An Architecture of IoT-Aware Healthcare Smart System by Leveraging Machine Learning

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Abstract: *In a healthcare environment, Internet of Things (IoT) sensors' devices are integrated to help patients and Physicians remotely. Physicians interconnect with their patients to monitor their current health situation. However, a considerable number of real-time patient data produced by IoT devices makes healthcare data intensive. It is challenging to mine valuable features from real-time data traffic for efficient recommendations to patients. Thus, an intelligent healthcare system must analyze the real-time health conditions and predict suitable drugs based on the diseases' symptoms. In this paper, an IoT architectural model for smart health care is proposed. This model utilizes clustering and Machine Learning (ML) techniques to predict suitable drugs for patients. First, Spark is used to manage the collected data on distributed servers. Second, the K-means clustering algorithm is used for disease-based categorization to make groups of the related features. Third, predictor techniques, i.e., Naïve Bayes and random forest, are used to classify suitable drugs for the patients. Two standard Unique Client Identifier (UCI) machine learning datasets have been conducted in the experiments. The first dataset consists of different types of thyroid diseases, while the second dataset contains drugs with recommended medicines. The experimental results depict that the performance, i.e., the accuracy of the proposed model, is superior in predicting the suitable drugs for patients, by which it provides a highly effective delivery healthcare service in IoT. Random Forest correctly classified 99.23% instances while Naive Bayes results are 95.52%.*

Keywords: *IoT, machine learning, big data, cloud computing, healthcare.*

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1. Introduction

Internet of Things (IoT) is forthcoming technology, which refers to the designing the internet-connected objects (things) such as heart monitoring, air-conditioner, fridge, wrist band, and umbrella. It enables devices to collect and exc0068ange data without human interaction. It addresses the controllability, visibility, and traceability of smart devices [7, 31]. The number of IoT devices is increasing dramatically. Based on an estimation that CISCO had created, around 50 billion devices will be connected to the internet by the end of this year, which constructs a large dense IoT environment [10]. These devices will be deployed to different application domains such as environmental monitoring [32], healthcare monitoring [22], production management [38], food chain management [30], transportation [14], smart homes and smart cities [47], social communication [43] and Vehicular Ad hoc Network (VANET) [13]. Although IoT emerges extensively still it is in the beginning stage due to various issues such as scalability, widely accepted standards, heterogeneity, integration in existing IT infrastructure [9]. Thus, the IoT has gained a fair share of attention from industries, developers, and researchers. In this regard, many different service applications have been introduced and developed. Among these applications is the healthcare system, which attracts many researchers due to outdoor and in-hospital patient monitoring through IoT.

Recently, there has been a noticeable increment in the number of wearable devices used to monitor patients' health. Therefore, this has a long-term impression on reporting health and clinical services to the patient's physiological information. Besides, this progress helps the supply of more details regarding the physical examination and daily routine. The IoT wearable things are connected to the personal body throughout the healthcare period to record various health metrics like heart rate, blood pressure, respiratory rate, blood circulation level, blood glucose level, and body temperature [36]. For example, Diverse sensors are attached to the human body for collecting detailed patient information. The location of sensors along the body is critical to better patient data collection [45].

In healthcare IoT, physical objects work based on embedded sensors networks and technology of Radio

Frequency Identifier (RFID) tags, which play vital roles in establishing an IoT environment. The unique identifiers, i.e., RFID, can identify these physical objects over the internet. Then the data can be collected from them [8]. Thus, by using IoT devices, the outdoor patients can be observed uninterruptedly and allow the acute disease to be detected at the right time so appropriate therapy can be taken and prescribed. For example, various sensors are attached to the human body for collecting detailed patient information. The location of sensors along the body is critical to better patient data collection [14].

Accordingly, IoT gives rise to several health care systems, including remote health monitoring, home treatment and medication by the health care service system. For example, based on the patient health data collected from the warm sensors, a health care system can better diagnose an indoor or outdoor hospital. In addition, it can recommend suitable drugs based on the patients' symptoms [14, 5]. Hence, different IoT technologies for healthcare such as implanted, environmental, and wearable sensors, devices, and diagnostic have assisted the development of new services and applications used especially in remote healthcare systems, such as providing the treatment according to the updates [4, 34]. In IoT, the data are collected from IoT-based wearable devices. Due to large volumes of resources, a large volume of big data needs to be analyzed to discover hidden information. Machine learning techniques are one of the most used for processing such a massive volume of data [19].

Currently, mobile healthcare monitoring got more attention. The nanofabrication of embedding devices, emerging micro, self-organizing, and unobtrusive wearable sensors can track affective states of the patients, electrocardiography (ECG), insulin level, pulse, blood gas, blood pressure, and so on. The wireless network can track the patient's activities, movements, and communication over assistive ability, extensive indicators of a critical health problem. The collected data are used to visualize user behavior, further used for health care [44]. It is efficiently combining spatially and temporally different multi-source information. It is used to gain valuable intuition and information from these foundations. The interoperability still has a significant load on the developers of IoT structures. These devices are varied in underlying protocols, data arrangements, and technologies. Also, due to the nonappearance of acceptable global standards, interoperability leftovers deficient. We can use this to suggest drugs and side effects for diverse symptoms gathered from mixed IoT devices.

