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Artificial Intelligence for Smoking Detection: A Review of Machine Learning and Deep Learning Approaches

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Abstract

Cigarette smoking poses a major challenge to public health worldwide and has serious health consequences. Recent advances in deep learning, machine learning, Artificial Intelligence (AI), big data analytics, and computer vision have greatly enhanced smoking detection. These technologies enable the analysis of diverse datasets to identify patterns that indicate smoking behavior By enhancing the effectiveness of smart smoking detection systems and so we can better protect public health and reduce exposure to secondhand smoke in public places. An AI-based monitoring system is crucial to enhancing the fight against smoking in restricted areas by establishing a framework for identifying the locations of smoke detection systems across the city. This paper aims to shed light on the effectiveness of these smart systems in facilitating smoking cessation efforts and ensuring compliance with no smoking rules by reviewing previous studies on smoker detection and the algorithms used in those studies and their degree of effectiveness and efficiency in achieving the intended goal. They were examined, analyzed, classified, A comparison was made between research that used machine learning and research that used deep learning, and a comprehensive scientific comparison was made, with special attention paid to the data used to build the model. Furthermore, this paper will provide data on the results of indoor and outdoor smoker detection using smart algorithms, contributing valuable insights for future research in this area.

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1. Introduction

The greatest avoidable cause of mortality and disability is smoking. According to figures from the World Health Organization, tobacco use directly causes over 7 million deaths, while secondhand smoke exposure for non-smokers results in an additional 1.2 million deaths. Children are particularly vulnerable to the health risks associated with secondhand smoke [1]. In addition to contaminating the surroundings, indoor smoking puts one's own and other people's safety in jeopardy. Simultaneously, there exist possible safety risks that could result in mishaps like fires causing financial damage and human casualties. Consequently, it is especially crucial to detect smoking behavior in areas where it is forbidden [2].

One fundamental problem that is extremely important in many different fields, from robotics and medical imaging to autonomous cars and surveillance systems is object detection. Due to the variety in item appearance, scale, orientation, occlusion, and lighting conditions, object identification is intrinsically complicated and entails both precisely localizing objects using bounding boxes and detecting them within photos or videos. Because deep learning allows algorithms to learn features straight from raw pixel data, it has completely changed object detection [3].

AI plays a crucial role in the accurate and efficient detection of smokers by employing various methodologies. Machine learning algorithms, including deep learning models, can analyze patterns in data collected from video feeds, images, or sensor inputs to identify smoking behavior. For instance, AI can process image data to recognize specific actions, such as bringing a cigarette to the lips or detecting smoke, allowing it to distinguish between smokers and non-smokers. Additionally, AI systems can enhance detection accuracy by incorporating biometric data, such as heart rate and breathing rate [4].

Deep learning and machine learning models have demonstrated significant promise in several applications in computer vision lately [5]. like object detection, Finding and detecting items inside an image or video feed is known as object detection [6].

The remaining parts of this paper are arranged as follows: The Types of Datasets are displayed in section two; section three includes Artificial Intelligence and detection; section four includes Basic Models Utilizing Artificial Intelligence Techniques for Detecting Cigarette Smokers; section five includes Discussion; and section six Conclusion.

2. Type of Dataset

To identify cigarette smokers, a variety of datasets are utilized, often based on the chosen methodology and approach. **Table 1** shows some typical types of datasets.

Table 1. Types of Datasets.

Dataset Types	Description	Usage
Annotated Image Datasets [7].	Sets of images in which smoking activities are labeled or annotated, commonly featuring bounding boxes around cigarettes or smoke, along with labels that signify smoking actions.	These datasets are crucial for Convolutional Neural Networks (CNNs) in particular to be trained and evaluated as machine learning models for identifying aspects of smoking in photographs
Video [8].	Video recordings obtained from surveillance cameras positioned in public or private areas, documenting individuals' activities, including smoking.	These datasets are used in computer vision models to identify cigarettes, detect hand to mouth movements, and detect the presence of smoke automatically in real time
Sensor Data Datasets [9].	These datasets contain readings from various sensors, including smoke detectors, air quality monitors, and specialized sensors that analyze the chemical composition of the air Examples: Data collected from sensors that measure particulate matter, carbon monoxide, or nicotine levels in the environment	These datasets are frequently utilized in Internet of Think (IoT) based systems to activate alarms or notifications in areas designated as non smoking
Physiological Data Datasets [10].	These datasets contain information pertaining to physiological parameters, including heart rate, respiratory rate, and breath composition. Examples: Heart rate variability, levels of carbon monoxide in breath, and other biometric indicators of smoking behavior.	machine learning models utilize these datasets to detect patterns that are consistent with smoking activity

As observed from Table 1 above, the data type for detecting smokers is through images, videos, sensors, and physiological measurements by analyzing visual cues, environmental conditions, and biological signals to achieve a high accuracy of smokers detection. This particular data is analyzed from images, videos, sensor signals, and biological measures to develop technologies that can detect smoking, which further plays its role in providing enhanced monitoring of smoking behavior and detection at different locations.

3. Artificial Intelligence and Detection

Artificial intelligence (AI) techniques are widely used in the industry, such as in video games, robots, self-driving cars, and other applications [11]. and uses a variety of algorithms to detect a cigarette smoker. Here are some common types of algorithms and techniques used in this field:

Machine learning models can be classified as either supervised or unsupervised. In supervised learning, a mapping function is used to predict dependent variables from independent ones, where the dependent values in the training data are predetermined based on sources like previous research or expert judgment for sample annotation. On the other hand, unsupervised learning does not rely on a specific outcome variable and instead gathers feedback on the independent variables. In any machine learning model, the training process involves tuning the model's parameters using a portion of the dataset. The model's performance is then assessed during the testing process using the remaining (unseen) data. Additionally, part of the training data is often used to assess how well the model parameters fit, known as the evaluation process. The model's prediction accuracy, which reflects its ability to recognize patterns and relationships within a new, unseen dataset, is used to measure its effectiveness [12].

Machine learning based categorization system that uses random forest, K-Nearest Neighbors (K-NN), Linear Regression (LR), and Naïve Bayes to predict the different types of smokers. It is found that both Naïve Bayes and random forest perform well among the four classification algorithms that were used. Random forest performs better than Naïve Bayes in this regard. Regarding recall, f1 score, and precision, random forest is the most superior model of the four models, achieving the highest scores for both smokers and drinkers. Given everything, random forest is a strong choice for predicting types of smokers due to its ability to handle complex, high dimensional, and imbalanced data, along with its interpretability and robustness [13].

Deep learning, machine learning development, uses sophisticated algorithms that mimic human cognitive processes to outperform shallow neural networks. Deep neural networks are made up of these algorithms that imitate the human brain's logical organization, allowing them to make decisions based on data analysis. Deep learning uses an end-to-end learning methodology architecture, which minimizes human interaction, in contrast to classical machine learning, which depends on manually derived characteristics. Deep neural networks have an architecture made up of several nonlinearly connected layers, which improves their capacity to recognize complicated patterns. On the other hand, human designed features are built into models by a methodical process of feature extraction in traditional machine learning, which is embodied by shallow neural networks. Handcrafted features are used by computer vision to reliably identify objects in images, an approach that is distinct from deep neural networks' automatic feature learning [14].

