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REAL-TIME INTELLIGENT DRONE MONITORING FOR WASTE AND INFRASTRUCTURE DETECTION WITH MACHINE LEARNING ANALYSIS

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ABSTRACT

Roads in disrepair and insufficient trash disposal pose serious problems for urban areas, having an adverse effect on public health and the environment. To solve these problems, creative fixes are required. This study suggests a drone-based waste and pothole detection system that uses machine learning (ML)-driven reporting to enable prompt maintenance and interventions. This study describes the architecture and implementation of a system that uses IoT components, aerial photography, and the YOLO object identification model to collect and analyze visual data in real-time, precisely recognizing potholes and trash sites. Geo-tagging allows for the classification and mapping of the places indicated in captured photographs by a reporting system. Our method can improve urban maintenance by encouraging public safety and environmental cleanliness, giving priority to places that require immediate attention. The study shows how combining drone technology with machine learning (ML) might lead to sustainable solutions for managing urban infrastructure, greatly enhancing the quality of life in metropolitan areas.

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INTRODUCTION

Waste management and infrastructure monitoring are critical components of urban planning and development. However, traditional methods of monitoring these areas are often manual, time-consuming, and prone to human error. The increasing use of drones in various industries has opened up new opportunities for efficient and accurate monitoring. Waste management is a significant challenge in urban areas, with millions of tons of waste generated daily. Effective waste management requires frequent monitoring of waste collection routes, dumpsters, and recycling facilities to ensure efficient and timely collection. Infrastructure such as bridges, roads, and buildings require regular inspections to detect potential damage or defects. Traditional methods of inspection can be time-consuming, expensive, and may not always detect issues before they become major problems. Some of the main problems in metropolitan areas that have an adverse impact on the environment and public health include crumbling roadways and inadequate garbage management. Pothole-related traffic accidents caused 600 fatalities and 491 injuries in 2023 alone, underscoring the importance of efficient infrastructure management and upkeep. These incidents have serious economic ramifications in addition to being fatalities. They emphasize how crucial it is to take preventative action in order to find potholes and fix them quickly, improving road safety and lowering the likelihood of accidents.

Table 1. The number of people killed or wounded as a result of potholes in 2023.

Road feature	Number of accidents	Persons killed	Persons injured
Potholes	600	197	491
Share in Total	0.8	1.2	0.7
Steep Grade	518	230	362
Share in Total	0.7	1.3	0.5
Ongoing Road Works/ Under Construction	1080	376	872
Share in Total	1.4	2.2	1.3
Others	15,197	2,552	14,260
Share in Total	19.8	14.9	20.7
Total Million Plus Cities	76,752	17,089	69,052

Innovative solutions are needed to solve these problems quickly and effectively. Scholars have investigated the possibility of employing drones and machine learning (ML) to address these urban issues. Drones with high-resolution cameras are able to take detailed pictures of road surfaces and trash sites through aerial photography. Compared to ground examinations alone, this airborne viewpoint offers a more thorough picture. After that, ML algorithms examine the visual data to accurately and automatically identify potholes and rubbish heaps. ML combined with drones allows organized reporting and real-time data collecting, which is necessary for timely maintenance and intervention. This system lowers the risks associated with delays by ensuring prompt action for clean-ups and repairs. Enhancing public and environmental safety through improved urban cleanliness and safety, it also aids in prioritizing locations for repairs and trash management. This strategy addresses current problems and advances long-term urban sustainability in a preventive and productive manner.

