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PREDICTING PLASTIC WASTE MISMANAGEMENT WITH MACHINE LEARNING MODELS

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Abstract. Predicting plastic waste mismanagement is critical in evaluating recycling processes and reducing the havoc of plastic waste crises. Mismanagement is a term synonymous to inefficient utilization and improper accountability of plastic wastes along the generation and consumption chains. Efficient tracking of these chains can aid efficient deployment of resources and safe rectification for efficient plastic recycling. Machine learning models are predominantly known to thrive under enormous high-quality data. Popular regions of plastic waste mismanagement like Africa are usually prone to lack of insufficient data hence a robust method is needed. This work utlizes Africa as a casestudy for tracking plastic waste mismanagement due to the unavailability of quality data to reasonably make predictions. Consequently, this work leverages the environmental and societal correlation in regions of Africa to create a correlative feature engineering technique that is leveraged by machine learning models to predict plastic waste mismanagement in Africa. To show the superiority of this work, we leveraged less efficient machine learning models with our technique to guarantee better predictions for regions of plastic waste mismanagement. Analytically, our approach shows an accuracy of 97.8% with SVM, 94.2%, with cat boost while other algorithms like KNN and linear regression showed 73.6% and 65.3%, respectively. This framework explains how analyzing plastic waste in Africa can be approached and how it results can be used by industry practitioners and related software vendors in establishing improved practices and tools for plastic management.

Keywords. Mismanagement, Regression, Machine Learning.

1. Introduction

The question starts when we see plastic waste littering the streets and its recycling pathway cannot be accounted for. The picture gets glimmer when it becomes the reason why a company is not operating optimally. It becomes critical and life threatening when plastic wastes block terrains, disrupts water bodies and causes environmental havoc [19, 21]. All which could have been avoided through proper plastic waste management. Most recycling structure would claim to have a proper plastic waste management structure but the key take away is in how they are able to predict spots of mismanagement within their pipeline. The ways and the strategy of rectification of this mismanagement is what machine learning can help with.

All over the world, the surge in plastic usage has given rise to a severe waste management challenge posing threats to ecosystems, public health and sustainable development. In this analysis, the multifaceted dimensions of the plastic waste. Understanding the dynamics behind the proliferation of plastic waste necessitates an examination of the root causes. Rapid urbanization, coupled with a burgeoning middle class and an increased reliance on single-use plastics has created a perfect storm. The lack of efficient waste management systems and inadequate recycling infrastructure further exacerbate the problem [1, 2, 4]. Machine learning (ML) provides powerful tools for improving plastic trash analysis

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FIGURE 1. Plastic wastes in Dandora Slum of Nairobi, Kenya, Dec 5, 2018 (AP Photo)

and management by using massive datasets and delivering insights that are not readily available using traditional approaches [13, 7]. This analysis aims to dissect these causative factors, shedding light on the interconnected issues that have propelled Africa into the throes of a plastic waste crisis. As plastic waste expands across African landscapes, its detrimental impacts on the continent's rich and diverse ecosystems become increasingly evident. From the sprawling savannahs to the coastal regions, plastic pollution is infiltrating natural habitats and disrupting delicate ecological balances.

Amidst the challenges posed by the escalating plastic waste crisis, there exist glimmers of hope and avenues for positive change. Innovative solutions, community-driven initiatives, and policy interventions are emerging to tackle the root causes and mitigate the impacts of plastic pollution in Africa. Exploring potential solutions ranging from policy reforms and waste management strategies to public awareness campaigns and the promotion of sustainable alternatives are avenues, this thesis aims to contribute to a constructive dialogue on charting a sustainable future for Africa in the face of the plastic waste challenge.

2. Literature Review

Global plastic waste is rising yet we cannot account for these plastic wastes in Africa. On the streets of Africa, we see that the biggest deposits of plastic wastes are through plastic bottles of soft drinks and plastic casings from spoiled consumer electronics parts. This became possible because of the environmental peculiarity of Africa from high intensity sunshine which prompts the need for cold refreshing liquids in plastic bottles and rate of deterioration of electronics casing. Every region in Africa is distinct, with its own operational environment and collection of localized plastic waste sources that must be investigated. As a result, the implementation of a plastic management system is subject to a slew of limitations that limit the start or development of recycling activities, all of which have a substantial negative influence on overall management performance. Theoretically, plastic waste management refers to any process intended to identify and provide accountability for plastics wastes for recycling or processing. Plastic waste management is a major environmental issue in Africa, having serious consequences for ecosystems, human health, and economies [18]. An inefficient plastic management system in any continent will worsen global climate change. Recent environmental irregularities and discovery of huge chunks of plastic waste in water bodies has led to a global outcry on the effect of plastic waste in the world and its disastrous effect on the climate, especially the water bodies [10, 17, 14]. New companies have increased their global product branding from glass or metallic cans to plastics. Every consumer electronics gadget utilizes plastics as casing which usually ends up as plastic waste [23].

When plastic waste data is nonlinear in nature, the most sought-after methods of statistical analysis for non-linear data is machine learning [12]. As it turns out, plastic data usage in Africa can be analyzed with machine learning techniques. With this analysis approach, a waste management framework that helps to know about plastic production, retrieval and transportation can be easily developed. Estimating plastic waste from captured plastic brands based on object detection algorithms can also aid plastic sorting which is a critical and time-consuming process of plastic waste recycling in Africa. According to a survey of the introductory literature, previous research has mostly concentrated on understanding and modelling plastic wastes outside of Africa, in places such as World Cup stadiums, airports, concerts, and exhibitions[15]. Additionally, only limited progress has been achieved in comprehensively identifying distinct plastic wastes based on their features[13]. Several ways for analyzing and modelling plastic trash have been proposed [8]. For example, knowledge-based systems were used to automate plastic waste identification, such as plastic waste with photoluminescence and machine learning [11]; a machine learning-based approach was developed to identify and categorize solid wastes [22]; and databases and population distribution were used to estimate and visualize the effects of plastic waste on climate change [3]. What has been sorely lacking in previous research is a thorough machine learning method to studying plastic garbage in Africa.