One of the algorithms for deep learning is (CNNs) that use a camera feed. CNNs can be utilized in real time to recognize motions associated with smoking or cigarettes. CNNs are particularly useful in image and video analysis. Furthermore, LSTM (long short term memory) and Recurrent Neural Networks (RNNs) are suitable for time series data that can analyze sequences of data points, such as heart rate or breathing rate, to identify patterns that indicate smoking [15].

In a number of application sectors, deep learning has been successfully used in the past few years to address a wide range of challenges. Examples include robotics, business, cybersecurity, image recognition, healthcare, and many more. Natural language processing and sentiment analysis are also included. In many computing processes, deep learning can be seen as a way to improve results and speed up processing times. [14] **Figure 1.** shows the relationship between artificial intelligence, machine learning, and deep learning.

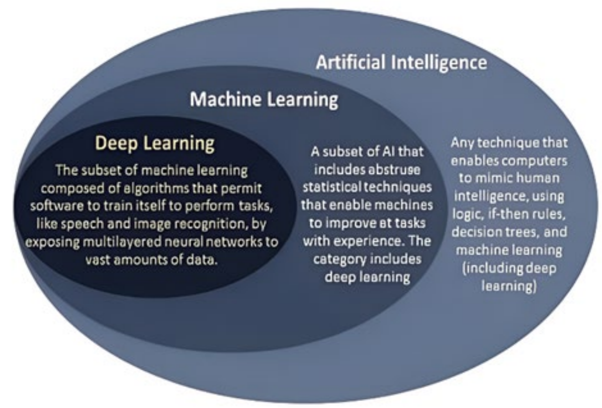

Figure 1. The relation between artificial intelligence, machine learning, and deep learning [16].

4. Basic Models Utilizing Artificial Intelligence Techniques for Detecting Cigarette Smokers

The use of AI methods, including machine learning and deep learning, for cigarette smoking detection has grown. A number of essential elements are usually included in these models: feature extraction, data collection, model training, and evaluation. An overview of a fundamental AI model for detecting cigarette smoking is provided below, along with a simplified schematic and references.

1. Data Collection: Data is gathered from multiple sources and sensors. Common data types include image data: captured from Surveillance cameras [8]. Breath analysis: Using sensors to detect chemical markers in breath [17]. Heart rate and breath rate: monitored through wearable devices [18].

2. Feature Extraction: is a critical step in smoking detection, where key characteristics are identified from raw data to help in classification [19]. For image data, features like the presence of a cigarette, distinctive smoke patterns, and hand to mouth movements associated with smoking behavior are commonly extracted [20]. In breath analysis, the focus is on identifying chemical signatures, such as elevated levels of carbon monoxide, which are often linked to smoking [21]. Physiological data, like heart rate and breath rate, is also useful; smoking tends to cause notable changes in these signals, making them reliable indicators. These extracted features are then processed by machine learning models for accurate smoking detection [22].

3. Model Training: The features that are extracted are used to train machine learning and deep learning models, Typical algorithms in use are: YOLO (You Only Look Once) for real time object detection [23]. CNNs for detection based on images, Support Vector Machines (SVMs) for physiological data and breath analysis [24]. random forests is one of the extremely methods for fusing several feature types [25]

4. Evaluation: To make sure the trained models are effective in identifying smokers, they are assessed using measures like accuracy, precision, recall, and F1-score [26]. See **Figure 2**.

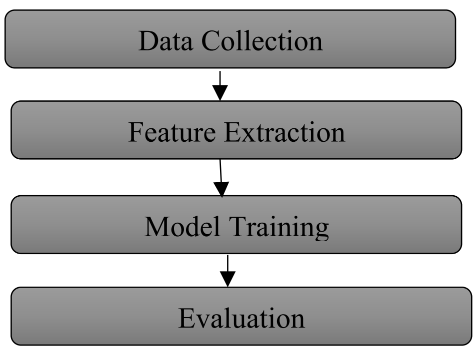

Figure 2. Basic Models Utilizing Artificial Intelligence Techniques for Detecting Cigarette Smokers.

The algorithms and methods used to detect smokers in terms of machine learning and deep learning have been discussed in the following subsections.

4.1 Machine learning approaches in smoke detection

Object detection is widely used in the field of computer vision and is essential for a variety of applications, e.g., self driving car. During half a century of development, object detection methods have been continuously developed, and many methods have been produced that have achieved promising achievements. Nowadays, object detection approaches have largely developed into two categories: traditional machine learning methods that use various computer vision techniques and deep learning methods. Deep learning, whose algorithms For example include Region based Convolutional Neural Network (RCNN) and YOLO [27].

Humans are naturally able to learn new things and advance through encounters. In a similar vein, machines may learn from data and get better as a result; this is called machine learning.

Machine learning, a branch of artificial intelligence, enables computers to recognize patterns on their own and make judgments with little to no human input. Algorithms are trained by subjecting them to a variety of scenarios; this allows them to gain additional data to refine their knowledge and increase accuracy. Businesses use machine learning to automate and streamline processes. Machine learning significance is demonstrated by computer vision applications such as image detection and facial recognition. Image analysis recognizes facial features for security systems and smartphone unlocking applications. Image detection allows autonomous cars to identify objects in real time and make well informed decisions. Machine learning combines supervised learning drawing conclusions from historical data with unsupervised learning, which finds patterns without labeled guidance and is flexible enough to be used in a variety of contexts [14]. There are many studies that have discussed the detection of smokers using different machine learning techniques, which will be explained with the strengths and weaknesses of each study as follows:

In 2010, the researcher Pin Wu and et all. [28] presented research entitled "Human Smoking Event Detection Using Visual Interaction Clue" study that uses the color ratio histogram to analyze and extract visual cues gleaned from the apparent interactions between the person and the burning cigarette to automatically and directly identify instances of smoking in a video. Techniques for color reprojection and Gaussian mixture models (GMMS) were applied. With the use of a ratio histogram, an accuracy analysis of cigarette detection was accomplished.93.2%, and 82.1% in terms of smoking event detection accuracy analysis. The research presents a new mechanism for automatically detecting smoking events in videos using color ratio analysis and Gaussian mixture models. However, the model may be less accurate when testing new events that the system has not been trained on and may need to be modified and developed to include multiple other cases.

In 2012,Amin Ashsan Ali and et al. [29] presented research entitled "mPuff: automated detection of cigarette smoking puffs from respiration measurement on introducing the Mpuff system, which is a system for automatically detecting smoking pus resulting from respiratory measurements, through It can be automatically built as a model to track cigarette use resulting from respiratory measurements and note that it achieved 91% accuracy during a session. Smoking. The algorithm was still able to identify smoking pus at an 86.7% recognition rate when included breathing measures taken during confounding situations like stress, chatting, and walking. The research is distinguished by the introduction of a large number of new features in breathing, which help in distinguishing between smoking puffs and other similar events such as stress, conversation, and walking. One of the most important weaknesses is that the system was tested on a small sample of participants (10 people), which may limit the generalization of the results to larger and more diverse population groups. Therefore, it needs further development and improvement and the participation of more people for the system to be more efficient.

