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Using Wearable Biometric Devices to Improve Patient Healthcare Outcomes with Machine Learning Algorithms

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***Abstract* -** While the smartphone remains Americans' device of choice, the tech world is creating a future of wearable devices that promises to entertain consumers, save them money and help them live healthier lives. Technology companies' interests in health and wellness have sparked the creation of a myriad of wearable devices, from fitness bands that monitor activity and sleep patterns to flexible patches that can detect body temperature, heart rate, insulin absorption levels, hydration levels and more. These devices produce data that, when enabled with analytics, can often be used by consumers to manage their health and by healthcare organizations to improve care and potentially reduce costs through systems such as remote patient monitoring. With the help of Machine Learning Algorithms, data generated by personal devices can be used by insurers and employers to better manage health outcomes, wellness and healthcare costs, and by pharmaceutical and life sciences companies to run more robust clinical trials and capture data to support outcomes-based reimbursement.

Index Terms - Wearables, eHealth, Machine Learning, Biometrics, Healthcare.

I. Introduction

The usage and reliance on Machine Learning Algorithms to improve healthcare outcomes is dependent on a framework that supports wearable technology platforms within healthcare settings [1]. This study focuses on best practices of integrating wearables and machine learning algorithms by:

1. Describing the methodology & framework of wearable technology in healthcare settings.
2. Defining technology platforms and implementation tracks.
3. Identifying predictive analyses.
4. Using Machine Learning to create a framework for future treatments based on current statistics.
5. Answering fundamental questions with respect to capabilities of improving healthcare outcomes.

When discussing Machine Learning Algorithms, we also utilize concepts such as big data and business intelligence. The current big data analytics trends in healthcare are vastly improved versions of the conventional RDBMS. Big data analytics is the process of examining large data sets containing a variety of data types to uncover hidden patterns, unknown correlations, market trends, customer preferences and other useful business information that can ultimately lead to more accurate healthcare decisions, rapid treatment tracks and improved medication choices. In addition, such data analysis plays a pivotal role in business intelligence and insights [2]. Business intelligence largely depends on the process for analyzing data and presenting actionable information to help corporate executives, business managers and other end users make more informed business decisions. The underlying platforms represent "mining" efforts – such data mining systems collate data from multiple sources thereby building predictive models of behavior for an enterprise and its products or services. Decision making is also dependent on the validity of the user's profile – medication targeting is directly correlated to data targeting; the relationship between a user's behavioral profile impacts decisions such as product efficacy, susceptibility to adverse events, or economic and monetary decisions of healthcare providers and insurers [3]. Thus, there is a natural convergence between the elements of profile validity, predictive analysis and the big data that is "mined".

II. Methodology & Framework of Wearable Technology in Healthcare Settings

Although the usage of wearable devices is becoming more wide-spread, for the purposes of this study, we examine the framework through which data points and decisions are interconnected [3,4]. Specifically, the data points to be captured should be clearly defined and confined to well-known factors such as vital signs, core temperature, weight, gender, age, blood glucose levels, general activity classification, fitness metrics, seizure detection and other points as determined by the study's parameters [5]. Once these data points become available, the next step would be to compile, aggregate and present such data using analytical constructs, including regression analysis, analyses of variance, histograms and visualization. Finally, the data and resulting analyses are stored using a cloud-based platform.

The data points that are divided into three subsets, identified in the Biosensors Interactivity Pyramid:

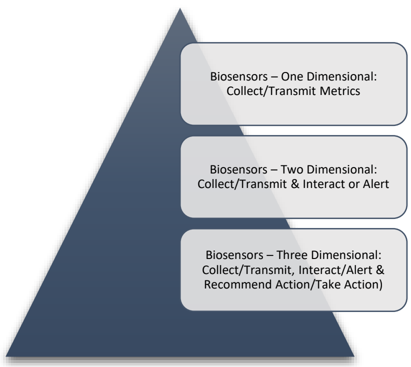

Figure 1-Biosensors Interactivity Pyramid (created by authors)

1. Biosensors – One Dimensional (Collect/Transmit Metrics) – includes data such as patient's heart rate, respiratory rate, skin temperature, body posture, fall detection guidelines, glucose monitoring, core temp fluctuations, abnormal heart activity, etc.
2. Biosensors – Two Dimensional (Collect & Interact or Alert) – includes data such as OB insulin pump, adaptive hearing aids, pain reduction administration, accelerometer for fitness pros, at risk of congestive heart failure and chronic obstructive pulmonary disease (COPD) patients, etc.
3. Biosensors – Three Dimensional (Collect, Interact & Determine Outcome / Recommend Action / Take Action) – includes data such as Smart hearing aids, ovulation rings, etc.

