Smoking Cessation System for Preemptive Smoking Detection

Gabriel Maguire, Huan Chen, Rebecca Schnall, Wenyao Xu, and Ming-Chun Huang

***Abstract*—Smoking cessation is a significant challenge for many people addicted to cigarettes and tobacco. Mobile health-related research into smoking cessation is primarily focused on mobile phone data collection either using self-reporting or sensor monitoring techniques. In the past five years with the increased popularity of smartwatch devices, research has been conducted to predict smoking movements associated with smoking behaviors based on accelerometer data analyzed from the internal sensors in a user's smartwatch. Previous smoking detection methods focused on classifying current user smoking behavior. For many users who are trying to quit smoking, this form of detection may be insufficient as the user has already relapsed. In this article, we present a smoking cessation system utilizing a smartwatch and finger sensor that is capable of detecting presmoking activities to discourage users from future smoking behavior. Presmoking activities include grabbing a pack of cigarettes or lighting a cigarette and these activities are often immediately succeeded by smoking. Therefore, through accurate detection of presmoking activities, we can alert the user before they have relapsed. Our smoking cessation system combines data from a smartwatch for gross accelerometer and gyroscope information and a wearable finger sensor for detailed finger bend-angle information. We compare the results of a smartwatch-only system with a combined smartwatch and finger sensor system to illustrate the accuracy of each system. The combined smartwatch and finger sensor system performed at an 80.6% accuracy for the classification of presmoking activities compared to 47.0% accuracy of the smartwatch-only system.**

***Index Terms*—Activity recognition, finger sensor, presmoking activities, smartwatch sensor, smoking cessation.**

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I. Introduction

In THE United States, tobacco kills more people annually than alcohol, illegal drugs, AIDS, murders, and suicides combined [1]. One in seven U.S. adults (34.1 million) smoke cigarettes and annual smoking-related costs total approximately $170 billion [1]. Many complex factors led tobacco to hold the place that it does today, including the legality, corporate lobbying [2], social acceptance [3], and addictiveness [4]. These factors create large barriers for individuals who are trying to quit smoking. Many current tobacco users desire to quit but require external guidance and motivation [5]. Wearable technology has the potential to help current users to achieve their smoking cessation goals through activity monitoring and real-time alert notifications [6].

The ubiquity of wearable devices and smart connected devices [7] has led to the development of applications aimed at reducing tobacco use through activity monitoring. Previous studies have used wrist-mounted smartwatch devices to collect and analyze motion data for smoking gestures. Chen *et al.* [8] demonstrated the ability to distinguish similar gestures using a wrist motion-sensing device for each forearm with an overall smoking activity detection accuracy of 72.6% when tested against similar activity data. To this point, wearable smoking detection methods have focused on classifying current smoking behaviors, meaning that at the time of detection by the smartwatch, the user has already started smoking. While this method of delayed detection may keep some users motivated to limit their future smoking, it may not be an effective tool to prevent smoking relapse.

To effectively prevent smoking relapse, a user must be notified before the act of smoking. Therefore, it is important to shift the focus of detection from smoking to presmoking activities, such as grabbing a pack of cigarettes or taking an individual cigarette from a pack. However, this poses additional classification problems when using smartwatch accelerometer data because the presmoking activities often involve fine motor skill finger movements that are not easily detected by a wrist-mounted accelerometer. For example, the previous detection of current smoking gestures relied upon large arm movements where the user would bring the cigarette to their mouth or take the cigarette out of their mouth and let their arm fall back down. Such gross arm movements are easily detected by a wrist-mounted smartwatch. In comparison, grabbing a pack of cigarettes from the table and pulling out an individual cigarette are a more difficult detection task for a smartwatch because these devices do not detect finger movements.

The purpose of this work was to develop a custom wearable finger bend-angle sensing device in combination with a smartwatch smoking detection system to enable a more accurate classification of presmoking behavior. We have also integrated a wearable air quality sensing device capable of contextualizing smoking behavior and reducing false positive smoking notifications. Our wearable finger sensing device provides constant data monitoring of the bend angle of the index finger. The finger sensing device uses Bluetooth LE for data transmission and wireless charging making it completely wireless. We perform real-time synchronization of the data collected from the smartwatch and the custom wearable finger sensor using an Android smartphone application. Finally, we analyze the collected data using a neural network classifier trained on a custom testing data set and notify the user via the smartphone application if smoking or presmoking activity is detected.

II. Related Works

Research into the field of human grasp recognition and prediction applies directly to human–computer interaction and is an integral part of robotic or prosthetic control and rehabilitation [9]. The extant literature has focused on two main areas of data acquisition for gesture recognition: 1) video data and 2) sensor data.

A. Video-Based Grasp Recognition

Many researchers have studied vision-based approaches to grasp recognition often including depth information from a stereo camera or low-cost system like a Kinect [10]. However, these vision-based approaches are restricted by the field-of-view of the camera and can encounter difficulties due to occlusion [11]. Taverne *et al.* [12] have attempted to blend wearable sensors and fixed video data by creating a forearm-mounted camera to predict hand preshaping for a given set of objects. Preshaping is the transition of the hand and fingers in preparation for grasping an object [13]. When generalizing the results of their grasp recognition model, Taverne *et al.* [12] reached per frame accuracies of up to 89%, which demonstrates the functionality of such a system. The size and placement of the current device can impede normal movement; however, Taverne *et al.* [12] discussed in future real-world applications that these factors could be optimized for improved usability.

