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DESIGN AND IMPLEMENTATION OF AN INTELLIGENT ROBOTIC SYSTEM USING DEEP LEARNING MODEL FOR REAL-TIME PIPELINE GAS LEAKAGE DETECTION

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Abstract

Pipeline gas leakage poses safety and environmental risks in the oil and gas industry which necessitates the adoption of efficient detection methods. This study presents the design and implementation of an intelligent robotic system using YOLOv8 model for real-time pipeline gas leakage detection. In the study, a comprehensive dataset of 8,881 annotated images representing different leak scenarios was used for the training and validation of the proposed model which is further enhanced with Spatial Pyramid Pooling Fast (SPPF) for improved feature extraction. The system was further integrated into an autonomous unmanned vehicle platform and evaluated through extensive simulation and experimental tests. The implementation results of the study demonstrated that it achieved high detection accuracy, with a precision of 83%, recall of 79%, and mean average precision (mAP) of 0.91, alongside rapid inference speeds enabling near real-time operation. From the results, it can be ascertained that the proposed system outperformed conventional detection methods, offering a reliable and scalable solution for enhanced pipeline monitoring.

Keywords: Pipeline Gas Leakage Detection; YOLOv8; Deep Learning; Real-Time Monitoring; Intelligent Robotics

1. INTRODUCTION

Nigeria, being one of the largest oil producers in Africa, operates an extensive network of pipelines used for the transportation of crude oil, refined petroleum products, and natural gas (Johnson et al., 2022). These pipelines span thousands of kilometers, connecting oil fields, refineries, export terminals, and local distribution centers (Enumah, 2025). While these pipelines play a vital role in the nation's economy and energy supply, they are also a major source of concern due to their vulnerability. Nigeria, being one of the largest oil producers in Africa, operates an extensive network of pipelines used for the transportation of crude oil, refined petroleum products, and natural gas (Johnson and Leon, 2020). These pipelines span thousands of kilometers, connecting oil fields, refineries, export terminals, and local distribution centers (Nwankwo and Ogbonna, 2010; Onuoha, 2008). While these pipelines play a vital role in the nation's economy and energy supply, they are also a major source of concern due to their vulnerability to leakage, vandalism, corrosion, and poor maintenance practices. Leakage hazards

in Nigeria's pipeline infrastructure are a frequent and critical issue, often resulting in devastating environmental, economic, and human impacts.

In addition to environmental degradation, pipeline leakages in Nigeria pose significant health and safety hazards (Ighariemy and Ebiloma, 2025). Explosions and fires caused by ruptured pipelines have led to countless deaths and injuries in communities living near the pipelines (Ambituuni et al., 2015; Nnadi et al., 2013). The presence of flammable gases and hazardous chemicals in leaked petroleum products increases the risk of respiratory illnesses, waterborne diseases, and long-term health conditions for affected populations (Onyenekwe et al., 2021). Moreover, the economic consequences are substantial, including loss of oil revenue, increased maintenance costs, and disruption. In addition to environmental degradation, pipeline leakages in Nigeria pose significant health and safety hazards. Explosions and fires caused by ruptured pipelines have led to countless deaths and injuries in communities living near the pipelines (Ambituuni et al., 2015).

The intelligent robot for pipeline gas leakage detection is an advanced autonomous system designed to monitor and identify gas leaks along pipeline networks with highly accurate persistent nature of these hazards highlights the urgent need for improved pipeline monitoring, leak detection, and control systems in Nigeria. Conventional methods have proven insufficient in providing real-time, accurate, and reliable surveillance across the vast and often inaccessible pipeline networks (Hua et al., 2016). As such, adopting intelligent robotic systems equipped with artificial intelligence and deep learning for autonomous leakage detection offers a promising solution. These systems can help Nigerian oil and gas stakeholders proactively prevent leakages, reduce environmental damage, and safeguard both lives and resources minimal human intervention (Jyoti, 2023). Traditional leak detection methods often rely on manual inspections, Pressure drop analysis, or fixed-location sensors, can be time-consuming, inefficient, and prone to delayed responses. In contrast, the intelligent robot is mobile, sensor-equipped, and capable of navigating complex pipeline routes both externally and internally while continuously scanning for anomalies indicative of gas leakage (Kochetkova, 2023).

Gas leakage in pipelines is a major concern for the oil and gas industry worldwide, particularly in regions like Nigeria where infrastructure vulnerability, vandalism, and environmental sensitivity compound the risks. Pipelines are the primary channels for transporting natural gas and petroleum products across vast distances from extraction sites to refineries, distribution centers, and end users (Kumar, 2020). However, over time, these pipelines are prone to leakages due to corrosion, mechanical failure, poor maintenance, third-party interference, and natural wear and tear. When not detected early, gas leaks can lead to catastrophic explosions, economic loss, environmental degradation, and serious health hazards.

The urgency and importance of efficient gas leakage detection systems cannot be overstated. Early detection allows for timely intervention, preventing minor faults from escalating into large-scale disasters. It also supports operational continuity, regulatory compliance, and public safety. To address this need, researchers and industry stakeholders have developed various methods and technologies tailored to detect, locate, and assess pipeline gas leaks (Liu et al., 2023; Shafin et

al., 2023). These methods range from conventional approaches such as pressure drop monitoring and fixed gas sensors to advanced technologies like acoustic emission analysis, thermal imaging, laser-based detection, and deep learning-driven robotic systems (Tian et al., 2016). Each method has its strengths and limitations, often influenced by the pipeline's environment, size, pressure, and type of transported gas. Selecting an appropriate detection method depends on these factors, as well as on the need for either continuous monitoring or periodic inspection (Maria, 2023).

Deep learning has emerged as a powerful tool for detecting gas leakage in pipelines due to its ability to learn complex patterns and make accurate predictions from large, multi-modal datasets. These models excel in tasks involving image recognition, time-series analysis, and sensor data interpretation making them ideal for intelligent pipeline surveillance systems (Okoli and Ubochi, 2021). This study addresses the challenge by proposing a deep learning-enabled robotic system that can not only detect leaks with high precision but also autonomously respond to minimize associated risks.