Upon completion of data collection using the aforementioned three-tiered approach, the analytics phase commences. This phase is delineated using another three-tiered structure [6,7,8]:

1. Data Mining/Big Data Collection – examples include:
   a. Association rule learning (Dependency modelling)
   b. Clustering
   c. Classification
   d. Summarization
2. Business Intelligence:
   a. Descriptive Statistics – examples include: Univariate & Bivariate Analyses, Distribution, Standard Deviation, Regression, ANOVA, Kurtosis, Correlation, Covariance.
   b. Exploratory Data Analysis (EDA): Scatter Plots, Pareto Charts, Multidimensional Scaling and Histograms.
   c. Confirmatory Data Analysis (CDA) – examples include: Statistical null and alternative hypotheses, P-Value, T-Distribution.
3. Data Communication:
   a. Integration
   b. Visualization
   c. Prediction
   d. Communication

Data storage can be addressed during the early stages of this framework. The robustness of data storage, redundancy, availability and integrity are the result of using a cloud-based data warehouse. The fundamental elements of this storage choice are:

1. Infrastructure as a Service (IaaS). It includes services like storage, backup, authentication and security.
2. Platform as a Service (PaaS). It provides the framework and a basic set of functions that customers can customize and use to develop their own applications.
3. Software as a Service (SaaS). Browser-based software or service delivered on a per-user, per-month basis or other subscription model.

III. TECHNOLOGY TRACKS & IMPLEMENTATION PLATFORMS

In this section, we discuss the choice of Wearable Devices (On-Body), taxonomy, architecture and some specific examples. Then we address the study's duration and population.

A 2014 statistical survey of the likelihood of United States of America consumers purchasing wearable devices between 2014-2015 may be summarized as follows [44]:

- Fitness band - 45%
- Smart Watch – 35%

- Smart Clothing – 20%
- Smart Glasses – 19%
- People Tracking Devices -13%

At the core of the wearables' architecture in Figure 2 is the miniaturized embedded microsystem that processes the I/O data to/from the sensors. The skin is naturally the largest organ in the human body, with the unique ability to responds to all the five senses of touch, sight, smell, sound and smell. In the computing world, the skin is a powerful and versatile sensor, that usually acts as the I/O interface device for most wearable systems.

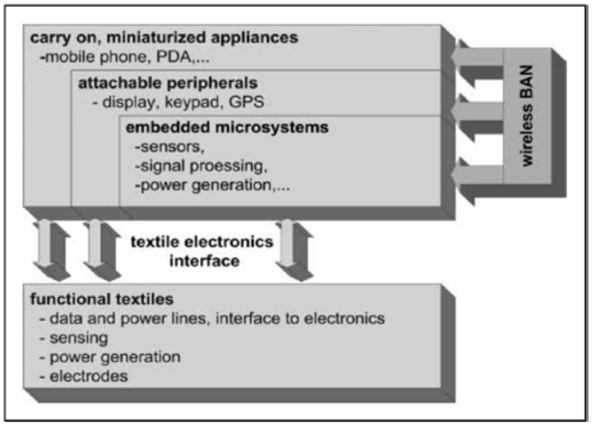

Figure 2 - Wearable Device Architecture [8]

An example of a functional textiles is the Smart clothing which uses Textile meta-wearable platforms, by adhering to all the physical and functional wearable attributes. These include lightweight, conformable shapes, multifunctional, configurable, responsiveness, bandwidth. Most functional textiles use stretchable electronics to track and wirelessly transmit real-time data or post processing of information, such as heart rate, brain activity, body temperature, glucose level and hydration level. Examples include the continuous glucose monitor (CGM) worn by diabetics and other self-trackers, under-the-skin CGM uses sensors to transmits glucose readings every preset interval to an external receiver and/or insulin pump. Also included are wearable sensor patches that are be very useful for heart monitoring. Another example of a sensor that conforms to the predictive model in Figure 3 is the iRhythm Zio-Patch for monitoring the cardiac rhythm and predicting/warns about arrhythmias [42, 43, 44].

