Enhancing Smoking Gesture Recognition: A Robust Cross-Platform Solution with Sense2Quit

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Abstract

Background: The Sense2Quit study introduces innovative advancements in smoking cessation technology by developing a comprehensive mobile application (app) that integrates with smartwatches to provide real-time interventions for people living with HIV (PWH) who are attempting to quit smoking

Objective: To develop an accurate smoking cessation app that utilizes everyday smartwatches and an AI model to enhance the recognition of smoking gestures by effectively addressing confounding hand gestures that mimic smoking, thereby reducing false positives. The app ensures seamless usability across Android and iOS platforms, with optimized communication and synchronization between devices for real-time monitoring.

Methods: The Sense2Quit system utilizes a Convolutional Neural Network (CNN) model specifically trained to distinguish smoking gestures from similar hand-to-mouth activities. By incorporating confounding gestures into the model's training process, the system achieves high accuracy while maintaining efficiency on mobile devices. To validate the model, 30 participants, all PWH who smoked cigarettes, were recruited. Participants wore smartwatches on their wrists and performed various hand-to-mouth activities, including smoking and other gestures like eating and drinking. Each participant spent 15 to 30 minutes completing the tasks, with each gesture lasting 5 seconds. The app was developed using the Flutter framework to ensure seamless functionality across Android and iOS platforms, with robust synchronization between the smartwatch and smartphone for real-time monitoring.

Results: The CNN model achieved an F1 score of 97.52% in detecting smoking gestures, effectively differentiating between smoking and 15 other daily hand-to-mouth activities, such as eating, drinking, and yawning. The cross-platform app, developed using Flutter, demonstrated consistent performance across Android and iOS devices, with only a 0.02-point difference in user experience ratings between the platforms (iOS: 4.52, Android: 4.5). The app's continuous synchronization ensures accurate, real-time tracking of smoking behaviors, enhancing the system's overall utility for smoking cessation.

Conclusions: Sense2Quit represents a significant advancement in smoking cessation technology. It delivers timely, just-in-time interventions through innovations in cross-platform communication optimization and the effective recognition of confounding hand gestures. These improvements enhance the accuracy and accessibility of real-time smoking detection, making Sense2Quit a valuable tool for supporting long-term cessation efforts among PWH trying to quit smoking.

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Keywords: Smoking Cessation, Confounding Gestures, Mobile Health, Wearable Technology, Real-time Monitoring, HIV

Introduction

The global health burden of tobacco use remains a formidable challenge for public health initiatives, with smoking-related illnesses claiming approximately 6 million lives worldwide annually [1]. Despite decades of efforts to reduce smoking rates through various interventions, including public education campaigns, taxation policies, and cessation programs, tobacco use persists as the leading preventable cause of morbidity and premature mortality worldwide [2]. The issue of smoking is prevalent and challenging to address among people with HIV (PWH). Approximately 50% of the one million PWH living in the United States (US) smoke cigarettes, which is about four times higher than the prevalence observed in the general U.S. adult population [3]. This highlights the urgent need for innovative, technology-driven smoking cessation interventions and real-time monitoring of smoking behaviors. Recent research has shown an increasing focus on developing smartphone apps for this purpose [4]. These apps offer various features like SMS reminders, progress tracking, and peer support [5]. Concurrently, the proliferation of wearable technology has opened new avenues for continuous health monitoring and behavior modification. Integrating wearable devices into smoking cessation programs holds considerable potential for enhancing intervention efficacy and enabling real-time monitoring of smoking behaviors [5-6]. Smartwatches and smartphones with sensors can detect smoking events in real-time, offering opportunities for timely interventions [8].

Several studies have established the feasibility of utilizing wearable devices to identify smoking events with high accuracy [8-9]. These systems primarily employ accelerometers and gyroscopes to recognize hand-to-mouth smoking-related gestures. For instance, the SmokeBeat app [11], which leverages wearable sensors to identify smoking gestures, has shown promising results in smoking reduction by alerting users to their smoking episodes. Current advancements in machine learning techniques, particularly convolutional neural networks, have been applied to analyze sensor data and accurately identify smoking puffs [12]. These automated detection systems can be integrated into mobile applications to provide real-time interventions and support for individuals attempting to quit smoking [12-13]. Notably, researchers have explored various approaches to enhance the effectiveness of these interventions. While some systems focus on detecting actual smoking events, others aim to identify pre-smoking activities to discourage relapses [15]. This proactive approach may offer additional opportunities for intervention before the smoking behavior occurs.

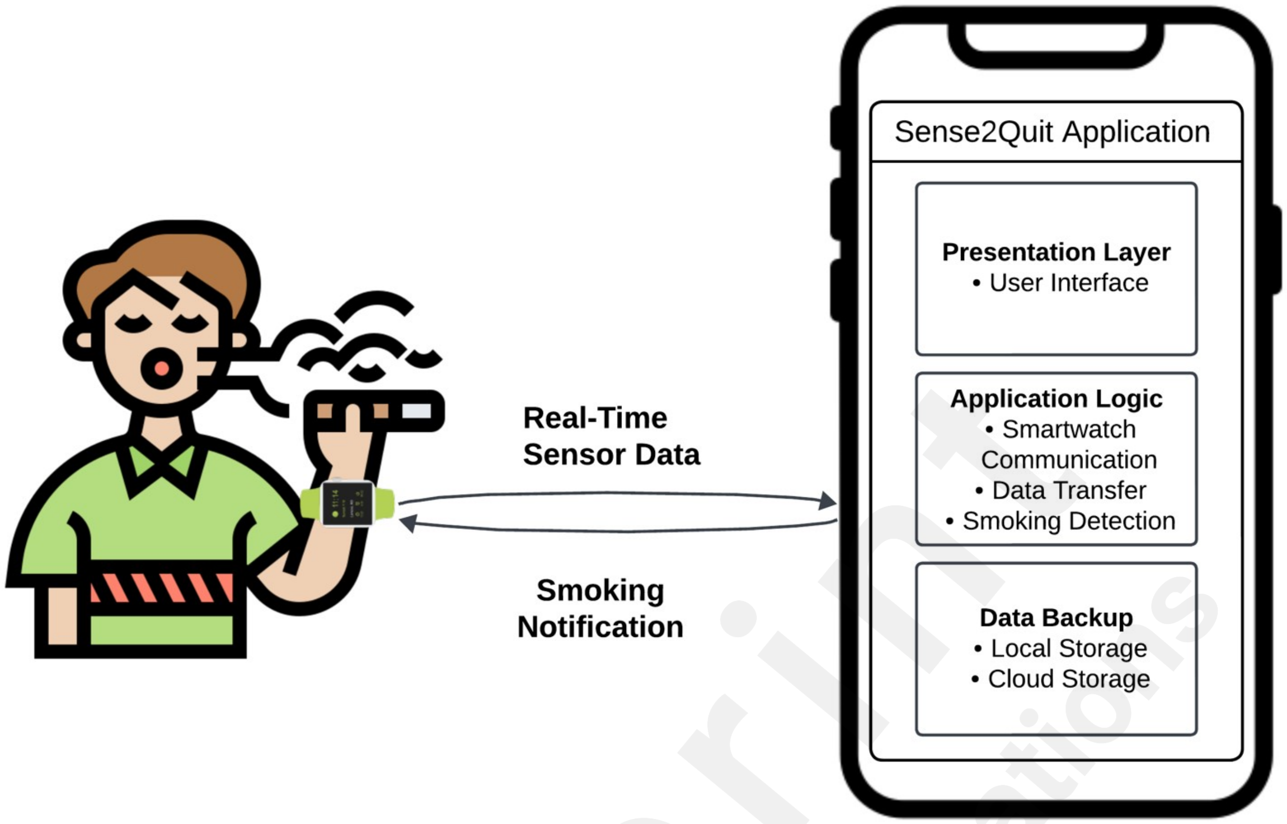

Figure 1. Overview of the Sense2Quit smartphone and smartwatch system architecture

However, despite the potential of wearable technology in smoking cessation, several challenges persist. A comprehensive review of existing apps revealed that only a minority incorporate advice from healthcare professionals, and many lack a theoretical framework aligned with established guidelines [16]. This gap between technological innovation and evidence-based practice raises concerns about the efficacy of these interventions. Technical issues also pose significant obstacles. Maintaining proper connectivity between wearable devices and smartphones remains a common challenge [10]. While using multiple sensors or higher sampling rates can improve complex activities like smoking recognition, these approaches lead to increased resource consumption [17]. This trade-off between accuracy and efficiency presents a significant hurdle for widespread adoption.
Moreover, the performance of smoking detection models often diminishes in real-world settings. While these models may demonstrate high accuracy under controlled conditions, their effectiveness can decrease substantially in free-living environments [18]. One key factor contributing to this decline is the presence of confounding gestures, which interfere with the model's ability to detect smoking-specific movements accurately [19]. The recognition of less-repetitive activities, such as smoking, presents additional challenges. Smaller segmentation windows, while beneficial for real-time applications, often struggle to capture these infrequent behaviors accurately. Conversely, increasing the window size can improve recognition but may introduce delays and reduce the system's real-time applicability [20]. As this field continues to evolve, there is a pressing need for more comprehensive evaluations of app effectiveness and long-term outcomes.

Our Sense2Quit study addresses the critical gaps in existing smoking cessation applications by adhering to a rigorous, theoretically guided development framework while collaborating closely with healthcare professionals. The study aims to develop mobile health (mHealth) technology to support tobacco cessation in PWH. The mobile app supports PWH quitting smoking by utilizing smartwatches for behavioral assessment and delivering just-in-time interventions. A pilot study was conducted to assess the feasibility, acceptability, and early effectiveness of the Sense2Quit App as a tool for individuals with HIV who are motivated to quit smoking. Upon enrollment, participants received Android smartwatches with the Sense2Quit app pre-installed. Some participants were provided with Android smartphones, while others had the Sense2Quit app installed on their own devices with assistance from the research staff. Both smartwatch and smartphone apps were used throughout the study. The pilot study lasted from March 2023 to January 2024 and involved 60 participants [21]. The development of the Sense2Quit app was guided by the Information Systems Research (ISR) framework, incorporating focus groups, design sessions [3], and usability testing [22]. This comprehensive framework ensures a user-centered and iterative development process, incorporating valuable feedback from focus groups and design sessions with the target population, specifically PWH. By tailoring the intervention to this high-risk group, we aim to enhance the app's efficacy and address the unique challenges faced by PWH in their smoking cessation journey. A key distinguishing feature of the Sense2Quit application is its innovative integration of smartwatches with a smartphone application (Figure 1), enabling the provision of real-time, just-in-time cessation interventions. This technology-driven approach leverages the potential of continuous health monitoring through smartwatches employing a sophisticated artificial intelligence (AI) model for accurate smoking gesture detection.

This paper outlines the comprehensive technical implementation of the Sense2Quit application, which is utilized for smoking detection. This study emphasizes the cross-platform functionality of the application, ensuring its operability on Android and iOS platforms. Critical connectivity and data transfer mechanism improvements are highlighted to provide continuous and reliable interactions between smartphones and smartwatches. Notably, the application features a robust artificial intelligence (AI) model that demonstrates resilience against confounding gestures, achieving a decreased rate of false positives and negatives, with an impressive F1 score of 97.52. Data collection methodologies are meticulously designed to capture confounding gesture data, and an application module is developed to ensure seamless data acquisition. The subsequent sections of this paper are organized as follows: First, we delve into the technical intricacies of the various components that constitute the Sense2Quit application. Next, we elaborate on the methodologies employed to enhance the smoking detection model's resilience against confounding gestures, including a detailed discussion of our data collection protocol and evaluation of the cross-platform application. Finally, we present the results of our study and explore potential future directions for this research.