Machine learning techniques in Electronic Health Records (EHRs) can produce actionable perceptions from refining patient risk systems. It is used to predict the inception of disease to streamline hospital processes [3]. Machine learning algorithms are used to predict chronic disease in societies. A new Convolutional Neural Network is proposed using Multimodal Disease Risk Prediction (CNN-MDRP) based on structured and unstructured data from the hospital. The latent factor model is used to rebuild the misplaced data to overwhelm the trouble of partial data [22]. The IoT sensor devices in the healthcare monitoring system generate a massive amount of data regularly. A scalable three-tier architecture is proposed for wearable sensors to manage and process this enormous volume of data to target the problem. The tier-1 emphasizes gathering data from IoT devices. Tier-2 uses Apache HBase for storing the massive capacity of data in the cloud. In addition, Tier-3 uses Apache Mahout for emerging the logistic regression-based prediction model for heart diseases [19].

In this paper, an architectural IoT model is used using a machine learning approach for the smart health care system. The doctor and patient communication through heterogeneous IoT devices. The wearable sensors IoT devices collect disease symptoms from patients and store them in the cloud. The doctor also stores the medicine details according to different symptoms on the cloud. The Spark is used to manage the distributed servers for big data, and the k-means cluster algorithm is used to predict the suitable medicine according to the symptoms of the patient's disease.

The main contributions of the paper are:

1. The spark method simulates the management and supervision of the collected real-time data on remote servers.
2. The K-means clustering technique is used to group the related features mined from the collected data. It helps to categorize the patients' data more efficiently for the given medicines.
3. The machine learning approach is used to classify the patients according to their diseases and recommend prescriptions.

The files used in the experiments are available for download on the GitHub link: https://github.com/hamzeh1984/SmartHealthcare

The rest of this paper is organized as the following: The literature review is given in section 2. The proposed methodology is detailed in section 3. The results and discussion are illustrated in section 4. Finally, the conclusion is given in section 5.

2. Literature Review

Healthcare tracking device of indoor position control has a long tradition, but outdoor location management struggles from location recognition precision. Such devices are now reliable due to the massive usage of smartphones , a sensor center with accelerometers, a gyroscope, and a GPS tracker that can be used for position monitoring using a gadget that users can happily carry the user-friendliness of such framework [37]. With the escalation in the implementation of the smart healthcare system's IoT technologies, incidences of privacy disclosure often upswing, it becomes essential to formulate a safe, smart healthcare system. Stable healthcare system requirement is focused on a crucial survey and this year's Thales India Data Threat Study [40]. The study exposes the percentage of data attacks in previous years and demonstrates the need to tighten patient data protection regulations. Consequently, the safe, smart healthcare infrastructure was identified as a high-priority target to enhance society's sustainability [1].

2.1. Machine Learning

The machine learning models can be used for prediction purposes to identify accurate IoT devices. In [27], the author used a machine learning approach to network traffic to identify IoT devices. The gathered data is labelled from nine different IoT smart objects and smartphones to analyze the classifier. The multi-stage meta-classifier is trained using the supervised algorithm. First, the classifier can differentiate concerning data produced by IoT and non-IoT objects. Second, every IoT device is related to a particular IoT device class. In [42], the author used machine learning algorithms for saving energy on coffee machines located. The proposed approach used ARIMA predictive learning algorithms to report the usage patterns of home-used appliances. Here, the goal of predictive models is to use these appliances back next week to manage them more effectively. The missing QoS values in IoT is a big issue, and it can be estimated through a machine learning approach. In [21], the Kernel Least Mean Square algorithm (KLMS) algorithm approach is used for predicting missing QoS values in industrial IoT (Iao). The Pearson Correlation Coefficient (PCC) is presented to estimate the appropriate QoS in similar service operators and web management objects. Then, the KLMS is used to examine the unknown interactions between all the known QoS values and conforming QoS values with the maximum comparisons. Getting clear implications from raw sensors' data is a challenging task in a noisy and complicated environment.

2.2. Deep Learning

Deep Learning is the best-assuring methodology for overwhelming this challenge to achieve more reliable inferences. In [20], the albeit preliminary measurement research of deep learning models, same as convolutional neural networks, are used in descriptive mobile devices and embedded systems. The proposed study aims to develop knowledge of the functioning features and resource necessities for deep learning models to identify classes of context and behavior. In [29], an end-to-end security approach is proposed to provide mobile healthcare using IoT. The recommended methodology contains a safe and well-organized user verification and approval established on the DTLS handshake procedure. It is used to provide robust mobility using connected smart gateways. The smart gateway works as a middle processing layer between IoT objects and sensors, and cloud services. The sensors continuously generate a huge amount of data and store it in cloud computing services for further analysis. In [24] a new MapReduce-based logistic regression is proposed to analyze the enormous quantity of sensors' data. Apache Mahout contains scalable logistic regression to practice huge information in scattered routines. The Apache Mahout with Hadoop Distributed File System is used to manage the sensors' collected data produced using wearable medical devices. Interoperability is a big issue in IoT amongst smart objects to connect and impart mixed devices to frame a financially savvy and straightforward to execute the network. The interoperability based on low cost amongst IoT devices is an energetic feature for smart devices [26]. It resolves the complication of society's infrastructure, decreases the expense of buildings, and assists in making distinct infrastructure. The IoT network upturns the workflow effectiveness and links smart devices from anyplace to everywhere based on heterogeneous IoT smart objects [41].

