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# Machine Learning-Based Plastic Waste Environmental Impact Prediction and Reduction Recommendation System

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**Abstract -** *Plastic waste that is not collected or disposed of safely is a growing environmental problem, and the way countries generate, collect, recycle, and dispose of it varies widely. This paper describes a machine -learning prototype that predicts mismanaged plastic waste at country level, turns the result into an Environmental Pressure Score, and suggests ways to bring that pressure down. We compared Linear Regression, Random Forest, and Gradient Boosting on 153 country records using an 80:20 train -test split with a fixed random seed. Random Forest performed best, with an R-squared of 0.7323, a mean absolute error of 145,979 tons, and a root mean squared error of 261,875 tons. Linear Regression followed closely at 0.7167, while Gradient Boosting reached 0.3821. Th e prototype also provides Shapley -value (SHAP) explanations and what -if scenarios for recycling, collection coverage, open dumping, and disposal. A preliminary correlation test between recycling rate and mismanaged waste was not statistically significant, with a p-value of 0.178. These results come from a single split of a small dataset whose original source and year are not documented, and the pressure score has not been checked against outside indicators. The work is best read as a working prototype that needs further validation before any operational use.*

**Key Words: Plastic waste, machine learning, random forest regression, environmental pressure score, explainable AI, SHAP.**

## 1. INTRODUCTION

Plastic is everywhere because it is cheap, durable, and easy to shape. The same qualities make it hard to deal with once it becomes waste, particularly where collection, recycling, and safe disposal have not kept up with consumption [1]. When plastic waste is mismanaged it can end up in open dumps, waterways, and eventually the ocean, and how much of it a country mismanages depends on its population, its economy, how much waste it produces, and how that waste is handled.

Machine learning (ML) can capture relationships among several variables at once, which helps when simple linear assumptions do not hold. A prediction on its own, though, does little for a planner. The people who make decisions also want to know why a number is high and what could bring it down. Our project tries to close that gap by pairing a regression model with a separately defined Environmental Pressure Score, explanations based on Shapley Additive Explanations (SHAP), and rule -based recommendations.

This paper documents the workflow, reports the results we obtained, and says plainly what the evidence does and does not show.

We describe the data and the models, report the metrics from our experiments, and point out the checks that are still needed before the system could be trusted outside a prototype setting.

## 2. PROBLEM STATEMENT

Decision-makers rarely have a simple, transparent country -level signal that brings waste quantities and waste -management indicators together to estimate mismanaged plastic waste and show where improvement is most needed. This project responds by building a prototype that (1) predicts mismanaged plastic waste in tons, (2) calculates an Environmental Pressure Score, (3) explains the prediction, and (4) suggests hypothetical improvements in recycling, collection, dumping, and disposal.

Several limits apply to the evidence we have. The source and reference year of the dataset were not recorded in the project files, the experiments rest on a single train-test split, and only one hypothesis test has been run so far. We treat these as limitations and do not fill the gaps with assumptions.

## 3. LITERATURE REVIEW

Research on artificial intelligence in waste management is broad. It covers forecasting, waste classification, collection planning, routing, and lifecycle management. Table 1 summarizes the five studies closest to our work, either in the prediction task or in their attention to interpretability. Each is described at the level of its published abstract, so the comparison is qualitative.

**Table 1 Summary of related studies**

| Study | Focus and method | Relevance to this project | Limitation or comparison point |
|---|---|---|---|
| Abdallah et al. [2], 2020 | Systematic review of 85 studies (2004–2019) on AI in solid waste management, covering waste forecasting, bin-level detection, process prediction, vehicle routing, and planning. | Abdallah et al. [2], 2020 | Systematic review of 85 studies (2004–2019) on AI in solid waste management, covering waste forecasting, bin-level detection, process prediction, vehicle routing, and planning. |
| Ayeleru et al. [3], 2024 | Supervised time-series models forecasting plastic-waste generation in Johannesburg from historical national statistics; | Ayeleru et al. [3], 2024 | Supervised time-series models forecasting plastic-waste generation in Johannesburg from historical national statistics; |
| Zou et al. [4], 2025 | Review of machine learning for prediction and optimization across the life cycle of solid waste management | Highlights data quality, data quantity, and interpretability as key considerations. | Review-level evidence; it does not offer a direct comparison for a country-level regression experiment. |
| Fejes, Kurdi, and Sebestyén [5], 2026 | Review of model structures for municipal solid-waste prediction, organized by the number of observations and the predictor variables available. | Supports choosing models according to the data at hand. | Municipal solid waste is broader than plastic waste, so target and scale may differ. |
| Bhattarai, Neupane, and Rasul [6], 2026 | Review of AI-based plastic waste classification for sorting. | Points to computer vision, deep learning, real-world data, and scalability as the main issues in sorting. | Image-based sorting is a different problem from country-level prediction of mismanaged waste. |
| Zou et al. [4], 2025 | Review of machine learning for prediction and optimization across the life cycle of solid waste management | Highlights data quality, data quantity, and interpretability as key considerations. | Review-level evidence; it does not offer a direct comparison for a country-level regression experiment. |

