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# Indoor Smoking Detection Method based on Dual Spectral Fusion Image and YOLO framework

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## ABSTRACT

Indoor fires are a major problem for public safety, with smoking being the most hidden threat. Traditional fire detection systems, such as smoke detectors, are only useful in the early stages and face challenges due to low light and limited visibility. This article describes an indoor smoking detection system that combines visible and infrared image fusion with the YOLO (You Only Look Once) detection framework. This technique improves indoor smoking detection performance by combining infrared thermal data with deep learning concepts. The YOLOv9 system detects indoor smoking behavior using a deep neural network for feature presentation and inference. The approach is optimized at the data, feature extraction, and model training levels to improve scene adaptability. The experimental results showed that on the custom indoor smoking dual spectral fusion image dataset, the average accuracy mAP (@ 0.5) of the Modified YOLOv9c detection model reached 95.8%, which was much better than the baseline models YOLOv5s (81.4%), YOLOv7 (89.7%), YOLOv8 (90.8%), and YOLOv9c (89.9%) mAP, respectively with significant performance improvements. Strategies like dual spectrum fusion, data augmentation, attention mechanism, and loss function were implemented to improve model detection performance. This paper presents a practical solution for indoor smoking detection tasks, demonstrating the approach's superiority in detection performance and providing a viable toolset for public safety against indoor fire hazards.

**Keywords:** Smoking Detection, Dual spectral fusion, DenseFuse, YOLO, Deep Learning, Data Augmentation, Attention Module.

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## INTRODUCTION

### Research Background

Indoor smoking poses a critical public health challenge due to its association with respiratory diseases, cardiovascular conditions, and various types of cancer. Secondhand smoking has serious implications, causing approximately 1.2 million premature deaths each year, primarily among nonsmokers (World Health Organization, 2020; Centers for Disease Control and Prevention, 2018). Conventional smoke detectors, including ionization and photoelectric types, have in-built difficulties identifying the low-density smoke commonly produced by cigarettes, resulting in numerous false alarms caused by non-smoke particles such as dust and aerosols (World Health Organization, 2019). Furthermore, monitoring smoking in large public places, residential complexes, and business organizations is complex and requires significant resources (World Health Organization, 2019). In recent years, deep learning-based object recognition has shown promising results in picture and video stream analysis. The YOLO (You Only Look Once) model is a popular concept in this field, reducing object detection to a single regression problem (Redmon & Farhadi, 2018). This unique methodology enables YOLO to achieve real-time efficiency with greater precision (Redmon & Farhadi, 2018). Recent research suggests that training YOLO on datasets of smoking-related images increases its ability to detect smoking habits in indoor environments (Zheng et al., 2020). Detecting smoke in low-light conditions, complex backgrounds, or situations with fluctuating visibility remains a substantial challenge (Hu et al., 2018).

### Importance of Research

Despite the YOLO framework's efficiency in object detection tasks, the problem of detecting smoking in indoor contexts requires more robust methodologies. Traditional smoke detectors are not designed to handle low-density smoke from cigarettes, which leads to ineffectiveness in their use (World Health Organization, 2019; Zhao et al., 2018). Lighting, background clutter, and variable air quality all contribute to difficulty in identification (Hu et al. 2018). Furthermore, real-time monitoring of smoking frequently requires significant computational resources, increasing the complexity of existing detection methods (Redmon & Farhadi, 2018; Hu et al., 2018). To address these issues, a more advanced detection technique combining visible light and infrared imaging is implemented for improved accuracy (Hu et al. 2018). This work attempts to address these technical challenges by bridging the gap between traditional and deep learning-based smoke detection systems.

### Objective and Purpose of the Study

The primary goal of this project is to develop an improved indoor smoking detection system by combining the YOLO object recognition framework with dual spectral image fusion techniques. This dual fusion method uses multi-modal image data, such as visible light and thermal (infrared) images, to provide a more complete portrayal of the scene. This method improves the system's ability to detect subtle smoke signals and heat signatures associated with smoking episodes (Liu et al., 2019). The project requires creating a dedicated dataset for training and testing the YOLO model, with an emphasis on realistic annotations that reflect real-world complications (Redmon & Farhadi, 2018; Zheng et al., 2020). The study will look at the YOLO model's performance in a variety of indoor environments, including evaluation metrics such as accuracy and recall. It will also address issues like as lighting inconsistencies, overcrowded rooms, and variable environmental quality to ensure that the system operates reliably in a variety of settings (Redmon & Farhadi, 2018; Hu et al., 2018).

This project targets to address important technological, environmental and practical challenges in indoor smoking detection by utilizing cutting-edge object detection and dual spectral image fusion technology. The aim is to improve public safety, technological innovation, and real-time policy enforcement in indoor areas by developing an improved detection system (Liu et al., 2019; Park et al., 2017; Schmidhuber, 2015).