3. Methodology

Our approach is to apply the prediction technique to the continent of Africa. This continent shows the proper metrics for testing this thesis. All parameters used would be itemized and abbreviations stated so it can be reusable in modelling plastic waste mismanagement for any region of research. Our approach leverages the conventional machine learning pipeline that spans from data collection to data preparation to model selection, model training and model evaluation. The key difference in our approach lies in the data preparation and model selection phase. These areas are where the nuances of our assumptions come in and the domain field of plastic waste mismanagement can be leveraged.

To create mathematical model for analyzing plastic waste in African countries, we considered various factors that influence plastic waste generation, accumulation, and management. These factors might include population growth, urbanization, economic development, plastic consumption patterns, waste management efficiency, and recycling rates base on the features in datasets. Here are some of the key parameters:

In machine learning, we all know that most data are different and so is the plastic waste data. With the key parameters which are specific to each waste generating nations in Africa, a mathematical correlation was formed utilized the parameters. Foremost is the plastic consumption per capital W(t).

$$W(t) = P(t) \times C(t)$$

This equation helps compute the total plastic waste generated as a product of population and per capita consumption. Furthermore, plastic waste that leaks into the environment was modelled below.

$$L(t) = W(t) \times (1 - R(t)) \times (1 - M(t))$$

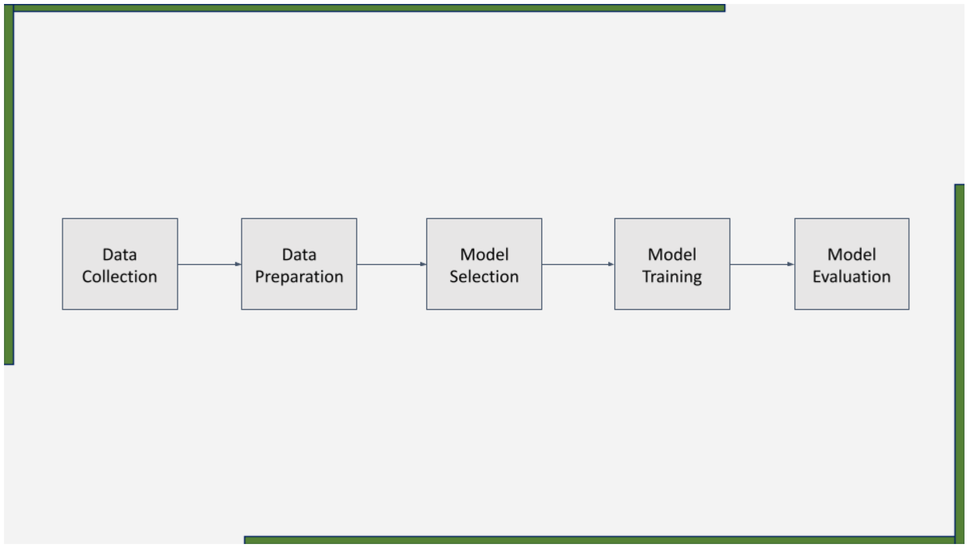

FIGURE 2. Operation flow for machine learning

This equation calculates the amount of plastic waste that leaks into the environment, assuming that part of the waste is recycled, and part is managed. Also, plastic wastes do accumulate hence the accumulation rate needs to be captured mathematically because it is also linked to the leakage rate as show below.

$$G(t) = G(t-1) + L(t)$$

This recursive equation tracks the accumulation of plastic waste over time. The plastic waste in the environment at year t is the waste from the previous year $G(t-1)$ plus the waste leaked into the environment. To apply this model, 4 key assumptions were made:

Given these assumptions and equations, we can simulate the amount of plastic waste generated, leaked into the environment, and accumulated in a given African country over time. Considering a scenario where:

- Population = Initial population $P_0 = 50$ million.
- Plastic consumption = Initial per capital plastic consumption $C_0 = 20$ kg/year.
- Recycling rate = Initial recycling rate $R_0 = 0.05$ (5%).
- Waste management efficiency = Initial waste management efficiency $M_0 = 0.60$ (60%).

Growth rates = Population grows by 2% per year, plastic consumption grows by 3% per year, recycling improves by 1% per year, and waste management efficiency improves by 0.5% per year.

Integrating machine learning (ML) into the plastic waste analysis model can enhance the ability to predict trends, optimize parameters, and evaluate the effectiveness of various interventions (e.g., recycling policies, plastic bans).To build an ML-enhanced model, we first need to gather relevant data and define features for prediction. These could include:

These features will aid in training the machine learning model to forecast future levels of plastic trash accumulation, waste leakage, and environmental deterioration. Population Growth and Plastic Consumption Prediction. Population increase and plastic consumption can be predicted using time-series or regression models. The model can forecast $P(t)$ (population at time t) and $C(t)$ (plastic consumption at time t) by analyzing historical trends and external factors (e.g., economic indicators).

Machine learning can help predict recycling rates and waste management efficiency based on past investments in infrastructure, environmental policies, and other socioeconomic factors. Supervised learning algorithms like SVM or Gradient Boosted Machines (GBM) can predict future recycling rates

Table 1. List of Parameters

S/N	Parameters	Abbreviation
1	Population of a country at time t (year).	P(t)
2	Per capita plastic consumption at time t (in kg/year).	C(t)
3	Total plastic waste generated at time t.	W(t)
4	Recycling rate at time t (as a fraction, 0 ≤ R(t) ≤ 1).	R(t)
5	Efficiency of waste management (percentage of plastic effectively managed).	M(t)
6	Plastic waste leakage into the environment at time t (plastic not recycled or managed).	L(t)
7	Accumulation of plastic waste in the environment at time t.	G(t)

$R(t)$ and waste management efficiency $M(t)$. The predicted values for plastic generation, recycling rates, and waste management efficiency can feed into the mathematical equations for waste leakage $L(t)$ and accumulation $G(t)$. Once the predictive models for population growth, plastic consumption, recycling rates, and waste management efficiency are built, they can be integrated into the mathematical equations. Instead of using fixed assumptions for population growth or plastic consumption, we can use the outputs from the ML models to dynamically update $P(t)$ and $C(t)$.

