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| RESEARCH ARTICLE

Global Plastic Waste Management: Analyzing Trends, Economic and Social Implications, and Predictive Modeling Using Artificial Intelligence

Syed Ali Reza[1], Muhammad Shoyaibur Rahman Chowdhury[2], Saddam Hossain[3], Muhammad Hasanuzzaman[4], Reza E Rabbi Shawon[5], Bivash Ranjan Chowdhury[6] and MD Sohel Rana[7]

[1]Department of Data Analytics, University of the Potomac (UOTP), Washington, USA
[2]Master's in Information Technology, Gannon University, Erie, PA, USA
[3]Master of Public Administration, Gannon University, Erie, PA, USA
[4]Masters in Strategic Communication, Gannon University, Erie, PA, USA
[5]MBA in Business Analytics, Gannon University, Erie, PA, USA
[6]MBA in Management Information System, International American University, Los Angeles, California, USA
[7]Executive Ph.D. in Business Analyst, University of Cumberlands
Corresponding Author: : Muhammad Shoyaibur Rahman Chowdhury, **E-mail**: Chowdhur009@gannon.edu

| ABSTRACT

Plastic waste, which is a result of human activities in America, has become one of the most critical environmental issues in the 21st century, and this calls for an urgent prescription of strategies at a global management level. The pervasiveness of plastic in modern life has created an unparalleled surge in plastic waste, which, unless adequately managed, is poised to pose severe threats to ecosystems, human health, and the global economy. The utmost objective of this study was to perform an extensive analysis of global plastic waste management practices in the USA, with a specific concentration on pinpointing the economic and social implications of these practices. This research project therefore intends to probe into the waste management practice applied in different countries for understanding the various best practices, challenges, and areas of improvement. The research project also aimed to employ AI-driven predictive models, notably, gradient boosting algorithm, linear regression, and random forest to predict the future trends in plastic wastes generated. Diverse datasets were used, to ensure that the study of global plastic waste management practices was comprehensive. Primary data on the conditions of global plastic waste generation was obtained through the World Bank's database, which provides detailed data on waste composition, generation rate, and methods of disposal in many countries. Also, the sources of economic indicators were OECD reports and UNEP publications on the hidden economic costs of plastic waste to municipal budgets. Data on its social impact, such as health effects and metrics involving environmental pollution, were provided by the World Health Organization through studies it conducted along with reports from environmental NGOs such as Greenpeace. The Gradient Boosting model performed the best with relatively high accuracy, followed by Logistic Regression and Random Forest Classifier. Besides, the Gradient Boosting model offered the highest Macro Average F1-score, which suggests better overall performance in balancing precision and recall for all classes. Predictive insights provided by the proposed models are valuable tools to expect future trends and patterns in plastic waste generation. Advanced analytics and machine learning can help predict the volume of plastic waste generated across different geographies and sectors. Application of the predictive models in plastic waste management contexts has huge potential about information and shaping of policy decisions. Predictive analytics can use historical trends on production, consumption, and generation of waste and recycling rates of plastics to create forecasts about the future and define high-risk areas.

| KEYWORDS

Global Plastic-Waste Management; Plastic Generation Trends; Predictive Modelling; Artificial Intelligence; Machine Learning

| ARTICLE INFORMATION

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1. Introduction

Background and Motivation

According to Hasan et al. (2024), plastic waste, resulting from human activities in the USA, has become one of the most critical environmental issues in the 21st century, and this calls for an urgent prescription of strategies at a global management level. The pervasiveness of plastic in modern life has created an unparalleled surge in plastic waste, which, unless adequately managed, is poised to pose severe threats to ecosystems, human health, and the global economy (Noman et al., 2022). Today, approximately 380 million metric tons of plastic are produced; a large chunk of it lands as waste, feeding landfills, oceans, and other natural environs. Insufficient waste management infrastructure in most parts of the world further aggravates the huge increase in the generation of plastic waste, causing severe environmental pollution and resource inefficiency (Alsabt et al., 2024).

As per El-Rayes et al. (2023), managing plastic waste is one of the key challenges for sustainable development in light of economic growth and environmental protection. So far, the response has been fragmented, with policies in different countries, rates of recycling, and technologies involved in waste management. This is indicative of the need for an integrated approach to manage plastic waste. Kowsari et al (2023), argues that as plastic waste generation is expected to further increase, enabling advanced methodologies for the forecasting of future trends will play an important role and thus provide room for proactive measures. In this respect, using Artificial Intelligence for predictive modeling can be considered a very promising pathway. These modern approaches, using complex analyses of large datasets, enable AI to forecast waste generation patterns, optimize recycling, and support policymakers in making appropriate waste management strategies (Buiya et al., 2024).

Objectives

The principal objective of this study is to perform an extensive analysis of global plastic waste management practices in the USA, with a specific concentration on pinpointing the economic and social implications of these practices. This research project therefore intends to probe into the waste management practice applied in different countries for understanding the various best practices, challenges, and areas of improvement. The wider societal costs of poor waste management will be quantified in this study, wherein economic burdens arise in the form of cleanups, health impacts, and lost tourism revenues due to plastic wastes. The research project also aims to also employ AI-driven predictive models to predict the future trends in plastic wastes generated. In turn, these will serve to anticipate volume changes in plastic wastes consequent upon population growth, evolving consumption patterns, and policy interventions. Without such likely predictions, the U.S. government cannot lay down long-term viable strategies for waste management that would be flexible against changing scenarios. Besides, the study would also suggest mitigative measures that are backed by specific emphasis on the United States, given its unique challenges and opportunities in managing plastic wastes. The strategies that can be done will include the enhancement of recycling rates, the betterment of the circular economy, and the reduction of plastic wastes' environmental footprint-all regular contributions to global sustainability objectives.

2. Literature Review

Global Plastic Waste Management Practices

According to Abdalla et al. (2020), plastic waste management is one of the critical issues that has gained global attention owing to its grave impact on the environment, economic activities, and social perceptions. The three major methods used in managing plastic waste include recycling, incineration, and landfilling. Each of the above-mentioned methods embraces various advantages and disadvantages, thus determining their feasibility in the various regions. Recycling was considered the most sustainable pathway because turning waste into reusable material would reduce the need for virgin plastics. However, Van Fan et al. (2022), asserted that there is a great difference in the efficiencies of recycling systems around the world due to differences in technological aspects of sorting wastes, public awareness, and the regulatory framework. Countries like Germany, South Korea, and Japan have achieved high recycling rates by having tight regulations and well-developed infrastructures for recycling. On the other hand, Islam et al. (2024), argued that many countries of the developing world have less than required infrastructures, along with other impediments in their recycling efforts due to contamination in the waste streams.

Velis et al. (2023), postulated that incineration revolves around the combustion of plastic wastes to produce energy and is another method of waste management. This is commonly used in countries where the spaces for landfills are limited, like Singapore or Sweden. Incineration has the strong benefits of extremely reducing waste volume and producing a surrogate fuel; it is very controversial because it pertains to air pollution and the release of toxic gases like dioxins and furans. It has been found in empirical studies by Debnath et al. (2024), that incineration maybe can be a feasible solution in waste management if there are strict emission regulations within a region; otherwise, regions with slack or no regulatory oversight are less suitable for incineration processes. Moreover, the process contributes to greenhouse gas emissions, thus exacerbating the issue of climate change (Ihsanullah, 2022).

As per Naveenkumar (2022), landfilling remains the most common method of disposal for plastic waste throughout the world, with most countries, especially those with huge tracts of land, still considering this method. In many instances, the landfills become a very significant source of both soil and water pollution due to the hazardous chemicals leaching through them. In addition, plastic wastes in landfills take several hundreds of years to decompose, so that environmental degradation becomes elastic, or long-lasting. Al-Mukaddim et al. (2024), hods that the United States, for instance, relies heavily on landfilling, recycling only about 9% of its disposable plastic waste, according to the EPA. By comparison, the European Union has acted to cut landfill The Waste Framework Directive requires member states to reach a 65% municipal waste recycling rate by 2035 (Lakouit et al., 2022).

