SCC Health: A Framework for Online Estimation of Disease Severity for the Smart and Connected Community*

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***Abstract*—Development of a smart and connected community (SCC) health framework is an indispensable part in the development of smart cities. Smartphones with increased processing capability, integrated sensors, storage capacity, and cloud connectivity have a key role to play in developing this SCC Health framework. In this paper, we report a novel smartphone-based framework for continuous monitoring of arrhythmia, obstructive sleep apnea (OSA), chronic obstructive pulmonary disease (COPD), and flu. In addition to personalized monitoring, community-wide temporal and spatial monitoring are also possible in this approach. A custom smartphone app is developed that has the ability for collection of body sensor data via Bluetooth, loading machine learning algorithms dynamically from the webserver, computing disease severity in real-time, sharing of anonymous data, and visualization of community health status via the webserver. The framework has been tested for online monitoring of OSA, COPD, and flu severity. An accuracy of ±1°F has been achieved for flu measurement and a mean absolute error (MAE) of 8.27 AHI has been achieved for OSA severity estimation using heart rate variability and SpO_2. The app has a power consumption of 218 mW when active, uses a memory of 7 MB, and requires a total storage space of 9.36 MB. This framework aims to improve community health, reduce waste in healthcare spending, and facilitate early treatment in case of disease exacerbation.**

Keywords—Connected health, Mobile Health, Smartphone app., Smart and connected community, Wireless body sensors.

I. Introduction

Smart cities around the world are entering a new era of transformation towards Smart and Connected Communities (SCC) where residents and their surrounding environments are increasingly connected through intelligent technologies. Smartphones can play a key role in this framework with Mobile Health (mHealth) technology that has already enabled a revolution in computerized health interventions, and will not only reduce cost of healthcare, but also improve community health. For instance, cardiovascular disease (CVD) is projected to cost over $1 Trillion by 2035 and almost 50% of US population will develop pre-existing CVD conditions [1]. Other chronic diseases such as obstructive sleep apnea (OSA), chronic obstructive pulmonary disease (COPD), and flu require continuous monitoring. Hence, there is a need for the development of a Smart and Connected Community Health (SCC Health) framework that can be used reliably for monitoring the patients with chronic diseases at home environment improving individual and collective health, while avoiding frequent hospital visits thereby reducing healthcare cost significantly.

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Past research activities primarily focused on a particular disease with wearables for mHealth. For instance, Oresko *et al.* investigated a wearable smartphone-based platform for cardiac arrhythmia detection using the electrocardiogram (ECG) signals [2]. Alhussein proposed a Parkinson's disease monitoring framework for use in smart cities [3]. Constantinescu *et al.* proposed a framework for a distributed mHealth Systems [4]. While many other researchers have proposed mHealth based frameworks, most of them are limited to disease classification, require multiple sensors, and did not address the online spatial-temporal severity estimation and visualization of the diseases throughout the community.

Our focus is the development of severity metrics that well correspond with standard severity metrics and can be estimated in real-time using minimal number of easy-to-use sensors. For example, the standard metric for severity assessment of OSA is Apnea-hypopnea index (AHI). An AHI ≤ 30 indicates mild-moderate OSA and AHI > 30 indicates a severe OSA [5]. The standard procedure for estimation of AHI is to conduct a polysomnogram test. Polysomnogram is a complex test requiring data collection using many sensors such as ECG, EEG, EMG, respiration, airflow, SpO_2, audio, and motion. Usually, polysomnogram is done at a sleep laboratory, and though there are options for home based polysomnogram, it requires the assistance and involvement of a certified sleep technician to perform the test properly and assess the results. In our study, we have addressed the online estimation of OSA severity using heart rate variability and SpO_2 collected using a wrist band and utilized machine learning technique for automated disease severity computation. For flu severity estimation, we captured body temperature using an inkjet printed (IJP) fully passive disposable sensor. The architecture utilizes on a lightweight smartphone app and performs edge-computing on the smartphone platform for data processing, feature extraction and severity estimation with machine learning methods. There is provision for data sharing from the user community to a central webserver, that allows monitoring the progression of a disease over time and visualize the spatial distribution of a disease within a geographical area.