Taken together, these studies span waste forecasting, lifecycle optimization, and image-based sorting. Our prototype is narrower in one respect, because it works on country -level regression, and wider in another, because it tries to connect a prediction to a pressure score, explanations, and recommendations. We do not claim it is better than any of these studies. A fair comparison would need the full papers, matching datasets, and a common evaluation protocol.

## 4. RESEARCH GAP

The gap we explore is a practical one. Many studies address a single task such as forecasting, sorting, collection, or lifecycle management, while fewer seem to place country -level mismanaged-plastic prediction, a transparent pressure score, feature -level explanations, and scenario-based recommendations in one workflow. We offer this as a proposed contribution and not as a proven first. Establishing novelty would take a full literature search and a verified comparison table.

## 5. RESEARCH QUESTIONS

RQ1: Can supervised machine -learning models predict country-level mismanaged plastic waste from demographic, economic, and waste-management variables?

RQ2: Which of Linear Regression, Random Forest Regression, and Gradient Boosting Regression performs best under the same evaluation protocol?

RQ3: Can a transparent Environmental Pressure Score turn waste and management indicators into a useful decision -support signal?

RQ4: Do SHAP explanations and what-if analysis make the model output easier to interpret and use for planning?

## 6. RESEARCH OBJECTIVES

1. To develop a supervised regression model that predicts mismanaged plastic waste in tons.
2. To compare Linear Regression, Random Forest Regression, and Gradient Boosting Regression using the coefficient of determination ($R^2$), mean absolute error (MAE), and root mean squared error (RMSE).
3. To construct a transparent Environmental Pressure Score from normalized plastic -waste and waste-management indicators.
4. To generate rule-based recommendations on recycling, collection coverage, open dumping, and disposal.
5. To use SHAP to interpret how each input feature contributes to the predictions.

## 7. HYPOTHESES

H01: There is no statistically significant difference in predictive performance among Linear Regression, Random Forest Regression, and Gradient Boosting Regression.

H11: At least one of the three regression models differs significantly in predictive performance.

H02: Recycling rate and collection coverage are not significantly associated with the Environmental Pressure Score after accounting for the other modelled indicators.

H12: Higher recycling and collection coverage are associated with lower pressure, while greater open dumping is associated with higher pressure.

These hypotheses were set out at the start of the project. Section X reports what has been tested so far, and none of the null hypotheses above is rejected on the basis of the current results.

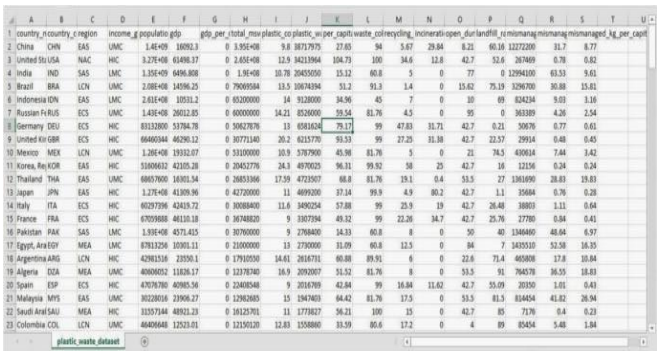
## 8. RESEARCH METHODOLOGY

### 8.1Research Design

The study is a quantitative, predictive ML prototype built on country -level records. It compares regression algorithms and adds a decision-support layer, made up of the pressure score, SHAP explanations, recommendations, and what-if analysis, that is served through a small web interface.