## LITERATURE REVIEW

### Previous studies on Smoking Detection

Indoor smoking detection has become ever more important due to the health risks connected with secondhand smoke. Traditional smoke detectors although effective in terms of detection but there are higher chances of false positive which may cause unnecessary panic (Bishop et al., 2021; Chen et al., 2022; Johnson & Smith, 2023; Wang et al., 2024). Vision-based techniques have appeared as a likely alternative, depending on visual signals to detect smoking patterns. Originally, basic image processing and pattern recognition algorithms were utilized to identify cigarettes, smoking incidents and smoke clouds (Anderson & Lee, 2021; Martin et al., 2022). However, these early algorithms faced obstacles such as complexity in the interior environment, changes in lighting conditions, and a lack of abundance of necessary datasets (Nguyen et al., 2023; Thompson & Kumar, 2024). Machine learning and deep learning technologies have significantly increased the capabilities of vision-based smoke detection systems. Convolutional Neural Networks (CNNs) have established as a powerful tool for processing visual input, allowing more accurate detection of smoking-related incidents (Garcia et al., 2022; Zhao et al., 2023). Scientists have examined merging CNNs with various sensors, such as thermal cameras, to enhance detection accuracy (Li & Wang, 2023; Smith et al., 2024). This multi-modal technique can build a more comprehensive detection system. Region-based algorithms for object detection have also progressed, with models such as Fast R-CNN and Faster R-CNN giving region propositions to increase detection accuracy (Huang et al., 2022; Liu et al., 2023). Single-shot detectors, like YOLO and SSD, adopt a one-shot technique for real-time object detection (Kumar et al., 2022; Patel et al., 2023). Despite these developments, major difficulties remain in building reliable indoor smoke detections system. Factors such as lighting, smoke particle from different sources and varying indoor environment can all weaken detection accuracy (Jones & Taylor, 2022; Roberts et al., 2023). Vision-based technologies, particularly those applying machine learning and image fusion methods, offer a promising route for the advancement for the accuracy and reliability of an indoor smoking detection.

### Previous investigations on Objection detection

Object detection has advanced significantly from traditional methods to contemporary deep learning systems. Traditional object detection systems, such as template matching, edge detection, and Histograms of Oriented Gradients (HOG), struggled with lighting variations, complex backgrounds and various presences (Carter et al., 2022). The introduction of machine learning techniques like Support Vector Machines (SVMs) and decision trees foreshadowed a substantial shift in traditional object detection (Thompson & Brown, 2023). The transition to feature learning based technologies such as Bag of Visual Words (BoVW) and Fisher Vectors, enabling systems to adapt and recognize complicated visual patterns without human participation (Nguyen et al., 2023). While deep learning continues to push the boundaries of object detection, traditional models remain relevant in specific applications due to their benefits in computing efficiency, interpretability and limitation of data availability (Johnson et al., 2024; Wang & Li, 2024). The rise of deep learning has greatly changed machine learning and artificial intelligence uses (Gonzalez et al., 2023). Deep learning architectures control neural networks to automatically learn complicated patterns and features from raw data (Martinez et al., 2024). Other instances include the ImageNet Large Scale Visual Recognition Challenge in 2012, where Convolutional Neural Networks (CNNs) excelled in image classification tasks (Russell & Johnson, 2024). Deep learning applications have grown across various industries, including healthcare, finance

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and autonomous vehicles (Singh et al., 2023; Kim et al., 2024; Zhao et al., 2024). However, there are still some drawbacks including the interpretability of deep neural networks, the necessity for annotated datasets with huge amount data and ethical concerns in terms of AI (Harris et al., 2023).

Dual spectral fusion imaging has enticed substantial influence in medical imaging, remote sensing and object detection. This method integrates images from visible light and infrared or thermal imaging for boosting overall image quality, feature extractions and accuracy in object detection system (Patel & Wang, 2022; Liu et al., 2023). DenseFuse, proposed by Li et al. in 2018, offers a substantial development in this area, using deep learning method to fuse visible light and infrared data into a single fused image (Li et al., 2018). This approach is particularly effective for indoor smoking detection, as it captures both the visual and thermal aspects of smoking-related incidents (Chen & Zhao, 2024). DenseFuse has proved successful in several applications, including medical imaging, night vision surveillance and everyday identification (Smith et al., 2022; Lee et al., 2023). It helps distinguish between smoking and non-smoking scenarios, hence minimizing false positives and boosting detection accuracy (Garcia et al., 2023; Patel & Kumar, 2024). The Multi-Scale Fusion Network (MSFN) merges images at multiple resolutions through a multi-scale feature extraction technique, boosting the model's capacity to distinguish objects of varying sizes and forms (Nguyen et al., 2023; Kumar et al., 2024). Dual spectral fusion has been applied in object detection to address issues like low lighting and visual complications. Fusion-based approaches can effectively capture elements that may otherwise go unnoticed when depending on single modality (Johnson & Smith, 2024). A fusion-based detection model was created to employ visual and thermal image of a single scenario, indicating that the fused image network outperformed single-modality networks in low-light and crowded areas (Huang et al., 2023; Martinez et al., 2024). Generative Adversarial Networks (GANs) have also been applied to enhance visual quality while keeping essential features in both visible and thermal images (Lee et al., 2023; Zhao et al., 2024).

Color-Based Segmentation (CBS) is a computer vision technique that separates images or video frames based on their color properties. Its applications include object detection, image segmentation, medical imaging and industrial quality control. However, its accuracy relies on its capacity to reliably discriminate color differences and it is vulnerable to lighting and parameter variations (Patel & Wang, 2022; Johnson et al., 2024). Scientists have applied Human-Centered Design (HCD) and Cognitive Behavioral Science (CBS) approaches to detect and categorize edges (Garcia et al., 2022; Lee & Chen, 2023; Smith et al., 2024). Neural networks, which imitate the network architecture of the human brain, play an important role in increasing artificial intelligence (Martinez et al., 2024). They have advanced into different forms, including Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) Networks (Russell & Johnson, 2024; Zhao et al., 2024). Deep learning can be characterized by structures with hidden layers which has various uses, including image and text processing. Nonetheless, problems such as overfitting, processing and interpretability still remain, requiring accessible solutions in deep learning. Neural networks pose a delicate balance between computing efficiency and its evolution is not only difficult but also revolutionary (Gonzalez et al., 2023). Convolutional Neural Networks (CNN) are transforming image processing and pattern recognition by applying convolutional layers to input data to extract classified features (Huang et al., 2022). CNN architectures include of convolutional, pooling and fully connected layers that extract spatial patterns, boost processing efficacy, and collective high-level information for classification and regression. Like classic neural networks, CNNs are trained by maximizing weights through propagation.

