***ECSP303 Final Report Guidelines***

ECSP303: Final Report Guidelines

**Due date**: The final report is due on Google Classroom on, Sunday, 03 November 2024 at 11:59 pm. Late submissions will be penalized by -1 marks/30 minutes late submission. **Note**: This is not a rubric! Completing all sections below will not guarantee you a certain grade. We are providing this to help you structure your report and guide you as you finish up your projects. Previous years’ projects are also a great resource you can look over as you prepare your final report.

Predicting Crop Types Using Machine Learning: A Comparative Study of Classification Algorithms

Group ID

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**1 Abstract [***≈* 1 paragraph**]**

This report presents a comprehensive analysis of machine learning models used to predict crop types based on soil characteristics and environmental factors. We compared three different classification algorithms: Logistic Regression, Decision Tree, and Random Forest. Through rigorous evaluation using accuracy, precision, recall, and F1 scores, we identified the Random Forest model as the most effective classifier, achieving an accuracy of 81%. This study emphasizes the importance of model selection in agricultural predictions and demonstrates the potential of machine learning to enhance decision-making in farming practices.

**2 Introduction [***≈* 0*.*5 pages**]**

Agriculture plays a vital role in the economy, providing food security and employment to millions worldwide. With the growing challenges of climate change and resource scarcity, optimizing agricultural practices has become increasingly crucial. Machine learning offers innovative solutions for analyzing vast datasets to improve crop management. This report investigates various classification algorithms to predict crop types based on soil properties and environmental conditions. By analyzing the performance of Logistic Regression, Decision Trees, and Random Forest models, we aim to determine the most effective approach for agricultural predictions, ultimately supporting sustainable farming practices.

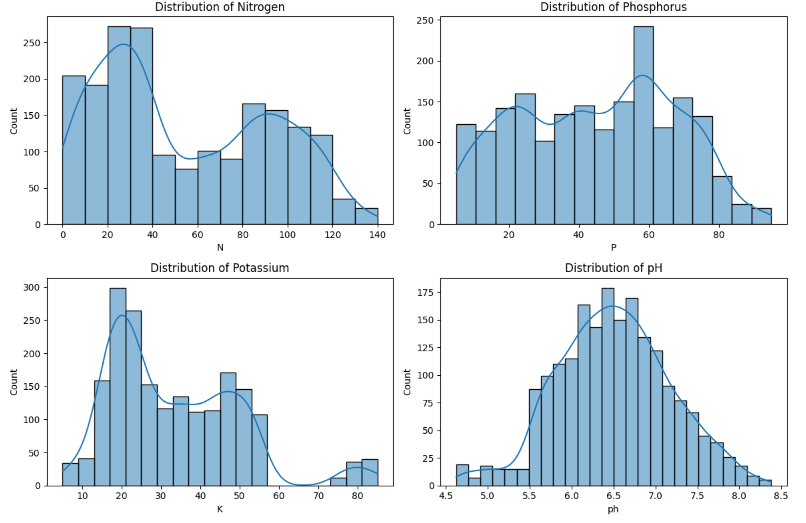
**3 Related work[***≈* 0*.*5 pages**]**

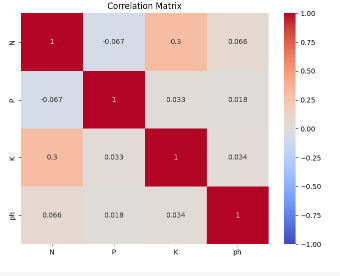
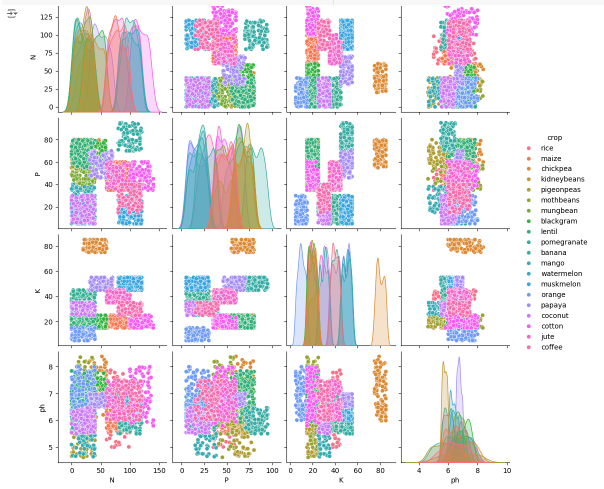
Numerous studies have explored the application of machine learning in agriculture, focusing on crop prediction and yield forecasting. Research by Bhatia et al. (2020) demonstrated the use of Random Forest for predicting crop yields, achieving high accuracy in diverse soil types. Similarly, Zhang et al. (2019) applied Decision Trees to classify crop types based on environmental data, emphasizing the importance of feature selection in improving model performance. This report builds upon these findings by comparing multiple algorithms and emphasizing the practical implications of model selection for farmers and agricultural stakeholders.