For example:

$$W(t) = \text{ML model prediction of } P(t) \times \text{ML model prediction of } C(t)$$

The recycling rate $R(t)$ and waste management efficiency $M(t)$ will also be dynamically predicted by the ML models. This allows the system to account for improvements due to new policies or technological advances.

For example:

$$L(t) = W(t) \times (1 - \text{ML prediction of } R(t)) \times (1 - \text{ML prediction of } M(t))$$

TABLE 2. Parameter Modeling for Plastic Waste Analysis

S/N	Assumptions	Modelling
1	Annual growth rate g exists, such that population evolves	$P(t+1) = P(t) \times (1 + g)$
2	Per capita plastic consumption grows at a rate r_c, where r_c is the growth rate in plastic consumption	$C(t+1) = C(t) \times (1 + r_c)$
3	Recycling rate improvement with time and better recycling technologies. Where ΔR represents the annual increase in recycling rates due to technological improvements or policy measures.	$R(t+1) = R(t) + \Delta R$
4	Waste management efficiency might improve as investments are made in waste collection and management systems where ΔM is the annual improvement in management efficiency.	$M(t+1) = M(t) + \Delta M$

TABLE 3. Modeling Assumptions in Africa

S/N	Modelling Considerations
1	Demographic data such as population, urbanization rates, and age distributions.
2	Economic data such as GDP, economic growth, industrialization, and development indexes.
3	Plastic waste data such as total plastic consumption, per capital consumption, recycling rates, and waste management efficiency.
4	Environmental data such as historical plastic leakage, environmental impact, coastal plastic pollution, etc.
5	Policy data such as the effect of bans, taxes, recycling incentives, etc.

3.1. **Capturing plastic wastes in African regions.** Africa is divided into five regions [20], with countries facing similar weather and economic conditions. Incorporating the five African areas (North, West, East, Central, and Southern Africa) into the plastic waste model, as well as accounting for comparable weather patterns and economic mismanagement, will make the analysis more realistic. These regions face similar issues, and taking them into account allows us to modify the model to reflect the continent's unique yet overlapping dynamics of plastic trash generation and management. Each African region can have unique characteristics in terms of population growth, economic development, plastic usage, waste management efficiency, and recycling rates. We can then generalize some variables across countries in the same region, recognizing shared facts.

North Africa has a generally desert environment, moderate to high income countries (e.g., Egypt, Morocco), relatively superior infrastructure, and major waste mismanagement owing to urbanization. West Africa is associated with fast urbanization, a tropical environment, high levels of economic mismanagement, inadequate infrastructure, and poor recycling rates. East Africa's economies are expanding, with large rural populations, moderate plastic consumption, and uneven success in waste management. Central Africa is recognized for its tropical climate, political instability, inadequate waste infrastructure, and high leakage rates. Southern Africa is noted for its greater levels of industrialization (South Africa being a significant role), dry and temperate climates, and mixed performance with recycling and garbage management. Specific variables that reflect the overall realities in each region can be defined as:

Using these regional factors, we adjusted the previous equations to reflect regional variations. Here's how we would modify the main components of the model. Plastic Waste Generation for Region r can be expressed as:

$$W_r(t) = P_r(t) \times C_r(t) \times \frac{1}{1 + E(t)}$$

where:

- $P_r(t)$ =Population of the region at time t.
- $C_r(t)$ = Per capital plastic consumption in the region.
- Economic mismanagement $E(t)$ impacts plastic waste through inefficient policies, which may increase the overall waste generated and unmanaged.

Recycling rate adjustment by region

$$R_r(t) = R_{base}(t) \times I_r(t) \times (1 - E(t))$$

- The Recycling rate $R_r(t)$ is now dependent on the regional infrastructure index $I_r(t)$ and economic mismanagement $E(t)$.
- Regions with poor infrastructure (lower $I_r(t)$) and higher economic mismanagement will have lower effective recycling rates, even if there is a national policy to improve recycling.

Plastic waste leakage by region:

$$L_r(t) = W_r(t) \times (1 - R_r(t)) \times (1 - M_r(t))$$

- $M_r(t)$ = Waste management efficiency, which can vary based on regional factors like infrastructure and weather.
- Weather factor $W_r(t)$ can influence how much waste leaks into the environment. For example, regions with heavy rainfall and poor drainage systems may experience more leakage (e.g., West Africa).

Regional accumulation of plastic waste

Plastic accumulation in each region will be influenced by the region's weather and economic realities:

$$G_r(t) = G_r(t-1) + L_r(t) \times W_r(t)$$

$W_r(t)$ could scale the impact of leakage depending on the weather patterns in the region. For example, a tropical climate might increase leakage and accumulation due to higher rainfall or flooding, while arid regions like North Africa might accumulate waste more slowly but still face challenges from wind and desertification.

TABLE 4. Regional parameter modeling

S/N	Parameter	Abbreviation
1	Economic mismanagement factor, capturing corruption, instability, and poor governance that can hinder the implementation of effective plastic waste management policies. Higher E(t) means lower efficiency in managing waste	E(t)
2	Regional weather factor, considering how the region's climate affects plastic degradation, waste leakage, and infrastructure (e.g., coastal erosion in West Africa, arid conditions in North Africa affecting waste breakdown).	Wr(t)
3	Regional infrastructure index, a measure of the infrastructure available for waste collection and recycling in each region. Southern Africa might have higher values due to better-established systems, while Central Africa would have lower values.	Ir(t)
4	Population of the region at time t	$P_r(t)$
5	Per capital plastic consumption in the region	$C_r(t)$
6	Recycling rate	$R_r(t)$
7	Waste management efficiency, which can vary based on regional factors like infrastructure and weather.	$M_r(t)$
8	Plastic Waste Leakage by Region	$L_r(t)$
9	Plastic accumulation in each region will be influenced by the region's weather and economic realities:	$G_r(t)$

