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Original Article

Region Extraction based Approach for Cigarette usage Classification using Deep Learning

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Abstract - *In this research paper, we created our database of cigarette smokers and classified them into smoking and non-smoking categories. Here, we have passed our database through different machine-learning models, such as Random Forest and KNN. We have also considered other deep learning models, such as DenseNet, Xception, Inception, and ResNet50, using which we created a voting classifier that gave an accuracy of 94.41.*

Keywords - *Deep learning, Voting classifier, DenseNet, Xception, Inception, ResNet50.*

1. Introduction

Although technology has advanced a lot, we still face several issues, such as rising traffic accidents, pollution, and health issues, such as visual impairments, respiratory ailments, and lung cancer. They can occur for numerous reasons, the most notable of which is regular cigarette usage. According to specialists, cigarette usage should be avoided because it negatively impacts the environment, our health, and our life span. Governments have also developed restrictions to prevent their usage in public places. However, some people disobey the law when they are not being supervised. Sadly, a person's cigarette usage harms the lives of others through pollution, health difficulties, and vehicle accidents. As a result, there is a need to build a system that is automated and can assist in determining a person's smoking behavior as they have a broad range of applications, including automatic devices to monitor smoke, filtering of cigarettes in movies, and reduce the amount of traffic accidents caused due to the smoking habit of the driver[1]. Few datasets have smog, and there is less smoke in the current dataset. The enhancement process on the dataset can be arduous, and solely relying on gestures for recognition can lead to lower recognition accuracy and a large proportion of false positive outcomes. This can be solved by detecting cigarettes. The wide input range makes it harder to improve the system due to the high fluctuation in the footage. Suppose the system is fine-tuned to label positive samples accurately. In that case, a significant number of false positives may follow, the converse may be true, and the color spectrum of smoke is reasonably large. When only a portion of the face is visible, the face classifier overlooks faces. For example, whenever the face is concealed by a hand or turned aside.

A sample of skin color can occasionally match backdrop items. Because of the tiny sample size and the enormous amount of variation: changes in backdrops, lighting, and the color of smoke, it is expected that any incidence of smoking will occur over a substantial number of frames. The video represents smoking if the proportion of smoking frames reaches a particular threshold. Although CNN decreases the properties of tiny objects, the information is concentrated primarily on feature maps which are shallow, thus making it unsuitable for detecting cigarettes. FPN with dilated convolution is a solution since it continually blends shallow features and dilated convolution; as long as pooling is not performed, there is no loss of information on features. The available dataset must be adequate to attain more accuracy than the current study.

Furthermore, compared to other network designs, the network structure in the article is more straightforward. Assume the programming language can be transformed and implemented in the platform in a language that the hardware operating motherboard supports. In such instances, it can fulfill the requirements of the driving scenario in reality.

2. Literature Survey

In the literature, several ways to support smoking cessation have been addressed. There are various effective pharmacological therapies [18] for treating nicotine addiction, such as nicotine replacement therapy (NRT), combination therapy, non-nicotine medications, and non-pharmacological treatments like training, behavioral therapy, counseling, e-cigarettes, etc. [19]. Combination therapy, which combines the use of Nicotine Replacement Therapy (NRT) with counseling, has been proven to be the most effective treatment method for nicotine addiction, as shown in a study conducted by Heydari et al. (2015) [15]. Research has shown that adults have a higher success rate in quitting smoking compared to older age groups, making it important to focus on this population in smoking cessation efforts [21,22]. Recent research has shown that by providing counseling support and promoting follow-up visits for patients in outpatient settings, physicians can greatly improve the chances of their patients successfully quitting smoking [23]. This approach is more effective than traditional methods and should be prioritized for the best results. The smoking cessation rate remains unsatisfactory despite numerous efforts and expenses, and it will take a lot of work to close the gaps. The biggest obstacles to successfully quitting smoking include difficulty tracking patients' progress, reliance on self-reported patient data, and lack of engagement and emotional connection [24]. These issues must be addressed to increase the chances of success.

As technology continues to evolve, the healthcare industry keeps pace with integrating information and communication technologies (ICTs). The delivery of healthcare services is also undergoing a rapid transformation. Using ICTs in healthcare can facilitate communication and information exchange between physicians and patients, regardless of location. By effectively utilizing technology, we can overcome the challenges that often stand in the way of providing effective treatment to patients. One area where this is particularly relevant is in the realm of smoking cessation. In recent years, a growing number of studies have been conducted on using mobile applications or wearable devices to help individuals quit smoking. This method of using technology to change behavior is called persuasive technology and has proven highly effective. In fact, According to a study, it has been suggested that computer-based interventions (CBIs) are more effective than brief in-person interventions (IBIs) when it comes to substance use. This is because CBIs are a cost-effective and reliable way of gathering patient information, allowing for honest self-reporting and regular feedback from healthcare providers. Patients can better self-monitor, track their progress and receive daily reminders, effectively increasing their chances of success in quitting smoking. Despite the proven effectiveness of various interventions for smoking cessation, a majority of mobile apps offering quit-smoking features on the Google Play store are found to be ineffective. This is often attributed to reasons such as lack of user engagement, insufficient incentives, lack of evidence-based practices, and reliance on self-reported data. It is crucial for future developments in this field to address these issues to improve the overall effectiveness of these interventions. Implementing methods to make these mobile apps more appealing may increase user engagement and ultimately improve the success rates of their interventions. Incorporating gaming elements in mobile applications can help increase usage and adherence to the interventions provided through them.

