A Novel Neural Classification Vector Machine (NCVM) For IOT Based Health Care Monitoring System

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ABSTRACT
Today, IoT (Internet of Things) is used in many applications. Some of the applications of IoT are smart parking, smart homes, smart cities, smart environments, industrial sites, agricultural fields, and health monitoring processes. One of such applications is monitoring patient health status through IoT in the healthcare field, improving the efficiency of medical teams by monitoring patient health status in real-time, where sensors acquire data from patients and reduce human errors. So far we have seen a health monitoring system that collects basic parameter information such as heartbeat, body temperature, blood pressure, and growth parameters. In this paper, we discuss monitoring of patient brain signals and real-time detection of patient status. To collect data from brain signals, we used Neurosky Mindwave mobile headsets powered by EEG technology. Display the output result in waveform mode. Display the output result in waveform mode. The remote monitoring system is geared toward people with intellectual disabilities and provides regular updates on the health status of caregivers while they are at work. It also reduces the workload for patients by staying at home rather than going to hospital to check their details. If the system recognizes any changes in the patient's heart rate, brain signal, or body temperature, the system will alert the doctor and corresponding family members of the patient's condition through the Internet of Things, and store the patient's detailed information in the cloud

Keywords: Healthcare, Machine Learning, IoT, Seizure, Prediction, Performance Measures, Monitoring System

INTRODUCTION

Healthcare systems provide remote health monitoring for high-risk populations. Play a life-saving role and prevent emergency deterioration in critically ill patients. Edge servers are now able to extract vital intelligence from IoT nodes, which can benefit a highly diverse range of IoT applications, including smart transportation and distribution networks (energy, people, water and food), agriculture and smart manufacturing; and healthcare and maintenance .Unfortunately, as infrastructures get smarter, they also become more vulnerable to cyber-attacks and data breaches. Additionally, the rich data collection and analysis involved in driving intelligent management greatly increases the risk of violating the privacy of the individuals and organizations you serve. Health Careful health monitoring and fall detection of patients is essential, as the sequel of falls can have serious consequences, especially in elderly patients. With a health support system accompanied by monitoring, preventive measures can be taken for such populations through active monitoring [1].

The Internet of Things (IoT) is a new Internet revolution. “The IOT is a network that connects uniquely identifiable things to the Internet. Things have sensing/actuating capabilities and potentially programmability. By utilizing unique identification and detection, information about things can be gathered and the condition of “things” can be changed anytime, anywhere” [2]. opened up a new path. Portable Internet of Things (wIoT) [3] important role in healthcare systems to monitor patients at risk to their health. This IoT-based application extends the reach of healthcare beyond the hospital environment for early detection and prevention of patient health deterioration [4]. These applications are designed to provide healthcare users with low-latency, low-cost, high-level convenience and energy-saving services. Many existing smart health monitoring systems are mainly based on cloud platforms [5].

Traditional healthcare systems require patients to enter a hospital and connect to biomedical devices, including oxygen sensors, blood pressure monitors, glucose sensors, and more. However, classical procedures struggle to address a wide range of healthcare needs, a critical consideration given the growing geriatric population and events such as global pandemics. Currently, global interest in tele-health technology is accelerating situation of the pandemic. In addition, the pandemic situation limited the use of health resources to minimize the risk of disease transmission A certain number of patients who do not require strong medical intervention can be connected to the hospital for remote monitoring and treatment. Elderly and post-treatment follow-up are potential patient categories. Reduce risk, improve patient comfort and satisfaction, and ultimately reduce costs Fog computing is suitable for the following applications and services for which the cloud computing paradigm is not suitable Applications that require very small latency, such as healthcare applications, security applications, military applications, etc. [6] Smart city, smart car, smart transportation, smart traffic management and other fast mobile applications. Large-scale distributed computing systems such as smart grids.

Healthcare Fog Computing: The use of IoT has covered major areas of the healthcare industry. In the a healthcare system that uses a variety of inexpensive sensors (wearable, implanted, and ambient) to enable the elderly enjoy contemporary medical services anytime and anywhere [7]. The IOT has the ability to connect device to machine (D2M), Object to Object (O2O), Patient to doctor (P2D), patient to machine(P2M), Doctor to machine(D2M), sensor to mobile phone (S2M) and Mobile to Humans (M2H) [8]. The Internet of Things (IoT) based Market size for healthcare was estimated at USD 60 billion in 2014 and is expected to reach a net value of USD 136 billion by 2021. The market will grow at a CAGR of 12.5% in 2014 over the forecast period [9]. Healthcare systems require low-latency based notification services, so healthcare systems are influenced by the The fog computing idea. Fog computing, with various advantages such as reduced latency, privacy, energy efficiency, low bandwidth, and reliability, has penetrated into the healthcare field.