B. Sensor-Based Grasp Recognition

The other prominent area of grasp recognition research focuses on sensor data, which often comes in the form of accelerometer or bend-angle sensors. As opposed to video data, which is typically captured from a fixed location on the subject's body, sensor data are primarily collected through wearable devices. There are many commercially available wearable sensor gloves on the market. Commonly available gloves include the CyberGlove, which provides 18–22 resistive bend-angle sensors, and the 5DT Data Glove, which contains either 5 or 14 resistive bend-angle sensors. Both of these commercially available options cost above $1000 depending on the model, making them only feasible in specialized research applications. De Pasquale [14] provided a comprehensive look at the recent advancements in wearable glove technology related to medical applications, which cover the variation in sensor types and application difficulties and underline the potential benefits of these technologies for future medical research. Many of these wearable gloves were developed with artificial and virtual reality in mind, but have proved integral to research in medical health and rehabilitation.

C. Low-Cost Sensor Gloves

Due to the high cost of a commercial wearable sensor glove, researchers have developed low-cost solutions with overall angle error within 5° of their commercial counterparts. The resistive bend-angle sensor technology is commonly implemented for wearable sensor gloves because of its simplicity, availability of resources, and low cost. Gentner and Classen [15] and Adnan *et al.* [16] showed that low-cost wearable resistive bend-sensor gloves can be used to sense finger bend-angle within 5° of error. More recently, the capacitive sensor technology has been implemented in wearable gloves, which has advantages over resistive sensors in the linearity of measured data for calibration of the device and reduced hysteresis [17]. Glauser *et al.* [18] demonstrated a glove developed using an array of capacitive silicone stretch sensors that boasts a 35% accuracy improvement over current state-of-the-art sensor gloves including the CyberGlove.

D. Capacitive Bend-Angle Sensing

Resistive bend-angle sensor error accumulates with finger digits farther from the hand because the calculation of the next angle depends on the previous angle. This is not true for the capacitive sensors because each bend angle is a measure of capacitance at the sensor that is independent of all other sensors. The ShArc sensor developed by Shahmiri and Dietz [19] took a slightly different approach to capacitive bend-angle sensing. Instead of using capacitive stretch sensors as Glauser *et al.* [18] that collects measurements by detecting the change in material properties under a given amount of strain, the ShArc sensor uses a geometric sensing technique that translates the change in capacitance due to a physical shift in two pads of a flexible parallel plate. The geometric sensing technique results in a more direct measurement of angular changes. The ShArc sensor was developed to provide a low-cost solution for multibend curve sensing [19].

E. Grasp Recognition Models and Data Sets

The previous discussion focused on the development of data collection methods for hand preshaping and grasp recognition. Once reliable data have been collected, the data must be examined and learned to determine which data patterns correspond to which physical motions. Research papers focused on developing a grasp prediction model often start by collecting data with a commercially available glove, like the CyberGlove, bypassing the need to develop a possibly unreliable alternative.

However, Nathan *et al.* [20] developed both the data collection device and a thumb and index finger-based grasp prediction model. Much research has focused on developing grasp recognition models based on finger joint angle data, as opposed to position markers or accelerometer data [21]–[26]. Each of these papers presents a different method to take finger angle measurements as input data and determine the object being grasped. They include multiple regression models, latent space mapping into a regression model, and neural network-based approaches. Chauhan and Sebastian [22] developed two unique prediction models based on the HUST finger and hand motion data set and validated their findings against experimental data collected from a commercial wearable glove.

The HUST data set provides a comprehensive database of hand motion data from 30 able-bodied subjects. Each subject performed 33 unique tasks, which were taken from the activities of daily living. Each task was repeated using three variations of object sizes, and each new object was repeated three times. Data collection was performed using the CyberGlove. Each trial in the data set contains timestamped information on the angle measurement in radians from 16 unique bend-angle sensors on the CyberGlove. Of the 16 sensors recorded, there are three per finger and thumb, and one additional sensor between the thumb and index finger. The HUST data set can be best utilized to develop and test grasp prediction and recognition algorithms.

F. Grasp Recognition for Smoking Cessation

Smoking detection is a well-studied topic in activity recognition due to its potential positive health impact. Previous work in smoking cessation research has focused on self-reporting-based strategies where a user is prompted throughout the day to report on their smoking behavior and mobile devices that attempt to classify smoking activity from sensor data. With the increased popularity and availability of smartwatch devices, they have become a common tool to collect wrist movement data that can shed light on smoking activity. Shoaib *et al.* [27] presented a smartwatch-based smoking detection method that notifies the user when it has detected smoking activity to correct behavior and hold the user accountable. Chen *et al.* [8] presented a smoking detection mobile application that is connected to two armband sensors, which provide a constant stream of data to the smartphone to monitor for smoking activity. The methods implemented by Chen *et al.* [8] and Shoaib *et al.* [27] attempted to classify smoking behavior while a person is smoking. Therefore, these systems detect smoking behavior after the participant has relapsed and started to smoke indicating the need for users to be alerted to potential smoking behavior before they start to smoke. Currently, there is no published work that documents the existence of a system that detects presmoking behavior through sensor-based learning methods. In this article, we will present an embedded finger bend-sensing device based on the capacitive ShArc bend-angle sensor that can be used to enhance presmoking activity detection when combined with a standard smartwatch detection method.

