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AI-Based Predictive Model Architecture for Beach Litter Monitoring

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Abstract — Different researchers have carried out Beach-litter prediction, with basis of their studies being detection and counting of existing litter. Forecasting requires integration of temporal litter patterns, with contextual conditions that influence accumulation. Continuous monitoring of beach litter is necessary within this area of study. Conventional process of monitoring provides observation to a given extent, which limits rapid or automated assessment. AI-based detection allows automatic identification and quantification, allowing monitoring to continue from detection towards prediction. Existing methods address detection, forecasting or contextual integration separately. Various predictive studies use historical litter records, contextual variables, camera observations and Machine Learning. Limited architectural integration connects AI-derived litter measurements directly with temporal and contextual information for multi-predictor variables within multi-duration dimensions. This study developed an AI-based predictive model architecture. The model connected automated litter measurement temporal construction, contextual integration, predictive modelling and forecasting generation. Images were captured through IoT-enabled cameras, subjected under RT-DETRv2, which detected, classified and counted the objects. The output of this process is category-specific quantitative litter observations. The image-level counts are aggregated into beach-week observations, forming temporal litter representation. The temporal information provides the predictive baseline. The predictive model generated category-specific forecasts at multiple future durations. These were weekly, bi-weekly and monthly forecasts. The architecture linked AI-based measurement (RT-DETRv2), data integration, prediction and monitoring output in one end-to-end flow. The model provides a framework for anticipatory beach-litter monitoring instead of detection alone. The output of the predictive model architecture provide diverse options necessary for specific management decision making as well as a feedback loop to the predictive process.

Keywords— Artificial Intelligence, Predictive Model, Internet of Things, Beach litter.

I. INTRODUCTION

Information technology tools provide solutions and assistance in coastal management together with improvement in the rate and scope of governance along the coast. [1]. However, complexity associated with new technologies is causing lack of interest by many stakeholders due to limited awareness about application and availability of appropriate technology [2].

Provision of solutions to challenges related to beach litter has for a long time attracted attention of researchers. Some of the notable beach litter data gathering methods include use of citizen science method in which beach-goers make use of devices such as smartphones to gather and send beach litter images, in-situ cameras, use of Un-manned Aerial Vehicles (UAVs), commonly known as drones, remote sensing data captured by remote sensors, among others.

IOT has been regarded by worldwide research community as an effective technology that can be used to solve or reduce problems related to coast through development of suitable solutions [3]. IOT-based techniques help not only in real-time decision making process but also allow monitoring of coast environment to be carried out instantly by managing diverse and voluminous data [4]. IOT applications can assist in gathering data associated with beach activities through use of devices such as sensors [5]. Other ways of IoT application is through surveillance cameras. This helps in providing suitable information related to a given area of interest. Data collected through use of IOT is suitable for training Machine Learning processes for development of predictive systems. This helps to reduce unforeseen dangers to the environment [6]. Use of AI such as deep learning models enable improved forecasting of dynamism associated with vegetation and detection of any abnormal change in vegetation, within different ecosystems [7]. This is done through use of change detection technology. Gathering of a large amount of images of objects from diverse places that are commonly seen in beaches is undertaken to help in modelling of litter within the coast environment [1].

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Comparison of previously taken image of the beach without litter can be compared with images of the same beach with various degree of litter to determine the pollution level. This is done through image detection technology. Object detection is a technology within computer vision that is able to differentiate various objects of a given type in images and videos [8]. The key function of object detection is to determine the present location of an object in an image (object localization) as well as the category under which every object is classified. Traditional models of object detection are composed of three stages: informative region selection, feature extraction and classification [8]. Algorithms used in object detection is either machine learning or deep learning approach. Machine learning processing deals with smaller datasets while processing of larger dataset can be done using Deep learning methods [9]. Deep learning algorithm enables

learning process through use of deep layers in Convolutional Neural Networks [10]. There has been extensive research on application of CNN techniques for beach litter detection. Such techniques include R-CNN, Fast R-CNN, Faster R-CNN among others. Different techniques have different levels of accuracy. Choice of a specific algorithm depends on available technology in terms of processing power and storage, area of application, type of data collected, volume of dataset and expected level of prediction.