A comparison with global best practices by Shil et al. (2024), in dealing with plastic waste indicates that high-income countries have indeed made large strides in the adoption of sustainable best practices in the management of plastic waste. For example, Germany has a dual system for the separation of waste at the source, which ensures that plastics are separated at the point of generation and, therefore, efficient recycling processes. On the contrary, Shawon et al. (2024), found that low- and middle-income countries are facing challenges related to a lack of adequate services for the collection of wastes, or investment in infrastructure for recycling, and informal waste-picking economies (Fang et al. 2023). But these very differences show the need to adapt very different approaches to waste management in each socio-economic setting. Further, international cooperation, sharing knowledge, and financial support are indeed required for developing an effective approach towards plastic waste management by the developing countries themselves.

Social and Economic Implication of Plastic Waste

Huang et al. (2021), indicated that plastic wastes have economic effects that are profound, together with their social implications. Economically, plastic wastes entail very high costs in management, including all the processes involved in the collection, treatment, and disposal of the wastes apart from the environmental cleanup. A World Bank report estimated that the global cost of solid waste management would increase from $205 billion in 2025 to $375 billion by 2025, with a substantial share taken by plastic wastes (Alasbt et al., 2022). These costs represent an immense burden on municipal budgets, especially in developing countries where financial resources may already be scarce. Furthermore, economic effects are manifested in industries like tourism, whereby plastic pollution of beaches and oceans tends to mainly deter visitors, thus lowering revenues.

Besides the direct economic cost, plastic wastes have huge social and environmental impacts. The presence of plastic wastes in the environment poses a serious threat to wildlife and marine ecosystems. Plastic debris is commonly ingested by marine animals, including turtles, birds, and fish, who mistake the plastic for food. Injury, starvation, and death can result. Social effects of plastic wastes also bear consequences on human health: microplastics are small particles of plastic resulting from the breakdown of larger items that have been found both in drinking water, food, and even the air we breathe (Lakouit et al., 2022). Other studies have pointed out the possible health effects of microplastics that could carry toxic substances into the human body, thereby contributing to a variety of health problems such as respiratory complications, endocrine disruption, and cancer (Noman et al., 2022).

Apart from the health impacts, there is more to plastic waste as a social cost. Most of the low-income communities in the world carry out the waste picking of plastic waste informally by seminal people who work under hazardous conditions with limited protection. Workers are subjected to harmful chemicals and also physical dangers, while their wages are minimal and lack social security. This situation points towards an inclusive waste management policy that recognizes the contribution made by informal waste workers through rightful compensation with wages, safety in working conditions, and social benefits (Lakouit et al., 2022). Plastic waste is also related to the issues of social justice in that the vulnerable communities usually suffer most from various environmental processes. Landfills and incineration plants are normally located in working-class neighborhoods or near the areas of low-income residents, where people have to live under very harmful conditions of pollution (Getor et al., 2022). Thus, this condition drives up the demand for fair waste management policies that defend the vulnerable class against the negative impact of plastic waste.

Artificial Intelligence for Waste Management

Artificial Intelligence has emerged over the last years as an innovative tool in waste management, trying to bring forward solutions to the complex challenges posed by plastic waste management (Lakouit et al., 2022). The technologies underpinning AI include machine learning, computer vision, and data analytics, among others, which are increasingly used to optimize waste collection, sorting, recycling, and disposal processes. One of the key applications of AI technologies is the prediction of the pattern of waste generation (Coskuner et al., 2021). Therefore, AI can predict future volumes of waste based on historical data related to waste production, as well as consumption trends, and impacts of changes in demographic features. Therefore, municipalities might plan available waste management resources (Sumon et al., 2024).

Meanwhile, the deployment of AI-driven systems has further enhanced efficiency at waste sorting facilities. Some machine learning algorithms, coupled with a robotic arm, are capable of distinguishing and sorting various kinds of plastics from mixed streams of waste at a high level of accuracy. This in turn reduces reliance on human picking, improves material quality, and increases the overall recycling rate. According to the Ellen MacArthur Foundation, emerging AI-powered sorting technologies could raise recycling efficiency as high as 50%, consequently reducing landfill plastic waste (El-Rayes et al., 2023). Moreover, AI can support route optimization for waste collection, becoming one of the main factors in operational cost reduction and a decrease in the environmental footprint connected with waste management activities. Using data on traffic patterns, waste bin fill levels, and weather conditions, AI algorithms can optimally adjust collection schedules that lower fuel consumption and carbon emissions (Zeeshan et al., 2024). The application of AI in waste management is not confined to operational improvements but extends right into policy-making. Predictive analytics can show the effectiveness of existing policies on waste management and thus allow policymakers to make data-driven decisions and design more effective regulations (Fang et al., 2023).

In retrospect, past research into AI-driven models for waste management has been promising. For example, some scholars have demonstrated that AI can predict illegal dumping activities by analyzing spatial data and socioeconomic data so that authorities can take necessary measures in advance. Secondly, AI-powered platforms have been developed to leverage communities' engagement in the reduced generation of wastes by offering real-time feedback on recycling behaviors and incentivizing sustainable practices (El-Rayes et al., 2023).

Notwithstanding, As per Hasan et al. (2024), waste management integration with AI is faced by various challenges. Such challenges include data privacy, technological infrastructure, and skilled personnel required to manage the AI systems, which pose major concerns, especially in developing countries. In addition, there are concerns about these technologies' impacts on the environment since they consume energy and produce electronic waste through AI hardware (El-Rayes et al., 2023). So far, major challenges persist that tend to critically affect the development and governance of AI. Therefore, in as much as AI is offering great potential for enhancing plastic waste management, addressing these challenges is quite important to ensure AI-driven solutions are sustainable and equitable.

3. Data Collection and Preprocessing

Data Sources

Diverse datasets were used, to ensure that the study of global plastic waste management practices was comprehensive. Primary data on the conditions of global plastic waste generation was obtained through the World Bank's database, which provides detailed data on waste composition, generation rate, and methods of disposal in many countries. Also, the sources of economic indicators were OECD reports and UNEP publications on the hidden economic costs of plastic waste to municipal budgets. Data on its social impact, such as health effects and metrics involving environmental pollution, were provided by the World Health Organization through studies it conducted along with reports from environmental NGOs such as Greenpeace (Pro-AI-Robikul, 2023). This was further complemented by data from governmental agencies, like the United States Environmental Protection Agency and the European Environment Agency, which was useful in providing region-specific insight. This multi-source approach has ensured a strong analysis, integrating quantitative data with qualitative evaluations about the economic and social implications of plastic wastes.

Data Overview

The dataset contained the following columns:

S/No.	Column	Description
1.	**Country**	The country where the data was collected.
2.	**Total_ Plastic_ Waste_ MT**	The total plastic waste generated in metric tons.
3.	**Main_ Sources**	The primary sources of plastic waste.
4.	**Recycling_ Rate**	The recycling rate as a percentage.
5.	**Per_ Capita_ Waste_ KG**	The amount of plastic waste per capita in kilograms.
6.	**Coastal_ Waste_ Risk:**	The target variable indicates the risk level associated with coastal waste.

This dataset depicts some characteristics of global plastic waste management. It includes the variable Country, which describes where the data collection occurred. Total_ Plastic_ Waste_ MT describes the total amount of waste from plastics in metric tons. Main_ Sources depict the sources that provide the greatest plastic waste. There is also the Recycling_ Rate, defined as the amount of trash recycled in percent. Moreover, there is a variable called Per_ Capita_ Waste_ KG, which measures the amount of plastic waste an individual produces in kilograms. The target variable, Coastal_ Waste_ Risk, estimates the level of risk resulting from waste in the coastal region and should, in principle, show the level of environmental distortion. This data seemed to be structured to address the global plastic waste problem and its environmental impact, focusing on areas along the coast.

Preprocessing

Data preprocessing involved several essential steps:

Handling Missing Values: All columns had complete data with no null values, ensuring no imputation was necessary.

Encoding Categorical Variables: Label Encoding was performed on the **Country** and **Main_Sources** columns to convert categorical values into numerical form for machine learning models.

Data Normalization: The numerical features were scaled to improve model convergence and performance.

