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Big data analytics and internet of things for personalised healthcare: opportunities and challenges

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ABSTRACT

With the increasing use of technologies and digitally driven healthcare systems worldwide, there will be several opportunities for the use of big data in personalized healthcare. In addition, With the advancements and availability of internet of things (IoT) based point-of-care (POC) technologies, big data analytics and artificial intelligence (AI) can provide useful methods and solutions in monitoring, diagnosis, and self-management of health issues for a better personalized healthcare. In this paper, we identify the current personalized healthcare trends and challenges. Then, propose an architecture to support big data analytics using POC test results of an individual. The proposed architecture can facilitate an integrated and self-managed healthcare as well as remote patient care by adapting three popular machine learning algorithms to leverage the current trends in IoT, big data infrastructures and data analytics for advancing personalized healthcare of the future.

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1. INTRODUCTION

With the increasing use of technologies and digitally driven healthcare systems worldwide, people expect enhanced health outcomes [1]. Today, several billion gadgets are manufactured and deployed as internet of things (IoT), majority of them being health monitoring or therapeutic devices [2]. Low-cost wearable and mobile gadgets are on the rise as they help individuals and healthcare professionals to measure and track various personal parameters such as level of exercise, heart rate, and weight [3]. Point-of-care (POC) screening tests for checking blood sugar to assess diabetes risks and monitoring blood oxygen or electro cardiograms for heart health are possible at home and remote clinics with telemedicine initiatives [4]. While IoT based devices are convenient, there is a huge amount of health data collected on a periodic basis that is not managed well for facilitating a better wellbeing and remote patient care. The history of data and live data streams forming big data of individual health records seem to be underutilized for personalized healthcare and patients' self-management and their wellbeing [5]–[7]. The focus of this research topic is to investigate the use of different POC tests for a combined effect on personalised healthcare. We consider the current personalized healthcare trends and challenges by first undertaking a systemic review of literature. There is a need for a system architecture to combine big data and IoT for personalized healthcare. The aim of this paper is to propose such an architecture to support big data analytics using POC test results of an individual.

Recent studies have shown evidence that by using data analytics of various forms of patients' health data collected over a period, disease risks and chronic conditions can be diagnosed and self-managed more effectively [8], [9]. In addition, IoT based POC devices can provide screening data including patients' genomic information [10]. With more and more use of electronic health record (EHR) technologies and wearable devices, standard medical practice is moving towards effectively integrating various forms of healthcare screening data and personal data to achieve knowledge discovery from the accumulation of such big data [11]–[13]. By applying data mining techniques with big data, undiscovered clinical symptoms could be extracted and predicted to trigger early intervention strategies [14]. In particular, it can benefit patients with chronic health issues with personalized therapies. With IoT health gadgets and POC devices of today, there is associated convenience of timely personal health information and more affordable healthcare services. However, the use of big data in several contexts is not exploited to the full potential [15]. In addition, several security and privacy concerns require attention in pervasive and personalised health to use big data analytics effectively [16]–[20].

Detecting patterns from high volumes of health data for assessing health risks and disease requires an appropriate big data infrastructure. Such an architecture should support big data analytics where health data gets processed intelligently deriving meaningful health patterns thereby capable of providing useful insight for improving personalized healthcare [21], [22]. Many key aspects of big data such as managing the 5 V's (volume, variety, velocity, veracity, and value) for healthcare applications pose a major challenge [13]. While the use of big data in some contexts of healthcare has been demonstrated to be effective for personalized patient care and wellbeing, there is a need for the technological infrastructure to enhance the big data analytics support integrated with IoT [23], [24]