### 8.2Dataset and Variables

Each record describes one country. Alongside identifiers such as country name, code, region, and income group, the cleaned file holds demographic, economic, and waste-sector variables (Fig. 1). The analysis used 153 country records. The target variable is mismanaged plastic waste, measured in tons per year, and the 11 predictors are grouped in Table 2.



| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R | S | T | U |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | country_n | country_c | region | income_g | populatio | gdp | | gdp_per_c | total_msw | plastic_co | plastic_wa | per_capita | waste_col | recycling_ | incinerati | open_dun | landfill_r | mismanag | mismanag | mismanaged_kg_per_capit | |
| 2 | China | CHN | EAS | UMC | 1.4E+09 | 16092.3 | | 0 | 3.95E+08 | 9.8 | 38717975 | 27.65 | 94 | 5.67 | 29.84 | 8.21 | 60.16 | 12272200 | 31.7 | 8.77 | |
| 3 | United Sta | USA | NAC | HIC | 3.27E+08 | 61498.37 | | 0 | 2.65E+08 | 12.9 | 34213964 | 104.73 | 100 | 34.6 | 12.8 | 42.7 | 52.6 | 267469 | 0.78 | 0.82 | |
| 4 | India | IND | SAS | LMC | 1.35E+09 | 6496.808 | | 0 | 1.9E+08 | 10.78 | 20455050 | 15.12 | 60.8 | 5 | 0 | 77 | 0 | 12994100 | 63.53 | 9.61 | |
| 5 | Brazil | BRA | LCN | UMC | 2.08E+08 | 14596.25 | | 0 | 79069584 | 13.5 | 10674394 | 51.2 | 91.3 | 1.4 | 0 | 15.62 | 75.19 | 3296700 | 30.88 | 15.81 | |
| 6 | Indonesia | IDN | EAS | LMC | 2.61E+08 | 10531.2 | | 0 | 65200000 | 14 | 9128000 | 34.96 | 45 | 7 | 0 | 10 | 69 | 824234 | 9.03 | 3.16 | |
| 7 | Russian Fe | RUS | ECS | UMC | 1.43E+08 | 26012.85 | | 0 | 60000000 | 14.21 | 8526000 | 59.54 | 81.76 | 4.5 | 0 | 95 | 0 | 363389 | 4.26 | 2.54 | |
| 8 | Germany | DEU | ECS | HIC | 83132800 | 53784.78 | | 0 | 50627870 | 13 | 6581624 | 79.17 | 99 | 47.83 | 31.71 | 42.7 | 0.21 | 50670 | 0.77 | 0.61 | |
| 9 | United Kir | GBR | ECS | HIC | 66460344 | 46290.12 | | 0 | 30771140 | 20.2 | 6215770 | 93.53 | 99 | 27.25 | 31.38 | 42.7 | 22.57 | 29914 | 0.48 | 0.45 | |
| 10 | Mexico | MEX | LCN | UMC | 1.28E+08 | 19332.07 | | 0 | 53109000 | 10.9 | 5787900 | 45.98 | 81.76 | 5 | 0 | 21 | 74.3 | 439014 | 7.44 | 3.42 | |
| 11 | Korea, Rep | KOR | EAS | HIC | 51606632 | 42105.28 | | 0 | 20452776 | 34.3 | 4970025 | 96.31 | 99.92 | 58 | 25 | 42.7 | 16 | 12156 | 0.24 | 0.24 | |
| 12 | Thailand | THA | EAS | UMC | 68657600 | 16301.54 | | 0 | 26853366 | 17.59 | 4723507 | 68.8 | 81.76 | 19.1 | 0.4 | 53.5 | 27 | 1361690 | 28.83 | 19.83 | |
| 13 | Japan | JPN | EAS | HIC | 1.27E+08 | 41309.96 | | 0 | 42720000 | 11 | 4699200 | 37.14 | 99.9 | 4.9 | 80.2 | 42.7 | 1.1 | 35604 | 0.76 | 0.28 | |
| 14 | Italy | ITA | ECS | HIC | 60297396 | 42419.72 | | 0 | 30088400 | 11.6 | 3490254 | 57.88 | 99 | 25.9 | 19 | 42.7 | 26.48 | 38803 | 1.11 | 0.64 | |
| 15 | France | FRA | ECS | HIC | 67059688 | 46110.18 | | 0 | 36748820 | 9 | 3307394 | 49.32 | 99 | 22.26 | 34.7 | 42.7 | 25.76 | 27780 | 0.84 | 0.41 | |
| 16 | Pakistan | PAK | SAS | LMC | 1.93E+08 | 4571.415 | | 0 | 30760000 | 9 | 2768400 | 14.33 | 60.8 | 8 | 0 | 50 | 40 | 1346460 | 48.64 | 6.97 | |
| 17 | Egypt, Ara | EGY | MEA | LMC | 87813256 | 10301.11 | | 0 | 21000000 | 13 | 2730000 | 31.09 | 60.8 | 12.5 | 0 | 84 | 7 | 1435510 | 52.58 | 16.35 | |
| 18 | Argentina | ARG | LCN | HIC | 42981516 | 23550.1 | | 0 | 17910550 | 14.61 | 2616731 | 60.88 | 89.91 | 6 | 0 | 22.6 | 71.4 | 465808 | 17.8 | 10.84 | |
| 19 | Algeria | DZA | MEA | UMC | 40606052 | 11826.17 | | 0 | 12378740 | 16.9 | 2092007 | 51.52 | 81.76 | 8 | 0 | 53.5 | 91 | 764578 | 36.55 | 18.83 | |
| 20 | Spain | ESP | ECS | HIC | 47076780 | 40985.56 | | 0 | 22408548 | 9 | 2016769 | 42.84 | 99 | 16.84 | 11.62 | 42.7 | 55.09 | 20350 | 1.01 | 0.43 | |
| 21 | Malaysia | MYS | EAS | UMC | 30220016 | 21906.27 | | 0 | 12982685 | 15 | 1947403 | 64.42 | 81.76 | 17.5 | 0 | 53.5 | 81.5 | 814454 | 41.82 | 26.94 | |
| 22 | Saudi Arat | SAU | MEA | HIC | 31557344 | 48921.23 | | 0 | 16125701 | 11 | 1773827 | 56.21 | 100 | 15 | 0 | 42.7 | 85 | 7176 | 0.4 | 0.23 | |
| 23 | Colombia | COL | LCN | UMC | 46406648 | 12523.01 | | 0 | 12150120 | 12.83 | 1558860 | 33.59 | 80.6 | 17.2 | 0 | 4 | 89 | 85454 | 5.48 | 1.84 | |

