International Research Journal of Engineering and Management Studies (IRJEMS)
Volume: 03 Issue: 05 | May -2019 ISSN: 2395-0126

IOT BASED CLASSIFICATION AND PREDICTION OF HEALTH CARE MONITORING AND ALERT SYSTEM FOR ELDER PEOPLE ON BIG DATA

PRIYANKA.P, MUTHULAKSHMI.B
PG student Department of CSE, A.V.C.College of Engineering, Mannampandal, India
Priyapill53@gmail.com
Assistant professor Department of CSE, A.V.C.College of Engineering, Mannampandal, India
Kavithakamalan240101@gmail.com

ABSTRACT

The main objective of this system is to predict the critical health conditions of elderly people using medical sensor data. Earlier detection and identification of diseases for treatment, and evaluation of the best alternatives can lower the involved complications of daily activities for the aged people. IoT sensors sense the elder's health status and transfer the clinical data to hospital database. The useful information mined from the clinical database is used for preventing and protecting the elder's health during the situation of emergency. Here, a new framework is developed for the public. In this work, a new systematic approach is used for the heart diseases and the related medical data is generated by using the prior clinical dataset, and the medical sensors for predicting the people who has affected with Heart disease severely. The historical rule base is formed statically using patient's prerecorded vital signals to form a base classifier and another base classifier is formed on the dynamically using continuously arriving time vital signal data. Then, these two base classifiers are combined to form a meta classifier to predict the level of health risk of monitored patients. The performance evaluation such as throughput, accuracy, error rate is calculated to prove the efficiency.

KEYWORDS:
Health Care, IoT, Hospitality, heart disease prediction, Patient Monitoring. Wireless Sensor Networks, WBAN, Real-time data stream mining, physiological signal processing

1.INTRODUCTION:

Internet of Things (IOT) driven health and wellness monitoring system enables remote and continuous monitoring of people, with applications in chronic conditions, such as obesity, hypertension, diabetes, heart failure, stress, preventive care and wellness. Medical care and healthcare represents one of the most attractive application areas for the IOT. The IOT driven healthcare system employs networked by biosensors to collectively collect multiple physiological signals and wireless to share or send gathered signals directly to the cloud diagnostic server and the caregivers for further analysis and clinical reviews.

Further, the IOT enabled remote monitoring applications can significantly reduce travel, cost, and time in long term monitoring applications. In the health and wellness monitoring environment, the IOT has emerged as one of the most powerful information gathering and sharing paradigms for personalized healthcare systems, ambient assisted living, uses posture detection, and activity recognition. Compliance with treatment and medication at home and healthcare, providers are another important potential application. In this paper, the core concept rests on IOT, the information sensed from the sensors is gathered and transmitted to the smartphone through IOT.

"Big Data" originally meant the volume, velocity, and various data that becomes difficult to process when using traditional data processing platforms and techniques. Especially, big data play a vital role in healthcare applications Nowadays, modern healthcare systems are adopting quickly clinical data used for increasing clinical record sizes available online Even, new technologies and tools are identified for processing data of large size and gleaning new business insights from that analysis. Thus, a number of options are identified to use Big Data for reducing the cost of healthcare and to diagnose diseases Bates have conducted a study on Big Data in healthcare and describe six use cases of Big Data to reduce healthcare cost.

