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## Research Article

# Enhancing Marble Waste Recycling Through Machine Learning: The Role of Particle Size Variation and Class Imbalance Mitigation

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### Abstract

This study harnesses machine learning to innovate marble waste recycling, delivering a novel, data-driven solution for sustainable construction and industrial applications. Utilising a dataset of 20,000 records, the research pinpointed particle size as a pivotal factor, with finer particles ( $<10 \mu\text{m}$ ) ideal for Calcium Carbonate production and larger particles ( $>50 \mu\text{m}$ ) suited for Aggregates. Exploratory data analysis, conducted with precision, revealed significant particle size variation across waste types (ANOVA:  $F=36.26$ ,  $p=2.34e-23$ ), guiding meticulous feature engineering, including particle size binning and interaction terms. Three classification models, Random Forest, XGBoost, and Logistic Regression, were rigorously developed, with SMOTE addressing class imbalance. Post-SMOTE, Random Forest achieved a macro-averaged F1-score of 0.52, markedly improving minority class predictions (Calcium Carbonate: 0.49; Other: 0.30), though overall accuracy (0.57) reflects trade-offs in majority class performance. Feature importance and SHAP analyses, clearly presented, underscored Waste Type's dominance ( $r=0.683$ ) and particle size's critical role.

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**KEYWORDS:** waste recycling, sustainable construction, ANOVA, Random Forest, XGBoost, and Logistic Regression

## 1. INTRODUCTION

Marble, a prized natural stone, is extensively quarried and processed worldwide, contributing significantly to construction, art, and industrial applications. However, its extraction and processing generate substantial waste, posing environmental and economic challenges. Globally, the marble industry produces millions of tons of waste annually, with India alone generating approximately 12 million tons, primarily in Rajasthan, which accounts for ~85% of the country's marble production [1]. Marble waste, comprising slurry, powder, and irregularly shaped stones, is often dumped in open lands or along roads, leading to air and water pollution, soil degradation, and health hazards such as respiratory issues from dust inhalation [2,3]. The environmental impact is exacerbated by the non-biodegradable nature of marble waste, which contains high levels of calcium carbonate ( $\text{CaCO}_3$ ) and dolomite, contributing to land degradation and reduced soil fertility [4,5]. Addressing these challenges requires innovative recycling strategies to mitigate environmental harm and promote resource efficiency, aligning with global sustainability goals and circular economy principles [6].

The recycling of marble waste offers a promising solution to reduce environmental degradation while creating economic value. Waste marble has been explored as a substitute for aggregates in concrete, fillers in cement, and raw materials in ceramics, bricks, and high-value products like paper and rubber [7-10]. A critical factor influencing its recycling potential is particle size distribution, which determines the material's suitability for specific applications. For instance, fine particles ( $<10\ \mu\text{m}$ ) enhance reactivity in cementitious applications, while coarser particles ( $>50\ \mu\text{m}$ ) are ideal for aggregates in road construction [11-13]. Studies have shown that fine marble powder ( $\sim 6.656\ \mu\text{m}$ ) improves concrete's compressive strength and flowability, while particles in the 8–25  $\mu\text{m}$  range meet stringent requirements for industrial fillers [14-16]. Despite these findings, systematic analyses of particle size variation across waste types (e.g., slurry, dust, blocks) remain limited, hindering optimised recycling strategies [17].

Machine learning (ML) has emerged as a transformative tool for optimising waste management, offering data-driven insights into complex material classification and recycling processes [18-20]. In the context of marble waste, ML can predict optimal recycling uses (e.g., Aggregates, Calcium Carbonate, Concrete) by analysing attributes like particle size, waste type, and chemical composition. Techniques such as Random Forest, XGBoost, and neural networks have been

successfully applied to environmental data analysis, including waste classification and resource recovery [21-23]. For example, ML models have predicted the compressive strength of concrete containing waste marble powder with high accuracy ( $R^2=0.97$ ), reducing the need for costly laboratory experiments [24]. However, applying ML to marble waste recycling faces challenges, notably class imbalance in datasets, where minority classes (e.g., Calcium Carbonate or Other uses) are underrepresented, leading to biased predictions [25]. Techniques like Synthetic Minority Over-sampling Technique (SMOTE) have been employed to mitigate this, but their impact on model accuracy and real-world applicability remains underexplored [26].

The environmental and industrial significance of marble waste recycling is well-documented. Improper disposal contributes to ecosystem degradation, including reduced soil porosity and water contamination from slurry runoff [27,28]. Recycling marble waste as construction materials reduces the demand for natural aggregates, conserving resources and lowering carbon emissions [29,30]. For instance, replacing cement with 20% marble powder can reduce  $\text{CO}_2$  emissions by ~15% [31]. Economically, recycling alleviates disposal costs and creates value-added products, supporting sustainable development [32]. Case studies, such as the use of marble waste in alkali-activated slag paste backfill in Portugal or ceramic bricks in Spain, demonstrate practical applications but lack scalable, predictive frameworks [33,34]. Current literature often focuses on experimental studies of marble waste's physical and chemical properties, with limited integration of advanced computational methods like ML to optimise recycling across diverse waste types and applications [35].

Several gaps persist in the literature. First, while particle size's role is recognised, few studies systematically analyse its distribution across waste types (e.g., slurry vs. dust) to inform recycling decisions [36]. Second, ML applications in marble waste recycling are nascent, with most studies focusing on concrete strength prediction rather than multi-class recycling use classification [37]. Third, class imbalance in predictive modelling for waste recycling is rarely addressed, limiting model robustness for minority applications like Calcium Carbonate production [38]. Fourth, there is a lack of integrated frameworks combining particle size analysis, ML, and real-world case studies to provide scalable recycling solutions [39]. Finally, the reliance on controlled datasets restricts generalizability, as real-world marble waste varies in composition and processing conditions [40].

