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Sky Sweeper:A Drone Survelliance Model Using YOLOV8 and Jetson Nano for Plastic Waste Monitoring System

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***Abstract*— The recent statistics reveals that our country India produces 22 million tons of plastic every year. It has been noted that the inappropriate collection and segregation of plastic garbage makes its disposal a severe concern. The major issue with plastic trash in India is not about how much is produced, but rather inefficient waste management practices, such as ineffectual collection and recycling. The urgent need to address the mounting environmental issues caused by litter and garbage in outdoor spaces, particularly in places like beaches, is what spurred the development of a trash detection drone surveillance model. The drone surveillance model's particular objectives include Trash Detection.Real-time monitoring, Geo-location and mapping, Notifications and alert system , data integration and analysis, efficiency and Cost effectiveness. The proposed UAV surveillance model rightly locates the most plastic populated area through YOLOV8 (You Only Look Once) object detection algorithm and then the deep learning algorithm is applied on the captured data to explore the right location and the location report will be forwarded to the concern official through the digital notification by integrating the model with NVidia Jetson Nano Kit to assist in delegating the workforce to the appropriate location thereby utilizing the available manpower in an efficient way. Also results of the proposed model is compared with YOLOV5 implementation and existing Ensemble models where it is concluded that the proposed YOLOV8 model provides higher accuracy comparatively.**

Keywords*— *UAV, YOLOV5, Modified YOLOV8, NVIDIA JETSON NANO.

I. Introduction

A large amount of polymer is created on a global basis as a result of plastic products having a significant impact on our daily lives. As per the recent statistics, our country produces 22 million tons of plastic every year. It has been noted that the inappropriate collection and segregation of plastic garbage makes its disposal a severe concern. This leads to many problems like impacting the health and making the oceans and water bodies dirty. Only 30 percent of the plastic waste is recycled whereas 3.4 million tons of plastic waste is produced in a year. The major issue with plastic trash in India is not about how much is produced, but rather inefficient waste management practices, such as ineffectual collection and recycling. The urgent need to address the mounting environmental issues caused by litter and garbage in outdoor spaces, particularly in places like beaches, is what spurred the development of a trash detection drone surveillance model. The major drivers for creating system are Environmental protection, Prevention of Pollution, Public Health and Safety Technological Innovation [4].

The existing models for plastic waste identification mainly includes the methods such as utilization of satellites for locating the plastics, manual identification through available manpower appointed by the government sectors and monitoring using aerial survey. Plastic garbage is typically visually inspected along the cross-section, which is laborious, time-consuming, and dangerous for the operators while monitoring the plastics manually [5]. The aerial survey monitoring method is considered to be bit costlier considering the time and professional surveyors required for accomplishing the monitoring task. The efficiency of satellite monitoring of plastic trash has been confirmed by modern experts, the accuracy of recognizing plastic waste is still constrained by temporal and spatial resolution that makes the model ineffective.

The use of unmanned aerial vehicles (UAVs) for surveying is growing as a result of its low cost, easy operation, and safety. UAV monitoring not only ensures the safety of investigators during fieldwork but also minimizes the impact of humans on other species compared to manual monitoring system. UAV survey is simple and less expensive than aerial exploration which involves skilled experts. Also UAVs have more modern sensors and can produce photos with higher resolution and a more flexible revisit cycle that

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competes with the satellite plastic monitoring system with high efficiency [6]. To identify plastic garbage in photographs taken by UAVs, researchers have created a variety of machine learning algorithms. While this method cannot take use of complicated garbage features and has a low accuracy rate, it can recognize objects more accurately than non-deep neural network-based algorithms in simple circumstances.

The major objective of the model is to safeguard the environment, advance sustainable lifestyles, improve public health and safety, and involve communities in protecting the beauty and ecological integrity of our environment is what spurred the development of a trash detection drone surveillance model. To design a system that can autonomously recognize and locate waste and debris in outdoor settings, such as beaches, parks, and waterways, a trash detection drone surveillance model is being developed. Also, it aids in increasing the effectiveness and accuracy of garbage detection in order to facilitate prompt clean-up efforts and lessen the harmful effects of litter on the environment [7]. The drone surveillance model's particular objectives include Trash Detection.Real-time monitoring, Geo-location and mapping, Notifications and alert system , data integration and analysis, efficiency and Cost effectiveness. The proposed UAV surveillance model rightly locates the most plastic populated area through YOLO (You Only Look Once) object detection algorithm and then the deep learning algorithm will be applied on the captured data to explore the right location and the location report will be forwarded to the concern official through the digital notification to assist in delegating the workforce to the appropriate location thereby utilizing the available manpower in an efficient way. The process of model development includes image acquisition, reprocessing the captured data including annotation [8]. The results of pre-processing step divides the data into three different phases such as training, testing and validation.