We propose an architecture that supports big data analytics using POC test results of an individual and provides opportunities for personalized healthcare for enhancing individual wellbeing. Various machine learning algorithms for combining POC test results to provide personalized data insights are considered. The key contribution of the proposed architecture would be to facilitate an integrated and self-managed healthcare as well as remote patient care. Overall, this work takes a positive step in emphasizing the role of big data analytics and computation in healthcare, and their potential in personalized healthcare and biomedical discovery. The rest of the paper is organized as follows. Section 2 provides a systematic analysis of literature related to this topic and highlights the need for this study. In section 3, we propose an IoT and big data architecture for personalized healthcare. In section 4, using big data analytics framework, we provide the commonly used data mining algorithms that we suitably modify for processing health data in rendering personalized outcomes in healthcare. Section 5 presents an evaluation of the proposed system and its limitations. Finally, section 6 gives the conclusion and future work in this direction.

2. LITERATURE REVIEW

A review of literature shows that IoT and big data are some of the terms associated with healthcare more recently. We conducted a systematic research with search keywords on studies that include "IoT", "big data", "big data analytics" related to "healthcare" as well as "personalized healthcare". We categorized each article found in literature based on the key words and a combination of them. Our literature search using these terms resulted in articles shown in Table 1.

Table 1. Cloud, IoT, and social media applications

References	Application	IoT	Big Data	Analytics	Personalisation
[2], [25]	Monitoring	✓	X	X	X
[26], [27]	Wearable	✓	X	X	X
[28], [29]	Diagnosis	✓	X	X	X
[30], [31]	Outbreak control	✓	X	X	X
[32], [33]	Prediction	X	✓	X	X
[34], [35]	Clinical	X	✓	✓	X
[36], [37]	Diagnosis	X	✓	✓	X
[38], [39]	Assessment	X	✓	✓	✓
[40], [41]	Management	X	✓	✓	✓
[42], [43]	Records	✓	✓	✓	X
[44], [45]	Detection, Diagnosis	✓	✓	✓	✓
[46], [47]	Security	✓	✓	X	X

IoT and big data analytics are usually studied independently in healthcare, a combination of these in personalized healthcare is minimal. In addition, there are few works in the literature that addressed "IoT", "big data" and "analytics" in the context of "personalised healthcare", these works were limited in scope to provide personalised view of an existing patient's health records. There is lack of studies that can offer personalisated healthcare services for any health-conscious IoT user with a preventive approach. There is a need to conduct more research to improve the personalized healthcare system for common man to proactively capitalise on recently popular industry advancements such as IoT, big data, and analytics. Keeping this in mind, we first propose an IoT and big data architecture for personalized healthcare. Then we present our proposal of a big data analytics framework using three commonly employed machine learning algorithms modified to deal with health data of any user. Hence, our proposed architecture caters to all types of users with different health assessment requirements and would pave way for the empowerment of a person's health with an effective use of latest technologies in IoT, big data and analytics [29], [35].

On the other hand pervasive health has seen much growth in the domain of healthcare. In this context, the work in [48] presented a thorough analysis that included parameters of environment type, service type, context data type, and the context data source. The environment type parameter shows the environment where the system has been developed, and hence existing methods can be classified into four types. The first is home, where healthcare services are provided in the smart house environment of the patient [25]. The second is medical facility, where services ar provided in smart medical facility environment such as hospital or clinic [49], [50]. In the third type, called hybrid, healthcare services can be managed at both the hospital and home environments by using a variety of remote and direct tools [51]–[53]. The last type is called mobile, where smart services are provided using the mobile phones remotely [54]. In another type of analysis, various services provided to the user can be identified, including monitoring, emergency management, assisted living, medical assistance, and pervasive access to health information.

3. PERSONALIZED SYSTEM ARCHITECTURE

Figure 1 presents a system architecture that integrates IoT and big data for achieving a personalised healthcare service with three main phases including acquisition, processing and analytics. The proposed system has three phases: acquisition, processing, and analytics and visualization. This multilayered architecture provides flexibility for choosing the proper technology to implement components within layers, and allows using combinations of technologies with the support information exchange standards.