Fig. 1. Improper garbage disposed on sideways in India

Problem Statement: India is encountering an increasing challenge with waste management and the upkeep of its infrastructure. As the population continues to rise and urban areas expand, the nation's waste disposal systems are finding it difficult to meet the growing needs. Moreover, the nation's aging infrastructure is susceptible to deterioration and damage, resulting in expensive repairs and potential safety hazards. The existing techniques for waste monitoring and inspecting infrastructure require a significant amount of labor, take a considerable amount of time, and often experience delays. Visual inspections conducted by humans can be costly, necessitate specialized training, and might fail to identify problems until they have escalated. Additionally, conventional sensor-based systems frequently struggle to identify intricate patterns and anomalies. To tackle these challenges, we recommend implementing a real-time intelligent drone monitoring system that employs machine learning algorithms to identify waste and infrastructure problems as they occur. The system will use computer vision and sensor information from drones to detect and categorize waste hotspots, assess the state of infrastructure, and forecast possible malfunctions. This study aims to develop a drone system powered by machine learning to detect and categorize urban issues such as potholes and litter. To achieve this, it is necessary to design a UAV equipped with a camera and GPS module that can autonomously capture high-resolution, geotagged images in urban environments. A key goal is to utilize a machine learning model to accurately classify images of potholes and litter. To achieve high accuracy and dependability in real-world situations, this model must be trained and refined using a unique dataset. By providing detailed mapping of identified concerns, the project seeks to enable real-time data collecting and geotagging. Effective maintenance effort prioritization will be aided by this for urban management authorities. Along with classifying and organizing geotagged photos, the initiative will create an organized reporting system that will produce detailed information that maintenance authorities may review.

Also, there are certain key challenges during the development of the prosed model, such as

- Developing a reliable and accurate machine learning model that can detect waste hotspots and infrastructure issues in real-time.
- Integrating multiple sensors (e.g., cameras, LiDAR, thermal imaging) to gather comprehensive data from drones.
- Developing an effective alert system that minimizes false positives and ensures timely notification of maintenance personnel.
- Ensuring data privacy and security while maintaining transparency on waste management and infrastructure conditions.

LITERATURE REVIEW

Current methods for waste collection and infrastructure inspection typically involve manual or semi-automated approaches that can be time-consuming, labor-intensive, and prone to errors. Some common methods used for waste collection are Manual sorting, Automated sorting systems, Route optimization, Sensor-based monitoring and for infrastructure inspection the methods include Visual inspections, Infrared thermography, Acoustic testing, Ultrasonic testing. The limitations of these current methods include:

- Limited visibility: Inspectors may not be able to access all areas or see all defects.
- Time-consuming: Manual inspections can be slow and labor-intensive.
- Error-prone: Human inspectors can make mistakes or miss defects.
- Limited data: Current methods may not provide real-time data or detailed information about waste composition or infrastructure condition.

Real-time Intelligent Drone Monitoring with Machine Learning Analysis aims to address these limitations by using drones equipped with sensors and machine learning algorithms to monitor waste collection and infrastructure inspection in real-time. This approach offers several advantages, including:

- Real-time data: Drones can provide real-time data on waste composition and infrastructure condition.
- Increased visibility: Drones can access areas that are difficult or impossible for human inspectors to reach.
- Improved accuracy: Machine learning algorithms can analyze sensor data to detect defects and anomalies more accurately than human inspectors.
- Reduced costs: Drones can reduce the need for manual inspections, which can save time and money.

To implement Real-time Intelligent Drone Monitoring with Machine Learning Analysis, the following components are needed:

- **Drones equipped with sensors:** Drones equipped with sensors such as cameras, LiDAR, ultrasonic sensors, or thermal imaging cameras can collect data on waste composition and infrastructure condition.
- **Machine learning algorithms:** Machine learning algorithms can analyze the sensor data to detect defects and anomalies in real-time.
- **Cloud-based data storage:** Data collected by the drones is stored in a cloud-based platform for analysis and reporting.
- **User interface:** A user interface is provided for users to access the data and receive alerts when defects or anomalies are detected.