There is limited understanding on how use of environmental, beach-specific factors and behavioural assessment can be combined to influence future beach litter trends. Measurement of the effectiveness related to this combination within predictive frameworks has not been determined. The impact of this integrated framework on how it can transform Deep Learning and IoT-derived beach litter observations into behaviour-aware, multi-duration predictions has not been sufficiently measured. There is limited knowledge on use of feature engineered predictor variables and comparative algorithm evaluation in production of decision support process for proactive beach litter management.
An integrated predictive framework is therefore needed in order to quantify influence of behavioural, environmental and beach specific factors on future beach litter trends. The framework is a combination of automated observations, beach-specific information and deep-learning techniques. The predictive model is capable of anticipating future beach litter accumulation patterns in support of beach management processes towards conservation initiatives and sustainable economic activities.

The overall purpose of this research was to apply IoT and Deep Learning technologies to monitor beach litter along selected Kenyan coastal beaches with the aim of developing a predictive model that is capable of anticipating future beach-litter trends. The influence of environmental, beach visitors' behavioural factors and beach-specific characteristics on beach litter accumulation was quantified and applied as predictor variables in the prediction process. This was realised through integration of DL-derived observations with predictive modelling techniques. The ultimate goal was to provide decision-support information necessary for beach management initiatives and a sustainable blue economy.

II. LITERATURE REVIEW

1. AI-Based Beach Litter Monitoring and Detection

Tackling environmental challenges has attracted use of technologies such as smart sensors, wireless sensor networks and artificial intelligence. Evolution from basic remote monitoring toward advanced environmental monitoring systems is notable, including machine-learning-supported monitoring, integration of IoT and complex networked sensing. [11]. Environmental research has increased tremendously, with the aim of comin up with diverse ways of providing solutions to evolving natural environment. There are multiple application of prediction modelling in solving various environmental challenges. Use of technologies to increase accuracy of prediction and providing the best solution to these emerging challenges is evident. IoT-based prediction modelling have been widely used by researchers to develop prediction models with remarkable results in most cases [12]. Combination of IoT wireless technologies and machine learning algorithms for predictive modelling of water-quality monitoring systems have been examined [13]. This include technologies such as cellular networks, Wi-fi, Bluetooth, Low-Power Wide Area Netorks, and Zigbee. Our architecture involve predictive modelling using a combination of iot, deep learning and machine learning algorithm. Our model uses computer vision/RT-DETRv2 as the principal litter-measurement mechanism for proving the data for predictive modelling. IOT-based litter observation is considered one of predictor variables within the model.

2. Human and Beach-Use Factors Associated with Litter Generation

Human beings mainly cause Beach litter. This is because areas occupied by people register twice-higher litter accumulation than in other areas with lower population. Change in beach user behaviour is essential in minimizing the effect of litter along beaches. [14]. One key challenge is that Beach users have diverse social-economic characteristics that influences their behaviour along the beach, resulting to various littering effects. Apart from behavioural aspect, other factors that affect littering include level of income and degree of literacy. Environmental awareness and installation of bins are notable preventive actions that help minimize littering [14]. Community-level education together with other multifaceted and localized options are likely to help minimize littering. Better understanding of those who cause littering on beaches can help reduce beach litter [15]. Control of beach visitors can also influence the amount of litter deposited on the beaches [16].

The period of the day when many visitors go to the beach especially in the evening is associated with increased amount of litter. Morning hours record little litter since only few visitors are on the beach. Change in weather conditions affects the beach visits, with sunny weather attracting more visitors in comparison to rainy, windy or cloudy weather in which only few visitors are on the beach. This implies that variation in weather has an impact on number of visitors, resulting to less littering on the beaches [17],[18]. Majority of likely beach users confirm weather condition before embarking on beach visit [18]. Rainfall/weather and visitor activity should not necessarily be conceptualised as completely independent influences. Weather can modify beach-user behaviour and consequently alter beach occupancy. Zoning of beaches can trigger litter accumulation. Different beach zones have varied amount of litter that can be due to preference of beach users. Litter accumulation patterns are because of factors such as beach user numbers, temporal dynamics and weather conditions. It is a multi-driver phenomenon, having varied multiple causes [19].

