PLASTIC BAG DETECTION SYSTEM

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CERTIFICATE

This is intended to authenticate that the project report titled "PLASTIC BAG DETECTION SYSTEM", submitted by AMIYA M P (Roll No. 223011), MUHAMMED AJMAL T (Roll No. 223036), ANITTA BIJO (Roll No. 223015), in partial fulfilment of the requirements for the award of Master of Science in Computer Science with a Specialization in Data Analytics, is a true record of the work completed at Kerala University of Digital Sciences, Innovation and Technology under our supervision.

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Dr. Manoj T K	Dr. Anoop V S
Professor, DUK	Professor, DUK

DECLARATION

This report is largely the result of our own work, unless otherwise stated in the text, and was completed between September 2023 and February 2024 by Amiya M P, Muhammed Ajmal T, and Anitta Bijo, students pursuing Master's Degree in Computer Science with Specialization in Data Analytics.

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ABSTRACT

The increase of plastic pollution poses a critical threat to ecosystems worldwide, necessitating innovative solutions for its detection and management. This project focuses on the development of a robust plastic bag detection system using the YOLO (You Only Look Once) object detection algorithm applied to pre-recorded video footage. The YOLO algorithm, renowned for its real-time processing capabilities and high accuracy, enables efficient detection of plastic bags within complex video scenes. By training the YOLO model on a meticulously curated dataset of annotated plastic bag images, the system learns to recognize and localize plastic bags with precision. The proposed solution offers a scalable and automated approach to monitoring plastic bag presence in diverse environments, providing valuable insights for waste management and environmental conservation initiatives. Through extensive experimentation and evaluation, the effectiveness and reliability of the system are validated, showcasing its potential for practical deployment in real-world scenarios to combat plastic pollution.

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INTRODUCTION

In our mission to combat environmental pollution, we present a groundbreaking initiative leveraging cutting-edge technology: the Plastic Bag Detection System powered by You Only Look Once (YOLO) object detection model. This innovative system aims to address the pervasive issue of plastic bag pollution by accurately identifying and tracking their presence in various environments, including urban areas, parks, and water bodies.

Operating through pre-recorded video footage, the Plastic Bag Detection System utilizes YOLO's robust capabilities to efficiently detect and classify plastic bags in real-time. By analyzing the video frames, the system can pinpoint the location and movement of plastic bags, allowing for timely intervention and mitigation strategies.

Furthermore, our system maintains a comprehensive database of authorized and unauthorized areas, enabling it to distinguish between permissible and prohibited zones for plastic bag disposal. Upon detecting a plastic bag, the system initiates immediate alerts and notifications, facilitating prompt cleanup and enforcement actions.

By systematically monitoring plastic bag presence and distribution, our solution not only aids in pollution control efforts but also provides valuable insights for policy-making and public awareness campaigns. Through the seamless integration of YOLO technology, we are poised to make significant strides in preserving the environment and fostering sustainable practices for future generation.

PURPOSE OF THE OBJECT

The primary objective of our Plastic Bag Detection System project is to develop a highly advanced and automated solution to address the pervasive issue of plastic bag pollution in various environments. Leveraging state-of-the-art technology, including You Only Look Once (YOLO) object detection model and Computer Vision, our system aims to accurately identify, track, and manage the presence of plastic bags in real-time.

By utilizing pre-recorded video footage, the system employs YOLO's robust capabilities to detect and classify plastic bags efficiently. This automated process significantly enhances the monitoring and tracking of plastic bag distribution, enabling timely intervention and mitigation strategies to combat environmental pollution effectively.

Furthermore, our system is designed to establish a comprehensive database of authorized and unauthorized areas for plastic bag disposal. By detecting plastic bags and initiating immediate alerts and notifications, the project aims to facilitate prompt cleanup efforts and enforcement actions, thus contributing to a cleaner and healthier environment.