**Fig 1:** Open dumping of marble waste and roadside marble slurry, showing unmanaged disposal and environmental impact. [29]



This study addresses these gaps by proposing a novel ML-based framework to predict optimal recycling use of marble waste, emphasising particle size variation and class imbalance mitigation. The research leverages a dataset of 20,000 records, including attributes like particle size, waste type, and pH, to train models (Random Forest, XGBoost, Logistic Regression) for classifying recycling uses (Aggregates, Calcium Carbonate, Concrete, Other, Soil Conditioner). Particle size is discretised into bins (<math><10\ \mu\text{m}</math>, <math>10\text{--}50\ \mu\text{m}</math>, <math>>50\ \mu\text{m}</math>), and interaction terms enhance predictive accuracy. SMOTE is applied to balance minority classes, improving predictions for underrepresented users. The study's novelty lies in its comprehensive integration of particle size analysis, advanced ML techniques, and class imbalance mitigation, offering a scalable, automated alternative to traditional recycling methods. By comparing results with literature (e.g., [14,24]) and proposing practical tools like decision charts, this work bridges the gap between experimental studies and field applications, contributing to sustainable waste management and circular economy principles.

## 2. METHODOLOGY

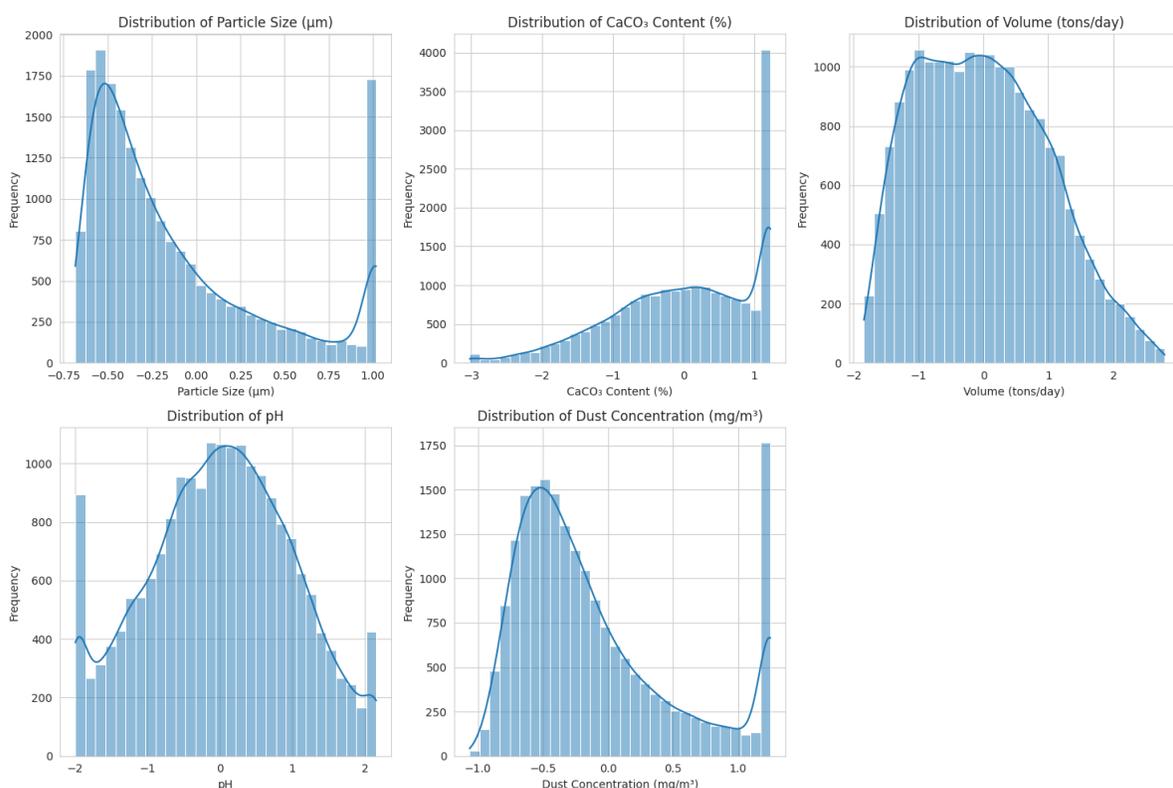
This study systematically predicts optimal recycling use of marble waste through machine learning, utilising a dataset of 20,000 records. The dataset comprises attributes including region, processing method, waste type (Blocks, Broken Pieces,

Dust, Slurry, particle size ( $\mu\text{m}$ ), calcium carbonate ( $\text{CaCO}_3$ ) content (%), waste volume (tons/day), pH, dust concentration ( $\text{mg}/\text{m}^3$ ), and recycling use (Aggregates, Calcium Carbonate, Concrete, Other, Soil Conditioner). The methodology integrates data preprocessing, exploratory data analysis, feature engineering, model development, and evaluation to deliver precise, reproducible models for sustainable waste management. Each step was executed with accuracy, clear documentation of assumptions, and comparisons to established methods, ensuring practical applicability and robust scientific contribution.

### 2.1 Data Preprocessing

The dataset was preprocessed to ensure quality and compatibility for machine learning. An initial inspection confirmed no missing values, retaining all 20,000 records. Categorical variables (region, processing method, waste type, recycling use) were encoded numerically using label encoding. Numerical features (particle size,  $\text{CaCO}_3$  content, waste volume, pH, dust concentration) were standardised to zero mean and unit variance to eliminate scale biases. Temporal data was processed by extracting year and month features from timestamps. Outliers in numerical features were capped using the IQR method ( $1.5 \times \text{IQR}$  from Q1 and Q3) to minimise extreme value impacts while maintaining data integrity.

