Smart Health Integrated Framework and Topology (SHIFT) for Smart and Connected Community

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***Abstract* — A smart and connected communities (S&CC) will utilize existing and emerging technologies to collect heterogeneous spatiotemporally distributed data and artificial intelligence (AI) to seamlessly generate meaningful knowledge that will benefit both individuals and S&CC. We have developed a framework for Health and Wellbeing of S&CC that includes existing and emerging sensors for data collection from users of the community, a custom smartphone app with real-time AI algorithms for edge-computing, and a webserver for spatiotemporal visualization of abstracted information for community stakeholders. We propose to extend this framework towards an enhanced Smart Health Integrated Framework and Topology (SHIFT) through incorporating a uniform hierarchical layer-based architecture for S&CC. The proposed concept was simulated to depict data processing and visualization approach. The proposed framework takes advantage of evolving topology of smart sensors and devices, in addition to being transferable and scalable.**

***Index Terms* — AI, Edge computing, Mobile health, Privacy, Scalable framework, Smart health, Spatiotemporal data.**

I. Introduction

Mobile Health (mHealth) technology in the last few decades has enabled an unprecedented capability in individual health monitoring and interventions. This transformational mHealth technology leverages data from smartphones to supplement clinical diagnosis. However, by incorporating new generation wearables, Internet of things (IoT), and other smart infrastructures including 5G, there is potential to gain further and novel insights into collective health patterns and behaviors that can provide substantial community benefits [1-3]. As communities are tied with interlocking physical, social, economic, and infrastructural challenges, the community health challenges need to be addressed with newer vision and collaborative efforts that must include stakeholders such as local, state, regional, and national institutes. In addition to technology aspects, social science aspects must be carefully considered as well. The new technology will improve for 21st century smart and connected community (S&CC), which will utilize existing and emerging wearables and IoTs to collect heterogeneous spatiotemporally distributed data and utilize embedded computing to seamlessly generate meaningful knowledge to benefit individuals and S&CC [4]. This can lead to improved health and safety, efficient public infrastructure, and better access to needed services.

Although mHealth technology is already tapping into widely used smartphone infrastructure [5-7], the community benefits of existing systems are severely limited. Some issues are lack of health sensor modalities in smartphones, homogeneity of software, ability to curate heterogenous data, generate useful knowledge from granular data, effective abstraction, and utilization of curated data for spatiotemporal visualization and use of this knowledge in decision making for the community.

In this paper, we propose a new uniform architecture for smart health (sHealth), named "*Smart Health Integrated Framework and Topology (SHIFT)*". This framework, in addition to preserving mHealth benefits for individuals to self-monitor their own health indicators, extends to sHealth by allowing participants to share individual health severity data for spatiotemporal visualization for the benefit of the community and other stakeholders towards sHealth. The spatiotemporal visualization of community-wide health data, which will be useful to abstractly and objectively analyze health trends, disease outbreaks (e.g., COVID-19), disease progression, and resource allocation.

II. Developed sHealth Framework

We have previously developed and reported a S&CC sHealth framework that includes multiple wearables and sensors (e.g., inkjet-printed flexible body-worn electronic sensors, smart wristbands, and smartphones) for data collection in *living labs* (i.e., at homes of participants) and real-time edge-computing AI algorithms implemented on a custom smartphone app to compute a disease severity metric related to a particular disease of interest [4,8,9]. We have used the sensors and commercial wearables to collect target disease related physiological signals, such as core body temperature, ECG, heart rate, and pulse oximetry [10-12]. We developed machine learning algorithms for target diseases using several public-access datasets (e.g., PhysioNet, MIT-BIH, and NIH repositories). The smartphone app (https://github.com/esarplab/) processes the collected data to compute disease severity in real-time using edge-computing technique [9]. We have also developed feature extraction and classification algorithms for several diseases including Obstructive Sleep Apnea (OSA), Chronic Obstructive Pulmonary Disease (COPD), flu, and arrhythmia severity detection algorithms [13-17]. In addition to feature extraction and ranking, we have explored a variety of algorithms such as Linear Regression, Ensemble Regression, Artificial Neural Network (ANN), Random Forest, Support Vector Machine (SVM), Quadratic Discriminant Analysis (QDA), and Genetic Algorithm (GA).