II. Materials and Method

A. Data Set

For OSA we have used the Sleep Health Heart Study (SHHS) dataset available from National Sleep Research Resource [6]. SHHS was implemented as a multi-center cohort

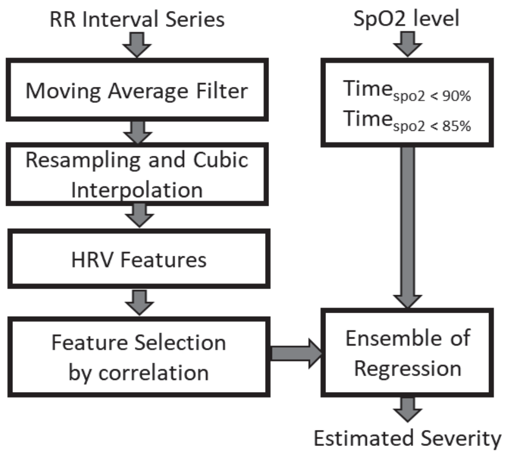

Fig 1. Method for Estimation of Sleep Apnea Severity

study in two phases by the National Heart Lung & Blood Institute. In both the phases, Polysomnograms were obtained in the homes of the participants, by trained and certified technicians. The polysomnogram data was saved in European Data Format (EDF). Two manual scoring was included to annotate the database with AHI, respiratory disturbance index, sleep stages, event start and end time identification, etc. In our study, we have considered 298 subjects who showed an exacerbation (progression to higher severity stages) in their diseases. Two records were obtained from each of these subjects, thus making the total number of records to 596. The AHI for the studied subjects ranges from 0-117.

For flu estimation, data have been collected from controlled heat pads at laboratory set up. A total of 69 data samples ranging from 70ºF to 108ºF have been collected in total. A precision fiber optic thermometer (Optocon FOTEMP with TS2 optical fiber probe, Weidmann Technologies, Germany) was used for establishing the ground truth.

B. Algorithms for Severity Estimation

For sleep apnea severity estimation, data from heart rate and SpO_2 sensor have been used. The inter-beat-interval (viz. RR interval) data series was filtered using a 3rd order moving average filter to smooth out the ripples and to remove the high frequency noises. Then the signal was resampled at 4 Hz and interpolated using cubic interpolation. Time domain and frequency domain heart rate variability (HRV) features as described in Table. I was extracted from the entire signal as recommended in HRV guideline [7]. For short term HRV features 5 min window has been used. Pearson correlation of HRV features with apnea-hypopnea index (AHI) has been done to find the features showing a significant correlation with AHI. Two more features based on the SpO_2 level - the percent of sleep duration with less than 90% SpO_2 and with less than 85% SpO_2, were added with significant HRV features. Then an ensemble of regression method (boosted, leaf size=8, number of learners=30, learning rate=0.1) has been used to estimate the severity (AHI) of sleep apnea. The method for OSA severity estimation has been shown in Fig. 1. For evaluating the model performance 5-fold cross validation has been used.

TABLE I. TIME DOMAIN AND FREQUENCY DOMAIN MEASURES OF HEART RATE VARIABILITY USED IN THIS STUDY

Feature	Description
AVNN	Mean of NN-interval
SDNN	Standard deviation of all NN intervals.
SDANN	Standard deviation of the averages of NN intervals in all 5 min segments of the entire recording.
RMSSD	Defined as the square root of the mean of the squares of differences between adjacent NN intervals.
SDNN index	Mean of the standard deviation of all NN intervals for all 5 min segments of the entire recording.
SDSD	Defined as the standard deviation of the differences between adjacent R-R intervals.
pNNx	NNx count divided by the total no. of all NN intervals where NNx is the number of pairs of adjacent NN intervals differing by more than x ms.
VLF	Power in very low frequency range (≤ 0.04 Hz)
LF	Power in low frequency range (0.04 – 0.15 Hz)
HF	Power in high frequency range (0.15 -0.4 Hz)
LF/HF	Ratio of LF power to HF power

WEKA has been used as the model development environment [8]. Trained, evaluated and hyperparameter tuned model from WEKA has been exported for use in Android. In android the trained model was stored in the asset directory and was loaded in the activity for online estimation of the severity of sleep apnea for a subject based on the real-time collected sensor data and on-device extracted features.