Through the seamless integration of YOLO technology and Computer Vision, our Plastic Bag Detection System sets out to revolutionize pollution control efforts, providing invaluable insights for policy-making, public awareness campaigns, and sustainable environmental management practices. By achieving these objectives, the project aims to set a new standard in combating plastic bag pollution and fostering a greener, more sustainable future for generations to come.

METHODOLOGY

We implement a surveillance system at the entrances of public areas such as university campuses and hospitals, utilizing cameras to record video footage. The objective is to identify instances of plastic object usage by individuals entering these spaces. To achieve this, we employ a pre-trained YOLOv8 model for object detection, enabling us to detect plastic objects within the recorded video footage. This approach provides valuable insights into the prevalence of plastic usage within the surrounding society.

Upon applying the YOLOv8 model, we can accurately detect instances of plastic object usage in the designated area. Subsequently, the collected data undergoes analysis to understand the extent of plastic usage within the environment. This analysis may involve identifying patterns, trends, and hotspots of plastic consumption over time.

Finally, the processed information, including detected instances of plastic object usage and relevant metadata, is stored in a database for further reference and analysis. This database serves as a comprehensive repository of information regarding plastic usage in public spaces, facilitating informed decision-making and actions to address plastic pollution and promote sustainability initiatives.

DATA COLLECTION

We have a dataset comprising approximately 1200 images, all images are collected through Roboflow. Also, we have augmented some of the images We selected a total of 1200 images, allocating 640 for validation and 640 for training purposes. While collecting data we ensure consistency in image quality across the dataset to avoid biases in model training. Also, we ensure that the dataset include variation in Indian license plate in terms of format, font and regional differences.

DATA PREPROCESSING

Data preprocessing and augmentations is important for ensuring the integrity of image and suitable for further analysis. At first, the augmentation of images was done by applying auto-oriented and resizing all the images to a standardized dimension of 640x640 pixels. Auto-oriented image will help for consistent analysis and model training. Resizing to a standard 640x640 resolution maintains consistency in input dimensions, Important for model compatibility and efficient processing. The "stretch" method is used for resizing and it will maintain the original aspect ratio of the images. Augmentation process ensure that all the images are correctly oriented. This approach is crucial as it prevents distortion and maintains essential features within the images. The model becomes more versatile in object detection when it is zoomed via cropping (0–20%), which allows the model to understand objects at different scales. Rotation augmentation (-15° to +15°) improves the dataset by exposing the model to objects from different angles. Grayscale additions (5%), saturation (-46% to +46%), and brightness adjustments (-25% to +25%) show the model to a wider range of colour variations and lighting conditions. These techniques allow for the use of diverse colour representations. To train the model to handle such scenarios effectively, minimal blur (up to 1px) and noise within bounding boxes (up to 1% of pixels) are used. Bounding box adjustments that include 90° clockwise and anticlockwise rotations as well as upside-down orientations improve the model's ability to identify objects in a variety of orientations. The diversity of the dataset is considerably increased by these preprocessing and augmentation steps.

MODEL ARCHITECTURE

The YOLOv8 model architecture is the latest version in the You Only Look Series. This model is designed for accurate real-time object detection and image segmentation. It employs a single convolutional neural network (CNN) that processes an entire image in one evaluation, predict both bounding boxes and class probabilities simultaneously. The Yolo v8 model divide the input images into grid, with each cell responsible for predicting bounding boxes and confidence scores indicating the presence of an object and predict the accuracy of the box. In addition to that it also predicts the class probabilities for each box and determine the category of detected objects. The optimization techniques like batch normalization, data augmentation and transfer learning are used to improve the model performance. YOLOv8 stands out for its balance of speed and precision, making it well-suited for applications requiring fast and reliable object detection.

