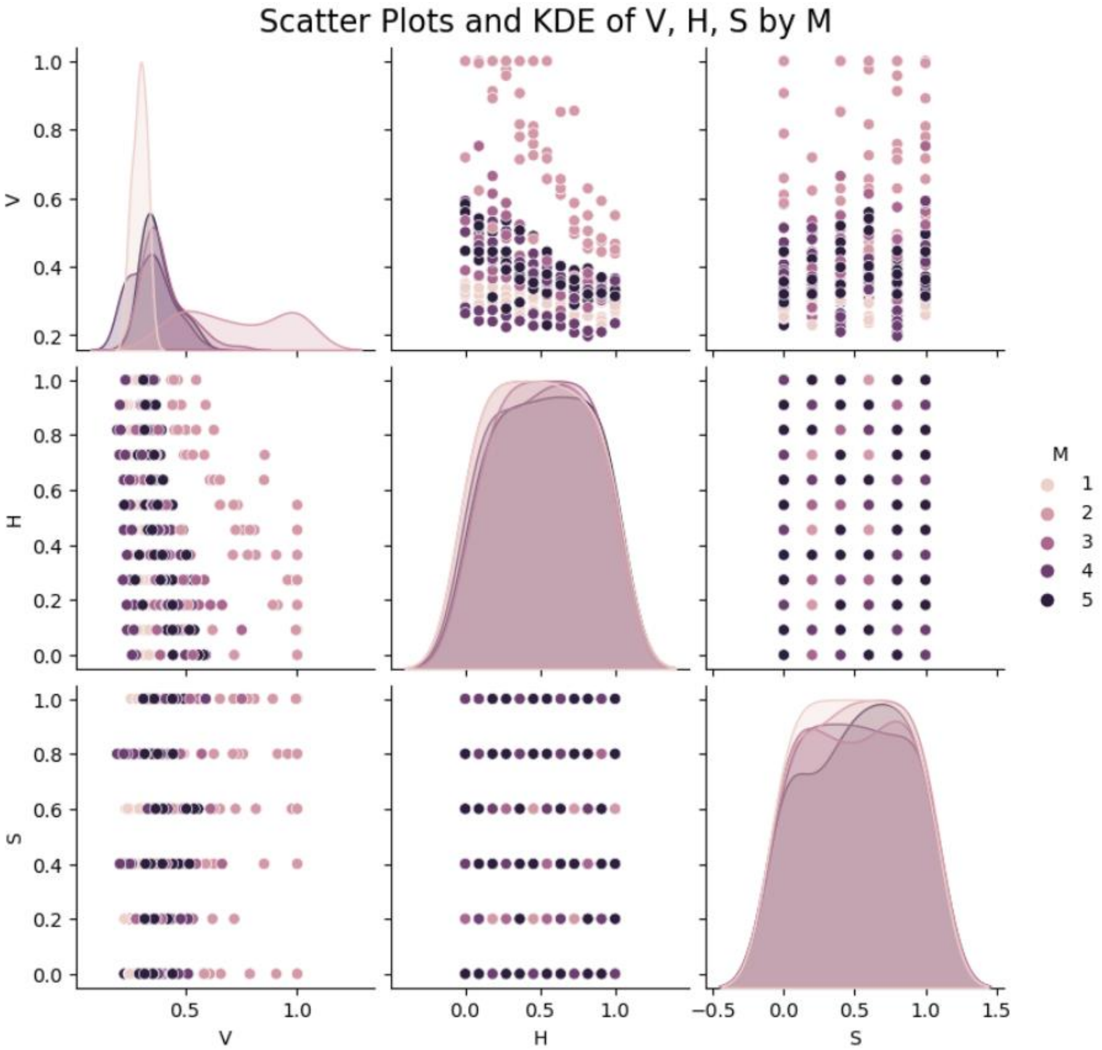
	V	H	S	M
V	1.000000	0.229235	-0.239160	0.014371
H	0.229235	1.000000	0.016862	-0.031508
S	-0.239160	0.016862	1.000000	0.582818
M	0.014371	-0.031508	0.582818	1.000000