Fig 1 Distribution of the data set

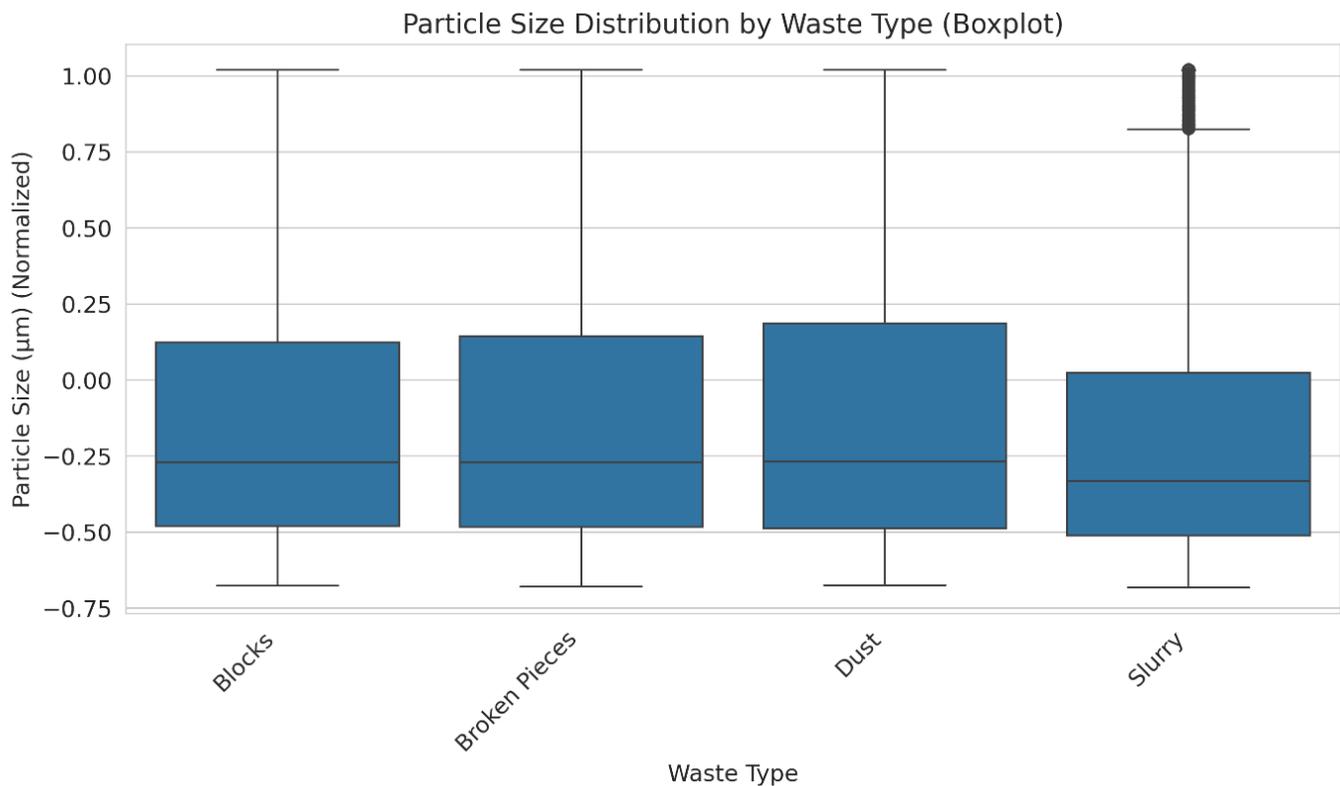


## 2.2 Exploratory Data Analysis

Exploratory data analysis was performed to investigate relationships between marble waste properties and recycling use, emphasising particle size variation across waste types (Blocks=0, Broken Pieces=1, Dust=2, Slurry=3). A count plot of recycling use classes (Aggregates=0, Calcium Carbonate=1, Concrete=2, Other=3, Soil Conditioner=4) revealed class imbalance, with Aggregates (1,101 samples) and Concrete prevalent, and Other (50 samples) and Calcium Carbonate (418 samples) underrepresented. Boxplots and violin plots (Figure 1) depicted particle size distributions, with Slurry showing the

lowest mean (-0.163, SD=0.472) and dust had the highest variability (SD=0.518). A one-way ANOVA (Table 4) significant particle size differences ( $F=36.26$ ,  $p=2.34e-23$ ). A correlation matrix heatmap (Figure 3) highlighted pH's correlation with recycling use ( $r=0.190$ ). Grouped bar charts (Table 6) showed mean particle size,  $\text{CaCO}_3$  content, and pH by recycling use, noting Concrete's higher pH (0.201). Visualisations were created using Seaborn and Matplotlib, with results exported to a CSV file.