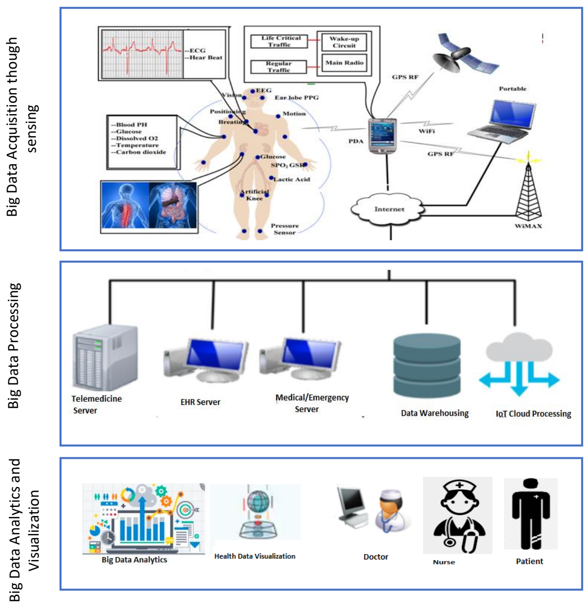

Figure 1. IoT and big data system architecture for healthcare

– Big data acquisition through sensing: In this phase, all the health-related data are acquired through different sensing IoT devices. For personalised healthcare, a typical scenario is when a patient's health related data is collected using wireless body area network (WBAN). This comprises of wearable sensors that can sense health parameters such as heart rate, pulse or blood pressure data continuously, an information procurement unit that organises these health data and the administration layer to broadcast the big data.
– Big data processing: In this phase, the acquired big data from different sensing devices in phase 1 is stored and integrated with different servers via the cloud and processed for further in-depth analysis in the next phase. Other healthcare data related to the patient's health data are integrated using different high-end computing infrastructures and big data processing.
– Big data analytics and visualization: This phase provides a user-friendly way to monitor and interpret the patient's big data processed during phase 2 using machine intelligence. Several data mining algorithms are employed to arrive at health trends for determining risks and plans for future follow-up. Not only doctors, but also patients and potential users who monitor their health proactively will be able to get insights into their health status through the visualization. An interactive data visualisation can highlight the trends and outliers thereby notifying the patients on the results of big data analytics.

4. PERSONALISED ANALYTICS HEALTHCARE SYSTEM

In the past decade, patient-centered healthcare has been given thrust over traditional disease-centered approach in areas such as clinical tests, medical expertise and evidence-based research [38], [40], [55]. Patient-centered healthcare promotes empowerment of patients to actively participate in their own health related monitoring and provides services with a focus on personalizing individual requirements, contexts, and preferences. Such a personalized healthcare is not only cost-saving but also improves the quality of disease management and prevention. Today, several IoT gadgets including wearables for various health related purposes, such as clinical testing, therapeutic and self-monitoring generate an individual's health-related big data [15]. Big data analytics could improve the accuracy of disease risk prediction and diagnosis with timely healthcare and wellness plan for an individual.

Big data collected from such IoT and POC devices and stored in electronic medical records, patient profiles, daily activity and historical records of an individual can be effectively analysed for developing a personalized health profile to identify any disease risk and a follow-up wellness plan [1], [56]. In addition, there is also a need due to compelling requirements of a cost-effective healthcare intervention strategy in using data analytics as governments are spending billions of dollars on unnecessary hospital admissions with overuse of emergency departments. Data analytics can be used to identify patients at high-risk so that timely care plans and treatments could be given to patients before it is too late. Hence, data analytics could help reduce the number of unnecessary hospitalizations as well as assist in monitoring the cost reductions and performance of such innovative strategies. For example, health care providers and governments could use data analytics with novel advanced predictive models to even forecast the number of days a patient is expected to be in a hospital and the cost impact.