Additionally, the use of information and communication technologies (ICTs) and persuasive technology can be powerful tools to overcome barriers to delivering effective treatment to patients. With the right strategies in place, we can improve the effectiveness of these interventions. Smoking event detection or automated tracking can aid in delivering individualized and customized feedback. It constitutes one of the problematic research topics in sensor-based human activity detection. Several real-time human activity identification techniques have been presented [27, 28].

Automatically detecting smoking needs some form of a sensor worn on the body, such as a smart lighter, accelerometer, smoke detection sensor, gyroscope, and respiration sensor. However, the main challenges in employing these devices are inconspicuous sensing [28] and ubiquitous sensing. Wrist-wearing IMU (Inertial Measurement Unit) sensors are commonly utilized in research to monitor smoking activity. In addition, heart rate sensors, smart lighter, respiration sensors, and smoke sensors have been used in research. In a research study, sensors were worn to record respiration data on the wrists and body. These sensors included a 6-axis IMU and a body-wearable electrocardiograph (ECG) sensor suite. The study results showed that the model performed well when both types of sensors were used together but poorly when used separately.

Additionally, the body-wearable suit was found to be impractical for everyday use, making it less accessible to the general population. A study was conducted that utilized four 6-axis IMU sensors on different parts of the arm, such as the lower elbow, wrist, lower arm, and upper elbow, to accurately identify smoking and non-smoking events, as well as determine the optimal number of sensors and their placement on the body. However, this study's results showed that the classification models' accuracy could be improved and that using four sensors in different positions on the body is not practical for everyday use. The researchers in this study aimed to develop precise predictive models without relying on obtrusive sensors, making them more practical for everyday use.

The sensor data collected from IMU is continuously generated and holds unique characteristics of various activities related to the movement of the human body. It has not been fully utilized in past research. As a result, prior approaches had limited performance and practical applications. However, in our study, we recognized the potential of this data and its importance in identifying everyday activities such as smoking, walking, running, eating, drinking, and talking. We could classify and detect these activities effectively by utilizing the convenience and widespread use of wristbands or smartwatches as sensors. Then we extracted features from the IMU sensor data and experimented with different time-window sizes to find the optimal one. In our study, we used a method of extracting data called a sliding window technique with a 50% overlap and window sizes of 1, 3, and 5 seconds to obtain features. The feature vector is derived by processing the raw data from each window, which encompasses a variety of time-domain, frequency-domain, and descriptive features. By utilizing properly labeled data, we were able to construct various machine-learning models that could classify different activities effectively.

3. Smoking Behavior Detection

Our suggested method cannot only handle complex settings such as poor illumination and restricted vision of cigarettes, but it can also easily distinguish various hand gestures. We decreased computational costs while improving the recognition rate by considerably lowering false positives using conditionally active detection. Our ablation research findings demonstrated the efficacy of our suggested strategy, which outperformed the existing latest approaches for recognizing tiny objects in photos. While most previous studies have concentrated on recognizing and detecting motions during smoking or while smog is present, our technique uses FPN to determine the driver's behavioral patterns, considerably decreasing the possibility of error. Our suggested technique is trustworthy and highly accurate, with a 96% recall rate, 94.75% accuracy, 95.5% area under the ROC curve, and a 95.05% precision rate.

3.1. Dataset Collection

The proposed platform is a local driver real-time monitoring system, a cutting-edge solution for ensuring the safety of drivers on the road. Our platform is built on a robust dataset of 7,000 images featuring drivers operating over 200 different types of vehicles. These images include 3,500 instances of drivers smoking, providing a comprehensive understanding of driving behavior.

Our data is meticulously divided into a training dataset of 6,000 images, including 3,000 images of smoking drivers, an evaluation dataset of 600 images, including 300 images of normal driving and a test dataset of 400 images, including 200 images of smoking drivers. The data used in this study is derived from video footage captured from a state-of-the-art vehicle monitoring platform, which is then processed frame-by-frame to generate the original driver images. These images are then cropped to remove background information and reduce its influence, resulting in a final image size range of 380 x 380 to 410 x 410, with an input of (400x400,3). Our model's performance is assessed using industry-standard metrics such as precision, accuracy, Receiver Operating Characteristic (ROC), specificity and recall. Our proposed approach, FPN-D, has achieved an outstanding ROC score of 95%, making it one of the most reliable and accurate driver monitoring platforms on the market.