2. METHODOLOGY

The methodology for this research begins with the characterization of the pipeline gas leakage detection system is presented in Figure 1. This stage involves a comprehensive assessment of current instrument used in pipeline monitoring within the Nigerian oil and gas sector. Data will be collected from field studies to evaluate parameters like detection accuracy, response time, coverage limitations, and environmental adaptability. Following the characterization, the next phase involves the development of a deep learning-based model for gas leakage detection using YOLOv8 a powerful, real-time object detection algorithm that combines speed and precision, making it highly suitable for applications involving dynamic surveillance and rapid anomaly identification.

In this research, a large dataset consisting of annotated images showing various gas leak scenarios will be collected and used to train the YOLOv8 model. The training process involves fine-tuning the model to recognize different leak images conditions. The third stage of the methodology focuses on the integration of the trained deep learning model into an unmanned vehicle platform, forming the core of the intelligent robotic system. This robotic system is drone and will be equipped with a suitable camera system capable of capturing live feeds which is then analysed in real-time by the onboard YOLOv8 model. This allows the robot to detect gas leaks autonomously while navigating pipeline routes above ground. To simulate and implement the robotic system, Rob flow and Simulink programming environments will be employed. Rob flow will be used for dataset preparation, annotation, augmentation, and training visualization of the YOLOv8 model. Simulink, on the other hand, provides a graphical environment for modelling and simulating the robotic control system, enabling interaction between the robot's movement, sensor inputs, and detection outputs. The combined use of Roboflow and Simulink ensures that both the detection logic and robotic behaviour are developed and tested in a controlled virtual environment before physical deployment. The final stage of the methodology involves conducting experimental tests on different gas leakage scenarios and validating the model's performance using real-world conditions.

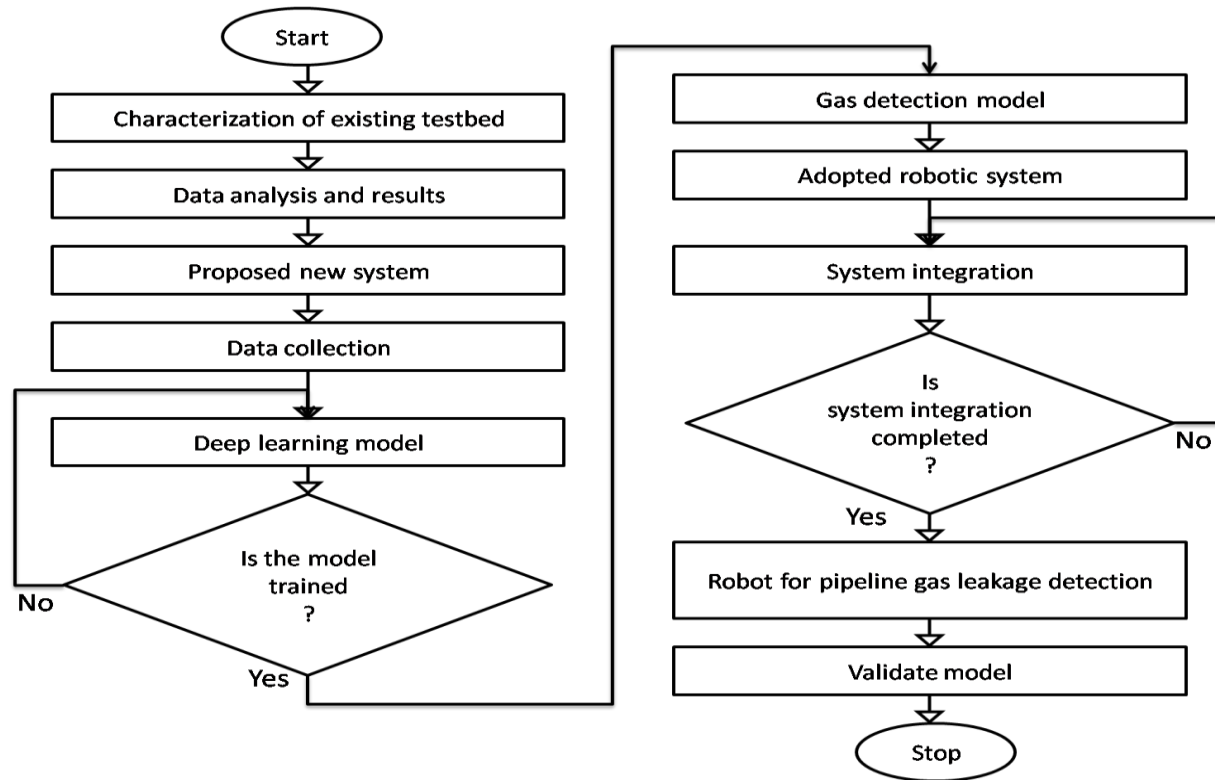


Figure 1: Flow chart of the research methodology

2.1 System Dataset

The data used in this study is real-time pipeline gas leakage data. Robowflow serves as the data source, and the URL is as follows:

[https://universe.roboflow.com/virajmodi/gas_leak/dataset/7/images]. The 8881 data sample was divided into training (8660) and testing (221). A vast range of photos depicting various leakage scenarios, including leaks and no leaks, are included in the dataset. Images depicting changes in illumination, viewing angles, pipeline materials, and backdrop settings including flora, urban infrastructure, and industrial surrounds were taken from both controlled tests and artificial simulated situations. In order to guarantee that the model can function dependably in a variety of field settings, the dataset additionally takes into consideration varying picture resolutions and leak intensities.

2.2 Data preparation

Roboflow, a cloud-based tool that simplifies picture annotation, augmentation, and formatting for deep learning models, was used to prepare the dataset for pipeline gas leak detection. After being submitted to Rob Flow, these photos were manually tagged with class names like "No Leak" or "Leak," as well as bounding boxes around any leaky areas. Rob flow's built-in augmentation features, including as rotation, flipping, brightness change, noise addition, and zooming, were used to improve the dataset after annotation in order to emulate different real-world situations and boost model resilience. After that, the annotated and enhanced dataset was automatically transformed into YOLOv8 format, which included a `diatryma` file outlining the dataset

structure and `.txt` files containing normalised bounding box coordinates. Finally, the dataset was split into training and testing sets (typically 80:20) and exported for use in the YOLOv8 model training environment. Figure 2 presents the data samples and Figure 3 presents the annotated images.