One of such causes is provision and control of beach litter infrastructure along the beach. Positioning of beach infrastructure has the potential to minimize littering along the beaches. Trash bins that are correctly positioned increases convenience that lead to modified litter disposal behaviour [20]. Beach users who spot the bin are most likely to use the bins. The physical features of such bins also need close attention. This is because design of trash bins can influence interaction with the bins and littering behaviours among beach users. Well-designed trash bins has potential to attract large number of beach users, meaning that design discipline could lead to minimized littering behaviour [21]. The issue of bin positioning and design can lead to cleanliness along various beaches. Such beaches attracts many beach users who prefer beaches that have characteristics such as cleanliness, low congestion, low litter levels and increased frequency of patrols [22]. With increased attractiveness, especially on fine weather days, very large numbers of people travel to beaches, creating substantial road and parking congestion. The implication is that beach travel behaviour and transport-mode choice respond to weather conditions. [23]. Weather influences the decision to make beach trips.

A weather index specifically for beach tourism was constructed, incorporating four weather dimensions [24]. These are thermal comfort, wind speed, precipitation and cloud cover. Crucially, they did not stop at people's stated preferences. Weather scores were aggregated and correlated with observed visitation at two beach parks in Ontario. Their optimized weather index showed substantial relationships with visitation. This implies that beach preference is multi-attribute. People do not select or use a beach according to one characteristic alone; access and management-related attributes can jointly shape preference. Other factors include amenities and crowding [25]. After carrying out their study, Donegan et al. [26] found that more centrally located beaches had more diverse land uses, better-equipped promenades and lighting. They were popular both during the day and at night. Less-central beaches had less infrastructure and tended to be used primarily during daytime. The least accessible beaches were not popular as respondents' first beach choices, whereas some of the most frequently selected beaches combined longer coastlines, easier access and usable sandy areas. Their findings implies that beaches have different physical, accessibility and infrastructural characteristics. Those characteristics are associated with different patterns and intensities of human use. This is an affirmation that Beach use and preference are influenced by identifiable characteristics of the beach environment and its management [27].

3. Predictive Approaches to Beach Litter Monitoring

Predictors used population trends, festivals, weekends, special days and seasonal variations in a study [28]. This is because human presence/activity influences waste generation. Beach-waste prediction connected human-activity patterns with temporal conditions. They used Random Forest together with linear regression as the Main Machine-learning prediction approach. Actual system workflow that connect prediction with beach-waste management was proposed as well. Collection of beach-waste weight was based on historical, seasonal and human-event data. It was used to undertake prediction using machine learning [28]. This system strongly justifies including human-use and temporal context. Only waste records already available numerically are used and it predicts overall waste quantity. Our architecture derives litter measurements from images, preserves litter categories, and predicts category-specific future conditions.

A forecasting model for future beach macro litter counts was developed using existing time-series monitoring data [29]. Historical beach-litter formed the temporal litter counts used by NB-GLM for prediction process. The purpose of forecasts was to support assessment against litter thresholds. It showed that observation of historical litter could enable temporal forecasting of future beach-litter conditions. NBGLM is one of the modelling approaches in our predictive framework. Historical litter observations therefore can provide a temporal basis for forecasting future beach-litter conditions. The approach starts from conventional survey counts and focuses mainly on total litter trends. Our architecture starts earlier with AI-derived category measurements and extends prediction through contextual human-use information and multiple forecast horizons.

Stationary-camera observations recorded marine-litter beaching events for 22-month duration [30]. They were connected with hydrophysical and meteorological reanalysis variables. Comparisons between Artificial Neural Networks, Random Forest and Gradient Boosting were made for predicting beaching of marine litter. Physical variables provided appropriate information for prediction, with most influential being wave steepness, sea level, and wave direction. It signifies that combination of Camera-derived observations with contextual variables and ML can predict a future beach-litter-related event. In this case, their target was marine-litter beaching, not freshly dropped recreational litter. The architecture used in this research is close to our architecture since it makes use of cameras to capture beach litter with Machine learning being considered for prediction process. The key difference is that the target is marine litter beaching driven by physical transport processes. Our architecture deals with fresh recreationally deposited litter. The architecture also incorporates human-use and behavioural consideration rather that waves driven transport variables.

Large beach-litter monitoring dataset was combined with anthropogenic variables, and beach characteristics/environmental variables and machine learning Modelling translated into management information [31]. CatBoost predicted litter density. SHAP was then use for explainability and DPSIR to translate the results toward management. This is an indication that beach-litter prediction is moving toward multi-source contextual integration and management-oriented interpretation. Our architectural distinction lies in the end-to-end integration of AI visual measurement and category-specific temporal representation. Other areas are human-use and behavioural inputs together with multi-horizon forecasting.