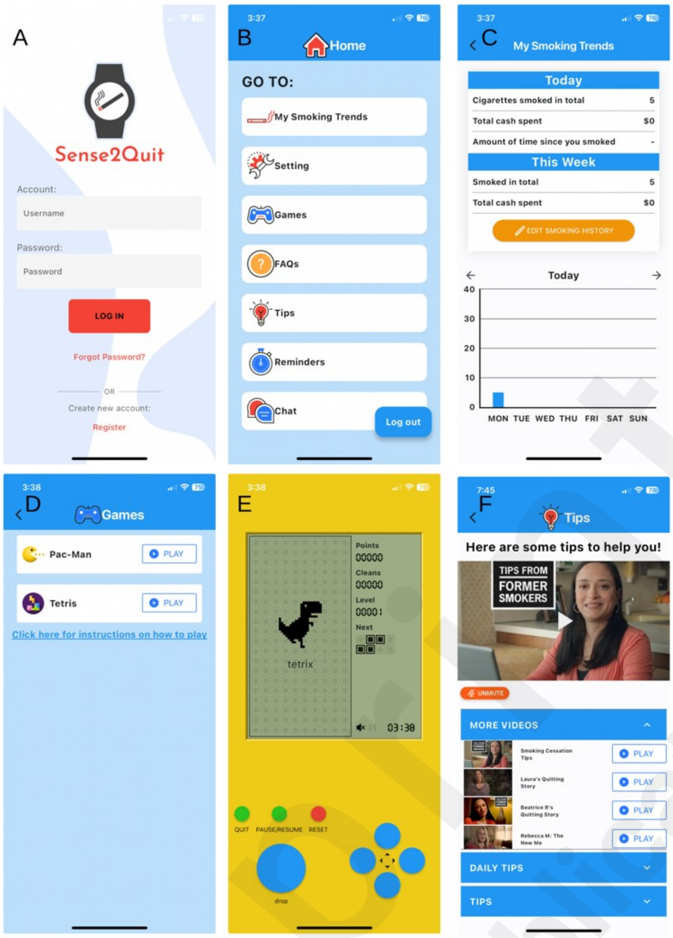

Figure 2. User interface screenshots of the Sense2Quit smartphone app, showcasing the (A) Login, (B) Home, (C) Smoking Trends, (D) List of Games, (E) Tetris Game and (F) Tips screens

Sense2Quit Application Overview

Sense2Quit consists of two primary components: the smartphone and smartwatch applications and an online dashboard. These elements synergistically work together to provide users with a comprehensive solution for smoking cessation, including real-time participant data tracking to address potential issues and minimize participant attrition proactively. The pilot study utilized Android smartphones and smartwatches, restricting participant recruitment to Android users. To overcome this limitation, we developed a cross-platform application version using Flutter, making it available for iOS and Android devices. This ensures smooth installation from both Google and Apple app stores, improving access to potential participants and enhancing user accessibility. The following sections provide a detailed overview of each component's technical functionalities and contributions, illustrating how they support users on their journey to quit smoking.

Smart Watch App Development

The Sense2Quit smartwatch application serves as a crucial instrument for collecting essential movement data, thereby enabling the detection of smoking behaviors in users. Strategically placed on the participant's wrist, this application leverages the advanced capabilities of built-in smartwatch sensors, including the 3-axis accelerometer and gyroscope, to capture intricate motion patterns. With a sampling rate of approximately 20Hz, the smartwatch records hand movement data in real-time. This sensor data is efficiently transmitted to the user's smartphone for comprehensive analysis. In addition to monitoring movement data, the smartwatch application offers valuable cessation tips to aid users in their journey to quit smoking. Importantly, this application is compatible with a broad range of smartwatches, encompassing Android and Apple devices. Extensive testing has been conducted on popular models such as the Ticwatch, Fossil watch, and Apple Watch SE, ensuring reliable performance and compatibility across various wearable platforms.

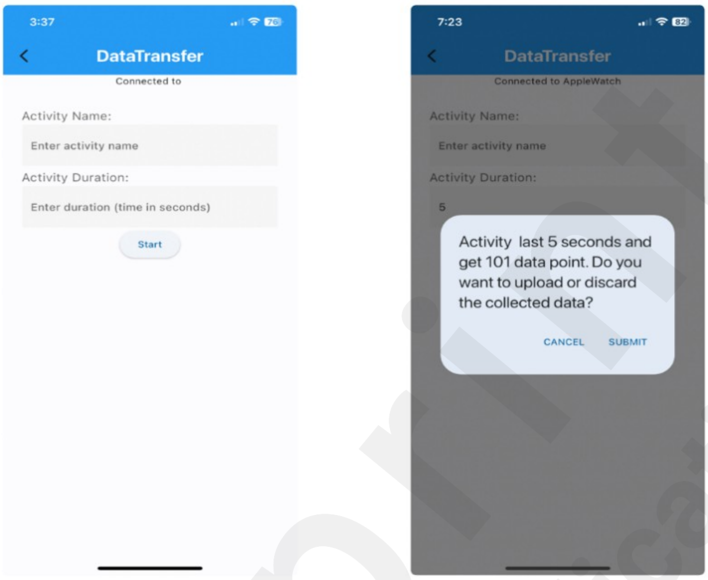

Figure 3. User Interface for the data collection screen demonstrating the states before data collection on the left and after data collection is completed on the right.

Smart Phone App Development

The Sense2Quit smartphone application serves as the central interface for users, offering comprehensive features to support smoking cessation (Figure 2). The app's smoking dashboard provides a detailed summary of smoking habits, including the number of cigarettes consumed, expenditure, and daily trends, all visualized through intuitive graphs. This functionality enables users to monitor their progress and make informed decisions effectively. To help manage cravings, the app includes interactive games like Pacman and Tetris, which serve as distractions to promote healthier coping mechanisms. Additionally, the Tips section provides informative videos and practical advice to help users overcome challenges. The Sense2Quit app empowers users to achieve a smoke-free lifestyle by integrating monitoring, distraction, and educational components. Our earlier work details the various UI features and usability testing [22].

A specialized data collection module was integrated into the application to facilitate data collection on confounding gestures. This module was designed to provide research staff with a streamlined system for gathering and uploading data to a cloud server, enabling the technical team to access and refine the baseline smoking detection model. The user interface (Figure 3) was engineered for efficiency and simplicity, allowing the collection and upload of gesture data from each subject to be minimally complex. A crucial UI feature was the prominent connection status indicator positioned at the top of the screen. This indicator dynamically displayed the pairing status between the smartwatch and smartphone. When successfully connected, it showed "Connected" and instantly switched to "Disconnected" if the connection was lost. Significantly, any ongoing data collection would automatically halt in the event of a disconnection. This real-time feedback mechanism ensured data integrity and continuity throughout the experiment. It allowed research staff to immediately identify and address connectivity issues, thereby minimizing data loss and reducing the need for repeated trials.

The user interface (UI) also included:

1. A connection status indicator at the top of the screen
2. An input field for activity names, where the gesture was performed, and the participant's username was entered.
3. A duration input field to specify the recording length in seconds.
4. A start button to initiate data collection.
5. A countdown display indicates the remaining time for data collection.
6. A confirmation dialog post-collection to verify data quality before upload.
7. Separate indicators for data saving and successful upload to provide real-time feedback to data collectors.

The confirmation mechanism was implemented to prevent the upload of data from instances where participants could not perform gestures as intended, thereby mitigating data corruption at the source. Upon confirmation, the data was transmitted to AWS cloud storage, specifically to a DynamoDB instance. Each entry in the database included 3-axis accelerometer and gyroscope data, along with the activity name, participant ID, and timestamp.

The Sense2Quit app, designed for iOS and Android platforms, was developed using Flutter [23]. This cross-platform compatibility significantly improved over the previous version, which only supported Android devices, thereby restricting the inclusion of participants who used Apple devices in the study. Porting the existing Android app to a cross-platform framework presented challenges, particularly about the core functionality of transferring sensor data between the smartwatch and the mobile device across both platforms. The standard open-source packages in Flutter were insufficient to achieve this functionality due to platform-specific limitations. We encountered restrictions related to how long the application could run in the background and the number of background operations permitted by the package. As a result, platform-specific code had to be implemented for Android and iOS. However, the UI code remained broadly consistent across platforms, ensuring a similar user experience for participants regardless of their device.

Connectivity

The smartwatch's accelerometer and gyroscope sensor data are transmitted to the smartphone via a Bluetooth Low Energy (BLE) connection. Establishing this connection involves a three-way handshake like the TCP protocol [24]. The handshake begins with the smartphone sending a greeting message, to which the smartwatch responds with an acknowledgment message. Subsequently, the smartphone sends a "heartbeat" message to prompt the smartwatch to start transmitting sensor data. Once a participant is onboarded and the connection between the devices is established, data transfer occurs continuously in the background.

The heartbeat mechanism maintains a stable connection and uninterrupted data flow. The smartphone sends a heartbeat every three seconds to ensure the smartwatch continues to send data. If the smartwatch does not receive a heartbeat for six seconds, the data transfer ceases, and the Sense2Quit application notifies the participant via the smartphone. This method ensures reliable data transmission between the smartwatch and the smartphone.

Automatic Smoking Detection

The sensor data is sent from the smartwatch to the smartphone. The sensor data contains a timestamp, 3-axis total accelerometer, and 3-axis gyroscope values. The force of gravity g always influences the measured acceleration; therefore, to accurately measure the actual acceleration, the contribution of gravitational force must be eliminated. This is typically achieved through filtering the data using either a high-pass or a low-pass filter. Our application implemented a low-pass filter that smooths out rapid fluctuations in the acceleration data, isolating the gravity component. The 3-axis accelerometer values sent to the smartphone are the total accelerometer values; the gravity component is separated using the following recursive low-pass filter formula:

$$\text{gravity} = \alpha \cdot \text{gravity} + (1-\alpha) \cdot \text{total acceleration}$$

Where α is a constant between 0 and 1 that determines the responsiveness of the filter, which is set to 0.8 in our application, this is performed for all the three readings (x, y, z) axes. Once the gravity component is separated, the linear acceleration is calculated using the Equation:

$$\text{linear acceleration} = \text{total acceleration} - \text{gravity}$$

The linear equation is also performed for all three readings, giving us the linear acceleration values without the gravity component. The gyroscope data from the smartwatch is sent as a rotation vector representing the orientation; no further filtering is applied to it.

Once the data is cleaned, the smartphone stores the linear acceleration and gyroscope values locally. It then schedules the local data to be uploaded to Amazon AWS cloud storage every hour. The data is transferred from local storage to two queues, each holding the values until they accumulate 200 entries. These values are then processed by the machine learning model for inference, which calculates a prediction to determine if a smoking gesture occurred within the sample period. This process is repeated continuously until a smoking gesture is detected. A notification is sent upon detection, and the smoking data is recorded in the application. To avoid redundancy, no further messages are sent for 450 seconds, which is assumed to be the average duration of smoking for this application and treated as a cooldown period for smoking detection.