WORKING OF CODE

The code starts by loading the YOLO V8 model for object detection to detect the plastic bags. Script begins towards training, assessing, and utilizing YOLOv8 models for object detection tasks. Initially, it sets up the environment by establishing connections with Google Drive ensuring seamless access to essential files and resources. Leveraging the Roboflow API streamlines dataset acquisition, simplifying dataset management and preprocessing procedures. With the acquired dataset, the script proceeds to the training phase, iterating over the data for a predetermined number of epochs to refine model parameters and enhance object detection accuracy iteratively. Throughout training, it vigilantly monitors diverse metrics such as loss, precision, and recall to gauge the model's convergence and efficacy. Following training, the script shifts focus towards evaluating the trained model's performance using a distinct validation dataset. This evaluative phase serves to assess the model's ability to generalize and uncover any potential overfitting or underfitting issues. Subsequently, the script transitions to the inference phase, employing the trained YOLOv8 model to analyze a sample video file. Frame by frame, the model accurately detects objects, annotating them with bounding boxes to facilitate visual inspection of its real-world performance. Furthermore, to exemplify real-time object detection capabilities, the script initializes a webcam feed using JavaScript within the Colab environment. Frames captured from the webcam undergo prompt processing by the YOLOv8 model, enabling object detection in live video streams. The annotated frames are displayed in real-time, showcasing the model's applicability in practical scenarios. By meticulously orchestrating these diverse components, the script offers a comprehensive demonstration of YOLOv8's utility in object detection tasks, providing insights into the intricacies of building and deploying advanced object detection models.

MODEL SUMMARY

We are using the pre- trained model named YOLO (You Only Look Once) model. First, we collect the images of different vehicles for training purposes. Then we manually annotated the bounding boxes for each image and distributed the vehicle images in train, test and validation parts. We have a dataset containing 1200 images for training purposes, 640 images for the validation process and 640 images for training the model. Then we are applying the Image preprocessing ang augmentation steps to maintain the dataset diversity and it will be boosting the object detection accuracy and the reliability. The image preprocessing steps include Auto-Oriented and Resize. Auto-Oriented adjustment corrects the image orientation inconsistencies. Resizing the images to a standardized 640x640 resolution maintains consistency in the input data dimensions and for efficient processing.

The Augmentation steps includes Horizontal flipping, Crop, Rotation, Gray Scale, saturation, Brightness, Blur, Bounding Box Modifications and the Noise in Bounding Box. All these augmentation processes have their own importance for improving the accuracy of object detection and reliability. After the data preprocessing and data augmentations then we must train our model using these clean data. Our model comprises of 168 layers with a total of 11,125,971 parameters. During the training phase, the model completed 50 epochs in approximately 0.556 hours. The stripped optimizer files for both the last and weights are 87.7 MB each

The Model's performance on validation showcases impressive results. It processed 107 images in the validation stage and detected a total of 154 instances across classes. Instances represent the total number of objects or instances detected across all images. The Precision metrics for the bounding box prediction is 94.9% and recall is 90.9%. The mean Average Precision (mAP50) stands at 94.8%. The overall Map50-95(mean Average Precision from 50% to 95% confidence) is about 72.9%.

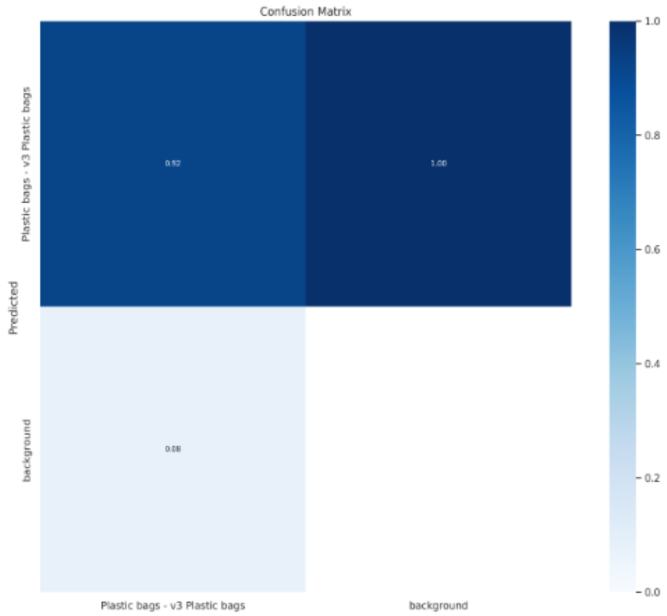
mAP50: Mean Average Precision at IoU (Intersection over Union) threshold of 0.5. This metric evaluates the precision of the model at different IoU thresholds (here, at 0.5) and calculates the average. A higher mAP50 indicates better precision at identifying objects