**Fig.1** Sample of Rows and Variables from the country-level plastic-waste dataset.

The name, source, and reference year of the original dataset were not recorded in the project files, so we cannot cite them here.

We list this among the limitations.

**Table 2. Predictors and target variable**

| Variable group | Variables |
|---|---|
| Demographic and economic | Population; GDP |
| Waste quantity | Total municipal solid waste per year; plastic composition (percent); plastic waste generation (tons); per-capita plastic waste (kg per year) |
| Waste management | Collection coverage (percent); recycling rate (percent); incineration rate (percent); open dumping (percent); landfill rate (percent) |
| Prediction target | Mismanaged plastic waste (tons per year) |

## 8.3 Data Processing

We began with exploratory analysis and a check for duplicate records before preparing the variables for modelling. One of the exploratory views (Fig. 2) ranks the ten countries with the largest plastic waste generation. China and the United States are far ahead of the rest, and India comes third; after that, the bars drop off sharply. This skew matters for evaluation, because errors measured in tons will be driven by a small number of very large countries. The project folder also keeps the trained model, a scaler, and the list of features as saved files so the web application can reuse them.

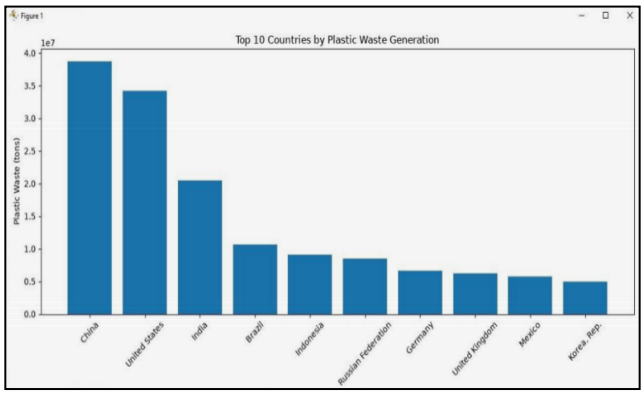



**Fig.2** Exploratory analysis: the ten countries with the largest plastic waste generation

## 8.4 Model Development

We compared three regression algorithms from scikit - learn: Linear Regression, Random Forest Regression, and Gradient Boosting Regression. Fig. 3 shows the training script, which loads the cleaned dataset, selects the 11 predictors, and sets mismanaged plastic waste in tons as the target. The data were divided 8 0:20 into training and test sets with random state set to 42, and the three models were scored on the same held-out countries so that the comparison is fair.