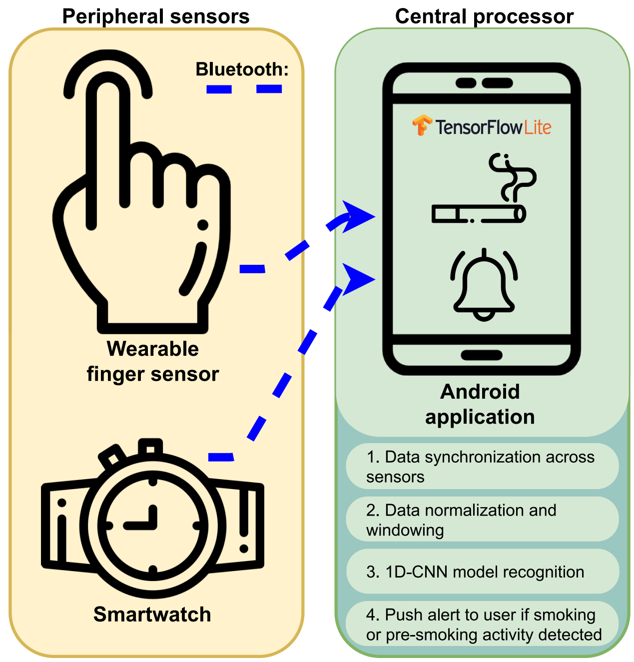

Fig. 1. Smoking cessation system overview diagram.

III. System Overview

The smoking cessation system includes three main components: 1) the smartwatch device for basic smoking detection; 2) the wearable finger sensor for comprehensive smoking and presmoking detection; and 3) the Android mobile application used to compile and analyze the incoming data and provide alerts for the smoker. An overview diagram of the combined smoking cessation system is shown in Fig. 1.

A. Smartwatch for Basic Smoking Detection

The smartwatch, highlighted in Fig. 3, acts as the mandatory sensor peripheral for the smoking cessation system. The smartwatch is responsible for the collection of accelerometer and gyroscope information on the gross arm and wrist movements of the user. All the information collected by the smartwatch is streamed directly to the smartphone over a Bluetooth connection. To optimize the transmission speed for real-time activity detection, we have capped the throughput on the communication line to avoid significant buffering of data collected on the smartwatch. By limiting the data rate to approximately one complete accelerometer and gyroscope reading every 110 ms, we can eliminate significant latency due to buffering during the transmission process.

In comparison to the wearable finger sensor, the smartwatch excels at collecting general information on the activity of the user. Orientation and acceleration information provides us with a solid framework for activity detection. Large body movements, such as walking or running, can easily be classified using the information from the smartwatch alone. As discussed above, researchers like Shoaib *et al.* [27] have achieved smoking detection results between 90% and 97% F-score using a smartwatch-based system across four possible activity classes. These results rely on the large arm movements

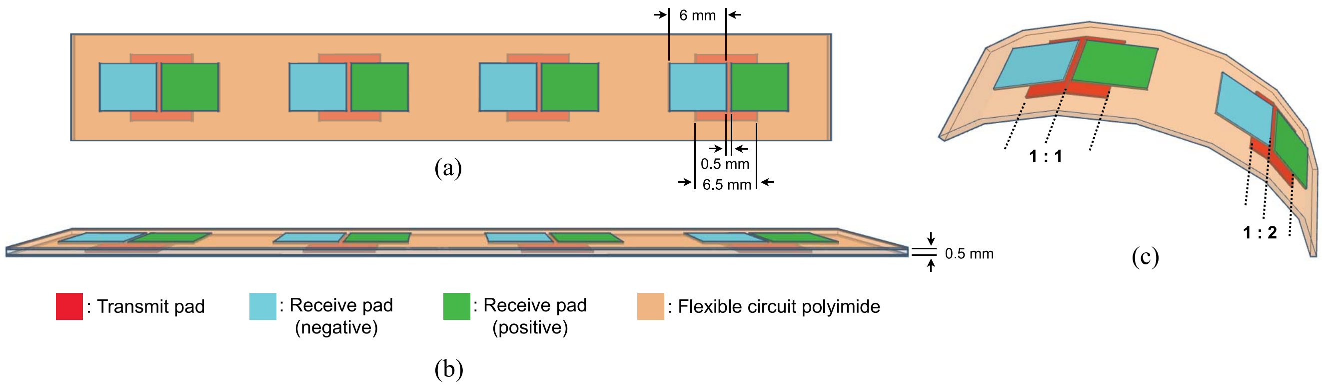

Fig. 2. (a) Top view showing pad dimensions. (b) Side view showing spacing between transmit and receive sensor strips. (c) Dimensionally exaggerated view to highlight pad displacement from bending.

seen when moving from smoking a cigarette to resting the arm. When dealing with smaller finger movements, such as opening a pack of cigarettes, wrist-mounted accelerometer systems will often fall short. Therefore, our goal with the smartwatch system is to provide a baseline of activity recognition, which can be improved with the inclusion of the wearable finger sensor.

B. *Wearable Finger Sensor for Presmoking Detection*

The wearable finger sensor acts as an additional peripheral for the smoking cessation system. This wearable was custom designed to provide our system with an accurate representation of the bend angle of the user's index finger. By accurately measuring the bend angle of the index finger, we can differentiate between many similar activities that may previously be confused with smoking. Most importantly, we have insight into the user's detailed finger movements, which can aid us in the detection of presmoking activities.