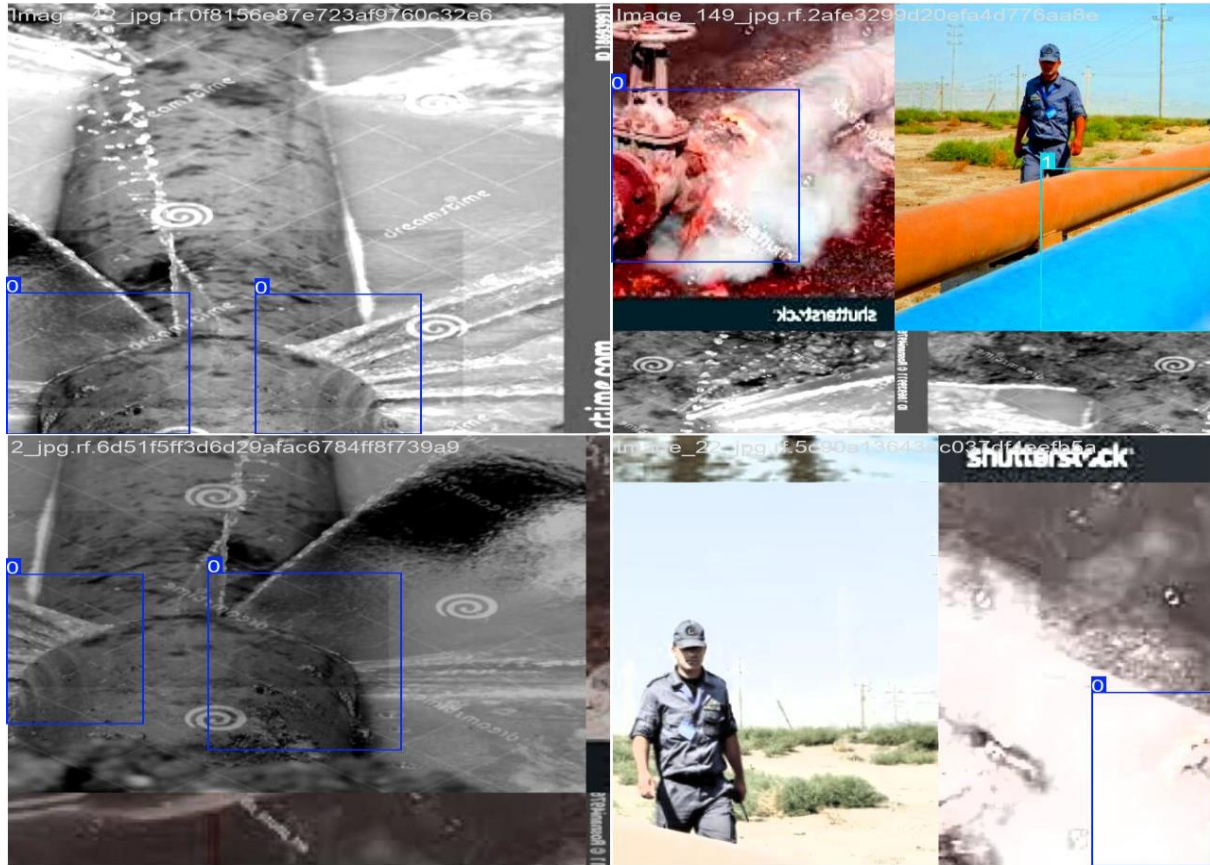


Figure 2: The annotated images

2.3 Develop a deep learning-based model for pipeline gas leakage detection using YOLOV-8

In this research, a deep learning-based object detection model YOLOv8 (You Only Look Once, version 8) is adopted for the detection of pipeline gas leakages. YOLOv8 is a real-time object detection architecture developed by Ultralights, known for its high speed, accuracy, and efficiency on both high- and low-power platforms. The architecture of YOLOv8 consists of four main components: input layer, backbone, neck, and head each of which plays a distinct role in the feature extraction and prediction process. Figure 3 presents the architecture of benchmark YOLOV-8. Figure 3 presents the architecture of the YOLOV-8. The input layer is responsible for receiving image data, typically resized to a standardized dimension (640×640 pixels) to ensure uniform processing. The backbone of YOLOv8 is a Convolutional Neural Network (CNN) structure that performs deep feature extraction. It optimized using the Cross Stage Partial connections with feature fusion (C2f) which enhances feature reuse and gradient flow. The backbone processes the input image through several convolutional and activation layers,

transforming it into a high-dimensional feature map that retains spatial information critical for detecting small leaks or thin vapor trails in the image.

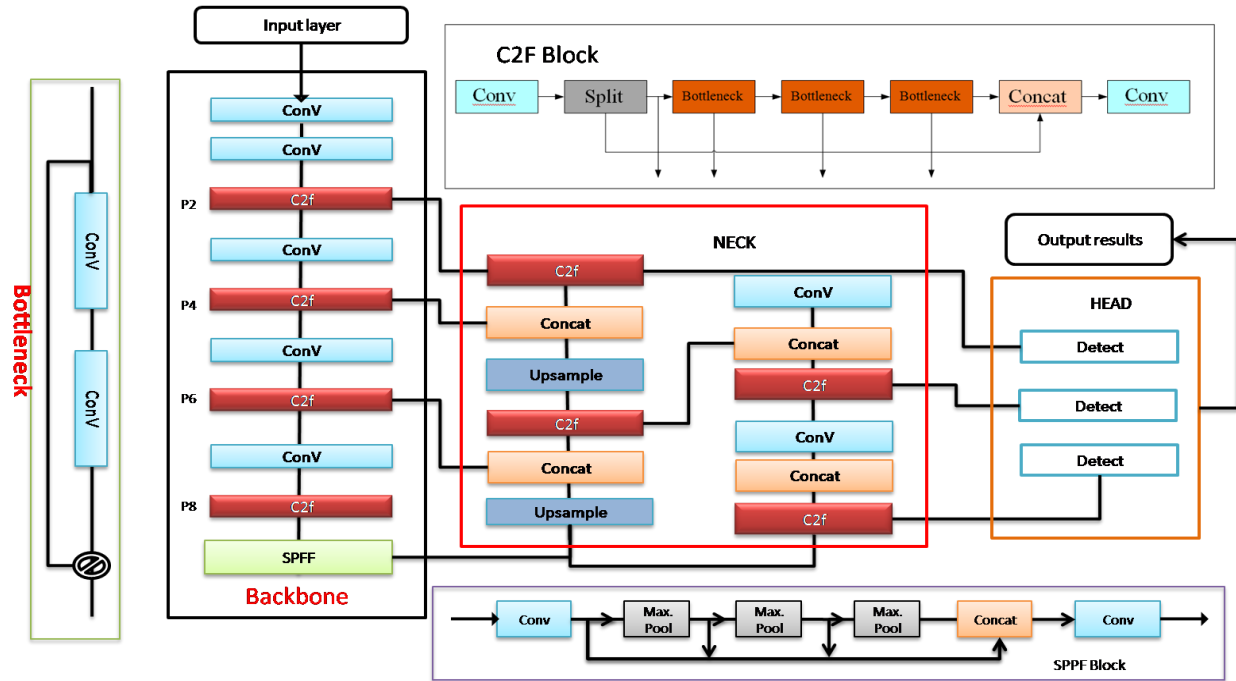


Figure 3: Architecture of benchmark YOLOV-8 (Ebere et al., 2025).

