Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

# Drone-Based Polluter Identification using YOLOv8 for Real-Time Image Processing

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***Abstract*-This study investigates using YOLOv8, a cutting-edge deep learning model, in cooperation with drone technology for real-time object detection applications. Due to their capacity to obtain high-resolution aerial imagery and access remote locations, drones have become beneficial instruments for environmental monitoring. Using YOLOv8, which is renowned for its speed and accuracy, allows for accurate object localization and identification in real time. The suggested system's main objective is to identify items linked to environmental contamination in densely populated urban areas, such as trash, litter accumulation, and illegal waste dumping activities. To ensure excellent detection accuracy in various environmental situations, YOLOv8 is trained on a specific dataset of pollution-related items. The technique allows for accurately mapping pollution hotspots by geotagging detections with GPS data. With practical implications for environmental management and policy-making, the results show that YOLOv8 and drones can be used for effective and scalable monitoring. The technique involves deploying drones furnished with high-resolution camcorders and edge computing devices to process images locally or transmit them for further analysis. The results demonstrate that the combination of YOLOv8 and drone technology enhances situational awareness and decision-making skills, enabling novel applications in real-time monitoring and response systems. This system is designed to provide academics and practitioners with a practical and efficient real-time object detection solution, leveraging the combined power of deep learning and drone technology for various applications.**

***Keywords* – Yolov8, object detection, image processing, Deep learning, Drone inspection.**

## INTRODUCTION

With the rapid development of urbanization and industrialization, environmental pollution has become an urgent global concern, such as in the current scenario, India Maha Kumbh Mela, one of the largest religious protests in the world, attracted millions of pilgrims, leading to an increase in the density of the population in a limited area. The mass associations pose significant environmental challenges, especially in waste production, water pollution, and air pollution. Traditional pollution monitoring methods, including ground sensors and manual inspections, often have difficulty providing effective and energetic monitoring in high-density and dynamic environments.The floor sensor, although useful for local data collection, is unable to include the effectiveness of crowded areas and cannot detect pollution sources in real time. Manual inspection, based on employees on the ground, often takes time, with high labor intensity, and suffers from human errors, making them ineffective for large-scale monitoring. In addition, the two methods face logistics challenges, such as difficult terrain, limited access, and rapidly growing environmental conditions, further limiting their efficiency and appropriate control. Detecting real-time objects is still difficult due to the variance in object size and relationships between the speed of reasoning and noise [1]. To meet these challenges, this study presents a Yolov8 unmanned aircraft monitoring system to detect real pollution in high-density regions. The proposed approach is to deploy a drone outfitted with a high-resolution imaging device to take aerial photography in densely populated areas, ensuring the scope of complete insurance. The images were then processed using Yolov8, a learning model in a unique data set to detect pollution indicators such as waste accumulation, illegal waste discharge, and gas Smoke emissions, which are very accurate. To raise awareness about the situation, the sources of pollution are detected by geography using GPS data, allowing the creation of hotspot pollution cards to help identify important schools that need to be addressed immediately. The system also facilitates transparent data transfer to environmental agencies, allowing timely intervention and application of policies. By integrating drones, the discovery of objects led by AI, and geographic mapping, this method significantly improves the ability to monitor in real-time and provides a solution. Evolution, efficiency, and automatic to manage pollution in major public gatherings or high-density areas.

This paper provides a detailed discovery of the proposed method, describing the main steps necessary to perform a drone-based pollution detection system at High-density areas. A current study focuses on the definition of data preparation, configuration of the model, and training method necessary to monitor pollution in real-time effectively. Research related to selection and processing before facts-related information, ensuring that they capture relevant environmental pollutants such as discharge, waste, and smoke emissions in a High event context. In addition, it discovers the configuration of the Yolov8 model, including the adjustment of homosexuality, increasing techniques, and optimization strategies to improve detection accuracy. Although the system has not been conducted, this research is confirmed in the future, providing a structured method to integrate AI drones into great environmental monitoring efforts.