By integrating these components, Real-time Intelligent Drone Monitoring with Machine Learning Analysis can provide a more efficient, accurate, and cost-effective solution for waste collection and infrastructure inspection. Pranay Sharma et al. [1] used advanced machine learning algorithms for identifying potholes on roadways. CNN techniques and Tiny YOLO object identification are used in the study to find potholes of various sizes. With an accuracy rate of 89%, this approach suggests that it could find practical use. They have concluded, in particular, that Tiny YOLO and CNN both contribute significantly to the most accurate pothole detection; as a result, both technologies, when used in conjunction with maintenance, increase road safety. It's possible that in the future, advancements in GPS module integration may enable the description of precise geographic coordinates for detected potholes, facilitating their location and expedited repair. Parag Achaliya et al. [2] proposed a smart waste monitoring system that uses drones to detect rubbish automatically. With a rate of 87.69%, the study employs DNN to increase garbage detection accuracy and capability to reduce false negatives and negative outcomes. The system uses data gathered from the field and computer vision to detect and gather garbage. It is connected to an Android-based platform that allows it to notify the relevant authorities of the locations of the waste disposal sites. This ensures that impendent intervention and clean-up that may be fundamental for avoiding latent hazards are precisely scheduled. As for the works of the authors, the major improvement still lies in garbage detection; however, the authors propose an extension to the next version of the framework to perform pothole detection, which could extend the applicability of the surveillance system for maintaining cities. Convolutional neural networks are the focus of the paper [3]. A measure of precision was found to be 0.96, accuracy was found to be 94%, and recall scores were zero for the two advanced CNN models reviewed. Recall scores had a minimum of 0.70 and an AUC-ROC of 0.95 during the experiment. In addition to highlighting the great accuracy and robust stability of the models, this article also confirms the viability of applying deep learning techniques for garbage detection. The study suggests the following areas for improvement for additional research with the goal of improving waste detection accuracy: It will be simpler to act and deal with the problem as quickly as feasible if the geographic coordinates of the waste are established. To identify potholes using drones the authors of [4] used the YOLOv3 object identification technique. Given that it yielded a high accuracy of 85%, it can be inferred that the YOLOv3 approach was effective in measuring potholes. utilization. The authors intend to increase the use of the drone-aided surveillance system for the management of urban infrastructure, and they proposed adding rubbish detection to the system as a potential future work. With the above-mentioned characteristics, the paper [5] offers an algorithm to obtain a 99% accuracy rate. read: 11% on spotting anomalies in the road, like structures and deformations. The system may detect many on-road flaws when it is connected to computer vision (CV), which can be very helpful in maintaining traffic safety. This enhances the precision of fault detection while also encouraging an efficient and methodical approach to the real-time tracking of roadways in need of upkeep and repair. It basically means that in order to improve safer and more dependable roadways, this approach will in fact depend on widespread implementation in metropolitan areas. The use of the Canny Edge Detector Algorithm is demonstrated in the study [6]. This method offers a straightforward and effective heuristic as the first step in using a single optical camera to locate pothole areas, with an accuracy of 81.8%. This method is simple to use and implement, in contrast to other approaches that rely on complex training models and require image processing before a method can identify potholes. However, the study suggests that in order to disclose more accuracy, the implementation of pothole detection can be strengthened by training models, which is a potential avenue for future research. As a result, this approach is particularly beneficial when establishing a sophisticated, more accurate pothole detecting system at the outset.

Table 2. Object detection algorithms and its applications

Use case	Algorithm	Application
Image-based object detection	Object detection algorithms like YOLO (You Only Look Once), SSD (Single Shot Detector), and Faster R-CNN (Region-based Convolutional Neural Networks)	Traffic monitoring: detecting vehicles, pedestrians, and road signs. Industrial inspection: detecting defects or anomalies in production lines. Surveillance: detecting people, vehicles, or objects of interest.
Computer Vision for Infrastructure Inspection	Computer vision algorithms like Deep Learning-based approaches (e.g., convolutional neural networks)	Road surface condition analysis: detecting cracks, potholes, and other defects. Bridge inspection: detecting damage or degradation. Building façade inspection: detecting cracks, damage, or weathering.
Waste Management	Machine learning algorithms (Recurrent Neural Networks (RNNs), Random Forests	Predict waste generation patterns and optimize collection routes. Identify waste types and quantities using computer vision and sensor data. Develop waste sorting systems using machine learning-based classification algorithms.
Environmental Monitoring	Machine learning algorithms (Support Vector Machines SVM)	Air quality monitoring: predicting pollution levels using sensor data and machine learning models. Water quality monitoring: detecting contaminants or pollutants in water bodies. Weather forecasting: predicting weather patterns and extreme weather events.