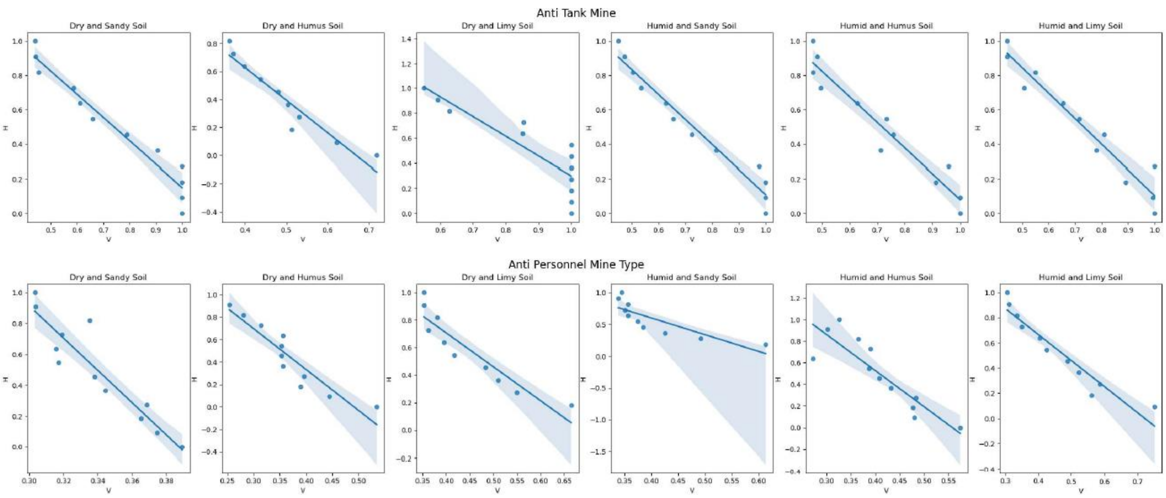
3. Box Plots: Box plots indicate the spread and outliers in the data. Measurement height (H) has several outliers, while magnetic anomaly (V) is fairly uniformly distributed.

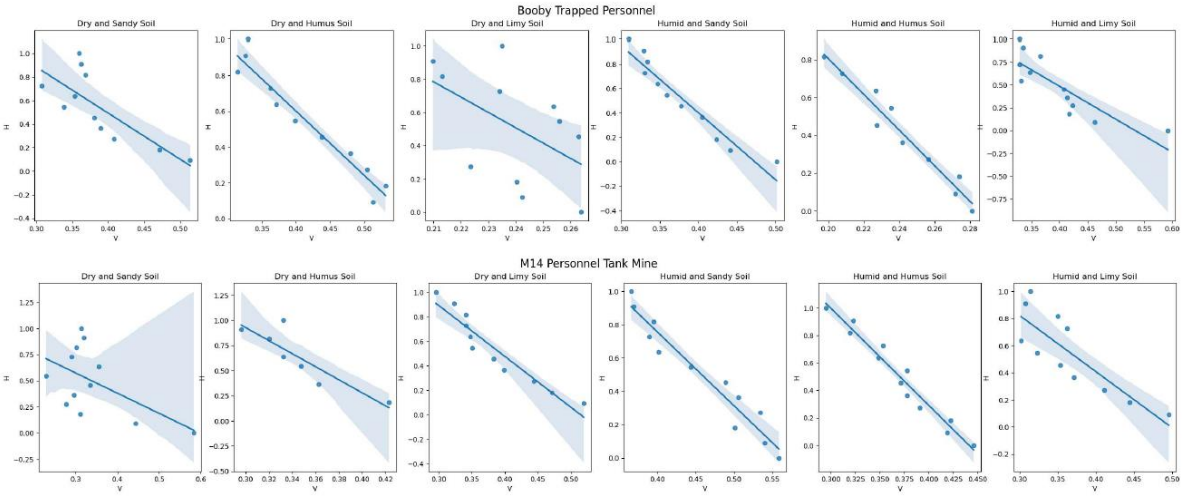


4. Scatter Plots and KDE: The scatter plots with KDE show the relationships between pairs of variables, colored by the presence of mines (M). There are clear patterns, particularly between soil type (S) and mine presence (M), which further supports the correlation matrix findings.