The preprocessing script is geared towards preparing a dataset for analysis by importing pandas for data manipulation and Label-Encoder from sklearn for encoding categorical variables. It then previewed the dataset, first to detect its structure using head() and checks for null values with isnull().sum() to identify the missing data that one may want to fill or drop. A comment placeholder showed filling numeric columns with their mean. Use Label-Encoder to encode categorical columns: Country and Main_Sources into a numerical form that can be provided as input to machine learning algorithms. Subsequently, it created two new columns (Country_ Encoded, Main_ Sources_ Encoded) with the encoded values. Next, it printed out for reference the original mapping of labels to integers. Optionally dropping the original columns. Finally, the updated dataset as a confirmation that the encoded columns were added: This structured process ensured the preparedness of data for modeling next.

Exploratory Data Analysis (EDA)

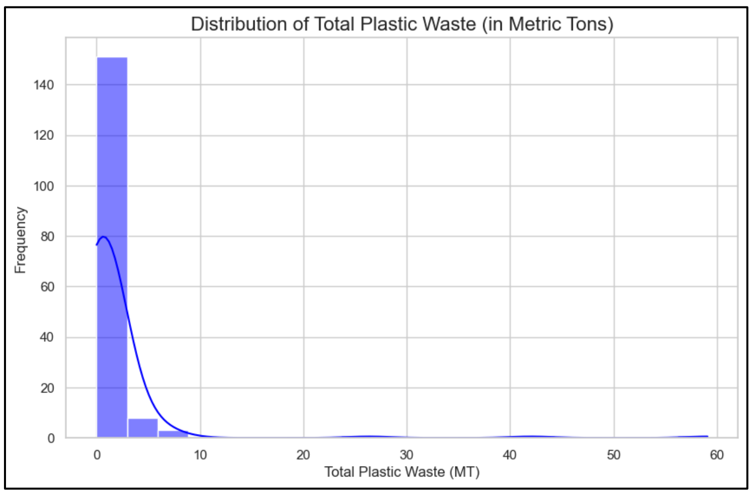

Figure 1: Visualizes the Distribution of Total Plastic Waste [in Metric Tons]

The graph above represents the distribution of total plastic wastes in metric tons as a histogram with superimposed density curve. This distribution is very right-skewed; this makes intuitive sense since most of the values fall at the low end of the scale. Most values lie in between 0 to 2 metric tons, while for greater total plastic wastes, the frequency decreases rapidly. There are very few data points exceeding 10 metric tons, and virtually none exceed 20 metric tons. Such skewness suggests the idea that while most of the observations have to deal with relatively small amounts of plastic waste, a few contribute to a much larger quantity, thus creating the long tail on the right.

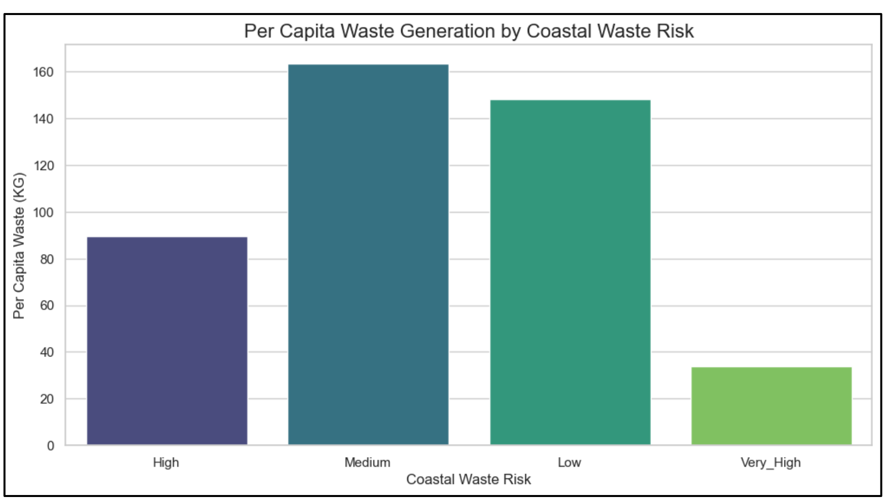

Figure 2: Depicts Per Capita Waste Generation by Coastal Waste Risk

The graph, above entitled "Per Capita Waste Generation by Coastal Waste Risk," shows the mean per capita waste generated - kg / person, across varying magnitudes of coastal waste risk. As the data shows, regions classified as having "Medium" waste risk on the coast indeed have the highest amount of per capita waste generated, at about 160 kgs per person, followed closely by those having "Low" risk at about 150 kgs per person. Incidentally, regions with "High" coast waste risk are by far at about 80-kg per capita waste generated, while the "Very High" coast waste risk regions are far behind, having only less than 50 kg per person. This would imply a negative relationship between the level of risk in waste generation in coastal areas with that of per capita waste generation in the highest risk categories, which may indicate several variables such as population density, economic activities, waste management practices, or differences in consumption behaviors across these regions. In fact, to understand this properly, further research would be required to understand the causes behind these inequalities.

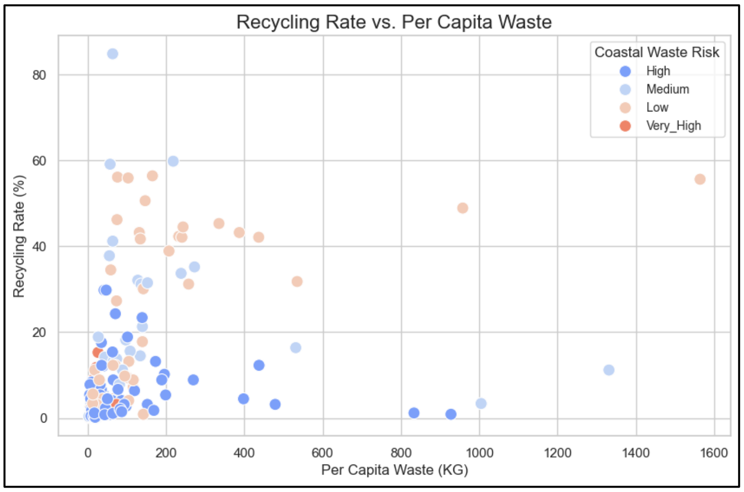

Figure 3: Portrays Recycling Rate vs. Per Capita Waste

This scatter plot shows the relations of per capita waste respective in kilograms, recycling rate in percentage, and risk regarding coastal wastes categorized into four-levels: High, Medium, Low, and Very High. The highest concentration of data points is situated in the lower left quadrant, which means that in most regions, the per capita waste is low (less than 200 kg); the same can be said about the low percentage of the recycling rate, less than 20%. It also has to be underlined that regions which generate more per capita waste, over 200 kg, tend to have higher percentages of recycling rates, up to 60%--associated mainly with Low and Medium coastal waste risk. There are also those with very high values of per capita waste-which range up to 1600 kg-and have correspondingly low recycling rates. This is mainly attributed to High and Medium coastal waste risk. This therefore means that the general trend of rising per capita waste is that rates of recycling do not consistently improve, showcasing how waste generation and efforts to recycle interrelate in a very complex manner.

