WASTE MANAGEMENT USING MACHINE LEARNING

Optimizing Waste Classification with Advanced Techniques

Presented By: Aditi Singh

PROBLEM STATEMENT

Challenges:

- Manual sorting of waste is time-consuming and error-prone.
- Inefficient classification impacts recycling and disposal processes.

Objective:

Automate waste classification using sensor data and machine learning

DATASET AND DATA CLEANING

Description:

- Dataset contains sensor readings for different waste types.
- Features: Inductive, capacitive, infrared, and moisture properties.

Data Cleaning

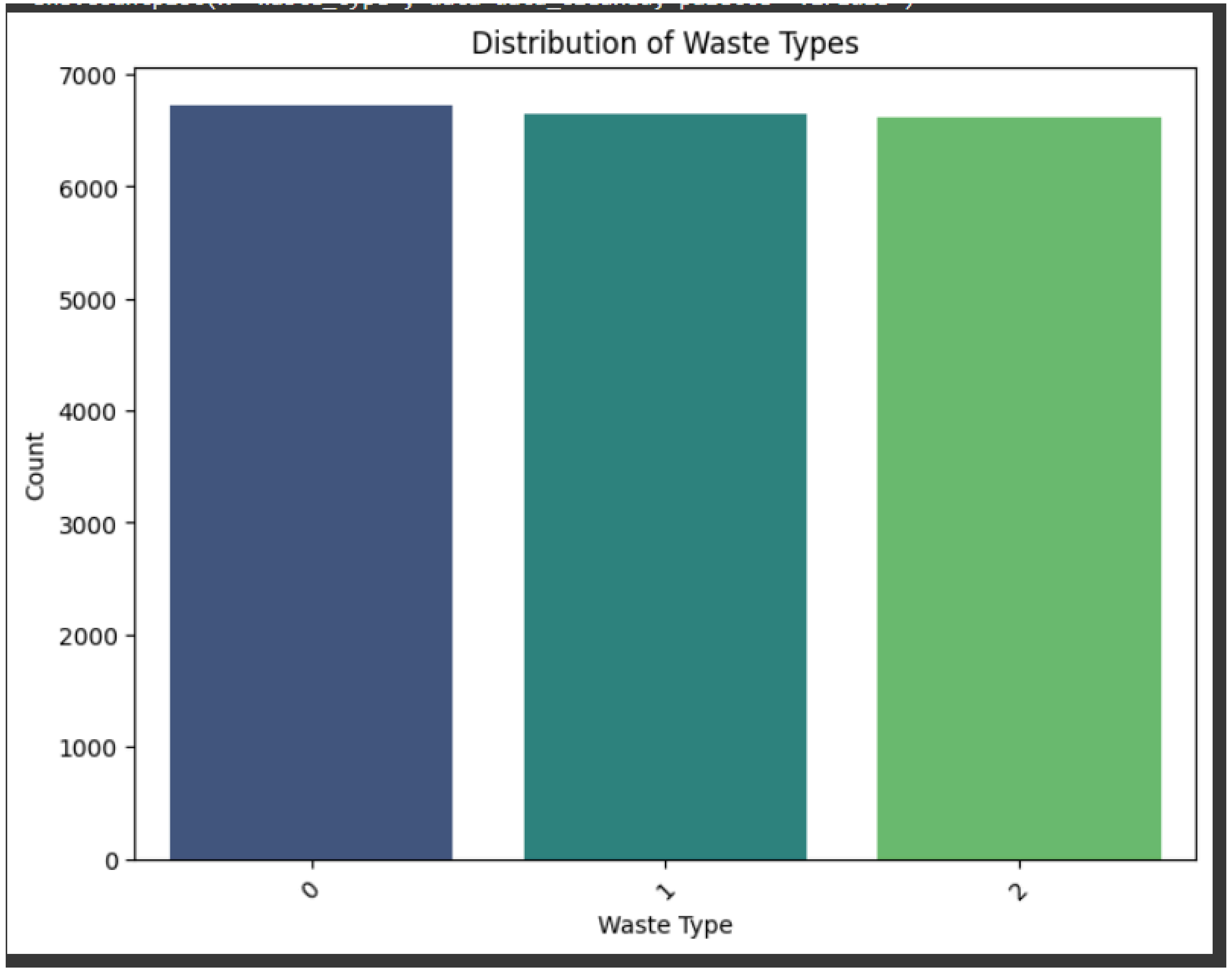
- Dropped redundant columns (e.g., timestamp).
- Encoded categorical labels for waste_type using label encoding.