This section shows how big data analytics can leverage on the ICT advancements for realising a personalized healthcare solution of the future. Figure 2 provides a big data framework and the components. As shown in the figure, big data analytics, employing different data mining algorithms should be customized to match with the context of health data for establishing a more accurate correlation between the principal and their supporting attributes. Typically, health data could be in different formats and with nominal/discrete attributes, missing values are quite common. We describe popular data mining algorithms that can be effectively adapted for personalised healthcare catering to different IoT data formats and big data streaming.

4.1. Decision tree algorithm

Clinical data analysis could be performed using a decision tree (DT) when a patient's health problem is uncertain to diagnose with complex choices or the outcomes of treatment are uncertain. When such choices or outcomes that determine the wellness or level of sickness of an individual are significant, a DT algorithm can be used to assign scoring values to the different states of the person's health. Several DT algorithms have advanced and recently been applied effectively in healthcare. A DT algorithm is used to partition data in the form of a tree where branches are represented by values of a particular selected health attribute. Any health data not in nominal/discrete format are required to be converted using discretization at each node of the DT where the attribute is selected. This is required for classification of data and the class value of a leaf node is then statistically determined. We provide a simple DT algorithm where an optimal tree is formed by selecting a feature that gives the highest information gain (IG) and this is subsequently used in subdivision of health data at each node. For making decisions, each leaf required for test case instance is directly evaluated by mining through the training data set. DT algorithm steps are listed as:

– Step 1. (DT initialization): Set a minimum size for the sample dataset from which personalised health inferences are made.
– Step 2. (DT direction): Select a feature among the list of features from a test dataset instance with the highest IG. This describes the data contained in the current leaf (the end node of the branch). Initial selection of features is from the entire training set.
– Step 3. (DT propagation): Select the subset of test data instances based on the best feature value, keeping the shorter branch. Repeat recursively from step 2 with a check in each iteration if the number of instances in the new leaf is no less than the minimum size set in step 1.
– Step 4. (DT Generalization): Evaluate the biggest class in the leaf comparing with the test data instance relying on class prior probabilities at the root. Update classification accuracy for the test dataset as the mean number of successes. Repeat from step 2 until all test data instances are processed.

