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Development of Personalised health monitoring system using Machine learning and AWS cloud computing

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Abstract

Health care is an essential aspect of daily life, necessary for the health and wellbeing of the population due to human resources and affordable care. Even so, continue to increase the corresponding costs for medical services. A contribution to health care growth costs is waste and fraud. In particular, with the rapidly expanding growth in the United States, the use of wearable devices such as smart gears and other wearable devices has implemented new health care monitoring programs and implemented health care telemetry. But machine learning is taking a step forward, which allows doctors and relatives to keep an eye on the health of the elderly family members. These algorithms used to understand the user profile, which enables potential health discrimination before health care professionals. Create models for personalized health profiles and monitoring. This method is critical to reducing health risks. Even using Medicare data, many studies do not provide adequate details about data processing and integration, which makes it even more difficult for challenging to understand the test results and for the revival of the test. In this thesis, we present the current research using Medicare Data, focusing on data processing and integration and defining a gap in the information-related details. We present discussions on essential information to see how to look at how to process and merge different Medicare datasets by suggesting opportunities to work in the future.

Keywords: Health Care, Machine Learning, AWS, Cloud Computing

Introduction

It is a fact that the global population is growing and growing [1], [2]. Due to these demographic changes, chronic infectious diseases such as congestive heart failure, dementia, sleep apnea, cancer, diabetes and chronic respiratory, pulmonary disease [1], [3], [4]]. Besides, the total number of people suffering from some disabilities (which is related to living, or traumatic, or chronic conditions) will increase. [5] Besides, 65% of the people aged 85 and 50% of the age of 50% of the population fall each year [6], [7]. For this population, health care costs are increasing [8], the quality of life and productivity is decreasing, and in many cases, the family members work as primary care assistants. As well as challenges to effectively manage and treat post-progressive rehabilitation patients, people with disabilities and special abilities, these issues show the need for new and innovative ways to provide health care to patients. In response, information and communication technologies are expected to offer means to offer personalized, low-cost and citizen-centric health care solutions to solve predetermined challenges. [9] Recent advances in sensor communication, sensor

detoxification, and microelectronics have enabled health care providers to monitor and manage chronic diseases and identify possible emergencies [10]. Health monitoring in the home environment can be done either by two or both of the following [11]:

1) To record physiological signals and ambulatory monitors using wearable sensors and devices

2) Sensors are unwantedly embedded in the home environment and home furnishings to collect behavioral and physiological data. Among the researchers involved in Dementia and other chronic conditions, the positive effects of attention and attention technology have been confirmed [12]. Moving one step further, diagnosing primary health and diagnosing serious health changes most of these problems can be prevented, billions of dollars are saved annually [13], [14]. Primary detection, however, requires continuous alerts. Due to the nature or training of their condition and lack of experience, many of these populations have become depressed or can make a difference that cannot detect and report critical observations. The primary methods of addressing this problem are to keep track of patients with health care professionals directly or through relatively crude and heavy physiological data collection devices. These types of devices and sizes, which include various cables and need to be immune to the patient to achieve reliable measurements, are not irrelevant when public, uncomfortable, long-term and low-cost health surveillance are inappropriate. However, the new generation's cheap, uncomfortable wearable / replaceable devices [15] can move towards initial and automatic detection of severe changes to the patient's health status. In this context, such devices should not be just simple data collection, nor should they report variations from sample demographic values only. Instead, they should be able to utilize the advanced data processing algorithm and diagnostics to discover different user baselines and to understand the dangerous health trends better and, as a result, to inform medical professionals for further assistance. These wearable systems should be engineered to integrate portable devices operated by first responders and integrated stable-system systems in hospitals. As a result, these devices will continually capture data, it will organize in customized patients, and condition models and each patient's unique information will be first reactionary and contact with hospital staff. On this paper, we present our perspective on establishing a useful framework for the novel, interactive and intelligent wearable health-monitoring prototype, which is known as Prognosis. The rest of the paper is organized as follows. The second section will give a brief insight into the Affordable Health-Monitoring System (WMIMS) and decision-assistance process. The third section will represent the overall concept of the proposed system based on the current availability of generic architecture and wearable biomass. Article IV, the combination of recommended physical information, will give details of the combination technique, its operating model and a formal definition of formal examples. At Section V, we provide an SPN-based model of the interaction scheme between the user and the system.