TABLE 5. Plastic Waste generation by Region

Region	Population (Pr(t))	Per Capita Plastic Consumption (Cr(t))	Waste Management (Wr(t))
North Africa	High	Average	High
West Africa	Very High	Low	High
East Africa	High	Average	Average
Central Africa	Average	Low	Low
Southern Africa	Average	High	Average -High

3.2. **Data modelling.** We modeled Africa as a continent comprising of five regions. Each region has a model that captures and can predict plastic waste in them. Our approach utilizes the world plastic wastes datasets from Kaggle. The data preprocessing was done to carve out a new dataset which comprises of data points for African countries. This dataset, along with its parameters, was used to develop

TABLE 6. Estimating recycling rate per region of Africa

Region	**Base(R(t))**	**Ir(t)**	**E(t)**	**Rr(t)=R*Ir*(1-E)**
North Africa	0.4	0.7	0.3	0.196
West Africa	0.4	0.3	0.7	0.036
East Africa	0.4	0.4	0.5	0.08
Central Africa	0.4	0.2	0.8	0.016
Southern Africa	0.4	0.8	0.3	0.224

TABLE 7. Plastic waste leakage risk

Region	Waste Management (Wr(t))	Rr(t)	Mr(t)	Lr(t)=Wr*(1-Rr)*(1-t)
North Africa	High	Average	Average	Average
West Africa	High	Low	Low	Very high
East Africa	Average	Low	Average	High
Central Africa	Low	Very Low	Very Low	High
Southern Africa	Average	High	High	Low

TABLE 8. Accumulation of Plastic Waste Overtime

Region	**Gr(t-1)**	**Lr(t)**	**Wr(t)**	**Gr(t)=Gr(t-1) + Lr * Gt**
North Africa	Average	Average	Low	Average
West Africa	High	High	High	Very high
East Africa	Average	High	Average	High
Central Africa	Low	High	High	Average
Southern Africa	Average	Low	Low	Low

the case study model for this work. The demographic distribution of Africa was categorized in line of North Africa, Southern Africa, Middle Africa, Eastern Africa, and Western Africa. This was because political policies, languages, cultural behaviors, and geographical conditions are quite similar between countries in the same region. For the categorization of the parameters for our analysis, we took a deep dive into the data sets. This dataset came with features for global analysis of plastic wastes for continents all over the world [9]. Our strategy is to juxtapose this to the economic and social understanding of the continent of Africa.

In the context or economic and waste management knowledge of Africa, we analyzed based on the global plastic production in millions of tones, the mismanaged waste-global-total, mismanaged-waste-Africa-global-total, per capita mismanaged plastic waste in correspondence to GDP per capita, Per capita mismanaged plastic waste, per capita mismanaged plastic waste in Africa, GDP per capita in Africa, mismanaged plastic wastes in Africa, Total population (Gap minder, HYDE and UN) in Africa, plastic-waste-per-capita in Africa, Per capita plastic waste in Africa (kg/person/day). In the context of the dataset at hand, various dataset parameters were discovered for plastic waste management, which include per capital consumption, plastic waste per capital, global plastics production, per capita mismanaged plastic waste compared to GDP per capita. Each of the African countries are modeled as an Entity, the year of data been analyzed is represented as Year, the average Plastic waste per Person (kg/day) in such country, the GDP per capita in PPP and the total population formed the core parameters of the preprocessed datasets created by merging all the datasets on 2010-year bases for African countries.

The analysis of plastic wastes can be based on the detection of plastic wastes or the prediction of regions of plastic waste mismanagement based on real environmental data. For the prediction of the region of plastic waste mismanagement across Africa, the metric of accuracy would be used in justifying such analysis. But waste plastic parameters of regions of Africa share similar traits which machine learning models can learn to provide deeper insight into plastic waste data from Africa. Plastic waste data are dynamic (structured or unstructured), for this case, the parameters are to perform both classification and regression tasks. These are the two key umbrellas where plastic waste analysis tasks fall into. A classification task that classifies regions of mismanaged plastic wastes and a regression task that predicts the volume of mismanaged plastic wastes.

3.3. **Region of plastic waste analysis.** This implies the locations in Africa that the plastic waste analysis is currently considered. The total plastic production of regions in Africa varies with the economic development of those regions. Plastics are produced from the bye products of crude oil extraction[16]. The petrochemical production regions constitute the plastic generation region. Plastic recycling regions are also common in Africa, they are regions with a high growth rate of reusable plastic consumption. The goal of plastic waste analysis is to discover regions in which plastic waste is being mismanaged. Plastic production does not necessitate plastic waste regions. Everyday experience shows that factories which generate plastics products need to send them far off to consumption areas where they are utilized and, in the end, dumped as plastic waste. Hence a region can be a high plastic production region yet be a low plastic mismanagement region. High plastic production regions tally with regions of high capital and economic developments.

In the context of Africa, they are the city capital which has factories and the import and exporting infrastructures. Plastic waste data can be obtained from detection or observation. The detection involves using intelligent systems to detect plastic waste. While some data are structured, some plastic waste data are not. This creates a vacuum in the utilization of a general machine learning approach in solving all plastic waste analysis problems.

We provided an excellent network for analyzing plastic in any part of Africa. Local branches and aggregation centers should be the first stop in any effective plastic analysis procedure. Recyclers or administrators at these centers will be well-paid locals who recycle. The compensation scale for the recyclers varies according to the areas and the caliber of the gathered plastics. The largest supporters should be included in the system and given more authority to conduct outreach. The function of these recyclers should be integrated into their identity, and the message of plastic recycling awareness and its influence on climate change should be promoted. This strategy can then extend from place to place throughout Africa's suburbs, going online and through applications to reach a larger audience. This strategy has already proven successful in Africa with banks, fast-moving consumer items, and gambling systems. With these models, we think the mechanism for aggregating plastic trash will flourish more.