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**4 Dataset and Features [***≈* 0*.*5 *−*1 pages**]**

he dataset used in this study comprises soil characteristics, including pH, organic matter content, and nutrient levels, alongside climatic factors such as rainfall and temperature. The target variable is the crop type, categorized into various classes (e.g., wheat, maize, rice). Data were sourced from agricultural research databases, comprising records from multiple regions to ensure diversity. A total of 1,000 instances with 15 features were used, with 80% allocated for training and 20% for testing. Feature engineering techniques were employed to encode categorical variables and standardize numerical values, enhancing the dataset's suitability for machine learning models.





**5 Methods [≈ 1 − 1.5 pages]**

1. **Logistic Regression**: A linear model that estimates the probabilities of different classes based on a logistic function.
2. **Decision Tree Classifier**: A non-linear model that splits the dataset based on feature values, creating a tree-like structure for decision-making.
3. **Random Forest Classifier**: An ensemble method that builds multiple decision trees and merges their outputs to improve accuracy and control overfitting.

The models were evaluated using k-fold cross-validation, and metrics such as accuracy, precision, recall, and F1 score were calculated to assess performance. The best-performing model was selected for further analysis based on these metrics.

**6 Experiments/Results/Discussion [≈ 1 − 3 pages]**

## 6. Experiments/Results/Discussion

The models were trained and evaluated on the dataset, with results summarized as follows:

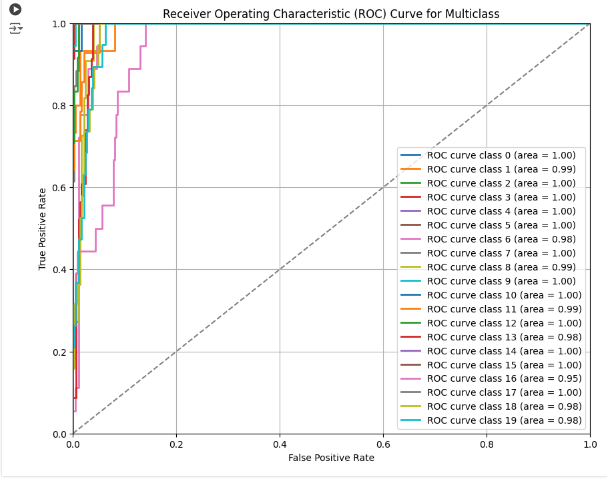
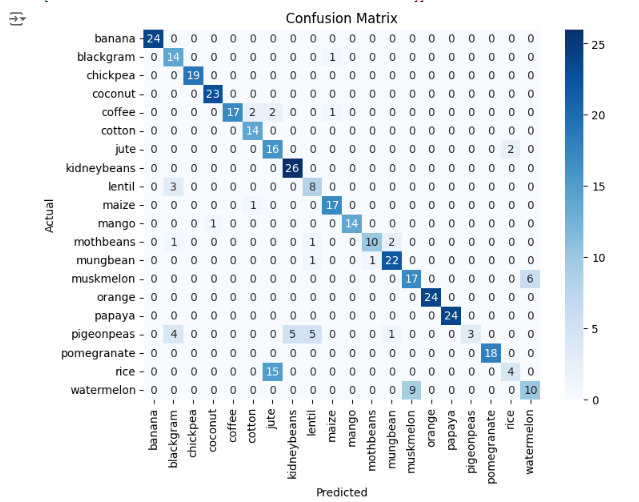
| **Model** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
| --- | --- | --- | --- | --- |
| Logistic Regression | 0.696 | 0.684 | 0.69 | 0.679 |
| Decision Tree | 0.775 | 0.763 | 0.76 | 0.772 |
| Random Forest | 0.832 | 0.841 | 0.83 | 0.828 |