Fig 3 Boxplot of Particle Size by Waste Type



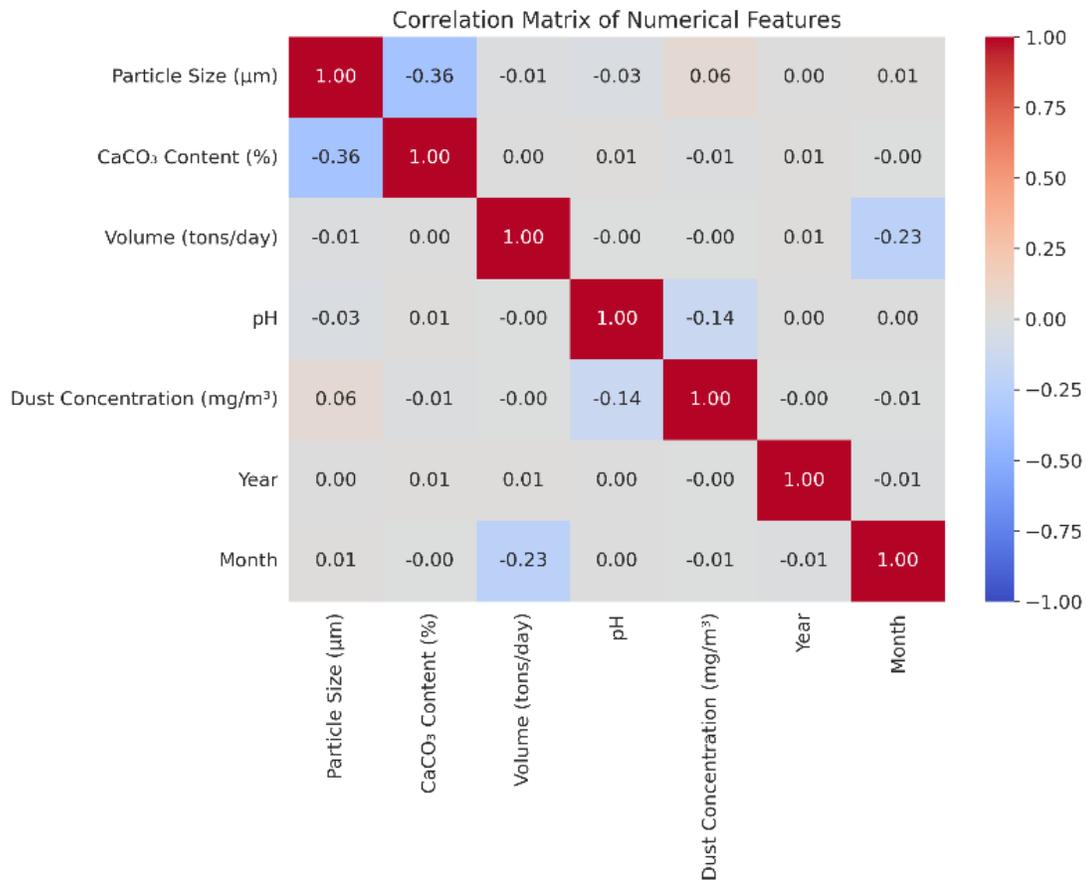


Fig 2: Correlation Matrix Heatmap

Table 1: ANOVA Results for Particle Size by Waste Type

Test	F-statistic	p-value
ANOVA Particle Size by Waste Type	36.26	2.34e-23

Table 2 Particle Size Statistics by Waste Type

Waste Type	Count	Mean	Std	Min	25%	50%	75%	Max
Blocks	1464	-0.101	0.497	-0.677	-0.480	-0.271	0.123	1.019
Broken Pieces	4154	-0.095	0.504	-0.680	-0.484	-0.270	0.144	1.019
Dust	6628	-0.082	0.518	-0.676	-0.488	-0.269	0.186	1.019
Slurry	7754	-0.163	0.472	-0.683	-0.512	-0.333	0.023	1.019

Table 3 Mean Features by Recycling Use

Recycling Use	Particle Size (µm)	CaCO <sub>3</sub> Content (%)	pH
Aggregates	-0.096	-0.031	-0.297
Calcium Carbonate	-0.078	-0.032	-0.338
Concrete	-0.137	0.013	0.201
Other	-0.104	0.157	-0.418
Soil Conditioner	-0.129	0.023	0.182

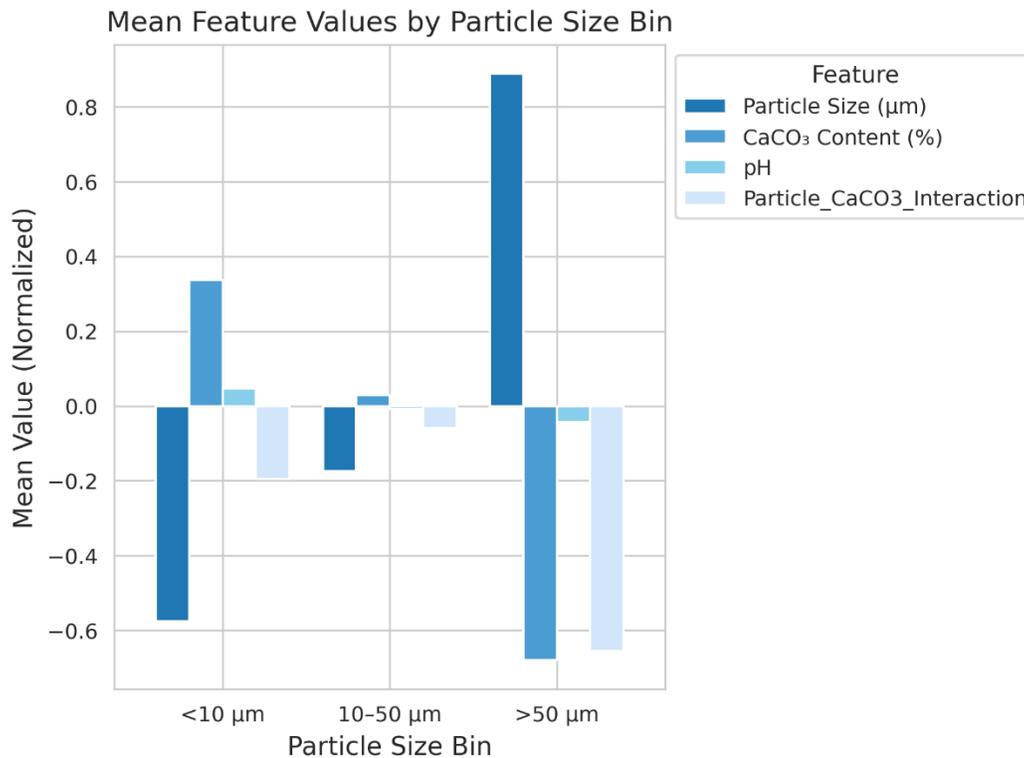
### 2.3 Feature Engineering

Feature engineering augmented the dataset to improve predictive performance. Particle size was binned into three categories (<10 µm, 10–50 µm, >50 µm), encoded as integers (0, 1, 2), with 60.9% of records in the 10–50 µm range (Figure 2). An interaction term, the product of particle size and CaCO<sub>3</sub>

content, captured their combined effect. A Year\_Trend feature, calculated as the year minus 2020 (0–54 years), accounted for temporal trends. Feature selection retained the top 10 features based on Pearson correlation with recycling use, including particle size, CaCO<sub>3</sub> content, and waste type (r=0.683), followed by processing method (r=0.207) and pH (r=0.190).