Each day, enormous quantities of data are produced, creating a volume that is difficult to evaluate. When dealing with big datasets, it is prudent to use techniques such as feature selection. Among the programs that provide this capability, Weka is one of the most popular, but its implementations suffer with big datasets, necessitating lengthy processing times. Parallel processing may help ease this issue by enabling people to work successfully with Big Data. Multithreading and distributed programming may be used to efficiently leverage the computing capacity of multicore computers, assisting in the solution of bigger problems. Both of these methods significantly accelerate the process of feature selection, enabling users to deal with bigger datasets. This work focuses on the reimplementation of four prominent feature selection algorithms featured in Weka. For each method, multithreaded implementations not previously available in Weka as well as parallel Spark versions were created. Experimental findings from real-world datasets demonstrate that the updated versions significantly reduce processing times [13, 18].

2.3. Heterogeneous Iot Devices

The IoT fundamental concept is the connection of objects through Communications channels, with things including radio frequency identification tags, sensors, actuators, and cell phones as examples of devices. IoT may be used extensively in a variety of areas, including logistics, medical, and power, throughout the household, neighborhood, city, and nation. The expanded concept of IoT is how to find and use IoT devices and the services they offer for a variety of industrial and commercial applications. To implement these concepts, many critical IoT technologies must be developed, including generic IoT device recognition, dynamic data incorporation, analysis, and transfer for IoT devices. Heterogeneous device services produced by a variety of devices in a variety of situations make it difficult for users to use device services effectively and properly. This is a significant obstacle to the growth of the Internet of Things [45].

This article discusses issues that arise during device detection and interaction [45]. It creates a basis for user interoperability that enables device users to communicate with heterogeneous systems of varying configurations using a consistent vocabulary and semantics. Within this framework, a novel separation technique is suggested; a device representation approach for actual, common, and virtual devices is developed; and a device transformability model is given to ensure that device syntax and semantics are properly transformed. To show UIF's validity, a UIF prototype is built, and various experiment techniques are compared to decide which should be used as meaningful actualization access to technologies in network discovery for smart phones and also in generic device sharing for smartphone suppliers [6, 25].

2.4. IoT-Aware Smart HealthCare

Smart systems to support and improve healthcare and biomedical processes are being developed due to recent advances in the design of IoT technologies [23]. Only a few possible examples include automatic identification and tracking of people and biomedical devices in hospitals, correct drug-patient associations, and real-time monitoring of patient's physiological parameters for early detection of clinical deterioration. The compelling forward steps in developing IoT enabling solutions have sparked the emergence of novel and fascinating applications in recent years [1]. This evolutionary trend is being led by, among other things, Radio Frequency Identification, Wireless Sensor Networks, and smart mobile technologies. In response to this trend, this paper proposes a new IoT-aware smart architecture for automatic monitoring and tracking of patients, personnel, and biomedical devices within hospitals and nursing institutes [39]. In` keeping with the IoT vision, the authors proposed a Smart Hospital System that combines various, yet complementary, technologies and smart mobile devices that communicate with one another via a network infrastructure [48]. Data is collected and delivered to a control center, where it is made available to both local and remote users via an advanced monitoring application [4].

3. Proposed Scheme: IoT Architectural Model for Smart Healthcare using Machine Learning

The IoT devices are used for the interaction of patients and doctors. Cloud services are helping healthcare users to communicate with each other. These devices are the medium of communication and a way to interact with each other. The sensors help the patients to send the data to the healthcare systems. This data may include different types of information like the temperature, blood glucose levels, heartbeat rate, and so on. When a doctor checks different patients, he can save the data in the computer, which can be used for case-based reasoning like an expert system can be developed or the machine learning techniques can be applied to that data. In this mixture of networking, application models, standards, and protocols, parties looking to deliver new services are rapidly forced to incorporate a wide range of various technology. By employing a standard interface on top of a virtual device abstraction, our proposal will accommodate a wide range of devices and link heterogeneous devices together so they can interoperate. We highlight the viability of our architecture with a real-life implementation made up of constrained devices that support open standards [41].

The machine learning approach is used to predict suitable medicines according to the doctor's prescription. The IoT architecture model using machine learning is proposed for the smart healthcare domain, as shown in Figure 1. The IoT is a mixture of discrete and smart devices that have abilities and are acknowledged through RFID technology. The IoT network connects devices like smart devices that can detect other devices rendering the atmosphere's behavior. It reports the traceability, visibility, and controllability of smart objects [2].

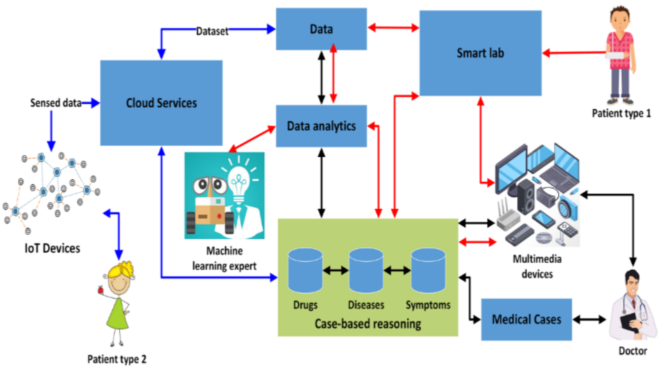

Figure 1. IoT architectural model using machine learning for smart and personalized healthcare.

