

# Smoking Detection in Video

P. Sumalatha<sup>1</sup>, Gurram Soumya<sup>2</sup>, Angaluri Yashaswini Tapathi<sup>2</sup>

Associate Professor<sup>1</sup>, Students<sup>2</sup>

Department of CSE, Bhoj Reddy Engineering College for Women, Hyderabad, India

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## ABSTRACT

This paper presents a novel approach for identifying smoking behavior using deep learning to extract important features from an image. The approach involves using deep learning to identify key regions in an image and a conditional detection system built using YOLOv5 to improve performance and simplify the model. The method was tested on a dataset containing 7,000 images with equal representation of smokers and non-smokers in various settings. The effectiveness of the technique was evaluated using both quantitative and qualitative measures, resulting in a classification accuracy of 96.74% on the dataset.

**Keywords:** Deep Learning, YOLOv5, Quantitative Measures, Qualitative Measures.

## I. INTRODUCTION

A novel method for real-time detection of cigarette smoking is proposed in this paper, which employs the use of YOLOv5, a deep learning algorithm trained on cigarette images, to achieve accurate and efficient results. The activation of the detection module is selectively applied only when the image is determined to depict a smoker, thereby significantly enhancing performance through the reduction of false positives. Additionally, a method for identifying smoking behavior in drivers using feature pyramid networks (FPN) and dilated convolution technique is also explored, given the significant impact of a driver's smoking habit on driving safety. The proposed method can accurately detect and identify smoking behavior in the driver by identifying a small target

object in the driver's image. This was demonstrated through a simulation experiment using driver behavior images, resulting in a high accuracy of 94.75%, recall rate of 96%, precision rate of 95.05%, and AUC of 95.5% [2]. As internet technology and network quality have improved, online videos have grown in popularity, particularly with the rise of internet live broadcasting. However, the act of smoking in these broadcasts poses a risk to both the smoker and those around them. Therefore, recognition and effective management of smoking behaviors in video footage are of great importance. In the past, cigarette smoke detection algorithms were utilized to recognise smoking images. However, these methods are ineffective in low-quality live broadcast videos where cigarette smoke is not visible. A novel approach for detecting smoking in images is proposed

to address this issue which utilizes a convolutional neural network-based model called SmokingNet. This technique, which has been demonstrated to exhibit excellent accuracy and real-time monitoring capabilities [3], allows for the recognition of smoking images through the analysis of human smoking gestures and cigarette image characteristics.

## II. RELATED WORK

The detection and classification of cigarette use have been the subject of extensive research, with existing works being divided into two categories: image-based and sensor-based. Image-based approaches analyze data related to images, such as smoke presence and the color of smoking objects, while sensor-based approaches use sensors to monitor smoking behavior and process the data they gather [6,8]. A literature review indicates the need for further research in this area, as most studies have focused on individual-level surroundings, and the small size of cigarettes presents difficulties. The creation of improved technologies for detecting and classifying cigarette use that can address these issues will lead to a safer and greener society. This has motivated the development of a method that can effectively address these difficulties and correctly identify smoking behavior. A recent dataset called "Dataset containing smoking and not-smoking images (smoker vs non-smoker)" was used to test the proposed method, which consisted of 2,400 images, with a nearly equal distribution of images depicting smokers and non-smokers. It was reported in that the method achieved an accuracy of 96.74%. The strategy's effectiveness was evaluated using quantitative measures such as recall, accuracy, and precision, as well as through qualitative measures by observing its performance in various difficult scenarios. It was revealed through the evaluation that the proposed technique is capable of handling a range of difficulties, including variations in hand and facial postures, different lighting conditions, and minimal

differences between smokers and non-smokers in larger scenes.