Following the backbone, the neck component is responsible for feature aggregation at multiple scales. It incorporates a Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) structure. The neck enhances the model's ability to detect objects of varying sizes by combining low-level spatial features (useful for detecting small, faint leaks) with high-level semantic features. This ensures that the model remains effective whether the leak is a subtle mist or a large-scale rupture. The head of YOLOv8 generates the final detection outputs. It predicts bounding boxes, objectless scores, and class probabilities.

2.3 System Integration of the robot for gas leakage detection in pipelines

The system integration of the Unmanned Vehicle (UV) for gas leakage detection in pipelines involves the cohesive fusion of hardware, trained deep learning based model, navigation, and communication modules to function as an intelligent autonomous inspection system. The UV is equipped with high-resolution cameras, a GPS module, motorized wheels, and a central processing unit that handles inference from a pre-trained YOLOv8 model. The YOLOv8 model was trained to detect gas leak signatures visually such as pipe cracks, vapor emissions, and leakage stains based on a custom dataset collected and annotated using Roboflow. The visual feed from the UV's camera is processed in real-time to detect such anomalies. The UV autonomously navigates through the pipeline environment using guided path tracking, controlled by a microcontroller interfaced with motor drivers. Upon detecting a gas leak visually, the UV logs the incident with GPS data and sends real-time alerts. To ensure performance and reliability, simulation tools such as Simulink, was used to validate the system integration. The simulation environment includes a virtual pipeline model populated with synthetic gas leaks and surface

anomalies. The UV's camera feed and movement were emulated in this virtual space, where the trained YOLOv8 model was deployed to detect leak features frame-by-frame. Figure 4 presents the screenshot of the programming interface.

The algorithm is presented as;

Algorithm: Autonomous UAV Pipeline Patrol and Gas Leakage Detection

Step 1: Initialization

- a. Start system
- b. Initialize flight controller
- c. Check battery level
- d. Establish link with Ground Control Station

Step 2: Mission Setup

- 2.1 Load waypoint coordinates for pipeline route
- 2.2 Define altitude, speed, and flight time constraints
- 2.3 Activate camera
- 2.4 Confirm system health status OK

Step 3: Takeoff and Stabilization

- 3.1 Arm motors
- 3.2 Execute takeoff to predefined altitude
- 3.3 flight controller engagement
- 3.4 Begin autonomous flight toward first waypoint

Step 4: Navigation and Data Acquisition

For each waypoint:

- 4.1. Fly to GPS coordinate
- 4.1 Maintain hover for data capture
- 4.2 Record gas concentration
- 4.3 Capture image frame using onboard camera
- 4.4 Pass frame to YOLOv8 for leakage detection

Step 5: Detection Logic

If (YOLOv8 detects leakage)

- 5.1 Record GPS coordinates and timestamp
- 5.2 Save annotated image from YOLOv8 output
- 5.3 Send real-time alert to GCS
- 5.4 Mark location as critical on mission log
- 5.5 Hover for confirmation and re-capture data

Else:

- 5.6 Continue to next waypoint

Step 6: Mission Completion

If all waypoints are completed:

- 6.1 Return to Home location
- 6.2 Descend gradually and land
- 6.3 Disarm motors