The smart health cloud gives interoperability to information composed of IoT. The sensor uses the network API to check the data in a sensor network unit. The data transfers to the Software as a Service (SaaS) division. The SaaS is a software allocation model which gives third-party requests available to patients and doctors over the internet. The SaaS is used to get patients' data from IoT sensors' network and accumulation on the cloud, accessible for supplementary treating. This data contains disease symptoms gathered from heterogeneous IoT sensors over the cloud. The data consists of diseases' names, which are used as keywords [32].

Patient due to illness or disease needs medicine prescribed by the concerned doctor. The patient and doctor need to know the combined impact of dosage of several medicines earlier. We used a machine learning approach to train the system about the patients' diseases, symptoms, and doctor's prescriptions accordingly. According to the doctor, the system reads patients' diseases an input and then replies to the required medicine with a prescription. Here, the IoT combines IoT sensors, patients, doctors, and treatment, as shown in Figure 2. These devices are sensors based, which work in mobility. The symptoms check the patient. Then the expert system searches the medical history of the patient if available. A machine learning approach trains the system. It searches for the required medicine according to the symptoms of the disease. The IoT and the expert system works as middleware. The treatment can be aregular or emergency case. The health box can be used for the treatment of patients. It works on sensors and alarms at a specific time to patients for medicine. It also gives helpful medical tips to patients daily. It directly informs the doctor whether the patient is taking medicine regularly or not.

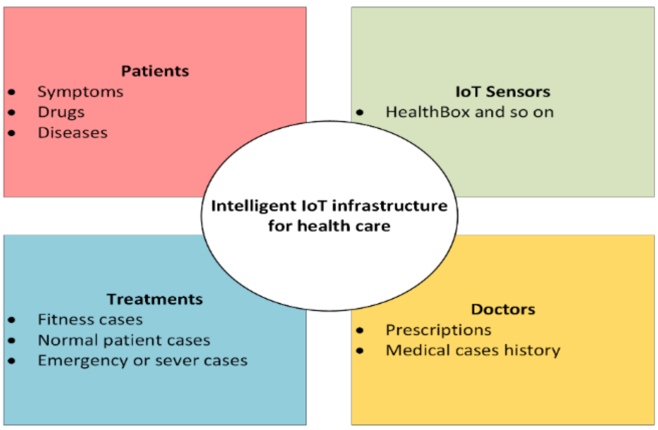

Figure 2. IoT architecture scenario for smart healthcare.

3.1. Data Processing, Intelligence, and Pervasiveness

The doctors and medical assistants can use healthcare-related data to provide the best care for patients with the help of an intelligent and pervasive system. Data dispensation involves storing patients' data in the database and the dataset gathered from the patients. Medical cases are stored in the database for the implication using a case-based reasoning approach. The knowledge base collected in these steps gives the medical assistants and medical students the facility to learn medical cases with ease with the help of medical informatics. It also helps the persons to take precautionary measures as well as guidance for fitness [28].

The cloud services are utilized to spare and recover the information from every one of the stakeholders. The information gathered utilizing the IoT devices of the patients is utilized for the upkeep of the recorded confirmations. Historical data is utilized to create investigation and perception. The profound learning-based arrangement is created to examine the information [12]. The patients are instructed and provided with sensor embed devices for monitoring their daily routine for health analytics. The collected periodic data from the sensor is sent using the sensor's network application programmer interface to some cloud-based storage.

Furthermore, data is passed through an automated case-based reasoner for the doctor to understand better the patient's history and current scenario for an optimal prescription. Then prescription is further examined based on drug ingredients and their side effects on the specific patient using periodic historical learning of the patient's condition. Ambient inferencing services are utilized for gaining better prediction through simulating data from ubiquitous computing devices.

3.2. Smart Lab Working

The idea of doctHERs means a phenomenon related to the working of the medical doctors, which is focused on female doctors and is being practiced in some specific countries. The patients must come to the remote clinic for the medical checkups, and the analysis is only done; the patient is present in the clinic. The availability of the 3G and 4G network facilities allows the patient to connect with the doctor directly. All the financial and medical records of patients can be kept using cloud services. Medically related sensors enable the user to provide the latest and historical data to the doctor for analysis. It creates freedom for the patient to connect to the doctor directly. Women are promoting now through outreach, as it is a huge step to move towards leadership. Though it is little progress, still it is a substantial way to fix the breach between trained and practicing women doctors, nurses, and community health workers.

The concept of the doc HERs program is to remotely connect different professional female doctors having a cultural barrier with patients. These female doctors have discontinued practicing healthcare due to their socio-cultural or family restrictions. The female doctor barriers reasons include underserved communities are after marriage becoming full-time housewife, family not comfortable with duty timings, and not liking the concept of working women [16]. In developing countries, many females are found other than males taking medical training in medical school.

These females are discouraged from becoming full-time professional doctors. At the same time, the growth of the gap between the number of doctors and patients is increasing broadly.

Meanwhile, the government is busy developing extended policies to intake female doctors using online sources for connecting them with the patients under the remote platform in rural and urban areas. Such innovations are creating employment possibilities for women with the possibility of enhancing healthcare centers. The medical centers have other staff like nurses, computer operators, and admin to support patients' information and test history. They are responsible for updating lady doctors with the schedule and information concerning patients' treatment and medical advice. Doctors are virtually supervising the nurses for all treatments. The program diagnostic system follows peripheral tools to support doctors in the vital check signs of the patients remotely. As per need bases, healthcare centers are equipped with equipment and professionals for additional support.

