

# Environmental Image Analysis for Smoke-Free Area Compliance Mapping Using YOLOv11 and Geographic Information Systems

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## ABSTRACT

Smoke-Free Areas are implemented to protect public health; however, monitoring and evaluating compliance remain challenging due to the lack of automated and spatially integrated monitoring systems. This study aims to develop a mapping and classification system for Smoke-Free Area (KTR) compliance using the YOLOv11 object detection algorithm and Geographic Information System (GIS)-based spatial analysis on environmental images. Data collection was conducted in Banda Sakti District, Lhokseumawe, at nine observation locations consisting of places of worship, public open spaces, and workplaces. The dataset consisted of three object classes, namely smoking activity, cigarette, and ashtray, combined with spatial variables such as latitude and longitude, where latitude represents the north-south geographic position and longitude represents the east-west geographic position of each observation point. These spatial variables were integrated with the YOLOv11 detection results to enable the mapping and visualization of KTR violations within the GIS environment. The YOLOv11 model was evaluated using precision, recall, mAP50, and mAP50-95 metrics. Experimental results showed that the model achieved a precision value of 0.772, recall of 0.741, mAP50 of 0.770, and mAP50-95 of 0.602, indicating moderate object detection performance under various environmental conditions. Spatial analysis results revealed that out of 145 observation points, 112 points were categorized as major violations, 25 points as minor violations, and only 8 points as compliant areas. Therefore, the integration of YOLOv11 and GIS provides a digital-based approach for supporting Smoke-Free Area compliance monitoring and spatial analysis.



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## I. INTRODUCTION

Smoke-Free Areas (KTR) are a public health policy stipulated in Law Number 17 of 2023 concerning health, which outlines the obligation of local governments to provide and enforce smoke-free areas. This policy is also regulated by Lhokseumawe Mayoral Regulation Number 25 of 2023 concerning Smoke-Free Areas. Smoke-Free Areas (KTR) include healthcare facilities, formal and informal educational institutions, children's activity areas, places of worship, sports arenas, workplaces, public places, and other public areas. Smoking within these areas is prohibited, meaning that smoking is prohibited either in or around these areas. For example, other areas not included in these categories are recommended to provide dedicated smoking zones.

This policy has long been implemented in Indonesia, but in practice, compliance remains very low [1][2]. The prevalence of smokers aged 15 and over in Indonesia reaches 33.8%, with Aceh Province itself being above the national average. The school environment, which is one of the main settings for KTR, in reality shows that many still do not have anti-smoking task forces, standard operational procedures, or adequate monitoring mechanisms so that violations of KTR still occur in the school environment[3][4].

The public health impacts caused by exposure to cigarette smoke can be very serious, such as increasing the risk of coronary heart disease, lung cancer, stroke, and chronic obstructive pulmonary disease [5]. Therefore, monitoring the implementation of KTR is an important issue and the

effectiveness of KTR implementation depends on field monitoring and community reports.

Current advances in information technology enable us to utilize environmental imagery with spatial analysis to analyze location-based phenomena and recognize human activity patterns, which are then displayed in the form of digital thematic maps [6][7]. In this study, this approach is used to automatically detect KTR violations using environmental images in the form of KTR location photos based on geographic information systems [8][9].

The primary data used are photos taken using a smartphone camera with GPS enabled, which stores the latitude and longitude of each image or photo [10]. To identify violations, the YOLOv11 algorithm is used, an object detection method capable of identifying objects in images in a single process [11]. This approach allows the model to predict bounding boxes and object classes in a single processing step [12]. After image detection with YOLOv11, secondary data is used in the form of OpenStreetMap-based digital maps integrated with Leaflet.js. Furthermore, information about KTR regulations is derived from existing provisions in Lhokseumawe Mayoral Regulation Number 25 of 2023, which refers to the types of public facilities that are categorized as KTR. All of this data will later be integrated into the Geographic Information System to produce a spatial map that displays the location of violations and the level of KTR compliance in Lhokseumawe City based on GPS coordinates from field images.

The administrative area of Lhokseumawe City consists of four sub-districts: Banda Sakti, Muara Dua, Muara Satu, and Blang Mangat. This study focused on collecting data in the Banda Sakti sub-district of Lhokseumawe City, as it is the center of community activity, commerce, public services, and transportation, considered representative of the implementation of the Smoke-Free Area (KTR) [13][14].

The data collection objects in this study included several locations representing the Smoke-Free Area (KTR) system, namely the Islamic Center Mosque, Mongeudong Mosque, Riyaddah Park, Hiraq Field, Keude Aceh Terminal, and the Old Terminal. Several previous studies only discussed the policy and social behavior aspects regarding Smoke-Free Areas (KTR), such as research by [15] who examined the obstacles and opportunities for implementing KTR in Banda Aceh [16] who analyzed the perceptions and social factors of the academic community regarding the implementation of KTR in the campus environment. However, research that integrates object detection and spatial analysis to map the level of KTR compliance is still very limited.

However, research that integrates object detection and spatial analysis to map KTR compliance is still very limited. This research is urgently needed because, based on a review of available policy documents and scientific publications, current KTR monitoring is still dominated by manual methods and has not been integrated into mapping systems. To date, there is no KTR monitoring mechanism capable of presenting visual evidence along with spatial information. The gap between regulations and implementation in the field

makes it difficult for local governments to assess the effectiveness of KTR policies, determine which locations will be prioritized for KTR enforcement, and carry out data-driven evaluations. Meanwhile, KTR violations in Lhokseumawe still show potential violations that require more attention, especially in educational areas and public areas where there are many children's activities. This condition requires a faster, more objective technological approach that can produce thematic compliance maps [17][18]. Therefore, this study proposes an object detection approach using YOLOv11 combined with spatial analysis to produce a dynamic KTR compliance map. The collected imagery can be processed to identify violations and extract spatial information, which is then used to periodically update the map layer.