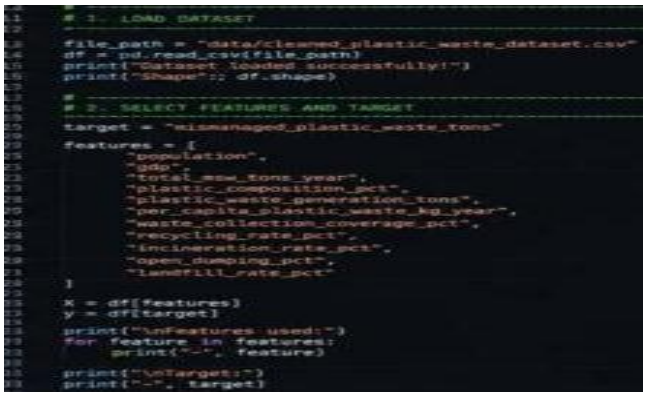


**Fig.3** Model training script

## 8.5 Evaluation Metrics

We report three metrics. $R^2$ shows the share of variation in the target that a model explains compared with simply predicting the mean, so higher is better. MAE is the average size of the prediction error in tons. RMSE is similar but gives more weight to large errors. For MAE and RMSE, lower is better.

Environmental Pressure Score, Explainability, and Recommendations. The Environmental Pressure Score is a weighted sum of five normalized component scores, and the interface reports it out of
100.

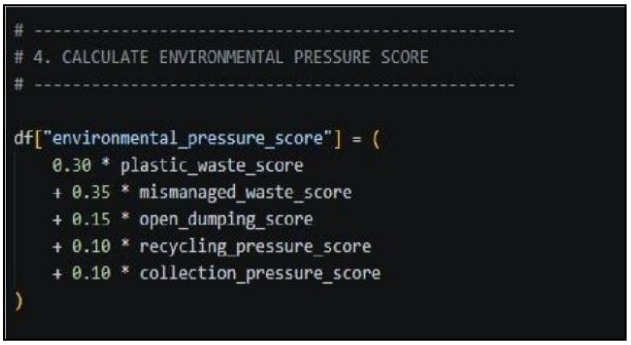



**Fig.4** shows the Formula as implemented in the project code.

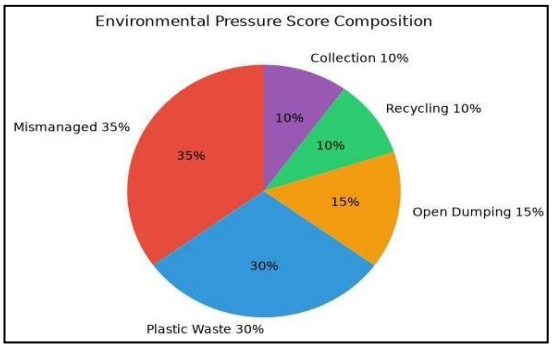



**Fig.5** shows the resulting weights : 0.30 for plastic waste

0.35 for mismanaged waste, 0.15 for open dumping, 0.10 for recycling pressure, and 0.10 for collection pressure. Mismanaged waste carries the largest single weight, and the two waste-quantity terms together make up 65 percent of the score. These weights are fixed values in the code. They have not been calibrated against data, and nothing yet shows that they are the right ones.

SHAP is used to show how strongly each input pushes a prediction up or down. Rule-based recommendations and a what-if module let a user change recycling, collection coverage, open dumping, or disposal values and see how the score responds. A what-if result reflects the behavior of the project's own score under hypothetical inputs. It does not, by itself, prove that a real -world intervention would have the same environmental effect.

## 9. TOOLS AND TECHNOLOGIES

Table 3 lists the tools that appear in the project files and screenshots.