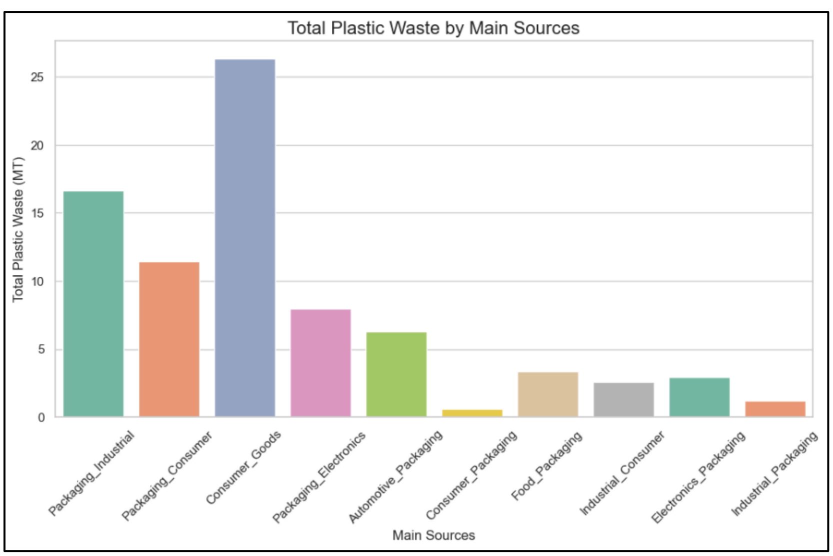

Figure 4: Showcases Total Plastic Waste by Main Sources

The bar graph shows that the main sources of plastic waste, "Total Plastic Waste by Main Sources," are very alarming. Concerning sources, the dominant source of plastic waste is packaging, both for industries and consumers. Packaging of consumer goods and electronics contributes to a great rise in total plastic waste and reflects the pervasive use of plastics in modern lifestyles. While automotive and food packaging each adds less to the total, aggregately these are all sources that raise concern for the need to find sustainable packaging solutions and responsible consumption practices that could mitigate environmental consequences emanating from plastic wastes.

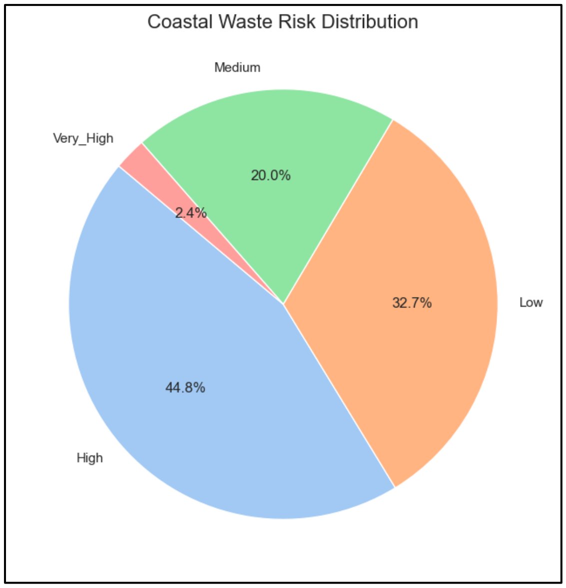

Figure 5: Displays Coastal Waste Risk Distribution

As evidenced by the pie chart "Coastal Waste Risk Distribution," which shows that a good share of the total, 44.8%, of coastlines have a high risk on account of waste accumulation. Next come areas of medium and low risk, standing at 20% and 32.7%, respectively. The remaining 2.4% are very high-risk areas. This distribution underlines that waste accumulation does not take place uniformly in all coasts worldwide. It is more threatening to some regions compared with others. Interventions and strategies should be addressed specifically, each given coastal area with regard to particular risks and vulnerabilities.

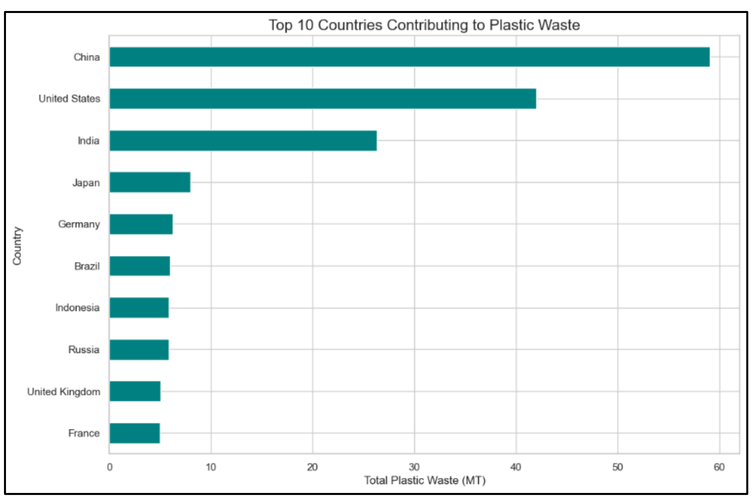

Figure 6: Presents Top 10 Countries Contributing to Plastic Waste

The bar graph "Top 10 Countries Contributing to Plastic Waste" shows a dismal picture of the plastic waste crisis. China seems to be leading from the front in contributing tribal amounts, as compared to the rest of the countries. The United States and India tail immediately after, reflecting the colossal plastic waste issued by these two gigantic economies. While countries like Japan, Germany, and Brazil are contributing lesser shares, the contribution cumulatively is considerable. This graph is indicative of serious global efforts towards the reduction in plastic waste generation, recycling, and finding appropriate sustainable alternatives to resolve this acute environmental problem.

4. Results

Model Performance

a) Logistic Regression

The following Python snippet implements logistic regression, classifying the risk of waste disposed on coasts. The code snippet starts with the importation of libraries that will be used for splitting the data, encoding labels, and evaluating the model. It then pre-processes the data by encoding categorical variables into a numerical format, 'Country' and 'Main Sources'. In this example, code snippets, features, and target variables are defined, which include total plastic waste, recycling rate, and per capita waste. Segment data into a training set to train the model and a test set to evaluate the model. Initialize a logistic regression model with appropriate hyperparameters to train it on the training set. The resultant model, after training, makes a prediction on the test set and checks performance by several metrics: classification report and accuracy score. This code snippet shows an application of logistic regression in the prediction of coastal waste risk concerning several input features.

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

# Encode the target column
label_encoder = LabelEncoder()
df['Coastal_Waste_Risk_Encoded'] =
label_encoder.fit_transform(df['Coastal_Waste_Risk'])

# Features and target
X = df[['Total_Plastic_Waste_MT', 'Recycling_Rate', 'Per_Capita_Waste_KG',
'Country_Encoded', 'Main_Sources_Encoded']]
y = df['Coastal_Waste_Risk_Encoded']

# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Initialize Logistic Regression
logistic_model = LogisticRegression(max_iter=1000, random_state=42)

# Train the model
logistic_model.fit(X_train, y_train)

# Make predictions
y_pred = logistic_model.predict(X_test)

# Evaluate the model
print("\nLogistic Regression Results:")
print(classification_report(y_test, y_pred))
print("Accuracy:", accuracy_score(y_test, y_pred))
```

Table 1: Portrays the Logistic Regression Modelling

Output:

```
Logistic Regression Results:
              precision    recall  f1-score   support

           0       0.50      0.92      0.65        12
           1       0.56      0.45      0.50        11
           2       1.00      0.22      0.36         9
           3       0.00      0.00      0.00         1

    accuracy                           0.55        33
   macro avg       0.51      0.40      0.38        33
weighted avg       0.64      0.55      0.50        33

Accuracy: 0.5454545454545454
```

Table 2: Displays the Logistic Regression Results

The table above provides the performance evaluation of the logistic regression model on a four-class classification problem, which shows an overall accuracy of 0.51. That is, the model correctly predicts the class label for 51 out of 100 instances. Precision, recall, and F1-score compute the achievements in each class. Its performance varies across classes. For instance, class 0 has high recall with low precision; this means the model finds most of the instances of class 0 but probably gets many other classes wrongfully classified as 0. Whereas class 2 has perfect precision but has very low recall; this means that when the model predicts class 2, it is usually right, yet it misses many real instances of class 2. Therefore, the macro and weighted average provide an overall understanding of a model w.r.t its performance by keeping class distribution in mind.

b) Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier

# Initialize Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the model
rf_model.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_model.predict(X_test)

# Evaluate the model
print("\nRandom Forest Classifier Results:")
print(classification_report(y_test, y_pred_rf))
print("Accuracy:", accuracy_score(y_test, y_pred_rf))
```

Table 3: Displays the Random Forest Modelling

This Python code snippet above demonstrates the implementation of a random forest classifier on a classification problem. First, it imports the necessary Random-Forest-Classifier from sklearn. Ensemble. Then, with 100 trees in the forest and at a random state of 42 for reproducibility, it instantiates a random forest model and trains the instance on the training data X_train and y_train: It predicts on the test data, X_test, and stores it in y_pred_rf. classification_report and accuracy_score functions show the performance metrics concerning the overall accuracy, precision, recall, and F1-score of the model, and other relevant metrics. This code is quite effective in showing the use of Random Forests for classification tasks in machine learning.