II. Literature Survey

A. ***Literature Survey***: Tamin et al [2022] profound a thorough analysis of YOLO's use in monitoring plastic trash. The authors go over the benefits of adopting YOLO for this activity, including its accuracy and quickness. They also reviewed many techniques that have been employed to train YOLO models to detect plastic garbage [1].

Jie Zhang et al [2021] provides a technique for YOLOv4-based plastic garbage detection in coastal locations. A collection of photos of plastic debris that was gathered from coastal locations was used by the scientists to train a YOLOv4 model. The model's performance was then assessed using a test set of photos [2].

Rui Li et al [2022] presents a YOLOv5-based drone-based method for monitoring plastic trash. On a collection of photos of plastic debris that was collected from various locations, the scientists trained a YOLOv5 model. The model's performance was then assessed using a test set of photos [3].

- ***Field and UAV Data***: The Field covers the area of SRM Institute of Science and Technology and the Potheri village as the student population is spotted very high in the village as well as in the campus. The field area is cited in the south Chennai of Tamil Nadu in India. The plastic usage is very high in the areas of potheri landscape as well as in lakes cited in potheri due to heavy human flow in the spotted areas. Covering the areas of about 5.23 Square Kilometre, valid images had been captured for preparing the dataset. Also, the available data set is also concatenated with the captured raw dataset for training and validating the model. The volume of the data prepared is about 4124 valid orthocaptures and 4682 RGB images through UAV.

- ***Image Acquisition***: The image acquisition is performed using Quad copter drone along with the DJI RC flight-controller. The longest time flight time recorder by the quad copter is 20minutes with high quality image capturing capability covering 30KMs of the village area. The inbuilt camera is used for capturing the images.

  The dataset was processed using the classification algorithm in order to classify the images into two categories such as the landscapes with plastic waste and without plastic wastes. The labelling graphic image annotation tool is used to outline the boundaries for each and every plastic image which is identified by the target detection algorithm. The target detection algorithms aids in identifying the target object (Plastics) in the captured landscape images. The objects trained by the model includes single time use plastics, plastic bottles, plastic cups, plastic bags and plastic spoons.

III. Proposed Modified Yolov8 Model

A. ***Proposed UAV YOLO Detection Model***: The proposed UAV plastic detection model uses YOLOV8 for achieving high performance in object detection process as the speed of the drones are too fast while it flies and captures the data and hence the object detection should also works at the same speed at which the drones fly. YOLO basically uses the backbone for training the data prior. The outline boundaries sketching and the classification will be achieved through the Head. The plastic waste detection is achieved using a two stage sparse prediction process. The self-Adversarial training method involves two stages in which the fist involves adjusting the weights of the captured images and the second results in training the data in order to detect the plastic in the new modified input image. The model once trained, it will be interfaced with the NVidia Jestson Nano kit to display the right location where the trash had been detected using modified YOLOV8 architecture as depicted in Figure1.

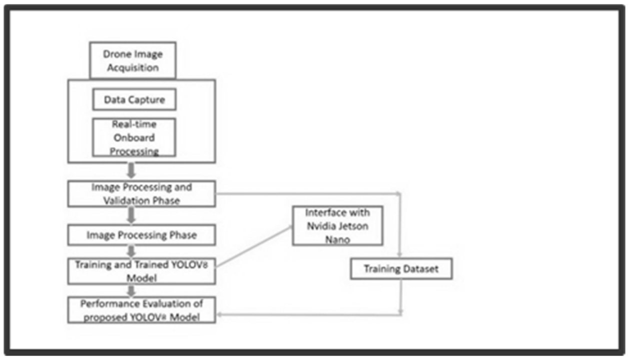

Figure 1. Architecture of the proposed Model

B. ***Object Detection Model***: The proposed model uses PyTorch framework for implementation.YOLOV8 incorporate the concept of CNN (Convolutional Neural Network) for training the model using the quad copter captured preprocessed images. The feature extraction is achieved using the cross stage partial network which acts as a backbone in YOLOV8.CSPDarkNet53 backbone aids in feature extraction for plastic waste detection model.CSPDarkNet53 is the CNN backbone in YOLOV8 that detects the plastic waste from the landscape More gradient flow throughout the network is analyzed during implementation due to split and merge technique. The resulting layer of CSPDarkNet53 is passed through the three layers of head results in anchor box predictions for an efficient object detection as depicted in Figure 2. The major advantage of using YOLOV8 is its optimization capability. The optimization is achieved using the integrated focus layer incorporated within the backbone layer that reduced the utilization of memory capacity through Compute Unified Device Architecture. The added advantage of the optimization makes the YOLO technique to be flexible and wide adaptability for various research implementations.