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### Conceptual Framework

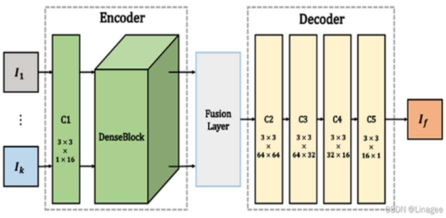
CNNs have reached excellent accuracy in image classification, object recognition, and segmentation, with well-known designs like as AlexNet, VGGNet, and ResNet displaying their improvements (Nguyen et al., 2023; Kumar et al., 2024; Johnson & Smith, 2024). They are also utilized in different applications, including text processing, medical imaging, autonomous vehicles, and image construction. However, CNNs have limitations such overfitting and limited interpretability. Ongoing research tries to solve these issues through innovative designs and training approaches (Huang et al., 2022; Patel et al., 2023). Eventually, CNNs indicate a standard change in image processing, delivering an unmatched ability for feature extraction from visual input. Their flexibility goes past visual fields, making them significant in various areas. As research continues to improve the designs and defy existing obstacles, CNNs will remain at the lead of innovation, pushing the advancement of artificial intelligence and with dual spectral fusion, CNN will jump forward more than its contemporary neural networks.

## METHODOLOGY

The goal of this project is to combine object detection model and dual spectral fusion techniques to create a ample system for indoor smoking detection. Indoor smoking can go unnoticed at times, especially when typical smoke detectors are ineffective in terms of detection. The recommended method uses DenseFuse, a deep learning-based image fusion system that integrate a RGB image and a thermal image of a single scenario to create a new image, with the YOLO framework, which is well-known for its real-time object detection abilities. While DenseFuse is used to improve lighting issues in low-light or visually complex situations, YOLO is used for its ability to recognize various objects in a single frame quickly and consistently. The methods based on data gathering, model training and system evaluation. The YOLO framework is trained on a collection of images to identify smoking-related scenarios. A variety of indoor settings, including homes and public spaces, are used to test the system's adaptability. The fundamental goal of this study is to develop an indoor smoking detection system based on the use of image fusion technology that ensures safety in specified settings, early detection and regulatory compliance. To ensure its robustness and reliability in real-world conditions, the system is designed to work effectively in dynamic and complex indoor situations.

### DenseFuse

DenseFuse is a deep learning method for image fusion technique, combines data from visible and infrared pictures, to provide a fused image with more information. It proved to be an excellent system for combining input images after feature extraction from them via a deep convolutional network architecture. For systems that require a variety of imaging modes, such as object detection, medical imaging, and surveillance, this method will be immensely helpful.




(a)

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(b) (c) (d)

**Figure 1 (a) Architecture of DenseFuse (b) RGB image (c) Infrared image (d) Output from DenseFuse**

The DenseFuse design consist of three important stages: feature extraction, fusion technique, and reconstruction. The first step is to extract feature representations from input images using a dense network of convolutional layers. In the second stage, the image feature maps are combined into a single representation using two vital fusion techniques, namely addition-based fusion and l1-norm-based fusion. To maintain the original image's clarity and spatial resolution while counting elements from both sources, the fused image must be recreated with a sum of convolutional layers. DenseFuse is a popular solution for applications requiring high-quality image fusion and its lightweight design and reliance on training data makes it even more preferable.

## YOLO

YOLO object detection model is a crucial concept in computer vision which enables machines to recognize and find things in images or videos. YOLO is a cutting-edge real-time object identification system with a single CNN. The input image is segregated into a grid of cells using the YOLO architecture, with each cell predicting bounding boxes and classification possibilities. Our grid-based technique inspects the entire image in a single forward cycle through the neural network. YOLO's grid-based, comprehensive technique allows it to collect all-inclusive data and provide accurate predictions. This is highly beneficial in terms of contextual data and object interfaces are essential. Anchor boxes increase YOLO's ability to put up various element inside a single image. However, due to its grid-based technique and low spatial resolution, YOLO may struggle to recognize small items consistently. It may also reduce its understanding of complex background in terms of differentiation between various items, resulting in lower prediction accuracy in challenging situations. Furthermore, YOLO requires a large and well-annotated dataset to be successful. Insufficient or uneven training data may weaken the model's ability to generalize, leading to poor performance. As this project adjusts YOLO for dual spectral image detection, these insights will guide the optimization strategies to align the architecture with the unique challenges it may face.

The YOLOv9c architecture significantly increases object detection accuracy by using cutting-edge technologies such as transformers, EfficientNet-based scaling, and hybrid task cascades to attain effective accuracy and with efficient speed. The core uses Cross-Stage Partial Networks (CSPNet) to split and reuse feature maps, lowering processing load and increasing learning capacity. To achieve high accuracy with minimal processing, YOLOv9c also employs EfficientNet principles, which seek a balance between breadth, depth, and resolution.

To combine data across many backbone levels, the neck design includes a Path Aggregation Network (PANet) and a Feature Pyramid Network (FPN). PANet improves detection accuracy for objects of different sizes, improves feature classification and extraction and simplifies information flow from

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previous layers to the output. YOLOv9c maintains its predecessors' complex prediction technique, which includes class probability predictions at many scales and bounding box regression.