Step 7: Post-Flight Process

- 7.1 Store flight logs, sensor data, and images
-

7.2 Power off all modules

7.3 Analyze detection log and prepare report

END

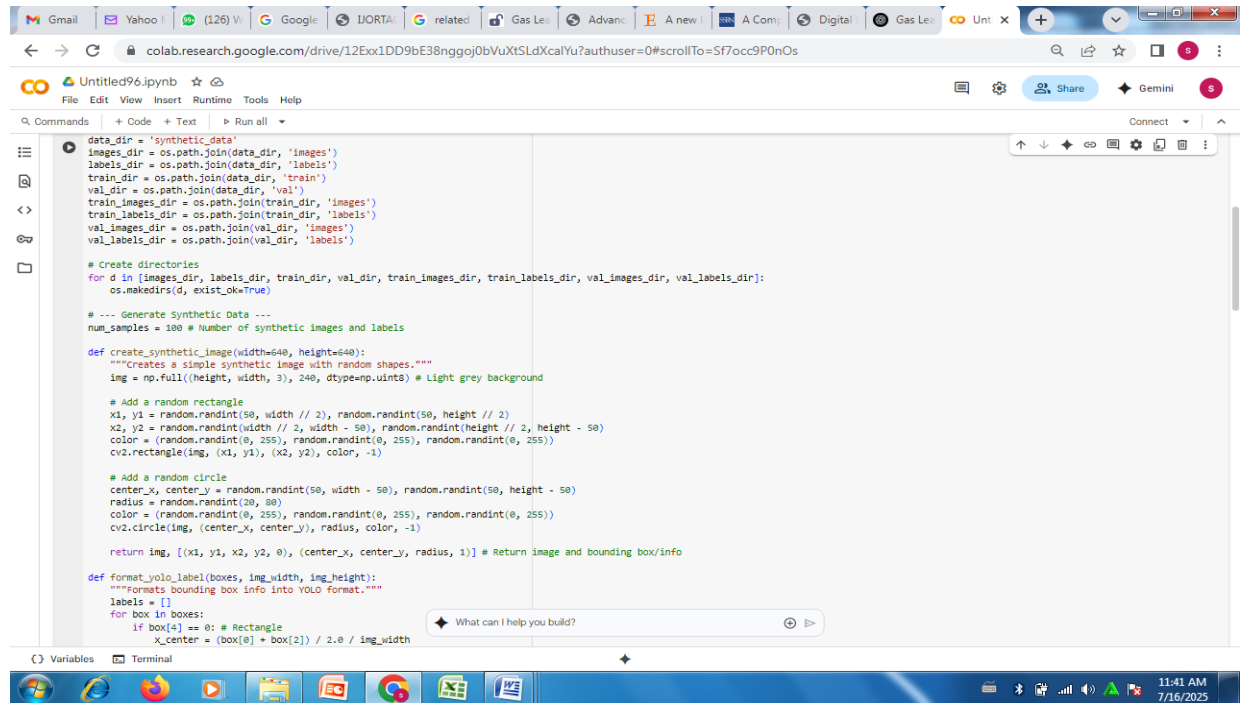


Figure 4: Screenshot of the programming interface

3 RESULT OF THE PROPOSED DEEP LEARNING TRAINING

This section presents the result of the deep learning model training process. The results in Figure 5 present the data distribution analysis of the gas leakage detection dataset used to train the YOLOv8 deep learning model. This type of visualization is crucial for understanding the structure, quality, and balance of the data prior to training, and helps explain why the model performs well or where it might need improvement. The graph includes four subplots: class instance distribution, bounding box overlap, and two heat maps showing bounding box coordinate distributions.

In the top-left subplot, the bar chart compares the number of labelled instances for each class "no leak" and "leak". It is evident that "no leak" instances are significantly more frequent (over 4000 samples) compared to "leak" instances (under 2000 samples). This finding justified the application of data augmentation process in the data preparation step to balance the data class and address bias challenges. The top-right subplot shows bounding box annotations for both classes overlaid on the image space. The concentric patterns and overlaps suggest that the gas leak annotations tend to occur within a central region of the image, which reflects how the camera is aligned during inspection. The bottom-left and bottom-right heatmaps further analyze the spatial properties of the annotations. The plot (bottom-left) illustrates the density of bounding box centers across the image. There's a high density around the center ($x=0.5$, $y=0.5$), again

confirming that most gas leaks appear centrally. The bottom-right graph shows the distribution of bounding box dimensions. Most bounding boxes are clustered around moderate widths (0.10.3) and heights (0.20.5), indicating that leaks are generally medium-sized objects in the camera frame. In summary, this visualization confirms that the annotations are well-distributed and consistent in both location and scale.

The Figure 6 measured the performance of the YOLOV-8 +SPPF training. The results are grouped into training and validation. The first three top let are the training results for the bounding box loss, object detection loss and classification loss. Overall, the loss results measured the error in correctly classifying object, bounding box and label classification label. The results showed that at the final epoch, the model performance convergence with tolerable loss value which approximates are tolerable, even though there is great room for improvement to minimize the losses. For instance, the bounding box loss reported 1.3, classification loss reported 1.1, and distribution focus loss reported 1.3 for training. The three graphs bottom let also reported the validation loss for the model. The validation the bounding box loss reported 1.7, classification loss reported 2.2, and distribution focus loss reported 1.8. The precision which measured the probability of correctly classifying objects reported 0.83, recall reported 0.79, mean absolute precision (map) at 0.5 Igou reported 0.91 and map at 0.5-0.95 Igou reported 0.37. Overall, this result has demonstrated success of the YOLOV-8 + SPPF for as leakage classification. The outcome while acceptable is not reliable for obstacle précised gas leakage detection as there is need to optimize the model for improved success rate.