Table 2. Object detection-based approaches

Reference	Input	Key algorithm(s)	Details
[13]	Colour image	YOLO	Based on YOLOv2, two object identification networks (F2-Anchor and Den-F2-Anchor) are trained to identify potholes in color road photos.
[14]	Colour image	SSD	Pothole detection in color road photos is trained using two SSD-based DCNNs with Inception-v2 and MobileNet as the backbone networks, respectively.
[15]	Colour image	Faster R-CNN	Two Faster R-CNNs (with ResNet-101 and ResNet-152 as the backbone networks, separately) are trained to detect road potholes.
[16]	Grey-scale image	YOLO	To identify potholes in the road, two Faster R-CNNs are trained, using ResNet-101 and ResNet-152 as the respective backbone networks.
[17]	Colour image	YOLO	To find potholes in the road, YOLOv2, YOLOv3, and YOLOv3 Tiny are trained. The highest mAP, precision, and recall are attained by YOLOv3 Tiny.
[18]	Colour image	YOLO	Road potholes (in the foreground) and autos (in the background) are detected by two YOLOv1 models that have been trained.
[19]	Colour image	Faster R-CNN	Initially, the country where the road image was taken is inferred by training a classifier. Next, a Faster R-CNN for pothole and crack detection on roads is trained considering each country.
[2	Colour image	Faster R-CNN, SSD	Road pothole detection is trained on three Faster R-CNNs (using Inception-ResNet-v2, Inception-v2, and ResNet-101 as the backbone networks, respectively) and one SSD (using MobileNet-v2 as the backbone network). With ResNet-101 serving as the backbone network, a faster R-CNN achieves optimal performance.
[21]	Thermal image	SSD	Two SSDs (with ResNet-34 and ResNet-50 as the backbone networks, separately) are trained to detect potholes in thermal road images. The latter significantly outperforms the former.

The government is notified, the general public can quickly update the database with real-time pothole reports, and it assists with an open-source mapping service for potholes. This research focuses on the potential for enhancing urban road maintenance via real-time data

The research by Khaled R. Ahmed and Subash Kharel [7] examines how well the YOLOv5 and Faster RCNN algorithms work in real-time pothole identification. With a precision of 91.9%, the employed methodologies demonstrate how thorough the current approach is in its quest to find flaws in the road. This research focuses on the prospect of using enhanced deep learning convolutional neural networks (CNNs) with better efficiency and performance for pothole detection. Consequently, the research's output is as follows: Although the research indicates that there is still potential to improve the actual precision of the detection algorithms, the current approach is acknowledged as adequate for accomplishing the current goal. Anjali Pradipbhai et al. [8] used Tensor Flow and Deep Neural Networks (DNN) for the identification of solid waste. The study highlights how successful these technologies are in identifying trash and raises the prospect of adding geotag determination to the program in the future. By adding this, the waste management programs' functionality can frequently be improved by pinpointing the precise position of the rubbish that has been discovered. Yunlong Pan, Zhao Lun, and Sen Wang [9] provided a Skip-YOLO model that is especially made for identifying household trash in multi-scene settings. With an accuracy of 88%, this model is theoretically stable for database applications because it retrains itself without much change. 77% for the reasons listed below: First, to fully extract high-level features at various scales and resolutions, densely connected blocks are employed. Not only does the method increase the detection stability, but it also speeds up the process. A number of the authors' suggestions for further research center on broadening the model's applicability as a pothole detection technique, hence increasing the scope of items that may be used to track the condition of urban infrastructure. In order to detect trash in road sceneries, Caiyun Zheng et.al [10] provided a CNN model that was heavily integrated with the Similarity Guidance Model (or SG). The accuracy rating of 87% attests to its efficiency and shows how quick and accurate their model is in its operation. The application of similarity advice aids in segmentation by improving both the picture categorization and feature extraction processes. The suggested model's short calculation time makes it suitable for real-time applications; the authors also go over how to use more training data and enhance the optimization process to further increase the model's accuracy. Real-time Intelligent Drone Monitoring for Waste and Infrastructure Detection with Machine Learning Analysis is an innovative application of machine learning algorithms in the field of environmental monitoring and infrastructure inspection. Few similar applications of machine learning algorithms used in various domains are considered in this section. The study's particular needs, the type of data, and the difficulty of the problem being solved ultimately determine which algorithm is best. These are few examples of the machine learning algorithms used in similar applications.