## II. METHODOLOGY

### A. Research Stages

This research was conducted systematically to develop a model for mapping and classifying Smoke-Free Area compliance using the YOLOv11 object detection method and spatial analysis on environmental images. The research process integrates computer vision technology with Geographic Information System (GIS) analysis to identify smoking-related violations and visualize their spatial distribution digitally. The stages of the research were designed to ensure that the developed system is capable of detecting smoking-related objects, classifying KTR compliance levels, and presenting the results through spatial visualization for supporting monitoring and evaluation of Smoke-Free Area implementation. The research stages include literature review and problem formulation, location planning and sampling design, field data collection, data annotation and preprocessing, YOLOv11 model training and validation, integration of detection results with GIS and spatial analysis, development of a digital Smoke-Free Area compliance map, and final report writing and system testing. The overall research stages can be seen in Figure 1.

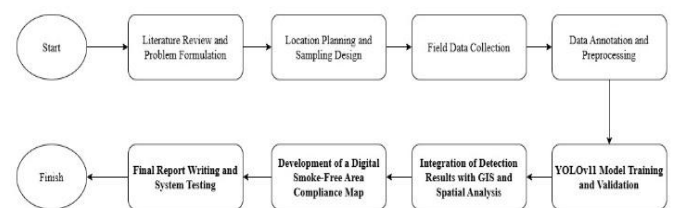


Figure 1. Research Stages

Figure 1, illustrates the workflow of the research conducted in this study. The process begins with a literature review and problem formulation to identify research gaps and determine the objectives of the study. The next stage involves planning the observation locations and designing the sampling process for collecting representative environmental image data. Field data collection is then carried out at several Smoke-Free Area locations, followed by data annotation and preprocessing to prepare the dataset for object detection

training. The annotated dataset is subsequently used for training and validating the YOLOv11 model to detect smoking-related objects such as smoking activity, cigarettes, and ashtrays. After obtaining the detection results, the data are integrated with Geographic Information System (GIS) technology and spatial analysis to visualize the distribution of KTR violations. The processed spatial data are then used to develop a digital Smoke-Free Area compliance map, which provides information regarding the compliance level and concentration of violations in the study area. Finally, the research concludes with final report writing and system testing to evaluate the overall functionality and performance of the developed system.

### B. Environmental Image Dataset and Observation Locations

The environmental image dataset used in this study was collected from several Smoke-Free Area (Kawasan Tanpa Rokok/KTR) settings located in Banda Sakti District, Lhokseumawe City. The dataset was developed to support the object detection process using the YOLOv11 model and to analyze the spatial distribution of KTR violations through Geographic Information System (GIS) integration. The collected environmental images represent various public activity conditions and contain visual indicators related to smoking behavior and KTR violations.

Data collection was conducted in Banda Sakti District because the area represents the center of community activities with relatively high mobility and contains several locations categorized as Smoke-Free Areas. Focusing the research on a single district allowed the data collection process to be more systematic, efficient, and capable of producing more consistent field data. The study concentrated on three KTR settings representing different types of public activities, namely places of worship, public open spaces, and workplaces. These locations were selected based on the high intensity of public visits, their relevance to the implementation of Smoke-Free Area regulations, and accessibility considerations during field data collection. The observation locations used in this study are presented in Table 1.

TABLE I  
OBSERVATION LOCATIONS AND KTR CATEGORIES

No	KTR Category	Observation Locations
1	Places of Worship	Masjid Islamic Centre, Masjid Mon Geudong, Masjid Alfalah
2	Public Open Spaces	Taman Riyadhah, Lapangan Hiraq, Lapangan Sudirman
3	Workplaces	PDAM Tirta, BSI Office, Inspectorate Office

The data collection process was carried out over seven days using three observation periods: morning (07.00–11.00 WIB), afternoon (12.00–14.00 WIB), and evening (15.00–18.00 WIB). These periods were selected because visitor density and public mobility tend to increase during these hours, thereby increasing the potential occurrence of KTR violations. Image acquisition was conducted at representative

observation points within each location, particularly in areas with high public activity such as parking areas, main gathering areas, and public facilities. This approach was intended to provide a representative overview of Smoke-Free Area compliance conditions at each location, although it did not cover all areas comprehensively.

TABLE II  
DATASET VARIABLES AND INDICATORS

Category	Variables	Description
Object Detection Variables	Smoking activity, cigarette, ashtray	Visual indicators used to assess the compliance level of Smoke-Free Areas (KTR).
Spatial Variables	Latitude, longitude, location name, KTR category	Variables used for digital map visualization and spatial distribution analysis of violations.
System Variables	Detection results, confidence score, number of detected objects, compliance category	Variables generated by the YOLOv11 detection system and classification process.
Output Indicators	Compliance level (compliant, minor violation, major violation), spatial distribution, heatmap visualization	Final indicators used to evaluate KTR compliance and identify high-violation concentration areas.

The detected objects are divided into three classes: smoking, cigarettes, and ashtrays. The smoking class is used to directly detect violations, while the cigarette and ashtray classes are used as supporting indicators of smoking activity in a location. The dataset annotation process was carried out using the Roboflow platform, where each object in the image is labeled according to its shape (segmentation). The dataset is then divided into three parts: training, validation, and testing data to support the training, validation, and performance testing processes of the model separately so that model evaluation results can be obtained more objectively. The dataset division can be seen in Table 3.

TABLE III  
DATASET VARIABLES AND INDICATORS

Dataset Type	Number of Images	Percentage
Training	370	92%
Validation	23	6%
Testing	8	2%
Total	401	100%

Table 3 shows the distribution of the dataset used in this study for the development and evaluation of the YOLOv11 object detection model. The majority of the dataset was allocated for training purposes, consisting of 370 images or 92% of the total dataset. The training dataset played an important role in enabling the YOLOv11 model to learn and recognize the visual characteristics of smoking-related objects within Smoke-Free Area (KTR) environmental images, including

smoking activities, cigarettes, and ashtrays under various environmental conditions. In addition, the diversity of training images helped improve the model's ability to generalize object detection performance across different lighting conditions, object positions, image backgrounds, and crowd densities.

