Noname manuscript No.
(will be inserted by the editor)

Cleo: Smart Glasses to Monitor Consumption of Alcohol and Cigarettes

Sibi Chakkaravarthy S* · Pranav Kompally · Saraju P. Mohanty · BKSP Kumar Raju · Meenalosini Vimal Cruz

the date of receipt and acceptance should be inserted later

Abstract It is estimated that over 60% of people around the globe consume alcohol and cigars daily. Many people use them beyond the permitted limit, which causes lung cancer, liver and kidney failure. If there is a system that could monitor their intake level, it will alert them in case of excess consumption, which could help them control the intake. To help the users monitor their consumption, we introduce Cleo Eyeglasses in this paper. Cleo is a wearable spectacle device with a mounted camera and single onboard computer that performs custom trained object recognition to identify alcoholic beverages and cigarettes. Upon recognition, a log is automatically maintained in the corresponding mobile application. If the intake exceeds the user threshold, then our system generates an alert to both the user and concerned medical personnel. Cigarette/Alcohol consumption can immediately affect the body without noticeable symptoms. Cleo addresses this with keen monitoring of vital body parameters and generates an alert when abnormalities are detected.

Sibi Chakkaravarthy Sethuraman
School of Computer Science and Engineering and
Center of Excellence in Artificial Intelligence and Robotics (AIR)
VIT-AP University
Tel.: +91 9585583918
E-mail: chakkaravarthy.sibi@vitap.ac.in

Pranav Kompally
School of Computer Science and Engineering and
Center of Excellence in Artificial Intelligence and Robotics (AIR)
VIT-AP University
E-mail: pkompally@gmail.com

Saraju P. Mohanty
Department of Computer Science and Engineering
University of North Texas
TX 76207
USA.
E-mail: saraju.mohanty@unt.edu

BKSP Kumar Raju
School of Computer Science and Engineering and
Center of Excellence in Artificial Intelligence and Robotics (AIR)
VIT-AP University
E-mail: bksp.kumar@vitap.ac.in

Meenalosini Vimal Cruz
Department of Information Technology
Allen E. Paulson College of Engineering and Computing
Georgia Southern University
Georgia, USA.
E-mail: mvimalcruz@georgiasouthern.edu

Keywords Deep Learning · CNN · Alcohol monitoring · Computer Vision · smart glasses · smoke monitoring

1 Introduction

Excessive alcohol consumption is harmful from different perspectives, leading to many short-term and long-term health risks [40]. The consumption of alcohol and cigarette together would increase the risk of developing chronic diseases. As a short-term risk, excessive drinking would result in general impairment of static balance control, which causes the inability to coordinate postural and voluntary activity. It is estimated that around 3 million deaths and 1 million people lose their lives in alcohol consumption-related accidents every year [1,2]. The leading cause for the excessive consumption of alcohol is that alcohol drinkers' inability to recognize the limit of consumption. Hence, there is a pressing need for an automatic system that can monitor alcohol and cigarette consumption.

The conventional technique to measure alcohol and cigarette consumption was invasive, requiring special equipment. The breathalyzer is an efficient non-invasive method that can measure the level of alcohol through one's breath. But the existing systems can only measure and covey the measured values, they cannot help the user realize the intake and then generate alerts upon detecting abnormalities. A low-cost non-invasive automatic alcohol and cigarette consumption monitoring system is proposed to address this problem. Cleo is a wearable spectacle with a mounted camera that detects the number of cigarettes or volume of alcohol consumed using a highly accurate Object Recognition model. The model recognizes the number of cigarettes and the quantity of alcohol the user consumed and sends a report to the mobile application for the user to comprehend. A simple system is deployed in the application to check whether the consumption level is within the permitted limit or not. If the consumption has crossed permitted levels, an alert is sent to the user and concerned medical officials.

Further, the application also displays the quantity consumed along with a timestamp for the user to monitor their daily routine, analyze the vital signs and alert the user during consumption. The report can be shared with the user's rehabilitation officer or therapist to understand and analyze the user's health status. This wearable device could help many people who monitor their consumption levels, change their habits periodically, and finally get rid of such problems. Rest of the paper is organized as follows: Section 2 explains the various existing solutions. Section 3 shows the novelty of our approach. Section 4 presents system level overview of Cleo Section 5 explicitly outlines our proposed methodology. Section 6 emphasizes results and performance acquired by our proposed methods alongside a comparative analysis with existing solutions. Finally, the paper concludes in Section 8.

2 Prior Research and Novelty of Cleo

As technology advances in the area of Internet-of-things, activity and health monitoring have become even more easy and robust. Sensors have played an important role in monitoring the alcohol intake of a beverage. An extended analysis has been conducted where wearable device comparison is made in terms of type of the device, intoxication measurement and availability in the market [9]. A wearable bracelet is designed to monitor the alcohol consumption of users and detects the presence of Ethyl Glucuronide present in sweat [16] [5]. A wrist band which uses transdermal alcohol (TAC) sensor that detects vapour-phase alcohol and monitors different doses [20], [21]. Using the TAC sensor, risk assessment of alcohol consumption is calculated and validated using various statistical approaches [31]. An approach used TAC based biosensors to check whether a person consumed alcohol or not. The robust five features are identified and extracted from the TAC data collected from sensors enabled anklet which eventually helped not only for detection but also to asses BAC/BrAC levels [11]. Moreover a study [7] on the various methods to assess the quality behind using TAC enabled wearable devices concluded that there is no unified standard approach followed by the existing methods in the literature to measure alcohol in the body which there by lead to ambiguity of the application to real time clinical operations.

A smart cup that records the liquid level and alcohol intake with subsequent analysis carried out using Machine learning algorithms like Support Vector Machine achieved an accuracy of 90% for alcohol detection [6]. A smart helmet for bikers that leverages the use of alcohol sensor MQ-3 to check the levels of alcohol in the body [28]. However, it requires an appropriate training process to support modular platforms. The other drunken driving prevention models that uses the concept of Internet-of-things to analyze the factors such as alcohol concentration, eye-blinking rate, and thereby recommends any protective measures [33] [34] [37]. Another model which is an IoT based Smart vehicle Ignition and Monitoring system that prevents the vehicle from starting in case the user or driver is found to be intoxicated with Alcoholic beverages[13]. Additionally, authors in [19] proposed a completely automated system to assess the alcohol concentration in vehicles.