4. Literature Synthesis and Architectural Gap

Different researchers in different fields of study have undertaken application of advanced beach-litter monitoring, automated detection, behavioural assessment and forecasting. These applications lack a unified strategy necessary for solving existing marine ecological challenges related to beach litter accumulation and short duration prediction of future beach litter trends. There is little evidence concerning integration of IoT-derived observations and DL-generated litter measurements with environmental, behavioural and beach-specific factors to come up with a unified behavior-aware, multi-duration predictive framework. Feature-engineered predictor variables, comparative prediction algorithm evaluation and decision-support mechanism have been incorporated in the predictive model with the aim of providing anticipated future trends of beach litter. The prediction information have an impact on coastal beach management decision making process, local communities together with other stakeholders.

III. METHODOLOGY

1. Study design and Data sources

The area of study was along the Kenyan coastal beaches. Among the five counties of Lamu, Tana River, Kilifi, Mombasa and Kwale, three counties were selected. These include Kilifi, Mombasa, and Kwale. Within those counties, there are multiple beach areas where visitors usually go. Two of the key beach areas in each county was selected for study. The beaches in each selected counties that were considered for this research are as follows:

- Kilifi county – Butwani Beach and Vidazini Beach
- Mombasa County – Jomo Kenyatta Beach and Maasai Beach
- Kwale County – Kongo River Beach and Trade Winds Beach
- The selection of these beaches was based on the following considerations:
- Their characteristics such as accessibility proximity, amenities, and geographical elevations made them suitable in attracting beach visitors.

These beaches experience large number of people in comparison to other beaches within a given county. They have increased recreational activities such as tourism, fishing, sports events, private and general activities. These characteristics made them suitable for studying the influence of human behaviour on litter accumulation. This is because they are prone to littering. Monitoring of these beaches provided data required to understand the litter pattern and the intervention strategies that need to be undertaken together with their effectiveness.

2. Architecture Development Approach

RT-DETRv2 was selected as the deep learning object detection architecture because the collected beach images contained multiple litter categories distributed under varying environmental conditions. The architecture was expected to accurately detect individual litter objects while maintaining computational efficiency during model training and inference. The detector in this case served as the environmental measurement instrument responsible for transforming raw beach images into structured litter observations that were subsequently used in the predictive model. Beach litter images collected during field monitoring were manually annotated using bounding boxes to identify individual litter objects. Each object was assigned to one of five predefined litter categories, namely plastic bottles, plastic cups, food packaging, plastic containers and non-plastic litter. The beach-week was adopted as the fundamental observational unit for predictive modelling. A beach-week represents all litter observations collected from one monitored beach during a single monitoring week. Individual object detections obtained from multiple images collected within the same week were accumulated to produce a single observation describing the litter condition of that beach during the corresponding monitoring period.

$$b \in \{1, 2, \dots, 6\}, w \in \{1, 2, \dots, 24\} \qquad (1)$$

where:

- b identifies one of the six monitored beaches;
- w identifies one of the 24 monitoring weeks, representing 6 months.

This established the spatial and temporal limits of the dataset. It produced beach-week observations in all counties for 6 months period. Each beach-week observation subsequently incorporated temporal, environmental, behavioural and compositional variables that collectively formed the predictor set used within the developed predictive model.

Each beach-week observation is represented by

$$X_{bw} = (L_{bw}, R_{bw}, V_{bw}, BUI_b, CBI_c) \qquad (2)$$

where

- represents the DL-based litter measurements
- for beach (b) during week (w);
- denotes the recorded rainfall during the corresponding monitoring period;
- represents the recorded number of beach visitors;
- denotes the Beach Use Index associated with beach (b); and
- represents the County Behavioural Index associated with county (c).

Equation (2) demonstrates that each beach-week observation integrates deep learning-derived environmental measurements with environmental and behavioural variables describing the monitored beach. The resulting observation therefore constitutes the fundamental analytical unit used throughout the development and implementation of the proposed predictive model.

3. Deep Learning-Based Beach Litter Vector

The deep learning object detection process generated quantitative measurements describing the number of detected objects belonging to each litter category. Rather than representing beach litter using a single total count, a five-category litter vector capable of preserving the composition of beach litter observed during each monitoring period was adopted. The vector representation enabled the predictive model to capture changes in both litter quantity and litter composition, thereby providing a richer description of beach litter conditions than would be obtained using total litter counts alone. Litter composition in this case consists of all the 5 categories of litter captured as objects during detection process.

$$L_{bw} = \begin{bmatrix} PB_{bw} \\ PC_{bw} \\ FP_{bw} \\ PLC_{bw} \\ NP_{bw} \end{bmatrix} \qquad (3)$$

Where

L_{bw} denotes beach litter vector

PB_{bw} denotes the number of plastic bottles detected at beach b during week w;

PC_{bw} denotes the number of plastic cups detected;

FP_{bw} denotes the number of food packaging items detected;

PLC_{bw} denotes the number of plastic containers detected; and

NP_{bw} denotes the number of non-plastic litter objects detected.