The problems in the idea of doctHERs are collecting medical information, sending it to the doctors for a further prescription, and using that data. The data is digitally collected, but it is not being used for further cases investigation. Mainly the developmental level issues are there. The data collection is performed at the clinic level without a medical doctor and the dissemination of that data. The medical student can be lean easily through electronically the help of ontologies as it provides the concepts and relationships. Semantic web languages provide relativity, interoperability, and reason-based formation of ontology, which, in this case, helps the system gather diverse information in the shape of a collaborative way against medicine drugs. For this purpose, medical vocabulary mapping is devised, which will get shaped into a new ontology [17], leading to the hierarchal related taxonomy of medical drugs against their side effects via multiple categorizations.

3.3. Real-Time Patient Monitoring

There is a jump to digital health from digital therapeutics to wearables and ingestible devices connected through sensors. The IoT became a broader usage of digital healthcare in the eye of investors. To identify and diagnose different diseases in patients more efficiently in real-time, IoT became the interest of researchers to deploy new applications. Many researchers focused on sensors network to deploy in hospitals to monitor the patient's record in real-time more efficiently far from their homes, while some focused on clinical-grade wearables to track the patient data [15]. The doctor can analyze the patient's condition remotely and suggest a prescription based on their current condition while monitoring through sensors. IoT is a significant innovation for the current era of automation, and remote treatment has become possible [23]. The issues having severity or no need for surgical expertise have now been controlled based on remote monitoring and diagnostics. They keep track continuously of the patient's condition and notifies the doctor or concern health department if immediate attention is required without involving the patient to interact. The intelligence incorporated in the system compares the drugs and symptoms for helping doctors in prescribing patient dosage effectively. Patient history is updated based on his progress using time-oriented schedules through the sensors implanted either inpatient or environment. Different types of sensors are used to monitor and care for the patients in a real-time manner.

A Thora Care is a sensor embedded in a smart watch that monitors the patient's "safe" zone in terms of his location. If the patient is outside from home, this device keeps alert and sends information to the doctor in a secure network. The temperature sensor is used to measure the heat energy of the patient and automatically alarm the IoT device about the patient's current condition. KARDIA is an IoT sensor embedded in a smart watch and connected with a mobile application, and continuously monitors the patient's heart condition. Next, the ClipsulinIoT sensor continuously tracks the insulin level of the patient. This sensor is connected with mobile applications that keep a logbook of the patient details and optimal tips daily.

The reasoning, machine learning, and data analytics are performed using the available dataset, i.e., UCI datasets. Once the classifier is trained, it can be used to classify the data coming through the sensors. Different patients use these sensors. Multimedia IoT devices and cloud services provide the interaction. The doctor identifies the symptoms using the diagnostic procedure and readings using different sensors. These symptoms formulate diseases. A dataset of drugs has a relationship with their related diseases and their symptoms. These relationships help the machine learning experts to predict the proper and accurate links.

4. Results and Discussions

There are two standard datasets hypothyroid diseases and diseases with drugs taken UCI machine learning repository. There are different 21 attributes with 7200 instances related to thyroid diseases [33]. The attributes are divided into categorical and real numbers. It was documented for Machine Learning Workshop by the University of California at Irvine by Ross Quinlan in 1987. The second dataset contains the diseases with drug details means which drug is useful for which disease. The selection of the Machine Learning (ML) model is difficult due to the nature of the dataset used for the training and prediction. The disease symptoms are taken from patients through IoT devices, and then the machine learning approach is used to recommend suitable drugs for treatment. There clustering of hypothyroid patients with distinctive features are given in Table 1. The k means clustering is used to divide patients according to their disease type. The first column shows the patient attribute, and all other column shows the cluster types. Some attributes are f means false, and few are t means true. Some are real numbers that indicate the measurement of different symptoms that cause hypothyroid disease. These clusters are used for further processing of patients' data, where f=female, m =male, T=True, and F=false.

Table 1. Clustering of hypothyroid patients based on different features in the dataset.

Attribute	Full data	Cluster 0	Cluster 1	Cluster 2	Cluster 3
age	51.7359	61.3847	46.1872	48.7014	48.4336
sex	f	f	F	f	m
on thyroxine	F	F	F	F	F
Query on thyroxine	F	F	F	F	F
pregnant	F	F	F	F	F
query hypothyroid	F	F	F	F	F
query hyperthyroid	F	F	F	F	F
TSH measured	T	T	F	T	T
TSH	5.0868	4.4723	5.1951	6.3725	3.158
T3 measured	T	T	F	T	T
T3	2.0135	1.5735	2.0362	2.2015	2.1275
TT4 measured	T	T	F	T	T
TT4	108.3193	97.9901	108.6843	116.935	102.5523
T4U measured	T	T	F	T	T
T4U	0.995	0.9241	0.995	1.0571	0.95
f TI measured	T	T	F	T	T
f TI	110.4696	107.7173	110.4696	112.3838	109.7307
TBG measured	F	F	F	F	F
TBG	0	0	0	0	0
referral source	other	SVI	Other	other	other

An often-held misunderstanding is that Weka's pattern recognition software cannot be used with larger data. When dealing with big datasets, it is critical to differentiate across training and implementing machine learning models for the prediction. Weka is used to create real-time forecasts in high-stakes real-world applications. This is possible with nearly all trained Weka models. However, training classifiers on big datasets may be difficult, much more so when using Weka's famous graphical Explorer user interface. The Explorer always loads the full training dataset into main memory of the machine and adds considerable cost due to visualization and other features. Additionally, the amount of memory accessible to the Explorer is dependent on the amount of “heap space” available to Java, which is often less than the amount of physical memory on the machine. This memory space may be increased by properly setting the Java environment for Weka. Additionally, Weka supports distributed data mining through Hadoop and Spark. The distributed WekaBase package offers common “map” and “reduce” activities that are not platform-specific. The distributed WekaHadoop package wraps these basic tasks in Hadoop-specific wrappers and jobs. The distributed WekaSpark package contains wrappers for Spark.