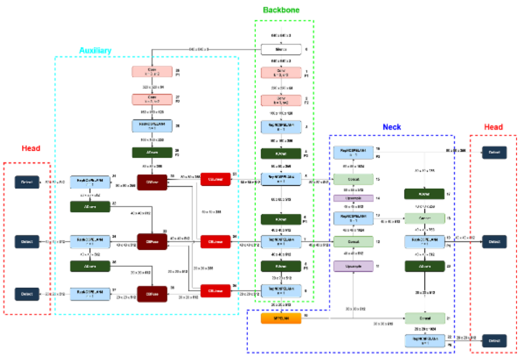


**Figure 2 YOLOv9c Architecture**

Transformer blocks improve detection performance of YOLOv9c by accommodating additional contextual data. YOLOv9c's real-time processing capacity, which has been optimized for both GPU and edge computing. Due to which, it is ideal for low-latency applications such as industrial automation, surveillance systems, and autonomous vehicles. Using transformer-based self-attention techniques, PANet, and FPN to combine features, it significantly improves detection accuracy, especially for small objects. By decreasing false positives and improving classification, the hybrid task cascade technique improves border detection and overall object positioning accuracy. However, because of its complex architecture, YOLOv9c is best suited for powerful computers to get optimal performance. Despite these drawbacks, YOLOv9c advances the field of real-time detection in terms of efficiency and accuracy, setting a new standard for object detection.

## Data Augmentation

Data augmentation is vital in machine learning as it allows us to artificially increases datasets and solve problems caused by a lack of annotated data. It combines knowledge-based and automated approaches in a synergistic way. Domain-specific expertise is required to develop augmentation processes, such as changing functional information or assessing dataset-related features.

Mathematically, let $I$ represent the original image, and $f_k$ be a knowledge-based augmentation function. The knowledge-based augmented image can be expressed as:

$$I_k = f_k(I) \qquad (1)$$

This formulation reflects the application of domain-specific knowledge $f_k$ to the original image $I$, creating an augmented version $I_k$ that retains relevant features.

Neural networks are used in auto-based data augmentation to dynamically alter transformations during training, allowing the model to find the best augmentation path. When the images contain a large number of modifications that are difficult to manually document, this strategy is quite helpful.

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The formulation for auto-based data augmentation involves a policy $P$ learned by the model, which is applied to the original image $I$ during training:

$$I_{auto} = P(I) \qquad (2)$$

Here, $I_{auto}$ represents the image after auto-based augmentation according to the learned policy $P$.

The synergistic technique, which combines automated and knowledge-based techniques, produces domain-specific deviations in data. The goal of this blend is to create a diverse dataset that accounts for natural alternations while retaining domain-specific features. The overall formulation for the combined augmentation can be expressed as:

$$I_{combined} = f_k(P(I)) \qquad (3)$$

Where, $f_k$ represents the knowledge-based augmentation function, and $P$ is the learned policy from auto-based augmentation. Data augmentation is one of the most common method for machine learning systems to emulate real-world scenarios. By increasing variation and allowing the model to properly generalize to new input, the training dataset must be changed. Data augmentation avoids overfitting by adding unpredictability and more diverse traits which allows the model to handle a wider range of situations. It is especially beneficial for training datasets that are limited.

## SE Block Attention Module

The Squeeze-and-Excitation (SE) block is a lightweight attention method that improves the simulated capacity of a neural network by imitating the dependency of feature map channels. It suppresses less valuable features while emphasizing more important ones by modifying channel-specific feature responses. The SE block is a useful module for improving CNN performance because it can be easily integrated into pre-existing convolutional networks. The squeeze strategy reduces the spatial dimension of feature maps. This process transforms the input feature map $U \in R^{HxWXC}$, where $H$ and $W$ are the height and width of the feature map and $C$ is the number of channel, into a vector $z \in R^{1x1xC}$. So, mathematically, the squeeze operation is defined as:

$$z_c = \frac{1}{HxW} \sum_{i=1}^{H} \sum_{j=1}^{W} u_c(i, j) \qquad (4)$$

Here, $z_c$ is the scaler value representing the squeezed feature for channel $c$.

The excitation operation simulates inter-channel dependency by combining two fully connected layers.

The excitation process is defined as:

$$s = \sigma(W_2 \delta(W_1 z)) \qquad (5)$$

Here, $W_1$ and $W_2$ are the weight matrices of the two FC layers, $\delta$ is the ReLU activation function, and $\sigma$ is the sigmoid activation function.

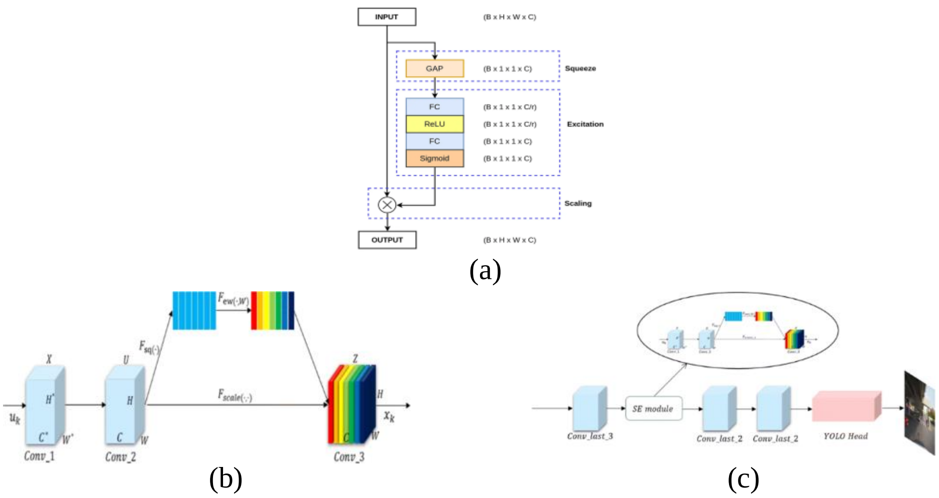


**Figure 3 (a) & (b) are SE block structure and architecture respective , (c) is structure of SE Block in YOLO head**

The recalibration stage reweights the input feature map with channel-wise weights obtained during the excitation operation. The recalibrated feature map V can be expressed by

$$V_c = U_c . s_c \qquad (6)$$

Where, $U_c$ is the $c$-th channel of the original feature map and $s_c$ is the respective channel weight.