**Table 3 Tools and technologies use**

| Tool | Role in the project |
|---|---|
| Python | Programming language for the analysis, training, and application scripts. |
| pandas and NumPy | Loading the cleaned dataset and performing numerical operations. |
| scikit-learn | Train-test split, scaling, the three regression models, and the evaluation metrics. |
| joblib | Saving the trained model, scaler, and feature list. |
| SHAP | Explaining how each feature contributes to the predictions. |
| Matplotlib | Exploratory charts, the actual-versus-predicted plot, and the SHAP summary plot. |
| HTML, CSS, and JavaScript | The Plastic Wise web interface that presents scores, recommendations, and what-if scenarios. |
| Visual Studio Code | Code editor and terminal used to run the scripts. |

For reproducibility, the random seed (42), the 80:20 split, and the definition of the target variable are fixed in the code. Package versions, the exact preprocessing steps, and the dataset provenance should accompany any release of the code and data.

## 10. DATA ANALYSIS AND INTERPRETATION

### 10.1Model Comparison

Table 4 and Fig. 6 give the results from the single 80:20 split. Random Forest scored best on all three metrics, with an $R^2$ of 0.7323, which means it explains about 73 percent of the variation in the test data, an MAE of 145,979.23 tons, and an RMSE of 261,874.55 tons. Linear Regression came close in $R^2$ (0.7167) and RMSE, although its MAE was about 35,000 tons higher. Gradient Boosting did much worse, with an $R^2$ of 0.3821 and an RMSE of 397,819.37 tons.

**Table 4. Test-set performance of the three regression models**

| Model | $R^2$ | MAE (tons) | RMSE (tons) |
|---|---|---|---|
| Linear Regression | 0.7167 | 181,339.77 | 269,369.75 |
| **Random Forest** | **0.7323** | **145,979.23** | **261,874.55** |
| Gradient Boosting | 0.3821 | 202,714.82 | 397,819.37 |

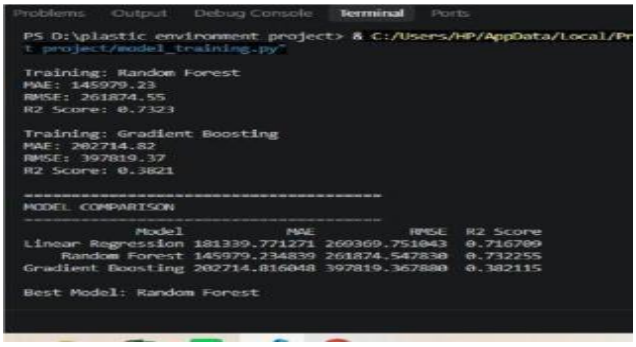



**Fig.6 Terminal output of the training script, including the three-model comparison**

The fact that the simplest model came so close to Random Forest suggests that much of the signal in these predictors is roughly linear. With only about 31 countries in the test set, the gap between the two may not hold up on a different split. Gradient Boosting's weaker result deserves a closer look. The actual -versus-predicted plot (Fig. 7) shows that it badly under -predicts the largest cases, and at least one prediction falls slightly below zero. Because hyperparameter tuning is not reported here, we cannot say whether the result reflects the algorithm itself or its settings on a small, skewed dataset. On this split, then, Random Forest is the best performer (RQ2), but its margin over Linear Regression is small and no statistical test has separated them yet.

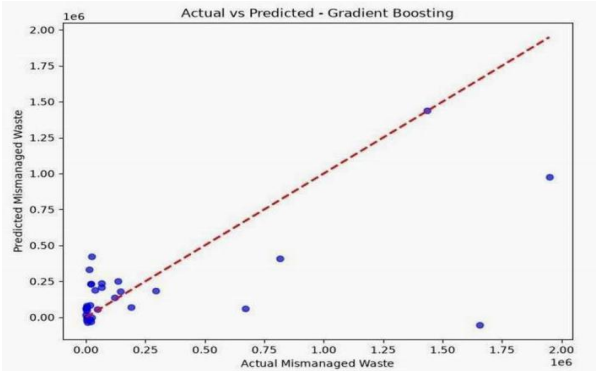



**Fig.7** Actual versus predicted mismanaged waste for the Gradient Boosting model on the test

Environmental Pressure Score in the Prototype

The Country Analysis page (Fig. 8) shows how the pieces fit together for a single country. For India, it reports 20,455,050 tons of plastic waste generated per year, of which 12,994,100 tons are mismanaged, together with a 5.0 percent recycling rate, 60. 8 percent collection coverage, and 77.0 percent open dumping. These inputs give a pressure score of 75.77 out of 100, which the interface labels Very High Pressure. This is a simple, readable output, which is the main thing RQ3 asks of it, although the score has not yet been checked against expert judgment or independent indicators.