In 2013, researchers Tse Lun Bien and Chang Hong Lin. [30] prepared a research paper entitled "Detection and recognition of indoor smoking events "They unveiled a brand new research plan for employing security cameras to automatically identify and detect smoking incidents. This approach introduces the analysis of human actions from their poses through the use of human pose estimation. The skin color detection approach is used in the human pose estimation method to separate the head and both hands from other human body parts. However, insufficient lighting can cause skin color techniques to fail. As a result, lighting correction is used to increase the accuracy of the skin color detecting technique. The body portions that are missing are tracked using the Kalman filter. Subsequently, assess the likelihood characteristics of hands reaching the head, using probability characteristics, the smoking events are learned and recognized by the support vector machine (SVM). The datasets created in the surveillance camera view in an indoor environment are examined in order to analyze the effectiveness of the suggested strategy. Our suggested strategy is effective, as demonstrated by the experimental findings, which show an accuracy rate of 83.33%. The study presents an innovative approach to indoor smoking detection using body pose estimation and machine learning techniques. However, the system's performance may be affected by factors such as imaging and lighting, suggesting the need to enhance its adaptability to different environments. Also, the experiments were conducted on a limited dataset containing only 30 videos, which may limit the system’s ability to generalize to other situations.

In 2017, the researcher Casey Acole and et al. [31] presented a study entitled "Detecting smoking events using accelerometer data collected via smartwatch technology" that used smart watches to identify smoking behavior. The second objective was to assess how well smoking behaviors utilizing smart watches performed in comparison to standard self-reporting methods. Over 95% of true positive detections using smart watch-based detections were accurate of the total 120 hours of observation time. What distinguishes the research is its reliance on modern technology, namely smart watches, which provides an objective means of recording data on daily behaviors such as smoking. However, one of the weaknesses is the small sample size (only 10 participants), which may affect the possibility of generalizing the study results on a wider scale. Also, the short battery life of the smart watches used was a challenge.

In 2019, a study was presented by Volkan Senyurek and et al. [32] entitled "Cigarette Smoking Detection with an Inertial Sensor and a Smart Lighter" In order to precisely identify smoking events, this work employs a wearable sensor system and suggests a technique that combines data from an instrumented lighter with a 6-axis inertial measurement unit (IMU) on the wrist. Thirty five moderate smokers participated in the study. The suggested method detected hand to mouth movements (HmG) in IMU data to estimate puff counts, and it identified smoking events from cigarette lighter data to binge in both regulated free dwelling situations (1.5-2 h) and unrestrained (approximately 24 h) living conditions. The suggested approach achieved 91% F1 score and 84% accuracy. One of the strengths of the research is that it presents a simple and effective system based on wearable sensors (IMU) and a smart lighter to accurately identify smoking events, and it is less intrusive compared to previous systems that require multiple devices or large sensors. However, the study did not evaluate the system for long periods in a daily life environment, making it difficult to determine the long term reliability of the system.

There is a study in 2020 by P. Kumar and et al. [10] entitled "Smoking detection using machine learning techniques on heart rate and breath rate data" that focused on using machine learning models to analyze heart rate and respiratory rate data to detect smoking. Logistic regression and random forests were among the algorithms used, and the accuracy was 90%. A major strength of this study is the application of random forest and logistic regression, modern machine learning techniques suitable for classification and pattern identification, indicating that researchers are interested in applying effective algorithms to analyze the data. A major weakness is the reliance on specific data such as heart rate and respiration, as each of these measurements can be influenced by other variables within the current environment or health conditions that cannot be directly attributed to smoking, leading to convergent results.

In 2021, researchers Nakayiza Hellen and Ggaliwango Marvin. [4] prepared a research paper entitled "Interpretable Feature Learning Framework for Smoking Behavior Detection" on creating a framework for interpretable feature learning to detect smoking behavior that uses a pre-trained VGG-16 deep learning network to predict and classify the input image class and propagate the relevance at the LRP layer level to explain the detection. The network or prediction of smoking behavior based on features/pixels achieved a rate of 93.35%. One of the strengths of this research is that the system achieved a good accuracy rate, with strong results in distinguishing between images. However, using the VGG-16 network is expensive in terms of memory and resource consumption, which may be an obstacle when trying to implement the model on a large scale.

There is a study in 2022 by Saurabh Singh and et al. [33] They presented a study entitled "Real time prediction of smoking activity using a machine learning based multi class classification model" that uses streaming data from a wrist mounted IMU (six-axis inertial measurement unit) sensor to construct machine learning based modeling framework to identify smoking activity among confounding daily activities in real time. A low-cost wearable gadget that is worn on the wrist was created in order to gather raw sensor data from individuals for various activities. The streaming raw sensor data was processed using a sliding window technique to extract various time domain, frequency domain, and descriptive properties. To find the best features and hyperparameters, respectively, feature selection and hyperparameter tuning were done. Afterwards, in sample and out of sample testing were used to create and validate multi class classification models. The generated models were able to predict smoking behavior with up to 98.7% predictive accuracy. The findings of this study will pave the way for a novel use of wearable technology to precisely identify smoking behavior in real time. It would also assist medical practitioners in keeping an eye on their smoker patients by offering prompt assistance to help them stop smoking. This research includes several strong aspects, including that the models used achieved high accuracy in detecting smoking activity, which enhances the reliability of the application. However, it also contains some weaknesses, including a limited data sample, as the study was limited to only 13 participants, which limits the generalization of the results.

In 2023, Priyanshu and et al. [34] presented a research paper entitled "Region extraction-based approach for cigarette usage classification using deep learning" in which a database was created for cigarette smokers, and they were classified into two categories: smokers and non-smokers. Various machine learning models, including random forest and KNN, were used to modify the database, yielding an accuracy of 94.41%. This research has several strengths, including high accuracy, which enhances the model's effectiveness in classifying smokers and non-smokers, and the ability to distinguish cigarettes even in complex situations such as low light, which demonstrates its effectiveness in different environments. However, although the database contains 7,000 images, the data is limited to a certain number and specific types of behaviors, which may reduce the ability to generalize the results to other situations. Several studies have discussed detecting smokers using various machine learning techniques, as shown in Table 2.

Based on previous studies that used machine learning, which were summarized in **Table 2**, where the table included information about the research, researchers, algorithms used, data set used, and accuracy obtained, it was noted that most of the research contained a small and limited data set that may affect the model's ability to generalize in new environments, so it is necessary to expand and increase the data set to ensure the validity of the model for various practical applications. It was noted that research No. 33 achieved good results, but it is indicated that the data set is very small.

4.2 Deep learning approaches in smoke detection

Deep learning models are superior to ordinary machine learning models because they include more learning layers and a higher level of abstraction. Another reason for this advantage is that data driven learning immediately benefits all model components. Because of the algorithm they rely on, traditional machine learning models become problematic as data accumulates and the need for adequate insights from the data increases. The amount of data available has spurred the creation of learning algorithms that are more sophisticated, fast, and accurate. To maintain a competitive edge, every company will use a model that produces the most accurate predictions [14].