There are many possible sensing techniques for a wearable finger sensor device, including resistive and capacitive-based sensing. For our smoking cessation system, we require accurate measurement of the bend angle of the finger at multiple points, preferably with a low cost and easily reproducible solution. Therefore, we chose to use the capacitive-based ShArc bend-angle sensing technique, which allows for high measurement accuracy, sensor customization, and simple implementation. The ShArc bend-angle sensing technique was developed by Shahmiri and Dietz [19]. The ShArc technique uses a pair of flexible printed circuits with pads aligned to create a series of differential parallel plate capacitor sensors. The differential parallel plate capacitor sensors are detailed in Fig. 2. Each differential capacitance sensor has a transmit pad to which an excitation pulse is applied when performing a measurement. The resulting voltage is measured on the positive and negative receive pads, which are used to calculate the capacitance. In the differential capacitive sensors neutral state, both the positive and negative receive pads overlap the transmit pad in equal proportion leading to a zero differential capacitance. However, when the receive pads are moved in relation to the transmit pad one pad will have a greater capacitance reading than the other leading to a nonzero differential capacitance.

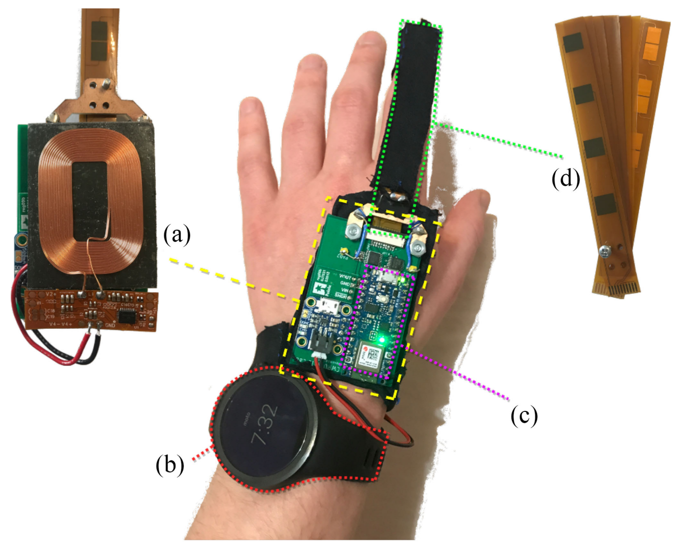

Fig. 3. (a) Qi wireless receiver (shown removed from system to uncover all components). (b) Smartwatch peripheral device. (c) Arduino Nano 33 BLE microcontroller. (d) ShArc sensor.

The transmit and receive strips of the sensor are separated by additional polyimide strips, which allow the transmit and receive strips to smoothly shift in relation to each other when a bend is applied to the sensor. Bending the sensor is similar to bending a book and watching the end of the pages no longer neatly align with each other. The same physical mechanism is at play in the capacitive finger sensor. Fig. 2 shows how bending the sensor changes the overlap of the transmit pad with respect to the positive and negative receive pads. The sensor uses differential capacitance sensors to differentiate between the upward and downward bending of the sensor. Therefore, bending in a given direction is characterized by an increase or decrease in capacitance. When this sensor is attached to the index finger, any movement in the index finger will cause a bend in the sensor, which will change the differential capacitance measured across the sensors. Using a series of four differential capacitance sensors down the length of the finger, we can accurately monitor the overall bend angle and shape of the finger. The flexible sensor we developed is highlighted in Fig. 3.

The transmit, spacing, and receive strips of the ShArc sensor must be held together to provide consistent measurements because the capacitance measurement is directly affected by the distance between the transmit and receive sensor pads. Therefore, we must have a flexible sleeve that allows the sensor strips to slide against each other but prevent separation. We created a sleeve using 1.5-mm thick neoprene that spanned the length of the sensor. We used an additional length of neoprene inside the initial sleeve to provide extra compressive support on the faces of the strips.

All four sensors are measured and bundled together before being sent to the Android smartphone. The circuitry on our wearable finger sensor performs each capacitive sensor reading serially. Each reading takes 11 ms, so a sequential reading of all four sensors can be completed in approximately 45 ms. At the Android application, the finger sensor data must be synchronized with the smartwatch data. In this situation, the smartwatch data collection period is capped at approximately 110 ms. Therefore, we have reduced the measurement period from 45 to 100 ms to better align with the smartwatch data collection and avoid oversampling.

The wearable finger sensor also includes technology to make it a completely wireless user experience. The device comes equipped with a Qi wireless charging receiver and a BLE-enabled microcontroller, making our wearable device capable of wireless charging and wireless data transmission. These devices are highlighted in Fig. 3. The Qi wireless charging standard allows our device to be compatible with the most commonly available wireless charging devices. During charging, the Qi wireless receiver produces a 5-V output, which is used to charge the onboard 500-mAh lithium-ion polymer battery. The battery output voltage ranges from 3.7 to 4.2 V and our microcontroller requires a constant 3.3-V input. We use a switching step-up/step-down voltage regulator to convert the variable battery voltage into a constant voltage source for our components. Our device uses an Arduino Nano 33 BLE microcontroller, which is responsible for the finger sensor capacitance measurements, data processing, and data transmission. The Arduino Nano 33 BLE is an easily implementable and low-cost solution. Using the built-in BLE chip on the Arduino Nano, all sensor capacitance data are streamed to the Android application for synchronization with the smartwatch data.