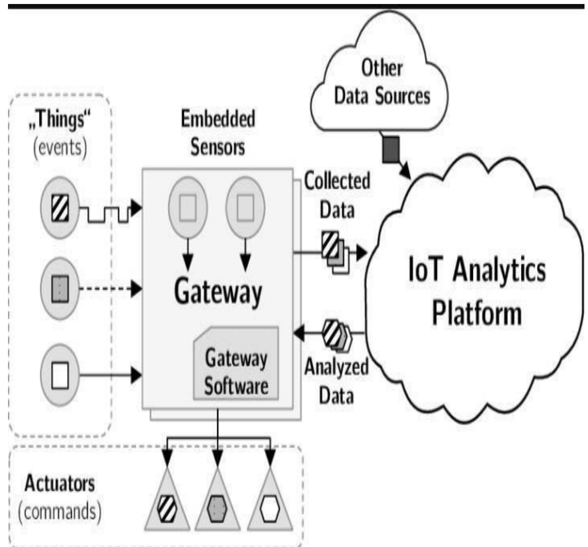

Figure 1. Internet of things

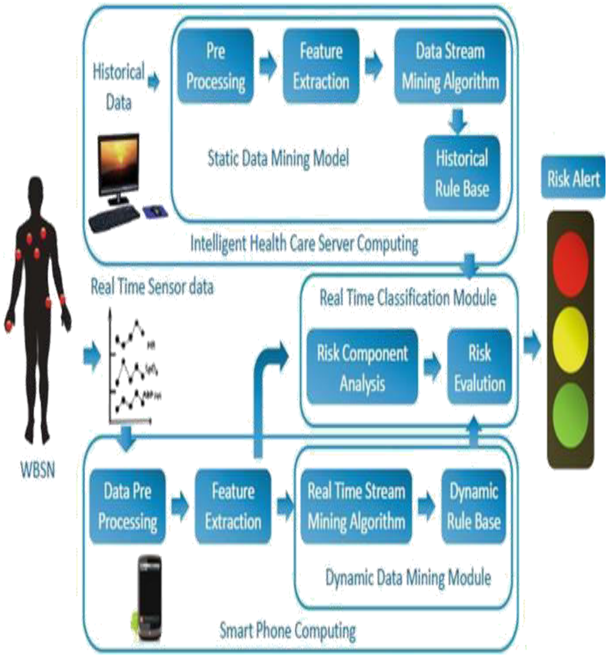

Figure 2.System architecture

2. RELATED WORK

Chiuchisan et al[6] The Internet of Things and information an Communication Technologies applied in development of health care systems have reached an evolutionary process. This paper presents the development of an integrated intelligent system for Parkinson's disease Screening.The Decision Support and Home Monitoring System are designed to assist and support physicians in diagnosis, home monitoring, medical treatment, medical prescriptions, rehabilitation and progress of his patients with Parkinson's disease. The system will be extended in future research for other Neurological Disorders. This paper has an interdisciplinary character and includes areas such as e-Health, Internet of Things, Information and Communication Technology and Artificial Intelligence with their application in medical domain.

Chong Zhi Hao Kevin et al[7] Ageing population would cause profound problems and the impact is already being felt today in many developed countries such as Singapore. The main concern for the Government is to help the citizens with active ageing through home ownership and good health care. With Internet of Things (IoT) gaining traction globally, Singapore is set to take advantage of this technology and leverage it to extend its capabilities towards a graceful Ageing-In-Place for the elderly. This ties in nicely with the expertise of shine Seniors project by SMU-iCity Lab, which integrates IT with healthcare in ways that creates innovative IT health solutions that meet the needs of the elderlies. In this project, we study the problem of predicting potential Alzheimer conditions in the elderly through the behavioural analysis models developed from IoT sensors data. Our findings shows that IoT room sensors for location detection can enable us the capture the key three variables of elderly behaviour; excess active levels, sleeping patterns and repetitive actions. The three variables are useful in predicting the early warning signs of

Alzheimer and we provide recommendations to care-givers based on the prediction analysis. We studied the task on 20 elderly living alone in the flats equipped with five sensors with the data spread over a period of 6 months**.**

Golda Jeyasheeli et al[13]Nowadays chronic diseases are the leading cause of deaths in India. These diseases which include various ailments in the form of diabetes, stroke, cardiovascular diseases, mental health illness, cancers, and chronic lung diseases. Chronic diseases are the biggest challenge for India and these diseases are the main cause of hospitalization for elder people. People who have suffered from chronic diseases are needed to repeatedly monitor the vital signs periodically. The number of nurses in hospital is relative low compared to the number of patients in hospital, there may be a chance to miss to monitor any patient vital signs which may affect patient health. In this paper, real time monitoring vital signs of a patient is developed using wearable sensors. Without nurse help, patient know the vital signs from the sensors and the system stored the sensor value in the form of text document. By using data mining approaches, the system is trained for vital sign data. Patients give their text document to the system which in turn they know their health status without any nurse help. This system enables high risk patients to be timely checked and enhance the quality of a life of patients.

Greeshma Sasi et al[2]Chronic Renal Failure (CRF) is one of the major disease which affect the human life. The stages of CRF start with loss of renal functions and gradually it leads to complete failure of all kidney functions. This disease is fatal at its end stage unless a replacement of kidney or a dialysis process which is an artificial filtering mechanism is not done. So an early prediction of disease is very important to save the human life. Machine learning is a part of artificial intelligence that uses a variety of techniques to learn from complex dataset. Machine learning techniques are widely used in medical field for disease prediction and prognosis. The objective of this work is to develop a clinical decision support system using machine learning techniques. In this paper first the classification techniques like neural network based back propagation (BPN), probability based Naive Bayes, LDA classifier, lazy learner K Nearest Neighbor (KNN), tree based decision tree, and Random subspace classification algorithms are analyzed.The accuracy of each algorithm found is 81.5%, 78%, 76%, 90%, 93% and 94% respectively on a dataset collected from UCI repository which contains 25 attributes and 400 instances. From the results obtained, the algorithm which gave better result was used for the developing the Clinical Decision Support System.