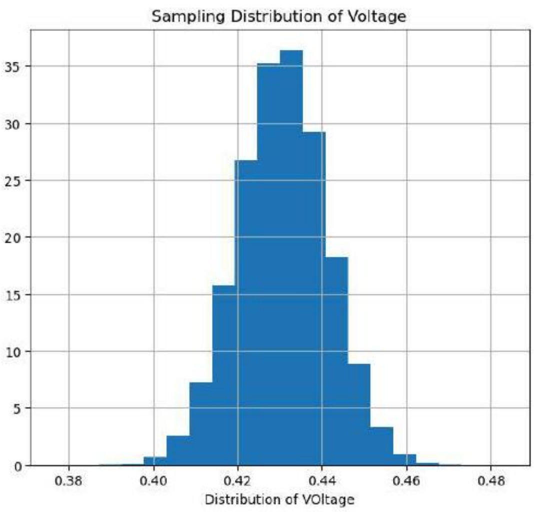


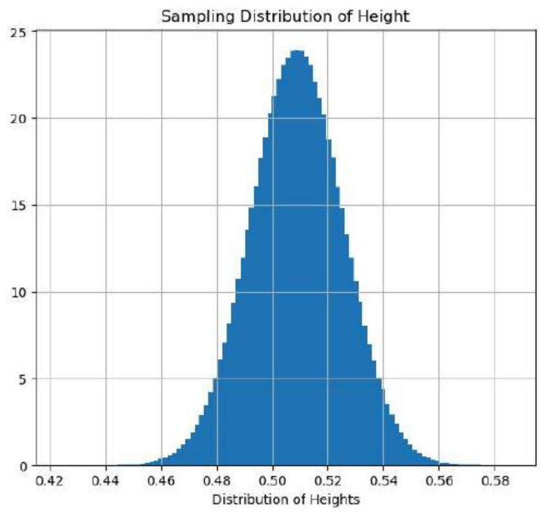
5. Exploring the relationship between soil type and Mine presence: We filtered the data so that for a given soil type and mine type, we can explore whether their exists some relation which may help us to infer which soil conditions are better suited for mine detection.





3.5. Sampling Distributions of V and H:





3.6. Conclusion: This EDA reveals important insights into the dataset, including key distributions, relationships, and potential areas of focus for further analysis or modelling efforts. Specifically, the strong correlation between soil type and mine presence suggests soil type as a critical factor in mine detection.

4. Model Selection: This is a supervised learning problem of classification. The application of regression algorithms may help us arrive are linear relationships, given the soil type and the mine type. This could be a useful insight which may help us to infer which soil conditions are better suited for mine detection.
   For the overall detection and classification problem, possible models that can be applied are classification algorithms such as:
   2) logistic regression,
   3) Decision tree,
   4) Random Forest Classifier,

5) Gradient Boosting Classifier and
6) SVC

5. Model Analysis: We will train each of these models on the dataset by dividing the dataset into train and test part. Once the model is trained on the training part of the data, we will test the accuracy of the model using the test past of the data. The above 5 models will be compared to see which model gives a better accuracy.

5.1. Logistic Regression:

The logistic regression model was used to detect and classify mines based on the inputs: Voltage (V), Height (H), and Soil type (S). The target variable is Mine type (M). The provided results include accuracy, a classification report, and a confusion matrix.

1. Accuracy: The model achieved an accuracy of 36.8%, indicating that the model correctly predicted the mine type for about one-third of the instances.
2. Classification Report: Precision measures the proportion of true positive predictions in each class out of all predicted positives. With this model, Highest precision is with Mine Type 22 (0.71) and Lowest precision is with Mine Type 4 (0.00).
3. Recall: measures the proportion of true positive predictions in each class out of all actual positives. With this model, Highest recall is with Mine Type 1 (0.91) Lowest recall is with Mine type 4(0.00)
4. F1-score: It is the harmonic mean of precision and recall. The Highest F1-score is with mine type 2 (0.83) and Lowest F1-score with mine type (0.00). The weighted average F1-score of 0.28 indicates the overall performance of the model across all classes.
5. Confusion Matrix: The confusion matrix reveals the model's prediction distribution across the classes:
   - Mine Type 1: Most instances (10 out of 11) were correctly predicted, but one instance was misclassified as Mine type 5.
   - Mine Type 2: All 12 instances were correctly predicted.
   - Mine type 3: Majority of instances were misclassified into other classes.
   - Mine type 4 : No instances were correctly predicted; most were misclassified as Class 1 or Class 3.
   - Mine type 5: Most instances were misclassified into other classes.

6. Conclusion: The logistic regression model shows varied performance across different mine types. While it performs well for certain types (1 and 2), it struggles significantly with others (4 and 5). This suggests the need for

further model tuning or exploring alternative models to improve classification accuracy.