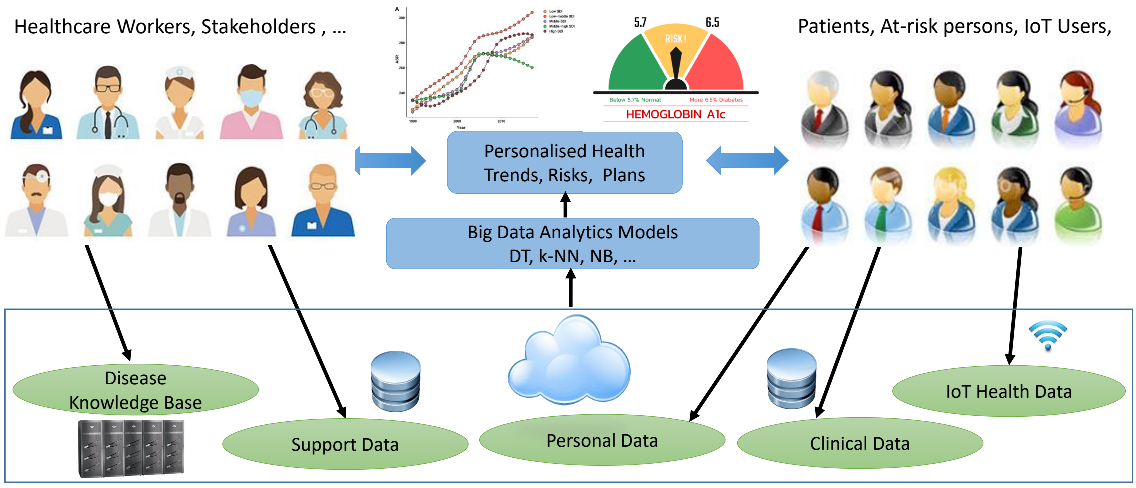

Figure 2. Big data analytics framework for personalised healthcare

In step 2, while determining the 'DT direction', the feature selection is based on IG which measures the mutual information between any two features. In the context of health data, one of the attributes is designated as the class that has categories such as "at risk" or "no risk" for a particular disease. It could even be adapted to have many risk levels for multiple personalized follow-up actions associated with the individual patient. IG is a probability function which can be estimated from frequencies indicating how the class is influenced by a chosen feature. The mathematical formula for IG for each class c uses Entropy H representing the average information contained in a feature f and is given by (1):

$$IG(c, f) = H(c) + H(f) - H(c \times f) \tag{1}$$

where x denotes the Cartesian product of data value sets. The formula for Entropy for any feature f is given (2):

$$H(f) = -\sum P(f = v).log_2 P(f = v_i) \tag{2}$$

where the values in a data set is represented by $v_i, i \in \{1, 2, \ldots, n\}$, P stands for probability, and $log_2 P(f = v_i)$ is the morsel of information with a particular value of feature f present in a subset of data values.

4.2. K-nearest neighbours (k-NN) algorithm

Several algorithms for finding the nearest neighbours in classification problem are based on the popularly adapted k-NN technique [57]. We make use of the Hamming loss distance function d between two instances of health data set of attributes. IG is employed as a weight setting in the distance function to reduce the influence of irrelevant attributes. This is essential since health data collected from IoT devices for healthcare have a large set of attributes and by employing IG in a k-NN algorithm, the most influencing attributes in determining the risk factors ensures efficacy. k-NN algorithm steps:

- Step 1. (k-NN initialization): Calculate IG for each feature as normalized weights in the Hamming loss distance function d. This is used to set a parameter k which represents the number of closest data instances forming the nearest neighbourhood of any test data instance.
- Step 2. (k-NN sampling): Find k closest data instances to a test data instance for assigning to a class. The distance measures are used to set the radius of the neighbourhood.
- Step 3. (k-NN classification): Classify the test data instance to the closest class based on the mean distance statistic that gives the highest feature representation in the neighbourhood. Repeat from step 2 until all test data instances are processed.

The formula for finding the k-NN distance function is given by:

$$d(p^1, p^2) = \sum_{i=1}^{n} g_i.\delta(v_i^1, v_i^2)$$

where

$$g_i = \frac{IG_i}{\sum_{i=1}^{n} IG_i}, \delta = 0$$

when v$_i^1 = v_i^2, and\delta = 1 when v_i^1 \neq v_i^2. Where the distance d between two data points$p^1 and p^2 in a data instance p is determined with g_i as the feature weights. With feature index $i = \{1, 2, \ldots, n\}$, the information gain factor g_i is set using IG for the set of feature values v in data instances, and δ is the Kronecker's symbol to express incidence of two features.

4.3. Naive Bayesian (NB) algorithm

Naive Bayes is a classification method using simple probability based on conditional independence of features by applying Bayes' theorem [58]. NB classifiers can be trained efficiently with smaller training data set and are highly scalable. For evidence-based decision making in healthcare, with a given evidence x, the NB classifier should select a class c_i such that the posterior probability is the highest as shown:

$$P(c_i|x) > P(c_j|x), \forall i \neq j$$

According to the classic formula attributed to Bayes' theorem, we have

$$P(c|x).P(x) = P(x|c).P(c)$$

where the conditional independence is given as

$$P(x|c) = P(x_1|c).P(x_2|c).\ldots.P(x_n|c)$$

where x_i are the features of x, and $i = \{1, 2, \ldots, n\}$.