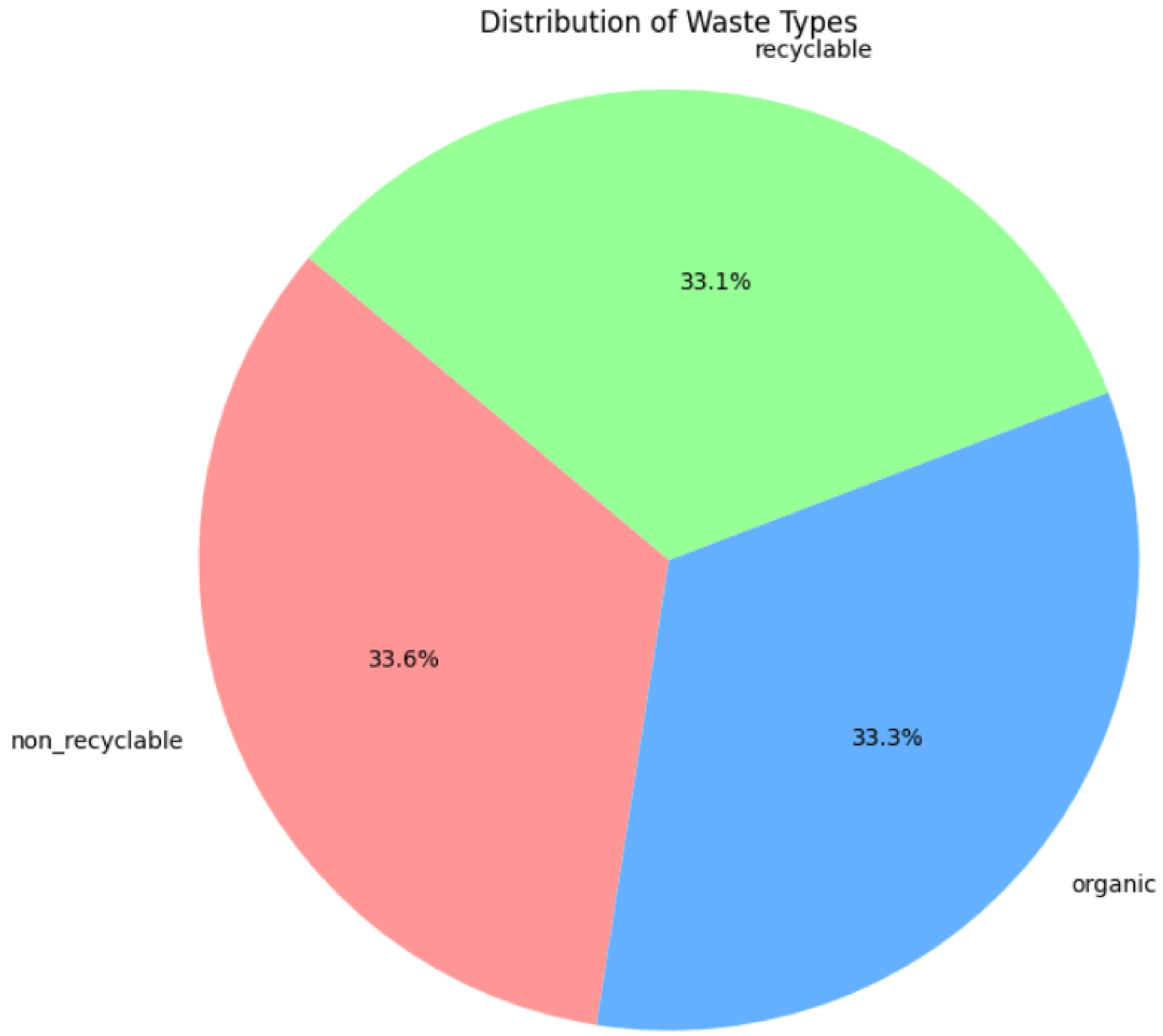
```
data_cleaned = data.drop(columns=['timestamp'])

label_encoder = LabelEncoder()
data_cleaned['waste_type'] = label_encoder.fit_transform(data_cleaned['waste_type'])
```

DATA VISUALIZATION

Charts:

- Bar Chart: Distribution of waste types.
- Pie Chart: Proportion of waste types.
- Insights: Identify class imbalance.





FEATURE ENGINEERING

Data Balancing
Technique:

- Resampled minority classes to balance the dataset.
- Ensures model fairness and improved predictions.

Feature Engineering

- inductive_to_capacitive: Ratio of inductive and capacitive properties.
- infrared_to_moisture: Ratio of infrared and moisture properties.

Preprocessing and Dimensionality Reduction

- Standardized features using StandardScaler.
- Applied PCA to reduce dimensions for better computation.

Model Training

- Algorithm: Boosted Random Forest using AdaBoost.
- Hyperparameters:
- Random Forest: 75 estimators, max depth = 10.
- AdaBoost: 50 estimators.

Model Evaluation

- Metrics:
- Accuracy: 65%
- Confusion Matrix: Visual representation of model performance.

CONCLUSION

- Summary:
  - Waste classification optimized using a machine learning pipeline.
  - Boosted Random Forest showed promising results.
- Future Work:
  - Integrate real-time IoT data for enhanced performance.

THANK YOU

For Your Attention