A nose sensor is used by the authors to detect alcohol, acetone and carbon monoxide [25]. A mobile based approach which uses built-in accelerometers in mobile phones to perform Gait Analysis and detect the presence of alcohol in the body of the user [15,38]. The authors in [8] developed a finger based non-invasive illumination device which can detect BAC levels with 85% accuracy using the subtle pattern changes in photoplethysmography signals after the alcohol consumption. A machine learning based approach utilized EEG signals for detecting alcohol-related EEG signals automatically [18,17,27]. A GAN based approach is devised for predicting the distribution which is then used to extract BAC levels by considering the patterns in TAC waveforms [26]. AlcoWear [24] is an integrated solution to detect alcohol levels using accelomerator and gyroscope data gathered from smart phone and smart watch. They have used tree based classifiers to categorize the BAC levels at various granularities with an average performance of 84 %. A light sensing ice cube [23] is designed to detect the quantity of alcohol con-

Table 1 Cleo vs State of the art systems

Features	Cigarette Counting	Visual Detection	Machine Learning on Edge capabilities
Smart helmet[28]	No	No	No
Smart Bracelet [16]	No	No	No
Smart Cup [6]	No	No	No
Cleo (Proposed)	Yes	Yes	Yes

Table 2 Comparison of Cleo technical features with other similar systems

Research Work	Features	Drawback(s)
Smart helmet[28]	– Face Recognition to authorise user. – Sensor to detect whether user has consumed alcohol or not. – Helmet is only compatible with customised bike.	– No real-time monitoring of volume of alcohol is observed. – The helmet doesn't not report/alert if excess alcohol has been over-consumed. – Alcohol sensor only detect if the user has consumed alcohol or not. And not the volume consumed. – As per the authors, face recognition only works if the camera is pointed right straight to the face.
Smart Bracelet [16]	– Pupil dilation and facial feature based alcohol consumption detection. – IoT integrated to alert response unit.	– Requires the user to be seated in the mobile. – Does not monitor the volume of alcohol consumed and the type of alcohol consumed. – Works with only customised automobile.
Smart Cup [6]	– User movement and locomotion tracking. – User Orientation based alcohol consumption level detection – Smart cup with visual signals to alert the subject	– The cup cannot detect if the liquid present in the container is alcohol or not. – Unnecessary Erratic movements can trigger false positives. No alert system is integrated to trigger emergency response unit.
Cleo (Proposed)	– In-ear PPG sensor to detect heart rate of the user. – Visual analysis of type and volume of alcohol intake – Post detection logging and report generation – IMU to analyse the user's gait from time-to-time. – System compatible with any type of eyeglasses.	– None.

sumption based on light wavelength distinguishability aspects between water and any beverage.

A non-invasive eye glasses [35] which stimulates tears from the user and captured to measure the alcohol concentration. The method used is different when compared with other approaches but creates additional uncomfortable aspects for the user.

SHelmet [22] is a multi-featured safety device which not only detects the alcohol consumption but also can alert the user in various other cases like, driving defect, drowsiness detection, reduced visibility, over speed and distractions.

Wearable devices are extremely common for tracking and alerting after identifying abnormalities based on physiological and psychological behavioural patterns. But they tend to generate subtle distortions in data collection process [12]. So, cleo also leverages custom defined image processing to detect whether a person is sober or not. Unlike Smart Steering [30], Cleo doesn't rely on sensor data, but recognizes the type and quality of alcohol consumed using the on-boarded camera. Cleo caches images at the time of instance where Alcohol beverage is detected. After an entry in the log and notifying a medical official, these images are also sent to keep a track of the amount and type of drink consumed by the user. When in use, and detected that the user has consumed more than the permissible amount, the user is notified not to drive and automatically recommended to book a cab, therefore opening a third party cab booking app. Cleo boasts a higher accuracy of recognizing whether the user is drunk or not in comparison with Smart Steering. Cleo is a portable solution that keeps a log of user drinking levels which is not the case with Smart steering. Donot-DUEye [29] detects whether the user is drunk or sober by monitoring the pupil dilation and blood pressure of the user. Donot-DUEye requires proper lightning and stable subject to detect the eyes and track pupil dilation, whereas Cleo doesn't require complex installation to use. Unlike Cleo, Donot-DUEye doesn't not keep of the drinking levels and time of the user. Therefore, not a portable solution if the user spends more time off-driving. Unlike Donot-DUEye, Cleo's image processing model doesn't require a stable image and can detect alcoholic beverages even in real-time without any manual trigger. Cleo, when worn by the user, keeps a track of drinking levels even when he/she is not driving without any requirement to customize the object tracking. Most importantly, a log is prepared and shared with a medical official, therefore keeping the user's health status monitored at all times.

3 Novel Contributions

3.1 Problem Statement

There are a few technological solutions for detecting the users with alcohol consumption. Completely preventing the habituated users not to consume alcohol/cigar may not be possible atleast in the initial treatment phase. In this direction, quantifying the cigar or alcohol consumption and alerting upon excessive limits helps the user to control the vital abnormalities and eventually leads to a better in time care. Existing works could not address this problem and the same is evident from Table 1.

3.2 Solution Proposed

Unlike the other state of the art systems available in the literature, the proposed system Cleo advances all of them by leveraging a technology stack that keeps the user updated on his intake of alcohol and nicotine in real-time, and their effects on the body, post consumption. This will aid the user to have a controlled intake and initiate the right treatment without any delay in case of abnormalities in vital parameters.

3.3 Novelty of the proposed solution

- Cleo provides the user an option to swap the default glasses with their desired powered lens, increasing their ease of use.
- Image recognition model that is fine-tuned on alcoholic beverages and cigarettes.
- Technology stack that leverages Heart-rate sensor and IMU to analyze the user's physical state post consumption.
- In-ear PPG sensor records heart-rate of the user and embedded earphone for sending voice prompts
- System Architecture that logs and generates a report for a medical official to assess.
- The proposed system features are far better than existing systems and the same is evident from Table 2.

4 A system level overview of Cleo to recognize and monitor alcohol and Cigarette consumption

The architecture of the Cleo is shown in Fig. 1. Cleo, is pair of eyeglasses that can be swapped with the user's powered lenses if needed. A 16 Mega-pixel camera is

