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DESIGNING AND IMPLEMENTATING PRE-STROKE DETECTION METHOD USING MACHINE LEARNING

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ABSTRACT

In this Project, a tentative design of a cloud-based Stroke prediction system had been proposed to detect impending Stroke using Machine learning techniques. For the accurate detection of the Stroke, an efficient machine learning technique should be used which had been derived from a distinctive analysis among several machine learning algorithms. The proposed algorithm was validated using two widely used open-access database, where 10-fold cross-validation is applied in order to analyze the performance of Stroke detection. An accuracy level of 97.53% accuracy was found from the ML algorithm along with sensitivity and specificity of 97.50% and 94.94%respectively. Moreover, to monitor the Stroke patient round-the-clock by his/her caretaker/doctor, a real-time patient monitoring system was developed and presented using Arduino, capable of sensing some real-time parameters such as body temperature, blood pressure, Blood flow, Heartbeat, Oxygen level. With the help of different decision-making algorithms decisions can be made easily and fast and according to its people can have access to the database. The main advantage of our system is it automatically generate the require prescription based on the vital parameters of the human.

Keywords: Machine learning techniques, learning algorithms and Nursing workflow

1. INTRODUCTION

Ischemic stroke is the most common cause for the loss of lives in the world. The symptoms of stroke in acute phase are evaluated by diffused magnetic resonance imaging (MRI) data and using these data, the degree of changes in vascular territory of the occluded blood vessel in stroke can be measured accurately. MRI is sensitive for the early identification of little infracts in the brain stem, and deep structures inside the cerebral hemispheres and also these scanners are extremely valuable in demonstrating early stroke infarcts. The diffusion weighted imaging (DWI) modality of MRI is the commonly used modality as it detects even small changes in water diffusion in case of acute ischemic brain. The manual delineation of abnormal brain tissue is the standard method for lesion identification; however, this method is very time-consuming, and operator dependent. An exact delineation and time of process in lesions identification is extremely important in disease diagnosis and treatment processes. Therefore, fully automated techniques have been recommended to eliminate inter subject variability in delineating affected brain tissue and analysing large MRI datasets Since last two decades, manual, semi-automated and automated approaches based on edge detection, thresholding, clustering, wavelet, watershed transformation (WT) and graph cut theory were presented to detect the stroke lesions. These methods include pre-processing, segmentation, feature extraction and classification of stroke.

2. LITERATURE SURVEY

Clinical monitoring systems have been implemented in the inpatient hospital setting for decades, with little attention given to systems analysis or assessment of impact on clinician workflow or patient care. This study provides an example of how system-level design and analysis can be applied in this domain, with specific focus on early detection of patient deterioration to mitigate failure to rescue events. Wireless patient sensors and pulse oximetry-based surveillance system monitors with advanced display and information systems capabilities were introduced to 71 general care beds in two units. Nursing workflow was redesigned to integrate use of the new system and its features into patient assessment activities. Patient characteristics, vital sign documentation, monitor alarm, workflow, and system utilization data were collected and analyzed for the period five months before and five months after implementation. Comparison unit data were also collected and analyzed for the same periods. A survey pertaining to staff satisfaction and system performance was administered after implementation. Statistical analysis was performed to examine differences in the before and after data for the target and control units. The enhanced monitoring system received high staff satisfaction ratings and significantly improved key clinical elements related to early recognition of changes in patient state, including reducing average vital signs data collection time by 28%, increasing patient monitoring time (rate ratio 1.22), and availability and accuracy of patient information. Impact on clinical alarms was mixed, with no significant increase in clinical alarms per monitored hour.

The Internet of Things (IoT) has facilitated services without human intervention for a wide range of applications including continuous Remote Patient Monitoring (RPM). However, the complexity of RPM architectures, the size of datasets generated and limited power capacity of devices make RPM challenging. In this paper, we propose a tier based End-to-End architecture for continuous patient monitoring that has a Patient Centric Agent (PCA) as its center piece. The PCA manages a Blockchain component to preserve privacy when data streaming from body area sensors needs to be stored securely. The PCA based architecture includes a lightweight communication protocol to enforce security of data through different segments of a continuous, real time patient monitoring architecture. The architecture includes the insertion of data into a personal Blockchain to facilitate data sharing amongst healthcare professionals and integration into electronic health records while ensuring privacy is maintained. The Blockchain is customized for RPM with modifications that include having the PCA select a Miner to reduce computational effort, enabling the PCA to manage multiple Blockchains for the same patient, and the modification of each block with a prefix tree to minimize energy consumption and incorporate secure transaction payments. Simulation results demonstrate that security and privacy can be enhanced in Remote Patient Monitoring with the PCA based End to End architecture.