3.4. **Understanding support vector machines (SVM).** Support Vector Machines, or SVM, is a powerful supervised machine learning algorithm used for classification and regression tasks. It is particularly well-suited for tasks that involve separating data into distinct categories or classes. SVM works by finding the hyperplane that best separates the data points into classes while maximizing the margin, which is the distance between the hyperplane and the nearest data points (support vectors). SVM can be used for binary classification, where data points are divided into two classes, or for multi-class classification, where there are more than two classes. In the context of plastic waste management in Africa, SVM can be applied in many ways to model and address the problem so SVM can be used to categorize plastic waste into diverse types based on features such as color, shape, and composition. This is valuable for recycling and disposal purposes, as diverse types of plastics have varying recycling processes and environmental impacts. SVM models can analyze data to identify regions or areas in Africa with high concentrations of plastic waste. This information can guide targeted cleanup and waste management efforts. This is known as the identification of hotspots. Also, SVM can predict future trends in plastic waste based on historical data, socio-economic factors, and urbanization rates. This helps with planning and resource allocation for waste management. SVM can be used to detect anomalies or unusual patterns in plastic waste data, which may indicate illegal dumping or irregular waste generation. SVM models can optimize waste collection routes by considering factors like the density of plastic waste in different areas, traffic conditions, and the capacity of collecting vehicles. This reduces operational costs and environmental impact.

4. Results and Discussions

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4.1. **Developing a unified framework.** One of the biggest challenges to this work was spotting the plastic wastes dataset to use to be able to develop a robust framework. While it was very daunting, a theoretical bases from data aggregation that can make dataset creation easier for the replication of this work was developed. To unify plastic classification knowledge and machine learning modelling efforts into a comprehensive framework for plastic waste management in Africa requires crucial steps such as establishment of a robust data infrastructure that collects, stores, and shares data on plastic waste. This infrastructure should be accessible to various stakeholders, including researchers, governments, and waste management organizations like the one we utilized in our analysis. Also, a fostered collaboration between experts in plastic classification, waste management, data science, and machine learning are crucial in sustaining this unified framework. This allows the interdisciplinary teams to ensure that the framework addresses diverse aspects of plastic waste management effectively. Tailoring the framework to suit the specific needs and challenges of different African regions is crucial. What works in urban canters may not be suitable for rural areas, and the framework should account for these variations. This framework was developed with scalability in mind which allows its adaptation to different scales of plastic waste management, from local communities to national governments.

The dataset was subjected to four models which include Linear Regression, Firefly, Catboost and Support vector machines. This study's findings will be useful to industry practitioners and related software

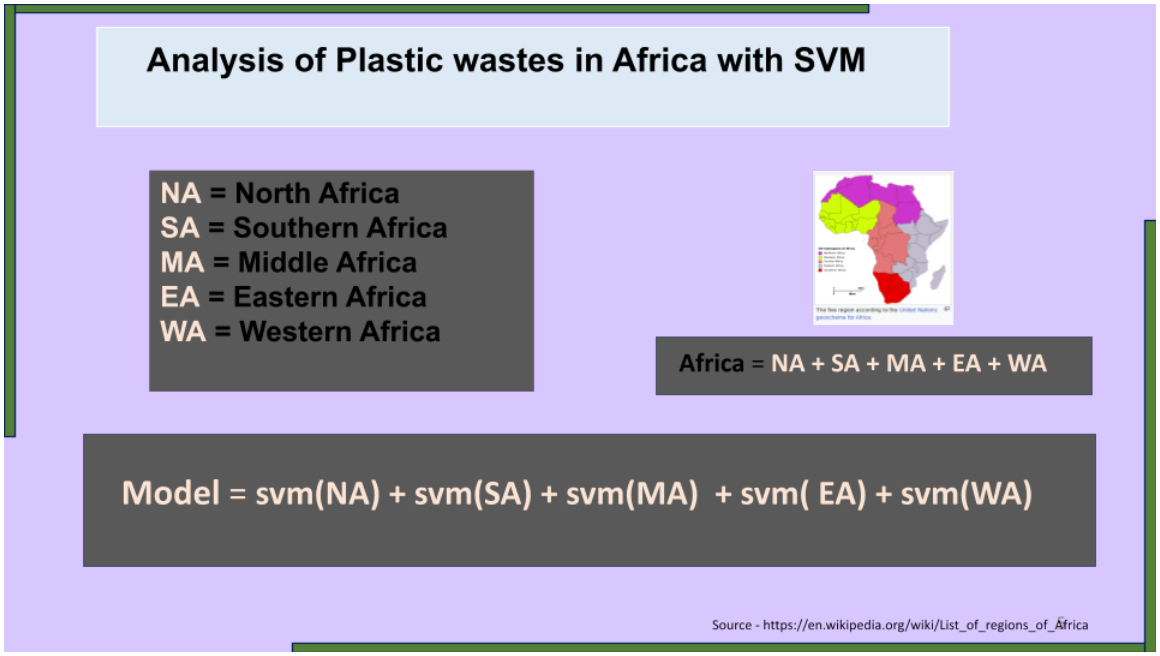


FIGURE 3. Plastic Analysis Framework

vendors in establishing improved practices and tools for plastic management and look-ahead scheduling. This method shows an accuracy of 97.8% with SVM, 94.2%, with catboost while other algorithms like KNN and linear regression showed 73.6% and 65.3%, respectively. This however concludes that exploring machine learning models to find regions of plastic waste mismanagement in the regions of Africa can be extremely useful in analyzing the future plastic wastes generation in Africa.

Using a five-code color scheme, a contextual visualization of the region of plastic waste mismanagement was also spotted within Africa. Regions 0.02 to 0.06 are marked deep blue, 0.06 to 0.11 are marked light blue. 0.11 to 0.17 are marked grey. 0.17 to 0.74 are marked orange and 0.74 to 0.34 was marked deep red. This constitutes the judging scale for visualizing the degree of severity of regions that needs to adopt plastic management policies based on the dataset analysis.