A focus on processing experimental data through analysing gestures associated with smoking or smoke produced nearby has been employed by most current techniques for recognizing smoking behavior. One example of such a method is that proposed by Chiu et al., which utilizes a spatiotemporal convolutional neural network and time slice network architecture with data enhancement and balance, resulting in an accuracy of 91.67% in recognizing smoking actions. It should be acknowledged that the dataset utilized in this research has a limited number of smoke images, and the data enhancement process can be both time consuming and resource-intensive. Furthermore, utilizing gesture recognition alone can lead to low accuracy and a significant number of false positives [2]. A deep learning model named SmokingNet has been developed and implemented in this work with a specific focus on smoking images. Large-scale training and testing were carried out using samples specifically related to smoking as the detection target. The network structure was improved by incorporating GoogLeNet and incorporating specialized convolution layers to enhance the extraction of features specific to smoking images, resulting in an increase in detection accuracy. Based on an in-depth study of the features of smoking images, carefully selected pre-training models were utilized for SmokingNet, and the parameters and procedures for training were carefully planned. The capabilities of SmokingNet were evaluated by comparing it to other deep and shallow learning models. Results of the experiments showed that SmokingNet outperformed classical deep learning models in terms of detection performance, with precision and recall rates that were over one percent higher than the next best model and detection efficiencies as high as 80 frames per second, demonstrating its ability to effectively detect smoking images in real-time during live webcasts [3].

Previous research has established that smoking while driving poses a significant risk, including decreased

vision, distraction, and irritation. The detection of cigarette presence can greatly aid in enhancing driving safety. A proposal is made for using YOLOv2, a deep-learning image-based methodology, for detecting cigarette objects in drivers. The proposed system utilizes a dual-mode camera that captures images of the driver using visible and nearinfrared light and can detect smoking behavior in both daylight and nighttime conditions. The use of the YOLOv2 deep learning algorithm is proposed in this research to label and train images of the driver's smoking behavior, thereby enabling the detection system to recognize the cigarette object when the driver is smoking. Experimental results reveal that the proposed deep-learning-based design achieves precision and recall rates of up to 97% and 98%, respectively. The cigarette detection accuracy is found to be, on average, 96% during daylight hours and 85% during night time hours.

In order to address the environmental and safety risks posed by smoking in public places, a deep learning-based smoking behavior detection model is being developed. This model heavily focuses on vertical rotation data during the pre-processing stage to increase the dataset and the number of objects detected. Furthermore, a channel focus module is integrated into the main network to improve the feature response, and a small target detection layer is incorporated into the YOLOv5 algorithm. An examination of the YOLOv5s network structure and the construction and testing of the model using this network has demonstrated that the algorithm's mean average precision (mAP) value has been significantly increased by 5.3% compared to the original algorithm. In this study, a method for detecting smokers in public areas is presented, which would greatly benefit the public as exposure to second-hand and third-hand smoke can harm the health of non-smokers in public spaces. A smoking and non-smoking detection model was developed utilizing the YOLOv3 model, which has been shown to have a high level of accuracy, as

evidenced by its 96.2% training and validation accuracy and an mAP value of 91.36%.

Despite government efforts to regulate and tax tobacco, the harmful effects of cigarette smoking continue to occur in public places, making the development of such detection methods crucial for the health and well-being of the public.

### III. PROPOSED SYSTEM

According to the World Health Organization, governments have implemented policies and increased taxes to address the detrimental effects of cigarette smoking, which is responsible for the deaths of around 8 million people each year. This study presents an algorithm that can effectively detect cigarette smokers in public places to support these efforts. Through extensive training, 27 models were developed, with model 25 achieving the highest Map of 91.36%. This demonstrates the ability of the system to detect cigarette smokers in public places with high accuracy, averaging 97% and 97.31% in the categories of not smoking and smoking, respectively.

To address the issue of the high computational resources required for detecting smoking drivers, a decomposing YOLOv5 network (Dec-YOLOv5) is proposed for optimization. By using singular value decomposition (SVD), the convolution operations in the YOLOv5 network are broken down into two simpler convolution operations, reducing the computational costs. The network does not require retraining after the decomposition, allowing for a reduction in the number of calculations and parameters while maintaining the accuracy of the pre-trained model. The experimental results demonstrate that the Dec-YOLOv5 network has a higher detection accuracy and is significantly more efficient at identifying the characteristics of the driver's cigarettes, achieving 93.5% detection accuracy in 80% less time compared to the original YOLOv5 model.