There are many studies that have discussed the detection of smokers using different deep learning techniques, which will be explained with the strengths and weaknesses of each study as follows:

In 2018, researcher Dongyan Zhang and et al. [20] presented research entitled "Smoking image detection based on convolutional neural networks" that includes a smoking detection model using the (CNN) algorithm. It uses visuals to automatically identify smoking patterns in video material. The only criteria needed for this method to identify photographs of smoking are human smoking movements and cigarette image attributes. Improve cigarettes, demonstrating excellent performance and high accuracy for real time monitoring. The research is distinguished by presenting a customized model called Smoking Net based on neural networks (CNN). This model has proven to be highly efficient in detecting cigarettes, making it effective for real-time applications. One of the most prominent weaknesses of the research is that it relies on data collected from videos available on the Internet and created by researchers, which may affect its ability to generalize to more diverse scenarios. In general, the model is strong and effective in detecting cigarettes, but it needs improvements to deal with different cases and environments.

In 2018, Chien Fang Chiu and colleagues. [35] presented research titled "Smoking Action Recognition Based on Spatial Temporal Convolutional Neural Networks" Their research proposed a system capable of identifying smoking actions. The system uses a temporal segment network architecture along with Google Net for data augmentation and balancing. Their experiments showed that the system achieved a 100% accuracy rate on the selected dataset for detecting smoking actions. For additional smoking clips from the HMDB51 dataset, the system achieved an accuracy of 91.67%. The research is characterized by presenting an effective model for recognizing smokers' behavior in video clips, but the performance can be improved by expanding the dataset and testing the model in different environments to ensure its ability to generalize.

Table 2. A summary of previous work that are related to this study that used machine learning.

No	Ref sequence	Author	Year	method used	Dataset	accuracy
1	[28]	Pin Wu and ect	2010	Gaussian Mixture Models and color re projection	image	accuracy analysis of cigarette detection.93.2%. & Analysis of smoking event detection accuracy, 82.1%
2	[29]	Amin Ahsan Ali and ect	2012	SVM and S3VM	ten smokers who smoke every day	SVM is 84.5 and S3VM is 86.7
3	[30]	Tse Lun Bien and Chang Hong Lin	2013	SVM	Thirty segments are set in an interior setting with varying actor and lighting configurations.	83.33
4	[31]	Casey A Cole and ect	2017	machine learning algorithms	sample of smokers was gathered , Ten participants used a smartphone and smart watch to record accelerometer data for twelve hours.	More than 95% within 120 hours of combined monitoring time
5	[32]	Volkan Senyurek	2019	(SVM) classification.	871 hours of data, 463 lighting occurrences, and 443 cigarettes	91% F1 score and 84% accuracy.
6	[10]	P. Kumar and ect	2020	random forest and logistic regression	heart rate and respiratory rate measurements collected from smokers and non smokers	90%
7	[4]	Nakayiza Hellen and ect	2021	The LIME algorithm	2400 raw photos in the collection, 1200 are of the smoking group (smokers), while the other half are of the non smoking category (non smokers).	93.35%
8	[33]	Saurabh Singh and ect	2022	sequential backward feature selection (SBFS)	data was collected using a custom wrist wearable device. The dataset was gathered from 13 male participants,	98.7%
9	[34]	Priyanshu1, Madabhushi and ect	2023	KNN and random forest	7,000 images featuring drivers working in more than 200 distinct car kinds. Among these pictures are 3,500 instances of smoker drivers.	94.41

In 2018, researcher Taiyu Chen and et al. [36] presented research entitled "Automatic alert system helping people keep away from cigarettes" the creation of a cutting-edge smoking cessation system that tracks smoking in real time using an Android software application and motion detection. A customized smoking cessation plan will be created by this system based on the objective of totally stopping or drastically cutting back on smoking. To detect smoking and non-smoking movements, motion data from two armbands was gathered and tested using an LSTM algorithm. When the sensor detects active smoking, an internet messaging service will be used to remind customers to

Follow their plan. Short message service (SMS) is used to push and pull relevant video links to users in an effort to help them stop smoking. The findings have effects on how tobacco cessation treatments are provided and how smoking status is determined. The research is characterized by high accuracy in detecting the movement of smokers, which indicates the model's ability to accurately recognize smoking and send immediate alerts to the user. One of the weaknesses of this research is that some movements, such as raising the hand to answer the phone, may lead to interference in classification. It is recommended to develop the classification algorithm to reduce the percentage of errors.

In 2020, Volkan Y. Senyurek and et al. [37] presented research entitled "CNN-LSTM neural network for recognition of puffing in smoking episodes using wearable sensors" on proposing a fresh algorithm designed to automatically identify puffs in smoking rings. Long term memory (LSTM) network layers and (CNN) were utilized to automate the process of learning features from primary sensor streams. The suggested method obtained an F1 score of 78% . The research shows efficiency in detecting smoking patterns using AI techniques, but it needs development and improvement to make the accuracy more realistic in different environments.

In 2020, Tzu Chih Chien and et al. [38] presented a research paper entitled "deep learning based driver smoking behavior detection for driving safety" that included applying the image based Yolov2 algorithm for deep learning to detect the driver’s cigarette body according to the proposed design. The average accuracy of detecting cigarettes reaches 96% during the day and an average accuracy of 85% during the night. The research is characterized by high detection accuracy, which enhances the ability of Yolov2 to detect cigarettes effectively in various lighting conditions. One of the most prominent weaknesses of the research is that despite achieving good results in detecting smokers during the day, the performance drops to 85% at night, so the system may not be completely reliable in all conditions.

In 2020, Johnel R. Macalisang and et al. [39] presented a study entitled "Eye smoker: A machine vision based nose inference system of cigarette smoking detection using convolutional neural network" This study proposed a system for detecting smokers that can identify cigarette smokers using deep learning system. The system is trained, tested, and evaluated by providing images, videos, and live detection using a camera. This study used the Pascal VOC format and the labeling tool. Overall, the system attained up to 90% test accuracy. The system is flexible in its handling of images and videos, making it suitable for monitoring people who smoke in public places. It has a graphical interface that makes it easy for users to use the system. One of the most prominent weaknesses is that it focuses on regular cigarettes and has difficulty identifying other forms, such as electronic cigarettes. It is possible to expand the system to include other forms of smoking, which would increase its effectiveness.

In 2021, Fangfei Shi and et al. [40] offered a study entitled "Faster detection method of driver smoking based on decomposed YOLOv5" to address the issue of the object detection network's current use of computing resources to identify driver smoking and suggest a way to enhance the Yolov5 network. The pre trained Yolov5 network's conventional convolution is split into two convolutional operations using singular value decomposition (SVD). When the total detection accuracy hits 93.5%, it is easier to lower the computational cost, and the detection time of Dec-yolov5 is 80% of the original yolov5. What distinguishes the research is the high efficiency by improving the Yolov5 model using SVD technology, which reduces the number of calculations, reduces the model size, and reduces the detection time. One of the most prominent weaknesses is that the data used for training comes from a data set collected from smoking scenes under specific conditions. There may be challenges when applying the model to diverse data that were not covered in the study.