Equation (3) represents the deep learning-based beach litter state associated with each beach-week observation. Unlike conventional approaches that summarise beach litter using a single aggregate count, the litter vector preserved the contribution of each litter category independently. In addition to that, the predictive model was capable of analysing changes in litter composition while simultaneously estimating overall litter accumulation.

4. Total Beach Litter

This was the first derived variable from the litter vector. Unlike the litter vector, which preserves category composition, the total beach litter provides a single quantitative measure of litter accumulation for each beach-week observation. This variable was used to describe the overall litter burden observed during each monitoring period and served as one of the principal response variables within the predictive model.

The total beach litter is defined as

$$T_{bw} = PB_{bw} + PC_{bw} + FP_{bw} + PLC_{bw} + NP_{bw} \quad (4)$$

Equivalently,

$$T_{bw} = \sum_{i=1}^{5} L_{i,bw}$$

Where

- T_{bw} is the total number of litter objects recorded for beach b during week w;
- $L_{i,bw}$ represents the count belonging to litter category i.
- $L_{i,bw}$ PB_{bw}, PC_{bw}, FP_{bw}, PLC_{bw}, and NP_{bw} are the five litter categories previously defined in Equation (3).

This gave the total number of detected litter objects in a beach-week.

Equation (4) combines the five litter categories into a single quantitative measure describing the magnitude of beach litter accumulation during each monitoring week. Although the total litter count provides an overall indication of pollution intensity, it does not preserve the contribution of individual litter categories. Therefore, additional compositional variables were derived to characterise the internal structure of beach litter.

5. Development of Predictor Variables

Recent environmental prediction studies have demonstrated that the predictive capability of machine learning models depends not only on the selected prediction algorithm but also on the relevance of the predictor variables incorporated during model development [32], [33]. Predictor variables should therefore represent the temporal, environmental and behavioural processes influencing the phenomenon under investigation. The beach-week observations were transformed into a structured predictor set describing litter accumulation, environmental conditions and human behavioural characteristics associated with each monitored beach. This integration was used to develop a multidimensional predictor representation, unlike conventional beach litter studies that primarily utilise total litter counts as predictor variables. The predictor variables were selected based on their expected influence on beach litter accumulation while preserving the natural temporal characteristics observed throughout the monitoring period.

The predictor vector for beach b during monitoring week w was represented by

$$\mathbf{X}_{bw} = [\mathbf{L}_{bw}, MA4_{bw}, CD_{bw}, R_{bw}, V_{bw}, BUI_b, CBI_c] \quad (5)$$

Where

- $\mathbf{L}_{bw}$ represents the deep learning-based litter vector defined in Equation (3.3);
- $MA4_{bw}$ denotes the four-week moving average describing recent temporal litter trends;
- CD_{bw} represents the Composition Dynamics variables developed in Equations (3.6)–(3.8);
- R_{bw} denotes the observed rainfall;
- V_{bw} represents the recorded number of visitors;
- BUI_b denotes the Beach Use Index; and
- CBI_c denotes the County Behavioural Index. Four-Week moving-average is represented as

For predicting week, the MA4 feature uses only weeks:

$$\mathbf{MA4}_{bw} = \frac{1}{4}\sum_{j=0}^{3} \mathbf{L}_{b,w-j} \quad (6)$$

Equation (5) represents the complete predictor vector used throughout the developed predictive model. The predictor set integrates deep learning-based litter measurements with temporal, environmental and behavioural variables describing each monitored beach which enables the prediction algorithm to capture complex interactions

6. Selection of Prediction Algorithm

The study adopted a several prediction algorithms whose output was later comparatively evaluated to make informed choice on accuracy of prediction process. The various prediction algorithm selected are Random Forest, XGBoost, NBGLM and MA. This is because the developed predictor vector combined temporal, environmental, behavioural and compositional variables that were expected to exhibit different interactions with different predictive algorithms. These variables interacted in linear, nonlinear and temporal ways. Since relying on a single algorithm could bias the results, multiple algorithms representing different prediction philosophies, which were later evaluated.