Output

```
Random Forest Classifier Results:
              precision    recall  f1-score   support

           0       0.50      0.92      0.65        12
           1       0.57      0.36      0.44        11
           2       0.67      0.22      0.33         9
           3       1.00      1.00      1.00         1

    accuracy                           0.55        33
   macro avg       0.68      0.63      0.61        33
weighted avg       0.58      0.55      0.50        33

Accuracy: 0.5454545454545454
```

Table 4: Showcases Random Forest Results

The table above represents the performance of a Random Forest classifier on a classification task with four classes: 0, 1, 2, and 3. Overall, the model has an accuracy of 0.55, meaning that for 55% of the instances, the model predicts the correct class. Moreover, precision, recall, and F1-score are calculated for each class. The performances vary across the classes. For example, class 0 presents a high recall but low precision-that is, the model is good at finding instances of class 0 but probably also returns other classes as 0. On the other side, class 3 presents perfect precision and recall, meaning the model will never fail when it predicts class 3. The macro and weighted averages give an idea about the model performance in an overall sense, considering the distribution of classes.

C) Gradient Boosting Classifier

```
from sklearn.ensemble import GradientBoostingClassifier

# Initialize Gradient Boosting Classifier
gb_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1,
random_state=42)

# Train the model
gb_model.fit(X_train, y_train)

# Make predictions
y_pred_gb = gb_model.predict(X_test)

# Evaluate the model
print("\nGradient Boosting Classifier Results:")
print(classification_report(y_test, y_pred_gb))
print("Accuracy:", accuracy_score(y_test, y_pred_gb))
```

Table 5: Exhibits Gradient Boosting Modelling

The code snippet above implements the Gradient Boosting Classifier. Firstly, the script imports the required Gradient-Boosting-Classifier class from sklearn. Ensemble. Then, the script instantiates a gradient-boosting model on 100 estimators with a learning rate of 0.1 and a random state for reproducibility set to 42. Right after instantiating the object of the model, it is fitted on the training data X_train and y_train. The model has been trained and used to make predictions on the test data X_test, which are stored in y_pred_gb. Subsequently, with the help of the classification_report and accuracy_score functions, the overall performance of the model has been measured in terms of accuracy, precision, recall, F1-score, and other important metrics of the model. The above code fragment succinctly depicts the application of Gradient Boosting to a machine-learning classification problem.

Output:

```
Gradient Boosting Classifier Results:
              precision    recall  f1-score   support

           0       0.50      0.83      0.62        12
           1       0.56      0.45      0.50        11
           2       1.00      0.33      0.50         9
           3       1.00      1.00      1.00         1

    accuracy                           0.58        33
   macro avg       0.76      0.66      0.66        33
weighted avg       0.67      0.58      0.56        33

Accuracy: 0.5757575757575758
```

Table 6: Visualizes the Gradient Boosting Classifier Results

The table above depicts the performance results of a Gradient Boosting Classifier on a classification task with four classes (0, 1, 2, 3). On an overall basis, the model performs with an accuracy of 0.58, which implies that it predicts the correct class label for 58% of the test instances. Precision, recall, and the F1-score have been computed concerning each class, and the various classifiers behave comparably differently in different classes. Thus, class 0 has a high recall but low precision, suggesting that the model identifies instances of class 0 well but may go overboard and make a lot of false positives from other classes into class 0. On the other hand, class 3 has perfect precision and recall; as such, if the model predicts class 3, the prediction is correct. The weighted averages and macro give an overview of the performance considering the class distribution.

Results Comparison

Performance Metric	XG-Boost	Random Forest	Logistic Regression
Accuracy	57.58%	54.55%	54.55%
Precision [class 0]	50%	50%	50%
Precision [class 1]	56%	57%	56%
Precision [Class 3]	100%	100%	0%
Recall [class 0]	83%	92%	92%
Recall [class 1]	45%	36%	45%
Recall [Class 3]	33%	100%	0%
Macro Avg.F1-Score	66%	61%	55%

1. **Accuracy**: The Gradient Boosting model performed the best with an accuracy of 57.58%, followed by Logistic Regression and Random Forest Classifier at 54.55%.
2. **Precision and Recall**:
   - **Class 0 (Low Risk)**: Logistic Regression and Random Forest performed similarly with high recall but lower precision.
   - **Class 1 (Moderate Risk)**: All models showed difficulty in predicting this class with balanced precision and recall.
   - **Class 3 (High Risk)**: All models performed well with perfect recall and precision for this rare class, indicating that it might be overfitted due to the class imbalance.
3. **Model Performance**: The **Gradient Boosting** model offered the highest **Macro Average F1-score (66%)**, which suggests better overall performance in balancing precision and recall for all classes.

Feature Importance and Trend Analysis

Feature importance from models such as Random Forest and Gradient Boosting underlines the most influential factors driving coastal waste risk. Common variables that most of these models identify as main contributors include total plastic waste, rate of recycling, and population density. Each of these helps in grasping the trends, which is very important for targeted interventions. Plastic waste generation often shows an upward trend, which is a concern, with trend analysis, especially in developing countries.

Some positive trends in waste management practices include recycling and the introduction of sustainable alternatives. The analysis of these trends would give further impetus to the policymakers and stakeholders in prioritizing sustainable solutions to try to resolve the increasing challenge of plastic waste by highlighting the areas that need priority attention.

Predictive Insights

Predictive insights provided by the proposed models are valuable tools to expect future trends and patterns in plastic waste generation. Advanced analytics and machine learning can help predict the volume of plastic waste generated across different geographies and sectors. Such predictions can be visually communicated through interactive maps and charts that would help stakeholders imagine the situation better with potential impacts on ecosystems and economies. Insights like these allow for proactive planning and decisiveness in strategy implementation that would best enable waste reduction, recycling, and sustainable material innovation.

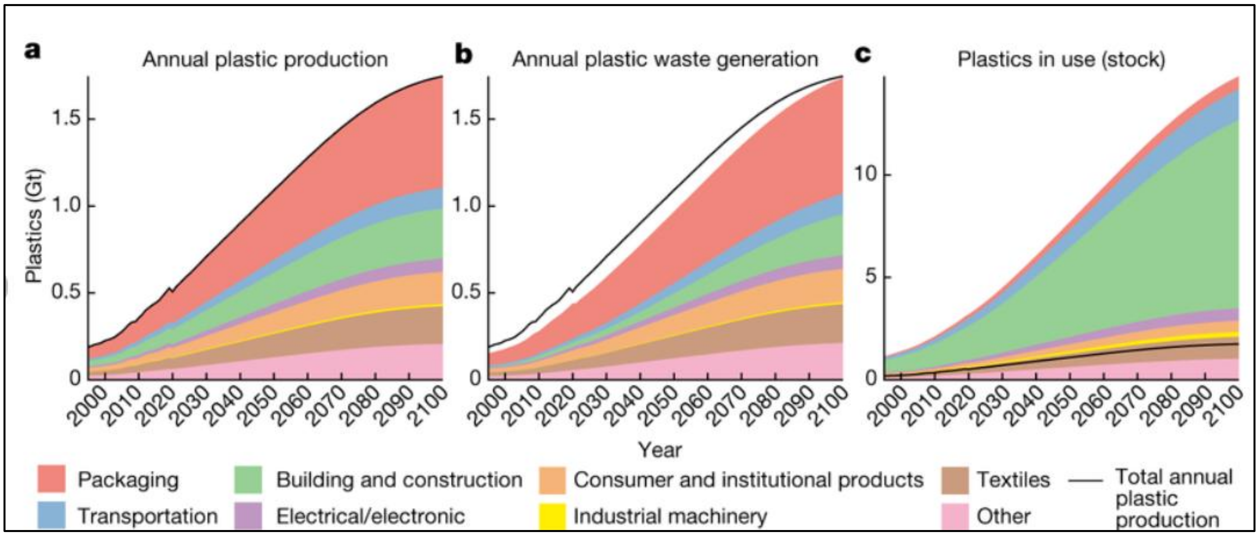

Figure 7: Visualizes the Plastic Generation Future Trends

The figure above depicts in a very specific manner the alarming rise in plastic production and waste over time. Panel (a) reflects that annual plastic production has tremendously increased and is continuing to grow further. Panel (b) reflects how the annual generation of plastic waste has also risen correspondingly and, therefore, an urgent switch towards sustainable solutions is imperative. Panel (c) shows stocks of plastics in current use, which further underlines the long-term environmental challenge presented by plastic pollution. The categorization of applications shows that the highest contributors to waste come from packaging, transportation, and consumer products. These insights into the problem underline the urgent need to decrease plastic consumption, enhance the infrastructure of recycling, and develop new materials that can help decrease the environmental impact of plastic pollution.