In 2021, Anshul Pundhir and et al. [41] presented a research paper entitled "Region extraction based approach for cigarette usage classification using deep learning" where a novel method was developed to classify people's smoking behavior by using deep learning to extract relevant regions from specific images. A dataset of 2,400 images, a balanced dataset of smokers and non smokers was gathered, and the proposed method's effectiveness was evaluated using both quantitative and qualitative metrics. The method, employing the YOLO v3 algorithm, demonstrated strong performance, achieving a 96.74% accuracy rating even in challenging conditions. The research provides a high classification accuracy, which demonstrates the effectiveness of the model in classifying images and has proven its efficiency in dealing with various challenges such as low light conditions and different face and hand positions, which increases its application in multiple environments. One of the most prominent weaknesses of the research is that the data used in training is limited to only about 2400 images, which may affect the performance of the model when applied to more complex data or in different conditions. The model also deals with small items, such as a cigarette, and may face challenges in accurately detecting them if they are camouflaged or unclear.

In 2022, a model was presented by researcher Ali Khan and et al. [42] entitled "deep learning methods and applications" to use the pre trained Inception Res Net v2 model to classify photos of smokers and non smokers, then compare the results to alternative CNN techniques based on a range of performance measures.

Using a freshly developed heterogeneous dataset, the suggested method predicted images of smoking and non smoking with an accuracy of 96.87%. The research presents an effective AI-based model to improve the monitoring of no smoking zones in smart cities, which contributes to preventing smoking in public places. However, further improvements are needed, such as expanding the size and variety of data and testing the model in real environments to ensure its accuracy and effectiveness in practical use.

In 2022, Y.Ma and et al. [43] present a study entitled "YOLO-cigarette: An effective YOLO network for outdoor smoking real time object detection" developed a deep learning based model to detect smoking photos. By adding the new fine spatial pyramid pooling units (FSPP) and (MSAM) to the original Yolov5 network, the detection accuracy was successfully increased. Reaches 95% accuracy on the test set with small targets. One of the strengths of this research is that the model achieves a high accuracy rate on the test set, which makes this model reliable for use in real world applications. Although the YOLOv5 model has been improved, it may be useful to compare the model's performance with other recent models in detecting small objects to ensure that YOLOv5 is the optimal solution to this problem.

In 2022, Dang Wang and et al. [44] present a study entitled "Design of Intelligent Detection System for Smoking Based on Improved YOLOv4" that revealed the creation of a YOLOv4 based real time smoking detection model that outperforms single stage methods. In this study, the data sets of each unit were utilized to determine the impacts of the three improved YOLOv4 on the model's accuracy. The enhanced K-Mean++ clustering algorithm outperformed the original system by 1.4% in ablation trials. The MAP value obtained with the modified loss function was 0.5% higher than with the original approach. Compared to the original algorithm, the attention mechanism's MAP value increased by 8.1%. The initial algorithm Thus, utilizing Yolov4, the three enhancements suggested in this study are successful in detecting smoking. Overall, the research represents a positive step towards improving smoking detection systems in public places through the use of advanced deep learning algorithms, but improving the database and increasing training on diverse scenes can enhance the accuracy and efficiency of the model.

In 2023, Madabhushi Aditya and et al. [7] presented a study entitled "Smoking detection using deep learning" that outlined a novel approach to recognizing smoking behavior that makes use of deep learning to extract key features from images and the Yolov5 algorithm to enhance performance and streamline models. A dataset comprising 7000 photographs with an equal proportion of smokers and non smokers. In separate data sets was used to test the method. Both quantitative and qualitative measurements were used to evaluate the technique, and the dataset yielded a classification accuracy of 96.74%. One of the strengths of this research is that the researchers used the YOLOv5 model and achieved good classification accuracy, indicating that the model is effective in recognizing smoking behavior with high accuracy. One of the weaknesses is that it may be difficult for the model to distinguish cigarettes in cases where the items are similar, such as pens or sticks, which may increase the percentage of false positives.

In 2023, the researcher M. Gopika Krishanon and et al. [45] presented research entitled "An integrated smoking detection method based on convolutional neural network" to design a project in which the faces of smokers are detected using a camera placed in specific locations. An improved method for detecting smokers was presented based on CNN (Yolov8) to detect cigarette smoke. The goal was This project includes avoiding smoking in prohibited places and issuing an audio warning not to smoke . One of the strengths of this research is the design of an integrated system that includes surveillance cameras and a system that sends notifications when smoking is detected, which contributes to improving compliance with the ban on smoking in indoor places. One of the weaknesses is that despite the speed of YOLOV8, the accuracy may be lower compared to some other models, which may negatively affect smoking detection in changing or complex environments.

In 2023, the researcher Jiang Chong. [46] presented a study entitled "Intelligent Detection Approach for Smoking Behavior" that offered a deep learning based smoke detection solution for areas where smoking is prevalent. The input frames of the camera captured video stream were processed by a CNN network. The CNN network's design does not minimize the quantity of model calculations; inference occurs and satisfies deadlines. But it also helps to increase the precision with which little target objects like cigarette butts are detected. The proposed algorithm achieved 98% in FPS and 79.3% in Map. The research provides promising solutions to improve smoking detection in public places by designing a robust real time performance system that makes it practical for public monitoring applications. However, the model suffers from the lack of diversity in the dataset used, as it was manually collected from limited sources, which may affect the system performance in diverse environmental conditions. In 2023, Zhong Wang and et al. [47] presented research entitled

"Smoking behavior detection algorithm based on YOLOv8-MNC" Experimental results from a bespoke smoking behavior data set demonstrated a considerable improvement in detection accuracy on smoking detection using YOLO v8. With a detection accuracy of 85.887%, YOLOV8-MNC outperformed earlier algorithms by a notable 5.7% in average accuracy (MAP@0.5). The research has provided clear improvements in the field of smoking detection using the YOLOv8-MNC algorithm; however, there are some limitations that need to be addressed to keep up with the diverse and complex real world applications.

In 2023, Tanya Singh and et al. [6] presented a research paper entitled "Real Time Cigarette Detection using deep learning Models" presenting a project to detect cigarettes in real time using deep learning models. Object detection was used using YOLO v3, which is deep learning model to detect objects, and an A 92.5% detection accuracy was attained for cigarettes. When the system was chosen at various angles, distances, and lighting circumstances, its performance remained consistent. Real time testing of the system's performance revealed that, on average, 0.3 frames were processed per frame. A strength of this research is the system's ability to process live video and send alerts when cigarettes are detected, making it useful for applications in public places. A weakness is that training the YOLOv3 model requires high resources (such as powerful graphics processors), which may make it difficult to repeat training and develop the model in environments with limited resources.

In 2023, Yingying Cao and Mingkun. [48] presented a paper entitled "Smoking Detection Algorithm Based on Improved YOLOv5" in which an enhanced algorithm for detecting smoking was suggested, utilizing YOLO v5. In order to enhance the ability of small objects to convey their features and better preserve target placement information, the EFFN architecture was proposed, which combines three nearby feature maps of varying sizes. Experiments demonstrate that the model presented in this study has a 1.5% higher MAP@0.5 than the original YOLO v5 model and that the enhanced model is able to recognize smoking behavior in real world scenarios. The research report demonstrates the excellent performance of the new smoking detection model compared to the YOLOv5 model, with high accuracy and recall values. However, insufficient dataset, model complexity, and lack of field testing are shortcomings of the study, which should be considered to make the model effective in different real world scenarios.