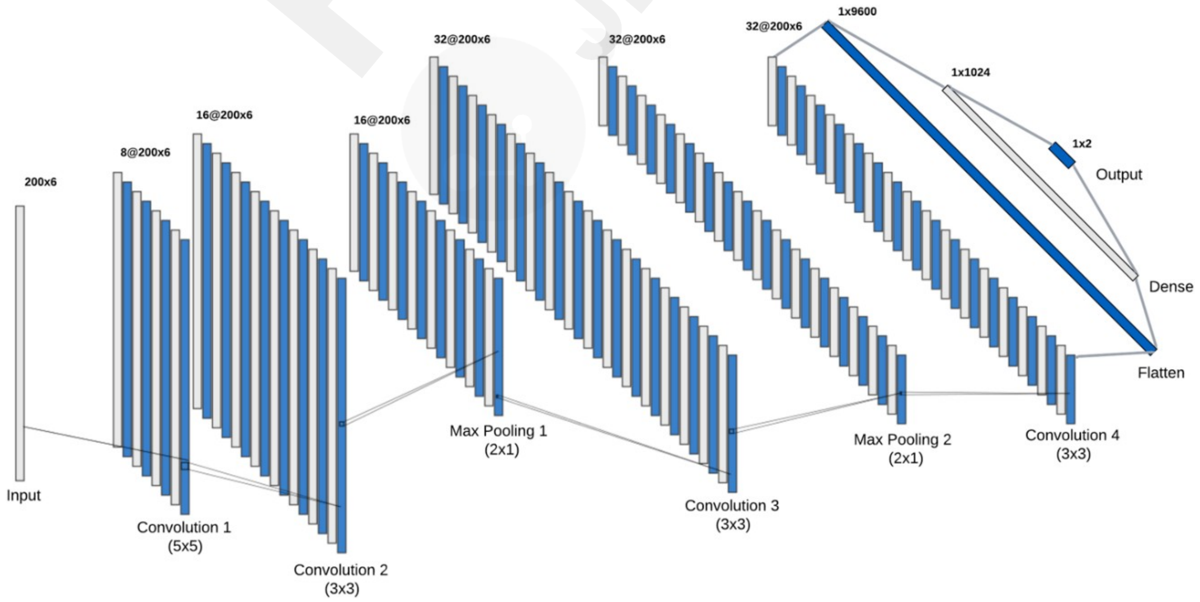

Figure 4. Smoking detection model architecture illustrating the underlying layers

Smoking Gesture Detection Model

The study utilized a Convolutional Neural Network (CNN) to enhance the accuracy of detecting smoking gestures from wearable sensor data. The CNN model was trained to classify smoking versus non-smoking gestures using time-series data from a smartwatch's accelerometer and gyroscope. The choice of a CNN architecture was driven by its ability to effectively extract spatial features from raw sensor data, a critical factor in differentiating smoking gestures from similar activities. Additionally, CNNs demonstrate strong performance in recognizing smoking gestures even when performed simultaneously with other actions [25], achieving high accuracy in person-independent evaluations. By integrating data from accelerometers and gyroscopes, the model's accuracy in gesture detection improves further [26]. The CNN's low computational complexity and high classification accuracy make it well-suited for real-time deployment on wearable devices [27].

The input data comprised 200 time points with six sensor values (3-axis accelerometer and 3-axis gyroscope). The model (Figure 4) incorporates four convolutional layers with progressively increasing filter counts (8, 16, 32) and decreasing kernel sizes (5x5 for the initial layer and 3x3 for subsequent layers). Leaky ReLU activation is employed in all convolutional layers to address the dying ReLU [28] problem and enhance gradient flow. Two MaxPooling layers (2x1) are interspersed to reduce dimensionality. The network also includes a dense layer with 1024 units and a 0.5 dropout rate for overfitting prevention. The output layer uses softmax activation for binary classification between smoking and non-smoking gestures. This architecture is specifically designed to capture the subtle temporal and spatial patterns characteristic of smoking gestures, with its progressive feature extraction and dimension reduction facilitating efficient and accurate classification. Using Leaky ReLU, strategic pooling, and dropout contributes to robust learning and generalization, making the model well-suited for real-time smoking gesture detection in wearable devices. The Categorical cross-entropy loss function, the learning rate 0.001, 100 epochs, and 32 samples per batch were used for training.

Online Dashboard

An online dashboard (Figure 5) was developed and implemented for the research staff to facilitate real-time monitoring of study participants. This web-based interface, created using the Flask framework and hosted on Amazon Web Services (AWS) Elastic Cloud, provided critical insights into participant engagement and data collection processes. The dashboard displayed vital metrics for each enrolled participant, including:

1. Total duration since onboarding with the application
2. Timestamp of the most recent local data backup to the cloud
3. Timestamp of the participant's last interaction with the application

This live information served as a vital data point for the study, enabling researchers to promptly identify any anomalies in application performance, monitor participant adherence to the study protocol, and initiate timely follow-ups with participants who demonstrated prolonged periods of inactivity.

Sense2Quit Dashboard

Username	Total Time	Last Recording Start Time	Last Used
sq82	87h 44m	09/28/2023	09/28/2023 17:10
SQ80	92h 11m	09/26/2023	09/26/2023 08:05
sq91	683h 26m	12/05/2023	12/05/2023 12:15
sq102	8h 52m	10/16/2023	10/16/2023 10:04
sq103	503h 33m	12/31/2023	12/31/2023 12:05
sq94	614h 25m	11/16/2023	11/16/2023 11:30
sq96	3h 38m	10/17/2023	10/17/2023 14:23
SQ105	329h 10m	01/01/2024	01/01/2024 16:15
Sense2Quit106	401h 55m	11/21/2023	11/21/2023 09:20
sq95	281h 18m	12/06/2023	12/06/2023 18:00
SQ101	227h 16m	12/13/2023	12/13/2023 12:02
S2Q100	19h 52m	11/13/2023	11/13/2023 12:05

Figure 5. Sense2Quit dashboard for research staff that provided usage information participants enrolled in the study

Methods

The pilot study revealed a significant challenge: frequent false positive notifications triggered by participants' routine activities [29]. Upon investigation, we identified a range of confounding gestures and actions that closely resemble smoking-related motions, compromising detection accuracy. Additionally, since the pilot study was conducted exclusively on Android devices, we could not recruit participants who used Apple devices, which limited the overall participant enrollment. Some participants also reported connectivity issues between their smartphones and smartwatches, further complicating data collection and analysis. Addressing these limitations became crucial for improving detection accuracy and system performance. To tackle these challenges, we implemented two methods:

First, we recruited 30 participants from the pilot study [21] and recorded 16 common hand-to-mouth gestures from their daily activities, including the smoking gesture. The typical smoking gesture sequence—characterized by the user bringing their hand to their mouth for inhalation, lowering it to a resting position, and then repeating the motion for subsequent puffs—is not unique to smoking. Similar action patterns can be observed in other activities, such as drinking or answering a phone call, which we have included in our investigation. This data evaluated the model’s ability to distinguish smoking-related gestures from similar actions, such as drinking or answering a phone call. These gestures were collected across three distinct postures to ensure comprehensive coverage of potential confounding movements.

Second, to evaluate the app’s cross-platform functionality and performance, we recruited eight additional participants who had yet to be part of the pilot study. These participants were asked to rate the smartphone application's usability on iOS and Android platforms. We also performed a power consumption analysis on the smartwatch to assess its energy efficiency when running the app. These combined methods enhanced the model's discriminative accuracy and addressed previous connectivity issues without introducing additional computational complexity.

Table 1. Characteristics of participants (N = 30)

Characteristic	Mean (SD) or N, %
Age (years)	59.07 ± 8.92
Female (%)	14 (46.7 %)
Male (%)	16 (53.3%)
White (%)	2 (6.7 %)
Black (%)	25 (83.3%)
Hispanic/Latino (%)	6 (20.0%)
Height (cm)	166.88 ± 8.83
Weight (kg)	77.14 ± 16.34
BMI (kg/m^2)	27.91 ± 6.54

Confounding Gestures Experiment Design & Evaluation

The experiment aimed to collect confounding gesture data from 30 participants aged 34 to 71 (mean age = 59.07 ± 8.92 years) who were PWH who smoked cigarettes and participated in the Sense2Quit pilot study. They were recruited at their 12-week follow-up appointment or through phone calls following completion of the study. The gender distribution among the participants was 16 males and 14 females. Regarding ethnicity, the cohort included 2 White participants (6.7%), 25 Black participants (83.3%), and 6 Hispanic/Latino participants (20.0%). The participants' mean height was 166.88 cm ± 8.83 cm, their mean weight was 77.14 kg ± 16.34 kg, and their mean BMI was 27.91 ± 6.54 kg/m^2 (Table 1). Participants signed a consent form before participating in any study activities and were compensated $30 for their time. The visits took place at Columbia University School of Nursing and lasted between 15 and 30 minutes. During the visits,

participants completed a series of tasks while wearing a smartwatch on their wrists under the instruction of a research staff member. The smartwatch was connected to the Sense2Quit smartphone app, which recorded accelerometer and gyroscope data of the gestures performed. The study included 16 distinct gestures, comprising 15 confounding gestures and one smoking-related gesture (Table 2). The gestures selected for this experiment were chosen because they closely resembled the motions involved in smoking, thereby serving as confounding gestures that an AI smoking detection model could misclassify. These confounding gestures simulate everyday actions that involve similar wrist and arm movements, such as eating, drinking, or waving, which are prone to generating false positives in smoking detection [30]. Each gesture was performed for 5 seconds, and participants executed them in three distinct postural conditions: seated, standing, and walking. However, it is essential to note that not all participants could perform the gestures in all three postural conditions due to the limited mobility of some participants. Data collection was limited to those postures in which participants reported and demonstrated comfort in performing the required gestures. This approach was adopted to ensure the ecological validity of the data while prioritizing participant comfort and safety.

Table 2. List of activities that the participants performed during confounding gestures data collection

Activities
1. Drinking without straw 2. Drinking with straw

3. Eating with fork
4. Eating without fork
5. Talking with hand gesture
6. Using a phone (making a phone call)
7. Adjusting glasses
8. Arm cross
9. Scratching face
10. Applying chapstick
11. Yawning
12. Pinching chin
13. Wiping nose
14. Messaging Head
15. Waving
16. Smoking

In the previous section, we re-trained the CNN model by incorporating newly acquired confounding gesture data to create the confounding gestures model. The CNN model trained without the confounding gestures data used in the pilot study will be called the baseline model. Notably, the baseline model's fundamental structure remained unaltered; the activation functions and training procedure were preserved to maintain consistency and facilitate direct comparison. This approach aimed to improve the model's discriminative capabilities without introducing additional computational overhead. The confounding gestures dataset comprised 1054 samples, partitioned using a 60:20:20 ratio into training, testing, and evaluation subsets. This partitioning strategy aligns with standard practices in machine learning, ensuring sufficient data for model training while reserving adequate samples for testing and final evaluation. The resultant confounding gestures model was evaluated rigorously following the training phase. This assessment utilized the held-out portion of the confounding gesture data—specifically, the samples not employed during the training process. This approach allowed for an unbiased comparison between the newly trained confounding gestures model and the original baseline model.