Hoa Hong Nguyen et al[11]Ageing populations and the increase in chronic diseases all over the world demand efficient healthcare solutionsfor maintaining well-being of people. One strategy that has drawn significant research attention is a focus on remote health monitoring systems based on Internet of Things (IoT) technology.This concept can help decrease pressure on hospital systems and healthcare providers, reduce healthcare costs, and improve homecare especially for patients with chronic diseases and the elderly. This paper explores the use of IoT-based applications in medical field and proposes an IoT Tiered Architecture towards an approach for transforming sensor data into real-time clinical feedback. This approach considers a range of aspects including sensing, sending, processing, storing, and mining and learning. Using this approach will help to develop useful and effective solutions for pursuing systems development in IoT healthcare applications. The result of the review found that the growth of IoT applications for healthcare is in areas of self-care,data mining, and machine learning.

3.PROPOSED WORK

Proposed an innovative wireless sensor network based Mobile Real-time Heath care monitoring (WMRHM) framework .which applies data mining techniques on real-time vital signals acquired through WSN and predict the health risk of the monitored person. The prediction will be based on patient's historical rule base, domain expert rules and currently monitored real-time signals. In healthcare domain, the physiological signals are continuous and time varying.We propose to apply above discussed real-time data stream mining algorithms on the vital signals to dynamically update the rule base and predict the health risk accurately.

This paper contains the general architecture of realtime data stream mining systems (RT-DSMS), different types of concept adapting algorithms, and finally finding useful patterns or knowledge from real-time data. Data streams are with the characteristics dynamic, non stationary, continuous, large volume, unstoppable, infinite. DSM system is to handle concept drift in real-time data.While processing the data noise, errors, unwanted data, missing values have to be removed. Additional data analysis techniques are required for in-depth analysis,

Volume: 03 Issue: 05 | May -2019 ISSN: 2395-0126

characterization of data changes over time..

4. DESCRIPTION

4.1 DATA PREPROCESSING MODULE

Due to the occurrence of noise, motion artifacts, and sensor errors in any wearable sensor networks, a preprocessing of the raw data is necessary. Preprocessing in the healthcare domain involves (1) filter unusual data to remove artifacts and
(2) remove high frequency noise. According to the literature, for filtering artifacts, designed modules have usually applied threshold-based methods to filter sensor data or used statistical tools to interpolate the missing data points . For example in ECG data, several works have been done to improve the quality of signals for accurate analysis. To remove frequency noise, the other methods in frequency domain such as such as power spectral density ,fast Fourier transforms , and low-pass/high-pass filtering tools are common to remove the fluctuations in sensor signals . When the data is gathered from numerous wearable sensors, normalization and synchronization of sensor data is required. The main challenges of the preprocessing phase in healthcare systems are addressed in which includes data formatting, data normalization,anddata synchronization. However, there is no tailored work considering these issues in detail for real life scenarios. Since the gathered sensor data is often unreliable and massive, the papers working with large scale and continuous data necessarily employed a preprocessing step.

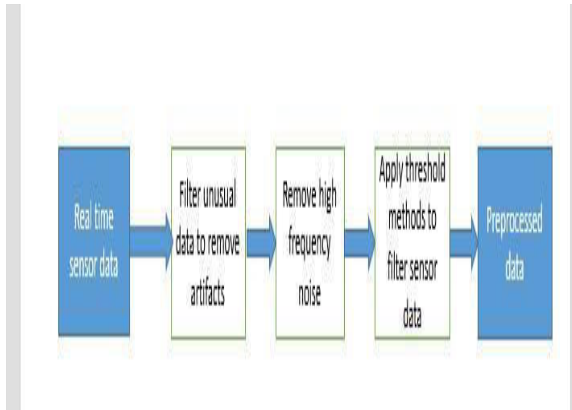

Fig. 4.2.1 Data preprocessing

4.2 FEATURE EXTRACTION

Generally, for mining massive and real world data sets, the abstraction of raw data in any data mining approach is a way to design and build a model in order to retrieve valuable information. The aim of feature extraction is to discover the main characteristics of a data set which are identically representatives of the original data . Especially in wearable sensor data, according to the magnitude and complexity of the raw data, feature extraction provides a meaningful representation of the sensor data which can formulate the relation of raw data with the expected knowledge for decision making . Moreover, reducing the amount of sensor network data is another task in feature extraction and feature selection phases which leads to have an arranged vector of features as an input of data mining techniques like classifier methods .Since Wearable sensor data which provide monitoring of vital sign parameters tend to be continuous time series readings, most of the considered features are related to the properties of time series signals. Two main aspects of analyzing signals are time domain and spectral domain. In the time domain, the extracted features usually include basic waveform characters and statistical parameters related to the visible attributes in data stream such as mean, variance, pick counts, etc..