For monitoring the flu severity body temperature has been estimated using a fully passive IJP temperature sensor. In addition, user reported flu symptoms has been collected using the app. A data check is performed online using the statistical measures-mean, standard deviation and range to rule out unreliable data being used. A random forest regression method has been used for the estimation of body temperature [9]. For flu severity a linear scale from 0-100 has been used based on estimated body temperature and flu symptoms [10]. The list of symptoms used is as follows:

i) Sore throat
ii) Nasal congestion
iii) Sneezing
iv) Muscle aches and pains
v) Cough
vi) Headache
vii) Chillness and fever

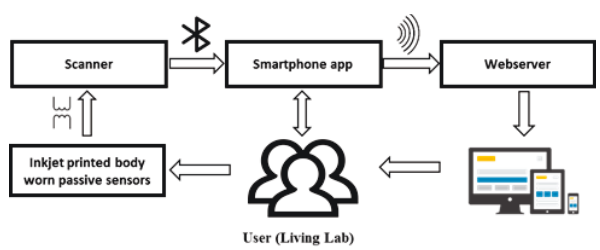

Fig 2. System Architecture of the SCC Health framework

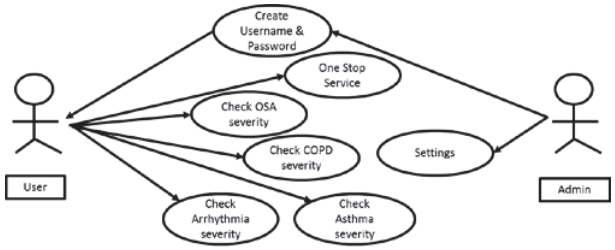

Fig 3: Use case diagram for SCC Health app

C. *SCC Health Framework and Smartphone App*

The system architecture of the SCC Health framework has been shown in Fig. 2. Details of our IJP sensors and scanner have been reported elsewhere [11]. Processed information from the smartphone can be shared with a web server using Wi-Fi/ cellular network for observing temporal and spatial distribution of the diseases. The webserver is accessible via the smartphone app.

As shown in Fig. 3, there are two main actors in the use case diagram of the app: one is the user and the other is the admin. The admin sets up account for the user, create username and password for the user and handle all settings related issues. The user uses the app to detect the severity of his/her diseases i.e. OSA, COPD, arrhythmia and flu. User may also use "one stop service" setting to detect the severities of all the diseases at once. The other use cases are sharing data with the SCC and visiting the SCC Health webserver. Based on the use cases the functional requirements for the app are: data collection, data processing, data storage, severity computation, and data sharing. In addition, non-functional requirements such as data privacy, security, performance optimization have been considered.

The application was developed according to the standard lifecycle of system development in the order of analysis-design-implementation-evaluation. Android Studio 2.3.1 has been used as the integrated development environment (IDE). The build tool version is 25.0.2 and minSdkVersion is 21. The application functionality was tested on various smartphones including Samsung Avant, Samsung Galaxy S6, and Samsung-SM-G900A. Fig. 4 shows the flowchart of the app. The user needs to get a personalized username and password provided by the admin to log in. Before assigning username and password, admin records user information including ID and address by creating a profile for the user. The same app can be used to create profiles for multiple users and all user profiles are saved in an SQLite database.

When the user login with correct username and password, the app greets the user, and the user may proceed to the main menu where she may choose any of the three buttons: About, Webserver, or Diagnostic. About activity describes the details of the project. Using Webserver activity, user may visit the SCC Health website. Diagnostics activity lead her to the disease severity detection process where she may choose any one of the four diseases or she may choose "one stop service" to test all the diseases at once.