C. Android Application System Coordinator

The Android application acts as the master node in our smoking cessation system. All information collected from the smartwatch and wearable finger sensor peripheral devices are sent to the Android application for synchronization, processing, and activity detection.

The smartwatch transmits linear acceleration and game rotation vector data. The linear acceleration data natively account for the acceleration due to gravity using both the accelerometer and gyroscope as their underlying sources. Likewise, the game rotation vector data uses both the accelerometer and gyroscope to calculate the orientation of the device with respect to a constant orientation. The linear acceleration data are scaled using experimentally derived constants to produce output values with a magnitude of approximately 1.5 at its estimated maximum during activity trials. The wearable finger sensor transmits raw 24-bit capacitance data. The raw data represent capacitance values between ± 4.096 pF. During processing in the Android application, the data are zeroed using initial values and scaled using experimental constants to produce output values with a magnitude of approximately 1.5 at the most extreme finger bend angle. The incoming 24-bit data from the wearable finger sensor are zeroed using initial values taken when the finger was straight. These initial values are used to account for the parasitic capacitances in the measurement circuitry and system.

Synchronization is achieved by matching the incoming data streams using timestamps within a margin of error. Incoming disparate data that were determined to be collected within 100 ms are packaged together to create a single output row. After aligning the smartwatch and wearable finger sensor, the final synchronized output logs data at a frequency of approximately 8.6 Hz. The synchronized data are grouped into batches of approximately 4.2 s and fed into the recognition model for activity classification. If a presmoking activity is detected, the user receives an alert notification from the application warning them to attempt to refrain from smoking. If the system fails to recognize a presmoking activity but recognizes a smoking activity, the application also sends an alert notification to encourage the user to refrain from smoking in the future.

The Android application implements a Tensorflow Lite learning model to assess the collected data. Once data are synchronized, normalized, and windowed into time segments, it is fed into a local Tensorflow Lite model in the Android application. To keep the computational load light for continuous real-time processing, our Tensorflow Lite model uses only four layers with one 1D-CNN, one flattening layer, and two fully connected layers. The model design uses the 1D-CNN layer to compile the time-series windowed data into a more actionable format.

D. Air Quality Sensor for Smoking Contextualization

The air quality sensing wearable is an auxiliary wearable device implemented in our smoking cessation system to help contextualize smoking activity among a wide range of other potential nonsmoking activities. An air quality sensing device will allow us to utilize additional contextual data to reduce the number of false positives when determining smoking versus nonsmoking activities. We chose to implement a commercially available air quality sensing device called the Atmotube PRO that will easily integrate with our current smoking cessation system as an additional wearable device. The Atmotube PRO is a standalone device that can be clipped to the belt loop or placed in the breast pocket of the user. The Atmotube PRO measures the total concentration of volatile organic compounds (TVOCs) and particulate matter (PM) in the surrounding air. Over 30 different volatile organic compounds (VOCs) have been identified in cigarette smoke as well as the release of additional PM into the air [28]. When the patient is smoking, the Amtotube PRO measures a higher concentration of

TVOC and PM in the air. Therefore, we expect that the additional data collected from the air quality sensor will allow our smoking cessation system to contextualize a much broader range of smoking and nonsmoking activities than those tested in the experiment section of this work. The air quality sensor will also serve to reduce the number of false-positive smoking classifications by checking the smartwatch and finger sensor classification against the air quality readings.

The air quality data measured by the Atmotube PRO are integrated into our smoking cessation system through a BLE connection with the Android application. After a connection has been established, the Android application can read the measured TVOC and PM data as BLE characteristics broadcasted by the Atmotube PRO. No initial message is required to start the measurements because the Atmotube PRO continuously measures the TVOC and PM concentrations. Since our smoking cessation system uses the air quality data as a point of reference to contextualize smoking versus nonsmoking activity recognition, we only require measured data from the Atmotube PRO when our system has detected smoking behavior from the user. Therefore, our activity recognition model and data synchronization methods that rely on the smartwatch and finger sensor data remain unaffected. Once smoking activity has been detected, the Android application polls the air quality data collected by the Atmotube and checks the TVOC and PM concentrations against experimentally derived thresholds to produce a more complete smoking activity recognition result. If the measured air quality data read above the threshold, our smoking cessation system proceeds as normal by classifying the behavior as smoking and sending an alert notification to the user. On the other hand, if the air quality data read below the threshold, our smoking cessation system reverts its classification to nonsmoking and does not send an alert notification to the user.

IV. Experiment

To demonstrate the capability of our smoking cessation system to detect presmoking behavior, we compared the activity recognition results from a smartwatch-only version of the smoking cessation system to a combined smartwatch and wearable finger sensor version. Data were collected from both a smartwatch and wearable finger sensor across a constant set of experimental activity trials. When considering the smartwatch-only system version, we analyze only data collected from the smartwatch sensors and disregard data collected from the wearable finger sensor.

A. Data Collection

A representative sample of common activities from daily living that share motion artifacts similar to that of smoking and presmoking behavior was used to assess the accuracy of the system. Common activities that share similar motion artifacts to smoking are the most important to include because they are the most likely to be confused for smoking behavior and therefore, provide the largest challenge for the detection algorithms to differentiate between these activities. We also conducted a survey of relevant smoking gesture recognition research to find the activities used to help inform our activity selection [8], [27], [29]–[32]. The relevant surveyed research work did not develop a device or study to detect presmoking activities, so our activity selection was designed to create a scenario similar to our research peers while making adaptions for presmoking activity detection. We have selected seven unique activities, including smoking gestures and gestures with similar finger and arm motions. The chosen activities can generally be described as either smoking related or nonsmoking related. As seen in Table I, three individual smoking-related activities cover both the act of smoking a cigarette and presmoking activities.