Usability Evaluation of the Sense2Quit Applications

To assess the usability of our smartphone application on both iOS and Android platforms, a user experience (UX) survey was conducted with eight student participants from the University at Buffalo (UB). The survey aimed to gather quantitative and qualitative data on the app's performance, feature parity, and user interface design. It was designed with questions that focused on key performance indicators such as app launch time, smoothness of the user interface (UI), and the application's responsiveness to user inputs. Participants rated these aspects on a Likert scale [31] from 1 to 5, with 1 indicating the lowest satisfaction and 5 the highest. Moreover, the survey explored the presence of feature parity between the iOS and Android versions, probing whether any significant features available on one platform needed to be added to the other. To gather insights into the app’s overall user interface design, respondents were also asked to rate the intuitiveness and usability of the app’s interface on both platforms. They provided feedback on the overall user experience to identify potential improvements to enhance usability and satisfaction across different devices.
Additionally, we wanted to understand the impact of continuous data transmission on smartwatch power consumption, so we conducted a test using the Mobvoi Ticwatch Pro 3, set up with an Android phone. The watch ran Sense2Quit, a custom application to collect power consumption data and the default pre-installed applications. The 20-minute test consisted of three phases: a 5-minute

baseline phase, a 10-minute active phase with the Sense2Quit app running in the background collecting and transmitting sensor data, and another 5-minute baseline phase after the active phase. Our custom power consumption monitoring application collected current and voltage information every 5 seconds.

Results

Confounding Gestures Evaluation Results

The results of our analysis underscore the substantial improvement achieved by the confounding gestures model over the baseline model, highlighting its effectiveness in the specific context of smoking gesture recognition. The baseline model's accuracy of 68.71% already provided a starting point, but the confounding gestures model's leap to 97.52% demonstrates a significant refinement in the model's ability to classify gestures correctly. However, the limitations of relying solely on accuracy as a performance metric become apparent, particularly in scenarios where the cost of false positives and false negatives can have profound implications. In smoking gesture recognition, false positives (incorrectly identifying non-smoking gestures as smoking) can trigger unnecessary interventions. In contrast, false negatives (failing to detect actual smoking gestures) can result in missed opportunities for timely action. To address this, we used confusion matrices (Figure 6), showing a marked reduction in false positive and false negative rates. Notably, the false positive rate dropped dramatically from 0.53 in the baseline model to 0.01 in the confounding gestures model. This significant reduction is critical, as it enhances the system's reliability by minimizing incorrect alarms, thereby reducing the risk of alert fatigue and maintaining user trust in the application's performance.

Similarly, the reduction in the false negative ratio from 0.07 to 0.03 indicates that the confounding gestures model is also more adept at correctly identifying smoking gestures. This enhancement is significant because it ensures that smoking gestures are less likely to go unnoticed, thereby improving the overall effectiveness of the system in its primary objective—identifying and potentially mitigating smoking behavior. We also considered the F1 Score, which combines false positives and negatives into a single metric to provide a more comprehensive assessment. The improvement in the F1 Score from 67.06 in the baseline model to 97.52 in the confounding gestures model further solidifies the latter's superiority. The F1 Score is particularly valuable because it provides a balanced measure for precision (the ability to avoid false positives) and recall (the ability to capture true positives). The substantial increase in this score reflects the reduction in false positives and negatives and the model's enhanced capacity to perform reliably across different scenarios.

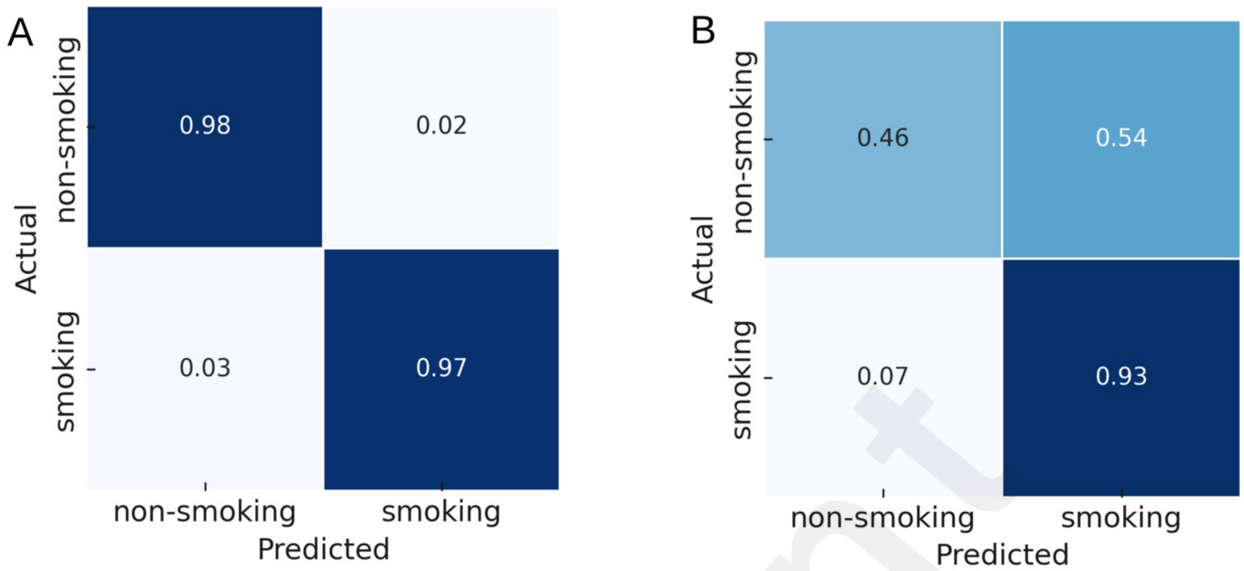

Figure 6. Confusion matrices for models (A) trained with and (B) without confounding gestures

Lastly, we also employed Receiver Operating Characteristic (ROC) curve analysis to visualize the trade-off between True Positive Rate (sensitivity) and False Positive Rate (Figure 7). This approach adds another layer of insight into the model's performance. The ROC curve allows a nuanced understanding of the trade-off between the actual positive rate (sensitivity) and the false positive rate. By analyzing the curve, we can identify an optimal classification threshold that balances correctly identifying smoking gestures and minimizing false alarms. This is especially important in real-world applications where the consequences of misclassification are non-trivial. The Area Under the Curve (AUC) derived from the ROC analysis is a robust summary of the model's discriminative power. A higher AUC value signifies the model can distinguish between smoking and non-smoking gestures across various threshold settings. This is particularly pertinent in applications where careful management of false positive and negative costs is crucial, as a higher AUC indicates that the model will perform well even as conditions or thresholds change. The confounding gestures model achieves an impressive AUC of 0.99 for both smoking and non-smoking categories, significantly outperforming the baseline model, which had AUC values of 0.66 and 0.67 for the smoking and non-smoking categories, respectively.

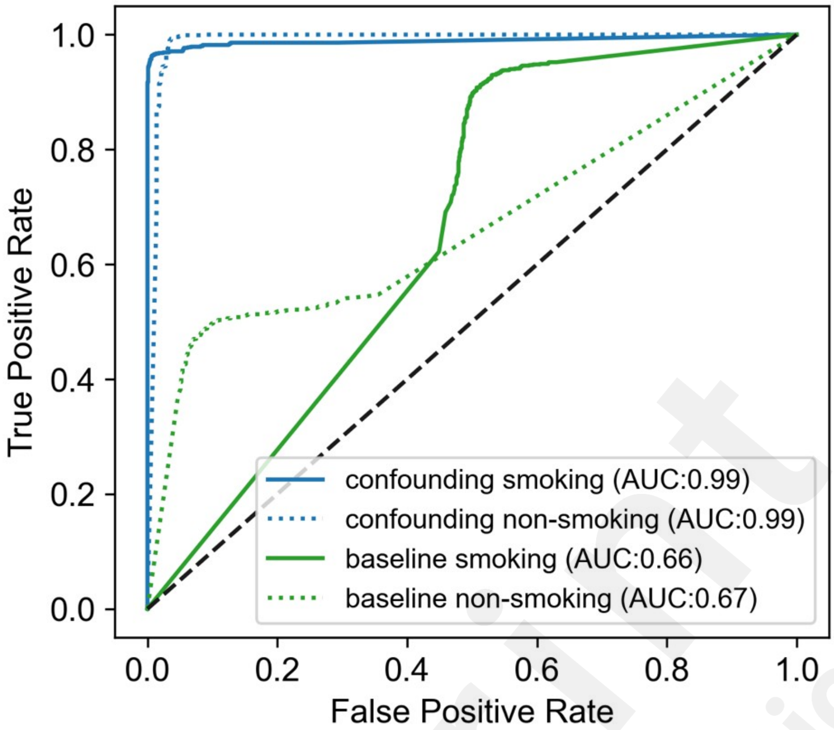

Figure 7. ROC Curves for Smoking Detection Model. The green lines correspond to the baseline model, while the blue lines correspond to the model trained on confounding gestures.

Contribution of Confounding Gestures

To better understand the confounding factors affecting gesture recognition accuracy in our model, we expanded the output layer from 2 to 16 classes. This allows us to visualize the model's predictions in a confusion matrix (Figure 8). The matrix reveals several key insights. The actual smoking gesture was correctly predicted as smoking 21% of the time. However, the model also frequently misclassified smoking as other gestures, a type of error known as a False Positive. Notably, eating with and without a fork, drinking with a straw, and yawning were incorrectly predicted as smoking 14% of the time. These gestures share similarities with smoking, such as hand-to-mouth movements, which explains the model's confusion.
On the other hand, false positives occur when the model incorrectly predicts other gestures, such as smoking. The confusion matrix reveals that applying chapstick and waving were misclassified as smoking 30% and 29% of the time, respectively. These errors underscore the model's difficulty distinguishing gestures with motion patterns like smoking.

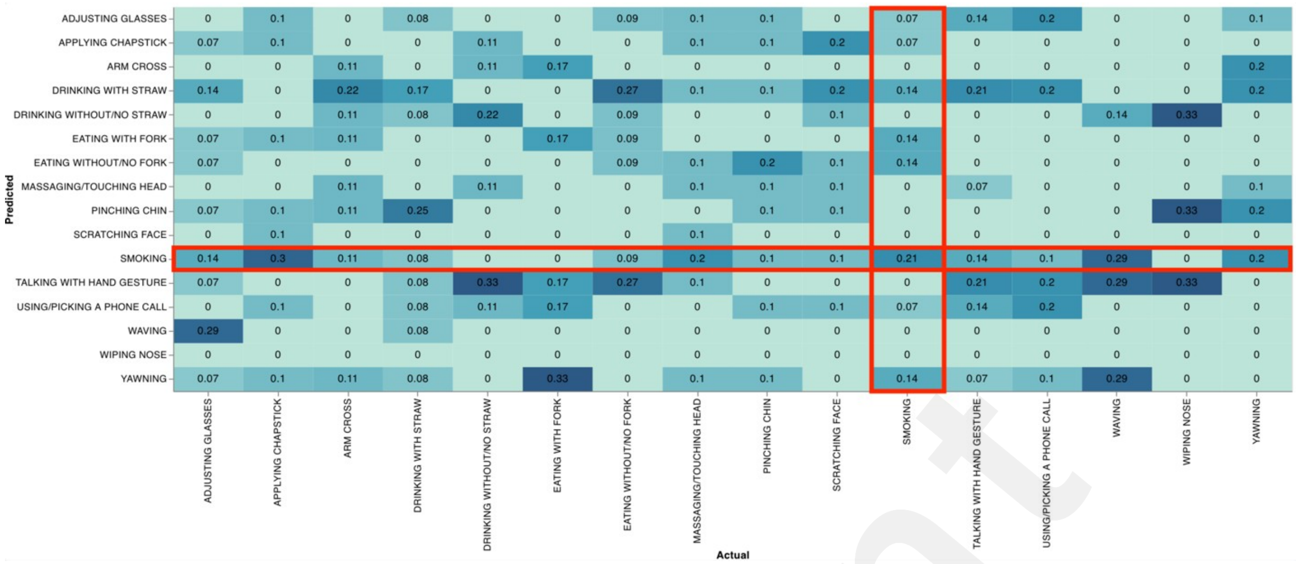

Figure 8. Confusion Matrix for 16-class classification: Red highlights indicate false negatives and false positives for the target class “Smoking.”