5. EVALUATION AND LIMITATIONS

Recently, early diagnosis of diseases and the health-related risks in patients have been given prime importance towards providing timely follow-up treatment and personalized healthcare services. The evaluation of proposed system considers various challenging factors such as privacy, performance, volume, scalability, modelling and storage. The classification algorithms considered in previous section, namely DT, k-NN and NB have been studied for the early diagnosis of critical diseases such as the risk of cardiovascular disease and diabetes [14]. There are similarities among these classifiers where each algorithm's prediction is achieved by the top-ranking attribute or having the highest weight or probability. A review of literature shows capabilities of big data analytics through several studies comparing the performance of different variants of such supervised machine learning algorithms for disease prediction [21], [59]. In summary, with our proposed framework we postulate an adaptive use of the above mentioned machine learning algorithms for performing big data analytics of health data to enhance personalized healthcare. In addition, more research in the topic of personalized healthcare using different techniques, such as IoT, big data and big data analytics is required in a combined effort. Figure 3 shows the challenges arise from the integration of IoT and big data for personalized healthcare. The main challenges in big data analytics include data volume, performance metrics, privacy and security concerns, modeling methods and capabilities, and final data storage and processing. On the other hand, IoT challenges include security issues, connectivity and communication, standards and regulations, complexity and interoperability, big data storage and processing, and finally, human in loop components. When these two are integrated, common concerns such as big data, scalability, storage and human in loop, will be more complex to handle, since they will be addressed from the two perspectives. In addition, new challenges will arise, such as interoperability and governance. Therefore, it is essential to identify directions arising in this domain. Follwoing, we list the most prevailing current trends, open issues and future research direction:

Figure 3. IoT and big data analytics integration for personalized healthcare

- Personlised data sets: applying the framework to personalised health datasets by combining supervised training and deep learning approaches.
- Standardization: achieving application-specific standards to enable patients to communicate effectively with healthcare entity using clinical terms to understand the details of the situation.
- Wearable technologies: integrate wearable technology into IoT cased healthcare systems, and provide common guidelines for these gadgets so that they can be more effective in this context.
- The integration of several technologies, such as wireless, mobile, wearable devices, and IoT has led to the creation of new paradigms such as wearable internet of things (WIoT). This can have several potential applications and there is still lack of research on this area.
- Integrating personalized healthcare systems with biometric identity systems in order to provide smart environment for identity management as well as personalized services.
- Security solutions that takes into consideration personalized healthcare system parameters requires further investigations, in particular, taking into considerations several design parameters that are sensitive for both security as well as personalized systems, such as computational overhead, bandwidth requirements, and real time operation [60], [61].

6. CONCLUSION AND FUTURE WORK

There is a growing complexity of healthcare data with the development of IoT health gadgets and wearable/tracking devices that aid in clinical tests, therapeutics and fitness checks and personalized and timely follow-up actions. This paper presented the current trends in personalized healthcare and proposed a big data analytics framework for healthcare in adapting popular machine learning algorithms such as DT, k-NN and NB for enhancing the inferences on health risks of an individual. We provided the details of the algorithmic steps for each of these machine learning approaches by adapting them suitably for health care context, and finally, identified open issues and potential areas for future research.

Since several approaches adopted cloud based environment, some limitations may arise in real-time and delay sensitive interactive applications, hence Fog and Edge computing can be good alternatives in this context as these paradigms incorporate a large network of computational and storage resources and are also able to execute real-time or interactive applications. This is one of the current growing research trends in this area, which needs more work. On the other hand, while several healthcare applications exist, the main focus has been limited toward a few limited illnesses types such as heart disease and diabetes, as well as particular contextual information, like blood pressure and heart beat. As a result, diagnosis and management of new types of diseases require more efforts in leveraging a comprehensive set of contextual information. Finally, one of the growing paradigms in eHealth is Blockchain, however, it has not been adopted for pervasive, personalized and context aware systems. This may create several opportunities, in particular, when combined with Edge, Fog, and mobile computing. Finally, there is a need for flexible applications in this domain that can provide reliable, real time, and interactive solutions while having the ability to customize the service based on the need, resources, medical situation, security requirements, and many other relevant factors.

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