4. Smoking Detection in Video Footage

The system detects smoking by assuming a smoker is near the cigarette smoke. The method classifies an event as smoking by searching for a cigarette's smoke near a person's face or hand. First, it starts by identifying faces in each frame; then, the algorithm collects a sample of each face's color to find areas where skin color is the same inside the frame. Beyond the recognized facial region, the hand is estimated to have the most skin. The device will then attempt to detect smoke in the areas designated as hand or face. The video frame is labeled a potential smoking frame if any smoke is detected. The system considers a video to contain an instance of smoking if the majority of the proportion of frames in the video have been identified as potential smoking frames.

The Gaussian Mixture Model for motion detection is limited to video shots with a stationary camera that cannot keep up with changes in the background. It was developed in C++ with the OpenCV library. The system examines each input frame in three stages: first is to look for a face in each frame, then it searches for a hand in the region where the face is detected, and finally, it looks for smoke in the region around the face in the frame and each hand. Face detection was utilized for the OpenCV library's face classifiers, one for recognizing frontward faces and the other for detecting the face in profile.

4.1. Hand Detection

4.1.1. Backpropagation

The system takes a small rectangular section which is 1/4th the size of the entire region from the centre. This sub-image is then taken as a sample of the person's skin color whosever face is. Using back projection and the -> histogram approach, the method detects other regions in the frame of a similar colour.

4.2. Color Analysis

The color of each skin-related pixel is measured in the Hue Saturation Value (HSV), Luminance Chrominance (YCbCr), and Red Green Blue (RGB) spaces to ensure it falls within acceptable ranges for skin color. The color analysis stage's output is combined using a bitwise AND operation.

4.3. Connected Components Analysis

The method filters off the face region and selects the hand with the most skin pixels left, which matches the face. Connected components analysis is used to identify the biggest cluster of skin pixels.

4.4. Smoke Detection

Motion detection: objects and object tracking can instantly mark possible targets of smoke. For more rigorous analysis, we can use Gaussian Mixture Model (GMM) [Stauffer,1999].

The colour of smoke varies with temperature, although it is often bluish-white to grey.

4.5. Disorder Analysis

It aids with the differentiation of genuine smoke from m oving, smoke-colored items. Short video snippets from contemporary movies were used to evaluate the system's performance. A number of movies from the HMDB [HMDB] and Bilkent [Bilkent] datasets were used in this study. The system should be refactored such that it can handle lengthier videos and videos taken with non-stationary cameras. The longer videos were cut into shorter ones, and then watched each one individually. The automated system can identify any smoking in a video stream.

This study aims to create a machine learning-based framework to identify smoking among other daily activities in real-time, using data from a wrist-worn inertial measurement unit (IMU) sensor. A low-cost wrist-worn device was developed to collect sensor data from subjects. The device employs a sliding window mechanism to process the streaming raw sensor data and extract several time-domain, frequency-domain, and descriptive features, providing a cost-effective solution for data collection. Optimization of model hyperparameters and feature selection is used to determine the optimal parameters and features. Our multi-class classification models are built and evaluated using both internal and external validation methods, guaranteeing the highest level of accuracy and reliability. The objective of this study is to develop a system for recognizing daily activities, including smoking, in close to real-time. This paper aims to create an automated system that can anticipate smoking activity in a near-real-time manner. To achieve this, the following research objectives were addressed:

1. Deriving characteristics from raw sensor readings of a continuous nature to construct models for predicting smoking behavior in addition to daily routine actions.
2. Establishing a comprehensive predictive modeling framework suitable for real-time activity predictions using data from an inertial measurement unit sensor.
3. Identifying crucial feature variables for the accurate prediction of activities.
4. Assessing the applicability of the modeling framework for predicting activities of interest in preventative healthcare settings. This research created models with a high level of predictive accuracy, with an area under the receiver operating curve reaching as high as 98.7%.

This research was conducted with strict adherence to ethical guidelines, having received approval from the Institute Ethical Committee of the Indian Institute of Technology Kharagpur, India. Data were collected from a diverse group of 13 male participants in March 2019 in accordance with the highest ethical standards. Participation in the study was entirely optional, and all participants gave their informed consent prior to the commencement of data collection. Out of the 13 participants, data for physical activities was gathered from 7 individuals aged between 22 and 24. In comparison, data for smoking activity was obtained from the remaining 6 participants who were regular cigarette smokers aged between 30 and 36.

The outcome of this study will pave the way for the creation of a novel application of wearable technology that can precisely identify smoking behavior in real-time. Furthermore, it will aid healthcare professionals in tracking their smoking patients by offering prompt interventions to aid in cessation. The methodology can also be adapted to other scenarios in preventive healthcare and the identification of other activities of interest. This research aims to enhance efforts to quit smoking by offering timely interventions by implementing a machine learning-based framework and data from a wrist-mounted inertial measurement unit sensor, which can accurately identify smoking activity among other daily activities. A cost-effective wearable device was created and employed for gathering sensor data, with a sliding window technique employed for processing data, extracting features, and applying hyperparameter tuning and feature selection. Multi-class classification models were created and tested to a high degree of predictive accuracy (98.7% for predicting smoking activity). This technology can be utilized as a wearable device to assist healthcare professionals in monitoring and aiding patients in quitting smoking. It can also be applied in other areas of preventive healthcare and activity detection [2].