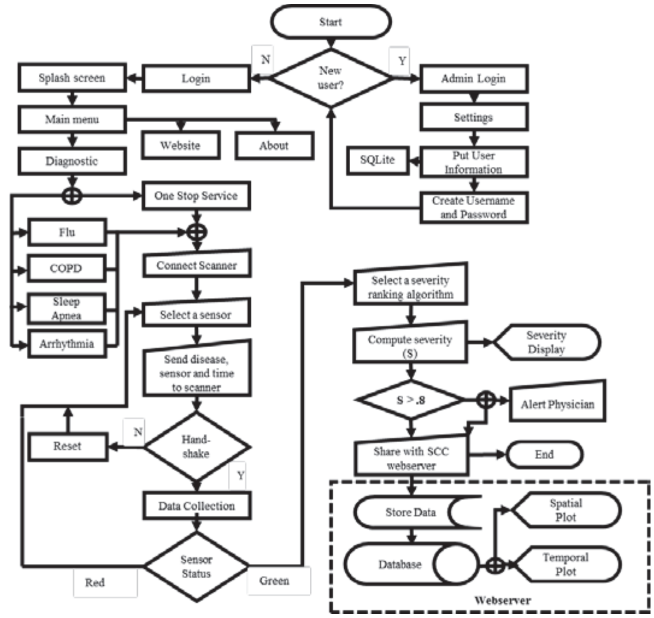

Fig. 4: Flowchart for SCC Health android application

The sequence diagram for the "one stop service" is shown in Fig. 5. The user first needs to connect to the scanner via Bluetooth. For that, the user needs to click "Connect scanner", then a list of available Bluetooth devices will pop up. The user selects the scanner from the list. There is a status bar above connect scanner button, which indicates whether the app is connected to a scanner or not. After connection has been established, a list of five sensors will appear from which the user needs to select one sensor that he/she will be collecting data from and click "Collect data" button to start collecting data from the sensor via the connected scanner. Before the data collection, handshaking protocol between the app and the scanner will be executed where information about type of disease, type of sensor, and duration of scan will be confirmed. If the handshaking is successful, the scanner power up the WRAP sensor and starts collecting sensor data.

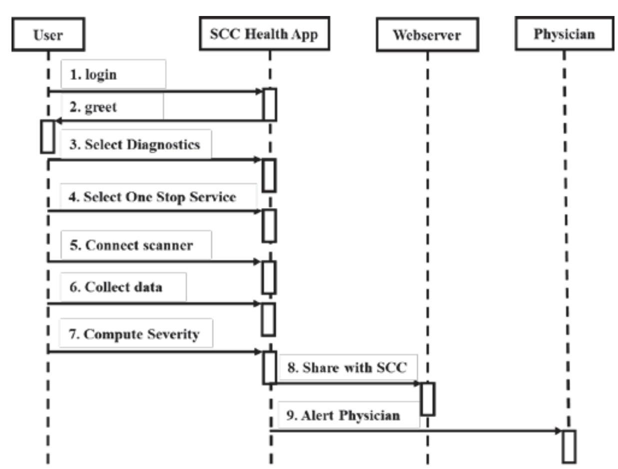

Fig 5. Sequence diagram for SCC Health app using "one stop service"

During data collection the app display a progress bar. when data collection by one sensor is completed, the app prompts the user to select the next sensor and collect data again. When data has been collected from all the sensors, the app prompts the user to select a severity-ranking algorithm, and then the user can click on "Compute severity". After severity calculation, the app will show the sensor data values and the degree of severity. At this stage the user has the option to save the test results and to share the result with the SCC Health webserver. The webserver can be accessed at www.sccmobilehealth.com.

D. Dynamically Executable Algorithms for severity assesment

The developed algorithms are pre-installed in the app but there is provision to download algorithms in the form of DEX file from a public GitHub repository and upgrade the algorithms dynamically. In future, when the framework becomes open access, a researcher can submit better algorithms and the user will be able to choose the algorithm for severity computation. Another possibility is that the user may choose an algorithm from available algorithms based on past user ratings or personal experience. In this way, the framework remains open for the whole research community and crowdsourcing of algorithms become possible.