Furthermore, the validation dataset consisted of 23 images or 6% of the total dataset and was used during the training process to evaluate the model's intermediate performance and monitor learning stability. The validation stage is important for identifying potential overfitting conditions, where the model performs well on training data but poorly on unseen data. Through validation monitoring, the model training process could be optimized by adjusting learning parameters and selecting the best-performing model weights.

Meanwhile, the testing dataset consisted of 8 images or 2% of the total dataset and was used to evaluate the final performance of the trained model on previously unseen data. The testing process aimed to measure the model's capability in detecting smoking-related objects objectively and independently from the training process. Although the testing data proportion was relatively small, the testing stage still provided an initial representation of the model's detection capability in real environmental scenarios. Therefore, the dataset distribution used in this study supports the development of a lightweight object detection model while maintaining stable training and evaluation processes.

### C. YOLOv11 Algorithm Implementation

The implementation of the YOLOv11 algorithm in this study was carried out to develop an object detection model capable of identifying violations of Smoke-Free Areas (Kawasan Tanpa Rokok/KTR) through environmental images. The model was designed to detect three main object classes, namely smoking activity, cigarette, and ashtray, which were used as visual indicators for assessing KTR compliance levels. The implementation process includes dataset preparation, object annotation, dataset splitting, YOLOv11 parameter configuration, model training, and model evaluation to obtain the best-performing model for supporting the mapping and classification of Smoke-Free Area compliance using spatial analysis. The overall implementation stages of the YOLOv11 algorithm can be seen in Figure 2.

Figure 2, illustrates the workflow of the YOLOv11 implementation process used in this study. The process begins with the input of environmental image datasets collected from several Smoke-Free Area locations. The dataset is then annotated by labeling three object classes: smoking activity, cigarette, and ashtray. After annotation, the dataset is divided into training and validation datasets to support the learning and evaluation processes of the model.

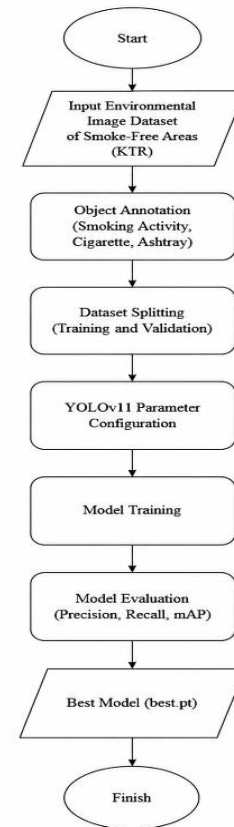


Figure 2. YOLOv11 Algorithm Implementation

The next stage involves configuring YOLOv11 parameters, including training settings required to optimize model performance. Subsequently, the model training process is conducted to enable the algorithm to learn the visual characteristics of smoking-related objects from the annotated dataset. After training is completed, the model performance is evaluated using precision, recall, and mean Average Precision (mAP) metrics to measure detection accuracy and consistency. Finally, the best-performing model is generated in the form of a trained weight file (best.pt), which is then used in subsequent stages for object detection, compliance classification, and spatial visualization of Smoke-Free Area violations.

### D. Integration Process Flow of YOLOv11 and GIS

The integration process between YOLOv11 and Geographic Information System (GIS) in this study was designed to support the mapping and classification of Smoke-Free Area (Kawasan Tanpa Rokok/KTR) compliance based on environmental image analysis. This integration enables the detection results generated by the YOLOv11 model to be spatially visualized through GIS technology, thereby providing geographic information regarding the distribution of KTR violations. The integrated system combines object detection, compliance classification, spatial coordinate retrieval, database storage, and digital map visualization into a unified workflow to support monitoring and evaluation of

Smoke-Free Area implementation. The overall integration process between YOLOv11 and GIS can be seen in Figure 3.

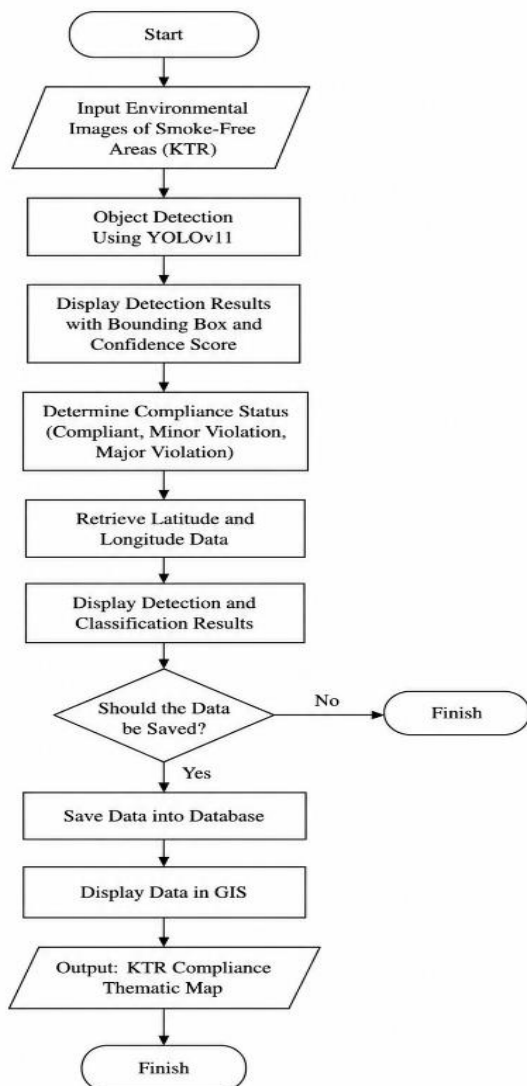


Figure 3. Integration Process Flow of YOLOv11 and GIS

Figure 3, illustrates the workflow of the integrated YOLOv11 and GIS system developed in this study. The process begins with the input of environmental images collected from several Smoke-Free Area locations. The images are processed using the YOLOv11 object detection model to identify smoking-related objects, including smoking activity, cigarettes, and ashtrays. The detection results are subsequently displayed using bounding boxes and confidence scores to indicate the accuracy and location of detected objects within the image. Based on the detected objects, the system determines the compliance status of each observation location, which is categorized into compliant, minor violation, and major violation levels. After the classification process, the system retrieves spatial information in the form

of latitude and longitude coordinates associated with the image acquisition location. The detection and classification results are then displayed and optionally stored in the database for further spatial processing and analysis. The stored spatial data are subsequently visualized within the GIS environment to generate a thematic map representing the spatial distribution of Smoke-Free Area compliance levels. This integration process enables the developed system not only to perform object detection automatically but also to provide spatial insight into areas with high concentrations of KTR violations.