The developed algorithms were implemented on smartphones to calculate a simple disease severity metrics (which has a fraction values between 0 to 1 and represent how well or worse the disease condition is compared to normal condition of 0). Instead of True/False classification as performed by most researchers, our algorithms compute a continuous severity metric between 0 to 1, that represents severity of the target disease. These severity metrics are compared and correlated with the clinical severity class descriptors (e.g., Normal, Mild, Moderate, Severe, Very Severe). We have implemented the developed AI algorithms in a custom Android smartphone app for real-time processing at the edge.

Finally, smartphone-computed abstracted severity metric can be sent (user elects) to the S&CC database in JSON (JavaScript Object Notation) format [8]. The computed severity shared by the participants with the S&CC sHealth webserver (http://sccmobilehealth.com/) were utilized for temporal and spatial visualization of the abstracted information of community-wide severity metrices for community stakeholders. These data include participant's hash ID, grid code, severity metric, disease type, date/time, and algorithm name. Data with temporal (Graph or Flow) or spatial (Static or Animation) plots. A heat map-like spatial domain visualization via Google Map overlay with animation capability was also developed to represent severity of health conditions at various arbitrary grids of the community over time.

III. Description of Proposed SHIFT Platform

A. SHIFT architecture

The proposed framework (Fig. 1) will incorporate health-related heterogeneous data from users that are naturally spatially and temporally distributed and synchronous in nature. It also incorporates hierarchical data abstraction from users to community while preserving privacy. The users can share their anonymized health severity data that will allow community stakeholders to utilize the spatiotemporal visualization for rapid action or policy generation. The framework components are dissociated for transferability and scalability. The composing components can be categorized in four classes: (1) lightweight smart devices composed of commercial and custom sensors for seamlessly collecting health data from users, (2) edge computing implementation using artificial intelligence (AI) based algorithms for real-time computation, (3) smartphone app to directly view current health status of the user, and (4) a cloud infrastructure for storing, visualizing, and analyzing shared community data for knowledge creation.

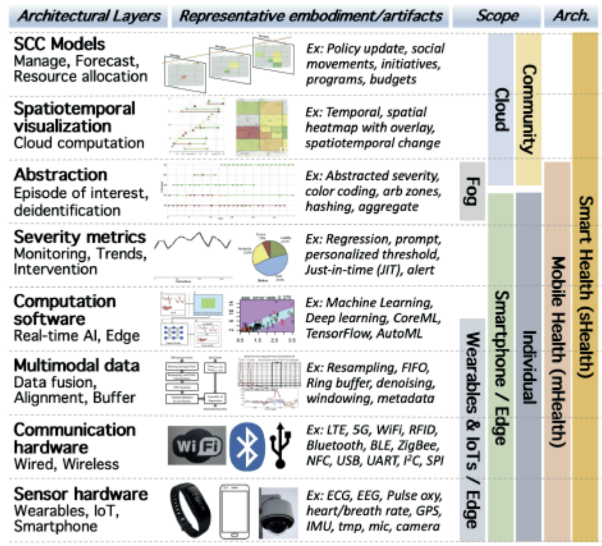

Fig. 1. SHIFT architecture.