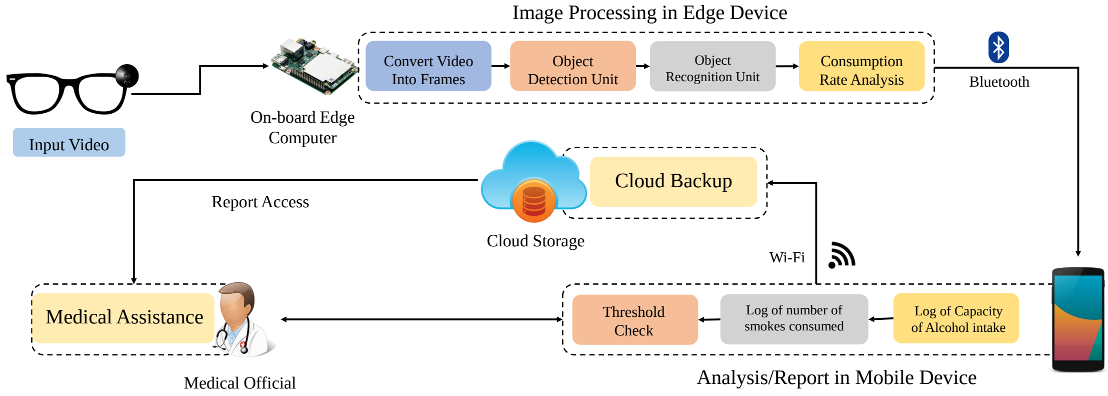

Fig. 1 The architecture of Cleo

attached to one end of the frame. On either end of the frames that sit on the ear, a heart rate sensor and an Inertial Measurement Unit (IMU) sensor are fitted. These sensors are connected to an on-board computer that has basic communication such as Bluetooth and Wi-Fi. The Heart rate or PPG sensor fits comfortably in the ear and sits on the earphone. While the PPG sensor records oxygen levels in the blood, the earphone is used to play the voice alerts depending on their level of intoxication. Cleo performs the machine learning operations right on the edge, logs data locally for a week's time and parallelly communicates with the Cleo app at any instance where both Cleo and the user's smartphone is paired and connected. Cleo also allows the user to use the smartphone mode that extends the machine learning operations of Cleo into the mobile application. Instead of performing the analysis on the edge, cleo allows the user to choose to perform the ML operations on the smartphone. In this case, real-time visual and sensor data collected on the glasses is transmitted to the smartphone for extensive analysis. The user can also choose to back up his/her reports to the cloud and the same can be shared with a medical official (see Fig. 2) depicts the proposed approach or flow for monitoring the consumption of alcohol and nicotine.

Once powered-on, Cleo started analyzing live feed from the camera. A Series of images are captured every 50 milli-seconds. The presence of any alcoholic beverage or cigarettes in the images is analyzed. If the deep learning model detects any of the above mentioned, the heart rate sensor and the IMU switch on automatically and start logging readings. Cleo's machine learning algorithm looks for any fluctuations in the sway or surge of the IMU and increase in the heart rate. If any of these conditions are met, an alert is raised on the Cleo app and the eyeglasses stating the user is tipsy/drunk in case of consumption of alcohol. Cigar consumption usually increases the heart rate of the user [39], post smoking, the number of smokes consumed along with the user's heart rate is logged in the mobile application. Post consumption of Alcohol, the user's BAC level is estimated. In case the estimated BAC level is beyond a certain threshold, the user is prompted either to call for help or book a cab in case he/she needs to travel. Additionally, an emergency button appears for the user to utilize if needed.

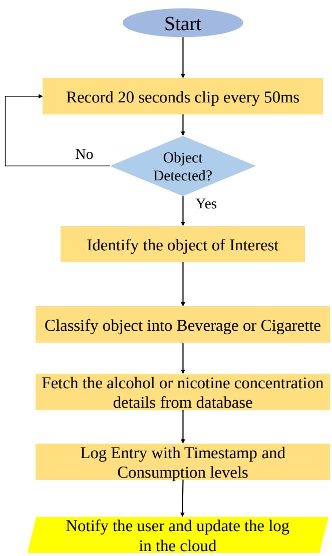

Fig. 2 Proposed approach for monitoring alcohol and cigarette consumption

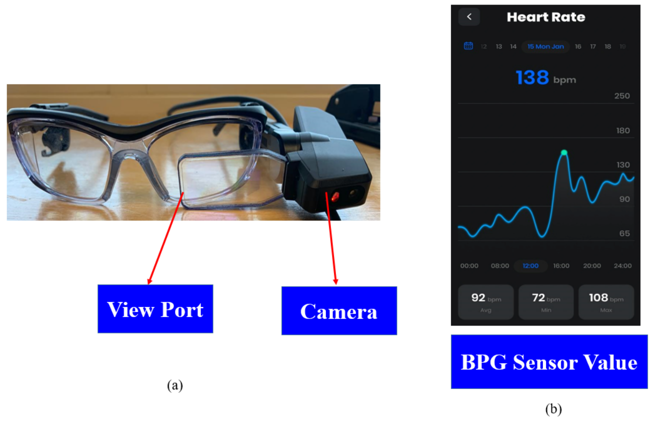

Fig. 3 Cleo prototype - (a) Smart Glasses and (b) Cleo user application

4.1 Edge Computing Platform

The single-board computer embedded in the eyeglasses (Fig. 3) takes care of all kinds of image processing and computing needs. Hence it eliminates the need to connect mobile devices to Cleo glasses as the on-board computers perform the same within the same time constraint. The computer triggers the camera to capture images in regular intervals of time. Custom trained neural networks perform image analysis to detect and identify target items such as any Alcoholic beverage and nicotine containing cigarettes. The user's gait pattern along with his/her heart rate analysis is also performed in real-time as soon as any alcoholic beverage is detected, the results are then transmitted to the mobile application. Image analysis on the edge or on-board computer doesn't make it mandatory for the user to have an active smartphone connection. Post analysis, a copy of data and the results are logged in the smartphone application as well.

4.2 Mobile Computing platform

As smartphones are considered to be a part of the body and 90% of users place their device in arms reach, making it quite accessible. Cleo leverages the connectivity between the eyeglasses and the cleo app to keep a track of alcohol intake and number of smokes consumed by the user. Post item recognition on the eyeglasses, the prediction is transmitted to the smartphone app to log in and produce a report at the end of the day. This helps the user keep a track of their consumption routine, and make sure it is within the permissible limit as stated by the medical official. In case the application finds that the threshold per day has increased or shot up, an alert or SOS message is pushed to medical officials utilising the smartphone's emergency call feature. This feature ensures the user's safety in times of blackout. Similarly, the PPG sensor monitors the user's heart rate in beats per minute metric(bpm). Bpm is also logged along with the timestamp that corresponds to the consumption of either nicotine or alcohol. The user can check his/her bpm live on the application whenever needed.

5 Proposed Methodology for Cleo

5.1 Collection of Dataset

The deep learning model is trained on 5+ classes that depict alcoholic beverages as shown in Table 3. The dataset contains manually annotated 2000 images for each class. The objects of interest in images were annotated using the graphical annotation tool [32]. This helped in pinpointing the necessary images with ease.