In 2023, research was presented by Retinder Deep Singh and et al. [49], who presented a study entitled "deep learning Based Smoking Detection System for Public Areas" which included research on using the CNN -deep learning algorithm to create a powerful and accurate system to identify cigarette smokers in public places. The experimental results show off the efficiency of the proposed technique with a remarkable accuracy rate of up to 90% in distinguishing between smokers. Cigarette and non smokers Moreover, key performance indicators like recall, accuracy, and F1 score were used to assess the model's performance, which demonstrates its ability to balance the positives and negatives. One of the strengths of this research is the diversity of the data. The research uses a large and diverse set of facial images, including smokers and non smokers, with a variety of age, gender, and ethnicity. This diversity makes the model more comprehensive and able to generalize to different datasets. At the same time, it can be difficult to apply this system in crowded public places due to the challenges of recognizing smokers in situations of crowding or visual interference.

In 2023, researchers Jinfan Huang and Rong Li. [50] presented a paper titled "Detecting Driving Behavior While Smoking Based on deep learning", The paper involves designing a model based on deep learning that quickly determines whether the driver is smoking and issues a warning to avoid unnecessary traffic accidents and life safety. This model is applied to the input frames of the video stream obtained from the camera using a convolutional neural network. The method judges the driving behavior while smoking by extracting the shape feature, processing the blur feature, detecting the motion feature, and comparing the color feature area. The model achieves an accuracy of more than 90%, which can not only meet the real time monitoring performance but also reduce the calculation amount of the model and improve the inference efficiency by designing a series of computer vision detection modules. One of the strengths of this research is that it integrates several smoke detection features, such as shape, color, and dispersion, making the model more accurate in identifying smoking behavior even under difficult interference conditions. One of the main weaknesses, according to the researchers, is that the model may not achieve optimal performance in practical applications due to the diversity of data, which limits its ability to handle multiple situations.

In 2024, the researcher Zhen Zhang and et al. [51] provided a study entitled "Research on smoking detection based on deep learning" and a model for smoking detection that is appropriate for real time observation. The self-made smoking dataset was discovered, and the Dlo4-nms approach was chosen to address the issue of missing detection. 86.32% was the average accuracy rate (MAP) attained. The detection model enhances the accuracy of smoking detection and, to some extent, enhances the effect of overseeing smoke free zones, helping to reduce the risk of fire. The detection speed reaches 55 frames per second.

The model achieved good accuracy and a processing speed of 55 frames per second, which is suitable for the time requirements of practical applications in monitoring public places, but the model was trained on a limited dataset specific to smoking, which may limit the possibility of generalizing it to other environments that were not tested during the development of the model.

In 2024, research was presented by Dhiraj Murthy and et al. [52] in a study entitled "Using computer vision to Detect E-cigarette Content in TikTok Videos "The study looked at 13 vaping related hashtags (e.g., #vape) on TikTok and extracted 826 images from 254 randomly selected posts. The images were labeled to indicate the presence of vaping devices, hands, and vapor clouds, and a computer vision model based on YOLOv7 developed., trained on 85% of the images (N = 705) and tested on 15% (N = 121). The model achieved a recall value of 0.77 and correctly recognized vape devices 92.9% of the time with an average F1 score of 0.81. The proposed system provides the ability to automatically detect the content of e-cigarettes, which contributes to saving human effort and allows regulatory authorities to more efficiently monitor harmful content on platforms such as TikTok. One of the most prominent weaknesses is that the model relies on current training data, which means that it may need to be updated over time to include new smoking devices.

In 2024, research was presented by Robert Lakatos and et al. [53] entitled "multimodal deep learning architecture for smoking detection with a small data approach" to identify smoking incidents in explicit, visual, and textual contexts—even with the largest training dataset currently accessible. The accuracy reaches 74% for images and 98% for text, which explains how the authors created a dataset for detecting smoking related terms in Hungarian by using existing dictionary resources and the generative abilities of ChatGPT to expand their list of relevant terms. A strength of this research is that the model combines text and image processing using a pre trained model, which enhances the detection of smoking content in multimedia even with limited data. A weakness is the lack of a public and reliable dataset on smoking content, which forces researchers to use a small dataset and limited processing.

In 2024, research was presented by Cinantya Paramita and et al. [54] entitled "Comparative Analysis of YOLOv5 and YOLOv8 Cigarette Detection in Social Media Content" The study used a dataset of 2188 photos gathered from Twitter to identify and track cigarette related images on social media platforms in an effort to limit exposure among kids and teenagers. This study used a thorough methodology that includes training the YOLOv5 and YOLOv8 models and preparing the data. The accuracy, recall, and efficacy of the YOLOv5 and YOLOv8 models in identifying cigarettes and cigarette pack items were assessed using mean average precision (mAP) and F1-Score metrics. Along with better accuracy and recall rates, the outcome outperformed YOLOv8, with a somewhat higher mAP value of 0.933 than YOLOv5's value of 0.919. This outcome demonstrates YOLOv8's sophisticated object detection capabilities, which are made possible by its innovative architecture and anchor free detection mechanism. The study also verified that there were no notable problems with overfitting or under fitting, suggesting that the models' learning processes were strong. One of the strengths of this research is that it addresses a major societal issue, the impact of smoking related content on social media on young people. The model only used Twitter data, so this could be a weakness because the prediction accuracy is possible on this social media platform, but if the same model is applied to another social media platform with different images and lighting resolution, it may not predict with high accuracy.

In 2024, research was presented by Yerniyaz Bakhytov and Cemil Öz. [55] entitled "Cigarette Detection in Images Based on YOLOv8 " This study investigates the development and testing of automatic cigarette detection in images using deep learning techniques such as YOLOv5 and YOLOv8. The main goal of the study is to improve the accuracy and reliability of smoking related object recognition, which can significantly enhance public space surveillance. The training results are presented, with YOLOv8 achieving an accuracy of 87.4% and YOLOv5 slightly outperforming it with an accuracy of 89.6%.A strength of this research is that it provides a comparative analysis between YOLOv5 and YOLOv8, providing insights for future researchers into the performance of these models and their weaknesses. Although YOLOv8 is assumed to be an improvement, the performance was slightly lower than YOLOv5, suggesting that the improvements in YOLOv8 may not be fully effective for this specific task. Additionally, the research does not explain how YOLOv8 can be improved to achieve higher performance.