5.2. Decision Tree: the same exercise was repeated with the decision tree algorithm. The results are as follows:

1. Accuracy: The model achieved an accuracy of 47.1%, indicating that the model correctly predicted the mine type for almost half of the instances.
2. Classification Report: Precision measures the proportion of true positive predictions in each class out of all predicted positives. With this model, Highest precision is with Mine Type 2 (0.92) and Lowest precision is with Mine Type 4 (0.27).
3. Recall: measures the proportion of true positive predictions in each class out of all actual positives. With this model, Highest recall is Mine Type 1 (0.92) Lowest recall is with Mine type 4(0.17)
4. F1-score: It is the harmonic mean of precision and recall. The Highest F1-score is with mine type 2 (0.92) and Lowest F1-score with mine type (0.21). The weighted average F1-score of 0.46 indicates the overall performance of the model across all classes.
5. Confusion Matrix: The confusion matrix reveals the model's prediction distribution across the classes:
   - Mine Type 1: Most instances (6 out of 11) were correctly predicted, but one instance was misclassified as Mine type 3,4 or 5.
   - Mine Type 2: 11 out of 12 instances were correctly predicted, with one misclassified as type 4
   - Mine type 3: Misclassifications were spread across Classes 4 and 5.
   - Mine type 4 : No instances were correctly predicted; Misclassifications were spread across Classes 3 and 5.
   - Mine type 5: Many instances were misclassified into Classes 3 and 4.

6. Conclusion: The Decision Tree Classifier shows improved performance over the Logistic Regression model, especially for Mine type 2. However, it still struggles with certain types, notably type 5. This suggests further model tuning or exploring alternative models could enhance performance.

5.3. Random Forest Classifier: the same exercise was repeated with the random forest classifier algorithm. The results are as follows:

1. Accuracy: The model achieved an accuracy of 52.9%, indicating that the model correctly predicted the mine type for more than half of the instances.
2. Classification Report: Precision measures the proportion of true positive predictions in each class out of all predicted positives. With this model,

Highest precision is with Mine Type 2 (0.85) and Lowest precision is with Mine Type 5 (0.36).

3. Recall: measures the proportion of true positive predictions in each class out of all actual positives. With this model, Highest recall is Mine Type 1 (0.91) Lowest recall is with Mine type 5(0.22)
4. F1-score: It is the harmonic mean of precision and recall. The Highest F1-score is with mine type 2 (0.88) and Lowest F1-score with mine type (0.28). The weighted average F1-score of 0.51 indicates the overall performance of the model across all classes.
5. Confusion Matrix: The confusion matrix reveals the model's prediction distribution across the classes:
   - Mine Type 1: Most instances (10 out of 11) were correctly predicted, but one instance was misclassified as Mine type 5.
   - Mine Type 2: 11 out of 12 instances were correctly predicted, with one misclassified as type 4.
   - Mine type 3: Misclassifications were spread across Classes 4 and 5.
   - Mine type 4: No instances were correctly predicted; Misclassifications were spread across Classes 3 and 5.
   - Mine type 5: Many instances were misclassified into Classes 3 and 4.
6. Conclusion: The Random Forest Classifier shows improved performance over the Logistic Regression and Decision Tree models, particularly for Classes 1 and 2. However, it still struggles with certain classes, notably Class 5, suggesting the need for further model tuning or exploring alternative models to enhance performance.

5.4. Gradient Boosting classifier: the same exercise was repeated with the Gradient Boosting classifier algorithm. The results are as follows:

1. Accuracy: The model achieved an accuracy of 58.8%, indicating that the model correctly predicted the mine type for nearly 60% of the instances.
2. Classification Report: Precision measures the proportion of true positive predictions in each class out of all predicted positives. With this model, Highest precision is with Mine Type 2 (0.92) and Lowest precision is with Mine Type 5 (0.27).
3. Recall: measures the proportion of true positive predictions in each class out of all actual positives. With this model, Highest recall is Mine Type 2 (0.92) Lowest recall is with Mine type 4(0.36)
4. F1-score: It is the harmonic mean of precision and recall. The Highest F1-score is with mine type 2 (0.92) and Lowest F1-score with mine type 4 (0.31). The weighted average F1-score of 0.59 indicates the overall performance of the model across all classes.

5. Confusion Matrix: The confusion matrix reveals the model's prediction distribution across the classes:
   - Mine Type 1: Most instances (9 out of 11) were correctly predicted, with few misclassifications.
   - Mine Type 2: 11 out of 12 instances were correctly predicted, with one misclassified as type 4.
   - Mine type 3: Most instances (10 out of 16) were correctly predicted, with some misclassifications into Class 4 and Class 5.
   - Mine type 4: Misclassifications were spread across Classes 1, 2, 3, and 5.
   - Mine type 5: Many instances were misclassified into Classes 3 and 4.