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Random Forest and XGBoost were considered as the primary machine-learning algorithm selected for predictive modelling. NBGLM and MA were considered as Benchmark Prediction algorithm.

7. Predictor Representation

The predictor variables developed in the preceding sections were integrated to form a unified representation of each beach-week observation. The predictor variables incorporated into the developed predictive model are represented by the predictor vector.

The complete predictor vector is represented as follows:

$$\mathbf{X}_{bw} = [\mathbf{L}_{bw}, \mathbf{MA4}_{bw}, \mathbf{CD}_{bw}, \boldsymbol{R}_{bw}, \boldsymbol{V}_{bw}, \boldsymbol{BUI}_{b}, \boldsymbol{CBI}_{c}]$$

$\mathbf{X}_{bw}$ is the predictor vector defined in Equation (5).

The prediction function implemented by the principal prediction algorithm is expressed as

$$\hat{\mathbf{Y}}_{bw+1} = f_{\mathrm{XGB}}(\mathbf{X}_{bw}) \qquad (7)$$

Where

$\hat{\mathbf{Y}}_{bw+1}$ represents the predicted beach litter state for the next monitoring period; and

$f_{\mathrm{XGB}}(\cdot)$ $f_{\mathrm{XGB}}(\cdot)$ denotes the nonlinear prediction function learned by XGBoost.

For prediction of the next beach litter vector:

$$\hat{\mathbf{L}}_{b,w+1} = f_{\mathrm{XGB}}(\mathbf{X}_{bw})$$

Where:

$\hat{\mathbf{L}}_{b,w+1}$ is the predicted five-category litter vector for the following week;

Equation (7) demonstrates that future beach litter conditions are estimated using the predictor variables developed throughout the preceding methodological stages. This formulation provides the mathematical basis upon which the principal prediction algorithm estimates the next beach litter conditions.

8. Model Validation

Assessment of prediction performance was carried out using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), the coefficient of determination (R2) and Mean Prediction Bias.

IV. AI-BASED PREDICTIVE MODEL ARCHITECTURE

1. Data acquisition stage

The images along the selected beach areas were subjected to IoT cameras which captured those images within a specified area of operation. As stated in limitations of chapter 1, special citizen-science cameras were used in case of failure or unavailability of the IoT camera. Still images were captured by the camera which had 4G-enabled Sim cad and a storage SD-card for backup in case of challenges in communication. The captured images were transmitted through public network and stored in specified secure location. Images were stored in weekly basis so that they can be subjected to detection process at a specified time. The storage process involved acquiring all the images from the six beaches every week for the 6 months period of research within the three counties. The images were stored within the six months starting from February to July, a low season along the coastal area of Kenya, as illustrated in table 1 below:

Table 1: Arrangement of Images In A File

County	Beach	Months/ Beach	Wks/ Month	Images/ Wk
Kilifi	Butwani	Feb-July	@Wk1-Wkn	Img1-Imgn
	Vidazini	Feb-July	@Wk1-Wkn	Img1-Imgn
Mombasa	J. Kenyatta	Feb-July	@Wk1-Wkn	Img1-Imgn
	Maasai	Feb-July	@Wk1-Wkn	Img1-Imgn
Kilifi	Kongo River	Feb-July	@Wk1-Wkn	Img1-Imgn
	Trade Winds	Feb-July	@Wk1-Wkn	Img1-Imgn

Every image captured contained one or more beach litter category. Some images had multiple objects for different beach litter categories in a given image.

2. Deep-Learning measurement stage

The RT-DETRv2 Object Detector was initially trained and validated. The total number of objects used for training was 1740, while 618 objects were used to validate the detector. The metrics of the detector are illustrated in the train/valid loss curves and the precision/recall/mAP50/50-95. The trained detector received the stored images and detected each image, identifying different beach litter category types, classified and counted the five litter categories in each image and then stored in a CSV file for further analysis and processing.

3. Beach-Week data formation

The stored litter categories were arranged based on the Beach the detected image was captured. They were stored in weekly basis. Each week contained the total number of beach litter categories accumulated from various images captured at that specified week. This was considered as beach-week data. The prediction process was later initiated at beach-week level, being the basic level of prediction process.