mAP50-95: Mean Average Precision across IoU thresholds from 0.5 to 0.95. This metric computes the average precision over a range of IoU thresholds from 0.5 to

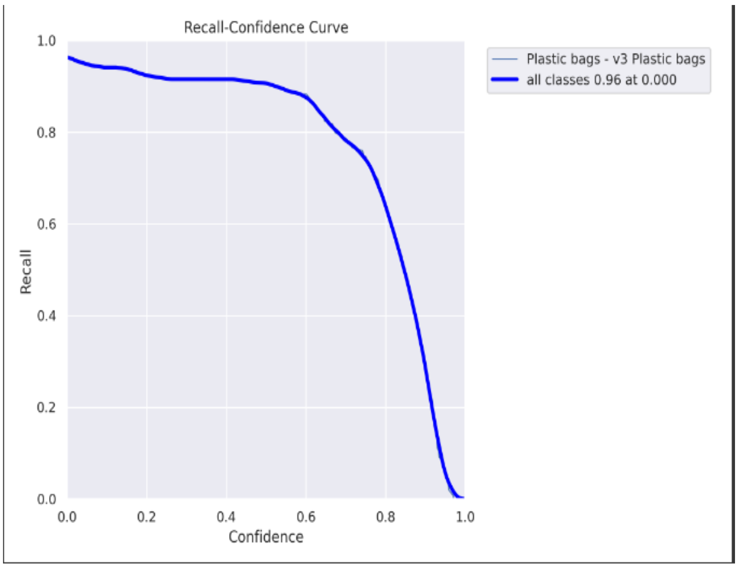
0.95, giving an overall performance evaluation across various levels of bounding box overlap.

Moreover, in terms of speed, the model exhibits efficiency, with preprocessing taking 0.2ms per image. Preprocessing time represents the time taken by the model to prepare or preprocess each image before it is fed into the neural network for inference. Preprocessing tasks might include resizing, normalization, or any transformations required to adapt the input image to the model's requirements. Then the Inference time of our model is 16.4ms per image. Inference time is the measurement of time taken by the model to perform its computations and provide output (e.g. Identifying objects in the image) based on the input data (e.g. .an image). The loss computation time is reported as 0.0ms per image which may suggest that this information might not be relevant or collected during inference. The Post processing of our model is 3.7ms per image, it represents the time taken after the model's inference to refine or process the predictions. Post processing involves tasks like filtering bounding boxes based on confidence scores and non-maximum suppression (removing overlapping boxes). These time measurements provide insights into the computational performance of the model at different stages of the inference pipeline, highlighting where most of the time is spent during the object detection process.

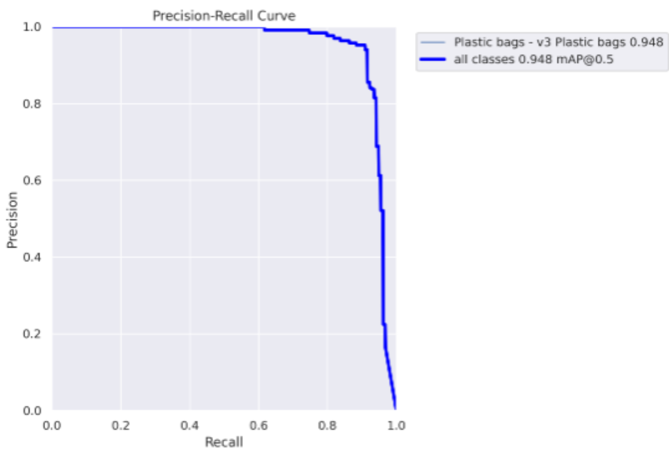
The proposed model is initially trained on 640 images and validated on a collection of 107 images. After validation, 30 external images were used the testing purposes. The performance of the model is evaluated in the form of training loss, training accuracy, validation loss and validation accuracy. The obtained confusion matrix of the model is shown below,