6. Conclusion: The Gradient Boosting Classifier shows the best performance among the models tested so far, with the highest overall accuracy and improved performance for most classes. However, it still struggles with certain classes, notably Class 4 and Class 5, suggesting the need for further model tuning or exploring alternative models to enhance performance.

5.5. SVC: The Support Vector Classifier (SVC) was used to detect and classify mines based on the inputs: Voltage (V), Height (H), and Soil type (S). The target variable is Mine type (M). The provided results include accuracy, a classification report, and a confusion matrix. The results are as follows:

1. Accuracy: The model achieved an accuracy of 42.6%, indicating that the model correctly predicted the mine type for slightly less than half of the instances.
2. Classification Report: Precision measures the proportion of true positive predictions in each class out of all predicted positives. With this model, Highest precision is with Mine Type 1 (1.00) and Lowest precision is with Mine Type 4 (0.25).
3. Recall: measures the proportion of true positive predictions in each class out of all actual positives. With this model, Highest recall is Mine Type 1 (0.96) Lowest recall is with Mine type 5 (0.11)
4. F1-score: It is the harmonic mean of precision and recall. The Highest F1-score is with mine type 2 (0.96) and Lowest F1-score with mine type 5 (0.17). The weighted average F1-score of 0.39 indicates the overall performance of the model across all classes.
5. Confusion Matrix: The confusion matrix reveals the model's prediction distribution across the classes:
   - Mine Type 1: Most instances (10 out of 11) were correctly predicted, with one instance misclassified as Class 3.

- Mine Type 2: 11 out of 12 instances were correctly predicted, with one misclassified as type 4.
- Mine type 3: Many instances were misclassified into Classes 1, 4, and 5.
- Mine type 4: Misclassifications were spread across Classes 1, 3, and 5.
- Mine type 5: Many instances were misclassified into Classes 1, 3 and 4.

6. Conclusion: The SVC shows varied performance, excelling particularly for Class 2, but struggling significantly with other classes, especially Classes 3, 4, and 5. This suggests that the model may need further tuning or alternative approaches to enhance overall performance.

6. Conclusions and inferences.

A table comparing all the above models is shown below:

Model	**Accuracy**	**Precision (macro avg)**	**Recall (macro avg)**	**F1- Score (macro avg)**	**Confusion martix**
Logistic Regression	0.368	0.34	0.42	0.31	[[10, 0, 0, 0, 1], [0, 12, 0, 0, 0], [9, 2, 2, 2, 1], [8, 2, 0, 0, 1], [11, 1, 2, 3, 1]]
Decision Tree Classifier	0.471	0.49	0.50	0.49	[[6, 0, 1, 2, 2], [0, 11, 0, 1, 0], [1, 0, 7, 5, 3], [0, 1, 2, 5, 3], [4, 0, 7, 4, 3]]
Random Forest Classifier	0.529	0.52	0.58	0.54	[[10, 0, 0, 0, 1], [0, 11, 0, 1, 0], [2, 0, 6, 5, 3], [1, 1, 1, 5, 3], [3, 1, 7, 3, 4]]
Gradient Boosting classifier	0.588	0.60	0.61	0.60	[[9, 0, 1, 0, 1], [0, 11, 0, 1, 0], [0, 0, 10, 5, 1], [1, 1, 1, 4, 4], [2, 0, 5, 5, 6]]
Support Vector Classifier	0.426	0.45	0.48	0.42	[[10, 0, 1, 0, 0], [0, 11, 0, 1, 0], [8, 0, 3, 3, 2], [5, 0, 1, 3, 2], [7, 0, 4, 5, 2]]

To summarize:

- Logistic Regression: Showed the lowest performance with an accuracy of 36.8% and struggled especially with Class 4 and Class 5.
- Decision Tree Classifier: Improved accuracy to 47.1%, with relatively balanced precision, recall, and F1-scores across classes.
- Random Forest Classifier: Achieved an accuracy of 52.9%, showing improved performance, especially for Class 1 and Class 2.
- Gradient Boosting Classifier: The best performer with an accuracy of 58.8%, providing better precision and recall for most classes but still struggling with Class 4 and Class 5.
- Support Vector Classifier: Achieved an accuracy of 42.6%, with high performance for Class 2 but poor performance for Classes 3, 4, and 5.

7. References:

1. Yilmaz, C., Kahraman, H. T., & Söyler, S. (2018). Passive mine detection and classification method based on hybrid model. IEEE Access, 6, 47870-47888.
2. Agresti, A., & Kateri, M. (2021). Foundations of Statistics for Data Scientists: With R and Python (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781003159834.