A novel wireless transducer that uses analog-based technology at 2.4 GHz is presented in this letter. The transducer consists of an electrocardiography (ECG) detection circuit and a novel three-stage amplitude modulation transmitter that up-converts the ECG signal to a 2.4-GHz carrier frequency. To minimize the effects due to local oscillator leakage as well as the interference at the image frequency, the intermediate frequency is carefully selected, and a bandpass filter with a very sharp selectivity is designed. As demonstrated by the experimental results, the full-wave ECG signals can be successfully demodulated from the transmitted signal using the presented transducer. This enables the possibility of using analog-based technology for remote patient monitoring in real time.

Many devices and solutions for remote ECG monitoring have been proposed in the literature. These solutions typically have a large marginal cost per added sensor and are not seamlessly integrated with other smart home solutions. Here we propose an ECG remote monitoring system that is dedicated to non-technical users in need of long-term health monitoring in residential environments and is integrated in a broader Internetof-Things (IoT) infrastructure. Our prototype consists of a complete vertical solution with a series of advantages with respect to the state of the art, considering both prototypes with integrated front end and prototypes realized with off-the-shelf components: i) ECG prototype sensors with record-low energy per effective number of quantized levels, ii) an architecture providing low marginal cost per added sensor/user, iii) the possibility of seamless integration with other smart home systems through a single internet-of-things infrastructure.

The paediatric intensive care unit (ICU) is a complex environment, in which a multidisciplinary team of clinicians (registered nurses, respiratory therapists, and physicians) continually observe and evaluate patient information. Data are provided by multiple, and often physically separated sources, cognitive workload is high, and team communication can be challenging. Our aim is to combine information from multiple monitoring and therapeutic devices in a mobile application, the *VitalPAD*, to improve the efficiency of clinical decision-making, communication, and thereby patient safety. We observed individual ICU clinicians, multidisciplinary rounds, and handover procedures for 54 h to identify data needs, workflow, and existing cognitive aid use and limitations. A prototype was developed using an iterative participatory design approach; usability testing, including general and task-specific feedback, was obtained from 15 clinicians. Features included map overviews of the ICU showing clinician assignment, patient status, and respiratory support; patient vital signs; a photo-documentation option for arterial blood gas results; and team communication and reminder functions. Clinicians reported the prototype to be an intuitive display of vital parameters and relevant alerts and reminders, as well as a user-friendly communication tool. Future work includes implementation of a prototype, which will be evaluated under simulation and real-world conditions, with the aim of providing ICU staff with a monitoring device that will improve their daily work, communication, and decision-making capacity. Mobile monitoring of vital signs and therapy parameters might help improve patient safety in wards with single-patient rooms and likely has applications in many acute and critical care settings.

3. METHODOLOGY

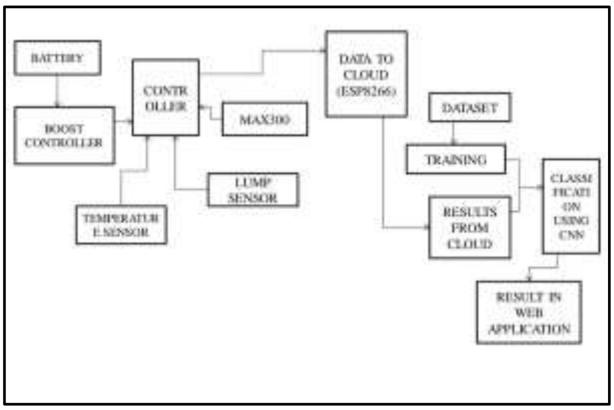
3.1 EXISITING SYSTEM

The main vision of the healthcare industry is to provide better health care to all the people anywhere and at any time in the world. This should be done in a more patient friendly and economic manner. Therefore, for increasing the patient care efficiency, there is a need to improve the patient monitoring devices. Because technology has made life easier so that impact is shown to reduce the tension of patient. The body sensor network (BSN) technology is one of the most imperative technologies used in IoT-based modern healthcare system. It is basically a collection of low-power and lightweight wireless sensor nodes that are used to monitor the human body functions and surrounding environment. Since BSN nodes are used to collect sensitive (life-critical) information and may operate in hostile environments, accordingly, they require strict security mechanisms to prevent malicious interaction with the system.