CGM uses the Glucometer-as-a-platform (GAAP), GAAP technology of the binding of short segments of DNA to a large number of potential molecules that might be present in blood, water, or food. It has been successfully used for the determination of the presence of cocaine, interferon, adenosine, and uranium.

The architecture of the wearables and the implementation Platforms are driving by the following wearables taxonomy:

- Functionality – Single or multifunction.
- Type – Active or Passive
- Deployment Modes – Invasive or Non-invasive
- Communication Mode – Wired or Wireless.
- Disposability - Disposable or none-disposable
- Field of use – Healthcare, Military, Public safety, Fitness-Tracking, Entertainment, Gaming, Acoustic and many more.

During a six-month cross-sectional study, the following technology implementation platforms are utilized:

- BTLE - Examples: Fitness-trackers, BluetoothTM-based ECG monitor, Flexible antennas for Body Area networking (BAN) , BlueTooth, or wireless LAN
- Sensors: with context awareness, Context-dependent configuration, seamlessly integrated, Minimal Cognitive Effort, e.g. simple binary choice.
- Google Contact Glasses to measure the glucose levels from eyes' tears, lens engineered 'to restore the eye's natural autofocus.

IV. Predictive Analysis & Analytics

As data analysis and analytics have become more sophisticated, that has given rise to the use of Predictive Analytics across a variety of industries and business disciplines. The block diagram of a Predictive Analysis model is shown in figure 3.

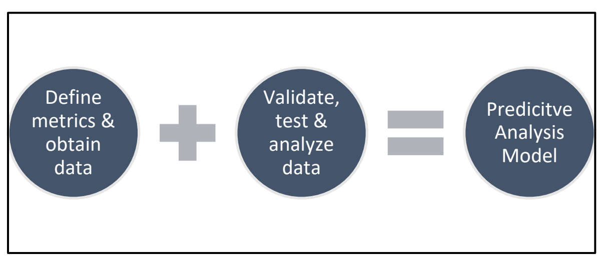

Figure 3-Predictive Analysis Model (created by authors)

One of the use cases of Predictive Analysis is to help businesses identify a customer's predisposition to act. By using both internal data collected from customer transactions (purchasing habits, interactions with customer service, etc.) and third-party data (market research, feedback surveys, focus groups, etc.), predictive models can be built to assist organizations in effectively planning business growth campaigns, increase revenue per customer, reduce production costs, focus on untapped markets and improve operational efficiencies. Without predictive analysis tools, businesses would be unable to capitalize on growing their product offerings, driving revenue-generation opportunities or expanding their customer reach [3,4]. Predictive analytics encompasses a variety of statistical techniques that include modeling, machine learning, data mining in order to analyze historical facts to make predictions about future events. For a business that is trying to improve its products or services, or is trying to enter a new market dominated by competitors, predictive models exploit patterns found in historical and transactional data to identify risks and opportunities. By building predictive analytics models, a business can understand the relationships between factors that can determines the success or failure of product launches, consumer acceptance or market expansion. In addition, such models aim at categorizing risk factors and subsequent mitigations approaches.

The 10 Critical Success Factors of Constructing Predictive Analytics Models: An Iterative Process

Some of the factors described below were identified from previous research I am currently conducting for my dissertation on the extension of the Technology Acceptance Model into user authentication and biometrics. The critical success factors represent the characteristics, conditions, or variables that have a direct and serious impact on the effectiveness, efficiency, and viability of how an organization creates and deploys a predictive analytics model. They are:

1. Define the problem, opportunity, threats and risks
2. Identify the key metrics to success
3. Identify which data (historic and current) can be used to drive the metrics
4. If internal data is insufficient, seek third-party data
5. Obtain, extract, refine and validate the data
6. Construct the predictive analysis model
7. Test the validated data within the model
8. Conduct thorough analysis of the resulting data
9. Identify then formalize implementation steps
10. Repeat, revisit, rework

In summary, Predictive models analyze past performance to assess how likely a customer is to exhibit a specific behavior in the future in order to improve marketing or line of business operational effectiveness [9].