Table 2: The Images and the Corresponding Categories Detected, Identified, Counted And Aggregated In A Specific Beach-Week

Img_ID	PB	PC	FP	PLC	NP
Img_001	8	2	1	1	0
Img_002	5	3	2	1	0
Img_003	10	3	0	1	1

The beach-week data from the six beaches within the 6 months period were summed up to form a predictor variable (Beach Litter Vector) for the predictive model process.

Each beach contains beach litter categories stored for 6 months. i.e. b v(1,2,..6)

Each beach was considered to have up to 24 weeks within the 6 months i.e. w v(1,2,..24)

The beach Litter vector, which later became a predictor variable, was composed of all the total number of categories per the various images in a specific week. The total beach-week litter per a specific week in a given beach was computed as follows:

$$T_{bw} = PB_{bw} + PC_{bw} + FP_{bw} + PLC_{bw} + NP_{bw} \qquad (4)$$

Therefore:

$$T_{bw} = \sum_{i=1}^{5} L_{i,bw}$$

4. Feature Set Construction

This section provides an explanation of how feature set was constructed from the beach litter categories plus other indicators and variables. Feature set consists of predictor variables which were combined and then subjected to a prediction algorithm to estimate future outcome.

5. Temporal Features

Category Specific 4-Week Moving Average (MA4) was derived from the beach week litter category vectors for the last four weeks.

It was computed as follows:

$$MA4_{i,b,w} = \frac{L_{i,b,w} + L_{i,b,w-1} + L_{i,b,w-2} + L_{i,b,w-3}}{4}$$

$$\mathbf{MA4}_{bw} = \frac{1}{4}\sum_{j=0}^{3} \mathbf{L}_{b,w-j} \qquad (6)$$

For predicting week, the MA4 feature uses only weeks:

6. Environmental and Behavioural Predictors

Based on literature review, the predictors were identified as rainfall, Visitors, BUI and CBI (Figure 4).

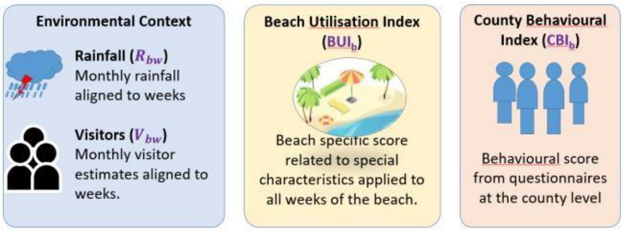

Figure 1: Context variables

7. Predictive model structure

Figure 2 below shows the beach litter observation vector that is composed of the various variables required to undertake the prediction process. The vector was used to make the next prediction. They were subjected to Rolling-Origin (Expanding Window), which is a temporal validation strategy/data-splitting technique common in time-series forecasting [34]. It was used in this research to preserve the chronological order of observations during the model training and testing. Additional key reason for using it other than other validation strategies is that it protects data from leakage and overfitting. Leakage involve early exposure of the next week variable before it is predicted.

The next stage involved selecting:

- Feature Set (F1 to F6)
- Comparative Algorithm: Random Forest, XGBoost, MA4, NB-GLM.

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- Multi-duration forecasting: 1WAF (1-Week-Ahead Forecast), 2WAF (2-Week-Ahead Forecast), 4WAF (4-Week-Ahead Forecast)

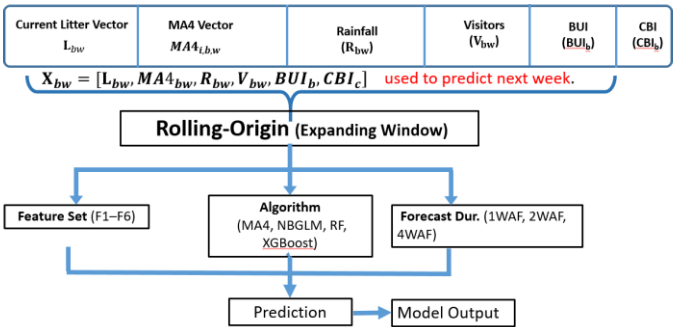

Figure 2: Predictive Model Structure

The same data was used for comparative evaluation with each Feature Set being subjected to an algorighm at a time within one specific Forecasting Duration.