#### E. YOLO Algorithm

The YOLO (You Only Look Once) algorithm is a real-time object detection method widely used in computer vision applications due to its ability to detect objects quickly and accurately in a single processing stage [19][20]. Unlike conventional object detection approaches that perform object localization and classification separately, YOLO integrates both processes into a single neural network architecture. The model divides an image into several grid cells and predicts bounding boxes, confidence scores [21][22], and object class probabilities simultaneously. This integrated architecture enables YOLO to achieve high computational efficiency and real-time performance, making it suitable for surveillance systems, smart city applications, environmental monitoring, and Smoke-Free Area compliance analysis.

The YOLO architecture utilizes Convolutional Neural Networks (CNN) to extract features from input images. The input image is resized and divided into an  $S \times S$  grid. Each grid cell is responsible for predicting object coordinates, width, height, and confidence score. The confidence score indicates the probability that an object exists within the predicted bounding box.



Figure 4. YOLO illustration

YOLOv11 is the latest version of the YOLO algorithm, released in 2024. Compared to previous versions, YOLOv11

introduces several improvements, including enhanced multi-scale prediction, optimized feature extraction, a more efficient backbone network, and improved computational efficiency for real-time object detection tasks. These developments enable YOLOv11 to achieve higher detection accuracy while maintaining lightweight performance and faster inference speed. The evolution of the YOLO algorithm and its performance improvements from 2015 to 2024 are illustrated in Figure 5.

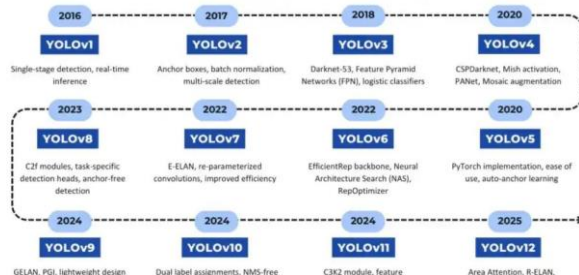


Figure 5. Model Performance From 2015-2024

The development history of the YOLO algorithm from YOLOv1 to YOLOv11 can be summarized as follows [23][24].

- YOLOv1(2015)**  
YOLOv1 was the first single-stage object detection model capable of processing the entire image in a single detection stage, enabling real-time object detection performance.
- YOLOv2(2016)**  
YOLOv2 introduced anchor boxes, batch normalization, and upsampling techniques to improve localization accuracy and overall detection performance.
- YOLOv3(2018)**  
YOLOv3 implemented the Darknet-53 backbone architecture, multiple anchor boxes, and multi-scale feature extraction to improve small-object detection capability and feature representation.
- YOLOv4(2020)**  
YOLOv4 improved training performance through Mosaic data augmentation, Cross Stage Partial (CSP) connections, and various optimization techniques to increase detection accuracy and computational efficiency.
- YOLOv5(2020)**  
YOLOv5 was developed by Glenn Jocher from Ultralytics as a flexible Python-based implementation framework that simplified deployment and model customization.
- YOLOv6(2022)**  
YOLOv6 introduced a lightweight and open-source architecture designed specifically for edge devices and industrial real-time applications.
- YOLOv7(2022)**  
YOLOv7 further optimized model architecture and training strategies to achieve better accuracy, faster inference speed, and improved computational efficiency.
- YOLOv8(2023)**  
YOLOv8 introduced architectural refinements involving

the backbone, neck, and head components, along with additional optimization modules to improve detection accuracy and model flexibility.

#### 9. YOLOv9(2024)

YOLOv9 introduced Programmable Gradient Information (PGI) and Generalized Efficient Layer Aggregation Network (GELAN) techniques to maintain deep feature representation and improve detection performance.

#### 10. YOLOv10(2024)

YOLOv10, developed by Tsinghua University, focused on computational efficiency through the implementation of large-kernel convolution and partial self-attention mechanisms for real-time object detection.

#### 11. YOLOv11(2024)

YOLOv11 represents the latest advancement in the YOLO series, offering improved architectural optimization, enhanced feature extraction capability, reduced computational complexity, and better performance for complex computer vision tasks.

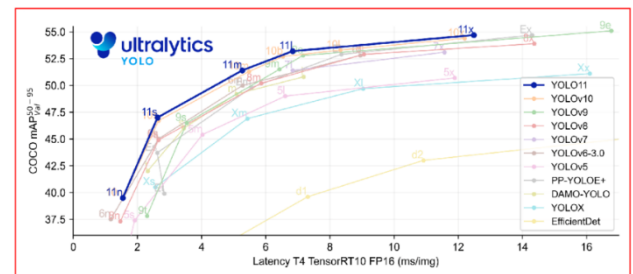


Figure 6. Benchmark Performance Evaluation Results Of The YOLO Algorithm On Various Datasets.