The scaling variation in the object is well identified by using the Model Neck. Feature pyramids are generated using the Model Neck and thus it results in efficient performance even on untrained data inputs. Feature aggregation is achieved using PANET neck.

The head of the YOLOV8 plays a vital role in detecting the objects. It detects the probability score of a class, prediction of the class and fixing the outline for the target plastic objects on the landscape. The bounding box represents the spatial location of the plastic object. The rectangular bounding box is calculated using the coordinates of top left corner and bottom right corner. The equation for locating the boundary box is as in Equation 1.

$$BB(y,x) = P(x,y) * IoU \text{ (true positive and predicted object)} \quad (1)$$

Where in equation (1) BB represents bounding box of the identified plastic object, y,x represents the bounding box of x^{th} sector. P(x,y) represents the probability of the target plastic object identification. The value of p is 0 when the bounding box doesn't have the targeted plastic object and 1 when the bounding box consist of the target objection represents Intersection over Union used for prediction accuracy calculation. It compares the plastic object in the landscape which is true positive (ground truth) with the predicted plastic object.

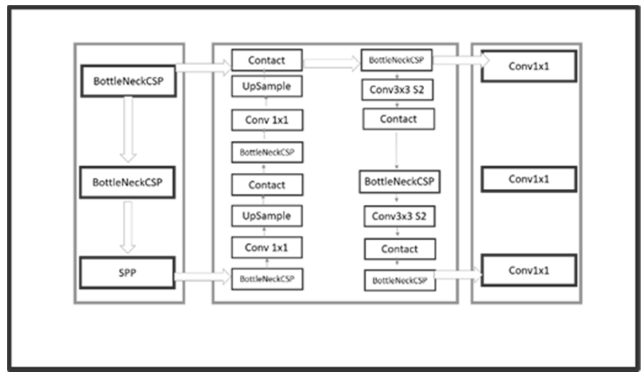

Figure 2. Working Principle of YOLOV8

The proposed model thereby provides an effective and efficient plastic waste monitoring system through the combination of YOLOV8,Nvidia Jetson Nano and UAV.

- ***Datasets***: Datasets captured by quad core is considered for preprocessing along with other sources such as kaggle, gettyimages.ae and also images downloaded from Google are considered for data training.

- ***Model Integration***: The model is integrated with the classification prediction threshold value in order to validate the efficient working of the proposed YoloV8 model.0.1 is set as low threshold value and 0.9 as high threshold value. If the BB value result is less than threshold value then the classification prediction outcome is declared as "no plastic waste detected" and if the BB predicted value is higher than the fixed threshold value then it is declared as "Plastic Waste presence in the landscape is confirmed with higher probability". If the BB predicted value is average in between the low and high, then the value is set to 0.5 and the result depends on the amount of plastic present in the intersection grid of the bounding box.

- ***Model Evaluation***: The confusion matrix is used to evaluate the proposed model using False Positive, True Positive, False Negative and False Positive values of the predicted classification. When IOU value is 0.5 and the BB consist of plastic waste object then it is true Positive else it is considered as False Positive. The accuracy of the model is calculated using equation 2.

  Accuracy = Rightly predicted Target object / Total Number of classification predictions (2)

  The precision and recall of the model is evaluated using equation 3 and 4.

  $$\text{Precision} = TP/\,(TP + FP) \qquad (3)$$

  $$\text{Recall} = TP/\,(TP+FN) \qquad (4)$$

  Whereas the TP represents True Positive, FP represents False Positive and FN is False Negative.

  The accuracy of the model responds well when the object grows exponentially. Also the precision and recall aids in evaluating the performance of the model along with the accuracy. If the precision and recall values alone is considered for evaluation, then the performance of the model is not been concluded because only the part of the evaluation is reflected in the performance. Hence the accuracy along with precision and recall is considered for performance evaluation of the model using confusion matrix.

  Training and classification results of YOLOv8

Figure 3. Object Detection using the trained modified YOLOV8 model

The model achieves high results of both precision and recall. Hence it's ensured that the model achieves high accuracy by correctly predicting and classifying the plastic wastes in the landscapes as in Figure 3. The positive samples are identified and classified as True positive samples correctly. The AUC obtained from the trained model is 0.98.It's the highest percentage of rightly classifying the plastic wastes as depicted in Figure 4.