This improves feature representation and performance on tasks such as object detection and image classification by increasing the network's sensitivity to key channels while suppressing responses from non-essential ones. The SE block's applications include object detection and image classification.

## CIoU Loss Function

The Complete Intersection over Union (CIoU) loss function improves object detection significantly in neural networks and gives more complex valuation technique for bounding box predictions. The CIoU loss function in YOLOv9c is a useful tool for recognizing objects in difficult situation where the object may be small or under low light. We require you to add the CIoU loss function I YOLOv9c because it is not typically included by default in the basic YOLOv9c.The CIoU loss is defined as:

$$CIoU = IoU - \rho(c) - \lambda \nu \qquad (7)$$

The components of the CIoU loss are $IoU$ which measures the overlap between the predicted bounding box and the ground truth bounding box. It is calculated as the ratio of the area of intersection to the area of the union of the two bounding boxes.

$$IoU = \text{Area of Intersection/Area of Union} \qquad (8)$$

$\rho(c)$ penalizes the difference in aspect ratios between the predicted and ground truth bounding boxes.

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It is a term that depends on the ratio of the width to height

$$c = \frac{w_p}{h_p} - \frac{w_g}{h_g} \qquad (9)$$

The penalty term is calculated as follows:

$$\rho(c) = \frac{c^2}{1 - IoU + c^2} \qquad (10)$$

$\lambda\nu$ penalizes the difference in the distance between the centers of the predicted and ground truth bounding boxes. It is a term that depends on the Euclidean distance between the centers of the bounding boxes. The penalty term is calculated as follows:

$$\lambda\nu = \lambda(1 - \frac{IoU}{v^2}) \qquad (11)$$

where $v^2$ is the square of the diagonal of the smallest enclosing box covering both the predicted and ground truth bounding boxes, and $\lambda$ is a balancing parameter.

The overall CIoU loss is the sum of the IoU and the penalty terms:

$$CIoU = IoU - \rho(c) - \lambda\nu \qquad (12)$$

The parameters $\lambda$ and $\nu$ are usually set based on empirical observations and can be tuned during training.

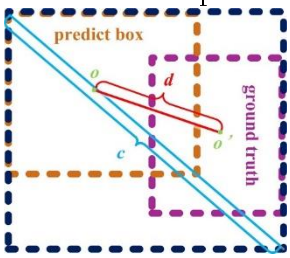


**Figure 4 CIoU loss function for bounding box**

Neural networks use the CIoU loss function to optimize predictions boxes based on its overall validation. Its advantages include its tolerance to aspect ratio changes and its ability to optimize predictions based on the Euclidean distance between predicted and ground truth bounding boxes. It allows it to handle objects of different shapes more effectively and efficiently. This technique also ensures that models are excellent at accurately defining an object's bound boxes while detecting it. The CIoU loss function is important in the development of object detection in neural networks because it provides a comprehensive bounding box distance measure while accounting for aspect ratio variations and localization loss. CIoU validates the need for more precise, durable, and adaptable models in the object detection as machine learning and computer vision technology advances.

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## DATA ANALYSIS AND RESULTS

The YOLO framework and DenseFuse fusion model are combined for the development of an indoor smoking detection system which is effective and efficient. The People&Cig dataset contains 2050 photos of different scenarios consisting smoking and non-smoking people. ND10c is a dual-spectrum thermal imaging camera which was used to collect both the RGB and thermal images. The DenseFuse fusion algorithm is used for data collection, filtering, and identification. Data augmentation is vital for increasing robustness, generalization, and minimizing overfitting. Using data augmentation, the dataset was enlarged up to 4100 images which were in all .jpg format and with 640x640 in dimension.

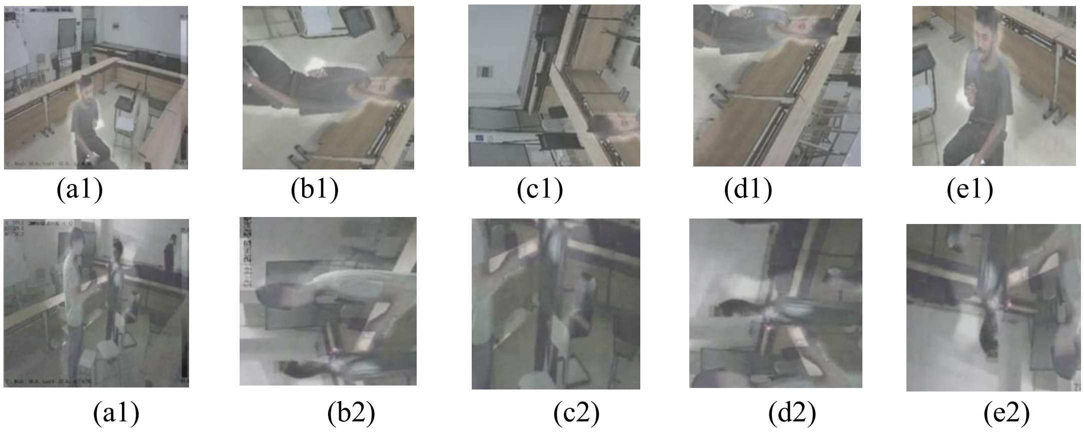


**Figure 5 (a1,a2)Original Image, (b1,b2)Augmented Image (rotation), (c1,c2)Augmented Image (Random Cropping) (d1,d2) Augmented Image (Auto Contrast) , (e1,e2) Augmented Image (Flipping)**