The framework abstracts user data at the edge to provide only the needed information (such as severity metric) to the higher levels (e.g., spatiotemporal visualization), instead of transmitting all of users' health data to server. This approach reduces data payload by several orders of magnitude. Furthermore, this allows ease of user's privacy incorporation. This also disassociates the community data pool from individual data processing at the edge, which provides scope for modular software development and asynchronous communication similar to Open System Interconnection (OSI) model of layered architecture used in operating systems. The framework can incorporate multiple disease severity algorithms that will be available in the webserver for download by the users based on their individual needs. Users at various communities might have

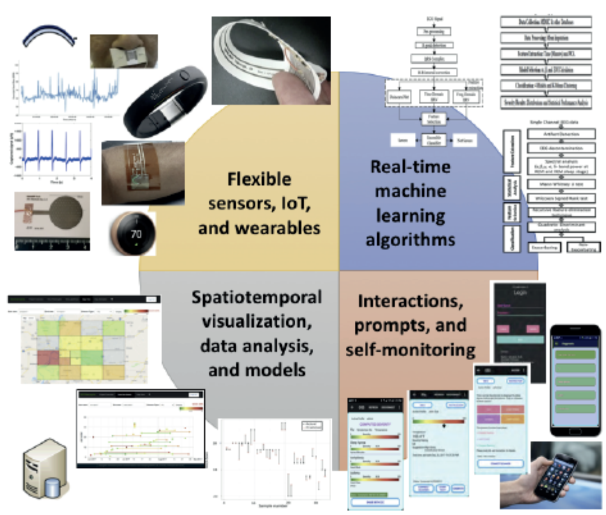

Fig. 2. Technological topologies of SHIFT.

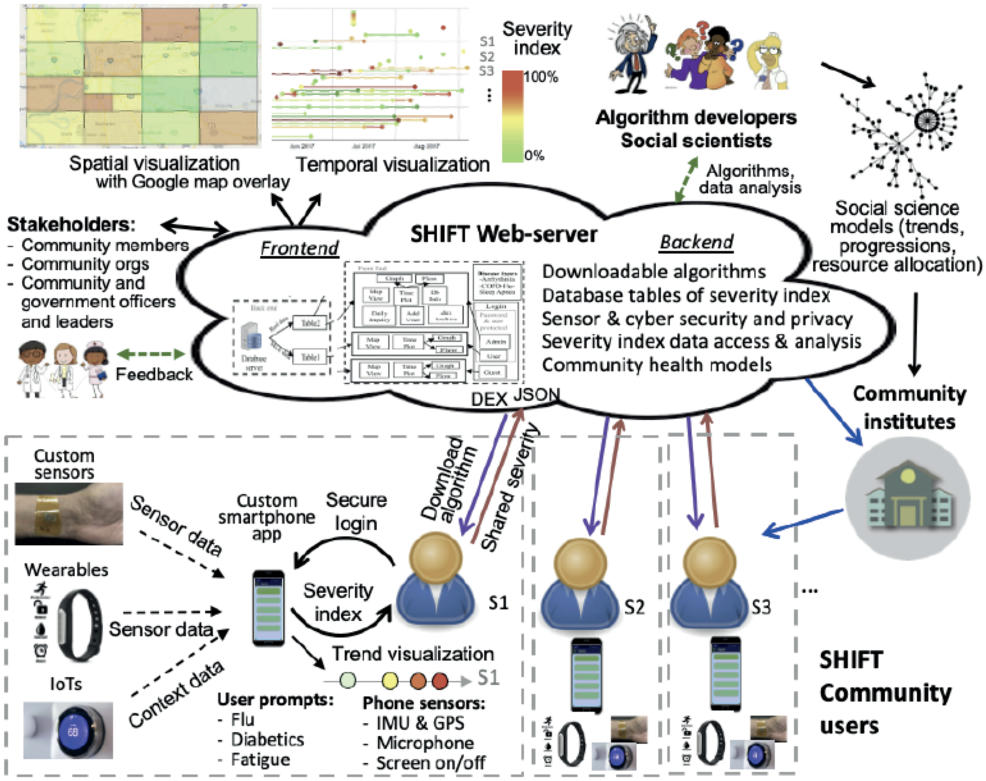

Fig. 3. Deployment diagram of SHIFT.

diverse needs. This will allow a user to download only the relevant algorithms from the server without overburdening and resource constraining the app. This topology further allows periodic update of algorithms in the server and can be updated by the users when suitable. This leaves options for user and stakeholder rating of algorithms (similar to App Store). The framework can be utilized further by various AI developers to host their algorithms with objective ratings towards a competitive and trustable AI algorithm test environment.