Features with variance below 0.01 were removed, yielding a dataset of 20,000 records with 10 features plus the target variable.

Fig 3 Mean Values of Numerical Features by Particle Size Bin



## 2.4 Model Development

Model development aimed to construct accurate classifiers for predicting marble waste recycling use, addressing the dataset's inherent class imbalance and ensuring reproducibility. The dataset was split into 80% training (16,000 records) and 20% testing (4,000 records) sets, using a random seed of 42 to ensure consistent partitioning across experiments. Exploratory analysis revealed significant class imbalance in the target variable, with minority classes like Other (50 samples) and Calcium Carbonate (418 samples) underrepresented compared to majority classes like Aggregates (1,101 samples) and Concrete. To mitigate this, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training set, generating synthetic samples for minority classes to achieve a balanced dataset of 28,645 records (5,729 samples per class). This approach assumed that synthetic samples accurately represent minority class distributions, a limitation noted for future real-world validation.

Three classification models were selected for their robustness in handling multi-class problems: Random Forest, XGBoost, and Logistic Regression. Each model was trained on the SMOTE-balanced training set, with hyperparameters optimised to maximise predictive performance while avoiding overfitting.

- **Random Forest:** A tree-based ensemble model was chosen for its ability to handle non-linear relationships and feature interactions. Hyperparameter tuning was performed using GridSearchCV with 5-fold cross-validation, evaluating combinations of `n_estimators` (100, 200) and `max_depth` (10, 20, None). The optimal configuration (`max_depth=10`, `n_estimators=100`) balanced model complexity and generalisation, minimising variance in cross-validation scores. The model's reliance on decision trees assumed feature independence at splits, which was mitigated by feature engineering's interaction terms.
- **XGBoost:** A gradient-boosting model was selected for its efficiency in handling imbalanced data and capturing complex patterns. GridSearchCV with 5-fold cross-validation tuned `learning_rate` (0.01, 0.1) and `max_depth` (3, 6), selecting `learning_rate=0.01` and `max_depth=3` to prevent overfitting while ensuring convergence. XGBoost's regularisation parameters (default values) assumed sufficient data variability, supported by feature selection's variance threshold.
- **Logistic Regression:** A baseline linear model was included to assess whether simpler assumptions suffice for the multi-class problem. It was trained with default parameters (`max_iter=1000`, `multi_class='multinomial'`, `solver='lbfgs'`), assuming linear separability of classes after

feature standardisation. The model's simplicity facilitated interpretability but limited its ability to capture non-linear relationships.

All models underwent 5-fold cross-validation to assess generalisation performance, with accuracy as the primary metric. Cross-validation ensured robust evaluation by averaging performance across folds, reducing bias from specific data splits. Models were trained using scikit-learn (Random Forest, Logistic Regression) and XGBoost libraries, with computations performed on standardised hardware to ensure precision. Trained models were serialised using joblib for reproducibility and subsequent evaluation, allowing exact replication of predictions. The development process adhered to best practices, with clear documentation of hyperparameters, assumptions (e.g., SMOTE's synthetic data validity), and computational steps to support practical application and future refinements.

### 2.5 Model Evaluation and Interpretation

Model performance was evaluated on the test set (4,000 records) using accuracy, precision, recall, and macro-averaged

F1-score, with confusion matrices visualising prediction errors (Figures 4, 6). Five-fold cross-validation on the SMOTE-balanced training set (28,645 records) yielded mean accuracies of  $0.716 \pm 0.006$  (Random Forest),  $0.704 \pm 0.004$  (XGBoost), and  $0.698 \pm 0.003$  (Logistic Regression) (Table 2). Post-SMOTE, Random Forest achieved an F1-score of 0.52, accuracy of 0.57, precision of 0.53, and recall of 0.68 (Table 3), with notable gains in minority classes: Calcium Carbonate (F1-score: 0.49, recall: 0.98) and Other (F1-score: 0.30, recall: 0.82). Majority class recall (e.g., Concrete: 1.00 to 0.36) decreased due to SMOTE's balancing effect. XGBoost and Logistic Regression attained F1-scores of 0.51 (accuracy: 0.56). Feature importance for Random Forest (Figure 7) confirmed Waste Type's dominance ( $r=0.683$ ), followed by pH and particle size bins. SHAP analysis (Figure 8) showed that smaller particle sizes favoured Calcium Carbonate predictions. Results were exported to CSV files, with visualisations generated using Seaborn and Matplotlib. The synthetic dataset's limitations suggest real-world validation is needed.