V. Using Machine Learning to create a framework for future treatments based on current statistics

Currently-available data acts as the springboard for future informed decisions. Frameworks helps one focus more on the problem domain rather than underlying code. Tools enable one to work more quickly by performing common tasks. These frameworks help with three types of critical solutions: Descriptive, Predictive and Prescriptive.

1. Descriptive Analytics, which use data aggregation and data mining to provide insight into the past and answer: "What has happened?"
2. Predictive Analytics, which use statistical models and forecast techniques to understand the future and answer: "What could happen?"
3. Prescriptive Analytics, which use optimization and simulation algorithms to recommend or suggest possible outcomes and answer: "What should we do?"

The following machine learning frameworks and tools represent a practical selection that supports the aforementioned analytics [41]:

1. Apache Singa: This deep learning framework is mostly used for image recognition and natural language processing. Written completely in C++, Singa is an Apache incubator that focuses on distributed deep learning by providing a scalable architecture that can accommodate a variety of hardware platforms with a unique focus on health-care applications.

2. Apache Spark MLlib: MLlib is Spark's machine learning library. Its goal is to make practical machine learning scalable and easy. At a high level, it provides tools such as: Machine Learning Algorithms, Pipelines Tools, Statistical and Data Handling Utilities, and Feature Extraction and Transformation. Apache Spark is an open-source cluster-computing framework that provides

cluster-programing interfaces featureing fault-tolerance capabilities.

3. Caffe: Is a widely used machine-vision library (using Paython for its API), that takes advantage of Matlab's implementation of fast convolutional nets using C++ and Python for its API. This framework is uniquely suited for image classification with convolutional nets due to its speed and modularity.

4. Google TensorFlow: This framework relies on dataflow graphs that defines how series of deep learning algorithms process data batches (tensors). The graphs trace the flows (movements) of data through the system. This can be used for complex machine learning problems.

5. H2O: Is an open-source software that primarily targets big-data analysis. The framework supports the manipulation and extraction of data with the use of its H2O prediction engine for statisticians. H2O can query data on existing databases as well as Hadoop.

6. Nervana Neon: Neon is an open source Python-based language and set of libraries for developing deep learning models. The platform is hardware-agnostic and is designed for ease-of-use as well as scalability/extensibility.

7. Shogun: The Shogun Machine learning toolbox provides uses a C++ architecture that unifies machine learning methods while allowing for multiple data representations, algorithm classes, and general purpose tools.

VI. Improving Outcomes

The ultimate goal of this research is to answer a simple question – how do machine learning algorithms improve healthcare outcomes? We attempt to answer this using an iterative process that includes: Presenting recommendations and best practices, identifying critical success factors and investigating limitations & boundaries.

Recommendations & Best Practices - Algorithm:

1. To make an accurate discrimination for selected features, the decision tree method is one of the significant learning a technique which provides an efficient representation of rule classification [33]. In this method, the most robust features have been detected for initial splitting the input data by creating a tree-like model. Decision tree is a reliable technique to use in different areas of medical domain in order to make a right decision [34,35]. Nowadays, upon dealing with complex and noisy data, the C4.5 algorithm is used which is estimating the error rate of initial nodes and pruning the tree to make a more efficient sub-tree [36,37].
2. A decision making task needs a strong modeling and inferring system with a proper usage of the contextual information. So, the role of statistical methods in this task is less, but SVM, NN, and decision tree techniques have usually applied for the healthcare problems with decision making tasks with good success [12]. The requirements for a real-time system should guide the selection of the data mining methods. To design a real-time health monitoring system, such methods like NN, GMM, and frequency analysis are not efficient for the sake of their computational complexities. But simple methods such as rule-based, decision tree and statistical techniques can quickly handle the online data processing requirements [12]. The properties of the data set and experimental condition also influence the choice of method. Data mining methods (e.g rule-based, decision tree) have been used in clinical situation with controlled conditions and clear data sets, but the efficiency of them are not tested in real experiments of healthcare services. In contrast, some studies in the literature have used NN, HMM, and frequency techniques in order to handle complex physiological data and discover the unexpected patterns in real world situations [12].