The framework will also have visualization for characterizing the spatiotemporal trends and abnormalities. The visualization captures the key knowledge from temporal and spatial heterogenous data that are fused for meaningful interpretation. The webserver visualization can highlight mismatches and unusual behavior. Unusual behavior can be at the individual level, such as the sudden increase in the severity of a disease, or at the community level (such as outbreak of flu). The community level trends are not detectable at individual level, thus depicting the need for the proposed sHealth framework. Furthermore, the stakeholders and decision-makers can use their domain knowledge to identify various worsening health conditions, abnormal disease explosions, or potentially harmful episodes.

B. SHIFT technological topologies

The technological topologies for SHIFT implementation are shown in Fig. 2. There are four classes of technology topology required for this implementation, which are: (a) sensors and wearables, (b) real-time AI analysis at edge, (c) interaction and intervention for users with a custom smartphone app, and (d) a webserver for spatiotemporal analysis and visualization of collected severity data. The SHIFT platform integrates all of these technological aspects under one uniform architecture for sHealth.

C. SHIFT deployment scenario

A deployment diagram of the SHIFT platform is given in Fig. 3. During the AI algorithm development phase for the target health conditions, we will need to identify suitable and reliable public repositories with various physiological datasets (e.g., PhysioNet, MIT-BIH) that closely matches with the target disease health data. For edge computing implementation, feature ranking process is recommended, after which the best top features should be implemented in the smartphone app. This approach allows reduced complexity, resource requirement, and real-time execution for edge computing, while providing satisfactory classification performance such as accuracy, sensitivity, and specificity [17-19]. After the algorithm deployment process with various AI technique, the best classifier can be pre-compiled and implemented with optimal parameters. This porting process can be performed with Tensor Flow, or AutoML. Performances can be analyzed using cross validation, accuracy, specificity, sensitivity, and latency. The algorithm then will be kept available in the webserver and can be downloaded by the users with the custom smartphone app for SHIFT deployment. The developed algorithms can thus be assessed and evaluated by the real-life users and rated. These AI algorithms will be hosted in the SHIFT webserver in dex format, which can be downloaded to the user's smartphone via the SHIFT smartphone app as per need basis. This will allow update of algorithms by various entities in an ongoing basis. In addition, using various data correlates, episodes, and identifiers of the targeted health conditions and demographics, the app can also be used to send users useful reminders and tips through prompts or notifications. Finally, users will be allowed to elect to share their severity data with the SHIFT server. Shared data from the custom SHIFT smartphone app will be transmitted to the SHIFT server securely and anonymously. These health data from community members will be used for visualizations, such as health trend models, hotspot detection, and behavior pattern analysis.

IV. SIMULATION AND RESULTS

Simulink® software (Mathworks Inc.) was used for proof-of-concept simulations of the SHIFT platform. Fig. 4 shows a setup of a user who utilizes a sensor to collect health individual health data. This raw data is then converted to disease severity data using an edge implemented AI algorithm (e.g., in wearables or in smartphone app). Note that this severity data needs to be intuitive. We propose to use a fraction number between 0 to 1, where 0 indicates normal and 1 indicates extremely severe. Through this process of severity computation at the edge, the amount of data produced by the sensor will be drastically reduced to the small amount of severity data. This reduction is typically a few orders of magnitude lower.

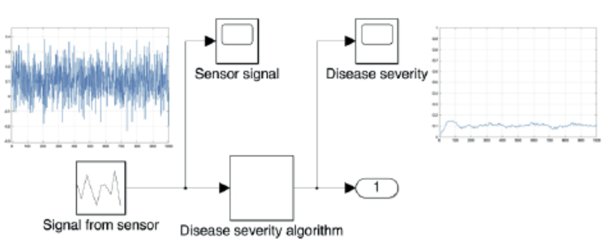

Fig. 4. Simulink SHIFT model of a user with a sensor and a disease severity detection algorithm.