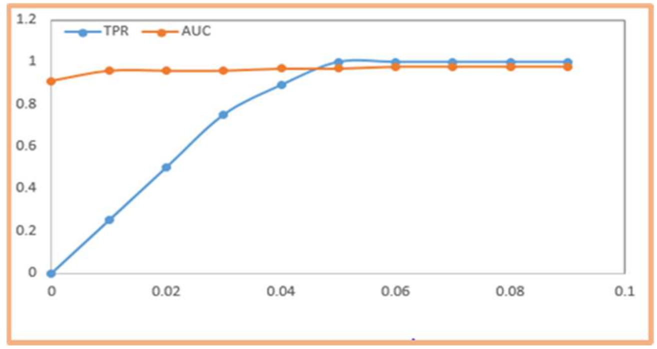

Figure 4. ROC for performance evaluation of the proposed modified YOLOV8 Model

IV. DISCUSSION

The existing system compares two ensemble methods to detect the plastic waste along the railway track using YOLOv8[10].The results of accuracy, precision and recall for the proposed YOLOV8 drone surveillance plastic monitoring model is higher in rates compared to the existing model results as tabulated in Table 1. The result comparison table is discussed in the table 1.The plastic waste object is detected using YOLOV5 and YOLOV8 model and the metrics measures depicted in Figure 5.The horizontal axis represents the number of epochs(14 Epochs in our implementation) and vertical axis represents the loss value of YOLOV5 and YOLOV8 trained model. The plastic waste object prediction and classification results are highly reliable where the precision, accuracy and recall results are higher compared to the results obtained by YOLOV5 trained model. Figure 8 clearly reveals that the existing ensemble1 and 2 performance is compared with the proposed modified yolov8 results and concluded that the proposed model provides greatest results compared to the existing models [11].

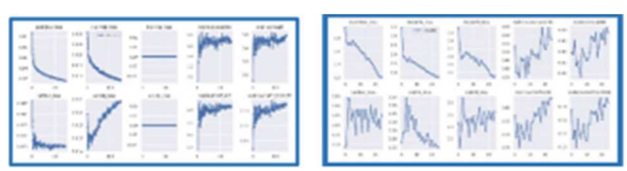

Figure 5. Metric Measures of YOLOV5 and YOLOV8 Model

TABLE I: PERFORMANCE EVALUATION OF PROPOSED MODIFIED YOLOV8 AND EXISTING ENSEMBLE MODEL FOR PLASTIC WASTE MONITORING

Model	Precision	Recall	Accuracy
Ensemble1-YOLOv5n,s,m	0.884	0.939	93.6%
Ensemble2-YOLOv5s,m,I	0.925	0.917	95.4%
Proposed modified YOLOv8	0.986	0.9613	99.6%

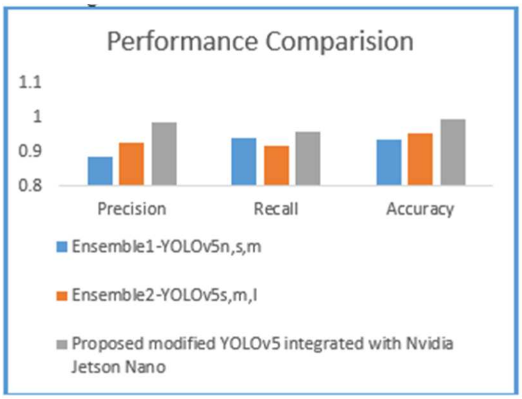

Figure 6. Comparative analysis of proposed modified YOLOV8 and existing Ensemble models.

V. Conclusion

Government of India is focusing the technology evolution that can be used to renew or remove the plastic wastes in order to save the counter from plastic pollution that spoils the soil fertility which results in ineffective agricultural yields through various schemes like Swacch Bharat Mission, etc. Hence it's vital to monitor and clean the plastic waste with the available human resource effectively. The proposed sky sweeper device that implements modified yolov8 along with the Nvidia Jestson Nano kit aids in monitoring and locating the plastic wastes on the landscapes efficiently with the precision of 98.6%, recall of 96.13% and accuracy with 99.6% which is higher in percentage when compared with the existing models. The drone helps in capturing the data through trained model and modified yolov8 implements the CNN algorithm to process the drone captured images very fast. The future work includes training the large dataset in order to improve the accuracy and also the challenges in identifying very tiny plastic wastes with various types can also be considered and processed using the advance YOLO versions in order to yield better results.

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