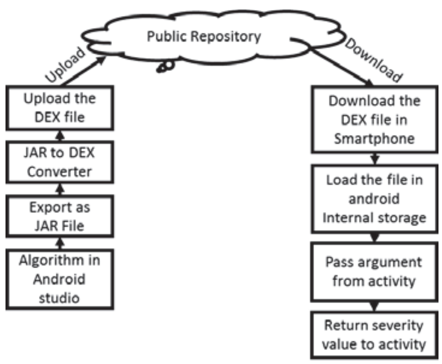

Fig. 6: Uploading and downloading algorithms from open repository

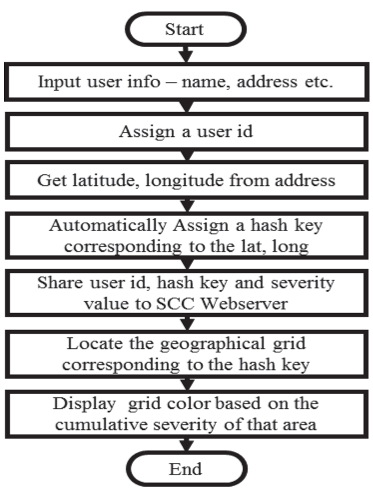

Fig. 7: Flowchart to anonymize user data

As shown in the Fig. 6, the sensor values are passed to the DEX file as an argument and the algorithm in the DEX file computes a severity value for the disease and then returns the severity value (type double) to the function in the activity. The GitHub repository for the algorithms is available https://github.com/esarplab.

B. Connected Health and Data Privacy

To maintain data privacy, the user's name, address, or any other personal information is not shared with the SCC. To visualize all data of the users, randomly generated user IDs are assigned to the users, and hash keys are used in the visualization of the temporal trend of the disease for a user and spatial distribution (weighted average of individual severity) of the disease in a geographical area. The flowchart of making the data anonymous has been shown in Fig. 7 the latitude and longitude derived from a user address, is represented by a hash key, and is named grid code. The grid code along with PID, severity value, disease type, time of diagnostic are shared with the webserver where the hash code is mapped to a large geographical area, which ensures privacy of the location of any user.

III. RESULTS

The correlation of HRV indices with AHI has been shown in Table I. As can be seen, 3 HRV features show a significant correlation (marked with asterisk) with AHI. To avoid multi-collinearity pNN40 was discarded from the regression model as it shows a high correlation with pNN50. Using 2 HRV features (1 from time domain and 1 from frequency domain) and 2 SpO_2 features, for 5-fold cross validation the ensemble of regression method achieved a mean absolute error of 8.27 AHI and an RMSE of 11.38 AHI. Fig. 8 shows the plot of actual AHI and estimated AHI for each record. In some cases, there is a good overlap between the actual and estimated AHI. The residual plot shown in Fig. 9. shows a random pattern of residuals on both sides of 0.

TABLE II. CORRELATION OF HRV FEATURES WITH AHI

	correlation	p-Value
AVNN	0.152	0.767
SDNN	0.150	0.377
SDANN	-0.156	0.357
RMSSD	0.269	0.108
SDNN index	0.221	0.188
pNN40	0.337	0.041*
pNN50	0.342	0.038*
VLF	0.179	0.289
LF	0.164	0.331
HF	0.278	0.096
LF/HF	-0.340	0.039*
LFnu	-0.298	0.073
HFnu	0.298	0.070