The negative impact of compulsive habits on one's health is widely recognized in the literature [3], with smoking being a leading cause of various non-communicable diseases such as heart disease, stroke, chronic lung disease, and cancer [4]. The difficulty of overcoming the addiction to tobacco smoking and the harmful impact on one's health is widely acknowledged. Despite the challenges of quitting smoking, including sudden cravings that can lead to lapses and relapses, the success rate for quitting smoking has not been satisfactory. Despite this knowledge, the lack of efficient techniques for offering timely support to individuals who want to quit smoking makes it even more challenging to improve cessation rates [5].

Overcoming the limitation of manual recording of smoking logs, the identification of smoking in close proximity to real-time is a complex research challenge. This also allows for the potential of mobile app-based interventions that provide immediate motivation to quit smoking. Recent developments in mobile health and persuasive technology offer an effective way to intervene and support smoking cessation efforts. The integration of technologies like IoT, sensors, machine learning and mobile computing makes it possible to continuously monitor daily activities through the use of discreet, body-worn sensor devices. By applying advanced computational methods, it is now possible to identify activities like smoking, walking, running and sleeping in real-time. Feedback on behavior can be instantly provided to the user through the use of smartphones and mobile apps. Additionally, mobile apps can be used to provide support for behavior modification.

This study aims to develop a solution for smoking cessation through the use of near real-time interventions that can motivate users to change their behavior [8-13]. The solution involves utilising body-worn devices such as smartwatches and bands capable of tracking physical activity and sleep behavior in real time. Equipped with sensors such as accelerometers, gyroscopes, and magnetometers, these devices provide raw data signals generated from body movements. Additionally, by leveraging the power of mobile technology, personalized interventions can be delivered to promote behavior modification, making it a powerful tool for preventative health care [11]. Through the use of data analytics, a personalized behavioral profile of the user can be created, which can be accessed through mobile apps, helping to motivate the adoption of healthy behaviors and improving overall health. The identification of cigarette smoking as a behavior that can be monitored through the use of intelligent wearable technology and mobile applications [5,16,17]. Previous research in this field has been limited to detecting smoking activity alone, without considering other daily activities, which hinders its practical application. Furthermore, these early-stage studies are restricted to predicting smoking instances, recognizing smoking gestures, identifying the first relapse, and using wearable sensors that can be perceived as intrusive.

5. Results and Discussions

We have taken our dataset and run it with different deep learning algorithms and Machine Learning algorithms, and the results of those respective algorithms are discussed below.

5.1. Inception

We have run the Inception model for ten epochs with 5000 images of the dataset of smoking and non-smoking this is the result we have obtained.

Table 5.1.1. Accuracy of Inception

Accuracy	Error
92.89	7.61

Table 5.1.2. Detailed Accuracy

	Precision	recall	F1-score	Support
Smoking	1.00	0.85	0.92	48
Not Smoking	0.86	1.00	0.93	44
Accuracy			0.92	92
Macro avg	0.93	0.93	0.92	92
Weighted avg	0.93	0.92	0.92	92

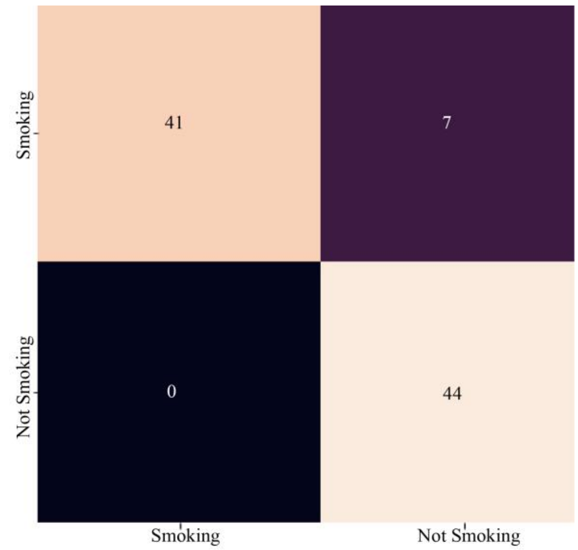

Fig. 5.1 Confusion Matrix of Inception

5.2. ResNet50

The ResNet50 was run for ten epochs with 5000 images of a dataset of smoking and non-smoking this is the result we have obtained.