The feature set predictor variable was subjected to algorithms based on specific content of a given Feature Set. The composition of each Feature set 1 to 6 is as follows:

Table 3: Feature Set Predictor Variable

Feature set	Variables included
FS1	Historical litter counts
FS2	FS1 + MA4
FS3	FS2 + rainfall
FS4	FS3 + visitor statistics
FS5	FS4 + Beach Utilisation Index (BUI)
FS6	FS5 + County Behavioural Index (CBI)

Forecasting duration was composed of:
- 1WAF (short-term forecast)
- 2WAF (medium-term forecast)
- 4WAF (longer-term forecast)

8. Prediction Outputs

Based on the derived formulas, the outputs of the predictive mode were as shown in figure 6 below:
- predicted category counts
- predicted total litter
- dominant litter category
- dominance gap

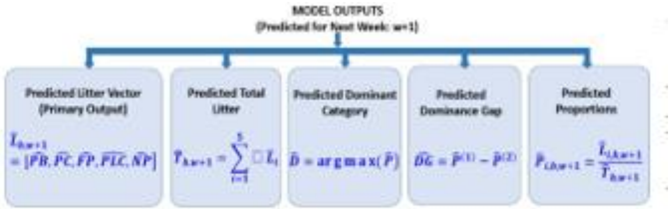

Figure 3: Predictive model output and derived output

9. Validation and Evaluation

The four algorithms were evaluated for the prediction durations (1WAF-4WAF). Performance was assessed using measures such as RMSE, MAE, coefficient of determination R2 and prediction bias.

The evaluation process main goal was to determine ability of each algorithm to accurately predict future beach-litter accumulation. This was done under different information represented by Feature Sets (F1-F6).The prediction was compared with actual category count of the next week's observation.

The output was also compared with the benchmark predictive algorithm. After the evaluation process, the suitable prediction algorithm output was generated. This was the output with minimal errors within the overall Feature Set and prediction duration. This output was made available for management decision support. It also became an input to Continuous monitoring and model update loop of the predictive model. It was expected to help make future improvement to the model through the feedback loop mechanism.

V. INTEGRATED ARCHITECTURE AND INFORMATION FLOW

The flow of data and information is illustrated in the overall predictive model architecture as shown in figure 4. The first step of the process was data collection. Beach images were captured from the six beaches based on beach-week monitoring. Environmental and Social-Behavioural data was keyed-in. Beach images entered the second step in which they underwent the detection process using RT-DETRv2 Deep Learning Object detector. The object counts were aggregated into weekly beach litter vectors under feature engineering and predictor construction step.

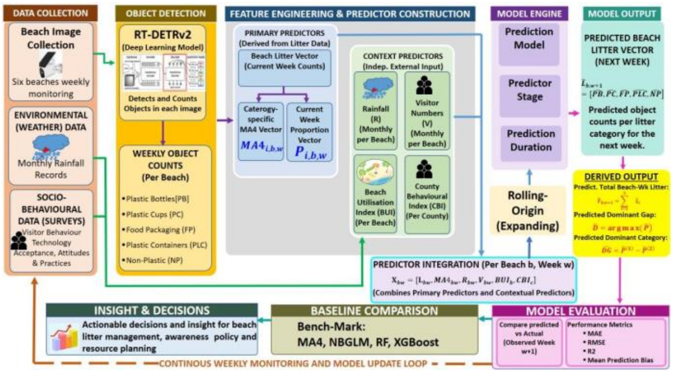

Figure 4: The predictive model architecture

Environmental, County behavioural index, rainfall, visitor numbers and Beach Utilisation index were appropriated into Context predictors. All the predictor variables were integrated at predictor integration step. They were subjected to Rolling-Origin (Expanding) whose output was passed to the model engine.

The predictive model output was obtained and derived output computed. Model evaluation was carried out with baseline comparison taking place afterwards. The output of this process was made available for management decision making as well as a feedback loop to the predictive process.

VI. CONCLUSION

The predictive model architecture was an indication of the reality that beach litter detection can be integrated with environmental variables and behavioural information in a unified prediction model to help support routine beach monitoring process. It possibly can assist in evidence based coastal management process and eventually help in sustainable blue economic activities. The comparative evaluation of the implemented prediction approaches was a clear illustration that different models can exhibit diverse predictive characteristics. This is especially when they are applied to the developed beach-week dataset. The evaluation indicated that perdition performance can depend on characteristics of available data set, apart from algorithm complexity along. The model was a demonstration of support for short-time beach litter forecasting as well as a basis for future intelligent coastal monitoring systems. The research was a demonstration also of how beach litter can reveal quantifiable and tangible geographical and temporal patterns through use of artificial intelligence. This beach litter can then undergo transformation to become actionable predictions for management of coast regions.

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