- **YOLOv3** or other object detection algorithms to detect waste objects or infrastructure components (e.g., roads, bridges).
- **CNNs** for image classification to identify waste types or infrastructure conditions (e.g., damaged roads).
- **RNNs** to predict waste generation patterns or infrastructure degradation over time.
- **Random Forests** to classify images based on multiple features (e.g., color, texture, shape).

Object detection-based methods: Object detection-based road pothole detection approaches can be grouped into three types: (1) single shot multi-box detector (SSD)-based, (2) region-based CNN (R-CNN) series-based and (3) you only look once (YOLO) series-based. The most representative object detection-based approaches are summarized in Table 2.

Proposed System: The proposed system uses a drone for object detection and classification in conjunction with a ground station for image processing and management. The system makes use of an Internet of Things (IOT) strategy. The primary goal is to use the YOLOv8 object identification model to recognize particular things in drone-captured images, like potholes or trash.

Computer Vision and Object Detection: Developing the ability of computers to see and understand visual data similarly to humans is the goal of the field of computer vision. In order to analyze photos and videos, glean insights from them, and comprehend their content, it is necessary to develop algorithms, models, and systems. Identifying occurrences of meaningful things, such as people, cars, and animals, in photographs or video frames is the main goal of object detection, a crucial component of computer vision.

YOLO Model

- YOLO (You Only Look Once) is a popular model developed by Joseph Redmon and Ali Farhadi at the University of Washington for object recognition and image segmentation. YOLO was released in 2015 and gained popularity right away thanks to its accuracy and speed. Because of its effective architecture, it may be utilized in applications on a variety of platforms, including edge devices and cloud APIs.
- YOLO uses a neural network (CNN) to predict the bounding boxes and class probabilities of objects in input photos, acting as a single stage object detector. Yolo was first developed on the Darknet architecture, which divides the input image into a cell grid. calculates the likelihood that an object will be present in each cell and provides the bounding box coordinates. It also predicts the item's categorization.
- Compared to earlier iterations, Ultralytics' most recent object identification model, YOLOv8, provides customers with a potent tool that delivers improved performance, versatility, and efficiency. This state-of-the-art model supports a variety of computer vision applications, including segmentation, pose estimation, tracking, and classification, in addition to simple detection. This adaptability enables users to handle a greater variety of difficulties in their apps across many sectors.

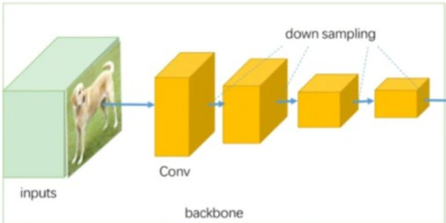

Fig. 2. Yolo Architecture

Yolo is incredibly quick since it doesn't deal with intricate pipelines. 45 frames per second (FPS) can be processed by it for photos. Furthermore, when compared to comparable real-time systems, YOLO achieves more than double the mean Average Precision (mAP), making it an excellent choice for real-time processing. With 91 FPS, YOLO is significantly faster than the other object detectors, as seen in the chart below.

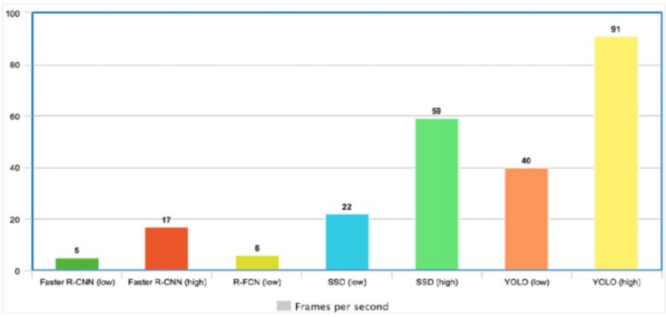

Fig. 3. YOLO Speed compared to other state-of-the-art object detectors

Model Architecture: A drone and a ground station are the two main Internet of Things (IoT) components used in this work. They cooperate to take pictures, process them to look for particular things, and arrange the output.