## II. LITERATURE SURVEY

Current pollution monitoring methods include different technologies, each with strengths and limits. Ground sensor networks are widely used to measure air, water and soil pollutants such as PM2.5, CO2, NOx, and heavy metals in real time. Although they provide accurate and local measures with continuous monitoring, their effectiveness is limited by the limited insurance scope and high maintenance costs. Satellite and remote sensing technologies, including Sentinel, Landsat, and MODIS, provide large-scale environmental monitoring, allowing air pollution, deforestation, and water pollution. However, low resolution and their periodic data collection offer challenges in the training of accurate pollution sources in real-time. Manual inspection and scene surveys are still very important in analyzing the environment, as they are related to the direct collection of samples and laboratory tests. Although these methods provide very detailed chemical composition data, they take time, with high and expensive labor intensity, which makes them unsuitable for real-time applications. Recently, unmanned air vehicles (UAV) or unmanned aircraft have become an effective replacement, equipped with high-resolution cameras, versatile sensors and gas analysts for detecting illegal overfill, air pollution, and water pollution. The unmanned aircraft provides data collection quickly and accesses dangerous or remote areas[14]. With the ongoing reduction in production costs for unmanned aerial vehicles (UAVs) and advancements in flight control technologies, their application has expanded significantly across various sectors, including power line inspections, traffic surveillance, and cultural studies. The identification of objects by UAVs has become a vital component of their operational functions, playing a crucial role in research within this area. Nevertheless, the broad field of view afforded by UAVs due to their elevated flight capabilities introduces challenges, such as a high prevalence of small objects and intricate image backgrounds, which complicate the object detection process.

The YOLO model has attained significant success within the realm of computer vision. Expanding on this groundwork, researchers have refined its approach by incorporating new modules, resulting in a total of 4,444 conventional models. Released on January 10, 2023, YOLOv8 signifies a notable progression in the YOLO series. In comparison to earlier versions like YOLOv5 and YOLOv7, YOLOv8 is distinguished as a cutting-edge model that provides improved detection precision and speed[3]. The unique OCO (YOLO) that you look at has attracted general attention as a method to detect objects quickly and accurately. It segments an image in the grid and predicts the object-limited boxes and the probability of the portfolio. Yolo network facilitates quickly detecting objects, making it adaptable to many applications. Although the Yolo network has shown great performance in the discovery of objects with a horizontal camera angle, it meets important challenges when applied to the images taken by unmanned aircraft or UAVs[10].To evaluate the quantitative prediction of the proposed model, the summary of the model, the confusion matrix, the accuracy, the recovery, and the F1 point are calculated with a test data set Train to train, and manual with 70:30, 80:20 and 90: 10. The model is tested on 4039 images with four types of recycled waste, paper, glass images, Metal, and plastic. After that, the first treatment with increased data to evaluate the experience with 10057 images. The test results show that the train test report on accuracy is 97.63%, the accuracy is 95.3%, recovering 93.03%, and the F1 point is 97.63%.[2] This model has shown that the prediction model is formed and tested on real-time data from the laboratory results that can be used to predict the four types of recycled waste and can be expanded to other types of waste and applications in other domains.

Executing AI-based contamination location utilizing UAVs in high-density urban zones presents a few challenges. Natural obstructions, such as magnetic areas, rotor-induced vibrations, and sudden climate changes, can affect the exactness of UAV-based estimations. Exploring UAVs securely in urban situations is another concern, as impediments like tall buildings, trees, and control lines must be maintained a strategic distance to guarantee both open security and information keenness. Moreover, strict administrative confinements on airspace utilization, protection concerns, and operational authorizations constrain the arrangement of UAV-based contamination observing. Sensor affectability and calibration pose challenges, as UAV-mounted sensors may have lower affectability compared to settled checking stations, requiring visit calibration for exactness. Moreover, dealing with expansive volumes of information collected by UAVs requires vigorous preparing capabilities and consistent integration with existing natural checking frameworks to extricate important experiences. Tending to these challenges is vital for the effective usage of AI-driven UAV frameworks in urban contamination observing.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

## III. METHODOLOGY

### YOLOv8 Architecture

The design of YOLOv8 builds upon the foundation established by its predecessors, introducing significant enhancements to support object detection capabilities. YOLOv8 utilizes a modified version of the CSPDarknet53 architecture for its backbone, which is equipped with 53 convolutional layers and incorporates cross-stage partial connections. This design improves the flow of information between layers, facilitating more effective feature extraction. The overall architecture of the YOLOv8 network is chiefly composed of a backbone, neck, and output, as depicted in Fig 1

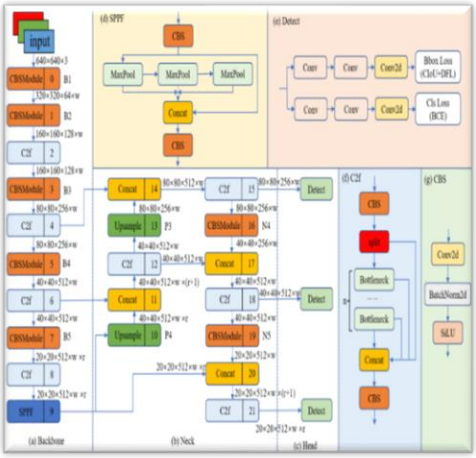

Fig 1. Diagrammatic representation of YOLOv8[3]