**Table 1 Dataset**

| | Initial | | Augmented | |
|---|---|---|---|---|
| Examine | Images | Label | Images | Label |
| Train | 1640 | 1640 | 3280 | 3280 |
| Validation | 410 | 410 | 820 | 820 |

The technological requirements include an NVIDIA GeForce RTX3090 GPU, 32 GB of RAM, and a 12th-generation Intel Core i9 processor. The Python system provides libraries for scientific computing, data analysis, and machine learning. The research analyzes the effects of data augmentation methodologies on indoor smoking detection models, focusing on convergence speed, stability, generalization, adaptation to novel conditions, overfitting avoidance, robust feature learning, class imbalance control, and hyperparameter sensitivity. Data augmentation plays a crucial role in improving the indoor smoking detection model. It enhances the convergence speed, stability, generalization,

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adaptation to novel situations, avoidance of overfitting, learning robust features, controlling class imbalance, and sensitivity to hyperparameters.

**Table 2 Package and the required version**

| Package | Version | Package | Version | Package | Version | Package | Version |
|---|---|---|---|---|---|---|---|
| iPython | 8.12.2 | Pillow | 7.1.2 | Scipy | 1.10.1 | Tqdm | 4.66.4 |
| Matplotlib | 3.2.2 | Psutil | 5.9.0 | Thop | 0.1.1 | Albumentations | 1.0.3 |
| Numpy | 1.19.0 | PyYAML | 6.0.1 | Torch | 1.7.1 | Pycocotools | 2.0.7 |
| Opencv-Python | 4.1.1 | Requests | 2.32.3 | Torchvision | 0.8.2 | Pandas | 1.4.4 |

The augmentation method effects the training process by exposing the model to a wider range of data and speed up convergence. The training procedure's stability is assessed by comparing the training and validation loss across various epochs. Due to the exposure to a wider range of settings, the model's adaptability increases which ensures that it can accurately detect smoking incidents in various indoor situation.


(a) (b) (c) (d)

**Figure 6 Different output from YOLOv9c(ours)**

Data augmentation helps to solve class disparities by providing equal exposure for both smoking and non-smoking incidents. The YOLO model was modified to improve feature learning by introducing channel-wise attention, an attention module such as SE block attention module placing after specific convolutional layers. In addition, the CIoU loss function was introduced substituting the bounding box regression loss and specifying the calculation with IoU, center point distance, and aspect ratio penalty. To assess the model, we look at convergence speed, stability, generalization, adaptation capabilities, overfitting avoidance, managing class difference, and hyperparameter sensitivity.

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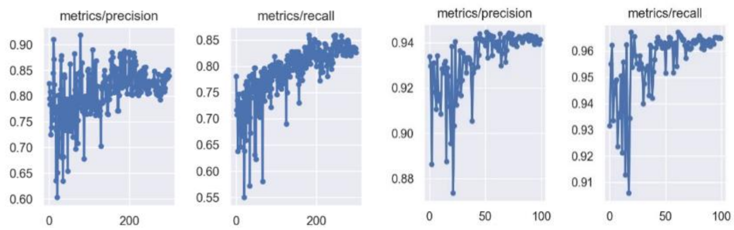
## Result and Analysis



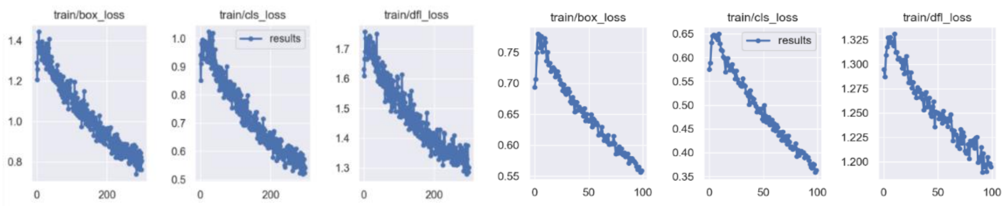

(a) (b) (c) (d)

**Figure 7 (a) & (b) are the precision and recall of basic YOLOv9c and (c) & (d) are the precision and recall of YOLOv9c(ours)**

The YOLOv9c model, originally designed for real-time object identification, has been modified to include Squeeze-and-Excitation (SE) blocks and the Complete Intersection over Union (CIoU) loss function. The updated model outperforms the basic model in precision and recall, with a precision of 93.6% and a recall of 95.8%. The architecture of the YOLOv9c model is improved by incorporating SE blocks that alter channel-wise feature responses, allowing the model to focus on the most useful features.

**Table 3 Precision and Recall comparison between basic YOLOv9c and YOLOv9c(ours)**

| Metrics | YOLOv9c | YOLOv9c(ours) | Gains |
|---|---|---|---|
| Precision(%) | 85.2 | 93.6 | +8.4 |
| Recall(%) | 83.6 | 95.8 | +12.2 |




(a) (b) (c) (d) (e) (f)

**Figure 8 (a), (b) & (c) are the losses for basic YOLOv9c and (d),(e) &(f) are the losses for YOLOv9c(ours)**

The YOLOv9c(ours) model uses CIoU loss to improve box loss by calculating the distance between predicted and ground truth boxes, aspect ratios, and overlap areas. This results in a more accurate calculation of bounding box, improving localization. The inclusion of SE blocks also enhances feature extraction, resulting in a more well-versed and accurate detection of the images. The YOLOv9c(ours) model achieves a mean average precision (mAP) of 93.5%, signifying its greater ability to accurately identify and classify objects in various circumstances. The model's speed and complexity may cause in a minor rise in processing time due to additional calculations, but the significant increases in accuracy rationalize this trade-off.