When a user decides to smoke a cigarette, there is a predictable series of activities that lead up to actively smoking a cigarette. First, the user will grab a pack of cigarettes from somewhere like their shirt pocket or on top of the table in front of them. The user will then continue to open the lid of the cigarette pack, pull out a single cigarette, and light the cigarette while holding it between their fingers. All of these actions have taken place before the user has begun to smoke the cigarette. The activities “cigarette table” and “cigarette pocket” cover the entire period between the first movement with the intent to smoke a cigarette and the act of smoking a cigarette. This includes presmoking activities from grabbing a pack of cigarettes to lighting an individual cigarette as described above. These two presmoking activities are the most important to our experiment because successful prediction will allow us to preemptively notify the user in an attempt to actively stop them from smoking a cigarette. An example of the “cigarette table” activity in action is shown in Fig. 4.

Current wearable finger sensor technology can be restrictive on the movements of the user and is impractical in certain situations. Acknowledging this, we examine the effectiveness of the smoking cessation system for two separate implementations. The first implementation uses only the smartwatch peripheral for data collection, excluding the wearable finger sensor. The second implementation uses both the smartwatch and wearable finger sensor peripherals for data collection.

Presmoking behavior primarily includes grasping activities, such as grabbing a pack of cigarettes or pulling an individual cigarette from a pack. When reaching to grasp an object, the hand and fingers automatically begin to contort to fit the shape of the object. The movement of the hand and finger in the expectation of grabbing an object is called preshaping. We expect the wearable finger sensor data to provide increased recognition accuracy of presmoking activities because of both the finger-preshaping used when reaching to grasp an object and the bend angle of the finger when settled on an object grasp.

All activities were performed while collecting data from both the smartwatch and wearable finger sensor simultaneously. We have developed an Android application that establishes Bluetooth connections with the smartwatch and wearable finger sensor to act as the main data collection and interpretation center. The Android application is responsible for synchronizing the incoming data from the smartwatch and wearable finger sensor in real time and feeding the collected

TABLE I
LIST AND DESCRIPTION OF ALL ACTIVITY RECOGNITION CLASSES

Category	Activity	Description
Smoking	cigarette smoke	The user is actively smoking a cigarette. The user's hand holding the cigarette moves from a resting position to the mouth to inhale and then back down to the resting position. This motion is repeated several times.
	cigarette table	The user is preparing to smoke a cigarette. The user grabs a pack of cigarettes from the table, pulls out an individual cigarette, and lights the cigarette.
	cigarette pocket	The user is preparing to smoke a cigarette. The user grabs a pack of cigarettes from their shirt pocket, pulls out an individual cigarette, and lights the cigarette.
Non-smoking	drink water	The user grabs a cup of water from the table and takes repeated sips from the cup of water.
	answer phone	The user picks up the phone from the table and brings the phone to their ear for a period of time before placing the phone back on the table.
	brush teeth	The user picks up a toothbrush from the table and brushes their teeth before returning the toothbrush to the table.
	clean glasses	The user takes off their glasses and cleans them with a rag before returning the glasses to their face.

Fig. 4. Panel depiction of the "cigarette table" activity showing each stage of detection and the smoking cessation application.

data into a local neural network for activity recognition processing.

To demonstrate the technical capabilities of the presented smoking cessation system, data were collected from five participants, following Saleheen *et al.* [30] and Maramis *et al.* [33] who demonstrated their smoking cessation systems using data collected from four and six participants, respectively. Each activity trial was performed discretely apart from the presmoking and smoking activities, which are performed consecutively during data collection. All participants performed every activity and every activity was performed between 20 and 40 times in total accounting for 1358 time window activity data samples for training and testing. The data collection scope is a system proof of concept and serves as the basis for future large-scale clinical implementations.

B. Data Processing

To extract useful information from the smartwatch and wearable finger sensor, the incoming data must be synchronized in our smartphone application in real time. Synchronization is handled by grouping disparate incoming data into 100-ms bins. The synchronized output data are logged at a frequency of approximately 8.6 Hz.

To prepare the time-series data for the learning model, we normalize the disparate data and apply a sliding window function to our data set, which aggregates continuous samples into a single array to be fed to the model. Applying a sliding window creates overlapping activity snapshots, which are necessary for the model to learn the progression of sustained activity. Each window snapshot contains 36 samples, which cover approximately 4.2 s and each window has a 50% overlap with the following window.

After the initial data processing, the data set is divided into a 64-16-20 split for training, validation, and holdout. The training and holdout sets were created manually to ensure an even distribution across individual participant data. The validation set was created automatically from the training subset using built-in Tensorflow methods. We implemented the Adam optimizer and used a learning rate of 0.001. We limited training to 20 epochs, after which we noticed signs of overfitting from the validation results.

C. Results

In this section, we show that it is possible to accurately classify presmoking behavior using our smoking cessation system and we discuss the added classification benefits when using the wearable finger sensor in combination with the smartwatch sensors.