Table 5.2.1. Accuracy of ResNet50

Accuracy	Error
82.6	17.4

Table 5.2.2. Detailed Accuracy

	Precision	Recall	F1-score	Support
Smoking	0.82	0.85	0.84	48
Not Smoking	0.83	0.80	0.81	44
Accuracy			0.83	92
Macro avg	0.83	0.82	0.83	92
Weighted avg	0.83	0.83	0.83	92

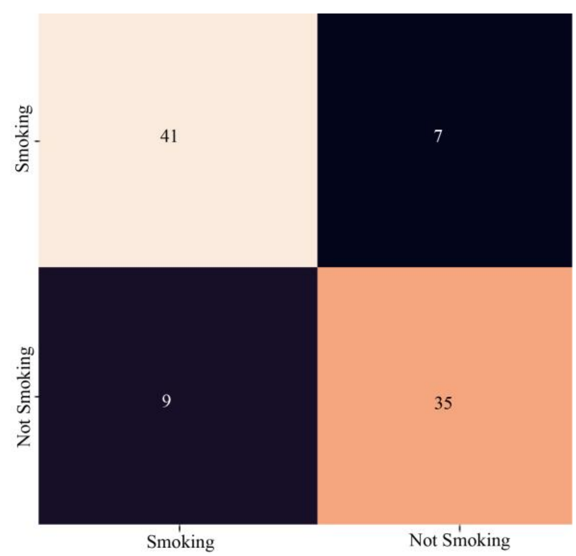

Fig. 5.2 Confusion Matrix of ResNet50

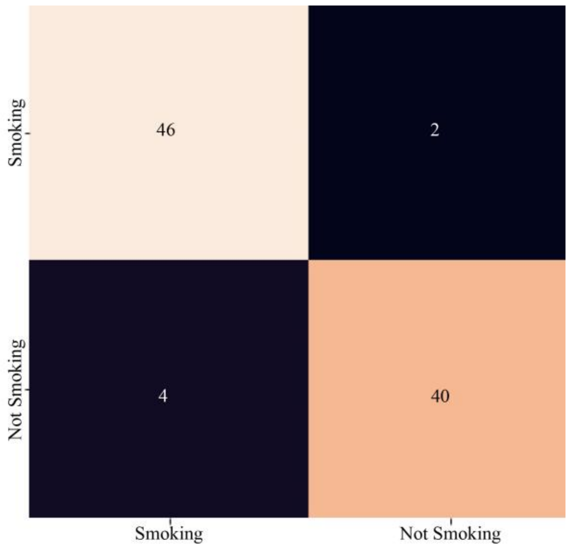

Fig. 5.3 Confusion Matrix of Xception

5.3. Xception

We have run the Xception model for 20 epochs with 5000 images of the dataset of smoking and non-smoking this is the result we have obtained.

Table 5.3.1. Accuracy of Xception

Accuracy	Error
93.47	6.521

Table 5.3.2. Accuracy of Xception

	Precision	recall	F1-score	Support
Smoking	0.92	0.96	0.94	48
Not Smoking	0.95	0.91	0.93	44
Accuracy			0.93	92
Macro avg	0.94	0.93	0.93	92
Weighted avg	0.94	0.93	0.93	92

5.4. DenseNet

We have run the DenseNet model for 20 epochs with 5000 images of the dataset of smoking and non-smoking this is the result we have obtained.

Table 5.4.1. Accuracy of DenseNet

Accuracy	Error
94.565	5.435

Table 5.4.2. Detail Accuracy

	Precision	recall	F1-score	Support
Smoking	0.92	0.98	0.95	48
Not Smoking	0.98	0.91	0.94	44
Accuracy			0.95	92
Macro avg	0.95	0.94	0.95	92
Weighted avg	0.95	0.95	0.95	92

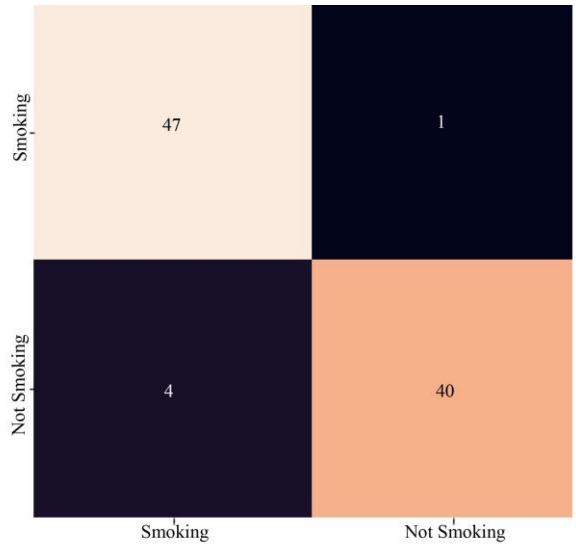

Fig. 5.4 Confusion Matrix of DenseNet

5.5. Voting Classifier

Here different deep learning models were taken, such as DenseNet, Xception, Inception and ResNet50, which were run for 20,10,10 and 10 epochs, respectively. After that, we applied a Voting classifier, which gave us an accuracy of 94.4%.