The expectation around this research revolves around four critical questions. Foremost is how effective is analyzing plastic wastes in Africa with machine learning. The statistical result from the machine learning algorithm shows how effective machine learning is as an approach towards analysis. Secondly is how might machine learning be used to categorize plastic garbage for better analysis and modelling and this is exemplified in my decision to adopt regional classification and prediction of regions of plastic waste mismanagement. Thirdly is how to unify the plastic classification knowledge and various machine learning modelling efforts into a framework for total plastic waste management for Africa. This can be done through the regional approach and exploration of machine learning models as new algorithms unfolds in the future. Lastly, comparing this approach against current industry practices as well as research advancements in modelling and resolving plastic wastes shows high level of accuracy, scalability, and more robustness for deployment from regions to regions in Africa base on interest.

4.2. **Model generalisation.** Based on the model's findings, a strategic framework can be built to tackle plastic waste mismanagement across Africa, with a focus on the regions most impacted by poor infrastructure, economic mismanagement, and environmental concerns. This framework should prioritize regional interventions, policy development, technical solutions, and community engagement, all while considering the realities of each region. This framework is intended to reduce plastic waste leakage into

Table 9. Estimating Plastic Waste Mismanagement in Africa

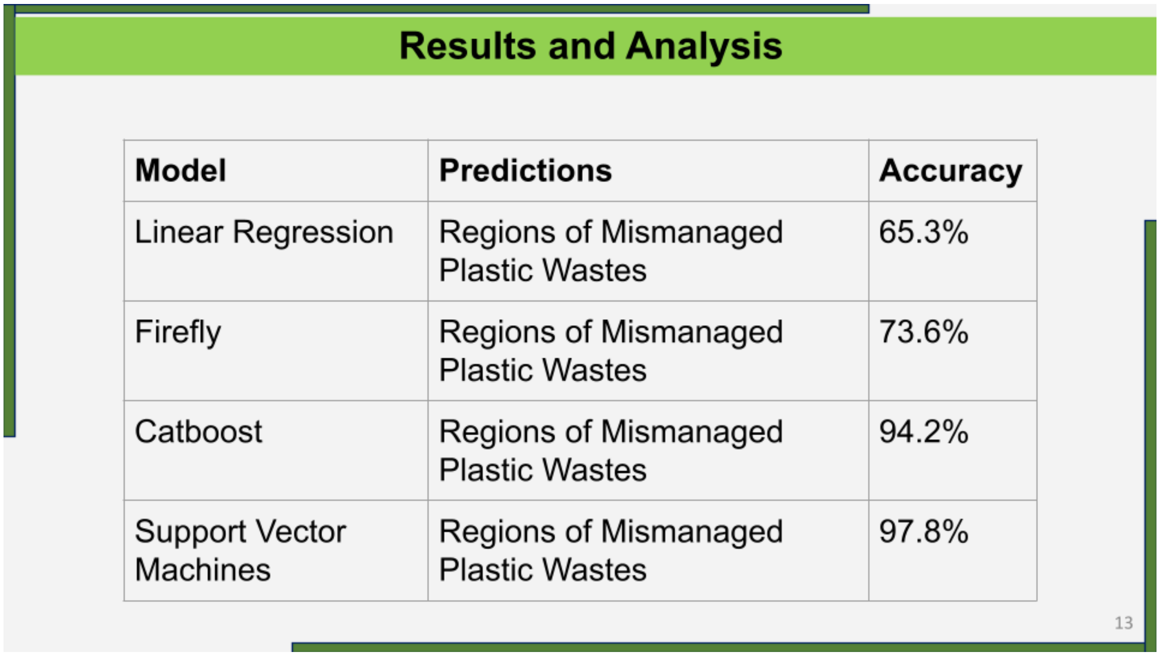
S/N	Parameters		Abbreviation
1	Plastic Waste Generation	Amount plastic waste is produced by a region.	$W_r(t)$
2	Recycling Rate	The efficiency of recycling systems in the region	$R_r(t)$
3	Waste Management Efficiency	Efficiency of waste collection, treatment, and disposal.	$M_r(t)$
4	Leakage	The amount of waste that leaks into the environment, contributing to pollution.	$L_r(t)$
5	Economic Mismanagement	Captures inefficiencies in governance, corruption, and infrastructure that directly affect waste management.	$E(t)$

Table 10. Comparing Regions Based on Waste Mismanagement

$Region$	$WasteGeneration$	$RecyclingRate$	$WasteEfficiency$	$EconomicMismanagement$	$Overall$
North Africa	Moderate	Moderate	Moderate	Moderate	Low to Moderate
West Africa	High	Very Low	Very Poor	High	Very High
East Africa	Moderate	Low	Moderate	Moderate	Moderate
Central Africa	Low	Very Low	Very Poor	Very High	Extreme
Southern Africa	Moderate to High	High	Good	Moderate	Low

the environment, improve recycling and waste management infrastructure, address economic mismanagement that harms waste management systems, and leverage regional and worldwide cooperation.

In West Africa, mismanagement is widespread. The primary causes include growing urbanization, low recycling rates, widespread plastic leakage into rivers and oceans, and severe economic mismanagement. To prevent plastic trash leakages, investment in waste collecting systems and enhance drainage, particularly in coastal cities such as Lagos and Accra must be done. Encouragement of private-sector participation in recycling through public-private partnerships is also crucial as well as the creation of recycling hubs near major urban centers. Tighter anti-corruption procedures in waste management systems to ensure that monies are allocated appropriately.