Literature Review

[1] The authors have described that the development of wearable sensor technology continues and plays a major role in the development of human health services, giving them opportunities and progress which helps in adjusting food consumption and energy consumption technology and becomes a partner for the people. Accessibility of technology has now reduced the barriers for low power computing and networking. Recent advances in wearable sensor technology help to monitor the movement of the neck and head injuries and the environment. The sensor integration system is done in the

health information collection system. Information integration and explanation play a key role. The wearable sensor helps to monitor the behavior of physical and technical flexibility in its environment. The goal is to utilize the wearable sensor, processor, and progress to show the study of the behavior of animals and humans in their neutral environment.

[2] Due to the vowel, due to the vowel, the author describes the frustration in the real world of signal signals, which reduces system performance in speech recognition. The hidden Markov model is used to rebuild the spoken components of the spectral, whose functionality is reduced by the unwanted acoustic noise. Construct Markov chains using the random process Markov property during discrete. In each level, there is an isolated state among the potentially limited states of nature. The number of techniques does speech Parameter Frequency Domain Encoding Speech Analysis. The signal is characteristic precisely. The nature of the strategy is that the speech recognition system is distributed. Incredible spectrum data is reconstructed for the recognition of robust sound lecture by Hidden Markov model.

[3] The authors have described that the systems available at present are very low-level living behavior monitoring and accuracy. This is also the reason behind the poor understanding of overweight and obesity ETIOLOGY. Studies have shown that the frequency of intake can be used to predict food intake. The separation of the liquid and solids can be completed, and the mass can be ingested. The system offers two approaches, and this method is used to detect acoustic acoustics from words and words corrupted by the comparison. The result shows the high efficiency of proposed methods in the separating sound from the artwork. This handmade head is derived from the movement, words, food involved. The accuracy of the system is not related to the body mass index. This system looks suitable to be used by the gross person.

[4] The author describes obesity research which is now a big problem. Due to the increase in awareness of public obesity-related diseases, pandemics cannot be understood. The ongoing scientific debate is subject to several views of the etiology of obesity and strong different opinion. The reason for obesity as changes in physical activity as our diet and lifestyle change. Powerful words of research made by popular media publications like Time Magazine The topic of debate is increased by research this summary. This paper focuses on people's relationship with weight control and energy consumption equations in humans. Etiology insight grows by understanding obesity. Technology is developed to measure the material of the energy equation accurately.

[5] Authors have been describing information about taking a significant diet of the person involved in using body sensors. This system is helpful to help weight loss professionals develop personalized programs for clients and to research nutrition information and eating behavior. Maintaining the balance of food consumption and spending energy in daily life is very important for long-term health. According to the World Health Organization, the number of peacocks is 700 million. Manual methods and automated solutions are used to capture the behavior of eating a person. The proposed system broadens the full self-reporting solution using the universal sensor. It simplifies the current manual monitoring techniques which are incompatible with the current manual reporting techniques. Manual logging is replaced. ADM system offers a self-report. Daily schedules are maintained for food use.

[6] The authors describe incentive behavior using chewing and melting non-invasive observation to study behavioral patterns of weight and volume and energy assumptions. This method has been improved. Non-invasive monitoring using bone absorption microphone or sound sensor consume is detected. In this method, the first two methods are used, the

sensor-based system and second protocol are used for manual scoring and intake of chewing gum and chewing. The key to maintaining a healthy lifestyle is to maintain the balance between healthcare and energy costs. To monitor the observance of greatness and noninvasive targets, sensor hardware and hardware-based systems are developed to obtain reliable information from sensors. Chews and Swallows are used as a standard for automatic pattern recognition scores. These systems are obtained which result in high quality of high reliability and readability information.