Several studies have discussed detecting smokers using various deep learning techniques, as shown in **Table 3.**

Table 3. A summary of previous work that is related to this study that used deep learning

No	Ref sequence	Author	year	method used	Dataset	accuracy
1	[20]	Dongyan Zhang and ect	2018	design a CNN-based model called Smoking Net	1,000 types of ImageNet datasets	accuracy stabilizing at approximately 95% after 95 epochs.
2	[35]	Chien Fang Chiu and ect	2018	Temporal CNN And Spatial CNN	3570-item dataset is split into two groups: 3500 non smokers and 70 smokers. There are 1500 non smoking clips and 30 smoking clips in the test dataset.	91.67%.
3	[36]	Taiyu Chen and ect	2018	LSTM	Each subject performed 600 motions, with 80% used for training and the remaining 20% designated as the testing dataset.	The smoking motion detection achieved an accuracy of 98.5%, however the accuracy of differentiating each individual motion categorization was only 72.6%.
4	[37]	Volkan Y. Senyurek and ect	2020	CNN-LSTM	40 participants, encompassing 467 recorded smoking events.	78% F1 score.
5	[38]	Tzu Chih Chien and ect	2020	Yolov2	A collection of different pictures of smokers	Average accuracy during the day is 96% and at night is 85%.
6	[39]	Jonel R. Macalisang and ect	2020	Labeling tool and Pascal VOC format	Photos, videos and live detection using your camera's webcam	90%
7	[40]	Fangfei Shi and ect	2021	YOLOv5	Videos capturing smoking behavior from different angles and under different weather and lighting conditions in real environments. These clips included a total of 120 minutes of smoking behavior	93.5%.
8	[41]	Anshul Pundhir and ect	2021	Yolov3	2,400 images featuring both smokers and non smokers in a variety of settings and conditions	96.74% classification accuracy on this dataset.
9	[42]	Ali Khean and ect	2022	Inception Res Net v2	Images, video, audio or text	96.87%
10	[43]	Yankai Ma and ect	2022	Enhanced yolov5	image	95%
11	[44]	Dang Wang and ect	2022	Yolov4	7000 pictures.	………….
12	[7]	Madabhushi Aditya and ect	2023	YOLOv3-tiny	7,000 pictures that equally depict smokers and non smokers	96.74% classification accuracy on the dataset.
13	[47]	Zhong Wang and ect	2023	YOLO v8-MNC	Images of smoking	85.887%
14	[6]	Tanya Singh and ect	2023	YOLO v3	image smokers and non smokers	92.5%
15	[45]	M.Gopika and ect	2023	Yolov8	image smokers and non smokers	…………
16	[49]	Retinder deep singh and ect	2023	CNN	Images collected from various public places	90%
17	[46]	Jiang Chong	2023	Proposed backbone	Number of smoking samples 3600	Detection results of different algorithms on proposed dataset map= 86.3 and Detection results on PASCAL VOC map= 79.3
18	[48]	Yingying Cao and ect	2023	YOLOv5_EC i	4848 pictures containing different scenes, scales and camera angles	Map is 81.5%
19	[50]	Jinfan Huang and Rong Li	2023	CNN	Set of video	More than 90%
20	[51]	Zhen Zhang and ect	2024	Dlo4-nms	Collection of pictures	86.32%.
21	[52]	Dhiraj Murthy and ect	2024	Yolov7	A total of 705 images were used for training, while 15% (121 images) were reserved for testing.	92.9%

22	[53]	R´obert Lakatosb and ect	2024	deep learning, generative methods, and human reinforcement	image	The accuracy reaches 74% for images and 98% for text
23	[54]	Cinantya Paramita and ect	2024	Yolov5,yolov8	dataset of 2188 photos gathered from Twitter	YOLOv8, with mAP of 0.933 ,YOLOv5's mAP of 0.919
24	[55]	Yerniyaz Bakhytov and Cemil Öz	2024	Yolov5,yolov8	containing 1200 images of people smoking	The training results YOLOv8 model is 87.4% and YOLOv5 model is 89.6%.

Based on previous studies that used deep learning, which were summarized in **Table 3**, where the table included information about the research, researchers, algorithms used, data set used, and accuracy obtained, , it was noted that most of the research indicated smoking detection through images, videos, or real time, and there is no comprehensive system that combines all cases: images, videos, and real time. Also, they had a small and limited data set, which may affect the model's ability to generalize in new environments. It requires expansion and increases in the data set to ensure the validity of the model for various practical applications.

4.3 Other research Using the IoT and computer vision to detect smokers

There are many studies that have discussed the detection of smokers using different IoT and computer vision techniques, which will be explained with the strengths and weaknesses of each study as follows:

In 2015, research was presented by Harikrishnan and et al. [8] entitled "Smoke detection captured from image features" wherein a sensor, camera, microcontroller, and GPS unit were employed as part of a combined system for detection. The camera uses face detection to identify the smoker by identifying their face from a database when the sensor detects smoke. The strengths of the research are that it addresses the problem of smoking in public places, which is a major health challenge, which adds societal importance to the proposed system and makes it useful for improving public health. Among the weaknesses are that the sensing accuracy can be affected by external factors such as the presence of other gases or changes in air quality, which may lead to false results or failure to detect smoke.

In 2018, research was presented by Zhenkai and et al. [56] entitled "Smoking Behavior Detection Based on Hand Trajectory Tracking and Mouth Saturation Changes." It included suggesting a useful and efficient video analysis detection technique. The two primary methods in the suggested method are smoke detection and smoking action detection. The first method uses an open source face detection system called Sweet faced to detect human faces. It then segments the mouth area and calculates the corresponding saturation and grayscale degrees. Finally, it determines whether the mouth has undergone a sudden change. The second method involves two main steps: first, using the skin color ellipse model in the YCrCb color space, detect the skin color area; next, based on the skin color area's location in relation to the face, determine the hand's initial position; finally, using optical flow to track the hand's movement path, determine whether the hand overlaps the mouth in real time. Ultimately, the smoker or non smoker can be recognized by combining the outcomes of the first strategy's result with the previous two phases' results in the second approach. The experimental findings demonstrate that the suggested strategy may obtain a 95% detection rate and successfully identify smoking behavior in real time using a minimal training sample, where the method used achieved an accuracy rate equivalent to 95%. Among the strengths of the research is that it presents a new methodology for smoking detection that combines smoke detection and hand movement, which distinguishes it from traditional methods that rely on only one of the two methods. Among the weaknesses is that it records a data set specific to the research, which may affect the possibility of applying the results on a large scale.

In 2018, Sancha Panpaeng presented and et al. [57] entitled "Cigarette Smoke Detectors for Non-Smoking Areas in the Building" This research focused on designing a cigarette smoke detector for non-smoking areas in buildings. The system uses an MQ2 gas sensor to detect smoke and a NodeMCU V2 (ESP8266-12e) to process sensor data. When smoke is detected and the sensor's voltage exceeds a set threshold, the system sends a notification to the administrator via the LINE API. The detector is effective in areas up to 20 square meters with a room height of up to 3 meters, promptly detecting smoke and notifying staff of smoking activity in the area. Overall, the research has good strengths related to the technologies used, including the use of gas sensors (MQ2), IoT technologies (NodeMCU V2), and system efficiency, but there are areas for improvement especially in terms of scale, comparisons and performance in large environments.

In 2018, Éamon Dunne. [58] presented a project entitled "Smoking Detection in Video Footage" A project aimed to develop an automated system to detect smoking in video footage, motivated by the frequent depiction of tobacco use in modern films and its potential influence on young audiences. The system identifies smoking by detecting smoke near a person's hand or face, classifying potential smoking events based on proximity to smoke. It uses facial recognition to locate faces, then identifies hands by matching skin color, and searches these areas for smoke. Frames with smoke near hands or faces are flagged as smoking instances. Developed in C++ with OpenCV, the system was tested on short clips and limited to footage from stationary cameras. Results were mixed due to the variability of modern film footage, suggesting potential improvements in handling longer sequences and non stationary cameras. Where the method used achieved an accuracy rate equivalent to 95.7 percent accuracy classification. One of the strengths of this research is that it aims to develop a system capable of automatically detecting smoking in video, which is a topic of social and health importance, as it can be used to classify films or reduce the impact of smoking scenes on young people. However, smoke detection depends on multiple criteria such as color and dispersion, but the variation of smoke color from one scene to another leads to the possibility of error in detection.