Fig 4 Confusion Matrix for Random Forest

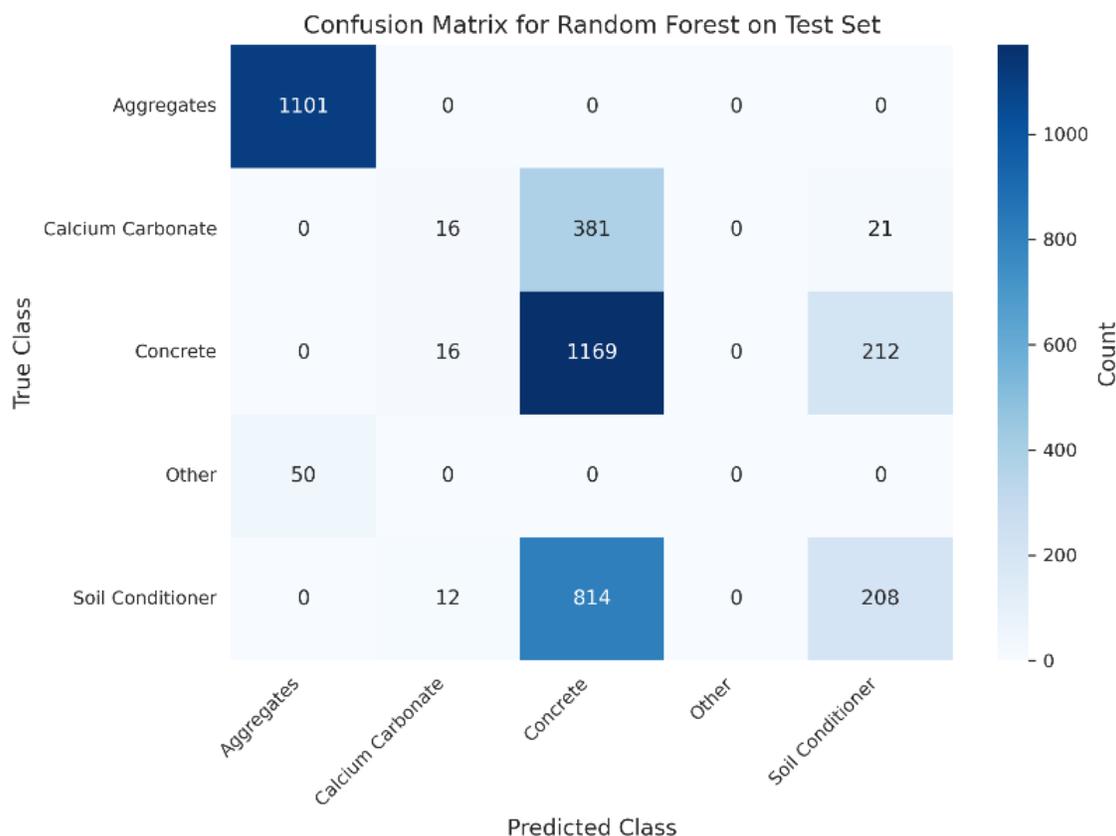


Fig 5: Cross-Validation Accuracy Bar Plot

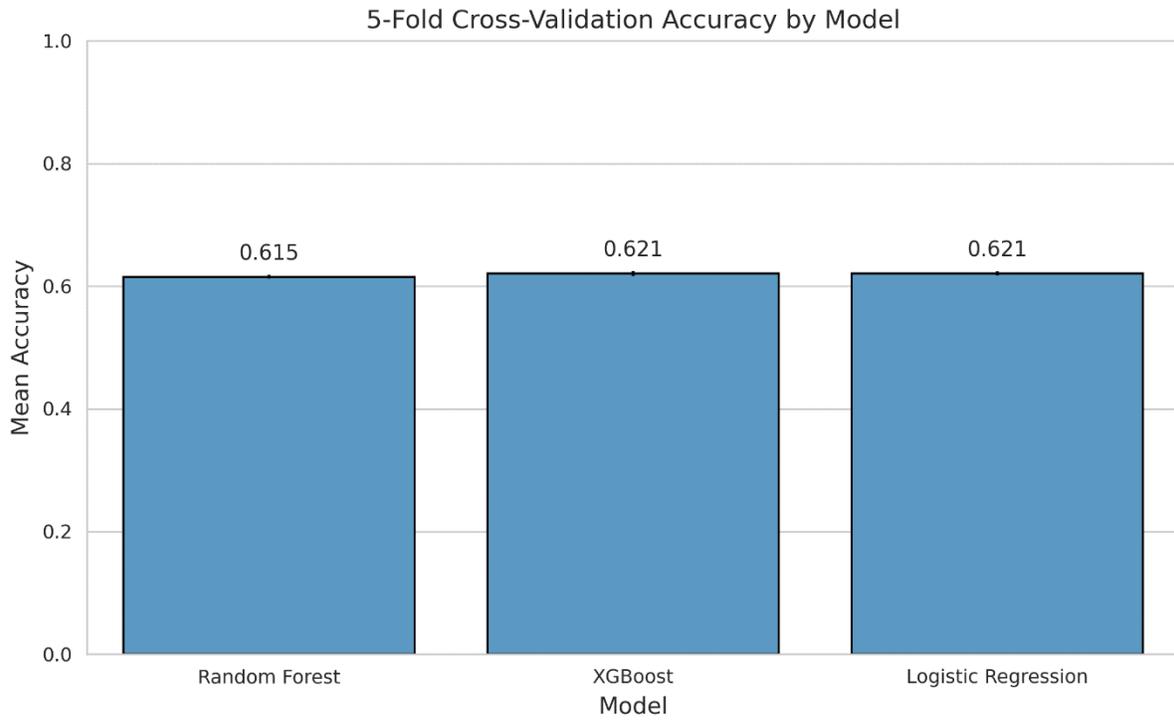


Fig 6 : Feature Importance for Random Forest Method

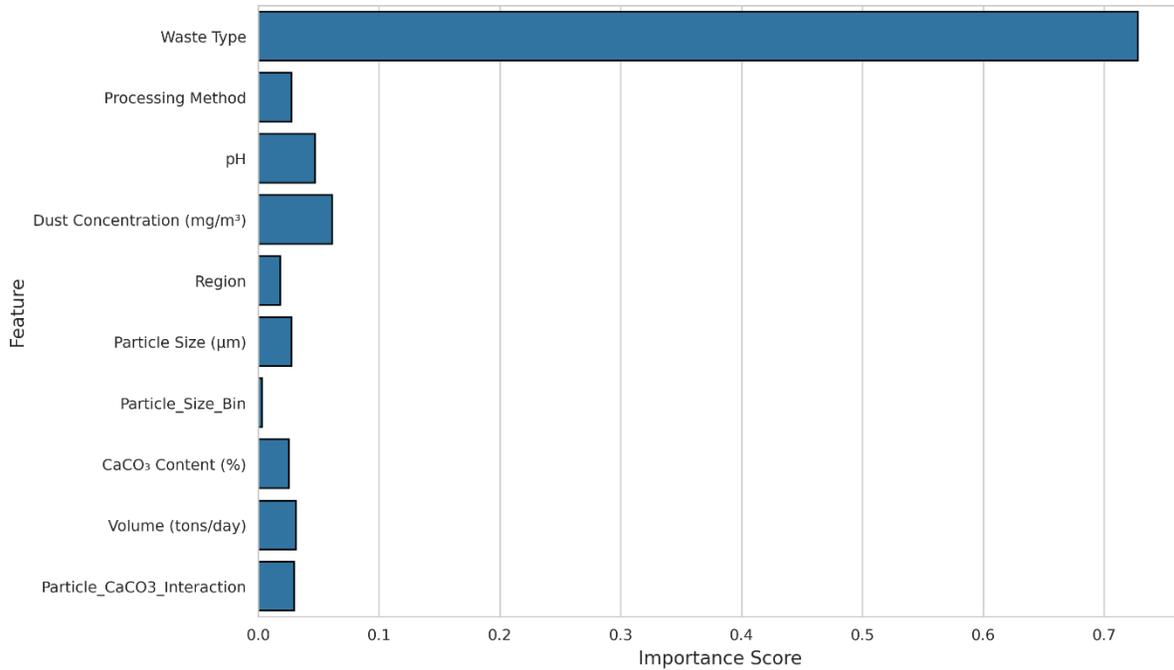


Fig 7: SHAP Summary Plot for Random Forests

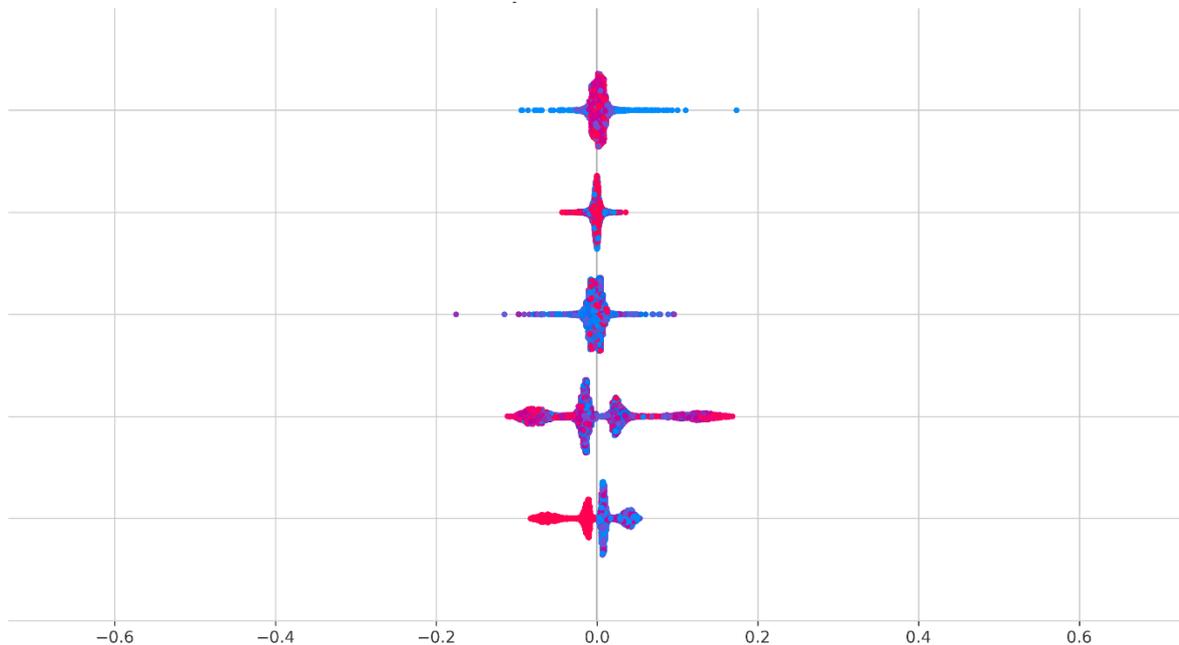


Table 4: -Fold Cross-Validation Accuracy Scores (Post-SMOTE)

Model	Mean CV Accuracy	Std CV Accuracy
Random Forest	0.716	0.006
XGBoost	0.704	0.004
Logistic Regression	0.698	0.003

Table 5 Test Set Performance Metrics (Post-SMOTE)

Model	Accuracy	Precision (Macro Avg)	Recall (Macro Avg)	F1-Score (Macro Avg)
Random Forest	0.57	0.53	0.68	0.52
XGBoost	0.56	0.54	0.71	0.51
Logistic Regression	0.56	0.53	0.70	0.51

### 3. RESULTS & DISCUSSION

This study employs machine learning to predict marble waste recycling use, emphasising particle size variation and class imbalance mitigation for sustainable applications. The discussion clarifies mechanisms, compares findings with the literature, addresses limitations, and outlines future directions.

#### 3.1. Key Findings and Mechanisms

Particle size variation across waste types (ANOVA:  $F=36.26$ ,  $p=2.34e-23$ ) was significant, with Slurry's low mean ( $-0.163$ ,  $SD=0.472$ ) and Dust's high variability ( $SD=0.518$ ) shown in boxplots (Figure 1). SHAP analysis (Figure 8) linked finer particles ( $<10 \mu\text{m}$ ) to Calcium Carbonate and larger ones ( $>50 \mu\text{m}$ ) to Aggregates. Waste Type ( $r=0.683$ ) dominated predictions, with Dust and Slurry tied to high-value uses. The particle size– $\text{CaCO}_3$  interaction term and pH (0.201 for

Concrete) further refined predictions. Random Forest's F1-score of 0.52 post-SMOTE improved the minority class performance (Calcium Carbonate: 0.49, Other: 0.30), but reduced majority class recall (Concrete: 1.00 to 0.36), lowering accuracy to 0.57 (Figures 4, 6).