Table 3 Standard Alcoholic Drinks and percentage of Alcohol present in them

Beverage	Volume(oz)	% ethanol present
Beer	12 Full	5
Malt Liquor	8 Full	7
Wine	5 Full	12
Spirits(Whiskey, Vodka)	1.3 Full	40

5.2 Design of Deep Learning Model

Since, the process of object detection has to be precise in identifying objects in the least amount of time, YOLOv5 has been used [14]. YOLOv5 (see Fig. 4) is a two stage object detector with three modules. Model Backbone, Model Neck and Model head. Model Backbone extracts important features from the given input image. The model neck generates feature pyramids to generalize object scaling and finally the model head performs the detection and anchors boxed on features generate output vectors of class probabilities. The activation and optimized functions used are Leaky ReLU and Stochastic Gradient Descent respectively. The entire model has 191 layers with Binary Cross Entropy as the Loss function. The complete workflow of the same is shown in Algorithm 1 where * is the convolution operation, S_U is the output of the partial transitional layer, S_T is the output derived from S_K states of dense layers, $S^{'}$ and $S^{''}$ are the partial feature maps of the base layer and obtained feature space is given as input to PaNet

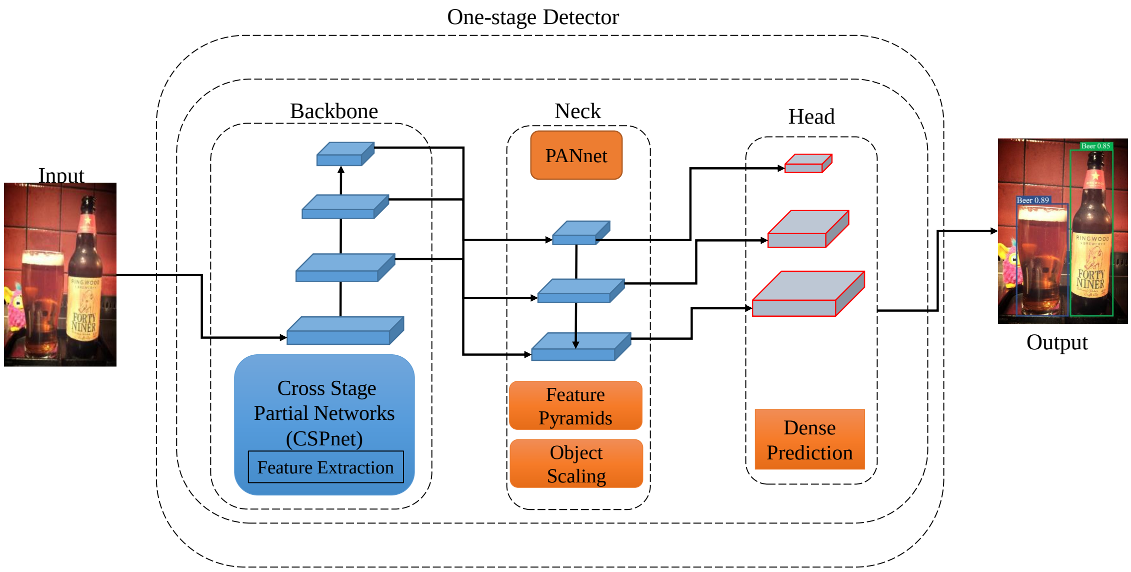

Fig. 4 YOLOv5 architecture and workflow

for constructing feature pyramids [14]. IOU is the intersection over union which evaluates the predicted bounding box coordinates X', Y', Z', H' with true values X, Y, W and H.

Algorithm 1: Workflow for Training Custom Object Detection

Data: Captured images through Cleo
Result: Bounding Box Coordinates
$D_{(i)(j)} \leftarrow train\_test\_split(Frames)$
Annotate(X,Y,W,H) on each target entity in $D_{(i)(j)}$
$S_k \leftarrow W_k * [S_0'', S_1,....S_{k-1}]$
$S_T \leftarrow W_T * [S_0'', S_1,....S_k]$
$S_U \leftarrow W_U * [S_0', S_T]$
$F_s \leftarrow$ combine obtained feature space using PaNet
$X', Y', Z', H' \leftarrow$ boundingBox(F_s)
IOU $\leftarrow$ Avg.Overlap($(X', Y', Z', H'), (X, Y, W, H)$)

5.2.1 Auto-Anchoring in Yolov5

Unlike the previous versions of Yolo, auto-anchoring is a relatively new approach that is used to generate custom anchor boxes for the training dataset in yolov5. Depending upon the model input size, the bounding boxes are resized, however the ration is preserved. The projected anchor boxes are considered to be a good fit if they are not larger or smaller than the bounding boxes by a factor of 4. A good fit is often achieved as an average i.e., the anchor boxes could somewhat be distanced apart from the bounding boxes. Subsequently, k-means clustering is performed to evolve a new set of anchor boxes, and the judged whether the new anchors are relatively a good fit to the previous ones, the evolved ones are selected, whereas the set that didn't outperform the previous fit are reiterated in search for generating a better set of anchors. This is the evolutionary algorithm that Yolov5 has introduced [14].

5.3 Real-time Heartbeat Monitoring

Cleo comes equipped with an in ear PPG sensor. The In-ear PPG Sensor projects a light on to the skin, with light penetrating the body(tissues of the skin), the photodetector on the earpiece measures the intensity of light reflectance. With blood vessels being good absorbers of light, there remains a constant range of absorption and reflection of light. Any changes in the flow or volume of blood results in varied levels of photoreceptive activity or in this case DC voltage signals. During abnormal conditions, the DC signal is observed to fluctuate dramatically. Abnormalities such as sudden increase in heart-rate are common symptoms of excess alcohol and nicotine consumption. These thresholds vary person-to-person and therefore calibrated with their body. The information is shown in mobile application as a flowing graph. Any fluctuations are reported and stored in the app for further references or in times of emergency. The PPG sensor is utilized to monitor and record the heartbeat or pulse of the user during and post consumption of alcohol and nicotine. The PPG sensor is calibrated to the ear fitting of the user to avoid unwanted artifacts. The sensor initializes right after Cleo glasses are powered on. As soon the image recognition model detects consumption of either alcohol or nicotine, the PPG sensor starts recording and logging heartbeat data in the mobile application. In case any fluctuations or a sudden spike in the pulse is detected, a voice message is evoked along with an alert sent to the medical correspondent noted in the application.

Algorithm 2: Quantification of Cigar and Alcohol Consumption

Data: Objects detected using Algorithm 1
Result: Quantification and alert generation
$C \leftarrow 0$;
$A \leftarrow 0$;
for *each* δ **do**
  $x \leftarrow objectDetection(F_c)$
  if $x \in cigar$ **then**
    record t_C^T
    $C \leftarrow C + 1$
  end
  if $x \in Beverage$ **then**
    record t_A^T;
    $A \leftarrow A + 1$
  end
  $C_{all} \leftarrow aggregate(t_C^T)$;
  $A_{all} \leftarrow aggregate(t_A^T)$;
  if *abnormality*$((C_{all})$ *or* $(A_{all}))$ **then**
    if *severity() returns True* **then**
      store in DB and raise emergency *alert*
    else
      store in DB but raise normal *alert* ;
    end
  end
end