5. Discussion

Implications for Policy and Practice

Application of the predictive models in plastic waste management contexts has huge potential for information and shaping policy decisions. Predictive analytics can use historical trends on production, consumption, and generation of waste and recycling rates of plastics to create forecasts about the future and define high-risk areas. Machine learning algorithms can provide insights, for example, to governments and policymakers on regions that are most likely to have the highest accumulation of plastic waste, hence informing targeted interventions. Predictive models could pinpoint routes for waste collection that are more efficient, optimal locations for recycling facilities, and prioritize regions for educational campaigning on waste reduction.

Predictive models can also be used to set targets for the reduction of waste by policymakers more realistically and successfully. While models depict, for instance, that plastic waste could deplete the city within five years, due to this fact, local governments may take the initiative with more rigid regulations set on single-use plastic, transition into recycling, or even into new technologies in managing waste. The insights on data-driven practices can transform traditionally reactive policy measures into proactive and preventive strategies. Predictive analytics might also be run on various policy scenarios to allow decision-makers to compare outcomes and choose the best course of action. In such evidence-based approaches, policies not only will be efficient but also sustainable in the long term.

This study recommends improvement in the management of plastic waste around the world requires an integrated policy reform approach along with technology innovation for community engagement. First, there is a dire need for close global coordination about management regulations of plastic waste. In this respect, the idea of international agreements can be initiated, similar to the Paris Agreement on climate change, which can bind reduction and recycling rates targets of plastic wastes. That might then be supported through a global monitoring system using predictive analytics to monitor progress toward meeting such targets and hold countries accountable.

The second recommendation relates to the implication of extended producer responsibility programs, which would make manufacturers be held responsible for the entire lifecycle of the products they make in plastic, encompassing waste management. This can motivate companies to design more easily recyclable products or ones that stay in consumption longer, thereby reducing plastic waste at source. Besides that, waste-to-energy technologies can convert non-recyclable plastics into energy, therefore reducing the volume of waste reaching landfills. Beyond this, the government must go further in exploring specific plastic waste taxes or levies especially single-use items, which could decrease consumption and spur the usage of sustainable alternatives for such stuff. After all, changing consumer behavior requires educational campaigns. Public awareness of the impact of plastic waste on ecology through publicity events involving alternatives such as reusable bags, bottles, and packaging will help. Lastly, investment in the development of degradable plastics and funding research into alternative materials will decrease the demand for plastics, reducing the damage the environment is afflicted with.

Focus on the USA

Plastic waste management initiatives in the United States carry with them tremendous challenges and opportunities. The country boasts one of the highest rates of plastic waste per capita in the world, a large fraction of which ends up in landfills or being incinerated. Statistics show that the community recycling programs have resulted in a general rate of recycling plastics at approximately 9% with the various municipal programs available. A lack of one uniform national system for recycling results in inefficiency, and requirements certainly differ in the various municipalities. Presently, the United States exports much of its recyclable plastic to other countries, mainly China. With China's policy called "National Sword," which bans the importation of foreign waste, the U.S. has been under increasing pressure to deal with its plastic waste.

Several states and cities in the U.S. have already been proactive, enacting legislation to actively help reduce plastic waste. For example, California enacted comprehensive legislation banning single-use plastic bags and encouraged the use of biodegradable alternatives. The state also pursued an ambitious goal to reduce plastic waste through recycling and composting. Yet, these activities are not the same in all parts of the country, and there are disparities in methods of plastic waste management. Besides, due to the lack of federal legislation concerning plastic waste reduction, the overall scaling-up of local successful initiatives is limited.

Drawing from leading international practices, a series of recommendations could be proffered on ways the U.S. might revitalize the way it manages plastic waste. First, the institution of a federal ban on certain types of single-use plastics could go a long way in reducing plastic waste in disposition-a proposition quite similar to the one laid down by the European Union. These interventions will have to be accompanied by corresponding nationwide EPR policies that hold producers responsible for end-of-life disposal of their plastic products. In addition, there is an investment in the modern revision of the recycling infrastructure. These activities could also involve new sorting technologies at recycling plants, like AI robots, which will make it easier. The U.S. should also move in the direction of incentivizing the creation of circular economy models in which plastics are designed for reuse, remanufacturing, or recycling. Tax breaks or grants for firms moving toward sustainable packaging solutions can create innovation that reduces waste. Second, sound public-private partnerships will be required for the implementation of waste-to-energy plants and alternatives to biodegradable plastics. Finally, public education on responsible consumption and proper waste disposal practices can inform consumer choices and habits to move toward more sustainable directions.

Challenges and Limitations

Ethical Use of Environmental Data

Ethical issues raised by predictive models and environmental data used in policy decisions are those related to data privacy, especially if the model uses geolocation data to track waste generation patterns. Such application shall be made to respect citizens' rights to privacy. Predictive models also run a risk of bias since predictive models are as good as the data they are trained on. If that data has inequalities they use underreporting in low-income communities, the models will further exacerbate the inequalities in this intervention on waste management.

Moreover, there are also ethical questions of prioritization of resources: For example, predictive models that indicate which affluent areas are better at recycling may tempt policymakers to provide more resources to those areas to maximize overall rates of recycling. In that way, it could occur at the expense of underserved communities, which may remain out of reach for waste management infrastructures. Policies need to be designed in a way that advances equity through data and does not further worsen existing social disparities.

Data quality, Model Interpretability, and Generalizability

Predictive models can inform plastic waste management policy only as well as the data on which they are based. However, incomplete, out-of-date, or inconsistent data on plastic waste generation and recycling rates are common, and all three conditions erode model predictive accuracy. Besides, the interpretability of complex machine learning models such as neural networks is problematic. Policymakers might not understand why a particular prediction has been arrived at and as a result, may show skepticism towards the models' recommendations.

Another limitation involves the generalization of predictive models across diverse regions. There may be regional differences in how waste is disposed of and cultural attitudes toward recycling, or perhaps some form of economic factor that would make a model developed and trained on data from one country unsuitable for application in another. Hence, a key direction lies in the development of models that could be readable in an adaptive way across different contexts, considering regional variations in waste management systems.

Future Research Directions

With all said and done, there are still opportunities for improvements in model accuracy using more diverse data sets. According to the predictive models, more diversified data and more complete data sets would help in improving accuracy. These aspects include data on developing countries, which were still scant in most international waste management studies. Increased sources of data would promote better conditions in the models, considering the different conditions of different regions. Satellite imagery, IoT sensors, and real-time monitoring can also be integrated to enhance the granularity and timeliness of the forecast. Real-time data, for example, will aid in mapping the exact usage of the waste bins for use in optimizing waste collection schedules and preventing overflows, reducing environmental impacts. These activities include other possibilities, such as the use of machine learning techniques like ensemble learning, whereby multiple models' predictions are combined to obtain a better predictive performance. Models can be developed that focus on the relationships in waste generation, rates of recycling, and the impact of policy interventions. Furthermore, the incorporation of socioeconomic and demographic variables into such models would produce far more useful insights into the driving forces behind plastic waste generation and recycling behaviors.