Identifying Critical Success Factors - Sensor Data:

1. Several input sources and data acquisition methods have been considered in the literature for wearable sensor data in health monitoring systems. Three major data gathering approaches have been identified such as experimental wearable sensor data, clinical or online databases of sensor data, and simulated sensor data [12].
2. Experimental wearable sensor data: The papers which have developed the health monitoring systems have mostly used their own data gathering experiments to design, model and test the data analysis step [13,14,15]. In this case the gathered data are usually obtained based on the predefined scenarios due to the test and evaluate the performed results [16], but usually these studies do

not provide the precise annotations and meaningful labels on physiological signals.

3. Clinical or online databases of sensor data: Despite the attention of articles in this review is the role data mining on vital signs in health monitoring, several studies in this area have used the stored clinical data sets [17,18]. In other words, developed data mining methods is defined and designed for wearable health monitoring systems, but to evaluate quantitatively and test the performance of output decision of the framework, the most of the works used categorized and complex multivariate data sets with formal definitions and annotations by domain expert [19,20,21]. Very common example of online databases is PhysioNet [22,23] database which consists a wide range of physiological data sets with categorized and robust annotations for complex clinical signals. Several papers in the literature have used two main data sets in PhysioNet bank, MIMIC data sets (e.g., [24,25,26]) and MIT data sets (e.g., [27,28,29]) that contain the time series of patients vital signs obtained from hospital medical information systems.
4. Simulated sensor data: For the sake of having a wide controlled analysis system, few works have designed and tested their data mining methods through shapely simulated physiological data [30]. Data simulation would be useful when the more focus of data processing method is on the efficiency and robustness of information extraction [31,32] rather than handling real-world data including the artifact, errors, conditions of data gathering environment, etc. Another reason to create and use simulated data is the lack of long term and large scale data sets [31] which helps the proposed data mining systems to deal with huge amount of data.

Identifying Critical Success Factors - Prediction Models:

1. Prediction is an approach that is widely used in data mining field that helps to identify events which have not yet occurred. This approach is getting more and more interest for the healthcare providers in the medical domain since it helps to prevent further chronic problems [10] and could lead to a decision about prognosis [11].
2. The role of the predictive data mining considering wearable sensors is nontrivial due to requirement of modeling sequential patterns acquired from vital signs. This approach is also known as supervised learning models [38] where it includes feature extraction, training and testing steps while performing the prediction of the data behavior. As the common examples of the predictive models, authors in [14,39] presented a method which predicts the further stress levels of a subject.

Limitations & Boundaries

1. Data mining techniques have progressed significantly in the past few years and with the availability of large and open data sets, new possibilities for achieving suitable algorithms for wearable sensors exist. Still, despite these developments, their application to health monitoring is hindered by the challenges that are present in data from wearable sensors which create new challenges for the data mining field [12].
2. The selected data mining technique is highly dependent on the data mining task to be performed. According to the considered data mining tasks, for anomaly detection task, SVM, HMM, statistical tools and frequency analysis are more commonly applied. Nevertheless, NN has not been addressed to detect anomalies. Prediction tasks on the other hand, have often used decision tree methods as well as other supervised techniques. It was shown that rule-based methods, GMM, and frequency analysis are not the most appropriate methods for predication due to the shortcoming in modeling the data behaviors [12].

VII. CONCLUSION

Machine Learning Algorithms make it easier to predict future treatments and optimize medications to achieve optimal efficacy as well as cost. However, before this promise can be realized, wearables need to provide more than just data. They need to provide useful insights and be interoperable, integrated, engaging, social and outcomes-driven. Analysis that provides insights or changes in behavior are of utmost importance to a successful integration where wearable data technologies and healthcare providers work in concert to ensure the continued well-being and improved outcomes for their patients.

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