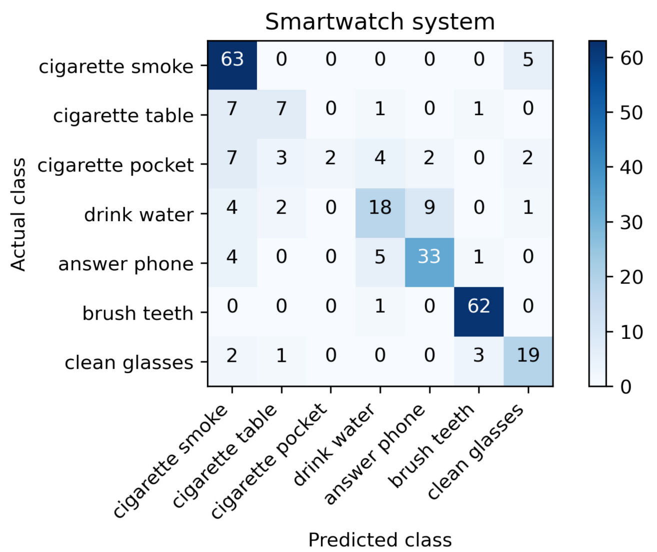

Fig. 5. Confusion matrix for the smartwatch-based smoking cessation system. Activity explanation is given in Table I.

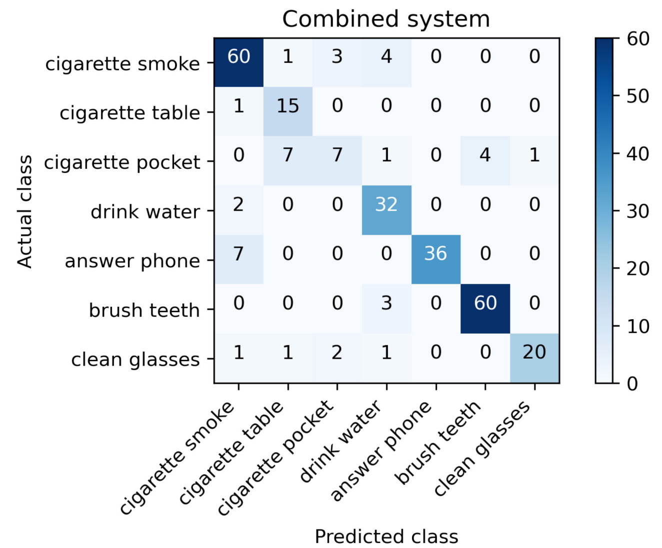

Fig. 6. Confusion matrix for the smartwatch and wearable finger sensor combined smoking cessation system. Activity explanation is given in Table I.

1) Smartwatch System: We first examine the results of our smoking cessation system using only the data collected from the smartwatch. The overall accuracy for this limited model was 75.8% across all activities. From the confusion matrix in Fig. 5, we see that our model struggled significantly with detecting the "cigarette pocket" activity. We also notice a significant amount of confusion across the smoking-related activities, which is likely due to their proximity in time because the presmoking activities are always immediately followed by the smoking activity. The ability to differentiate smoking-related activities is our main point of concern because the accurate detection of presmoking activities is integral to the success of our system. Table II shows the precision, recall, and F1 scores for each of the smoking-related activities. The presmoking detection activity "cigarette pocket" shows a 100% precision and 10% recall for an 18.2% F1 score, while the other presmoking activity "cigarette table" is slightly better at 53.8% precision and 43.8% recall for a 48.3% F1 score. If we combine both presmoking activities into one class label, we see a 13.8% average increase up to a total 47.0% F1 score. This demonstrates the significant amount of cross-categorical prediction errors between the "cigarette table" and "cigarette pocket" classes. The relatively low results compared to the combined smoking cessation system are expected because many of the activities involve movements that are difficult to distinguish using only a wrist-mounted accelerometer. However, the F1 score for the "cigarette smoke" activity is higher at 81.3%, which shows that the smartwatch system alone is adequate for the detection of current smoking behavior.

2) Smartwatch + Finger Wearable System: Next, we move on to examine the results of our smoking cessation system when taking advantage of both the smartwatch and wearable finger sensor. The overall accuracy for this combined model is 85.5%, which shows a 9.7% increase over the smartwatch-only system. From the confusion matrix in Fig. 6, we see there is still difficulty discerning the "cigarette pocket" activity from the "cigarette table" activity. However, compared to the smartwatch-only system, there is significantly less confusion across the smoking and presmoking activities. Table II details an increase in F1 scores of 5.0%, 26.7%, and 25.6% over the smartwatch-only system in the "cigarette smoke," "cigarette table," and "cigarette pocket" activities, respectively. When combining both presmoking activities into a single class label, we see a 21.2% F1 score increase over the average F1 score of the presmoking activities. This shows that there remains overlap between the presmoking activities in the combined smoking cessation system. However, we can predict the combined presmoking activities with 33.6% greater accuracy than the smartwatch-only system. This shows that after the inclusion of the wearable finger sensor, our smoking cessation system can classify presmoking activity with 80.6% accuracy and current smoking activity with 86.3% accuracy.

TABLE II
CLASSIFICATION RESULTS FROM SMARTWATCH-ONLY SYSTEM AND COMBINED SYSTEM

System	Activity	Precision (%)	Recall (%)	F1 (%)
Smartwatch	cigarette smoke	72.4	92.6	81.3
	pre-smoking*	80.0	33.3	47.0
	cigarette table	53.8	43.8	48.3
	cigarette pocket	100.0	10.0	18.2
Combined	cigarette smoke	84.5	88.2	86.3
	pre-smoking*	80.6	80.6	80.6
	cigarette table	62.5	93.8	75.0
	cigarette pocket	58.3	35.0	43.8

* Pre-smoking activity category is a direct combination of the 'cigarette table' and 'cigarette pocket' activities.