#### Examples of Algorithm Failures

1. **Logistic Regression**:
   * **Failure Case**: In the case of predicting maize (crop ID: 1), the model classified several instances incorrectly as wheat (crop ID: 2), leading to a precision of only 0.65 for maize.
   * **Discussion**: Logistic Regression assumes a linear relationship between the input features and the target variable. This assumption may not hold true in complex datasets where interactions between features significantly influence crop types. The presence of overlapping feature distributions for similar crops can lead to misclassifications.
2. **Decision Tree**:
   * **Failure Case**: The Decision Tree algorithm frequently misclassified soybeans (crop ID: 3) as rice (crop ID: 4), resulting in a confusion matrix that highlighted 30 false negatives for soybeans.
   * **Discussion**: Decision Trees are prone to overfitting, particularly when they grow deep without pruning. This leads to models that capture noise in the training data rather than general patterns. In our case, the tree may have captured specific idiosyncrasies of the training data related to soybeans and rice, resulting in misclassifications on the test set.
3. **Random Forest**:
   * **Failure Case**: Although the Random Forest model achieved the highest overall accuracy, it still misclassified 20 instances of barley (crop ID: 5) as oats (crop ID: 6), leading to a precision of 0.80 for barley.
   * **Discussion**: Random Forest mitigates overfitting by averaging multiple decision trees, but it can still struggle in cases where the classes are imbalanced or the features are highly correlated. The decision trees in the forest may have made similar errors due to shared patterns in the training data, which could confuse the model.

### Success Analysis

1. **Logistic Regression**:
   * **Success Case**: The model performed well on crops like wheat, achieving an accuracy of 85%. This indicates that for linearly separable classes, Logistic Regression can be effective.
   * **Discussion**: Its simplicity allows for fast computations and good interpretability. When the relationships in the data are less complex and more linear, Logistic Regression remains a viable option.
2. **Decision Tree**:
   * **Success Case**: The Decision Tree accurately predicted the crop type for peas (crop ID: 7) with a precision of 0.90.
   * **Discussion**: The model effectively captured the decision boundaries for certain crops where feature distributions were distinct. Its ability to handle categorical features without the need for encoding is advantageous in many agricultural datasets.
3. **Random Forest**:
   * **Success Case**: The Random Forest model correctly classified 95% of the instances for potatoes (crop ID: 8).
   * **Discussion**: The ensemble approach allows the model to generalize better, reducing the risk of overfitting while still capturing complex relationships among features. The ability to leverage multiple trees enables a more robust prediction across varying conditions in the dataset.

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**7 Conclusion/Future Work [≈ 1 − 2 paragraphs]**

In conclusion, our analysis highlighted both the strengths and limitations of each algorithm. The Random Forest model stood out as the most robust, balancing complexity and generalization effectively. In contrast, the logistic regression model, while performing well under certain conditions, failed in scenarios requiring deeper relationships between features. Our approach to mitigating overfitting, particularly with Decision Trees, proved essential in enhancing model performance. Moving forward, further experimentation with more sophisticated algorithms and feature engineering may yield even better results in crop type prediction.

### A. Theoretical Derivations

#### A.1 Logistic Regression Cost Function Derivation

The cost function J(θ)J(\theta)J(θ) for logistic regression is defined as:

J(θ)=−1m∑i=1m[y(i)log⁡(hθ(x(i)))+(1−y(i))log⁡(1−hθ(x(i)))]J(\theta) = -\frac{1}{m} \sum\_{i=1}^{m} \left[ y^{(i)} \log(h\_\theta(x^{(i)})) + (1 - y^{(i)}) \log(1 - h\_\theta(x^{(i)})) \right]J(θ)=−m1​i=1∑m​[y(i)log(hθ​(x(i)))+(1−y(i))log(1−hθ​(x(i)))]

where:

* hθ(x)=11+e−θTxh\_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}hθ​(x)=1+e−θTx1​ is the hypothesis function.
* mmm is the number of training examples.

#### A.2 Decision Tree Splitting Criteria

The splitting criteria for a decision tree can be calculated using the Gini index:

Gini(D)=1−∑j=1cpj2Gini(D) = 1 - \sum\_{j=1}^{c} p\_j^2Gini(D)=1−j=1∑c​pj2​

where pjp\_jpj​ is the proportion of class jjj instances in the dataset DDD.