Figure 6 illustrates the benchmark performance evaluation results of various YOLO algorithm versions and other object detection models based on COCO mAP accuracy and inference latency on NVIDIA Tesla T4 TensorRT FP16. The figure shows that the development of the YOLO algorithm has consistently improved both detection accuracy and computational efficiency from YOLOv3 to YOLOv11. Earlier versions such as YOLOv3 and YOLOv5 provided fast inference speed but lower detection accuracy, while newer versions including YOLOv6, YOLOv7, YOLOv8, YOLOv9, and YOLOv10 introduced architectural optimizations, feature extraction improvements, and lightweight computational designs to achieve a better balance between speed and accuracy. Among all models, YOLOv11 demonstrates the best overall performance with higher COCO mAP values and relatively low inference latency, indicating superior real-time object detection capability. Compared to other object detection frameworks such as EfficientDet, DAMO-YOLO, PP-YOLOE+, and RT-DETR, the YOLO series, particularly YOLOv11, provides a more efficient trade-off between accuracy and processing speed, making it suitable for real-time environmental image analysis and GIS-based Smoke-Free Area (KTR) compliance monitoring systems.

The performance evaluation of the YOLOv11 model aims to measure the capability of the system in detecting and classifying objects accurately. Several evaluation metrics are commonly used, including Recall, Precision, F1-Score, Accuracy, and mean Average Precision (mAP). These metrics are calculated based on the confusion matrix, which consists of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values.

Recall is a metric used to measure the ability of the model to detect all relevant objects within the dataset. A higher recall value indicates that the model can identify more actual objects correctly.

Recall Formula:

$$Recall = \frac{TP}{TP + FN} \quad (1)$$

Precision is a metric used to evaluate the accuracy of the detected objects by measuring how many predicted objects are truly relevant.

Precision Formula:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

The F1-Score combines precision and recall into a single metric using the harmonic mean, providing a balanced evaluation between detection accuracy and completeness.

F1-Score Formula:

$$F1-Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

Accuracy is used to evaluate the overall correctness of the model in making predictions for both positive and negative classes.

Accuracy Formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Mean Average Precision (mAP) is one of the primary metrics used in object detection to evaluate the average detection performance across all object classes. The mAP value is calculated from the average precision (AP) values of each class.

mAP Formula:

$$mAP = \frac{1}{N} \sum_{i=1}^N AP_i \quad (5)$$

TABLE IV  
CONFUSION MATRIX

Predicted / Actual	True	False
True	TP (True Positive)	FP (False Positive)
False	FN (False Negative)	TN (True Negative)

The confusion matrix provides a framework for evaluating the performance of the object detection model based on the comparison between actual labels and predicted results, which are then used to calculate precision, recall, F1-score, accuracy, and mAP values.

### III. RESULT AND DISCUSSION

This section presents the results obtained from the implementation of the YOLOv11 algorithm and Geographic Information System (GIS)-based spatial analysis for mapping and classifying Smoke-Free Area (Kawasan Tanpa Rokok/KTR) compliance using environmental images. The discussion includes the performance evaluation of the YOLOv11 object detection model, analysis of detected smoking-related objects, classification of KTR compliance levels, and spatial visualization of violation distribution through digital thematic maps. Furthermore, the results are analyzed to evaluate the effectiveness of the proposed system in identifying KTR violations and supporting spatial-based monitoring of Smoke-Free Area compliance.

#### A. Dataset of Smoke-Free Area Environmental Images

The dataset used in this study consists of environmental images collected from several Smoke-Free Area (Kawasan Tanpa Rokok/KTR) locations in Banda Sakti District, Lhokseumawe City. The dataset was developed to support the training and evaluation process of the YOLOv11 object detection model for identifying smoking-related violations within environmental settings. The collected images represent various environmental conditions, lighting variations, object scales, viewing angles, and public activities to improve the robustness and generalization capability of the detection model. The dataset includes three main object classes, namely smoking activity, cigarette, and ashtray, which are used as visual indicators for evaluating KTR compliance levels. The visualization of the environmental image dataset used in this study can be seen in Figure 7.

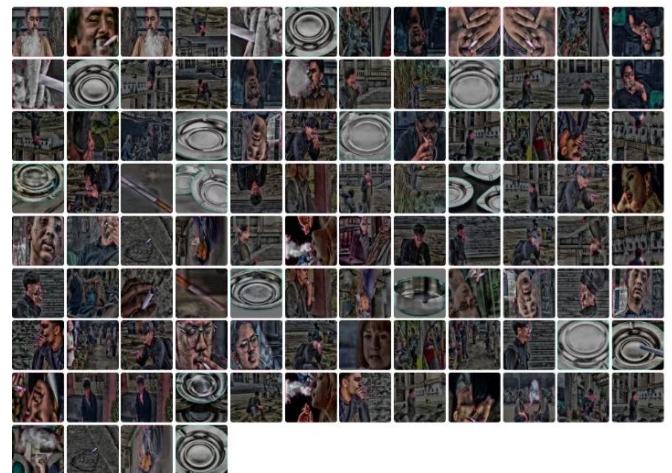


Figure 7. Dataset of Smoke-Free Area Environmental Images

Figure 7 illustrates a sample visualization of the environmental image dataset used in this study. The figure shows various image samples containing smoking-related objects captured under different environmental conditions and observation scenarios. Several images display individuals performing smoking activities, cigarette objects, and ashtrays with varying object sizes, positions, and backgrounds. The

diversity of the dataset is important for improving the capability of the YOLOv11 model in recognizing objects under complex environmental conditions, including differences in illumination, occlusion, image orientation, and crowd density. The variations in image characteristics also support the model in achieving better detection performance and improving its adaptability for real-world Smoke-Free Area monitoring applications. In the dataset preparation stage, the annotation process was carried out manually by labeling smoking-related objects such as smoking activities, cigarettes, and ashtrays using bounding boxes according to the object location within each image. To maintain labeling consistency and reduce annotation bias, the annotation results were reviewed and validated through a cross-checking process between annotators, ensuring that the object labels and bounding box placements remained consistent across the dataset before being used in the YOLOv11 training process.

**B. Implementasi Deteksi YOLOv11**

The implementation of YOLOv11 detection in this study was carried out to identify smoking-related objects from environmental images and classify the compliance level of Smoke-Free Areas (Kawasan Tanpa Rokok/KTR). The developed system integrates object detection results with compliance classification and Geographic Information System (GIS)-based visualization to support spatial monitoring of KTR violations. The YOLOv11 model detects three main object classes, namely smoking activity, cigarette, and ashtray, along with their corresponding confidence scores. Based on the detected objects, the system automatically determines the compliance category, including compliant, minor violation, and major violation. The implementation results of the YOLOv11 detection system can be seen in Figures 8–11.