V. Discussion and Future Work

We presented a smoking cessation system capable of detecting smoking and presmoking activities with 86.3% and 80.6% accuracy, respectively. Our system is the first to tackle the problem of prediction of future smoking behavior by using the detection of presmoking activities in a sensor-based approach.

A. ShArc Sensor Implementation

We chose to implement the ShArc bend-angle sensing technique for our wearable finger sensor because of its precision and customizability. Our results show that the ShArc technique provided sufficient accuracy for detecting finger position and movement; however, the construction and implementation of the ShArc sensor itself were challenging due to several sensitive physical attributes.

One concern is the consistent spacing between the transmit and receive strips of the sensor. A large disparity between the amount of copper deposited on each side of a flexible printed circuit can create bending in the final product. The ShArc design prints copper only on a single side of the flexible circuit. Bending occurring from the development of the flexible printed circuit will inhibit the sensor strips from laying flat against each other and maintaining a constant distance between the transmit and receive pads. To counter this issue and attempt to further compress the faces of the sensor, we added an additional rolled-up length of support neoprene inside the initial neoprene sleeve. The additional support piece improved upon the initial compression sleeve design; however, the underlying bending and separation problems continue to require devices to have meticulous and time-consuming development processes. This creates an additional barrier to developing such devices on a larger scale.

A second concern we have with using the ShArc technique is the rigidity of the sensor material itself. The ShArc sensor is created using polyimide, a common flexible printed circuit material. This material will bend to match the shape, but it will not stretch to maintain a specific point on the hand or finger. If the ShArc sensor is attached to the back of the finger and the finger moves from straight to retracted, the end of the ShArc sensor will not remain at the end of the finger because of the difference in curvature radiuses. In practice, this means that the individual differential capacitance sensors shift in relation to the finger during bending. While this is acceptable for our current use case, the problem will be accentuated with longer ShArc sensors, for example, those extending from the base of the wrist to the fingertip.

B. Air Quality Sensing

We chose to implement a commercially available air quality sensor to help contextualize the smoking classification result from the data collected by the smartwatch and finger sensor wearables. First, it may seem that relying on air quality data to determine smoking activity may introduce additional classification problems due to environments with poor air quality, such as those with secondhand smoke or dust. However, because our system relies on the air quality sensor only when our other system components, the smartwatch and finger sensor, have already detected smoking, the user simply being in an environment with poor air quality will not alone trigger smoking activity detection.

The air quality sensor will primarily serve to reduce the number of false-positive smoking classifications although it also has the potential to provide additional contextual information. As discussed previously, environments containing secondhand smoke will not alone trigger the detection of smoking activity; however, the air quality data can provide insight into the users' actions in secondhand smoke environments. For example, when the air quality sensor detects high concentrations of TVOC and PM associated with smoking, but smoking or presmoking activity is not detected by the smartwatch and finger sensor wearables, we can infer that the user was in a smoking environment and successfully resisted the external temptations to partake in smoking. This information can be useful to the overseeing clinicians or therapists to inform the user's smoking cessation progress.

C. Real-World Feasibility

Our smoking cessation system can be implemented in two ways for different use cases. The first implementation uses only the smartwatch as the peripheral sensor for data collection. The smartwatch-only version of our smoking cessation system is designed for scalability and ease of implementation. Smartwatches are common, consumer friendly, and incur little to no restrictions on daily activities or movements. This makes them ideal for smoking cessation users whose primary concern is convenience. Our smartwatch-based smoking cessation system can be easily incorporated into a potential user's lifestyle by simply installing our software and wearing the associated smartwatch. Therefore, this system provides a substantial user benefit while sacrificing little to no convenience.

Our combined smartwatch and wearable finger sensor smoking cessation system significantly improves upon the detection accuracy of the smartwatch-only system with an average increase of 33.6% across the presmoking activities and 5.0% for the smoking activity. However, the increase in prediction results comes at the cost of an additional wearable device. Increasing the number of wearable devices can be cumbersome for the user. Wearable finger sensor devices often change the natural movements and activities of the user because the device covers part or all of the hand and fingers. Any change to the users' natural movements or activities is unfavorable. The wearable finger sensor that we developed for our smoking cessation system covers the back of the hand and index finger. Although our wearable finger sensor does not cover the full hand and fingers, it will still impact the user's natural movements and activities. Therefore, our combined smoking cessation system is geared toward clinical test settings or short-term use cases.

Although wearable finger sensors are currently obtrusive in some manner. we believe that the technology and research surrounding skin printed sensors will flourish in the near future and enable a host of wearable sensors, which were previously hindered by their physical shape. Recent research regarding skin-printed sensors done by Zhang *et al.* [34] demonstrated the capability to apply sensor circuitry directly to the skin at room temperature. This research gives us confidence that we could soon extend this technology to implement a skin-printed wearable finger sensor device for use in our smoking cessation system.

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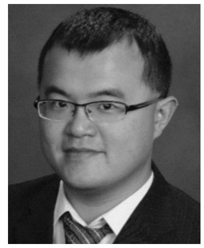

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