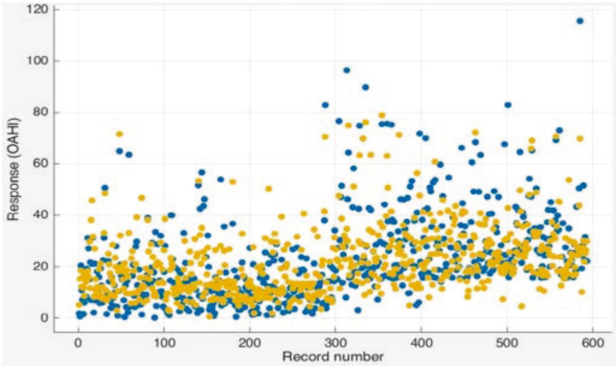

Fig. 8 Plot showing actual and estimated AHI for the subjects

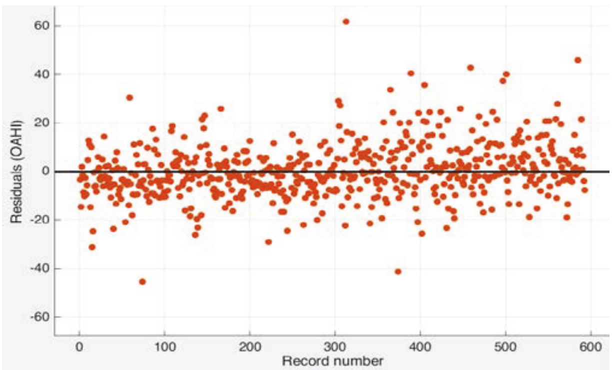

Fig 9. Residual plot for actual versus estimated AHI

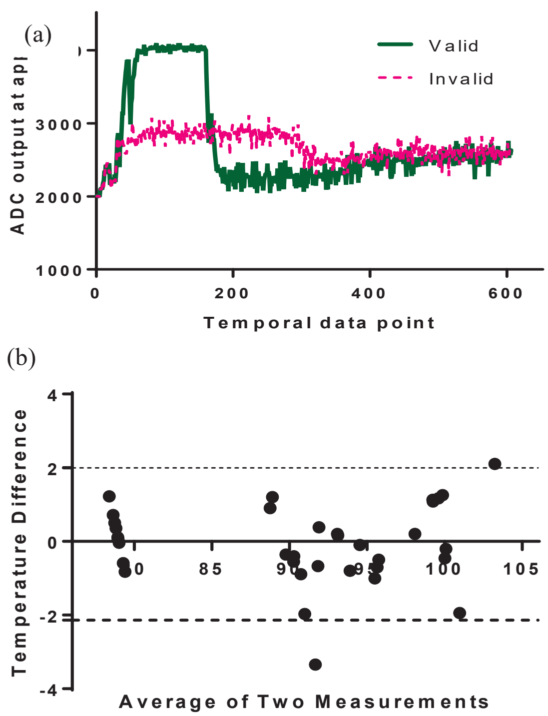

Fig 10. (a) comparison of valid and invalid response from the temperature sensor (b) Bland-Altman plot for the estimated and true temperature.

The Android app has been tested using IJP temperature sensor printed on polyamide substrate for body temperature estimation. Fig. 10(a) compares a valid response from the temperature sensor with an invalid response. It can be seen that the valid response has a good transition, whereas the transition for invalid response is negligible. This is due to the circuit implemented in this temperature sensor [11]. Residual plot for temperature estimation has been shown in Fig. 10(b). The overall accuracy obtained for temperature sensor is ±1.27°F. An overnight instantaneous heart rate signal collected in the app from a subject using the wrist band has been shown in Fig. 11. Snapshots from the app and the server has been shown in Fig. 12 depicting password protected log in, disease monitoring facility, provision for automated data quality checking, estimated severity of the disease, temporal plot for tracking disease progress over time and geo-spatial plot for monitoring the disease severity in the city neighborhoods.

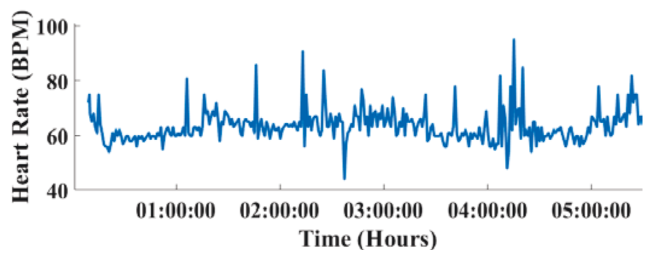

Fig 11. Example overnight heart rate signal collected in the app from a subject during sleep using wristband