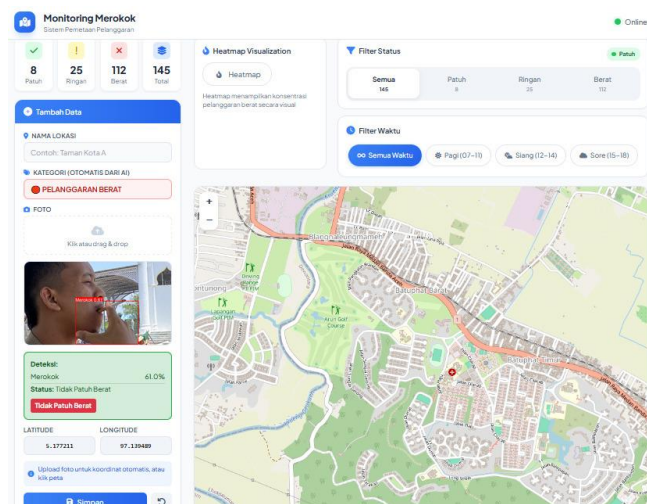


Figure 8. Implementation of YOLOv11 Detection and GIS-Based Monitoring System

Figure 8 shows the overall implementation of the developed monitoring system integrated with GIS

visualization. The system interface displays the total number of compliant, minor violation, and major violation categories obtained from the detection results. The map visualization presents the spatial distribution of KTR violations, while the left panel displays the uploaded environmental image, detected object labels, confidence scores, compliance status, and geographic coordinates. This integration enables the system to perform object detection and spatial visualization simultaneously for monitoring Smoke-Free Area compliance.



Figure 9. Detection Result of Smoking Activity (Major Violation Category)

Figure 9 illustrates the detection result of smoking activity using the YOLOv11 model. The system successfully detects the “Merokok” (smoking activity) object with a confidence score of 94.0% and the “Rokok” (cigarette) object with a confidence score of 26.0%. Based on these detection results, the system classifies the observation as “Tidak Patuh Berat” (Major Violation) because active smoking behavior is identified within the Smoke-Free Area environment.



Figure 10. Detection Result of Cigarette Object (Minor Violation Category)

Figure 10 presents the detection result of a cigarette object identified by the YOLOv11 model. The system detects the “Rokok” (cigarette) object with a confidence score of 91.0%. Since only the cigarette object is detected without visible smoking activity, the system categorizes the condition as “Tidak Patuh Ringan” (Minor Violation). This classification indicates the presence of smoking-related objects within the

Smoke-Free Area without direct evidence of active smoking behavior.



Figure 11. Detection Result of Ashtray and Cigarette Objects (Minor Violation Category)

Figure 11 shows the detection result of ashtray and cigarette objects within the environmental image. The system detects the “Asbak” (ashtray) object with a confidence score of 97.0% and the “Rokok” (cigarette) object with a confidence score of 28.0%. Based on these detection results, the system classifies the condition as “Tidak Patuh Ringan” (Minor Violation), indicating the existence of supporting smoking-related facilities or objects within the Smoke-Free Area environment.

### C. Spatial Analysis of Smoke-Free Area Violation Distribution

The spatial distribution analysis of Smoke-Free Area violations in this study was conducted based on the object detection results generated by the YOLOv11 model and visualized through a Geographic Information System (GIS). This analysis aims to identify the distribution pattern of KTR violations, evaluate the compliance level at each observation point, and analyze the spatial concentration of violations within the study area. The observation locations consist of places of worship, workplaces, and public areas with relatively high community activity, which potentially increases the occurrence of KTR violations. Through spatial visualization, the developed system is able to provide geographic information regarding violation hotspots and the overall compliance condition of Smoke-Free Areas in Banda Sakti District, Lhokseumawe City.

TABLE V  
OBSERVATION LOCATIONS

No	Area Category	Observation Location
1	Place of Worship	Islamic Center Mosque
2	Place of Worship	Al-Falah Mosque
3	Place of Worship	Mon Geudong Mosque
4	Workplace	Bank Syariah Indonesia (BSI)
5	Workplace	Inspectorate Office
6	Workplace	Tirta Pase
7	Public Area	Taman Riyadhah
8	Public Area	Lapangan Hiraq
9	Public Area	Lapangan Sudirman

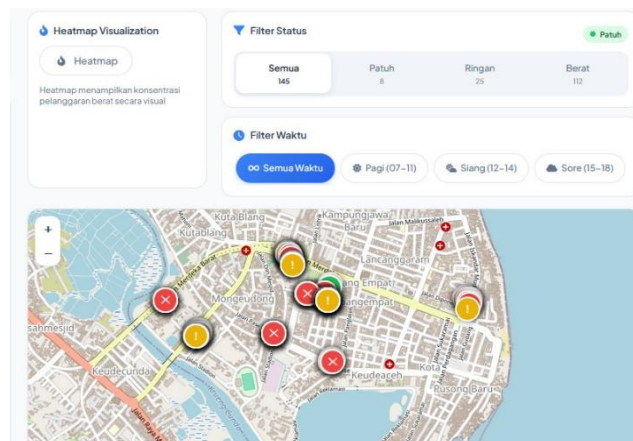


Figure 12. Spatial Distribution of Smoke-Free Area Violations

Figure 12 illustrates the spatial distribution of Smoke-Free Area (KTR) violations generated from the YOLOv11 object detection results integrated with GIS visualization. The figure shows that most observation points are categorized as major violations, represented by red symbols distributed across several public areas and workplaces with high community mobility, while several observation points are classified as minor violations, represented by yellow symbols, and compliant areas are indicated by green symbols. The classification results show that out of 145 observation points, 112 points belong to the major violation category, 25 points belong to the minor violation category, and only 8 points are classified as compliant. The dominance of major violation categories indicates that the level of compliance with Smoke-Free Area regulations within the study area is still relatively low. In this analysis, the spatial variables consisting of latitude and longitude were used to represent the geographic coordinates of each observation point, where latitude indicates the north–south position and longitude represents the east–west position of the detected location. These spatial variables were integrated with the YOLOv11 detection results by linking each detected smoking activity or object with its corresponding geographic coordinates collected during field observations. The integration process enabled every detection result to be spatially mapped and visualized within the GIS environment, allowing the identification of distribution patterns and clustering of KTR violations across the study area. Furthermore, the spatial distribution pattern demonstrates clustering in several specific locations, particularly in public areas and urban activity centers with high population movement, indicating a higher potential for KTR violations in densely visited environments.