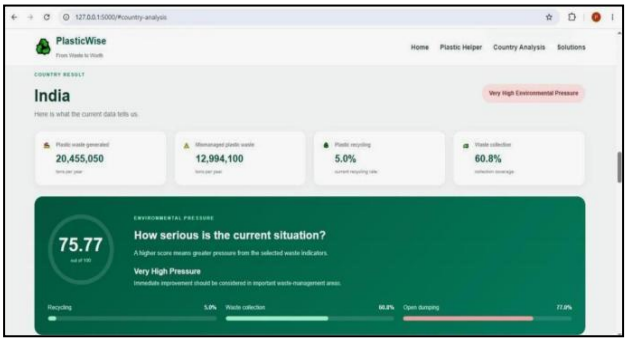



**Fig.8** Country analysis page of the Plastic Wise prototype for India. Showing the pressure score and its indicators.

**10.1SHAP Explanation**

The SHAP summary plot (Fig. 9) ranks the predictors by their influence on the model's output. Population and plastic waste generation have by far the widest spread of SHAP values, followed by GDP, total municipal solid waste, and per -capita plastic waste. The management indicators (collection coverage, open dumping, recycling, landfill, and incineration) and plastic composition contribute much less in this model. The largest positive values belong to countries with high feature values, which fits the way the target is measured: mismanaged waste in tons grows with country size, so the model leans mainly on scale. Two cautions apply. SHAP shows how the model uses its inputs and does not prove that changing an input will change the outcome in the real world. Several predictors are also arithmetically linked, since plastic waste generation appears to be total municipal solid waste multiplied by plastic composition, so individual contributions should be read with that overlap in mind.

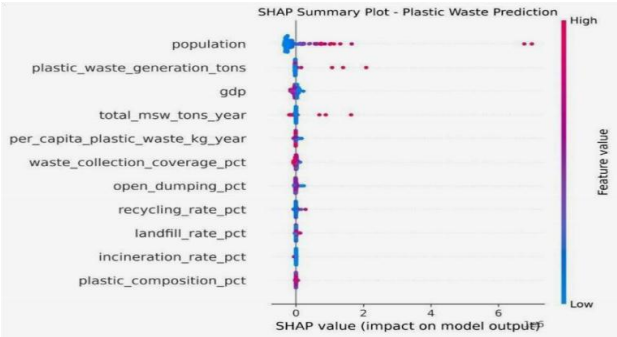



**Fig.9** SHAP summary of feature contributions to the plastic-waste prediction

### 10.2What-If Analysis

In the scenario shown in Fig. 10, the simulated change moved India's score from 75.77 to 75.75, an improvement of 0.02 points or 0.03 percent. The effect is tiny. Because the score puts 65 percent of its weight on the two waste - quantity terms, moving management indicators alone has limited leverage on it, and a sensitivity analysis would be a sensible next step. The interface also offers a search for better simulated strategies, which could combine several indicators at once.

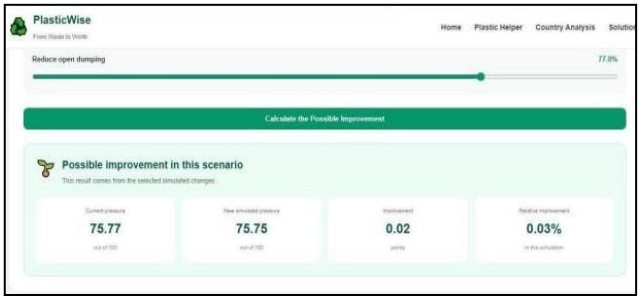



**Fig.10** What-if scenario in the prototype: simulated change in India's pressure score

### 10.3Statistical Hypothesis Testing

So far we have run one formal test (Fig. 11). A two -tailed Pearson correlation between recycling rate and mismanaged plastic waste across 153 countries gave r = −0.1093 and p = 0.1785 at a significance level of 0.05, so we fail to reject the null hypothesis of zero correlation. The relationship is weakly negative but not statistically significant.