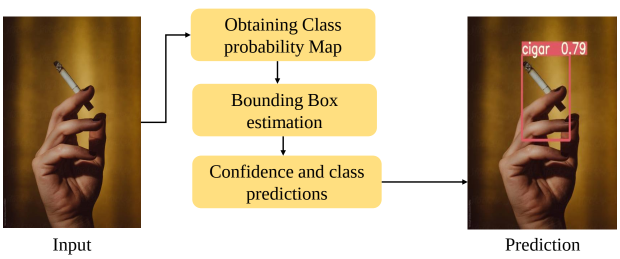

Fig. 5 Cigarette Identification and Counting

5.4 Cigarette Predictions and Counting

Cleo identifies and counts the number of cigars or cigarettes consumed by the user. YOLOv5 has been trained over 2000 annotated images. As shown in Fig. 5, the captured images by the eyeglasses are fed through the YOLOv5 model. The neural network first obtains the class probability map and extracts features from the image. The model then tries to estimate the positioning of the bounding box on the target item in the image. After which, YOLOv5 outputs the confidence and class predictions of whether the said item is present in the image or not. Upon identifying a cigarette with a confidence over 55%, counter initialized with zero increments by one. The increment happens after every successful rhythmic degradation and spike in object detection probabilities. A complete workflow of quantifying the consumption is shown in Algorithm 2 where we detect the Objects of Interest (here, Cigar and beverages) for every δ units of time. Upon detection, the respective counter is incremented by recording the time. Each triggered event is stored with details like, time and duration of consumption. This information is aggregated to check the abnormality based on the respective user history of consumption. When abnormality is detected, Cleo checks for changes in vital body parameters and if found then an emergency alert is generated else data is stored in the database and a normal alert is sent to the user.

The approach is further extended to detect and generate a stress alert based on the deviation of photoplethysmograms captured through the PPG sensor of Cleo in normal and stress situations.

Fig. 6 Results of Cleo object detection

6 Analysis of Alcohol Monitoring and Cigarette Counting

6.1 Validation of Cleo

Custom trained YOLOv5 models yielded an accuracy of 85% in recognizing classes pertaining to alcoholic beverages and cigars. The average class loss function is 0.04 (Ref Fig.6.1). YOLOv5 parses over 40 frames per second in real-time. After training on over 300 epochs, the model detected 8 of 10 test classes in real-time without an error (See Fig. 5.4) The average precision and recall of Cleo is 89% and 90% respectively. The mean Average Precision of the object recognition system was 0.72. The activation function used in each layer was Leaky ReLU and was trained on 6000 images. Fig. 6.1 and Fig.6.1 shows the precision and recall of the deep neural network. The precision and recall of the model can be increased with extensive training for a longer period and a large dataset [36]. To ensure model robustness, we have calculated the F1 score, mAP and the same is shown in Fig.6.1 and Fig. 6.1 respectively.

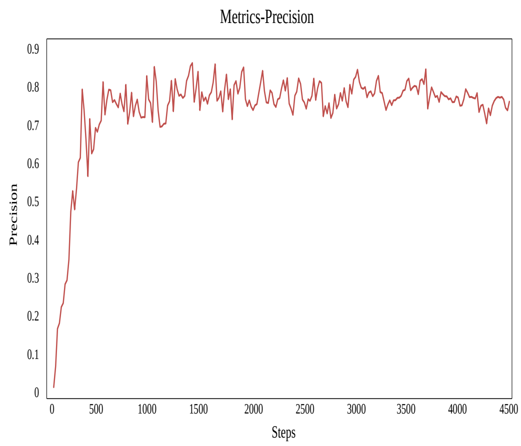

Fig. 7 Performance measures of the YOLOv5 - Precision

6.2 Calculating Alcohol Concentration

It is often observed that Blood Alcohol Concentration (BAC) levels are often considered as a metric to estimate the intensity to which a person is drunk or intoxicated with alcohol [3] [26]. The most reliable method still remains conducting an alcohol check using a blood test, however, calculating BAC levels using Equation. 1 gives an approximation of the BAC the person holds.

$$BAC = \frac{()(VAC)(\%ethanol)}{(B.W)} \quad (1)$$

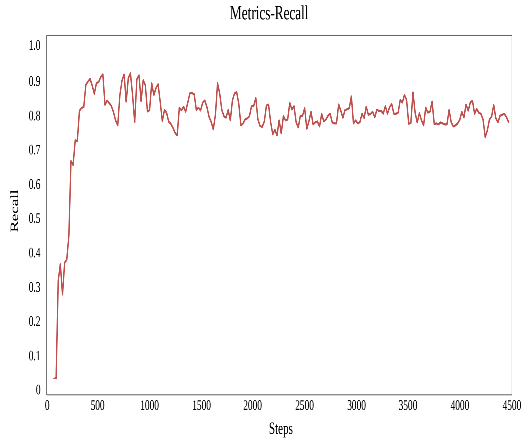

Fig. 8 Performance measures of the YOLOv5 - Recall

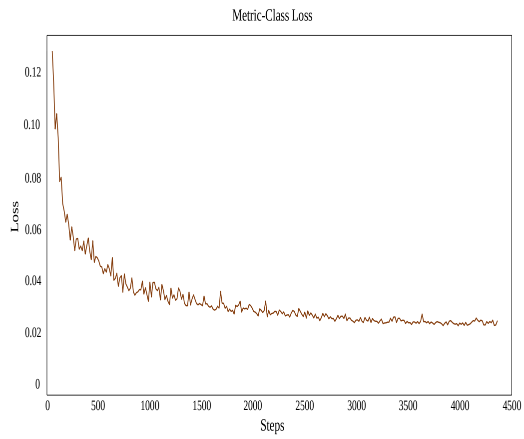

Fig. 9 Performance measures of the YOLOv5 - Loss

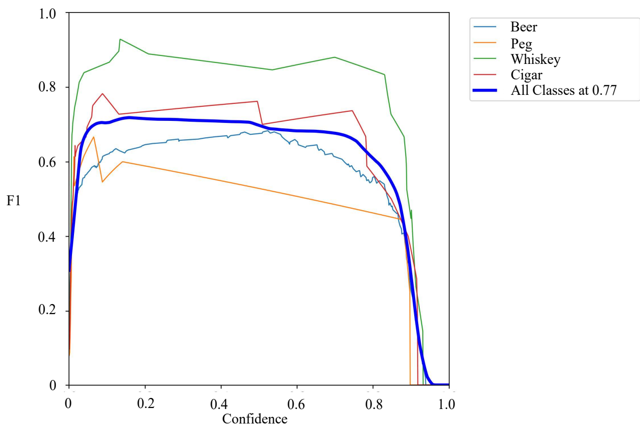

Fig. 10 Performance measures of the YOLOv5 - F1 Score

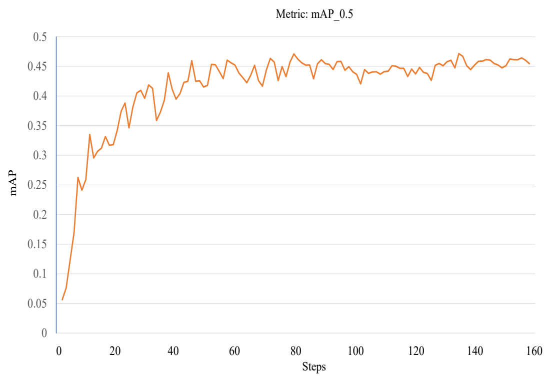

Fig. 11 Performance measures of the YOLOv5 - mAP

Where, B.W is Body Weight measured in pounds, ¥=0.071 for male while ¥=0.085 for female, Volume of Alcohol Consumed (VAC) = number of drinks (n) and capacity of each drink (oz).