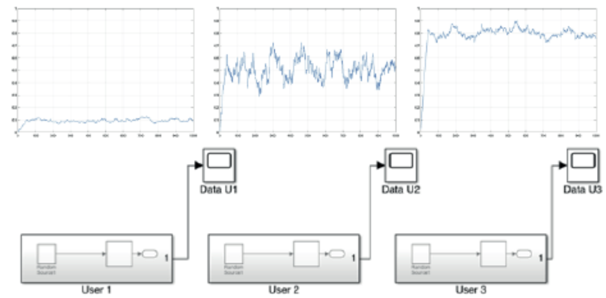

Fig. 5. Simulink SHIFT model of 3 users with their individual disease severity tracking (as in mHealth).

Thus, instead of transmitting raw data as done in most mHealth or sHealth platforms, we will be transmitting the severity data to SHIFT webserver which greatly reduces data payload of wireless network, while being sufficient for the higher levels of the proposed SHIFT architecture. In fact, this abstraction is essential for large-scale deployment of this type of system with a large number of community participants using one or more sensor devices. This also limits the user's raw data to the edge, which is preferred by vast amount of community members worried about privacy and loss of control over personal data.

Fig. 5 shows 3 of these users (shown in Fig. 4) with various levels of severity for an arbitrary disease within a community. The severity values range from ~0.0 (User 1 – indicating normal disease condition or no disease) to ~1.0 (User 3 – indicating severe disease condition). Although each user has access to their own data and can monitor individual disease trends over time, but none has access to other users' data or trends. Although this is still beneficial to individuals (like in mHealth framework), this does not

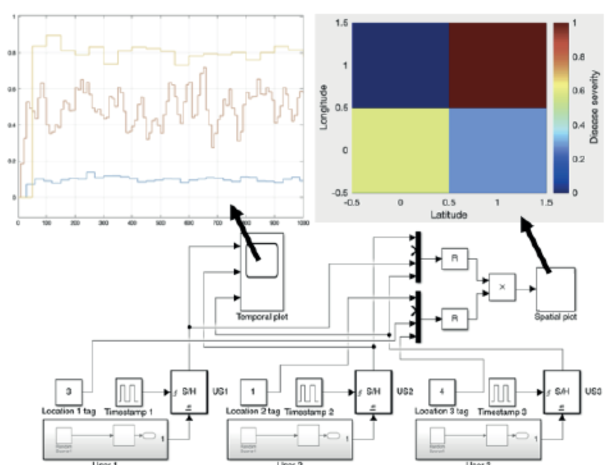

Fig. 6. Simulink SHIFT model of spatiotemporal visualization of collective community health based on user shared disease severity data (extending for sHealth) using temporal and spatial plots for S&CC.

directly provide ability for community-wide monitoring, analysis, and decision making required for sHealth. For this purpose, users can elect to share anonymized severity data that preserves privacy, but allows SHIFT webserver to track community health. The effect is show in Fig. 6, that depicts the aggregated results of these three users by sharing their severity data (only) with the SHIFT webserver. The data from the users now can be aggregated and shown in time domain (like trend lines of all community members who shared data) or in spatial domain (like heat map showing which grid has more disease severity and which grid is doing well). Data visualization over time will allow monitoring spatiotemporal change of severity throughout the community. Thus, the proposed framework can lead to utilization of heterogeneous spatiotemporal data of the community members for the benefit of the community and stakeholders such as health-department, hospitals, non-profit organizations, and policy makers.

V. Conclusion

The proposed "SHIFT" platform not only spans the traditional mHealth domain, but rather extends the scope to sHealth, enabling study of health impact on the city, community, and society. It incorporates and integrates health-related heterogeneous data that are spatially and temporally distributed, as well as provides a hierarchical data abstraction to allow community stakeholders to utilize the visualization for rapid action or policy generation.

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