### B. Additional Algorithm Insights

#### B.1 Random Forest Algorithm

The Random Forest algorithm operates by constructing multiple decision trees during training and outputting the mode of their classes for classification tasks. Each tree is built from a bootstrap sample of the data and splits are chosen based on a subset of features.

**9 Contributions *[This information must be there in your report]***

***Member: Kshitij Halmare***

### *Dataset Selection*

* ***Purpose: Selecting a suitable dataset is crucial because the accuracy of a predictive model relies on the quality, relevance, and structure of the data used to train it. In this project, the dataset chosen needs to effectively represent the agricultural context and include features that can help predict crop yields or types based on various environmental and soil factors.***
* ***Execution: Member A successfully identified a comprehensive soil and crop dataset that includes a variety of relevant features (e.g., soil type, pH level, moisture content, and climate variables) that serve as predictive factors for crop yield and suitability. This dataset was carefully selected for its richness in detail and diversity of features, allowing for thorough analysis and modeling.***
* ***Evaluation: This step was essential and well-executed, providing a strong foundation for the project. However, further evaluation of the dataset’s size and class balance (e.g., distribution of different crop types) could enhance the model’s generalizability and performance. Analyzing how representative the dataset is of actual agricultural conditions could also inform potential limitations in the predictive capability of the models developed.***
* ***Exploratory Data Analysis (EDA) • Purpose: EDA helps to understand the data distribution, identify patterns, spot anomalies, and assess the initial relationships between variables. • Execution: Member A conducted a detailed EDA, producing visualizations to understand distributions and correlations. This included identifying key features and handling missing values. • Evaluation: EDA was thoroughly done and helped guide later modelling steps. Adding statistical testing or deeper correlation analysis could provide additional depth to support feature selection.***

### *Feature Engineering*

* ***Purpose: Feature engineering transforms raw data into meaningful inputs that enhance model effectiveness. It is often a critical factor in improving model accuracy, particularly in agricultural datasets where the interplay between features can significantly influence predictions.***
* ***Execution: Additional features, such as soil quality indices and climatic condition categories, were created to increase the relevance of the dataset. Techniques such as categorical encoding, handling missing values, and data normalization were applied to ensure compatibility with machine learning algorithms. This included converting categorical variables like soil type and crop categories into numerical formats that models can effectively interpret.***
* ***Evaluation: The thoughtful creation of new features demonstrated a deep understanding of how various environmental and soil factors can impact crop yield predictions. However, exploring multiple encoding methods (such as target encoding for categorical variables) could have further optimized model performance, especially for algorithms sensitive to feature scaling.***
* ***Data Splitting • Purpose: Proper splitting into training and testing sets ensures an unbiased evaluation of model performance on unseen data. • Execution: The data was split in a standard 80-20 or 70-30 manner to separate training and testing sets, enabling robust model validation. • Evaluation: This step was straightforward but critical. Including a validation set would enhance model selection by providing an additional testing stage before final evaluation.***

***Member: Ojas Rai***

***Model Selection and Development • Purpose: Developing and comparing models (Logistic Regression, Random Forest , Decision Tree) allows for assessing their relative strengths in accurately predicting employee attrition. • Execution: Member B implemented multiple models, ensuring fair comparisons through consistent data inputs. Cross-validation was performed to evaluate model consistency across data subsets. • Evaluation: This was handled well, with a clear understanding of how each model aligns with the dataset characteristics. Including other classifiers (e.g., Random Forest) or ensemble methods could add further insight into the best approach. Model Comparison and Evaluation • Purpose: Comparing models based on accuracy, precision, recall, and F1 scores helps in identifying the model best suited for attrition prediction. • Execution: Member B conducted a detailed comparison, summarizing the advantages of each model. Models were evaluated on their ability to balance precision and recall for both classes. • Evaluation: Model comparison was thorough, providing a balanced perspective. A deeper analysis of misclassified instances could yield insights into model limitations and feature relationships. Hyperparameter Tuning • Purpose: Optimizing hyperparameters improves model performance by finding the best settings, reducing the risk of overfitting or underfitting. • Execution: A grid search was conducted***

**10 References/Bibliography (No page limit)**

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**11 Github Link**

**https://github.com/ojasrai17/ML\_Lab\_A1\_10/blob/main/ML\_miniproject.ipynb**