For every hour that passes since the user consumed his first drink every day, the BAC Level is subtracted by a factor of 0.015. If the BAC level is zero it means the user is no longer intoxicated or his/her alcohol concentration present in the blood is approximately zero. Although the above equation only gives an estimate of blood alcohol concentration level in the user, it is sufficient to assess whether a person is very impaired or suffering some serious complications. Table 3 shows the concentration of alcohol present in each of the alcoholic beverages that are detected in Cleo. A portable solution to measure BAC levels through dense sampling is devised by exploiting the data from transdermal sensors which resulted an average error of 18% [10].

6.3 Determining User-State post consumption

Post consumption of alcohol, it is often noticed that sensory and motor impairment starts as soon as the BAC level crosses 0.8. Therefore, it is considered to be unstable to take any decision consciously. When the user signs up on the Cleo app, his/her body weight is taken. Cleo detects every drink consumed by the user along with the time stamp. A pre-configured database in the Cleo app is used to log the type of alcoholic beverage consumed and the ounces consumed using the custom trained image recognition model. The above equation is used to calculate to estimate the BAC level of the user. Simultaneously, the readings from the IMU and heart rate sensor are analyzed to find an increase in the heart rate in comparison to the readings taken before alcohol consumption, and fluctuations in the user's physical position are noted from the IMU. In case the user sways in the range of 0.20m to 0.8m rhythmically on his/her Y-axis while walking or running, the application is configured to consider the user to be unaware of his/her senses and their motor control is not in their control.

6.4 Post Analysis

After calculating the BAC level of the user along with his/her gait pattern or heart rate fluctuations, (if any), the application generates a report that displays a log of every drink the user had along with the volume and percentage of alcohol present in each drink. These logs are well informed with time-stamps and come with the graph of the heart rate and the user activity mode such as walking, sitting etc.

The app also calculates the amount of time (in hours), it takes for the user's BAC Level to reach zero using the Equation 2

$$BAC - 0.015(t) = ZBAC \tag{2}$$

Where, ZBAC= Zero Blood Alcohol Concentration and t = number of hours it takes for BAC to reach 0. Eqn. 2 allows the app to give the user an estimated time, in hours, for the user to reach a conscious state of mind, void of any alcohol induced impairments.

The application popups an alert asking if the user is in need of cab service in case the user needs to travel along with any alert asking if he/she needs medical assistance. The application initiates voice prompts over the earphone in the following cases:

- Type and amount of alcohol consumed.
- Number of smokes finished.
- The user had consumed more alcohol and can be declared legally intoxicated.
- The user's gait is irregular and he/she is swaying often.
- A cab or taxi recommended and booked successfully.

6.5 Cigarette Counting and Analysis

Cleo counts the number of cigarettes smoked by detecting a fully present, unburned tobacco rod or the white paper to the remaining butt of the cigarette, through which it counts as one cigarette. In a similar fashion, after every cigarette is completely smoked, the image recognition model increments the counter by one, and simultaneously heart rate is taken into consideration.

Table 4 Comparative analysis of Alcohol Monitoring System

Research Work	Sensors used	Algorithms Employed	Data Logging integrated companion app	Emergency Response System	Accuracy
Smart helmet[28]	IR sensor,Camera,Alcohol Sensor	Support Vector Machine	No	No	87%
Smart Bracelet [16]	Heart Rate sensor,Blood Pressure, Respiration,Humidity, SpO2	FCNN, SSD-MobileNetBAC	No	No	99%
Smart Cup [6]	IMU sensor	RTQF fusion algorithm	No	No	90%
Cleo (Proposed)	PPG Sensor, Camera, IMU	Custom trained YOLOv5	Yes	Yes	90%

Studies have shown that smoking tobacco causes an increase in the heart rate and regular smoking causes diseases. The user is notified after every smoke, and a report is generated automatically at the end of the day with all the logs created. The user can choose to generate a report at any instance in time, in case he/she needs to share the report with a medical official.

7 Integration of Cleo with MyWear[36] for continuous vital parameter monitoring

MyWear [36] is a smart garment that monitors the body's vital parameters. MyWear uses a novel convolution neural network model to classify the heart rate as normal or abnormal. The system tracks the heart rate and identify the abnormalities through successive root mean squared differences of R-peak impulses (i.e. Variability Score). MyWear identifies and quantifies the stress levels in the body considering the inverse relationship associated with variability score and stress levels. The system can even predict and detect the fall of a person with a keen monitoring of stress levels or other vital parameters based on which an alert is sent to the concerned medical officer.

7.1 Reasons for Integration

We combine Cleo with MyWear for the following reasons:

- The user of Cleo smart glass cannot wear it while sleeping where we miss the vital body parameters assessment. We address this problem by recommending the user to use MyWear for continuous analysis of heart rate, stress levels and body orientation.
- Cleo takes the consumption threshold for overdose from the user based on which alert is generated. But the user either intentionally or unintentionally may increase the threshold and it further leads to the damage of vital organs due to over-consumption. To handle this problem, we do pre and post assessment of variations in vital body parameters before and after the consumption of cigarette/alcohol. If these changes are abnormal when compared with recent history, the integrated system would recommend the user to reduce the threshold set for smoking or alcohol consumption.
- The impact of smoking or alcohol deteriorates the health condition and our integrated system can work collaboratively to send the collected data continuously for abnormality detection and alert generation.
- Adverse effects of cigarette/alcohol consumption are not always in long run and can badly impact the body immediately after the use. But the symptoms are not noticeable by the user. This problem is addressed by our integrated system with a close monitoring of vital parameters at multiple stages due to which abnormalities can easily be tracked and alerted in the initial stages.

The integrated architecture of both systems is shown in Fig. 12.