This pattern of errors indicates that the model's learning process aligns with human intuition regarding gestures that resemble smoking visually or contextually. For instance, the misclassification of yawning and drinking with a straw likely stems from the model’s difficulty distinguishing between subtle hand movements near the face daily across these gestures. The raw sensor data of these confounding gestures have been visualized (Figure 9) for better understanding. While the model effectively identifies smoking when all confounding gestures are combined, the confusion matrix highlights which specific gestures the model struggles to differentiate from smoking when each gesture is classified individually.

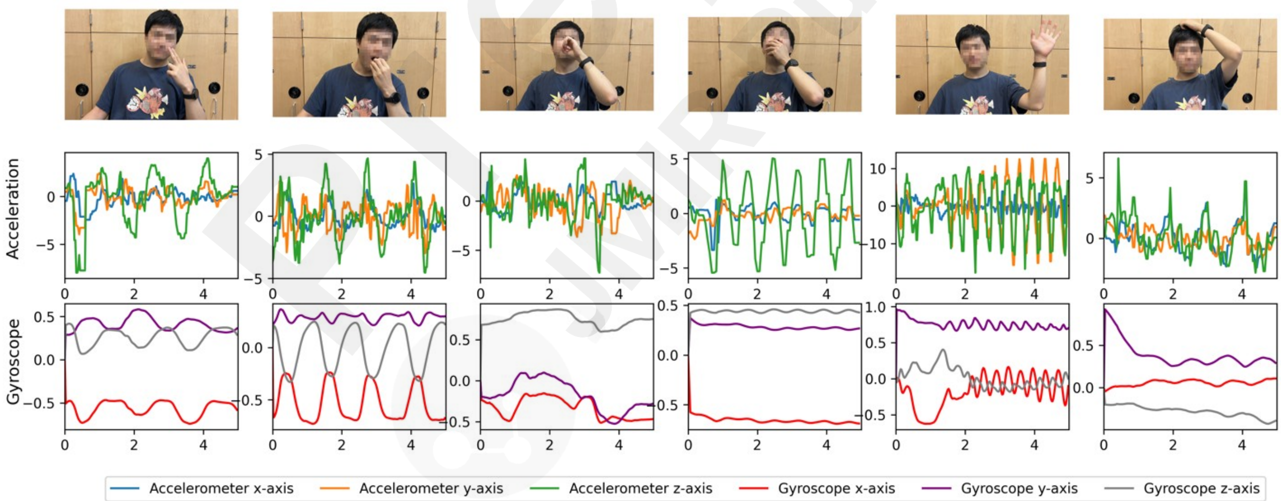

Figure 9. Visualization of raw accelerometer and gyroscope data of various confounding gestures (Smoking, Eating, Drinking, Yawning, Waving, and Scratching Head)

Evaluation Results of the Sense2Quit Applications

The user experience (UX) survey results confirmed minimal difference in usage between the Sense2Quit applications developed for iOS and Android, highlighting the application's cross-platform functionality without negatively affecting usability (Table 3). Participants provided similar ratings across both platforms, with iOS scoring an average of 4.75 and Android scoring 4.7 for application performance. Both platforms received high scores for responsiveness, with iOS rated 4.7

and Android rated 4.8. Feature parity, however, showed a slightly lower average, with iOS scoring 4.1 and Android scoring 4.3. This difference is attributed to two factors: on iOS, the smoking detection feature must be manually activated by pressing the smartwatch, a restriction that stems from Apple's watch OS, while on Android, it starts automatically. Additionally, users reported a noticeable lag in the game feature due to a bug in the Flutter package, which will be addressed in future updates. Despite these minor discrepancies, the overall user interface was rated similarly on both platforms, with iOS scoring 4.7 and Android 4.5, reinforcing the app's consistent cross-platform experience.

The smartwatch power consumption results demonstrated that the Sense2Quit application consumed an average of 356.49 mW when active, compared to baseline averages of 121.75 mW before and 150.42 mW after the active phase. A graph (Figure 10) illustrating power consumption over time, with overlaid average power lines for baseline (green) and active (orange) phases, visualizes these results. This evaluation is crucial given that our application operates continuously in the background, potentially affecting the device's overall power consumption and battery life. The slight increase in baseline power consumption after the active phase (from 121.75 mW to 150.42 mW) may indicate residual effects on the device's power management.

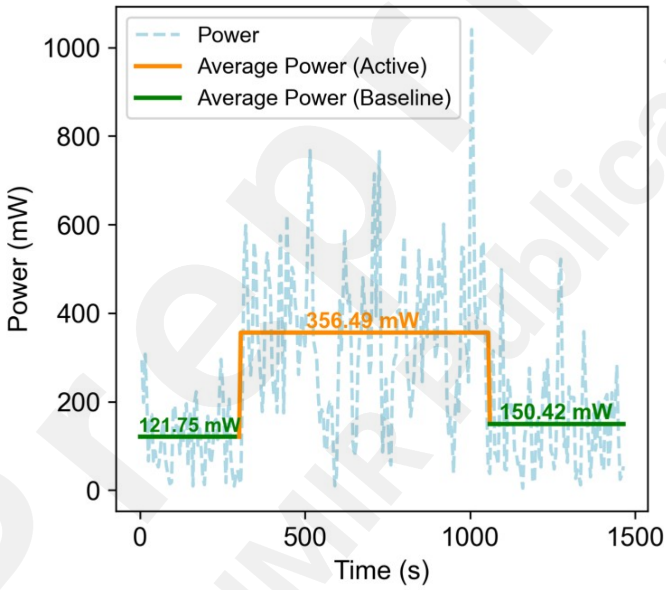

Figure 10. Smartwatch power consumption during Active and Baseline states

Table 3. Average Likert scores of the participants to assess the performance, feature parity, and user interface of the Sense2Quit smartphone applications

Evaluation Type	iOS Score	Android Score
Application Performance	4.75	4.7
o How would you rate the app launch time on the device you tested?	4.8	4.6
o How responsive is the app to your inputs on the device you tested?	4.7	4.8

Feature Parity	4.1	4.3
o How well do the following features work on the device you tested: Games, adding reminders, watching tips videos, performing smoking gesture?	4.1	4.3
User Interface	4.7	4.5
o How would you rate the overall user experience of each device	4.7	4.5

Discussion

The Sense2Quit study represents a significant advancement in smoking cessation technology by innovating in two key areas: real-time smoking gesture recognition and cross-platform app development. First, it demonstrates highly accurate smoking detection, effectively distinguishing smoking gestures from similar hand movements with a lower false positive rate, achieving an impressive F1 score of 97.52%. Second, the study introduces a robust, cross-platform app that ensures continuous and reliable connectivity between the smartphone and smartwatch, enabling seamless real-time monitoring. Sense2Quit provides just-in-time interventions tailored to the specific needs of high-risk populations, such as people with HIV (PWH) who smoke. The system's precise detection of smoking gestures underscores its robustness and reliability, making it an invaluable tool for smoking cessation efforts. A key strength of this study is its ability to address the long-standing challenge of confounding gestures—movements such as drinking, eating, or other hand-to-mouth actions that closely mimic smoking. These gestures have traditionally led to high false positive rates in smoking detection models. This study overcomes that issue by systematically collecting data on these similar movements from 30 participants and integrating it into the training of the Convolutional Neural Network (CNN) model. As a result, the model’s ability to differentiate between smoking and non-smoking gestures is significantly improved, greatly reducing the false positive rate from 0.53 to 0.01 and boosting overall detection accuracy with an AUC value of 0.99. Notably, this high level of precision is achieved without adding unnecessary complexity, ensuring the model remains efficient and capable of running smoothly on mobile devices. Sense2Quit was developed using the Flutter framework, enabling seamless integration across Android and iOS platforms. This cross-platform compatibility significantly expands the app’s accessibility, allowing a broader user base to benefit from its real-time smoking gesture detection and intervention features, regardless of device preference. The user experience of both applications was evaluated in three main categories: Application Performance, Feature Parity, and User Interface. This evaluation was based on the feedback from 8 participants. The average score for iOS was 4.52, and for Android, it was 4.5. The score difference was only 0.02 on a 5-point Likert scale, indicating a similar overall user experience on both platforms. The smartphone application incorporates engaging interactive elements, including tips, reminders, and games like Pacman and Tetris. These help users manage cravings while keeping them actively involved with the app over extended periods. This focus on engagement through gamification enhances user retention and supports long-term smoking cessation efforts. The app fosters continuous interaction by combining real-time tracking with behavioral interventions and gamification, which is critical for sustaining smoking cessation progress. Regular reminders serve as behavioral prompts, reinforcing users' focus on their quitting goals and increasing the app’s effectiveness as a daily tool in their cessation journey. The online dashboard developed for research staff provides real-time user engagement and behavior insights. This feature allows healthcare providers to monitor participant adherence, address potential drop-offs in engagement, and ensure adherence to the study protocol, ultimately improving the overall success rate of the smoking cessation program. This study also examined the power usage of a smartwatch running the Sense2Quit app and looked at how other movements could affect the accuracy of detecting smoking. These findings are essential for understanding how the app affects the smartwatch's battery life and ensuring it remains usable for a long time. The analysis of other movements also showed that the model's learning closely matches human intuition when distinguishing visually or contextually similar gestures, like smoking.

While the Sense2Quit system shows great promise, areas for improvement and limitations still need to be addressed. Real-world testing is essential to validate the system's enhanced performance in everyday situations, as the current results have been primarily obtained from controlled environments. However, insights gained from the pilot study and the promising results of integrating confounding gestures suggest that the system will likely perform better in real-world settings. The fixed cooldown period, during which no further smoking alerts are triggered after initial detection, along with the fixed sampling rate for collecting sensor data from the smartwatch, could be dynamic to enhance detection accuracy and improve battery life. By adjusting these parameters based on real-time conditions, the system could optimize performance, reducing unnecessary power consumption while maintaining high levels of accuracy. Although the model’s ability to handle confounding gestures has significantly improved smoking detection by reducing false positives, a limitation remains in its ability to differentiate between specific non-smoking gestures, such as eating or drinking. While distinguishing individual gestures is beyond the current scope of this study, future versions of the system could address this challenge to enhance its accuracy further. Addressing these limitations will be crucial for refining the system’s practical application and ensuring its success in real-world use.