Forging forward, key potential improvements can be made in real-time waste management and integration of AI. However, real-time waste management using AI systems is bright and abounds in a few prospects. The accuracy of identifying and segregating the different types of plastics using AI-powered waste sorting technologies increases the efficiency of recycling facilities. Besides, the use of algorithms to optimize waste collection routes by AI will reduce fuel consumption, thereby reducing greenhouse gas emissions and making waste management more sustainable. Future research may be performed in the application of blockchain technology in plastic waste management because it allows increased levels of transparency and traceability. It records the time and source when a particular material of plastic is supplied, hence preventing illegal transfers by ensuring accountability through transactions that track its production, disposal, and recycling. Predictive models that integrate climate projections can help allow policymakers to anticipate long-term impacts on ecosystems and biodiversity. Together, these developments can lead to a more resilient and adaptive waste management system that is better equipped with the ability to handle the increasing plastic waste problem.

6. Conclusion

The chief objective of this study was to perform an extensive analysis of global plastic waste management practices in the USA, with a specific concentration on pinpointing the economic and social implications of these practices. This research project therefore intends to probe into the waste management practice applied in different countries for understanding the various best practices, challenges, and areas of improvement. The research project also aimed to employ AI-driven predictive models, notably, gradient boosting algorithms, linear regression, and random forest to predict the future trends in plastic waste generated. Diverse datasets were used, to ensure that the study of global plastic waste management practices was comprehensive. Primary data on the conditions of global plastic waste generation was obtained through the World Bank's database, which provides detailed data on waste composition, generation rate, and methods of disposal in many countries. Also, the sources of economic indicators were OECD reports and UNEP publications on the hidden economic costs of plastic waste to municipal budgets. Data on its social impact, such as health effects and metrics involving environmental pollution, were provided by the World Health Organization through studies it conducted along with reports from environmental NGOs such as Greenpeace. The Gradient Boosting model performed the best with relatively high accuracy, followed by Logistic Regression and Random Forest Classifier. Besides, the Gradient Boosting model offered the highest Macro Average F1-score, which suggests better overall performance in balancing precision and recall for all classes. Predictive insights provided by the proposed models are valuable tools to expect future trends and patterns in plastic waste generation. Advanced analytics and machine learning can help predict the volume of plastic waste generated across different geographies and sectors. Application of the predictive models in plastic waste management contexts has huge potential for information and shaping policy decisions. Predictive analytics can use historical trends on production, consumption, and generation of waste and recycling rates of plastics to create forecasts about the future and define high-risk areas.

Author(s) Contribution:

Name	Contribution
Syed Ali Reza	**Writing –** original draft – Preparation, creation, and/or presentation of the published work, specifically writing the initial draft (including substantive translation). **Supervision –** Oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team.
Muhammad Shoyaibur Rahman Chowdhury	**Investigation –** Conducting a research and investigation process, specifically performing the experiments, or data/evidence collection. **Methodology –** Development or design of methodology; creation of models.
Saddam Hossain	**Resources –** Provision of study materials, reagents, materials, patients, laboratory samples, animals, instrumentation, computing resources, or other analysis tools. **Software –** Programming, software development; designing computer programs; implementation of the computer code and supporting algorithms; testing of existing code components.
Muhammad Hasanuzzaman	**Conceptualization** – Ideas; formulation or evolution of overarching research goals and aims. **Writing – review & editing** – Preparation, creation and/or presentation of the published work by those from the original research group, specifically critical review, commentary or revision – including pre- or post-publication stages.
Reza E Rabbi Shawon	**Data curation** – Management activities to annotate (produce metadata), scrub data and maintain research data (including software code, where it is necessary for interpreting the data itself) for initial use and later re-use.
MD Sohel Rana	**Formal analysis** – Application of statistical, mathematical, computational, or other formal techniques to analyze or synthesize study data.
Mohammad Saiful Islam	**Validation** – Verification, whether as a part of the activity or separate, of the overall replication/reproducibility of results/experiments and other research outputs. **Visualization** – Preparation, creation, and/or presentation of the published work, specifically visualization/data presentation.

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References

[1] Abdallah, M., Talib, M. A., Feroz, S., Nasir, Q., Abdalla, H., & Mahfood, B. (2020). Artificial intelligence applications in solid waste management: A systematic research review. *Waste Management*, *109*, 231-246.

[2] Alam, M., Islam, M. R., & Shil, S. K. (2023). AI-Based Predictive Maintenance for US Manufacturing: Reducing Downtime and Increasing Productivity. International Journal of Advanced Engineering Technologies and Innovations, 1(01), 541-567.

[3] Al Mukaddim, A., Mohaimin, M. R., Hider, M. A., Karmakar, M., Nasiruddin, M., Alam, S., & Anonna, F. R. (2024). Improving Rainfall Prediction Accuracy in the USA Using Advanced Machine Learning Techniques. *Journal of Environmental and Agricultural Studies*, *5*(3), 23-34.

[4] Al Mukaddim, A., Nasiruddin, M., & Hider, M. A. (2023). Blockchain Technology for Secure and Transparent Supply Chain Management: A Pathway to Enhanced Trust and Efficiency. International Journal of Advanced Engineering Technologies and Innovations, 1(01), 419-446.

[5] Alsabt, R., Alkhaldi, W., Adenle, Y. A., & Alshuwaikhat, H. M. (2024). Optimizing waste management strategies through artificial intelligence and machine learning economic and environmental impact study. Cleaner Waste Systems, 8, 100158.

[6] Buiya, M. R., Laskar, A. N., Islam, M. R., Sawalmeh, S. K. S., Roy, M. S. R. C., Roy, R. E. R. S., & Sumsuzoha, M. (2024). Detecting IoT Cyberattacks: Advanced Machine Learning Models for Enhanced Security in Network Traffic. *Journal of Computer Science and Technology Studies*, *6*(4), 142-152.

[7] Buiya, M. R., Alam, M., & Islam, M. R. (2023). Leveraging Big Data Analytics for Advanced Cybersecurity: Proactive Strategies and Solutions. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 882-916.

[8] Chowdhury, M. S. R., Islam, M. S., Al Montaser, M. A., Rasel, M. A. B., Barua, A., Chouksey, A., & Chowdhury, B. R. (2024). PREDICTIVE MODELING OF HOUSEHOLD ENERGY CONSUMPTION IN THE USA: THE ROLE OF MACHINE LEARNING AND SOCIOECONOMIC FACTORS. The American Journal of Engineering and Technology, 6(12), 99-118.

[9] Coskuner, G., Jassim, M. S., Zontul, M., & Karateke, S. (2021). Application of artificial intelligence neural network modeling to predict the generation of domestic, commercial, and construction wastes. *Waste Management & Research*, *39*(3), 499-507.

[10] Debnath, P., Karmakar, M., Khan, M. T., Khan, M. A., Al Sayeed, A., Rahman, A., & Sumon, M. F. I. (2024). Seismic Activity Analysis in California: Patterns, Trends, and Predictive Modeling. *Journal of Computer Science and Technology Studies*, *6*(5), 50-60.

[11] Debnath, P., Karmakar, M., & Sumon, M. F. I. (2024). AI in Public Policy: Enhancing Decision-Making and Policy Formulation in the US Government. International Journal of Advanced Engineering Technologies and Innovations, 2(1), 169-193.

[12] El-Rayes, N., Chang, A., & Shi, J. (2023). Plastic Management and Sustainability: A Data-Driven Study. *Sustainability*, *15*(9), 7181.

[13] Fang, B., Yu, J., Chen, Z., Osman, A. I., Farghali, M., Ihara, I., ... & Yap, P. S. (2023). Artificial intelligence for waste management in smart cities: a review. *Environmental Chemistry Letters*, *21*(4), 1959-1989.

[14] Getor, R. Y., Mishra, N., & Ramudhin, A. (2020). The role of technological innovation in plastic production within a circular economy framework. *Resources, Conservation and Recycling*, *163*, 105094.

[15] Hasan, R., Islam, Z., & Alam, M. (2024). Predictive analytics and machine learning applications in the USA for sustainable supply chain operations and carbon footprint reduction. *Journal of Electrical Systems*, *20*(10s), 463-471.

[16] Hasan, M. R., Shawon, R. E. R., Rahman, A., Al Mukaddim, A., Khan, M. A., Hider, M. A., & Zeeshan, M. A. F. (2024). Optimizing Sustainable Supply Chains: Integrating Environmental Concerns and Carbon Footprint Reduction through AI-Enhanced Decision-Making in the USA. *Journal of Economics, Finance and Accounting Studies*, *6*(4), 57-71.