7.2 Advantages of our integrated system

- Applicability is not limited only to the smart glasses. The system can be integrated with the other smart glasses without any constraints.
- It is a common myth that cigarette would reduce the stress levels in the body. But studies have proven

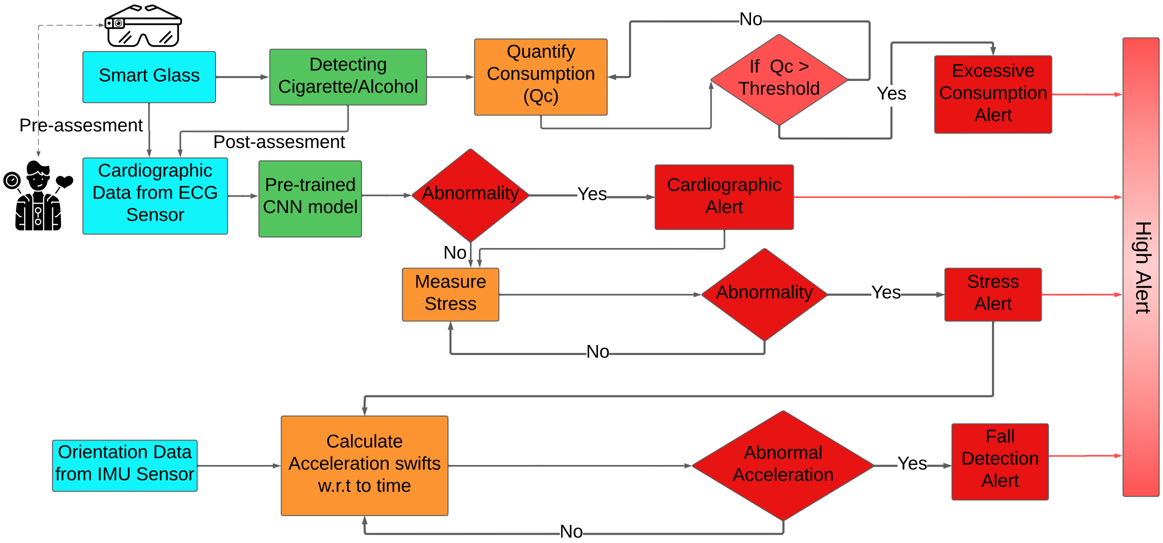

Fig. 12 Integrated architecture of Cleo and MyWear

that smoking/alcohol consumption would instead increase the stress [4]. The track record of stress changes is clearly shown on the user registered mobile application which would aid to stop the consumption. A group of users, drink alcohol or consume cigarettes with a daily limit but when this is followed for a long run, it would still impact health and may lead to sudden death if left unmonitored. So the users with either controlled or uncontrolled consumption behaviour can still use our integrated system.

- Both Cleo and MyWear work independently and the data collected from both sources are collated for effective report generation.
- Our integrated system is far better than existing systems not only in terms of features but also in performance and the same is shown in Table 4.

8 Conclusion

Consuming cigarettes/alcohol not only deteriorates the physical health but also the mental status of the person. Rapid addiction and irreparable effects are inherent properties of this consumption. Ignoring the symptoms in the initial stages will cost the life of a person. Moreover, the signs are not noticeable by many individuals. Many users want to stop consuming alcohol/cigars but majority of them cannot be succeeded due to the lack of a quantifying approach for the intake and also due to system unavailability to alert health risks associated with the same considering the real time constraints. Cleo smart glasses address the above issues through continuous monitoring of vital parameters before and after consumption of cigar/alcohol. The proposed approach yielded an average accuracy of 90%. Cleo has a comprehensive alert system and gets activated when abnormalities are found in the body after excessive consumption. Thus, recommending and recording the same could potentially help the doctors in treating their patients for alcohol treatment and deaddiction. Cleo can be further extended to enhance the exact quantity assessment of alcohol consumption considering smart calibration of different views of reference objects.

Acknowledgment

The authors Pranav Kompally, Sibi C. Sethuraman, BKSP Kumar Raju thank Dr. S. V. Kota Reddy, Vice Chancellor, VIT-AP University for motivating and supporting Center for Excellence in Artificial Intelligence and Robotics (AIR) at VIT-AP University in building this project.

Compliance with Ethical Standards

Funding: This study was funded by Center for Excellence in Artificial Intelligence and Robotics (AIR), VIT-AP University.

Conflict of Interest: The authors declare that they have no conflict of interest. Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