Table 5.5.1. Accuracy of Voting Classifier

Accuracy	Error
94.41	5.69

Table 5.5.2. Detailed Accuracy

	Precision	recall	F1-score	Support
Smoking	0.92	0.98	0.95	48
Not Smoking	0.98	0.91	0.94	44
Accuracy			0.95	92
Macro avg	0.95	0.94	0.95	92
Weighted avg	0.95	0.95	0.95	92

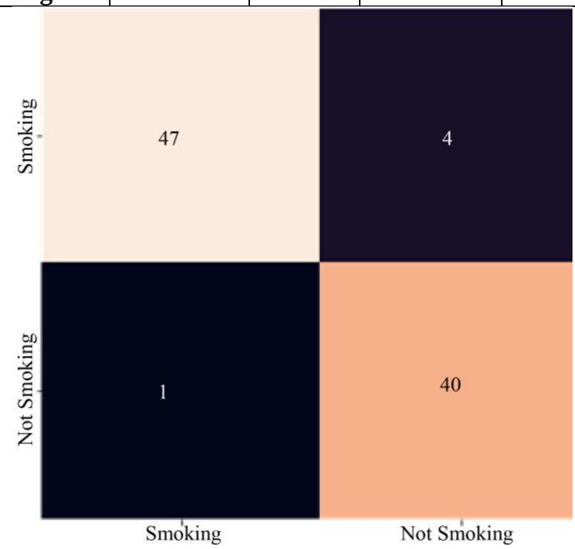

Fig. 5.5 Confusion Matrix of Voting Classifier

Table 5.6. Detail Accuracy report of Random Forest

	Precision	Recall	F1-score	Support
Smoking	0.20	0.92	0.32	36
Not Smoking	0.98	0.59	0.74	330
Accuracy			0.62	366
Macro avg	0.59	0.75	0.53	366
Weighted avg	0.91	0.62	0.70	366

Table 5.7. Detail Accuracy report of K-Nearest Neighbors (KNN)

	Precision	recall	F1-score	Support
Smoking	0.28	0.90	0.43	52
Not Smoking	0.97	0.61	0.75	314
Accuracy			0.65	366
Macro avg	0.63	0.76	0.59	366
Weighted avg	0.88	0.65	0.71	366

Table 5.8. Detail Accuracy report of Support Vector Machine (SVM)

	Precision	recall	F1-score	Support
Smoking	0.38	0.82	0.52	79
Not Smoking	0.93	0.64	0.76	297
Accuracy			0.68	366
Macro avg	0.66	0.73	0.64	366
Weighted avg	0.81	0.68	0.71	366

Table 5.9. Detail Accuracy report of Naïve bayes

	Precision	recall	F1-score	Support
Smoking	0.54	0.67	0.60	135
Not Smoking	0.78	0.66	0.71	231
Accuracy			0.67	366
Macro avg	0.66	0.67	0.66	366
Weighted avg	0.69	0.67	0.67	366

Table 5.10. Detail Accuracy report of Decision Tree

	Precision	recall	F1-score	Support
Smoking	0.33	0.67	0.44	83
Not Smoking	0.86	0.60	0.71	283
Accuracy			0.62	366
Macro avg	0.68	0.64	0.58	92
Weighted avg	0.74	0.62	0.65	366

Machine Learning algorithms were not yielding good results compared to the deep learning algorithm. The results of these machine learning algorithms, such as Random Forest, KNN, SVM, Naïve Bayes, and Decision Tree, are discussed below.

6. Conclusion and Future Directions

Using a predictive modeling framework developed in this study, we could predict smoking behavior in everyday activities in real time. This study has primarily contributed to developing a wrist-worn device that utilizes a 6-axis IMU sensor. The device recorded walking and running activity, stair climbing, smoking and stair descending in a free environment. Here, we introduced a method to extract features by streaming sensor data generated by the wearable wrist device using a sliding-window mechanism. This is the first research of its sort to look at the ideal size of a sliding window. To find out the optimal sliding window size, we experimented with various sliding window sizes until the optimal size had been determined for the feature generation. A framework based on supervised machine learning was created to construct models that can classify to aid the identification of activities such as smoking and other physical activities. The approach employed for classification models also includes techniques for identifying the important features and finding the optimal combination of hyperparameters, resulting in highly effective and efficient models. Then the prediction models are developed using the selected hyperparameters and important features. By thoroughly evaluating the models through in-sample and out-of-sample testing, we can confidently select the optimal model for the application. The SVM model was found to be the most effective in this study, with an impressive AUC of 98.78%. The results of this investigation can be utilized as a basis for future research on utilizing wearables to detect addictive behaviors in real time and create intervention systems that can prompt individuals to stop these addictive behaviors. The developed framework has multiple use cases, such as creating various healthcare applications and many more. This study aimed to assess the practicality of the system by predicting smoking behavior within daily activities. While the proposed model outperforms other models in the literature, despite some limitations, the suggested model has the ability to be a success and a valuable tool in the battle against smoking addiction.

The study is focused on the classification of smoking and the limited number of physical activities, but there is an opportunity to expand on this research in future. Include other activities such as sleeping, eating, drinking, talking, and other relevant activities in future studies. This will further improve the system's practical applicability. It will make it possible to apply this model to real-world situations, and its performance in such situations remains to be seen. One way to achieve this is by implementing the model through a mobile application, which would make it more accessible to a wider range of users and allow for a more in-depth evaluation of its effectiveness. There is also a potential to provide healthcare services that can offer real-time interventions to aid people to help them refrain from smoking through the mobile application.