[7] The lecture description for the author's recognition of speech and recognition of speech describes the use of various discrimination attributes of the element. Using the AdaBoost method from the larger features pool, discrimination properties can be removed. Use this extruded feature set in data-driven methods. This lecture can be recognized by listening to non-lecture helps improve performanceperformance. Ad Boost based algorithm is used to select a feature set from the larger features on the proposed system. Research interest in detecting acoustic events is increasing rapidly. Although the source of lectures may sound useful information other words. Acoustic events can occur in many different ways. So identifying literary events helps to describe social and human activity in their environment.

[8] The authors described how to define predefined categories in free text documents automatically, text categorization is the main problem. The number of documents available online is quite difficult without a document retrieval index. Solving this problem is document categorization. The new and advanced machine learning techniques are applied in text categorization. Feature The space document contains different words and phrases. For reducing the purpose of text categorization. Feature space selection can easily be easy to categorize text in applications like neural networks

Proposed Model

We can combine measurements in a structured and meaningful way by creating a mathematical model for each measurement regarding others. Consider leaving a compressor exhaust pressure. It is influenced by moderate temperature, machine rotation rate, medium structure, and several other parameters. It is possible to calculate what the pressure should be, to let these parameters know. To count it, we need to find out the relation between these parameters in our mathematical form.

Forming this equation from expert knowledge is very time consuming since this equation will be different for each model of the model and model of the machine and each condition of the device. For real-life purposes, if it can be achieved with the speed of the model and very few people, it is OK to do it.

This machine learning:- These methods receive experimental experiences that are measured on this specific machine when it was known as healthy. From this data, machine learning methods create mathematical representations of the relationships of all the parameters around the computer automatically and without human effort.

It can be mathematically proved that a neural network can accurately represent a complex data set, as long as the system is sufficient and the data consistently follows the same laws [1, 2]. The machines are following the requirements of nature, and these ideas are easily correct. We use a neural network as a template for modeling each measurement on the device regarding others. The machine learning algorithm finds the value for model parameters such as neural networks that accurately represents the data.

It is important to consider selecting a measurement when a specific measurement modeling can be done automatically. We use coordination of mutual modeling and core material analysis to do this. [1]

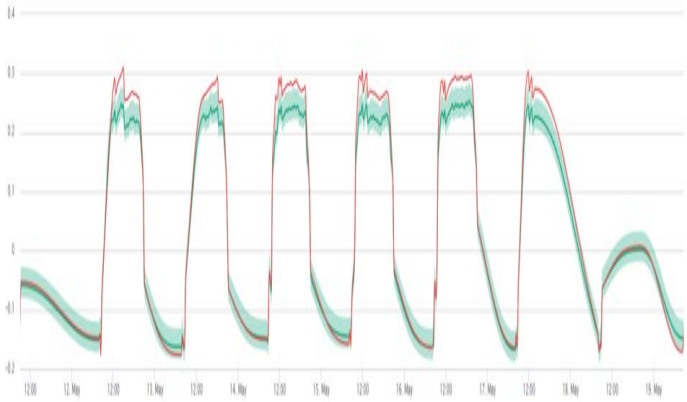

Figure 1: The displacement of the Central Axle of the compressor is measured (green) of the model (green) and the model (green) of the model (light green).

It is seen that the model also model the model of the model while the load changes and model loads of both the load and the low. We keep a deviation between each load model and measurement while reaching full capacity. It is a hint of a mechanical problem and will be cautious.

As a result, each measurement on the machine gets a source that can calculate the expected value for this measurement. The formula was trained on information known as healthy, and this formula is a health definition for this machine. The disadvantage is then considered to be the deviation from health. See Figure 1 for an illustration.