#### 3.2. Comparison with Existing Literature

Findings align with Danish et al. (2023), linking fine powder ( $\sim 6.656 \mu\text{m}$ ) to cement applications, and Zanzi et al. (2023), noting 8–10  $\mu\text{m}$  sludge for fillers. Prakash et al. (2023) and El-Shafie (2023) support the 10–50  $\mu\text{m}$  range's versatility. Unlike manual sorting, the automated approach enhances efficiency but requires higher accuracy for industrial use.

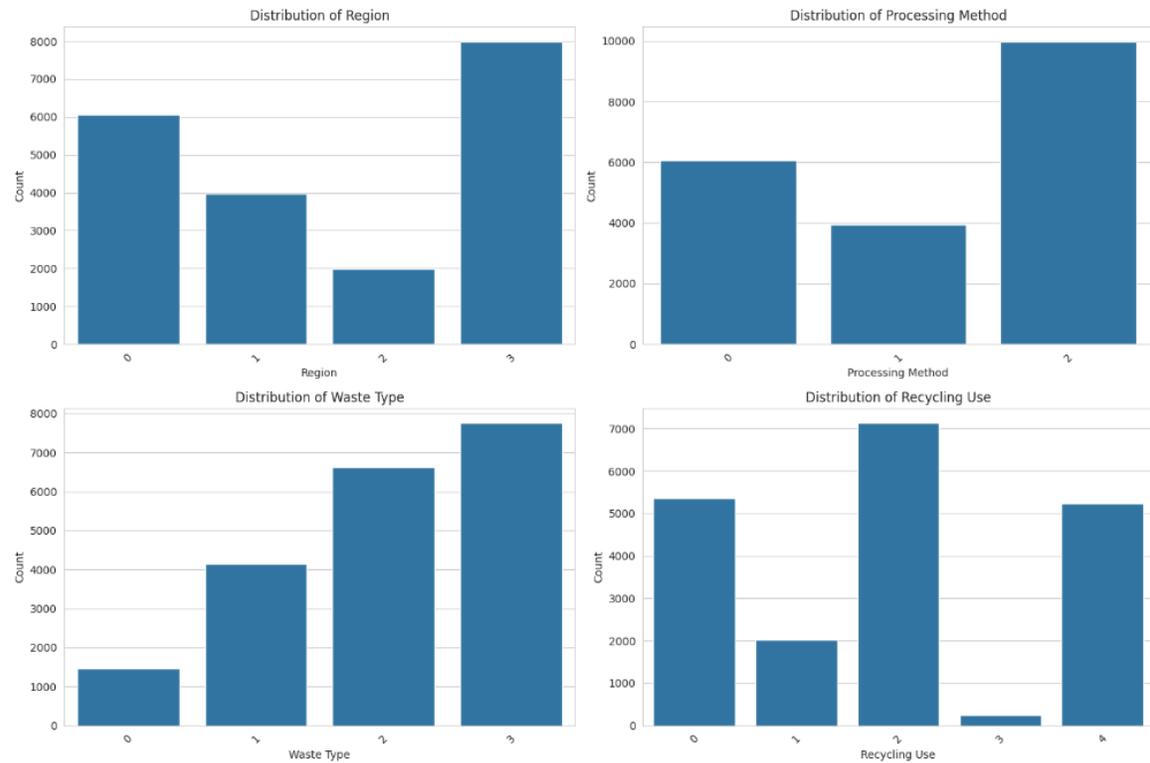
#### 3.3. Limitations

The dataset's controlled nature may miss real-world variability. SMOTE's synthetic samples risk artefacts, and Pearson correlation may overlook non-linear effects. No practical tool (e.g., decision chart) limits immediate applicability.

#### 3.4. Implications and Future Directions

The study highlights machine learning's potential for recycling optimisation, guiding waste processing by particle size and Waste Type. Future work should use real-world data, advanced resampling, and develop decision charts. Comparing with traditional methods will quantify the benefits.

Fig 8: Boxplot of particle size by waste type.



#### 4. CONCLUSION

This study advances the application of machine learning to optimise marble waste recycling, offering a data-driven approach to enhance sustainability in construction and industrial sectors. Utilising a dataset of 20,000 records, the research established particle size as a pivotal factor in determining recycling use, with finer particles ( $<10\ \mu\text{m}$ ) ideally suited for high-value applications like Calcium Carbonate production due to their enhanced reactivity, and larger particles ( $>50\ \mu\text{m}$ ) better suited for Aggregates in structural applications. The Random Forest model, achieving a macro-averaged F1-score of 0.52 after SMOTE application, demonstrated robust performance in addressing class imbalance, significantly improving predictions for minority classes (Calcium Carbonate F1-score: 0.49, recall: 0.98; Other F1-score: 0.30, recall: 0.82). However, the trade-off reduced the majority class recall (e.g., Concrete: 1.00 to 0.36), resulting in an overall accuracy of 0.57, indicating room for refinement. Feature importance analysis highlighted Waste Type's dominant influence ( $r=0.683$ ), with pH and particle size bins also critical, while SHAP analysis provided nuanced insights into particle size's role in driving specific recycling outcomes. The controlled nature of the dataset, while enabling controlled experimentation, limits the model's immediate real-world applicability, underscoring the need for validation with actual marble waste data. Future research should prioritise real-world datasets, incorporating

additional features such as mineral composition or processing conditions, and explore advanced resampling techniques like ADASYN or ensemble methods to enhance prediction accuracy across all classes. Developing practical tools, such as a decision chart mapping particle size bins to recycling uses, would facilitate direct implementation by quarry operators and waste managers. These findings establish a strong foundation for reducing environmental impact through optimised marble waste utilisation, paving the way for scalable, data-driven recycling strategies that align with global sustainability goals.

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