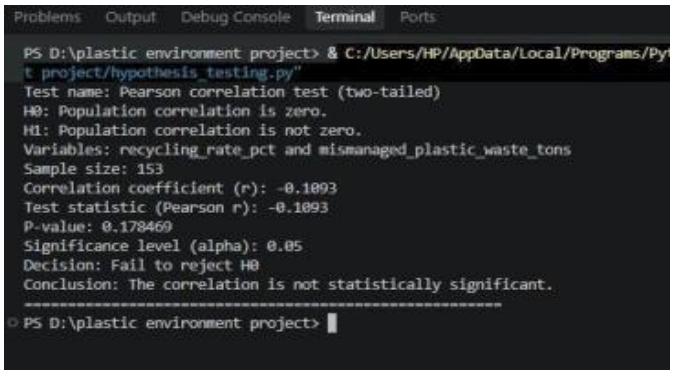



**Fig.11** Output of the Pearson correlation test between recycling rate and mismanaged plastic waste

This test is narrower than H02, which concerns the pressure score and adjusts for the other indicators. It also uses raw tonnage, which depends heavily on country size, so a non-significant raw correlation says little about whether recycling matters once scale is taken into account. For H02 and H12 we therefore recommend a regression or association test with the score and its predictors defined in advance. For H01 and H11 we recommend scoring all three models on the same repeated cross-validation folds and comparing the fold-level errors with a Friedman test, followed by a post -hoc comparison if the overall test is significant. Each result should be reported with its test statistic, p-value, effect size, and confidence interval. Until then, we draw no conclusion about statistical significance for the model comparison.

## 11. MAJOR FINDINGS

- Random Forest gave the best test -set results in the reported run: $R^2$ of 0.7323, MAE of 145,979.23 tons, and RMSE of 261,874.55 tons.
- Linear Regression was close behind ($R^2$ of 0.7167), while Gradient Boosting trailed clearly ($R^2$ of 0.3821).
- The prototype links prediction with a separately defined pressure score, SHAP explanations, rule - based recommendations, and what-if scenarios.
- Mismanaged plastic waste has the largest weight (0.35) in the pressure score, followed by plastic waste generation (0.30), open dumping (0.15), recycling (0.10), and collection (0.10).

SHAP ranks population and plastic waste generation as the most influential inputs; the management indicators contribute much less in this model.

- A preliminary correlation test between recycling rate and mismanaged waste was not statistically significant (r = −0.1093, p = 0.1785, n = 153).
- A single split cannot establish a statistically superior algorithm. Dataset provenance, repeated validation, uncertainty estimates, and external validation of the score remain open gaps.

## 12. RECOMMENDATIONS

The following are decision-support suggestions drawn from the prototype's logic. They are not measured causal effects.

- Improve recycling systems and monitor recycling rates consistently.
- Expand reliable waste collection coverage, especially where verified data show collection gaps.
- Reduce open dumping and strengthen safe disposal practices.
- Use SHAP explanations to communicate which inputs influence the model's predictions, while making clear that a feature's contribution is not proof of causation.
- Test proposed interventions against local feasibility, cost, and independently measured environmental outcomes before deploying them.

## 13. CONCLUSION

This study documents a machine -learning prototype that predicts country-level mismanaged plastic waste and supports environmental planning through a pressure score, SHAP explanations, and what -if scenarios. Of the three regression models, Random Forest did best on the test split ($R^2$ of 0.7323, MAE of 145,979.23 tons, RMSE of 261,874.55 tons), Linear Regression was a close second, and Gradient Boosting lagged. These results are encouraging for a project demonstration, but they do not prove that Random Forest is better in a statistical sense, and the what-if outputs do not prove that any real intervention would work. To answer the research questions more firmly, the dataset source and year should be documented, the models should be compared with repeated cross-validation and formal tests, and the pressure score should be checked against expert judgment or independent environmental indicators.

## 14. LIMITATIONS OF RESEARCH

- The source, reference year, and sampling method of the dataset are not documented, and the handling of missing values, outliers, and transformations was not written down.
- The results rest on one 80:20 split of 153 records, which leaves roughly 31 countries for testing, with no repeated validation or confidence intervals.
- Hyperparameter settings are not reported, so the weak Gradient Boosting result may change un der tuning.

## 15. FUTURE SCOPE OF RESEARCH

- Document the data dictionary, provenance, observation year, and collection process, and add multi-year observations where available.
- Use k-fold or repeated cross-validation with hyperparameter tuning, and report uncertainty intervals.
- Run the formal tests described above for the model comparison and for the score -based hypothesis.
- Validate the Environmental Pressure Score with environmental experts and independent indicators, and test how sensitive it is to its weights.
- Extend the what-if module to multi -indicator scenarios and compare the simulated effects with observed outcomes where data exist.

## 16. REFERENCES

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