Drone's Role: The role of the drone is to take pictures from its vantage point by carrying a camera. The brains of the drone are a Raspberry Pi, which initiates image capturing and incorporates the associated GPS location (longitude and latitude) into every picture. The SD card of the Raspberry Pi is then used to save these photos that were taken.

Ground Station's Role: For control and picture processing, the drone is connected to the ground station, which in this example is a laptop. Mission Planner software allows the drone to be remotely controlled, including arming, disarming, and adjusting settings. Additionally, it is able to obtain real-time GPS data straight from the drone's GPS module. The ground station makes use of several instruments to gain access to the Raspberry Pi and control over photos that have been taken. A secure Wi-Fi connection is established between the laptop and Raspberry Pi via an SSH link. Using TigerVNC software, one can observe the Raspberry Pi's desktop remotely while keeping an eye on the camera capture procedure. WinSCP also makes file management and transfer on the Raspberry Pi easier, allowing for things like accessing photos that have been taken.

Object Detection and Image Organization: The ground station laptop is used for the core analysis. A YOLOv8 object detection model that has been tweaked and pre-trained is utilized. This model is intended to recognize particular things in the collected photos, like potholes or trash. The drone takes photographs, and the model uses a watchdog script to wait for fresh images in a specified folder. The YOLOv8 model examines each newly discovered image. A script automatically classifies the image into a certain folder with a label (such as "Garbage" or "Pothole") if it contains a classed object (such as garbage or a pothole).

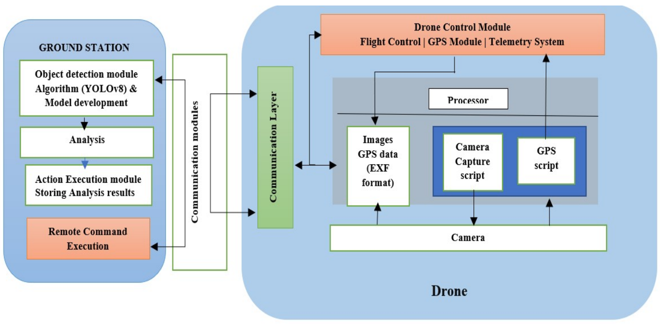

Fig. 4. Architecture of the working model

Final Outcome: The classification of collected photographs into distinct folders according to the item recognized by the YOLOv8 model is the ultimate outcome of this model. Crucially, every picture keeps its integrated GPS information, enabling analysis and future reference depending on its location.

METHODOLOGY

Hardware Setup

Drone Configuration:

- Drone Platform: Utilizing ArduPilot firmware, the Pixhawk flight controller is outfitted with ArduPilot software for navigation and stabilization.
- GPS Module: Offers current location information necessary for geotagging photos that are taken.
- Webcam: Fixed on the drone, it takes pictures on a schedule.
- Raspberry Pi 3 Model B: Acts as the on-board processor, retrieving GPS data and capturing images.

Flight Control and Navigation

Integration with ArduPilot:

- Flight Controller: ArduPilot is an open-source autopilot firmware that is used by the Pixhawk flight controller to control the drone's flight.
- Mission Planning: To guarantee the drone performs as intended, use ArduPilot's mission planning tools to configure and assign flight modes (such as Auto, Loiter, and Stabilize), modify PID settings, and establish other control parameters

Image and GPS Data Collection

Image Capture:

- A Raspberry Pi Python software uses the webcam to take pictures at a rate of one frame per second (1 fps).
- Every picture is kept with the capture timestamp included.
- GPS Data Retrieval: Using the Pixhawk, the script retrieves GPS data from the GPS module using Pymavlink. Each time an image is taken, the GPS coordinates (latitude and longitude) are simultaneously stored.
- EXIF Data Storage:
- The GPS information and the photographed image are stored in the image file's EXIF metadata. This guarantees that the place and time of capture are included in every image.

Fig. 5. Potholes captured and detected

Data Transfer to Ground Station

SSH and File Transfer:

- After the data capture session is over, SSH programs like PuTTY, WinSCP, and TigerVNC are used to move the photos from the Raspberry Pi to the ground station, which is a laptop.
- The files are stored in a directory on the ground station, and a watchdog script keeps an eye on it for any new data that arrives.