In physiological data, the time-domain features are common, because the traditional decision making frameworks on vital signs are based on the observable trends in the signal. However, for extra knowledge about the periodic behavior of time series, research in the medical field has given more attention to the features acquired from frequency-domains such as power spectral density, low-pass/high pass filters, spectral energy, and wavelet coefficients of the signal summarises the most appeared features in the literature that extracted from wearable sensor data. As an example, for the works studying ECG signals, although Bsoul et al. have proposed dozens of features, the main focus of research is to consider R points (the pick point of each beat), and its properties in ECG pulses such as R-R intervals, pick counts, etc. Besides the features from these domains, there are other considered features which such as heuristic and specific field features

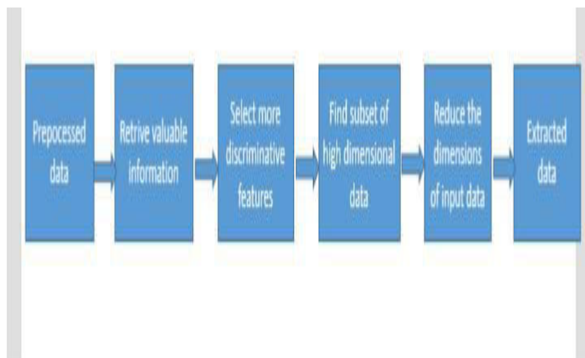

Figure .4.2 Feature extraction

4.3 STATIC AND DYNAMIC DATA MINING MODULE

As the sensed signals are continuous and time dependent, stream mining algorithms are needed to analyze this data. The architecture consists of two modules, viz. Static data mining module (SDM) and dynamic data mining (DDM) module which make use of data stream mining algorithms. In SDM, after extracting the relevant features, themining algorithms are used to cluster these features into three types of risk levels, i.e., normal, moderate and high; this forms the historical rule base. The same procedure is followed inDDMmodulewith the only difference being the usage of real-time Stream Mining algorithms like PARC-Stream. These algorithms dynamically update the rule base if any concept drift occurs.

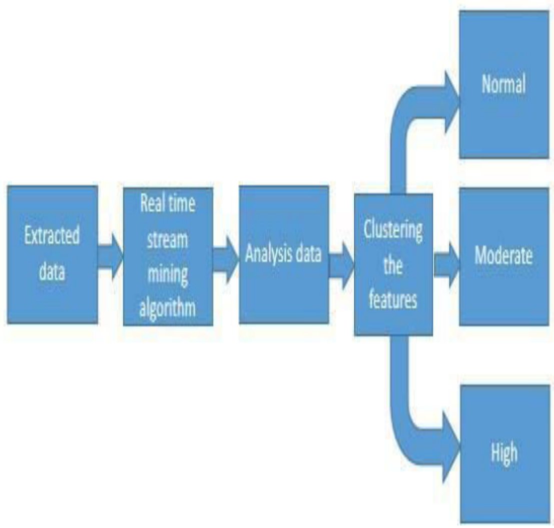

Figure 4.3 Static and dynamic data mining module

4.4 REAL TIME CLASSIFICATION MODULE

In this module, risk components are classified into their appropriate risk level based on the historical as well as the dynamic rule base computed using meta learning process.