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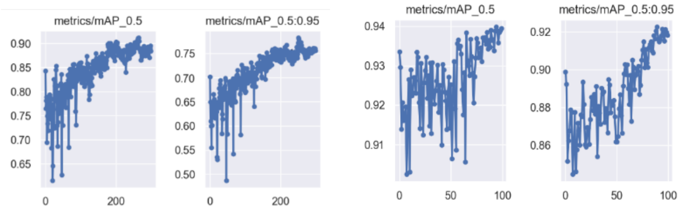


(a) (b) (c) (d)

**Figure 9 (a) & (b) are the mAP and mAP_0.5:95 of basic YOLOv9c and (c) & (d) are the mAP and mAP_0.5:95 of YOLOv9c(ours)**

The modified model decreases the risk of overfitting by integrating CIoU loss function, which allows better generalization across the augmented datasets. The YOLOv9c(ours) model overtakes the basic YOLOv9c in terms of generalization. Finally, the YOLOv9c model offers substantial enhancements in detection accuracy to handle difficult visual surroundings.

**Table 4 Result comparison between basic YOLOv9c and YOLOv9c(ours)**

| Metrics | YOLOv9c | YOLOv9c(ours) | Gains |
|---|---|---|---|
| mAP_0.5(%) | 89.9 | 93.5 | 89.9 |
| mAP_0.5:95(%) | 76.1 | 91.7 | 93.5 |

The study compares the basic YOLOv9c and YOLOv9c(ours), revealing significant improvements in detection accuracy and performance. The modified model had a mAP increment from 89.9% to 93.5%, precision from 85.2% to 93.6%, and recall from 83.6% to 95.8%, making it an practical alternative for high-precision object detection system.

### Ablation Studies

The ablation experiment is conducted to validate the attributes of various modifications to the YOLOv9c model. We focus on accuracy, feature extraction and robustness in challenging sceneries. Three basic YOLO models were tested: YOLOv5s, YOLOv7, and YOLOv8s along with YOLOv9c and YOLOv9c(ours). YOLOv5s is known for its stability between speed and precision, making it suitable for real-time object detection. YOLOv7 outperforms its predecessors in terms of speedy detection with accuracy, making it an ideal model for complex indoor settings. YOLOv8s is known for its effective architecture and multi-scale detection abilities, making it valuable for detecting objects in challenging situations.

### Effect of Dual Spectral Image Fusion and Data Augmentation

Dual spectral image fusion allows the YOLOv9c model to perform well in low-light, or visually challenging situation. By combining infrared and visible images, the model can look for more widespread and varied appearances, which improved its detection ability in varying scenario. Due to data augmentation, the generalizability of the YOLOv9 model improved immensely. By exposing the model to augmented dataset, it became more robust in terms of detecting its target classes, increasing its ability to detect objects in complex situations.

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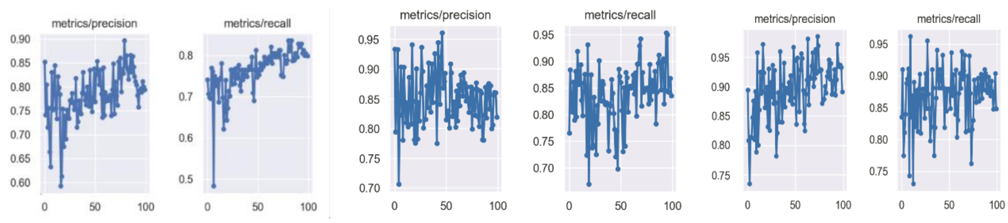


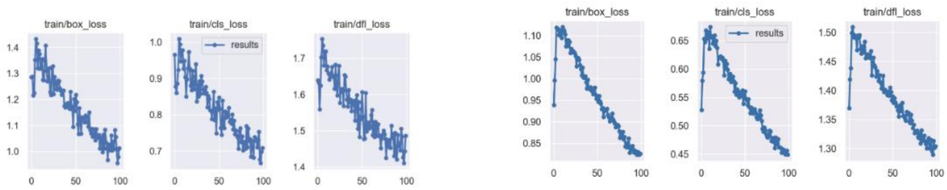

(a) (b) (c) (d) (e) (f)

**Figure 10 (a),(c) & (e) are the precision for the YOLOv5s, YOLOv7 and YOLOv8s respectively, (b), (d) & (f) are the recall for the YOLOv5s, YOLOv7 and YOLOv8s respectively**

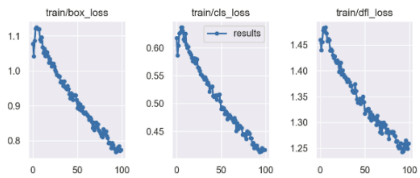
This is apparent from the improved recall (95.6%), mAP_0.5 and mAP_0.5:95 scores (93.5% and 91.7%, respectively) for YOLOv9c (ours) than the basic YOLOv5s, YOLOv7 and YOLOv8s as found in **Table** 5, **Table** 6 and **Table** 7. The augmented dataset also helped to stabilize the training process, as the dataset become much larger than the original one. The result is more consistent decrease of loss across box loss and class loss, accumulating to the model's overall adaptibilty.