### A. backbone

The backbone of YOLOv8 is designed with a focus on feature extraction and is based on a modified Cross Stage Partial (CSP) Darknet architecture. It features a central layer that reduces the resolution of the input image while retaining essential characteristics. Additionally, the backbone includes several Convolutional Layers that employ Conv2D, Group Normalization, and SiLU (Sigmoid Linear Unit) activations to enhance representation. Furthermore, the use of Residual Blocks improves gradient flow and learning efficiency, thereby increasing the robustness of the network. To further enhance feature extraction, YOLOv8 incorporates Spatial Pyramid Pooling Fast (SPPF), which expands the receptive field by aggregating multi-scale features, resulting in improved object detection performance. One notable feature of yolov8 is its incorporation of a self-attention mechanism within the head. This enables the model to adaptively prioritize regions of an image and assign varying levels of importance to features based on their relevance to the detection task. This adaptability to the context of each image significantly enhances the model's flexibility and overall detection capabilities.

### B. Neck

The neck section of the YOLOv8 architecture plays a crucial role in enhancing the feature maps produced by the backbone. It usually incorporates elements like Feature Pyramid Networks (FPN) or concatenation operations to merge features from different layers of the backbone for improved detection accuracy.This multi-scale feature fusion is essential for detecting objects of different sizes, as it combines detailed information from lower layers with high-level semantic data from deeper layers. The enhanced feature maps produced by the neck are subsequently forwarded to the output stage, where the final predictions for object detection, including bounding boxes and class probabilities, are generated.

### C. Head

The location component of yolov8 utilizes a decoupled head architecture, illustrated in Fig.2. This architecture is built on two distinct branches: one dedicated to object classification and the other to bounding box regression, each utilizing specialized loss functions. Binary cross-entropy loss (BCE Loss) addresses classification errors, while distribution focal loss (DFL) and Complete Intersection over Union (CIoU) refine bounding box predictions. This design not only boosts detection accuracy but also accelerates inference. YOLOv8 functions as an anchor-free detection system, effectively distinguishing between positive and negative samples. Furthermore, it employs the Task-Aligned Assigner to dynamically allocate samples, enhancing detection precision and strengthening the model's reliability. The proposed framework effectively integrates drone technology, deep learning (YOLOv8), and data collection and preprocessing, facilitating efficient real-time monitoring and detection of pollution.

### SYSTEM ARCHITECTURE

The suggested system combines drone technology with the YOLOv8 object detection model to oversee environmental pollution in densely populated regions. This system features drones outfitted with high-resolution cameras and GPS units to gather aerial images and location information. Onboard processors perform preliminary image processing and inference utilizing YOLOv8, which minimizes data transmission delays. For more intricate analyses, the collected data can be sent to a ground control station for additional processing and visualization.ground control station for further processing and visualization

### SYSTEM WORKFLOW

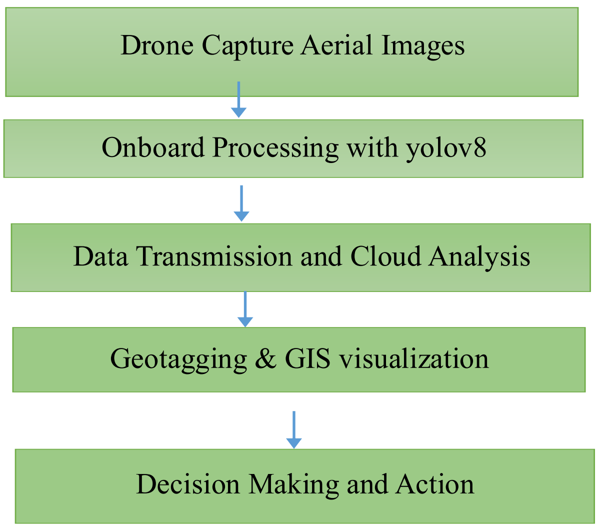


Fig 2. Diagrammatic representation of system workflow

Published by :
http://www.ijert.org

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### A. DATA COLLECTION AND PREPROCESSING

To create a comprehensive object detection model, a specialized dataset is assembled, focusing on images pertinent to pollution identification. This dataset encompasses various categories, including trash, litter, illegal waste disposal sites, and indicators of pollution such as smoke. Images are sourced from drones operating at different altitudes and angles to ensure a wide range of perspectives, with GPS data recorded during image capture for accurate geotagging. The annotation of these images is performed using the LabelImg tool, which facilitates the creation of bounding boxes around the objects of interest. Rotation, flipping, and brightness modifications are examples of data augmentation strategies used to improve the model's generalizability. The dataset is then split into three parts: 10% for testing, 20% for validation, and 70% for training.. This structured approach ensures that the model is well-equipped to recognize and classify pollution-related objects effectively.