1. Alcohol – Key facts (2021). URL https://www.who.int/news-room/fact-sheets/detail/alcohol. Last accessed on 30 Jan 2021
2. Tobocco-report (2022). URL https://www.who.int/news-room/fact-sheets/detail/tobacco. Last accessed on 17 Oct 2022
3. Aschbacher, K., Hendershot, C.S., Tison, G., Hahn, J.A., Avram, R., Olgin, J.E., Marcus, G.M.: Machine learning prediction of blood alcohol concentration: a digital signature of smart-breathalyzer behavior. NPJ Digi. Med. **4**(1), 1–10 (2021)
4. Avery, A.R., Tsang, S., Seto, E.Y.W., Duncan, G.E.: Stress, anxiety, and change in alcohol use during the covid-19 pandemic: Findings among adult twin pairs. Front. Psych. **11** (2020)
5. Bhide, A., Muthukumar, S., Prasad, S.: Clasp (continuous lifestyle awareness through sweat platform): A novel sensor for simultaneous detection of alcohol and glucose from passive perspired sweat. Biosens. Bioelec. **117**, 537–545 (2018)
6. Bobin, M., Amroun, H., Anastassova, M., Boukallel, M., Ammi, M.: Smart cup for festival alcohol consumption awareness. In: Int. Work. Internet of Things, pp. 718–723 (2018)
7. Brobbin, E., Deluca, P., Hemrage, S., Drummond, C.: Accuracy of wearable transdermal alcohol sensors: Systematic review. J. Med. Int. Res. **24**(4) (2022)
8. Chen, Y.Y., Lin, C.L., Lin, Y.C., Zhao, C.: Non-invasive detection of alcohol concentration based on photoplethysmogram signals. IET Imag. Proc. **12**(2), 188–193 (2018)
9. Davis-Martin, R.E., Alessi, S.M., Boudreaux, E.D.: Alcohol use disorder in the age of technology: A review of wearable biosensors in alcohol use disorder treatment. Frontiers in Psychiatry **12** (2021)
10. Fairbairn, C.E., Kang, D., Bosch, N.: Using machine learning for real-time bac estimation from a new-generation transdermal biosensor in the laboratory. Drug alco. depend. **216**, 108205 (2020)
11. Fridberg, D.J., Wang, Y., Porges, E.: Examining features of transdermal alcohol biosensor readings: A promising approach with implications for research and intervention. Alcoholism: Clinical and Experimental Research **46**(4), 514–516 (2022)
12. Iqbal, S., Mahgoub, I., Du, E., Leavitt, M.A., Asghar, W.: Advances in healthcare wearable devices. NPJ Flex. Elec. **5**(1), 1–14 (2021)
13. Jabeen, F., Rupanagudi, S.R., Bhat, V.G.: Iot based smart vehicle ignition and monitoring system. In: Int. Conf. Adv. Comp. Comm. and Cont., pp. 1–7 (2019)
14. Jocher, G., Chaurasia, A., Stoken, A., Borovec, J., NanoCode012, Kwon, Y., TaoXie, Michael, K., Fang, J., imyhxy, Lorna, Wong, C., Yifu), V, A., Montes, D., Wang, Z., Fati, C., Nadar, J., Laughing, UnglvKitDe, tkianai, yxNONG, Skalski, P., Hogan, A., Strobel, M., Jain, M., Mammana, L., xylieong: ultralytics/yolov5: v6.2 - YOLOv5 Classification Models, Apple M1, Reproducibility, ClearML and Deci.ai integrations (2022). URL https://doi.org/10.5281/zenodo.7002879
15. Kao, C.H.L., Ho, B.J., Lin, A., Chu, H.H.: Phone-based gait analysis to detect alcohol usage. In: Int. Conf. Ubiq. Comp., pp. 661–662 (2012)
16. Kinnamon, D., Selvam, A.P., Prasad, S., Muthukumar, S.: Electronic bracelet for monitoring of alcohol lifestyle. In: Proc. Int. Conf. Sensors, pp. 1–3 (2016)
17. Kinreich, S., Meyers, J.L., Maron-Katz, A., Kamarajan, C., Pandey, A.K., Chorlian, D.B., Zhang, J., Pandey, G., Subbie-Saenz de Viteri, S., Pitti, D., et al.: Predicting risk for alcohol use disorder using longitudinal data with multimodal biomarkers and family history: A machine learning study. Molecular Psych. **26**(4), 1133–1141 (2019)
18. Kumari, N., Anwar, S., Bhattacharjee, V.: A deep learning-based approach for accurate diagnosis of alcohol usage severity using eeg signals. IETE Journal of Research **0**(0), 1–15 (2022)
19. L. Rachakonda A. K. Bapatla, S.P.M., Kougianos, E.: Bactmobile: A smart blood alcohol concentration tracking mechanism for smart vehicles in healthcare cps framework. SN COMPUT. SCI. **3** (2022)
20. Li, B., Scott Downen, R., Dong, Q., Tran, N., LeSaux, M., Meltzer, A.C., Li, Z.: A discreet wearable iot sensor for continuous transdermal alcohol monitoring—challenges and opportunities. IEEE Sens. J. **21**(4), 5322–5330 (2021)
21. Li, B., Scott Downen, R., Dong, Q., Tran, N., LeSaux, M., Meltzer, A.C., Li, Z.: A discreet wearable iot sensor for continuous transdermal alcohol monitoring—challenges and opportunities. IEEE Sensors J. **21**(4), 5322–5330 (2021)
22. Magno, M., D'Aloia, A., Polonelli, T., Spadaro, L., Benini, L.: Shelmet: An intelligent self-sustaining multi sensors smart helmet for bikers. In: M. Magno, F. Ferrero, V. Bilas (eds.) Sensor Systems and Software, pp. 55–67. Springer International Publishing, Cham (2017)
23. Matsui, H., Hashizume, T., Yatani, K.: Al-light: An alcohol-sensing smart ice cube. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. **2**(3) (2018)
24. McAfee, A., Watson, J., Bianchi, B., Aiello, C., Agu, E.: Alcowear: Detecting blood alcohol levels from wearables. In: Proc. SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI, pp. 1–8 (2017)
25. Miller, T.C., Morgera, S.D., Saddow, S.E., Takshi, A., Palm, M.: Electronic nose with detection method for alcohol, acetone, and carbon monoxide in coronavirus disease 2019 breath simulation model. IEEE Sensors J. **21**(14), 15935–15943 (2021)
26. Oszkinat, C., Luczak, S.E., Rosen, I.: Uncertainty quantification in estimating blood alcohol concentration from transdermal alcohol level with physics-informed neural networks. IEEE Trans. Neu. Net. Learn. Sys. (2022)
27. Prabhakar, S.K., Rajaguru, H.: Alcoholic eeg signal classification with correlation dimension based distance metrics approach and modified adaboost classification. Heliyon **6**(12), e05689 (2020)
28. Preetham, D.A., Rohit, M.S., Ghontale, A.G., Priyadarsini, M.J.P.: Safety helmet with alcohol detection and theft control for bikers. In: Intl. Conf. Int. Sus. Sys., pp. 668–673 (2017)
29. Rachakonda, L., Mohanty, S., Kougianos, E.: Donotdueye: An iot enabled edge device to monitor blood alcohol concentration from eyes. In: Intl. Symp. Smart Elec. Sys., pp. 87–92 (2019)
30. Rachakonda, L., Mohanty, S.P., Kougianos, E., Sayeed, M.A.: Smart-steering: An iomt-device to monitor blood alcohol concentration using physiological signals. In: Intl. Conf. Cons. Elec., pp. 1–6 (2020)
31. Russell, M.A., Turrisi, R.J., Smyth, J.M.: Transdermal sensor features correlate with ecological momentary assessment drinking reports and predict alcohol-related consequences in young adults' natural settings. Alco-

holism: Clinical and Experimental Research **46**(1), 100–113 (2022)
32. Russell.B.C, A., T., Murphy.K.P, William.T.F: Labelme: A database and web-based tool for image annotation. Int. J. Comput. Vis. **77**, 157–173 (2008)
33. Sahabiswas, S., Saha, S., Mitra, P., Chatterjee, R., Ray, R., Saha, P., Basu, R., Patra, S., Paul, P., Biswas, B.A.: Drunken driving detection and prevention models using internet of things. In: Ann. Conf. Info. Tech. Elec. Mob. Com., pp. 1–4 (2016)
34. Selvaraj, S., Umakanth, N.: Providing safety and detecting accidents in bike transport with smart helmets using iot. In: Resear. Dec. Sci. App. Trans. Sect., pp. 280–303. IGI Global (2021)
35. Sempionatto, J.R., Brazaca, L.C., García-Carmona, L., Bolat, G., Campbell, A.S., Martin, A., Tang, G., Shah, R., Mishra, R.K., Kim, J., Zucolotto, V., Escarpa, A., Wang, J.: Eyeglasses-based tear biosensing system: Non-invasive detection of alcohol, vitamins and glucose. Biosensors and Bioelectronics **137**, 161–170 (2019)
36. Sethuraman, S.C., Kompally, P., Mohanty, S.P., Choppali, U.: Mywear: A novel smart garment for automatic continuous vital monitoring. IEEE Trans. Cons. Elec. **67**(3), 214–222 (2021)
37. Sinha, S., Teli, E., Tasnin, W.: An iot-based automated smart helmet. In: Sus. Comm. Net.App., pp. 371–384. Springer (2022)
38. Suffoletto, B., Gharani, P., Chung, T., Karimi, H.: Using phone sensors and an artificial neural network to detect gait changes during drinking episodes in the natural environment. Gait & Posture **60**, 116–121 (2018)
39. Vlachopoulos, C.: Cigar smoking has an acute detrimental effect on arterial stiffness. American J.Hypertens. **17**(4), 299–303 (2004)
40. Wang, Y., Fridberg, D.J., Shortell, D.D., Leeman, R.F., Barnett, N.P., Cook, R.L., Porges, E.C.: Wrist-worn alcohol biosensors: Applications and usability in behavioral research. Alcohol **92**, 25–34 (2021)