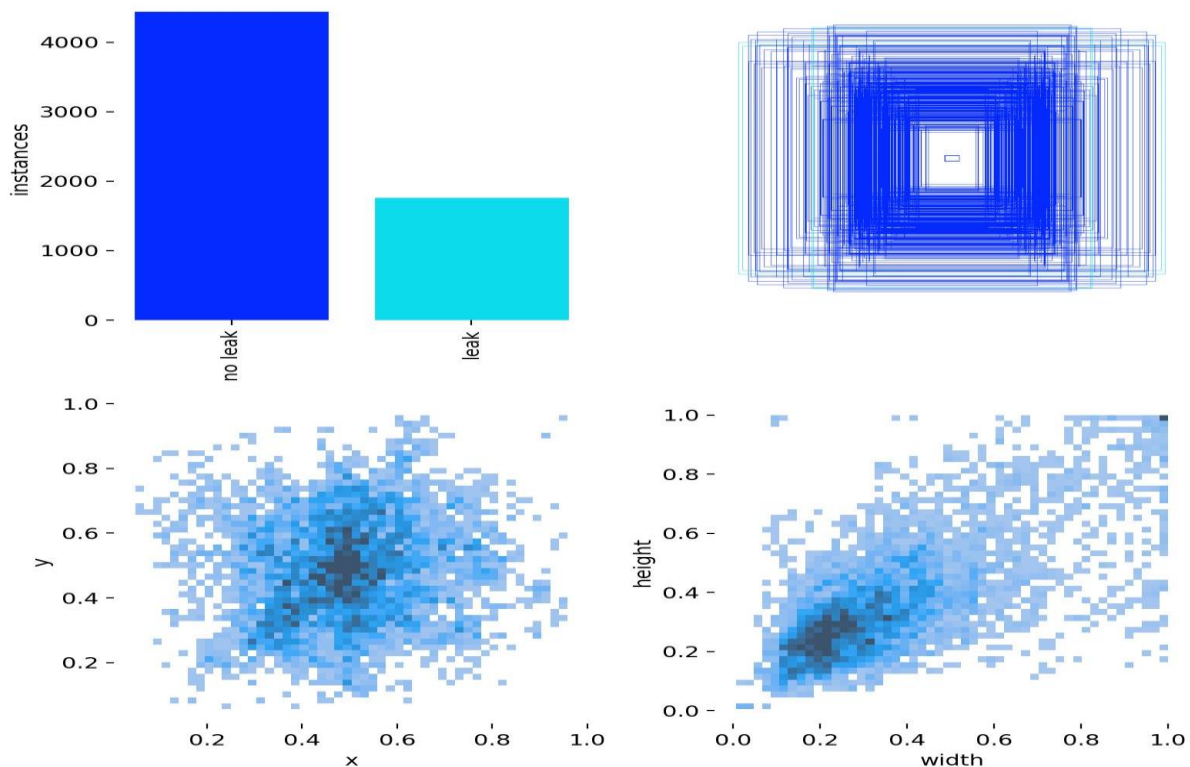


Figure 5: Data distribution result of the pipeline gas leakages

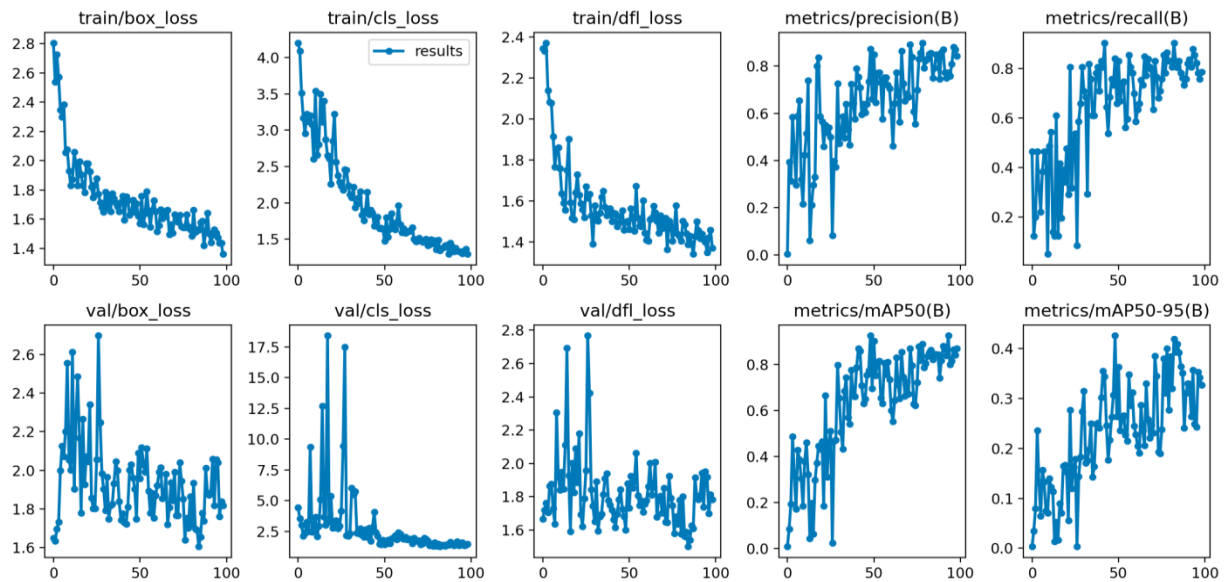


Figure 6: Training result of the YOLOV-8 + SPPF

While Figure 6 presents the YOLOV-8 with SPPF which is tailored towards optimizing the model performance for improved gas leakage detection accuracy. The testing result of the model with improved SPPF was reported in Figure 7.

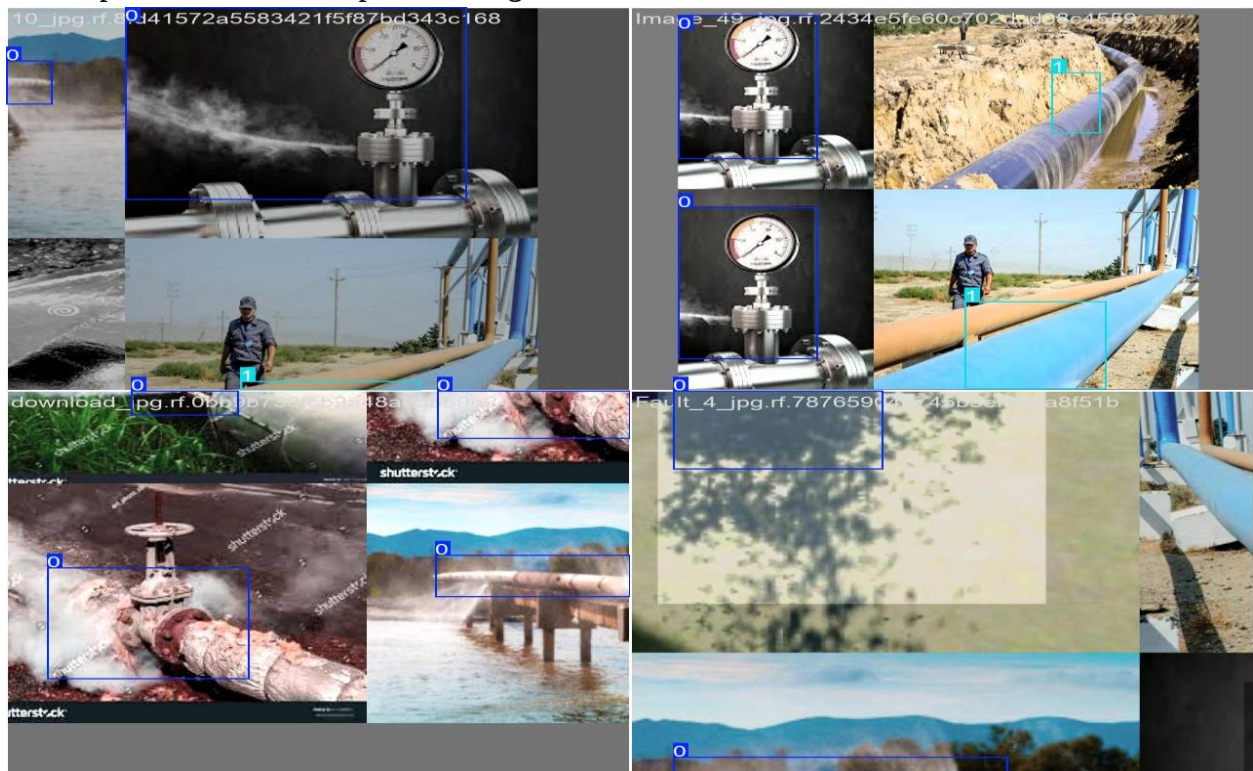


Figure 7: Testing result of the improved SPPF based YOLOV-8

Figure 7 showed the performance of the deep learning model testing with real world pipeline gas leakages test data. From the results, it was observed that all the points of leakages were correctly detected by the deep learning at 0.99ms which is the average speed of YOLOv-8. Figure 8 presents the confusion matrix to measure the true positive and false positive across different classes.