It is essential to find out the model of health and deviations from it because many information is available for health, general conditions and normal healthy behavior. Preferably, little information is available for unhealthy public response, and this small amount is very diverse due to the host of different failure modes. Differences between the making of each of the machines and the failure modes for the model are very complicated. Analysis of poor health modeling data is a problem, but information availability is not a problem. As such, this problem is fundamental and cannot be tackled in a real and comprehensive way.

Scary

At any one time, we can compare the expected strong value of the sensor value. Since the expected value is calculated from a model, we know the probability distribution of deviations, i.e., how much the measurement measure of a certain amount can be, see Figure 2. So we can calculate the health feasibility of this distribution, or in contrast, use this confidence level to judge whether the sensor value is far from healthy. If this case is available, an alarm is sent.

Figure 2: Deviation between the probability (vertical axis) of the deviation in the model and the sensor value (horizontal axis).

We hope to have a bell-shaped curve for a good model, as there are several points with little deviation and several deviations in the above and below differences of the models, with overall parallelism. From this distribution, how quickly we can read any observation deviation and how healthy a measurable state is. This image translates directly to a sensor measurement of a health index.

By providing the possibility of poor health, how the state offers insufficient information can be enriched. Since the expected value is counted from the number of other machine parameters (usually small), it is generally possible to blame any other measurement. To help solve this problem and design some steps, improve the human engineer receiving alarms.

Along with observing the normal condition, it is often found that when a machine is moved from one stable position to another, many (false) alarms are released because the simple analysis method can not conform to the rapidly changing conditions. A neural network could easily represent highly non-linear relationships; even if the startup or load change of a machine were also everything, it would be modeled correctly without the alarms.

Results

This system has been thoroughly testing for rotating types of machinery like compressors, pumps, gas and steam turbines from different manufacturers in the operational context of power generation, chemical production, oil refining, and production. In particular, company man diesel and turbo, this method uses alarms in its compressors and gas turbines to see human engineer data once.

Our partners have observed in practice that due to the automatic support of machine learning methods, the human effort has been reduced to set up and maintain a system monitoring method of more than 50%. It is predominantly generated automatically as each measurement is mainly due to the above and the lower limits carefully not for carefully.

False alarms (false positives) and missing alarm (false negative) have exceeded the event rate of 90%. This reduces human engineering efforts to diagnose machine flaws by cutting 60%, reducing maintenance budgets and improving machine availability by about 10%.

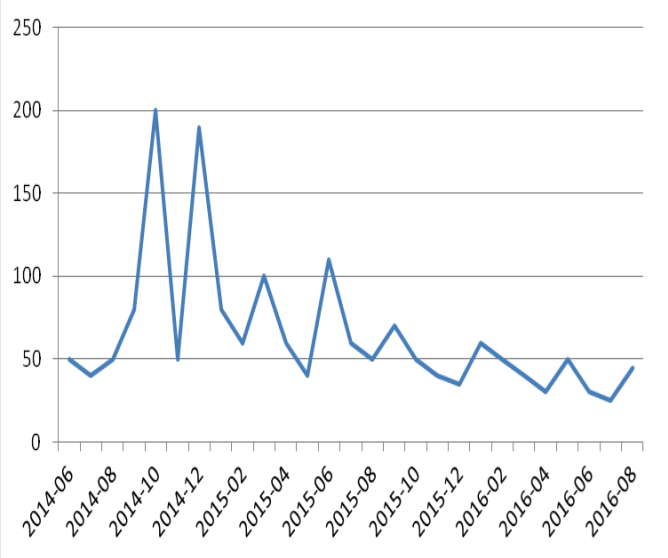

Figure 3: An example of the maintenance budget over time with thousands of US dollars. Over time, due to less responsive and more active maintenance, the budget size decreases.

Conclusion

The institution adopts new methods, maintains less responsive and more active. This saves money in various ways. As a result of the consecutive trip to the plant, we identify problems before, to prevent any parallel damage completely. Potentially lost production is reduced. The cost due to order to push both people and materials is also avoided. Of course, the real problem must be repaired, but it can now be designed in a predefined way, in opposition to a firefighter mode. It can reduce a maintenance budget as 50%.

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