In 2019, Sulistiyowati et al. [59] present a study entitled "Cigarette detection system in closed rooms based on (IoT)" An MQ2 sensor is used in the system to identify cigarette smoke in a space, and a Nadem cu microcontroller is used to handle the data. The system sounds an alarm and flashes an application to notify users when it detects smoke. By detecting cigarette smoke, this device makes use of IoT technology to provide a practical means of improving safety and comfort in enclosed environments. One of the strengths of this research is that the system relies on different sensors such as MQ2 to detect smoke and send notifications via the Internet, which makes it an integrated system that can be developed for commercial uses, but the instability of the alerts due to environmental factors such as wind or ventilation inside the room may affect the accuracy of detection, which requires improvement in adjusting the sensitivity of the sensors.

In 2020, Somantri and et al. [9] presented a study entitled "Cigarette Smoke Detection System for Non Smoking Areas Based on IoT and Face Recognition" were able to offer a technique for spotting cigarette smoke in areas designated for nonsmokers. The cigarette smoke detection system was built using a Raspberry Pi B+ device, a gas sensor (MQ2), a camera, a global positioning system (GPS), and data transfer. Must connect to the Internet via Ethernet or WiFi in order to transmit data to the database server. When the sensor promptly releases the cigarette, the system communicates the location and photographs of the smokers and notifies the administrator. The system will identify the smoker. The goal of the test was to find out how well facial recognition was, and the initial findings come from adjusting the captured image's size. One of the strengths of this research is the use of modern technologies such as the IoT and facial recognition, which enhances the accuracy and efficiency of smoker detection. One of the weaknesses is that the system camera may have difficulty capturing clear images in crowded areas, which may affect the accuracy of facial recognition.

In 2020, Mohammad Alif and et al. [60] present a study entitled "An IoT based Cigarette Smoke Detection System for Green Environment" This paper presents the development of an adaptive cigarette smoke detection system that monitors gas levels and logs data to a webpage in real time. The project aimed to improve existing systems by comparing parameters and developing a prototype using an Arduino UNO controller, MQ135 gas sensors, and an ESP8266 WiFi module. The system detects cigarette smoke concentrations between 250 and 500 ppm at 0.5 meters and 0 to 100 ppm at 1 meter. This adaptive system provides real time alerts on air quality, offering valuable insights for environmental monitoring. One of the strengths of this research is the innovation in design, as the research presents an innovative system for detecting cigarette smoke using (IoT) technologies and gas sensors (MQ135), which enhances the continuous monitoring of air pollution levels in different environments. One of the weaknesses of this research is that the system may have difficulty distinguishing between different types of gases that affect air quality, which may lead to inaccurate results if there are other sources of pollution besides cigarette smoke. Several studies have discussed detecting smokers using IoT and computer vision, as shown in **Table 4.**

5. Discussion

This paper reviewed several artificial learning models that address smoker detection using AI algorithms and techniques. The choice between machine learning and deep learning algorithms for smoking prediction depends on a number of variables, such as the difficulty of the task and the available information. In general, deep learning algorithms, especially deep neural networks, have shown remarkable success in handling complex, high dimensional data, making them well suited for tasks such as image analysis and natural language processing. Deep learning excels at tasks such as classifying and interpreting images of smokers, where identifying complex patterns is essential for accurate detection. Smoking motion detection achieved an accuracy of 98.5% for the research. For research No. 36 that used the LSTM algorithm. The strengths of the model are its ability to accurately recognize smoking and send immediate alerts to the user, but it needs improvements to achieve greater effectiveness in practical application. On the other hand, machine learning algorithms such as sequential backward feature selection can be effective in dealing with structured data and when interpretability and feature selection are essential, reaching 98.7% accuracy. For research No. 33, indicating that these models are effective in distinguishing between smokers and non smokers based on the dataset used, which enhances the reliability of the application. However, the study was limited to 13 participants, which limits the generalization of the results, especially in different smoking related activities. The research indicated that the use of deep learning may improve the model, but the available data are insufficient for this purpose, which requires additional efforts to collect more data. The choice often involves balancing model complexity, data availability, computational resources, and the need for interpretable results. In practice, combining machine learning and deep learning techniques, known as hybrid models, can achieve the best results by leveraging the strengths of each approach to comprehensively predict smoker detection.

Table 4. Summary of previous work using iot and computer vision for smoking detection.

No	Ref sequence	Author	year	method used	Dataset
1	[8]	Harikrishnan and ect	2015	a sensor, camera, microcontroller and a GSM module	captured image sequences
2	[56]	Zhenkai and ect	2018	The proposed method involves two main approaches: smoke detection and smoking action detection	110 video clips in the dataset.
3	[57]	Sancha Panpaeng and ect	2018	MQ2 gas sensor to detect smoke and a NodeMCU V2 (ESP8266-12e) to process sensor data	Data from the sensor
4	[58]	Éamon Dunne	2018	Motion detection, Colour analysis, Disorder analysis	used a selection of videos from the Bilkent and HMDB datasets.
5	[59]	Sulistiyowati and ect	2019	MQ2 sensor , the NodemCu microcontroller and the blynk application	data received from the sensor
6	[60]	Mohammad Alif and ect	2020	Arduino UNO controller, MQ135 gas sensors, and an ESP8266 WiFi module	The sensing data is recorded, transferred adaptively to a webpage, and watched over the internet.
7	[9]	Somantri and ect	2020	Raspberry Pi B+, an MQ2 gas sensor, GPS, and a camera	data that can be detected by the Sensor

Conclusion

In conclusion, the researchers looked at a number of studies and research articles on the application of AI to identify smokers, as the choice of AI model to detect smokers is an important issue. The analysis revealed that deep learning and machine learning techniques constituted the majority of the research mentioned, and most of these studies and research showed high accuracy rates in detecting smokers, suggesting that they may be applied more widely in the future through research and study evaluation. Whether machine learning or deep learning algorithms does not mean that one is completely better than the other, but the right tool between them must be chosen deep learning algorithms shine for their ability to handle unstructured and complex data, and in tasks such as "natural language processing and image analysis" for smokers, they provide remarkable accuracy in diagnosis. In contrast, the application of machine learning techniques remains valuable, especially when the data is structured and feature selection and interpretability are critical. Through previous research, the strengths were represented in the fact that the results achieved by some research were good and highly accurate in the detection process, and the weaknesses were represented in the lack of accuracy of other research when testing new events that the system was not trained on, and it may need to be modified and developed to include multiple other cases, as well as the limited data set, which limits the system's ability to generalize in other cases. Therefore, choosing the correct and most promising algorithm must be compatible with the available data and the unique requirements of the problem of diagnosing smokers, informing the responsible administration of the place where smoking occurs, and issuing alerts about the presence of smokers.

As future work, it is recommended that the research should expand applications in different smoking detection environments, adopt interesting and diverse datasets to obtain effective system results, expand the images used to include e-cigarettes in addition to regular cigarettes due to their widespread use by community members, and apply the smoking detection system to all scenarios, such as images, videos, and real time to be a comprehensive system.

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Conflict of interest

None.

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