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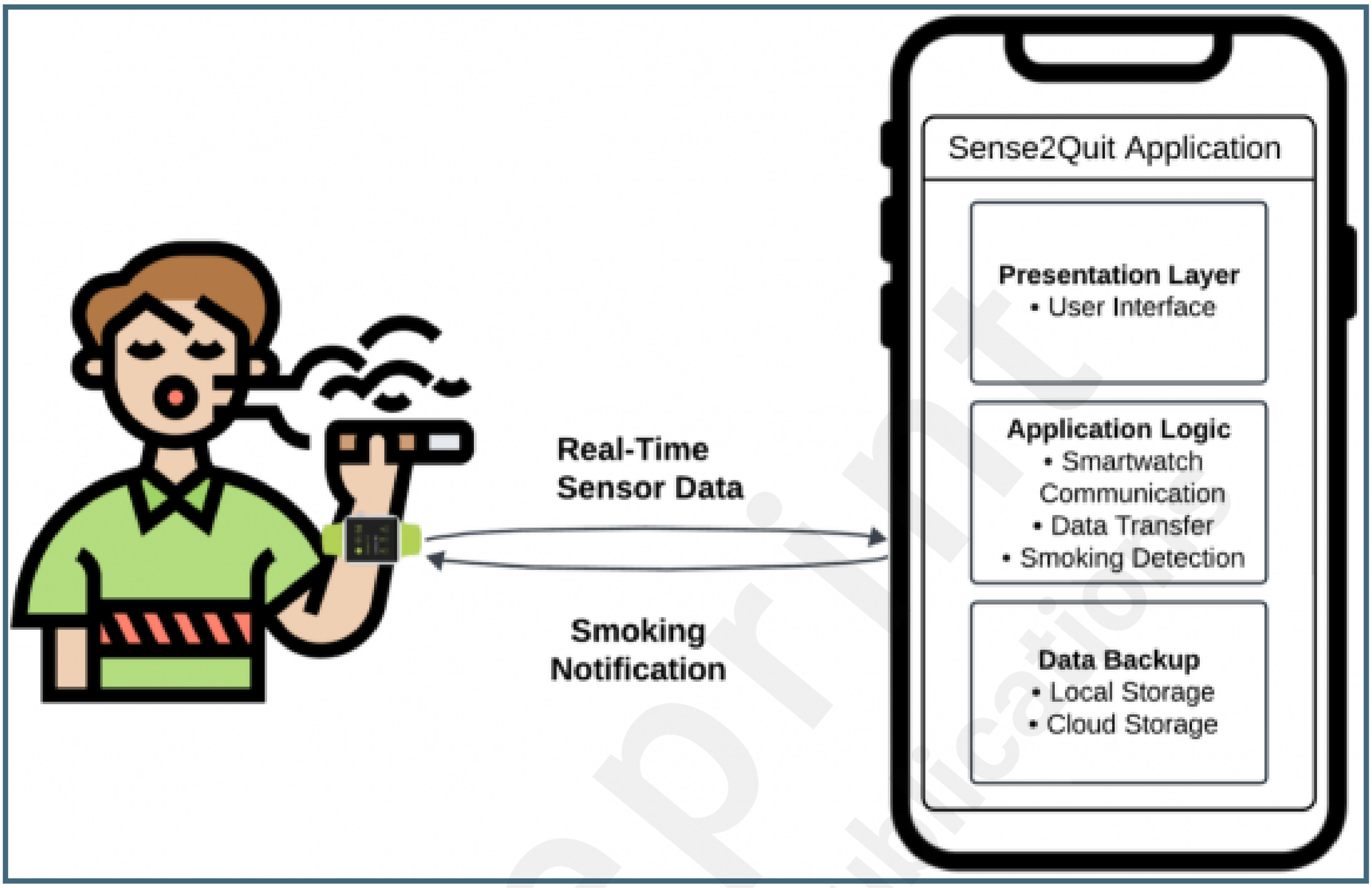
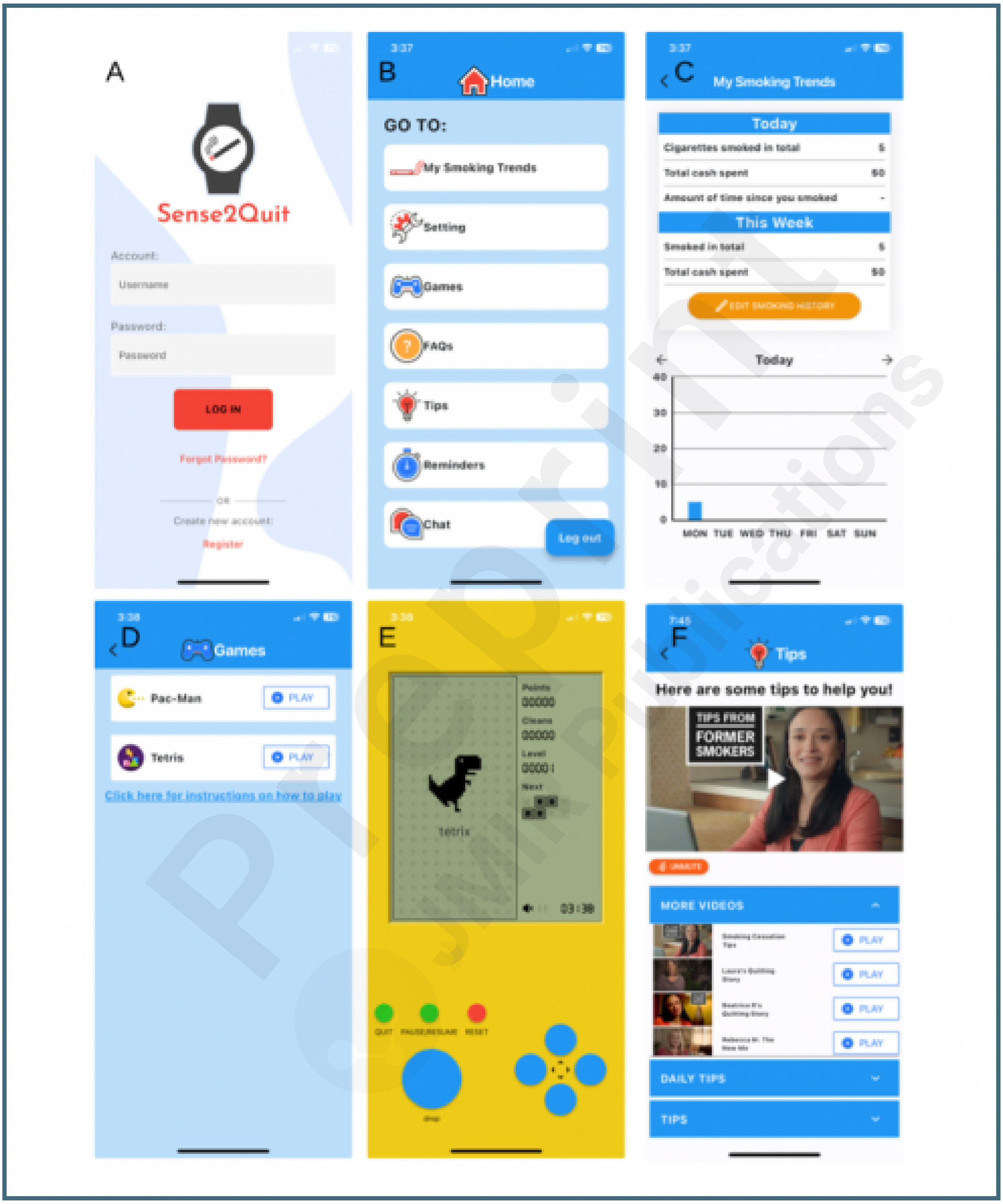
Supplementary Files

Figures

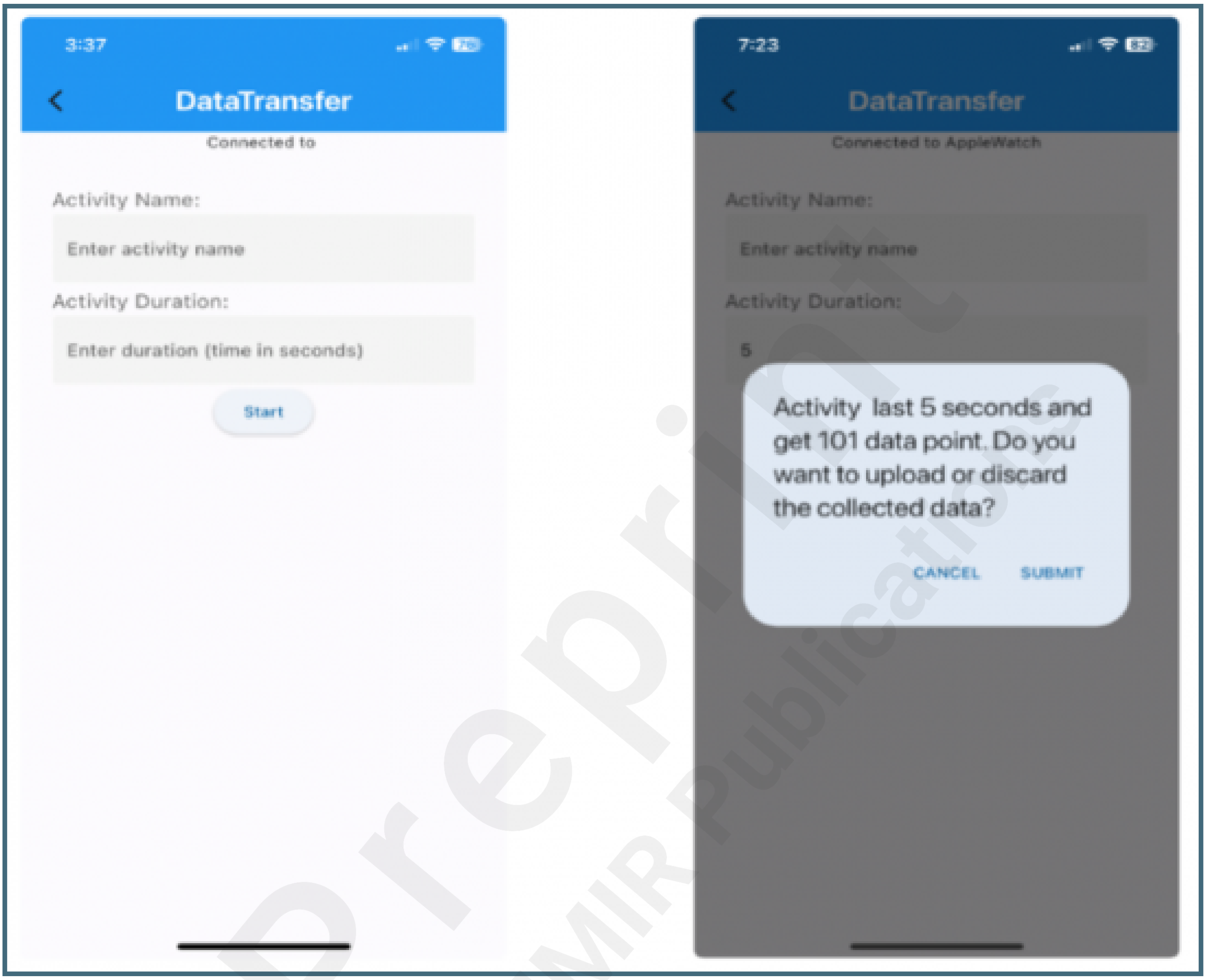
Overview of the Sense2Quit Smartphone and Smartwatch System Architecture.