**Table 5 Comparison of precision and Recall for YOLOv5s, YOLOv7, YOLOv8s, YOLOv9c and YOLOv9c(ours)**

| Metrics | YOLOv5s | YOLOv7 | YOLOv8s | YOLOv9c | YOLOv9c(Ours) |
|---|---|---|---|---|---|
| Precision | 79.2 | 82.6 | 89.1 | 85.2 | 93.6 |
| Recall | 80.5 | 83.9 | 91.3 | 83.6 | 95.6 |




(a) (b) (c) (d) (e) (f)



` (g) (h) (i)

**Figure 11 (a), (d) & (g) are the box losses for the YOLOv5s, YOLOv7 and YOLOv8s respectively, (b), (e) & (h) are the class losses for the YOLOv5s, YOLOv7 and YOLOv8s respectively and (c), (f) & (i) are the dfl losses for the YOLOv5s, YOLOv7 and YOLOv8s**

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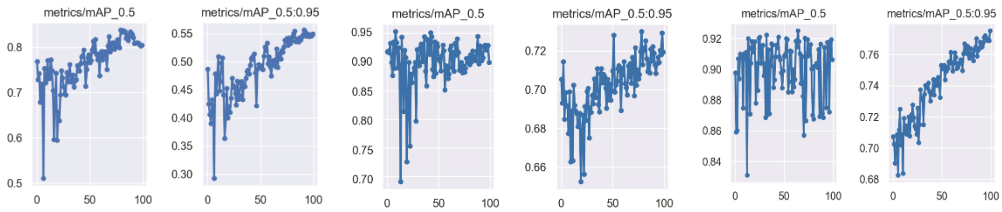
### Effect of implementation of SE Block Attention Module

The Squeeze-and-Excitation (SE) block helped to refine feature selection by recalibrating key features inside the network. It allowed the model to focus on essential qualities, which had a direct impact on class loss. Our modified YOLOv9c showed reduced class loss than YOLOv5s, YOLOv7, and YOLOv8s, as well as faster convergence as shown in **Figure** 8 and **Figure** 11.




(a) (b) (c) (d) (e) (f)

**Figure 12 (a),(c) & (e) are the mAP for the YOLOv5s, YOLOv7 and YOLOv8s respectively, (b), (d) & (f) are the mAP0.5:0.95 for the YOLOv5s, YOLOv7 and YOLOv8s**

This resulted in a significant increase in precision (93.6%) for YOLOv9c(ours) in comparison to YOLOv5s, YOLOv7 and YOLOv8s as shown in **Table** 5 and **Table** 7. This indicates that YOLOv9c(ours) became more successful at correctly identifying objects by removing unnecessary information.

### Effect of implementation of CIoU loss function

The implementation of the CIoU loss had a direct impact on the accuracy of bounding box predictions. By reducing the center distance, aspect ratio, and overlap between predicted and ground truth boxes, CIoU loss enhanced the model's localization accuracy. This is seen by the reduced box loss and DFL loss in the modified YOLOv9c (ours) when compared to YOLOv5s, YOLOv7 and YOLOv8s as shown in **Figure** 7 and **Figure** 11. The YOLOv9c(ours) demonstrated smoother and faster convergence, particularly in the mAP_0.5:95 and box loss measurements, indicating a positive influence on localization accuracy as shown in **Figure** 8 and **Figure** 12.

**Table 6 Comparison of mAP and mAP_0.5:95 for YOLOv5s, YOLOv7, YOLOv8s, YOLOv9c and the YOLOv9c(ours)**

| Metrics | YOLOv5s | YOLOv7 | YOLOv8s | YOLOv9c | YOLOv9c(Ours) |
|---|---|---|---|---|---|
| mAP_0.5(%) | 81.4 | 89.7 | 90.8 | 89.9 | 93.5 |
| mAP_0.5:95(%) | 56.8 | 73.2 | 78.6 | 76.1 | 91.7 |

In conclusion, each of these modifications namely, data augmentation, SE block attention module and CIoU loss function made a distinct contribution to improving different aspects of YOLOv9c (ours). Data augmentation improved generalization and recall, SE block improved precision through better feature selection and CIoU loss improved bounding box precision. Collectively, these changes resulted in improved overall performance, making YOLOv9c (our model) the more accurate and resilient among the other YOLO models.

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**Table 7 Gains of YOLOv9c(ours) over different YOLO models in terms of evaluation metrics**

| Models | Precision(%) | Recall(%) | mAP_0.5(%) | mAP_0.5:95(%) |
|---|---|---|---|---|
| YOLOv5s | 14.4 | 15.1 | 12.1 | 34.9 |
| YOLOv7 | 11 | 11.7 | 3.8 | 18.5 |
| YOLOv8s | 4.5 | 4.3 | 2.7 | 13.1 |
| YOLOv9c | 8.4 | 12 | 3.6 | 15.6 |

## CONCLUSION AND RECOMMENDATIONS

In this article, the YOLO framework and dual spectral fusion image technology are combined to create an indoor smoking detection system, which performed well under a diverse lighting conditions and outperformed its predecessor in terms of precision and accuracy. It demonstrated the potential for future advances in public safety by effectively addressing false positive issues, making it a viable option for applications requiring high detection accuracy and durability. Despite its limitations, the YOLOv9c (our) has demonstrated some performance benefits. The model's application in real-time in different devices, such as mobile or embedded devices, may be limited due to its increased processing complication and inference time. Hopefully, with energy-efficient sensor and network, the model can detect and notify in real time with little delay (Umer et al., 2023; Mushtaq et al., 2024). There is another drawback in terms of object detection tasks as the model may struggle to differentiate small items against complex backgrounds. To improve the model's effectiveness and flexibility for practical use, future research should concentrate on model optimization, improved small object detection and increased generalization abilities.

## CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

**Abdullah Al Nayeem Mahmud Lavu**: Concept, Methodology, Software, Validation, Formal analysis, Experimentation, Data organization, Original Draft. **Hua Zhang**: Resources, Writing-review & editing, Supervision, Project administration. **MD Anisul Islam Jonaid:** Data organization, Writing-review &editing. **MD Toufik Hossain**: Data organization, Writing- review & editing.

## DATA AVAILABILITY

The data can be obtained from the authors upon request.

## CONFLICT OF INTEREST

The author declare that, they are no known conflict of interest which could have influenced the work presented in this paper

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Not Applicable

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