3.2 PROPOSED SYSTEM

A person's health will be monitor by wearable device every day. Stroke beat, pressure, temperature all the data is sent to cloud and machine learning is performed with the uploaded data. The main role of machine learning is to classify the hardware sensor data is normal or not. The data set contains the medical characteristics is compared with real hardware data through ML which intern gives the accurate status which reduces the time complexity and can save many lives. We use this algorithm to predict stroke by taking different independent variables and we take pulse beat time to time as it varies from time to time. We use multiple regression to predict Stroke attack and we use IOT to communicate to the person and we use IOT devices and cloud platform in order to remind the person about his health condition of a stroke.

3.3 BLOCK DIAGRAM



Random Forest is another machine learning algorithm that can be used for pre-stroke detection. Here's a detailed methodology and description of how the pre-stroke detection system works using the Random Forest algorithm:

DATA COLLECTION: The first step is to collect the data on patients who have had a stroke in the past. This data should include their medical history, age, gender, lifestyle habits, family history, and any other relevant factors that may contribute to the likelihood of a stroke.

FEATURE EXTRACTION: After collecting the data, the next step is to extract relevant features from the data. This involves selecting the most important variables that can help to predict the likelihood of a stroke.

DATA PREPROCESSING: Once the features have been extracted, the data is pre-processed to make it suitable for use in the Random Forest algorithm. This involves cleaning the data to remove any outliers, missing values, and irrelevant variables.

DATA SPLITTING: The data is then split into two sets: a training set and a testing set. The training set is used to train the Random Forest algorithm, while the testing set is used to evaluate the performance of the model.

RANDOM FOREST ALGORITHM: The Random Forest algorithm works by building multiple decision trees using a randomly selected subset of features and data points. The algorithm then combines the results of these decision trees to make a prediction.

CLASSIFICATION: After building the decision trees, the Random Forest algorithm classifies the patient as either high risk or low risk based on the majority class of the decision trees.

MODEL EVALUATION: The performance of the model is evaluated using metrics such as accuracy, precision, recall, and F1 score. These metrics help to determine how well the model is performing and whether any changes need to be made to improve its performance.

In summary, the pre-stroke detection system using the Random Forest algorithm works by collecting data on patients who have had a stroke in the past, extracting relevant features from the data, pre-processing the data, splitting the data into a training set and a testing set, using the Random Forest algorithm to classify patients as high risk or low risk, and evaluating the performance of the model using metrics such as accuracy, precision, recall, and F1 score.

4. RANDOM FOREST

Random forest is a supervised learning algorithm which is used for both classification as well as regression. But however, it is mainly used for classification problems. As we know that a forest is made up of trees and more trees means more robust forest. Similarly, random forest algorithm creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting. It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result.

Working of Random Forest Algorithm

We can understand the working of Random Forest algorithm with the help of following steps −

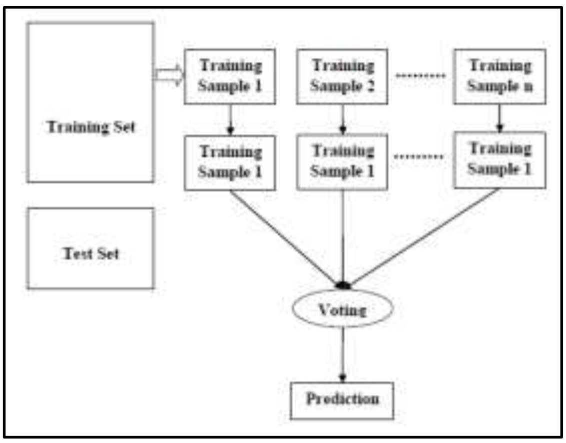
Step 1 − First, start with the selection of random samples from a given dataset.

Step 2 − Next, this algorithm will construct a decision tree for every sample. Then it will get the prediction result from every decision tree.

Step 3 − In this step, voting will be performed for every predicted result.

Step 4 − At last, select the most voted prediction result as the final prediction result.

The following diagram will illustrate its working −



5.RESULT & CONCLUSION

Thus All the parameters of the patient are sent and Machine learning is processed and the status and prescription is viewed in the Mobile Application.ML based Patient Monitoring systems are especially useful because they let the patients live their life while at the same time afford constant medical attention. The need for visiting the clinic/doctor is pushed to only deserving cases. Although many patient monitoring system is familiar with in-hospital medical care, patients are relatively less experienced and confident with using this system. Hence, promoting patients' active and voluntary participation is very important. Besides interaction between medical providers and patients, communication among chronic disease patients is also important.

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