### D. Evaluasi Model YOLOv11

The performance evaluation of the YOLOv11 model was conducted to measure the capability of the trained model in detecting objects on the validation dataset. The evaluation process used the best training weight file, namely best.pt, to ensure that the testing results represented the optimal model performance obtained during training. Several evaluation

metrics were used in this study, including precision, recall, mAP50, and mAP50-95. These metrics were utilized to evaluate the accuracy of object detection, the capability of the model to identify all relevant objects, and the detection quality based on the Intersection over Union (IoU) value. The evaluation results of the YOLOv11 model are presented in Table 4.3 and Figures 12–16.

TABLE VI  
YOLOV11 MODEL PERFORMANCE EVALUATION

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
All	23	39	0.772	0.741	0.770	0.602
Cigarette	2	3	0.818	1.000	0.995	0.962
Smoking	17	18	0.599	0.667	0.695	0.521
Ashtray	14	18	0.898	0.556	0.620	0.323

Table 6 shows the evaluation results of the YOLOv11 model for each detected object class. Overall, the model achieved a precision value of 0.772, recall of 0.741, mAP50 of 0.770, and mAP50-95 of 0.602, indicating that the model is capable of detecting smoking-related objects with relatively good performance. The “Rokok” (cigarette) class achieved the highest performance with mAP50 reaching 0.995 and recall value of 1.000, indicating that the model was highly effective in detecting cigarette objects. Meanwhile, the “Merokok” (smoking activity) and “Asbak” (ashtray) classes obtained relatively lower results due to variations in object appearance, environmental conditions, object scale, and background complexity within the dataset.

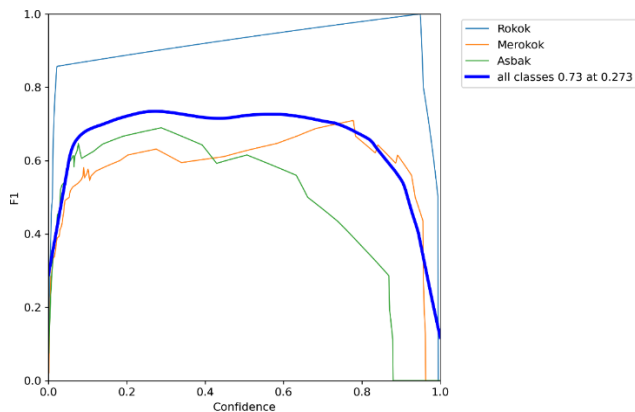


Figure 13. F1-Confidence Curve of YOLOv11 Model

Figure 13 illustrates the relationship between confidence threshold and F1-score for each object class and all classes combined. The graph shows that the overall model achieved the best F1-score of approximately 0.73 at a confidence threshold of 0.273. The “Rokok” class demonstrates the highest and most stable F1-score compared to the other classes, indicating strong detection consistency.

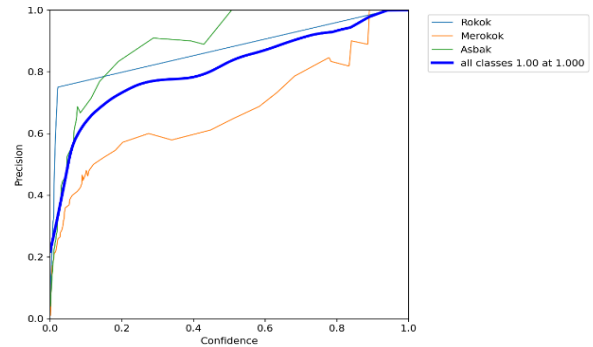


Figure 14. Precision-Confidence Curve of YOLOv11 Model

Figure 14 presents the precision values across different confidence thresholds. The graph shows that precision increases as the confidence threshold becomes higher. The “Asbak” and “Rokok” classes achieved high precision values approaching 1.0, indicating that the model produced relatively few false positive detections for these classes.

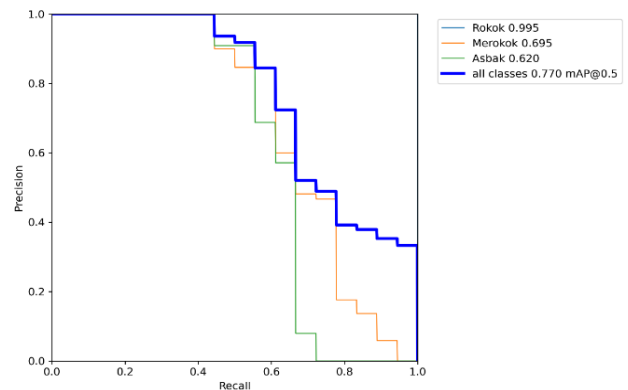


Figure 15. Precision-Recall Curve of YOLOv11 Model

Figure 15 illustrates the Precision-Recall (PR) curve for each object class. The graph shows that the “Rokok” class achieved the highest Average Precision value with mAP50 reaching 0.995, while the “Merokok” and “Asbak” classes obtained lower performance due to greater object variability and environmental complexity.