Image Inference and Classification

Watchdog for New Data:

- A watchdog script keeps an eye out for fresh information in the specified directory.
- The script starts the inference process when it detects fresh photos.
  Conclusion Making Use of YOLOv8:
- For picture inference, the Ultralytics library-implemented YOLOv8 model is used. Pre-training of the algorithm was conducted on a bespoke dataset that included over 9000 photos labeled with pothole and rubbish detection.
- Every new image is processed by the inference script, which determines whether it contains garbage or potholes.

Data Storage and Management

Classification Results

- The results of the classification, including the image path, timestamp, and GPS location (extracted from the EXIF metadata), are stored in respective CSV files.

- Separate CSV files are maintained for garbage and pothole classifications.

RESULTS AND CONCLUSION

Both photographs directly taken from the drone and a variety of images from the dataset were used to evaluate the YOLO v8 model. Greater accuracy and precision were made possible in locating the photos as well as the essential spots and data components. The accuracy of the trained YOLOv8 model is 100%, and the data's confusion matrix is provided below. This makes it possible to assess the potholes and trash sites from a higher, more critical vantage point.

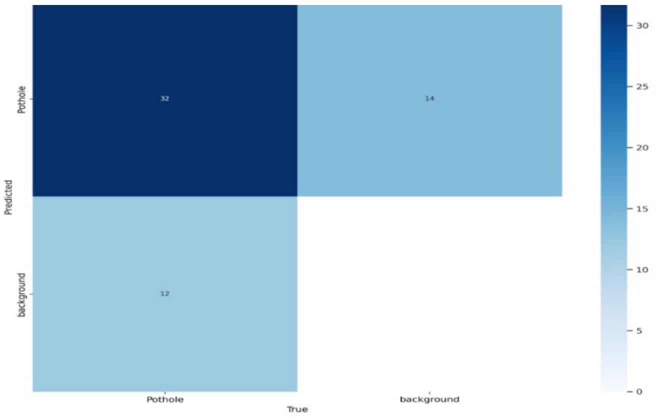

Fig. 6. Confusion Matrix on the model trained

The Attributes of the dataset with 11 images and 44 instances is described below, which has 100% accuracy with YOLOv8 model. May be this accuracy will vary while considering the dataset with more than 11 images and much more instances.

Class Images Instances Box (P R mAP50
mAP50-95: 100% 1/1
all 11 44 0.735 0.727 0.732 0.495

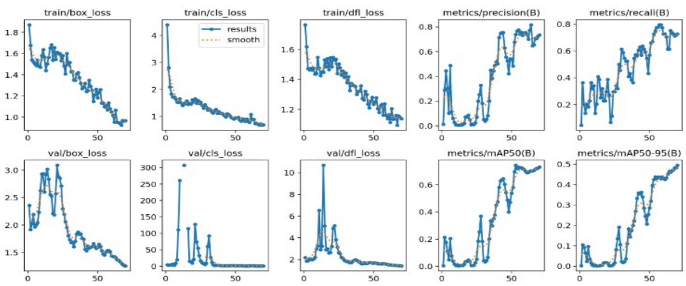

Fig. 7. Training and validation results

Figure 7 shows the trained and validated results with precision score 0.735, Recall score 0.727. The mean average precision at a threshold of 0.5 is obtained as 0.732 and 0.495 at a threshold of up to 0.95. Relevant data is stored in CSV files, which are used to implement structured reporting. This makes it possible to quickly and consistently get the image's details, including its classification and GPS position, which provides its longitude and latitude. It's necessary to consider the possible drawbacks and areas for advancement. The intricacy of the urban environment, the lighting, and the variety of datasets could all have an impact on the model's accuracy. By optimizing the model and enhancing the training data, one can eventually improve the model's performance and generalization skills. In conclusion, the proposed drone-based urban monitoring system holds out a lot of potential for resolving urban pothole formation and rubbish accumulation problems. By doing this, we can pave the way for more sustainable and successful urban maintenance strategies, which will eventually benefit locals' quality of life as well as the environment.

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