Furthermore, in the future, research can be done to assess the effectiveness of the such intervention. It is crucial to highlight that the selection of hand-crafted features limits the performance of machine learning models, which can significantly influence the performance of supervised machine learning models. It is possible to extract features from raw data automatically using deep learning models. By incorporating deep learning-based classification models such as Long Short-term Memory (LSTM) and Recurrent Neural Networks (RNNs), there is a potential further to enhance the real-time activity detection system's performance as we can expect to see an improvement in terms of predictive accuracy and faster prediction times. A liability of this study is that it used a small dataset, which can be a hindrance when training deep learning models that require large data to work effectively. This can be addressed in future research by using a larger dataset to test the deep learning model for real-time prediction of smoking activities.

Additionally, other techniques for human activity recognition (HAR) can be explored, such as using video and environmental sensor data like infrared sensors. These techniques can provide valuable insights and improve the performance of the system. For further research, comparing techniques for human activity recognition (HAR) that use video or environmental sensors with those that use wearable sensor devices would be fascinating.

Furthermore, it would be beneficial to analyze the computational time complexity of these methods to evaluate their suitability. The system also has the potential to be expanded to detect unusual activities and small objects. In the future, we hope to improve the effectiveness of the given approach by incorporating data from different modalities, such as feeds and videos from night-vision cameras. It will provide more comprehensive information and make more accurate predictions even in the night environment.

References

[1] Pundhir, A., Verma, D., Kumar, P., Raman, B, Region Extraction Based Approach for Cigarette Usage Classification Using Deep Learning. In: Raman,B.,Murala,S., Chowdhury, A.Dhall, A., Goyal,P.(eds) Computer Vision and Image Processing. CVIP 2021. Communications in Computer and Information Science, vol.1568, 2022. Crossref, https://doi.org/10.1007/978-3-031-11349-9_33

[2] Saurabh Singh Thakur, Pradeep Poddar, and Ram Babu Roy, "Real-Time Prediction of Smoking Activity Using Machine Learning Based Multi-Class Classification Model," *Multimedia Tools and Applications*, vol. 81, pp. 14529–14551, 2022. *Crossref*, https://doi.org/10.1007/s11042-022-12349-6.

[3] Prabhat Jha, and Richard Peto, "Global Effects of Smoking, of Quitting, and of Taxing Tobacco," *The New England Journal of Medicine*, vol. 370, no. 1, pp. 60–68, 2014. *Crossref*, https://doi.org/10.1056/NEJMra1308383

[4] G O'Donoghue et al., "Assessment and Management of Risk Factors for the Prevention of Lifestyle-Related Disease: A Cross-Sectional Survey of Current Activities, Barriers and Perceived Training Needs of Primary Care Physiotherapists in the Republic of Ireland," *Physiotherapy*, vol. 100, no. 2, pp. 116–122, 2014. *Crossref*, https://doi.org/10.1016/j.physio.2013.10.004

[5] Nazir Saleheen et al., "PuffMarker: A Multi-Sensor Approach for Pinpointing the Timing of First Lapse in Smoking Cessation," *ACM International Conference Ubiquitous Computing*, vol. 2015, pp. 999–1010, 2015.

[6] Sasan Adibi, *Mobile Health A Technology Road Map*, 5th edition Springer International Publishing, 2015.

[7] K. Archana, and K.G.Saranya, "Crop Yield Prediction, Forecasting and Fertilizer Recommendation using Voting Based Ensemble Classifier," *SSRG International Journal of Computer Science and Engineering* , vol. 7, no. 5, pp. 1-4, 2020. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V7I5P101

[8] Philipp M. Scholl, and Kristof van Laerhoven, "A Feasibility Study of Wrist-Worn Accelerometer Based Detection of Smoking Habits," *Sixth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing*, pp. 886–891, 2012. *Crossref*, https://doi.org/10.1109/IMIS.2012.96

[9] Saurabh Sing Thakur, and Ram Babu Roy, "A Mobile App Based Smoking Cessation Assistance Using Automated Detection of Smoking Activity," *ACM India Joint International Conference on Data Science and Management of Data*, pp. 352–355, 2018. *Crossref*, https://doi.org/10.1145/3152494.3167989

[10] Atallah Louis et al., "Sensor Positioning for Activity Recognition Using Wearable Accelerometers," *IEEE Transactions Biomedical Circuits and Systems*, vol. 5, no. 4, pp. 320–329, 2011. *Crossref*, https://doi.org/10.1109/TBCAS.2011.2160540

[11] Juha Parkka et al., "Activity Classification Using Realistic Data From Wearable Sensors," *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 1, pp. 119-128, 2006. *Crossref*, https://doi.org/10.1109/titb.2005.856863