The Spark is a framework for handling large capacities of data with good speed and simplicity. It is appropriate to analyze big data applications. It manages data placed on distributed servers and monitors from a centralized data structure.

Spark is a quicker, easy-to-use, and efficient data processing platform constructed modules for streaming, SQL, machine learning, and graph processing. This technique is an in-demand specialty for domain experts, but, of course, data analysts can benefit from learning Spark’s machine learning capabilities by using exploratory data analysis, extraction of features, and Natural Language Processing (NLP) [46]. The spark package in WEKA is used to simulate and manage data on distributed real-time data collected from patients, as shown in Figure 3. It shows the knowledge flow from Spark to text mining results.

The dataset is given in the “.arff” format, then spark is applied to randomly shuffle the patients’ information and distribute it on spark servers. Then k means clustering algorithm is applied to categorize each patient according to the disease. The thyroid disease information of each patient is given in Figure 4.

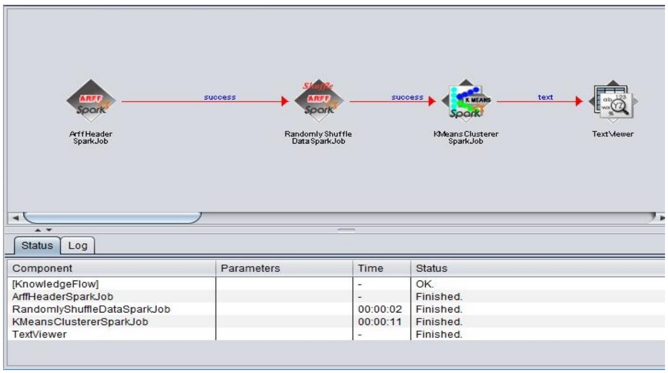

Figure 3. Spark-based knowledge flow in WEKA for the classification of patients.

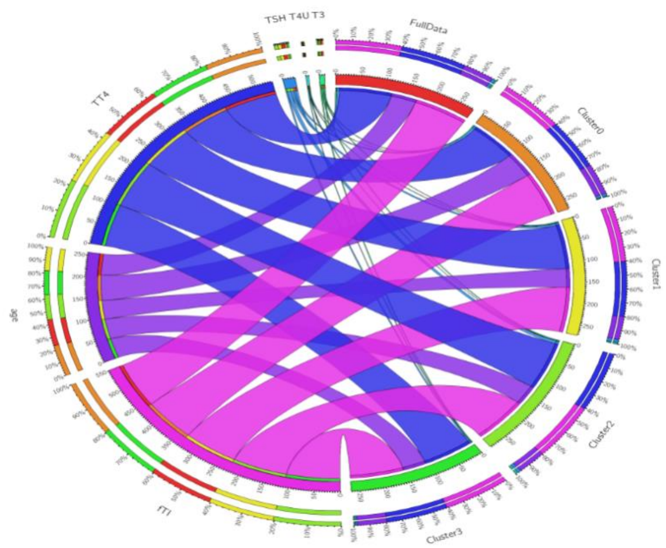

Figure 4. Circular graph for the clusters concerning the age, TSH, T3, TT4, T4U, and fTI attributes of the patients.

It shows the relation of age, TSH, T3, TT4, T4U, and fTI attributes of the patients concerning clusters. The TSH T4U and T3 attributes contribute truly little in each cluster, while fT1 contributes more. It gives the effect of attributes of patients against each cluster. The doctor should care about this effect and should be counted on an early basis.

We fixed regular training and testing proportions, i.e., 80%, 20%, recommended by numerous findings. These evaluation measures are True Positive Rate (TPR), False Positive Rate (FPR), precision, recall, and f-measure, accuracy. The number of True Positives (TPs) and False Positives (FPs) signify the sum of features predicted as true and false, respectively. Also, the number of True Negatives (TNs) and False Negatives (FNs) describe the number of categorized features for the conforming patient as true and false, respectively. The evaluation matrices are specified in Equations (1), (2), (3), and (4), respectively.

$$TPR = \frac{TP}{TP+FN} \tag{1}$$

$$Recall = \frac{FP}{FP+TN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$F-measure\ \frac{2*TP}{2TP+FP+FN} \tag{4}$$

The experiments compare two classifiers, i.e., Random Forest and Naïve Bayes classification based on Spark, which can be carried out using WEKA's knowledge flow, as shown in Figure 5. The knowledge flow for this experiment is created by first a spark job header, which takes the dataset as input. After loading the dataset, a data spark job shuffles the data randomly. The next step is to evaluate the dataset by extracting the results of the classifiers. The output is shown in a text viewer component of the knowledge flow. The working of the knowledge flow in the pseudo-code format is shown in Algorithm (1).