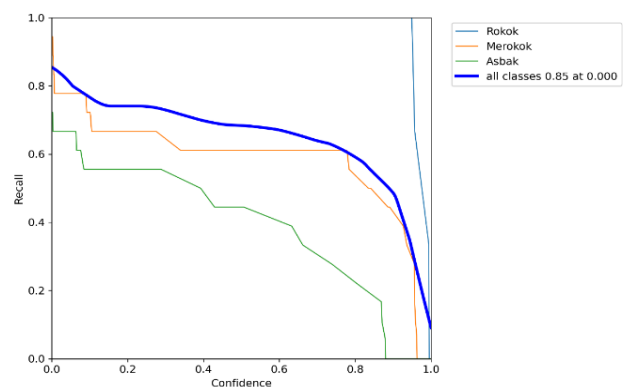


Figure 16. Recall-Confidence Curve of YOLOv11 Model

Figure 16 shows the relationship between confidence threshold and recall value. The graph indicates that recall decreases as the confidence threshold increases because the model becomes more selective in accepting detections. The “Rokok” class maintained the highest recall performance among all classes.

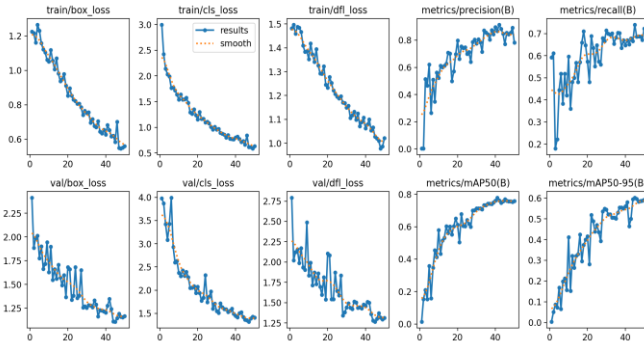


Figure 17. Training and Validation Results of YOLOv11 Model

Figure 17 illustrates the training and validation performance of the YOLOv11 model during the training process. The graphs show that the training loss and validation loss values gradually decreased over the training epochs, indicating that the model successfully learned object features from the dataset. In addition, the precision, recall, mAP50, and mAP50-95 values consistently increased during training, demonstrating improvements in model detection capability and overall training stability.

#### E. YOLOv11 Model Computation

The YOLOv11 model was computed to determine the resource requirements and detection speed of the model. This computational evaluation is important because object detection models are not only assessed based on their accuracy but also on their ability to perform processing efficiently. In this study, the model's computational performance was analyzed based on information about the model's architecture, number of parameters, computational operation requirements, devices used, and processing time at each detection stage. The YOLOv11 model computational performance can be seen in Table 7.

TABLE VII  
YOLOV11 MODEL COMPUTATION

Computational Aspect	Result
Model	YOLOv11n
Model Weight	best.pt
Model File Size	5,5 MB
Number of Layers	101 layer
Number of Parameters	2.582.737 parameter
Number of Gradients	0 gradient
Model Computation	6,3 GFLOPs
Testing Device	CPU
Processor	12th Gen Intel Core i7-12700F
Python	3.11.9
PyTorch	2.11.0+cpu
Ultralytics	8.4.46

Table 7 shows the model used is YOLOv11n with the best weight in the form of the best.pt file. The model file size of 5.5 MB indicates that the model is relatively lightweight and does not require a large storage space. This is an advantage because the model can be more easily implemented on devices with limited specifications. The YOLOv11n model has 101 layers with a total of 2,582,737 parameters and a computational requirement of 6.3 GFLOPs. The number of parameters and GFLOPs indicates that the model has a relatively efficient computational complexity. The smaller the number of parameters and GFLOPs, the lighter the computation process required by the model when detecting objects. Testing was conducted using a CPU device with a 12th Gen Intel Core i7-12700F processor. Although the evaluation process did not use a GPU, the model was still able to perform the detection process in a relatively fast time. This indicates that YOLOv11n is able to work efficiently on CPU-based devices.

TABLE VIII  
COMPUTATIONAL SPEED OF YOLOV11 MODEL

Process Stage	Time per Image
Preprocessing	1,4 ms/image
Inference	72,9 ms/ image
Loss Calculation	0,0 ms/ image
Postprocessing	0,4 ms/ image
Total Processing Time	74,7 ms/ image

Table 8 shows that the inference process requires the longest computation time, namely 72.9 ms per image, because inference is the main stage where the model performs object prediction and recognition. Meanwhile, preprocessing only requires 1.4 ms per image, loss calculation 0.0 ms per image, and postprocessing 0.4 ms per image, resulting in a total processing time of approximately 74.7 ms per image. These results indicate that the YOLOv11n model is relatively lightweight and capable of processing images in a short time with good detection performance. However, although the computational performance demonstrates the potential for monitoring applications, this study has not yet evaluated real-time implementation scenarios or the direct involvement of regulatory institutions in operational system usage. Therefore, the effectiveness of the system for practical KTR compliance monitoring still requires further validation through real-world implementation and institutional testing.

#### IV. CONCLUSION

This study successfully developed an object detection model using the YOLOv11 algorithm to identify violations of Smoke-Free Areas (Kawasan Tanpa Rokok/KTR) through environmental images. The model was trained using three object classes, namely smoking activity, cigarette, and ashtray. Based on the evaluation results, the model achieved a precision value of 0.772, recall of 0.741, mAP50 of 0.770, and mAP50-95 of 0.602, indicating moderate detection

performance under various environmental conditions. Furthermore, the developed system successfully classified KTR compliance into three categories: Compliant, Minor Violation, and Major Violation.

This study integrated YOLOv11 object detection results with GIS-based spatial analysis to generate a digital map of KTR compliance in Lhokseumawe. The spatial analysis results showed that most observation points were categorized as major violations, indicating that the level of compliance with KTR regulations remains relatively low. However, the observation coverage in this study is still limited and may not yet represent overall city-scale conditions. Although the integration of YOLO and GIS has been widely used in previous studies, this research specifically applies the approach to Smoke-Free Area monitoring, providing an initial framework for digital-based KTR compliance analysis and spatial visualization.

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