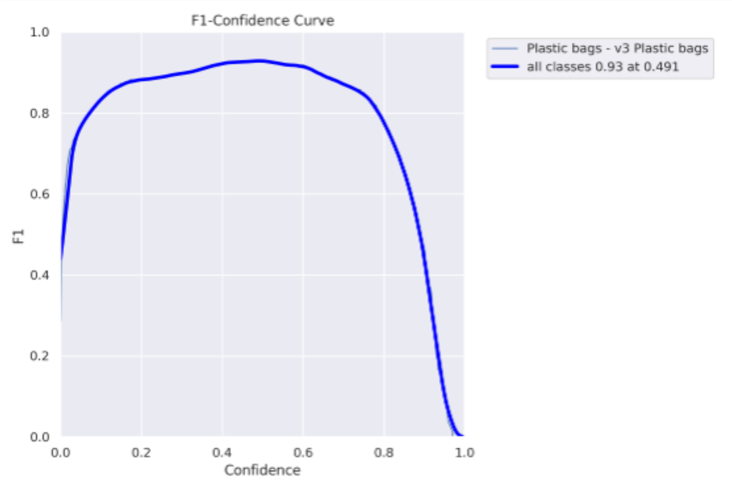
A confusion matrix is a crucial tool for assessing a machine learning model's accuracy for each class. The matrix has two axes, "True" on the horizontal axis and "Predicted" on the vertical axis. "True" refers to the actual class labels, while "Predicted" refers to the labels predicted by the classification model. There seem to be two classes, which are "0" and "background." one class to represent the positive class (e.g., presence of an object) and another to represent the negative class (e.g., absence of an object or just the background). The top-left cell (dark blue) with the number 0.92 indicates true positives (TP) or true negatives (TN), depending on which class is considered positive. It represents the number of times the model correctly predicted class "0." The bottom-right cell (light blue) with the number 3 represents the true negatives (TN) or true positives (TP), again depending on class designation, showing the instances where the model correctly identified the "background”. The top-right and bottom-left cells are not visible due to the colour scheme, but they would typically show the number of false positives (FP) and false negatives (FN), respectively. These are the instances where the model incorrectly predicted the class. By using the obtained confusion matrix, precision, recall is calculated. Moreover, it offers details on other crucial performance measures including F1score, recall, and accuracy. All these measures should be considered when evaluating a model's performance. The obtained recall vs confidence curve is shown below, it demonstrates how, as the amount of confidence rises, the recall of the model's predictions varies. This curve may be used to assess the model's effectiveness and choose a confidence level that strikes a balance between strong recall and adequate accuracy.



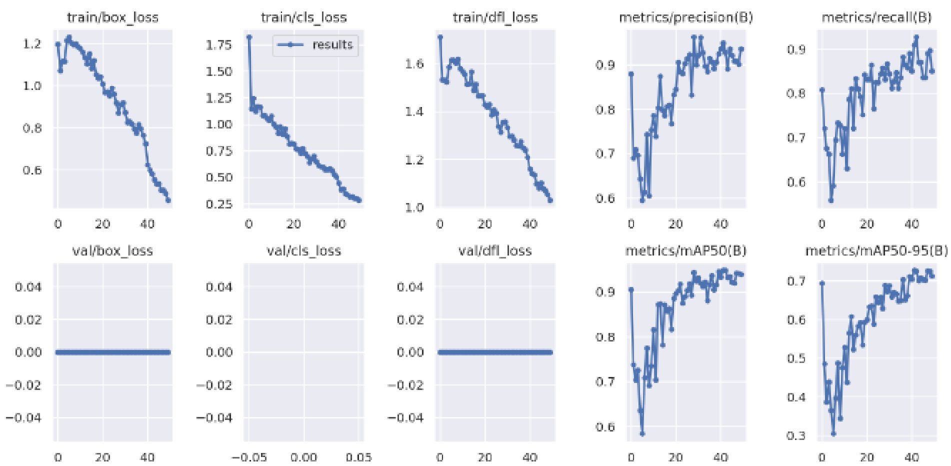
When it comes to assessing a model's performance where both lowering false positives and lowering false negatives are crucial, the accuracy vs recall graph is helpful. The obtained precision VS recall curve is shown below,