The steps involved in meta learning process are:

1. Partition the input data (in this case Historical and Real-time patient data).
2. Build a base classifier for each partition.
3. Combine the outputs of the base classifiers.
4. Apply the rules from combined decision table for risk prediction.
5. Get the final classification. WIMRHM is designed in such a way that the meta learning and classification phase is carried out in parallel as shown in Fig. 2. Base learners form the historical and dynamic meta model using prerecorded and real-time vital signals' extracted risk components Z1, Z2, and Z3. This process of forming combined classifier is called meta learning. In parallel to meta learning, the incoming vital signals are also classified as one of the three health risk levels using the meta model named as TT() as represented in Fig. 4.4

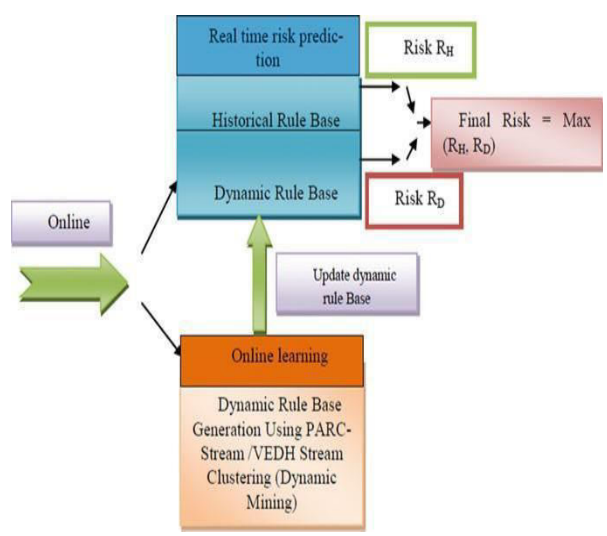

Figure 4.4 Real time classification

5. CONCLUSION

An innovative combinatorial approach for learning and adapting vital signal behavior of human body and predicting health risk level in real time on smart phone, based on both patient history and current health status. Real-time patient monitoring system is modeled and tested using newly designed real-time clustering algorithm named PARC-Stream. Designed PARC-Stream algorithm is resource-aware as it handles memory constraints in real time and suits any kind of ubiquitous computing. The algorithm is adaptive to changes called as concept drift, occurring in incoming signals. Number of clusters may vary accordingly. The PARC-Stream algorithm is designed on the principle of triangle inequality using which loop required for distance calculations among data to centers is skipped and performance gets accelerated.

6. FUTURE ENHANCEMENT

This research work is now looking towards developing the various disease and patient-specific healthcare systems. Future works in this direction could be the introduction of effective security mechanism using novel cryptographic algorithms for providing better security to the medical data on cloud database.

REFERENCES

[1] Ani, R., Krishna, S., Anju, N., Aslam, M. S., & Deepa, O. S. (2017, September). Iot based patient monitoring and diagnostic prediction tool using ensemble classifier. In 2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI) (pp. 1588-1593). IEEE.

[2] Ani, R., Sasi, G., Sankar, U. R., & Deepa, O. S. (2016, September). Decision support system for diagnosis and prediction of chronic renal failure using random subspace classification. In 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI) (pp. 1287-1292). IEEE.

[3]Anupama, K. R., Adarsh, R., Pahwa, P., & Ramachandran, A. (2018, October). Machine Learning-Based Techniques for Fall Detection in Geriatric Healthcare Systems. In 2018 9th International Conference on Information Technology in Medicine and Education (ITME) (pp. 232-237). IEEE. Engineering, 65, 222-235.

[4] Azimi, I., Rahmani, A. M., Liljeberg, P., & Tenhunen, H. (2017). Internet of things for remote elderly monitoring: a studyfromuser-centered perspective. Journal of Ambient Intelligence and Humanized Computing, 8(2), 273-289.

[5]Bates, D. W., Saria, S., Ohno-Machado, L., Shah, A., & Escobar, G. (2014). Big data in health care: using analytics to identify and manage high-risk and high-cost patients. Health Affairs, 33(7), 1123-1131.
[6]Chiuchisan, I. U. L. I. A. N. A., & Geman, O. A. N. A. (2014). An approach of a decision support and home monitoring system for patients with neurological disorders using internet of things concepts. WSEAS Transactions on Systems, 13(1), 460-469.
[7]CHONG, Z. H. K., TEE, Y. X., TOH, L. J., PHANG,. (2017). Predicting potential Alzheimer medical condition in elderly using IOT sensors.
[8] Fki, Z., Ammar, B., & Ayed, M. B. (2018, May). Machine learning with Internet of Things data for risk prediction: Application in ESRD. In 2018 12th International Conference on Research Challenges in Information Science (RCIS) (pp. 1-6). IEEE.
[9] Kumar, P. M., & Gandhi, U. D. (2018). A novel three-tier Internet of Things architecture with machine learning algorithm for early detection of heart diseases. Computers & Electrical .
[10]Manogaran, G., Thota, C., Lopez, D., Vijayakumar, (2017). Big data knowledge system in healthcare. In Internet of things and big data technologies for next generation healthcare (pp. 133-157). Springer, Cham.