[12] Jun Qi et al., "A Survey of Physical Activity Monitoring and Assessment Using Internet of Things Technology," *IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*," pp. 2353–2358, 2015. *Crossref*, https://doi.org/10.1109/CIT/IUCC/DASC/PICOM.2015.348

[13] Saurabh Sing Thakur, and Ram Babu Roy, “Smartphone-Based Ubiquitous Data Sensing and Analysis for Personalized Preventive Care: A Conceptual Framework,” *Computational Intelligence: Theories, Applications and Future Directions*, vol. 798, pp. 119–132, 2019. *Crossref*, https://doi.org/10.1007/978-981-13-1132-1_10
[14] Ya-Li Zheng et al., “Unobtrusive Sensing and Wearable Devices for Health Informatics,” *IEEE Transactions on Biomedical Engineering*, vol. 61, no. 5, pp. 1538– 1554, 2014. *Crossref*, https://doi.org/10.1109/TBME.2014.2309951
[15] Gholamreza Heydari et al., “Assessment of Different Quit Smoking Methods Selected by Patients in Tobacco Cessation Centers in Iran,” *International Journal of Preventive Medicine*, vol. 6, no. 81, 2015. *Crossref*, https://doi.org/10.4103/2008-7802.164118
[16] Philipp M. Scholl, and Kristof van Laerhoven, “A Feasibility Study of Wrist-Worn Accelerometer Based Detection of Smoking Habits,” *Sixth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing,* pp. 886–891, 2012. *Crossref*, https://doi.org/10.1109/IMIS.2012.96
[17] Tang Qu et al., “Automated Detection of Puffing and Smoking with Wrist Accelerometers,” *8th International Conference on Pervasive Computing Technologies for Healthcare,* pp. 80–87, 2014. *Crossref*, https://doi.org/10.4108/icst.pervasivehealth.2014.254978
[18] Raka Jain et al., “Pharmacological Intervention of Nicotine Dependence,” *Biomed Research International,* 2013. *Crossref*, https://doi.org/10.1155/2013/278392
[19] Gholamreza Heydari et al., “A Comparative Study on Tobacco Cessation Methods: A Quantitative Systematic Review,” *International Journal of Preventive Medicine*, vol. 5, no. 6, pp. 673–678. 2014.
[20] Nithya B, and Anitha G, "Drug Side-effects Prediction using Hierarchical Fuzzy Deep Learning for Diagnosing Specific Disease," *International Journal of Engineering Trends and Technology*, vol. 70, no. 8, pp. 140-148, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I8P214
[21] David Méndez et al., “Has Smoking Cessation Increased? An Examination of the US Adult Smoking Cessation Rate 1990–2014,” *Nicotine & Tobacco Research*, vol. 19, no. 12, pp. 1418-1424, 2017.
[22] Karen Messer et al., “Smoking Cessation Rates in the United States: A Comparison of Young Adult and Older Smokers,” *American Journal of Public Health,* vol. 98, no. 2, pp. 317–322, 2007. *Crossref*, https://doi.org/10.2105/AJPH.2007.112060
[23] Wei-Hsin Huang et al., “Factors Correlated with Success Rate of Outpatient Smoking Cessation Services in Taiwan,” *International Journal of Environmental Research and Public Health*, vol. 15, no. 6, pp. 1218, 2018. *Crossref*, https://doi.org/10.3390/ijerph15061218
[24] Robyn Whittaker et al., “Mobile Phone-Based Interventions for Smoking Cessation,” *Cochrane Database of Systematic Reviews*, vol. 4, no. 4, 2016. *Crossref*, https://doi.org/10.1002/14651858.CD006611.pub4
[25] Bruno M C Silva et al., “Mobile-Health: A Review of Current State in 2015,” *Journal of Biomedical Informatics,* vol. 56, pp. 265–272, 2015. *Crossref*, https://doi.org/10.1016/j.jbi.2015.06.003
[26] Peter Paul Verbeek, *Persuasive Technology,* Encyclopedia of Applied Ethics, Elsevier, pp. 431–437.2012.
[27] Zan Gao et al., “Adaptive Fusion and Category-Level Dictionary Learning Model for Multiview Human Action Recognition,” *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 9280–9293, 2019. *Crossref*, https://doi.org/10.1109/JIOT.2019.2911669
[28] Shaohua Wan et al., “Deep Learning Models for Real-Time Human Activity Recognition with Smartphones,” *Mobile Networks and Applications*, vol. 25, pp. 743–755, 2020. *Crossref*, https://doi.org/10.1007/s11036-019-01445-x
[29] Hari Narayanan A G, and J Amar Pratap Singh, "Skin Disease Ensemble Classification Using Transfer Learning and Voting Classifier," *International Journal of Engineering Trends and Technology*, vol. 69, no. 12, pp. 287-293, 2021. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V69I12P234
[30] Bethany R Raiff et al., “Laboratory Validation of Inertial Body Sensors to Detect Cigarette Smoking Arm Movements,” *Electronics Basel*, vol. 3, no. 1, pp. 87–110, 2014. *Crossref*, https://doi.org/10.3390/electronics301008778