### B. MODEL TRAINING

YOLOv8 is developed utilizing a preprocessed dataset, with essential training parameters configured to achieve peak performance. The model undergoes training with a batch size of 16 for a total of 100 epochs, employing the AdamW optimizer at a learning rate of 0.001, accompanied by cosine decay. This training is executed on high performance GPUs, and hyperparameter optimization is carried out via grid search to enhance detection accuracy.

### C. REAL-TIME INFERENCE AND DEPLOYMENT

In the deployment phase, drones conduct surveillance operations along predetermined routes, capturing images every second. The YOLOv8 system analyzes these images in real-time, incorporating bounding boxes to emphasize recognized objects. Each detected object is tagged with its corresponding GPS coordinates, and the gathered data is transmitted to the ground control station for visualization and storage.

### D. EVALUATION AND VALIDATION

The evaluation of the system is conducted through an analysis of test sets and field trials conducted in urban settings. To determine the effectiveness of the model, various performance metrics are employed, including precision, recall, F1-score, mean average precision (mAP), and inference speed. Additionally, field trials provide further validation of the system's real-world applicability by assessing detection accuracy across different lighting and weather scenarios.

### E. MAPPING AND VISUALIZATION

Finally, geotagged detections are plotted on digital maps to visualize pollution hotspots. Heatmaps and clustering algorithms help identify high-risk areas, providing valuable insights for environmental management and policy-making. This methodology ensures a scalable, efficient, and accurate system for real-time pollution monitoring using drone and deep learning technology.

## IV.DISCUSSION

The combination of YOLOV8 technology with unmanned aerial vehicles significantly enhances environmental monitoring by effectively identifying pollution levels in urban settings. Drones equipped with high-resolution cameras and advanced IT capabilities enable swift detection of various pollutants, including litter, waste, and illegal dumping. The speed, precision, and adaptability of YOLOV8 in diverse environmental conditions contribute to its high effectiveness in these applications. The integration of GPS technology allows for precise identification of pollution hotspots, which aids in targeted interventions and trend analysis. However, challenges persist; the model's effectiveness is contingent upon a diverse training dataset, as a limited range can lead to inaccurate detections. Additionally, battery limitations of unmanned aerial vehicles affect flight duration and operational capacity, necessitating careful planning. The processing of real-time images demands substantial computational resources, and employing a hybrid approach that balances edge and cloud processing can enhance efficiency. This study highlights the potential of YOLOV8-powered unmanned aerial systems in shaping environmental policies by delivering accurate pollution data, curbing illegal dumping, and fostering community-driven initiatives.

## V.CHALLENGES

- Environmental factors- weather conditions such as wind, rain and fog may have an impact on the clarity of the image and the stability of unmanned aircraft, affecting the accuracy of the detection.
- Time of battery life and stealing battery- Drones have a limited battery life, limit continuous supervision and require regular charging.
- Data transmission and storage- Handling high-resolution images produces large amounts of data, effective archives, and safety transmission methods.
- Regulatory & Privacy Concerns- Drone-based monitoring raises legal and ethical issues related to privacy and restricted airspace regulations.
- Cost & Maintenance- Deploying and maintaining a fleet of drones with high-end computing hardware can be expensive.

## VI.FUTURE SCOPE

The potential for incorporating YOLOv8 into drone technology for environmental monitoring is substantial. The combination of artificial intelligence, advanced imaging techniques, and

ISSN: 2278-0181
Vol. 14 Issue 04, April-2025

unmanned aerial vehicle operations can significantly enhance detection accuracy, broaden capabilities, and increase operational efficiency. Such advancements will facilitate more effective pollution monitoring, bolster sustainable initiatives, and enable informed decision-making in environmental management. Several key areas stand to benefit greatly from this integration.

●The integration of IoT and cloud computing enhances the connectivity of unmanned aerial vehicles with cloud-based servers, thereby significantly improving the capacity for large-scale pollution monitoring and response.

●Autonomous decision-making capabilities enable unmanned aircraft, powered by artificial intelligence, to independently detect, track, and report pollution incidents without the need for human involvement.

●The technology of swarm unmanned aerial vehicles enables the coordinated use of multiple drones, which can cover larger areas more efficiently, thereby enhancing environmental monitoring capabilities.

●AI models are enhanced through the training of Yolov8 with a broader range of data sets, which can lead to increased detection accuracy in varying environmental conditions..

## VII. CONCLUSION

The utilization of drone technology for identifying polluters through YOLOv8 presents a significant advancement in real-time environmental monitoring. This approach improves the efficiency of pollution detection, minimizes the need for human involvement, and enables prompt responses to offenders. Nevertheless, obstacles such as environmental influences, regulatory constraints, and computational challenges must be overcome to promote broader implementation. Future developments in artificial intelligence, the Internet of Things, and drone capabilities are expected to enhance the system' effectiveness, positioning it as an essential instrument in the fight against environmental pollution.

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