Algorithm 1: Spark-based Naïve Bayes and random forest classifiers evaluation using WEKA

Input: ARFF based dataset
Output: Trained Naïve Bayes and random forest tree classifiers

1. Get the data tuples by tuple from ARFF source
2. Randomly shuffle the data using data spark job scheduler
3. Feed the data to a classifier (first Naïve Bayes and then random forest)
4. Divide the dataset into ten equal parts
5. Loop until
6. Train on one part and perform the testing on other parts until complete
7. End Loop
8. If a model is trained successfully, then
9. Train the next classifiers (i.e., random forest tree)
10. end if
11. Show the reports of trained models
12. Output the trained models and terminate the process

The dataset is divided into 10 equal parts, and two machine learning models are trained to be compared. We can follow the sequence to calculate the algorithm's time complexity as the first data is shuffled randomly, so it will take constant time to perform this operation. The division of the dataset into 10 equal parts is also a constant operation. The time complexity of the algorithm is $c \times 2 \times (10n) \in O(n)$.

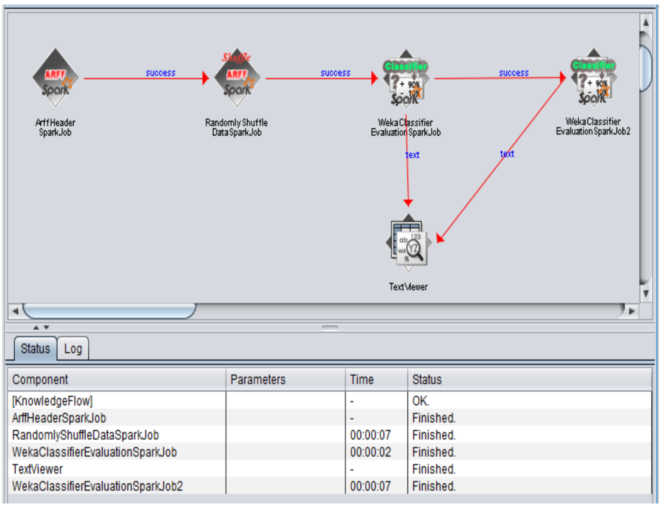

Figure 5. Spark-based knowledge flow in WEKA for the comparison of naïve bayes and random forest classifiers.

Naïve Bayes classification is performed with 10-fold cross-validation, and seed is 1. Relative measures might be slightly pessimistic due to the mean/mode of the target being computed on all the data rather than on training folds. Several predictions are retained for computing Area Under the Curve (AUC)/ Area Under the Precision-Recall Curve (AUPRC): 1879. Random Forest classification is performed with 10-fold cross-validation, and seed is 1. P is 100, several slots are 1, K is 0, M is 1.0, V is 0.001, and S is 1. The results are shown in Table 2. The results have proved that the correctly classified instances are more as compared to the Naïve Bayes classifier.

Table 2. Summary of the evaluation using spark with naïve bayes and random forest.

	Naïve Bayes		Random Forest	
Correctly Classified Instances	3605	95.52%	3745	99.23%
Incorrectly Classified Instances	169	4.48%	29	0.77%
Kappa statistic	0.6293		0.9466	
Mean absolute error	0.0347		0.021	
Root mean squared error	0.1343		0.0775	
Relative absolute error	47.45%		28.74%	
Root relative squared error	70.30%		40.56%	
Total Number of Instances	3774		3774	
Correctly Classified Instances	3605	95.52%	3745	99.23%

The different statistical calculation of Naïve Bayes and Random Forest for the hypothyroid dataset is given in Table 3. It shows the accuracy details on various levels of each algorithm. The mathematical values show that the Random Forest is better than Naïve Bayes. The True Positive (TP) rate, False Positive (FP) rate, precision, recall, ROC of the random forest gave better results as compared to Naïve Bayes. The weighted average of a random forest is also better for each statistical measure. The detailed accuracy and other statistical measures for the classifiers are calculated using formulae as specified in Equations (1), (2), (3), and (4). Some of the values are not possible to calculate due to mathematical problem like division by zero. Hence '?' in the output means that the result (value) is mathematically cannot be defined.

Table 3. Detailed accuracy for the naïve bayes and random forest classifiers.

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
Naïve Bayes	0.345	0.006	0.753	0.345	0.473	0.494	0.93	0.629	Compensated hypothyroid
	0.993	0.457	0.963	0.993	0.978	0.665	0.937	0.994	Negative
	0.832	0.003	0.868	0.832	0.849	0.846	0.994	0.885	Primary hypothyroid
	0.75	0	0.75	0.75	0.75	0.75	?	?	Secondary hypothyroid
Weighted Avg.	0.955	0.422	0.949	0.955	0.948	0.661	?	?	
Random Forest	0.948	0.003	0.953	0.948	0.951	0.948	1	0.992	Compensated hypothyroid
	0.998	0.058	0.995	0.998	0.996	0.953	1	1	Negative
	0.926	0.001	0.967	0.926	0.946	0.945	1	1	Primary hypothyroid
	0	0	?	0	?	?	?	?	Secondary hypothyroid
Weighted Avg.	0.992	0.054	?	0.992	?	?	?	?	

The clustering information of the drugs and diseases dataset is given in Figure 6. The related features mined from medicines are clustered according to the respective patients. By doing this, the proposed approach can easily detect the corresponding patients for the specific disease. It shows the recommended medications by the physicians for the patients. It implies that the use of medications, which patients usually use, often induces diseases. The colors show different medicines. The drug frequency details are given in Figure 7. It shows the hierarchy of commonly used drugs and their frequency of how many times and for which specific diseases. One drug may be used for more than one disease, so the drug used for more than one disease makes a cluster of drugs concerning diseases. It gives direction to the doctor which disease mainly occurs in patients and which drug is mostly suggested.