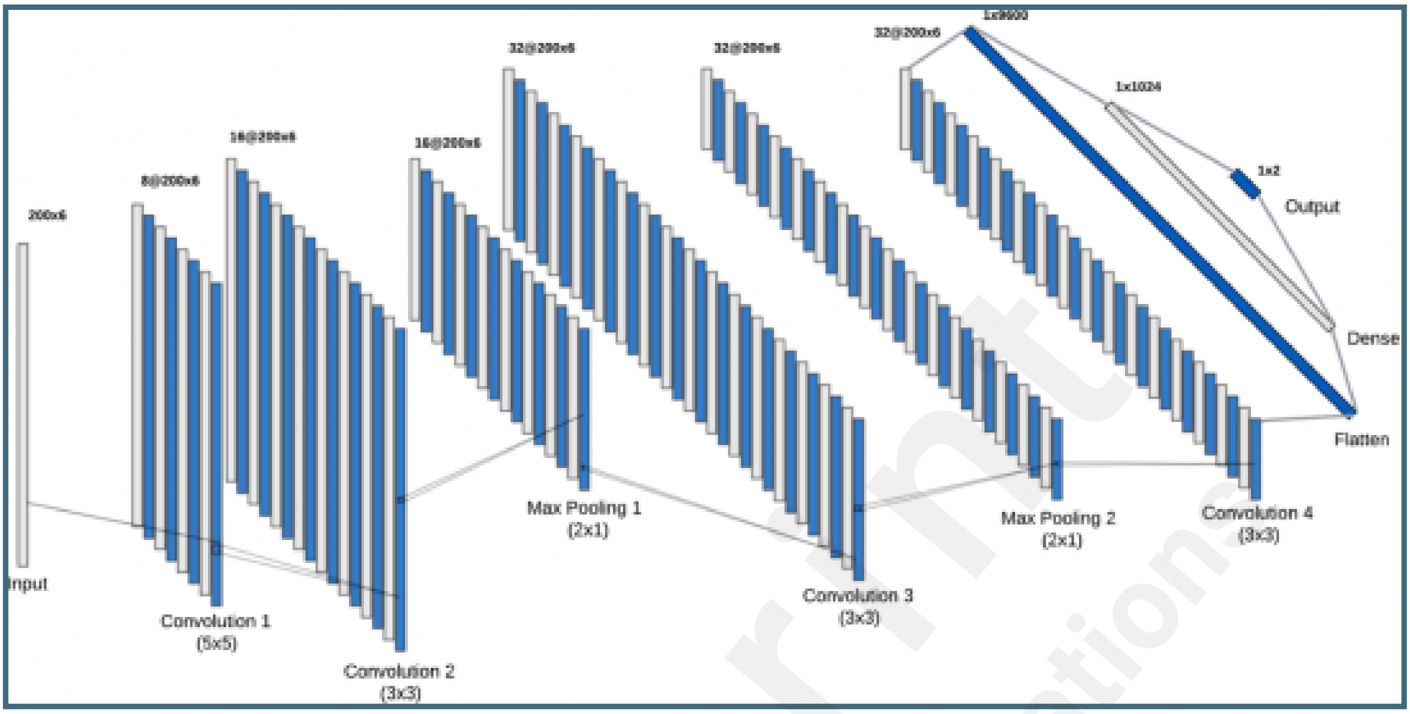
User interface screenshots of the Sense2Quit smartphone app showcasing the (A) Login, (B) Home, (C) Smoking Trends, (D) List of Games, (E) Tetris Game, and (F) Tips screens.



User Interface for the data collection screen demonstrating the states before data collection on the left and after data collection is completed on the right.



Smoking detection model architecture illustrating the underlying layers.

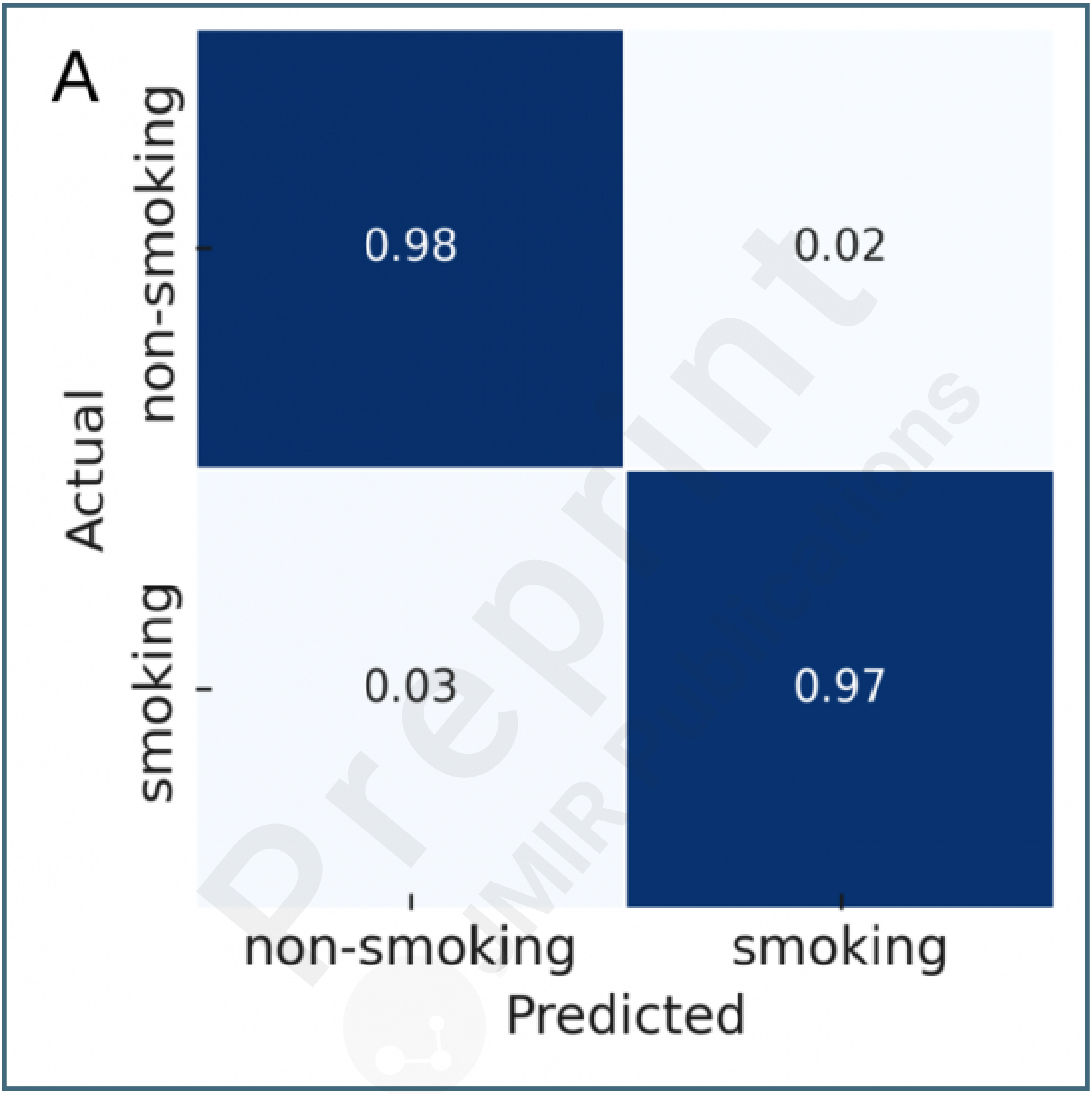


Sense2Quit dashboard for research staff that provided usage information to participants enrolled in the study.

Sense2Quit Dashboard

Username	Total Time	Last Recording Start Time	Last Used
sq82	87h 44m	09/28/2023	09/28/2023 17:10
SQ80	92h 11m	09/26/2023	09/26/2023 08:05
sq91	683h 26m	12/05/2023	12/05/2023 12:15
sq102	8h 52m	10/16/2023	10/16/2023 10:04
sq103	503h 33m	12/31/2023	12/31/2023 12:05
sq94	614h 25m	11/16/2023	11/16/2023 11:30
sq96	3h 38m	10/17/2023	10/17/2023 14:23
SQ105	329h 10m	01/01/2024	01/01/2024 16:15
Sense2Quit106	401h 55m	11/21/2023	11/21/2023 09:20
sq95	281h 18m	12/06/2023	12/06/2023 18:00
SQ101	227h 16m	12/13/2023	12/13/2023 12:02
S2Q100	19h 52m	11/13/2023	11/13/2023 12:05

Confusion matrices for models (A) trained with and (B) without confounding gestures.