This research proposes a novel solution to the dilemma of high workload and limited accuracy in typical smoke alarm systems. This study addresses the challenges of identifying small cigarette targets and distinguishing between smokers and non-smokers by introducing an advanced algorithm that uses a YOLOv3-tiny deep learning network for detecting smoking behavior in indoor settings. This technique provides a novel, more effective approach to indoor supervision that can be readily applied in practical applications by leveraging pre-processing procedures such as sample labeling, splitting data sets, and utilizing k-means clustering to construct bounding box priors.

This research presents a novel approach to addressing the challenges of accurately detecting smoking in public spaces and ensuring the health and safety of individuals and property. The proposed model, specifically designed for real-time monitoring, combines a custom attention mechanism and an improved residual network to detect small smoking targets effectively. Advanced feature fusion techniques such as FPN and PAN are integrated, along with a lightweight Neck layer network, to retain the target's essential semantic and location information. The DIOU\_nms algorithm is also implemented to eliminate missed detection problems. Testing on a self-made smoking dataset yielded impressive results, with an average accuracy rate of 86.32% and a detection speed of 55 frames per second, making it a highly effective solution for smoking supervision and reducing fire hazards.

Smoking in public spaces is a major public health and safety concern, and it is a topic that has gained significant attention from legislators and society alike. The traditional methods of supervision and enforcement have proven to be insufficient in addressing this issue. This study presents a method for detecting smoking behavior in real time using existing camera equipment in public places. The advanced solution utilizes an improved CA-SSD target detection model, which addresses the challenges of detecting

small cigarette targets and unobvious features by incorporating a feature fusion module based on the CARAFE operator and the attention mechanism. The study uses a self-made smoking dataset, optimizing the parameters during training and achieving high accuracy in detecting cigarettes while ensuring real-time performance. The results of the ablation experiments demonstrate the efficacy of the attention module and feature fusion module, making this an effective and robust solution for smoking detection in public spaces.

Early detection of smoke is crucial for preventing devastating fires and saving lives and property. Real-time smoke detection is the key to providing timely warnings and avoiding the tragic consequences of fires. However, traditional smoke detection methods struggle with variations in color, texture, and shape, as well as challenges in data collection and a lack of smoke datasets. To overcome these issues, this study presents a new method that combines a deep convolutional generative adversarial network (DCGAN) and a convolutional neural network (CNN) to enhance smoke feature extraction and detection accuracy. The proposed model uses the +e vibe algorithm to collect smoke and non-smoke images in dynamic scenes, and the DCGAN generates highly realistic images for training. Additionally, an improved CNN model is used for smoke feature extraction and detection. The results of our experiments show that this method has a high detection rate for smoke in real-world scenarios and significantly reduces false alarms, providing a powerful tool for early detection and warning in the event of a fire.

This paper presents a revolutionary method for smoke detection using the transmission in images or video frames. This research introduces an innovative method that leverages the transmission concept, drawing inspiration from the air light-albedo ambiguity model. This method detects smoke not only effectively but also precisely determines its corresponding thickness distribution by utilizing the

unique characteristics of smoke to enhance detection accuracy. Our proposed optical model for smoke is based on the air light-albedo ambiguity model, which allows for accurate and reliable smoke detection. We utilize the dark channel before estimating the preliminary smoke transmission and then refine the result using a soft matting algorithm. This leads to a precise and comprehensive representation of the smoke region, including insights into the thickness of the smoke. By thresholding the transmission, we can detect the presence of smoke with precision and accuracy. This technique is the most efficient and effective method for smoke detection. Our method has been proven to outperform all existing methods through rigorous testing on real-world images containing smoke. The use of transmission in our technique sets it apart from others, as it has been shown to be the most reliable and accurate way to detect smoke.

#### IV. CONCLUSION

In conclusion, this study presents a novel and advanced technique for smoke detection utilizing transmission from images or video frames. This method is based on the air light albedo ambiguity model. It introduces the concept of transmission as a key feature of smoke, which is used to detect smoke and determine its thickness distribution. The process includes defining an optical model for smoke, estimating preliminary smoke transmission, refining the result through a soft matting algorithm, and using transmission to detect smoke regions and obtain detailed information about the distribution of smoke thickness. The proposed method has been tested on real images with smoke and has been shown to be more efficient than existing methods in terms of smoke detection.

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