Results and Analysis

Model	Predictions	Accuracy
Linear Regression	Regions of Mismanaged Plastic Wastes	65.3%
Firefly	Regions of Mismanaged Plastic Wastes	73.6%
Catboost	Regions of Mismanaged Plastic Wastes	94.2%
Support Vector Machines	Regions of Mismanaged Plastic Wastes	97.8%

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FIGURE 4. Results of Machine Learning Analysis

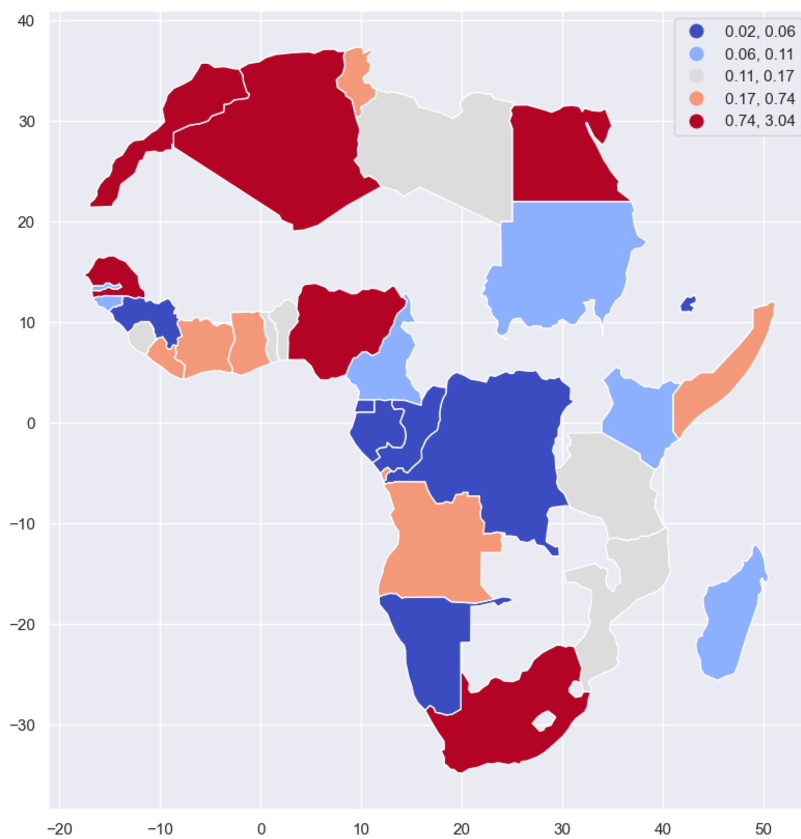

FIGURE 5. Visualizing Regions of Plastic Waste Mismanagement in Africa

Central Africa is also recognized for severe mismanagement, which necessitates rapid action. The causes are extremely low recycling rates, insufficient waste management infrastructure, high plastic leakage, and extreme economic mismanagement because of political instability. Collaboration with international organizations is one strategy for stabilizing the region and increasing institutional capacity for waste management. It also entails emphasis on the construction of critical waste management infrastructure, such as landfills, collecting systems, and recycling facilities. Local authorities and communities are also being trained in rubbish collection, recycling, and environmental stewardship. Mobile waste collection and treatment units will be deployed in hard-to-reach places to prevent plastic leakage in rural and conflict zones. Lastly, economic recovery efforts that enhance transparency in the allocation of funds for public services, including waste management should be encouraged.

In East Africa, minor mismanagement is observed, but great progress has been made. This is due to increased plastic usage, moderate recycling efforts, and waste management gaps in rural and coastal areas. Improvements can be observed further by expanding the effectiveness of plastic bag bans (e.g., Kenya's example) and enforcing policy compliance more thoroughly throughout the area. Furthermore, regional eco-innovation canters will be established to develop regionally relevant recycling technology and business models (for example, waste-to-product programs). Developing targeted waste management programs in rural and coastal communities to prevent plastic pollution in rivers and the Indian Ocean. Increasing initiatives to convert plastic garbage into electricity, particularly in quickly increasing cities such as Nairobi and Addis Ababa. Lastly s the promotion of cross-border collaboration to share best practices in plastic waste management, especially around shared water bodies (e.g., Lake Victoria). In Southern Africa, we have witnessed better management and continuous progress due to improved infrastructure and recycling in urban areas (South Africa), although gaps still exist in rural areas and informal settlements. This can be expanded by using the region's existing infrastructure to support circular economy models, in which waste is reused and repurposed extensively. Creating innovative waste collection solutions in informal communities and underdeveloped rural areas. Increased incentives for the private sector to invest in sustainable waste management solutions, particularly for remote populations. Positioning Southern Africa as a regional leader in recycling technology and innovation, hence facilitating knowledge transfer to other African regions. North Africa has a low to moderate mismanagement pattern and hence serves as a role model for other places. This is due to better waste management, but it is susceptible to plastic pollution in coastal areas and certain economic mismanagement in nations such as Libya. Continuity is achieved by increasing efforts to prevent plastic trash leaking into the Mediterranean Sea by improved waste collection and coastline cleanup activities. Harmonizing regional waste management policies to promote collaboration and efficiency, particularly with neighboring countries. Supporting the growth of recycling markets, with a particular emphasis on converting trash into valuable resources for economic reuse (for example, plastic-to-fuel technology). Improve governance and economic stability to improve waste management systems in nations such as Libya.

West Africa and Central Africa have the greatest rates of plastic garbage mismanagement. West Africa suffers from excessive leakage, economic mismanagement, and inadequate infrastructure, resulting in significant environmental contamination. Central Africa's low plastic generation does not change the reality that its waste management systems are non-existent. East Africa has moderate mismanagement, with some countries making improvements (e.g., Kenya), while many continue to struggle with rural infrastructural and economic difficulties. Southern and North Africa manage plastic garbage more effectively. Southern Africa, notably South Africa, has the continent's most advanced recycling and garbage management infrastructure[6]. North Africa's infrastructure has improved, yet leakage persists in some locations, including as along the Mediterranean coast.