F1 confidence curve analysis how changes in the confidence threshold affect the F1 score. By analysing the curve, we can understand the trade-off between precision and recall. The given graph shows whether increasing the confidence threshold leads to higher precision but lower recall or vice versa. The obtained F1 confidence curve of our model is shown below



The obtained results of YOLO model in terms of train/box loss, train/cls_loss, Val/box loss, Val/cls_loss, train/dfl_loss, precision, metrics/recall(B), metrics/mAP50(B), metrics/mAP50-95(B)is shown below,



RESULT AND DISCUSSION

The Plastic Bag Detection System successfully analyzed pre-recorded video footage to detect and classify the presence of plastic bags within various environments. Utilizing the You Only Look Once (YOLO) object detection model and Computer Vision techniques, the system demonstrated efficient detection capabilities. The system's performance was evaluated using a confusion matrix, providing insights into its classification accuracy. Key metrics such as precision, recall, and F1-score were calculated to assess the system's effectiveness in plastic bag detection. Precision represents the proportion of correctly detected plastic bags out of all items classified as plastic bags by the system. Recall measures the proportion of correctly detected plastic bags out of all actual plastic bags present in the video footage. F1-score is the harmonic mean of precision and recall, providing a balanced assessment of the system's performance. Additionally, the system's sensitivity to environmental factors, including lighting conditions and background clutter, was analyzed. Potential challenges and limitations were discussed, along with recommendations for improving the system's robustness and accuracy in real-world deployment scenarios. Overall, the results demonstrated the efficacy of the Plastic Bag Detection System in accurately identifying and tracking plastic bags from pre-recorded video footage. By leveraging advanced technology and Computer Vision techniques, the system offers a promising solution for combating plastic bag pollution and promoting environmental sustainability. Further research and development efforts are recommended to enhance the system's performance and address any remaining challenges in practical implementation.

FUTURE SCOPE

Real-time Monitoring and Alerts:

Integrating real-time monitoring capabilities into the surveillance system can enable immediate detection and response to instances of plastic object usage. This could involve implementing automated alerts or notifications to relevant stakeholders when plastic objects are detected, facilitating prompt action.

Integration with Waste Management Systems:

Integrating the surveillance system with existing waste management systems can streamline the process of identifying and managing plastic waste. This could involve linking detected instances of plastic object usage with waste collection and recycling programs to ensure proper disposal and recycling of plastic materials.

Community Engagement and Awareness:

Leveraging the project as a platform for community engagement and awareness-raising initiatives can foster greater understanding and collaboration in addressing plastic pollution. This could involve organizing educational campaigns, workshops, or events to raise awareness about the environmental impact of plastic usage and promote sustainable alternatives.

Policy Support and Advocacy:

Partnering with government agencies responsible for environmental protection and waste management can facilitate the development and implementation of policies aimed at reducing plastic usage and promoting sustainable practices. The project's findings and insights can inform formulation of evidence-based policies and regulations to address plastic pollution effectively.

CONCLUSION

The project successfully shows how advanced technologies like object detection can be used to automate the detecting the plastic bags entering and exiting out of a place. The system effectively records and processes plastic bags movements instantly, offering a secure and dependable way of detecting that is better than the traditional methods. This system will help us to reduce the pollution.

REFERENCE

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