[17] Hasanuzzaman, M., Hossain, S., & Shil, S. K. (2023). Enhancing Disaster Management through AI-Driven Predictive Analytics: Improving Preparedness and Response. International Journal of Advanced Engineering Technologies and Innovations, 1(01), 533-562.

[18] Huang, J., & Koroteev, D. D. (2021). Artificial intelligence for planning of energy and waste management. *Sustainable Energy Technologies and Assessments*, *47*, 101426.

[19] Ihsanullah, I., Alam, G., Jamal, A., & Shaik, F. (2022). Recent advances in applications of artificial intelligence in solid waste management: A review. *Chemosphere*, *309*, 136631.

[20] Islam, M. Z., Islam, M. S., Al Montaser, M. A., Rasel, M. A. B., Bhowmik, P. K., & Dalim, H. M. (2024). EVALUATING THE EFFECTIVENESS OF MACHINE LEARNING ALGORITHMS IN PREDICTING CRYPTOCURRENCY PRICES UNDER MARKET VOLATILITY: A STUDY BASED ON THE USA FINANCIAL MARKET. The American Journal of Management and Economics Innovations, 6(12), 15-38.

[21] Islam, M. R., Shawon, R. E. R., & Sumsuzoha, M. (2023). Personalized Marketing Strategies in the US Retail Industry: Leveraging Machine Learning for Better Customer Engagement. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 750-774.

[22] Islam, M. R., Nasiruddin, M., Karmakar, M., Akter, R., Khan, M. T., Sayeed, A. A., & Amin, A. (2024). Leveraging Advanced Machine Learning Algorithms for Enhanced Cyberattack Detection on US Business Networks. *Journal of Business and Management Studies*, *6*(5), 213-224.

[23] Islam, M. Z., Shil, S. K., & Buiya, M. R. (2023). AI-Driven Fraud Detection in the US Financial Sector: Enhancing Security and Trust. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 775-797.

[24] Karmakar, M., Debnath, P., & Khan, M. A. (2024). AI-Powered Solutions for Traffic Management in US Cities: Reducing Congestion and Emissions. International Journal of Advanced Engineering Technologies and Innovations, 2(1), 194-222.

[25] Khan, M. A., Rahman, A., & Sumon, M. F. I. (2023). Combating Cybersecurity Threats in the US Using Artificial Intelligence. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 724-749.

[26] Khan, M. T., Akter, R., Dalim, H. M., Sayeed, A. A., Anonna, F. R., Mohaimin, M. R., & Karmakar, M. (2024). Predictive Modeling of US Stock Market and Commodities: Impact of Economic Indicators and Geopolitical Events Using Machine. Journal of Economics, Finance and Accounting Studies, 6(6), 17-33.

[27] Kowsari, E., Ramakrishna, S., Gheibi, M., & Chinnappan, A. (2023). Marine plastics, circular economy, and artificial intelligence: A comprehensive review of challenges, solutions, and policies. *Journal of Environmental Management*, *345*, 118591.

[28] Lakhouit, A., Shaban, M., Alatawi, A., Abbas, S. Y., Asiri, E., Al Juhni, T., & Elsawy, M. (2023). Machine-learning approaches in geo-environmental engineering: Exploring smart solid waste management. *Journal of Environmental Management*, *330*, 117174.

[29] Nasiruddin, M., Al Mukaddim, A., & Hider, M. A. (2023). Optimizing Renewable Energy Systems Using Artificial Intelligence: Enhancing Efficiency and Sustainability. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 846-881.

[30] Naveenkumar, R., Iyyappan, J., Pravin, R., Kadry, S., Han, J., Sindhu, R., ... & Baskar, G. (2023). A strategic review on sustainable approaches in municipal solid waste management and energy recovery: Role of artificial intelligence, economic stability, and life cycle assessment. *Bioresource Technology*, *379*, 129044.

[31] Noman, A. A., Akter, U. H., Pranto, T. H., & Haque, A. K. M. (2022). Machine learning and artificial intelligence in the circular economy: a bibliometric analysis and systematic literature review. *Annals of Emerging Technologies in Computing (AETiC)*, *6*(2), 13-40.

[32] Pro-AI-Rokibul. (2024). Analyzing-Trends-Economic-and-Social-Implications-and-Predictive-Modeling-For-Plastic-Waste-/README.md at main · proAIrokibul/Analyzing-Trends-Economic-and-Social-Implications-and-Predictive-Modeling-For-Plastic-Waste-. GitHub. https://github.com/proAIrokibul/Analyzing-Trends-Economic-and-Social-Implications-and-Predictive-Modeling-For-Plastic-Waste-/blob/main/README.md

[33] Rahman, M. K., Dalim, H. M., & Hossain, M. S. (2023). AI-Powered Solutions for Enhancing National Cybersecurity: Predictive Analytics and Threat Mitigation. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 1036-1069.

[34] Rahman, A., Debnath, P., Ahmed, A., Dalim, H. M., Karmakar, M., Sumon, M. F. I., & Khan, M. A. (2024). Machine learning and network analysis for financial crime detection: Mapping and identifying illicit transaction patterns in global black money transactions. Gulf Journal of Advance Business Research, 2(6), 250-272.

[35] Shawon, R. E. R., Dalim, H. M., Shil, S. K., Gurung, N., Hasanuzzaman, M., Hossain, S., & Rahman, T. (2024). Assessing Geopolitical Risks and Their Economic Impact on the USA Using Data Analytics. Journal of Economics, Finance and Accounting Studies, 6(6), 05-16.

[36] Shil, S. K., Chowdhury, M. S. R., Tannier, N. R., Tarafder, M. T. R., Akter, R., Gurung, N., & Sizan, M. M. H. (2024). Forecasting Electric Vehicle Adoption in the USA Using Machine Learning Models. Journal of Computer Science and Technology Studies, 6(5), 61-74.

[37] Shil, S. K., Islam, M. R., & Pant, L. (2024). Optimizing US Supply Chains with AI: Reducing Costs and Improving Efficiency. International Journal of Advanced Engineering Technologies and Innovations, 2(1), 223-247.

[38] Sumon, M. F. I., Khan, M. A., & Rahman, A. (2023). Machine Learning for Real-Time Disaster Response and Recovery in the US. International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, 14(1), 700-723.

[39] Sumon, M. F. I., Osiujjaman, M., Khan, M. A., Rahman, A., Uddin, M. K., Pant, L., & Debnath, P. (2024). Environmental and Socio-Economic Impact Assessment of Renewable Energy Using Machine Learning Models. Journal of Economics, Finance and Accounting Studies, 6(5), 112-122.

[40] Sumsuzoha, M., Rana, M. S., Islam, M. S., Rahman, M. K., Karmakar, M., Hossain, M. S., & Shawon, R. E. R. (2024). LEVERAGING MACHINE LEARNING FOR RESOURCE OPTIMIZATION IN USA DATA CENTERS: A FOCUS ON INCOMPLETE DATA AND BUSINESS DEVELOPMENT. The American Journal of Engineering and Technology, 6(12), 119-140.

[41] Van Fan, Y., Jiang, P., Tan, R. R., Aviso, K. B., You, F., Zhao, X., ... & Klemeš, J. J. (2022). Forecasting plastic waste generation and interventions for environmental hazard mitigation. *Journal of hazardous materials*, *424*, 127330.

[42] Velis, C. A., Wilson, D. C., Gavish, Y., Grimes, S. M., & Whiteman, A. (2023). Socio-economic development drives solid waste management performance in cities: A global analysis using machine learning. *Science of the Total Environment*, *872*, 161913.

[43] Zeeshan, M. A. F., Sumsuzoha, M., Chowdhury, F. R., Buiya, M. R., Mohaimin, M. R., Pant, L., & Shawon, R. E. R. (2024). Artificial Intelligence in Socioeconomic Research: Identifying Key Drivers of Unemployment Inequality in the US. Journal of Economics, Finance and Accounting Studies, 6(5), 54-65.