Table 11. Comparing Regions Base on Mismanagement

Region	Waste Generation	Recycling Rate	Waste Efficiency	Economic Mismanagement	Overall
North Africa	Moderate	Moderate	Moderate	Moderate	Low to Moderate
West Africa	High	Very Low	Very Poor	High	Very High
East Africa	Moderate	Low	Moderate	Moderate	Moderate
Central Africa	Low	Very Low	Very Poor	Very High	Extreme
Southern Africa	Moderate to High	High	Good	Moderate	Low

Finally, the model identifies West Africa and Central Africa as the locations with the highest levels of plastic waste mismanagement, which is caused by poor infrastructure, low recycling rates, and economic mismanagement. Southern Africa and North Africa have had greater success in waste management, with Southern Africa outperforming in terms of recycling and trash infrastructure. This knowledge can assist drive targeted policy actions to improve waste management in the most impacted areas, such as prioritizing investment in garbage collection infrastructure and policies that address economic mismanagement in West and Central Africa.

With these metrics in mind, the plastic trash creation in North Africa is moderately high because of urbanization and industrial expansion. Recycling rates are reasonable, with some initiatives in nations like as Morocco and Egypt, but not very efficient. Their waste management efficiency is higher than in other places, although it is nevertheless inconsistently implemented. Leakage is low due to improved garbage collection systems, however coastal areas such as Egypt's Nile River confront plastic pollution. Their economic mismanagement is minimal, yet some nations (such as Libya) face political instability, which affects waste management.

Also, West Africa has chronic plastic waste mismanagement, which is fueled by high leakage, weak infrastructure, and major economic mismanagement. Plastic pollution is widespread throughout the region, particularly along the coast and in rivers. Others can be summarized as follows. Plastic waste generation is high, driven by fast population increase and urbanization. The recycling rate is quite low due to inadequate recycling infrastructure. Waste management efficiency is low because informal waste collection systems dominate, and many regions lack adequate waste management facilities. Plastic garbage floods into rivers and oceans in coastal towns such as Lagos, Accra, and Dakar, causing significant leakages. Finally, economic mismanagement, such as high corruption, ineffective legislation, and a lack of investment in waste infrastructure, lead to bad results.

In East Africa, plastic waste generation is moderate with rising consumption as the economy grows. The recycling rate is low but improving in nations such as Kenya, which has implemented severe plastic bag bans and recycling programs. Waste management effectiveness varies by country, with metropolitan areas improving but rural ones being underserved. The leakage is minor, however some coastal

Table 12. Summary Table of Comparison

Aspect	*ConventionalMethods*	*ML − EnhancedApproach*
Model Complexity	Simple, static, often linear	Dynamic, complex, and adaptable
Prediction Accuracy	Depends heavily on fixed assumptions, limited flexibility	High accuracy, adaptive, non-linear predictions
Handling Uncertainty	Limited to deterministic modeling	Models uncertainty via probabilistic methods and complex interactions
Policy Optimization	Static scenario analysis, limited to fixed assumptions	Optimizes policies dynamically via reinforcement learning
Computational Cost	Low computational cost, easy to implement	High computational cost, requires advanced tools and expertise
Data Requirements	Lower data requirements, works with historical averages	Requires large datasets, continuous data updates

areas (such as those bordering the Indian Ocean) face substantial plastic pollution issues. Economic mismanagement is also modest, with some countries (such as Somalia and South Sudan) experiencing political instability and others (such as Kenya and Ethiopia) achieving progress.

Plastic waste generation is low in Central Africa due to its lower industrialization and population density. The recycling rate is exceedingly low, with most countries in the region without formal recycling systems. Political instability, a lack of infrastructure, and widespread poverty all contribute to ineffective garbage management. There are numerous leaks, particularly in locations near rivers such as the Congo River, where trash is deposited directly into the water. Economic mismanagement is rampant; political instability, corruption, and conflict significantly impede the region's ability to manage trash properly.

Furthermore, the plastic waste generation in Southern Africa ranges from moderate to high, and it is mostly driven by economic activity, particularly South Africa. South Africa has the greatest recycling rate in Africa, and it leads in recycling activities and infrastructure development. Their waste management efficiency is higher than that of other regions, particularly in cities, although rural areas continue to suffer with trash management. Leakages are mild, with better control of plastic trash in metropolitan areas, but some leakage occurs in informal settlements. Economic mismanagement is modest; while South Africa has the best infrastructure in the region, economic difficulties such as inequality and political challenges can limit waste management efficiency in other countries.

In concept, while conventional models are easier to implement, they often fail to capture the complexity, uncertainty, and dynamic nature of plastic waste systems, especially in fast-evolving contexts like African countries. Machine learning-enhanced models offer improved accuracy, adaptability, and the ability to optimize policies, making them more powerful tools for tackling complex environmental challenges, such as plastic waste management. However, the trade-off is in higher computational costs and data requirements. The choice between the two approaches depends on the availability of resources and the specific goals of the analysis.

5. Conclusion

This work shows that with feature engineering that leverages the environmental and societal correlation in economic areas to create correlative feature engineering technique that is leveraged by machine learning models to predict plastic waste mismanagement. Machine learning models are predominantly known to thrive under enormous high-quality data. For regions of plastic waste mismanagement, there is usually lack of insufficient data to back the issue hence a robust method must be sort after. In developing continents like Africa, ways for tracking plastic waste mismanagement are quite crucial especially due to the unavailability of quality data to reasonably make predictions.

This work explores the effectiveness of using machine learning to analyze plastic waste in Africa, shedding light on its potential benefits, challenges, and the role it can play in mitigating this pressing environmental concern. According to this result, the context of plastic waste problem in Africa can be analyzed via regions of mismanaged plastic waste analysis. The effective identification of these regions lunches a hold on the in-depth plastic management analysis across regions of Africa.

While this work is centered around Africa, the baseline framework can be applied to datasets for any region or country where plastic waste mismanagement with machine learning needs to be studied. Also, while it does not dive into specific nuances of machine learning methods. It generally highlights how it can be adopted in the feature engineering process that can be leveraged by any machine learning technique. This work has shown form theory to practice and application to a specific region how critical feature engineering approach can help scale the predication of plastic waste mismanagement using machine learning models.

Statements and Declarations

The authors declare that they have no conflict of interest, and the manuscript has no associated data.

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