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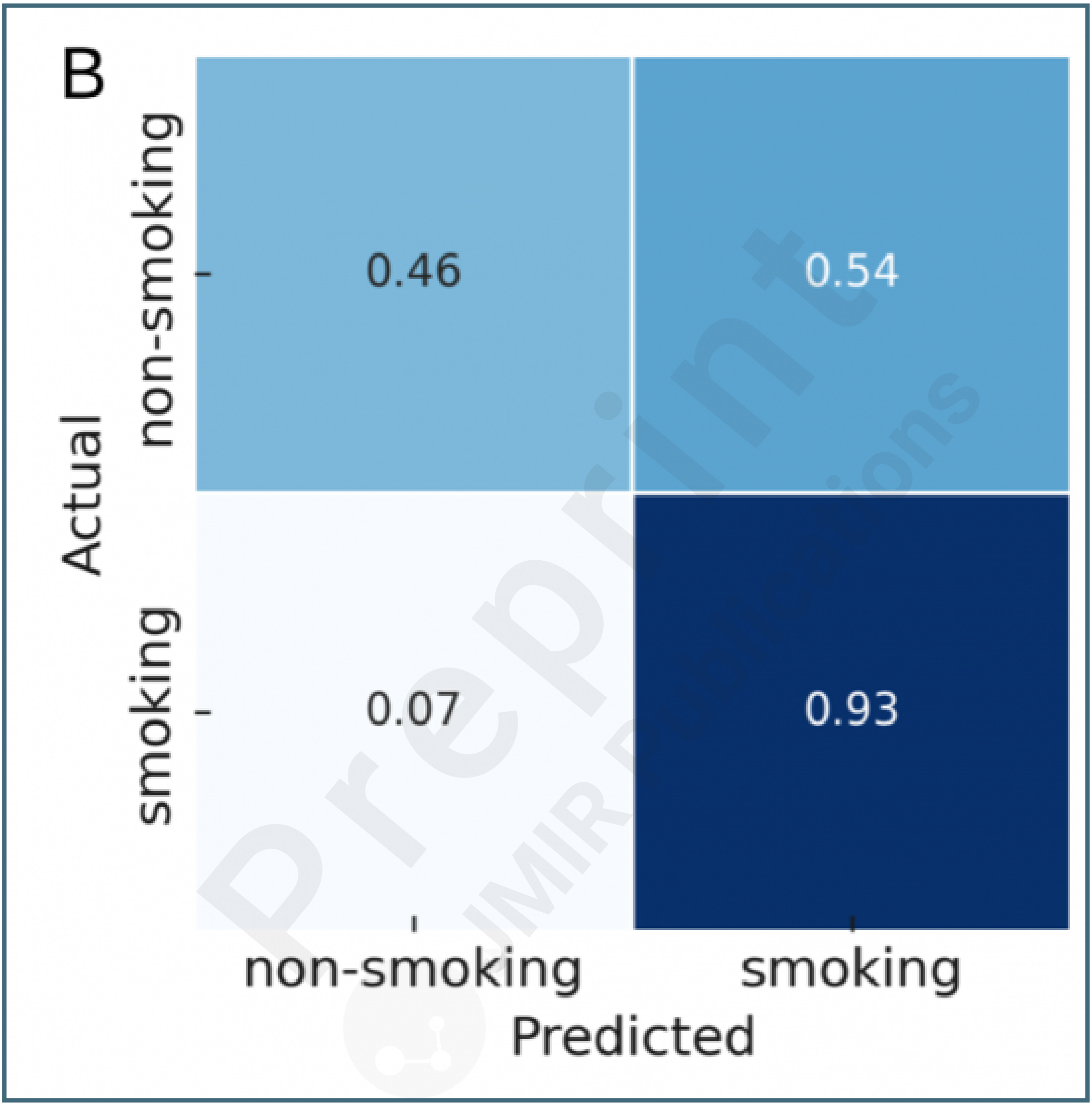
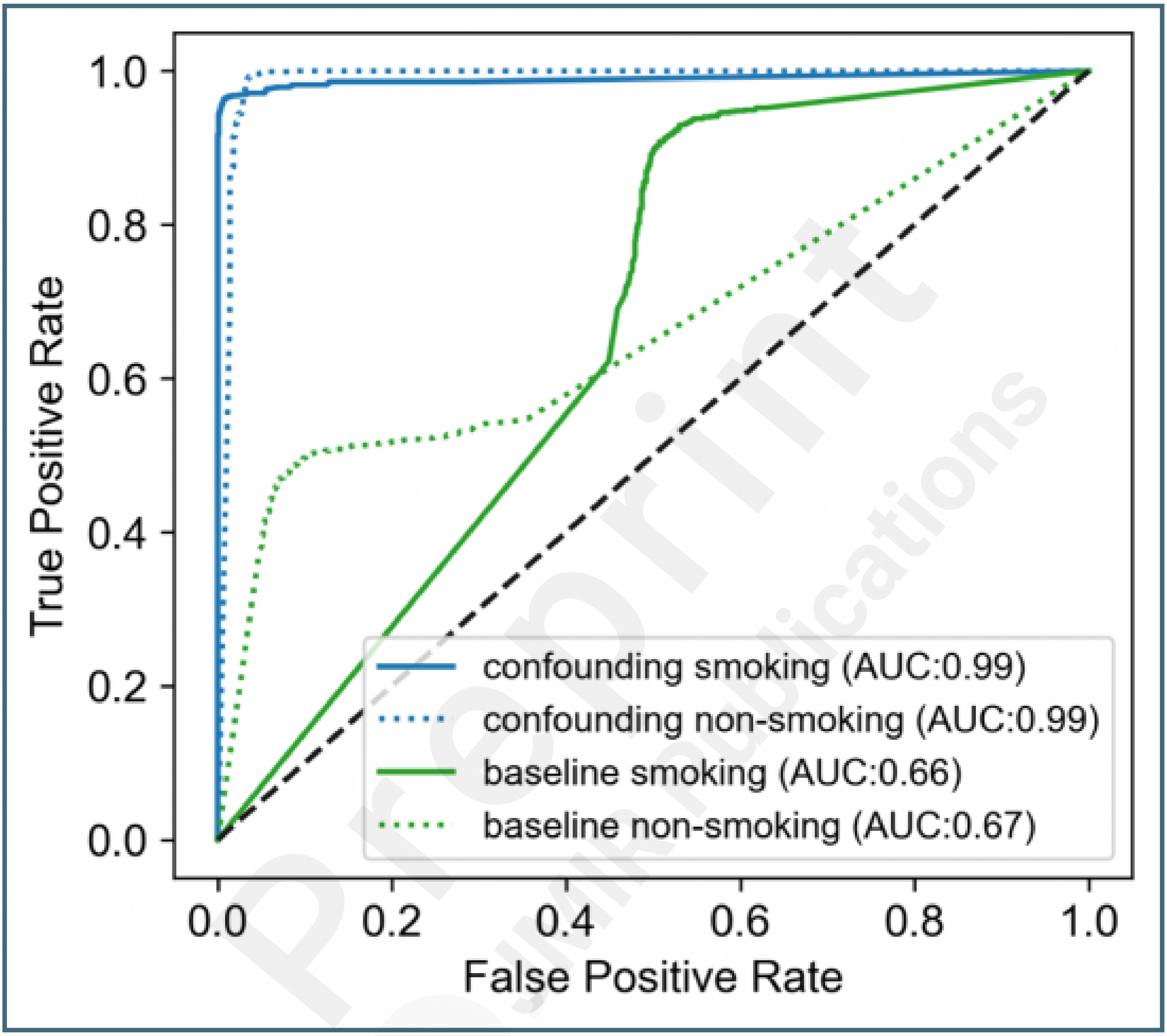
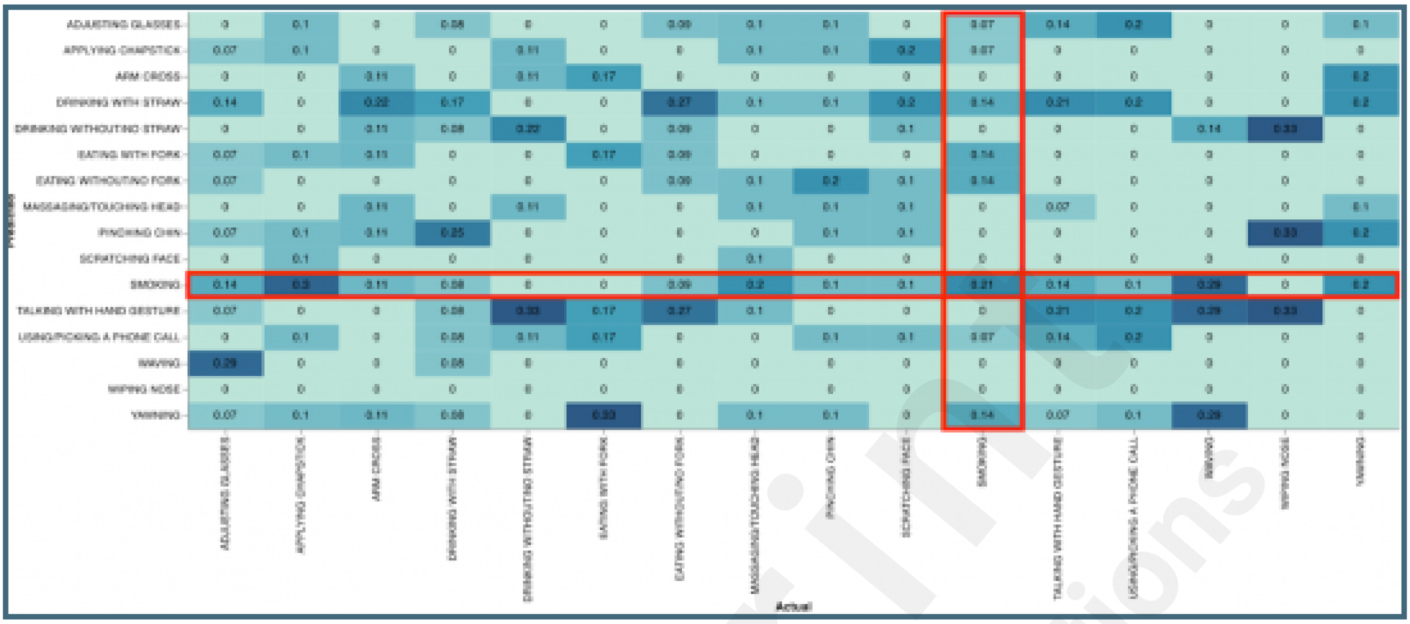


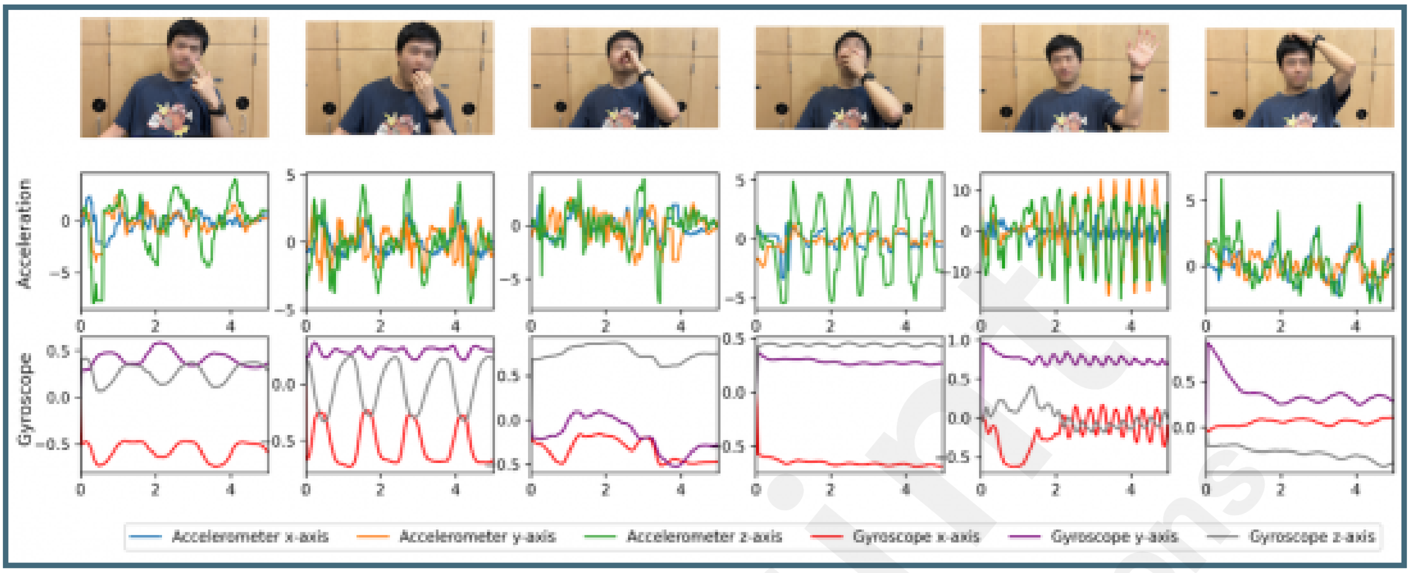
ROC Curves for Smoking Detection Model. The green lines correspond to the baseline model, while the blue lines correspond to the model trained on confounding gestures.



Confusion Matrix for 16-class classification: Red highlights indicate false negatives and false positives for the target class "Smoking".



Visualization of raw accelerometer and gyroscope data of various confounding gestures (Smoking, Eating, Drinking, Yawning, Waving, and Scratching Head).



Smartwatch power consumption during Active and Baseline states.