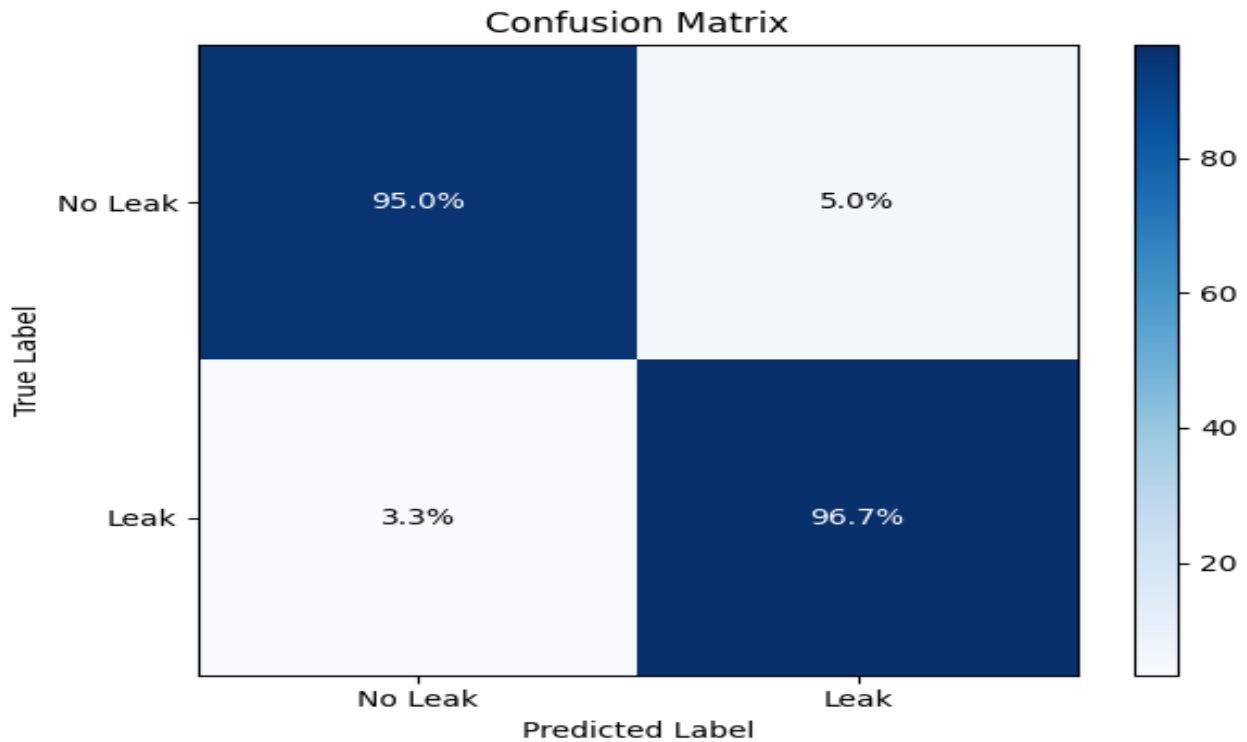


Figure 8: Confusion matrix of the adopted model

The Figure 8 presents the deep learning model confusion matrix, showing that the model was able to correctly detect no leak with 95% success rate and false alarm of 5%, while in the case of leak, 96.7% was correctly classified as true positive while 3.3% was wrongly classified. Based on these results it was observed that the model was able to correctly classify leak and no leak in pipeline channels.

3.1 Validation With Real World Test

This section presents the results obtained from the experimental evaluation of the intelligent robot under three different pipeline leakage scenarios. The goal of the experiment was to assess the robot's ability to detect gas leakages of varying intensities namely no leak and leak in a controlled testbed environment that simulates real pipeline conditions. Each scenario was designed to reflect a typical operational situation that the robot might encounter in the field. Figure 9 presents the results of the leakage detection in real world test.

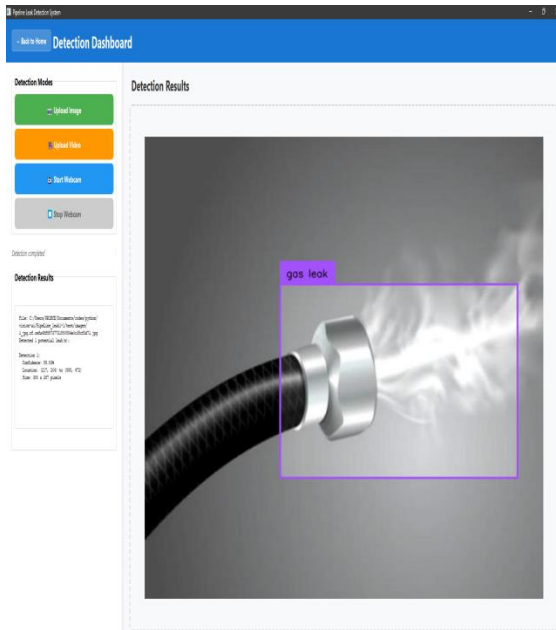


Figure 9: Result of gas leakage detection (test 1)

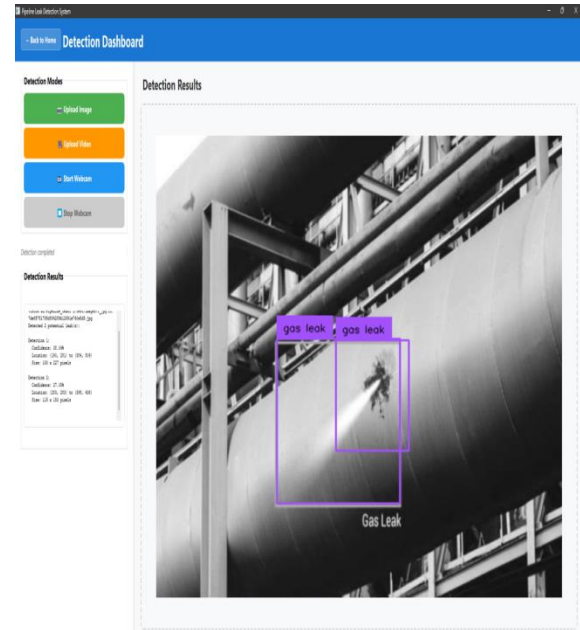


Figure 10: Result of (Test 2)