The plot Matrix graph abridges the relationships between commonly used drugs and the patients' conditions in a matrix of accurate X-Y plots. The scatter plot matrix shows the diversity of the data for both variables. The horizontal placement of the data in the graph shows the proportionality of the data, which indicates the relation of the drugs and their conditions, as shown in Figure 8.

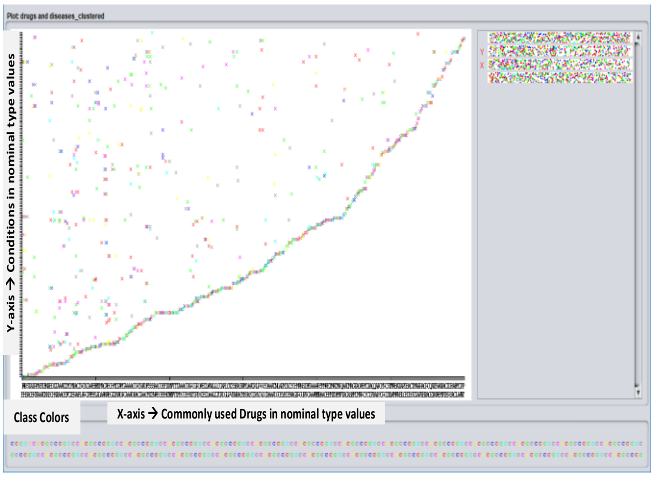

Figure 6. Clustering assignment for the commonly used drugs and conditions.

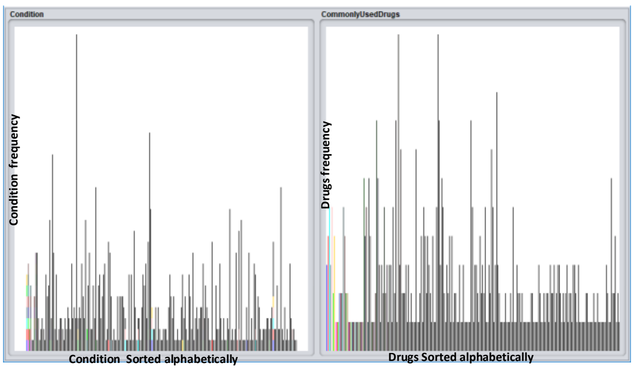

Figure 7. A hierarchy-based graph for the conditions and commonly used drugs.

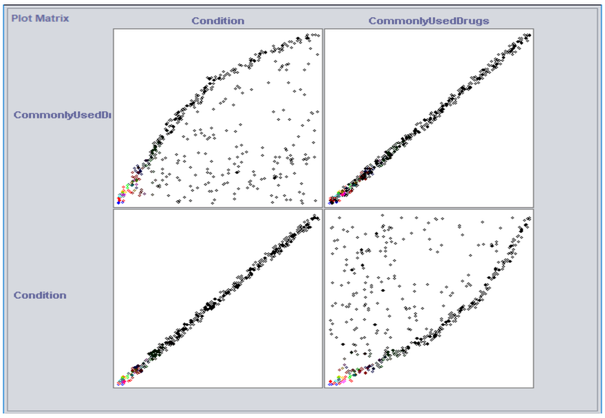

Figure 8. Plot matrix for the conditions and commonly used drugs.

5. Conclusions

This paper proposes an IoT architectural model for smart healthcare, which helps patients by accurately prescribe suitable drugs. The new ways of interaction, diagnosis, treatment, and personalization are the fundamental features of such a model. The proposed model consists of IoT devices and machine learning. The IoT part consists of a set of wearable sensors used to collect different symptoms from patients. At the same time, the machine learning part handles prescribing suitable drugs for the patient based on the disease's symptoms. Later, the spark technique is used to simulate and manage the real-time data collected from patients through IoT devices and then distribute it on spark servers. The k-means clustering algorithm is used to make clusters of patients according to diverse types of hypothyroid diseases. It also analyses which disease occurs in patients and which drugs are commonly used by the patients. After that, predictor techniques, i.e., Naïve Bayes and random forest, suggest the right drugs to patients.

The experiments have been conducted by using two standardized datasets are collected from the UCI machine learning database. The first dataset holds the hypothyroid disease details of different patients, and the second dataset includes the drugs with disease details. The experimental results show the performance of the proposed work, which outperforms the existing systems for disease prediction. Random Forest correctly classified 99.23% instances with precision of different classes as 0.753, 0.963, 0.868, 0.75 while Naive Bayes correctly classified instance by 95.52% and with precision of 0.953, 0.995, 0.967.

5.1. Limitations and Future Research Directions

Though the proposed work supplies better results still there are few limitations that can be improved. We used the machine learning approaches that is difficult to be fine-tuned according to the requirements. Mostly the parameters are fixed, and we must use those elements to experiment. In the future, we will try to implement the deep neural network for better performance. To get better performance, we can fine-tune the deep neural network based on the diverse types of layers, activation functions, epoch and batch sizes, and so on. Moreover, we can resolve the over fitting problem using the dropout layer and other parameters to get high classification accuracy.

The future work of this study will focus on using different machine learning techniques to select suitable features from the data collected from IoT devices.

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