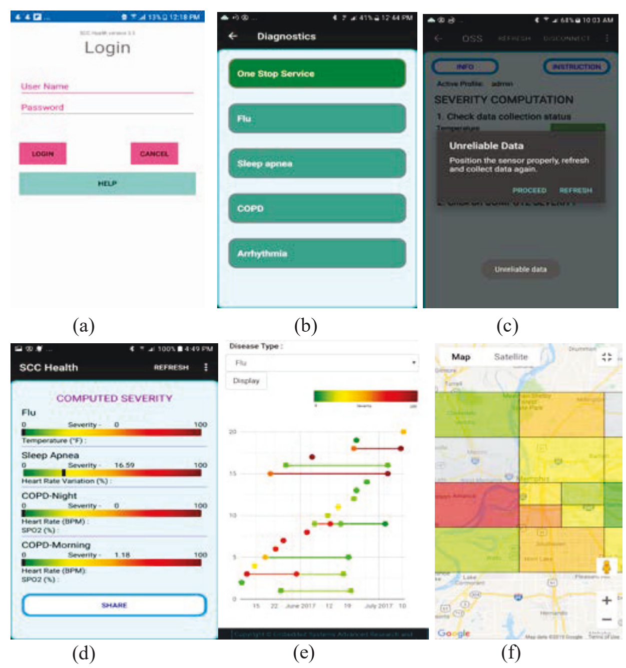

Fig. 12 Snapshots from the App and the server (a) Log in, (b) Main window, (c) Automated data quality check (d) Estimated disease severity, (e) Temporal plot showing disease progression (f) Spatial plot for disease severity in the city neighborhoods

The app has been optimized for power consumption. For active data collection the power consumption is 218 mW, Memory usage is 7 MB and storage size is about 9.4 MB. A comparison of this work with previous related works have been shown in Table I. This framework has several advantages over the others including online severity estimation, dynamic upgradation of algorithms, crowdsourcing of algorithms, integration with IJP passive sensors etc.

TABLE III. COMPARATIVE STUDY WITH SIMILAR WORKS.

Metric	**Oresko *et al.* [2]**	**L. Constantinescu *et al.* [4]**	**A. Benharref *et al.* [12]**	**U. Satija, *et al.* [13]**	**G. Muhammad *et al.* [14]**	**This work**
Individual Health Status	Y	Y	Y	Y	Y	Y
Community Health Status	**N**	**N**	**N**	**N**	**N**	**Y**
Cloud/webserver connectivity	N	Y	Y	Y	Y	Y
Online severity estimation	**N**	**N**	**N**	**N**	**N**	**Y**
Dynamic upgradation of algorithms	**N**	**N**	**N**	**N**	**N**	**Y**
Data Encryption/Privacy	X	X	Y	X	X	Y
Data Security	X	Y	Y	X	Y	X
User control on data sharing	**N**	**N**	**N**	**N**	**N**	**Y**
Database	Y	Y	Y	Y	Y	Y
Data export for clinical study	Y	Y	Y	Y	Y	Y
Low power consumption	**X**	**X**	**X**	**X**	**N**	**Y**
Integration with IJP passive sensor	**N**	**N**	**N**	**N**	**N**	**Y**
Crowdsourcing of disease monitoring algorithms	**N**	**N**	**N**	**N**	**N**	**Y**

Y- Yes, N- No, X- Not Reported, boldfaced items show novel/important contribution of this work.

IV. CONCLUSION

The proposed smartphone-based SCC Health framework has the potential to improve the healthcare monitoring significantly and can be easily integrated in the smart city infrastructure. In addition, sharing anonymized severity metrics with their community will empower the users, permit the community stakeholders to assess population health status, might reduce the healthcare cost, and help identify potential individual and community actions to achieve improvement in community-wide health status. For our future work, we have recruited volunteers through our community partner- the United Methodist Church, Memphis for a large-scale deployment of this framework and further improvement based on feedbacks from the users, medical experts and public health professionals.

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