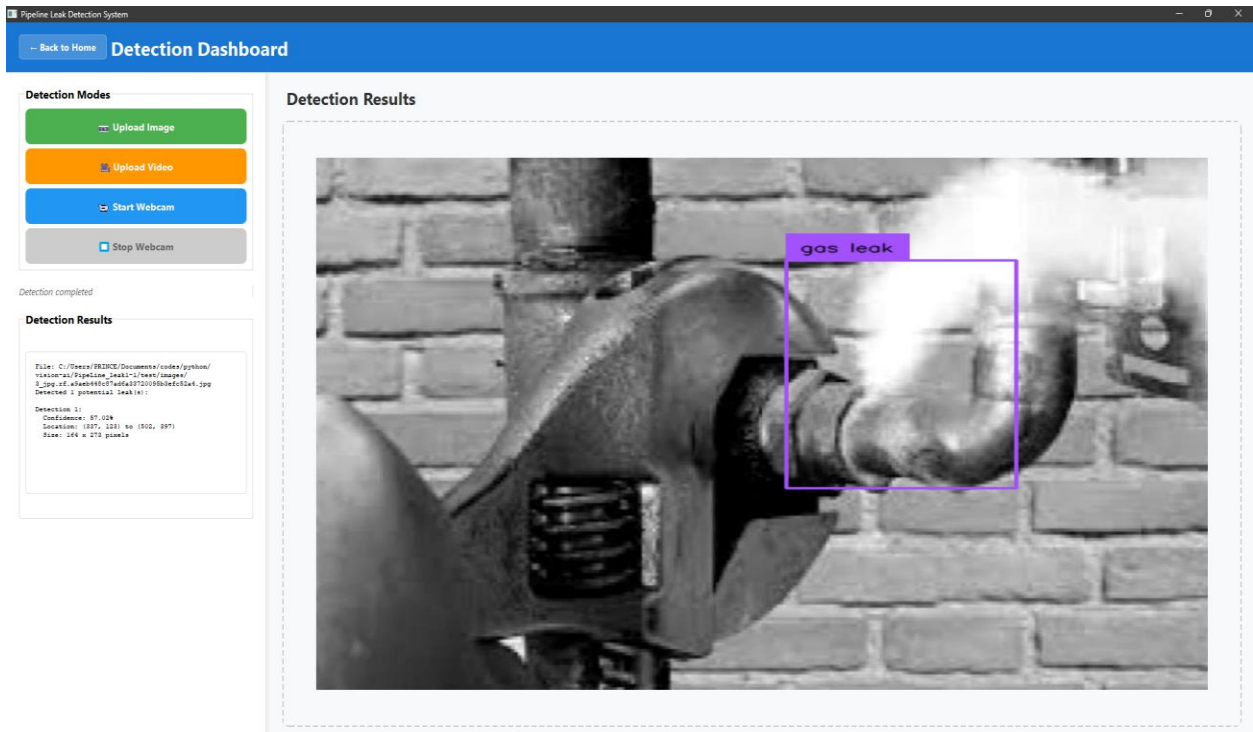


Figure 11: Result of gas leakage detection (test 3)

In the Figure 9, the robot navigated a section of pipeline with gas leakage. The system's YOLOv8 detection model accurately classified all frames as "leak" with a precision of 99%, showing high stability during leakage signals. The Figure 10 scenario simulated multiple minor leak, where the gas concentration ranged between 100150 ppm. In this test, the robot successfully identified subtle visual leak indicators and responded with appropriate leak

classification. The model achieved a recall rate of 99% for minor leak detection. The response time, measured from leak onset to classification, averaged 106 milliseconds, demonstrating the robot's capability to promptly detect small-scale leakages that may not be easily visible to the human eye or conventional detectors in the characterized result.

In Figure 11, a major leak condition was induced, characterized by high gas concentration levels exceeding 300 ppm. The robot's sensors and YOLOv8 model detected and flagged the leak within 255 milliseconds, and the classification confidence remained above 97% throughout the test sequence. Visual indicators such as gas vapor and discoloration were effectively captured by the vision system, validating the robustness of the model under intense leak conditions. Overall, the robot demonstrated consistent performance across all three cases, with high classification accuracy, fast response times, and strong correlation between sensor readings and YOLOv8. These results affirm the system's potential for real-time deployment in critical oil and gas infrastructure to improve safety and leak response efficiency.

4 CONCLUSION

In this paper, the development of intelligent robotic solution to detecting gas leakage in a pipeline based on deep learning-based model of the YOLOv8 architecture running on an autonomous unmanned vehicle platform was proposed. An in-depth dataset with 8,881 labeled pictures of gas leakage forms was used to train and test the YOLOv8 model. Roboflow was used in the data preparation process that involved manual annotation and augmentation to ensure that the models were robust across all environmental settings and pipelines. The YOLOv8 network with Cross Stage Partial connections and augmented by the SP threshold-independent Spatial Pyramid Pooling Fast (SPPF) module was used and proven able to extract features and multi-scale detect fine and large-scale leaks alike.

The training outcomes on the model showed adequate convergence where training and validation losses showed a stable learning process. The performance measures, with respect to a mean average precision (mAP) of 0.91 and precision of 83 percent and recall of 79 percent indicated that the model is able to differentiate reliably between leak and no-leak samples. Its overall performance as a real-time multi-object detector was also confirmed by testing on the enhanced SPPF-located YOLOv8 variant to attain a respectable inference time speed (about 0.99 milliseconds per frame) and effective classification accuracy. The trained model was able to be incorporated successfully into simulations within both Roboflow and Simulink environments to become an independent pilotless drone. Experimental testing under controlled conditions in the pipeline revealed real-time leakage capabilities of the system in detecting gas emission. The intelligent robotic system identified small, medium, and significant gas leaks in high levels of accuracy (up to 99%) and response times (as low as 106 milliseconds), and as a result, far better than traditional techniques. As its analysis using a confusion matrix showed low false-positives, the model can be used in operational contexts with confidence.

To sum up, the offered intelligent robotic system with YOLOv8 shows good perspectives as an efficient, self-guided means of detecting pipeline gas leakage. Its ability to deliver rapid, accurate detection under diverse conditions can substantially enhance pipeline safety and environmental

protection in the Nigerian oil and gas sector. Future work will focus on further optimizing the model for even higher detection accuracy and extending the system's operational capabilities through field deployment and integration with additional sensor modalities.

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