These systems transmit health-related data generated by IoT devices to the cloud via the Internet, and return diagnostic results obtained through deep learning technology deployed in the cloud. However, such a system does not appear to be suitable for health services where low latency is an important parameter. Therefore, healthcare support systems require a new computational model for latency-sensitive monitoring with intelligent and reliable control.

The goals of the proposed work are (i) monitoring of individual diabetic patients with disease using wIoT devices. (ii) Build a cloud-based paradigm-based health support system to diagnose critical situations for at-risk people. (iii) Combining embedded intelligence with early-retirement devices at the edge to enable real-time smart diagnostics for energy efficiency.

RELATED WORK

Sandeep Kumar et. al., WBSN is used to monitor people's heart rate and exercise rate at home. The edge nodes are associated with the internet and allow sending alerts (on smartphones) to relatives or specialists in case of rapid changes in measurements (falls, early detection of tachycardia or bradycardia).

Saha et. al., proposed a system to monitor home patients and monitor their cardiac function by performing basic analysis of ECG data. Patients can interact with the system through a common TV interface.

An interesting study was presented by Kaur et. al., among them, environmental sensors, optitrack cameras, and sensors embedded in smart watches are used to collect video, motion, and audio signals, as well as dedicated wearable devices for collecting physiological parameters. It is actually a fog-to-cloud collaborative architecture, where indoor location, data preprocessing, and Algorithms for activity recognition are used by the home gateway, while a private cloud is present for remotely accessible data.

Unal et. al., provides research on integrated cloud analytics and distributed computing readiness, familiarity with latency constraints, real-time analytics, and utility cloud network congestion to monitor traffic. The cloud and fog framework's planned approach is tied to Twitter to send alerts about traffic congestion.

Rajavel et. al., proposed a two-way trust management based on subjective logic, allowing the service seeker should confirm whether the service provider provides safe and reliable services, and the service provider can verify the trustworthiness of the service requester.

Hartmann et. al., proposed a solution to an automatic fog node audit certification method that uses a promising fog layer mechanism to attest to secure fog layers.

Vimal et. al., have planned to provide an integrated health monitoring solution for soldiers deployed in harsh environments through the IOT with distributed computing. . Each individual's health parameters require real-time monitoring and subsequent review of datasets to initiate proper healthcare support on time.

Singh et. al., demonstrated a fog- comparable to a cloud-based IoT health monitoring system system through environmental and physiological signals, which allows the generation of information related to

daily activities. The proposed system monitors behavioral changes and health status in older adults. The proposed system provides recovery and monitoring of the patient's rehabilitation process.
Kishor et. al., propose a taxonomy of offloading methods currently used in areas such as cloud computing, FC, and IoT. This study discusses the middleware innovations for offloading in cloud IoT cases, and the important factors for offloading in specific scenarios.
Kaur et. al., proposed a privacy-preserving localization protocol for mobile edge computing architectures to maintain the privacy of wireless sensor locations. Two privacy-preserving localization protocols, trilateration and multilateration, have been developed using the Paillier homomorphic encryption scheme.

METHODOLOGY

A. Introduction Machine Learning

Over the two decades ago, machine learning has become one of the pillars of data technology and thus a fairly important, if sometimes hidden, part of our lives. As more and more information insights become available, there is every reason to believe that intelligent data analysis may become more commonplace and a necessary part of technological advancement. Aiming for is to give an summary of the various applications centered around machine learning and bring some order to the zoo of things. Some basic applied math and statistics tools, as they are written in languages that must be used to write a variety of machine learning problems to be sure. Finally, a rather basic set of optional algorithms to solve a key problem, in particular the problem of sorting.
With a machine, we would say very generally that a machine learns whenever it changes its structure, programs, or knowledge (based on its input or in response to external information) to improve its expected future performance. Some of these changes, such as adding records to a database, fall within the purview of other disciplines and do not seem to be better understood as learning in nature. But, for example, once a speech recognition machine's performance improves by listening to many samples of a person's speech, in that case we tend to say that the machine has learned, and thus feel fairly balanced. Machine learning sometimes refers to changes to systems that perform computing (AI)-related tasks. These tasks involve reconnaissance, diagnosis, planning, mechanism management, forecasting, and more.

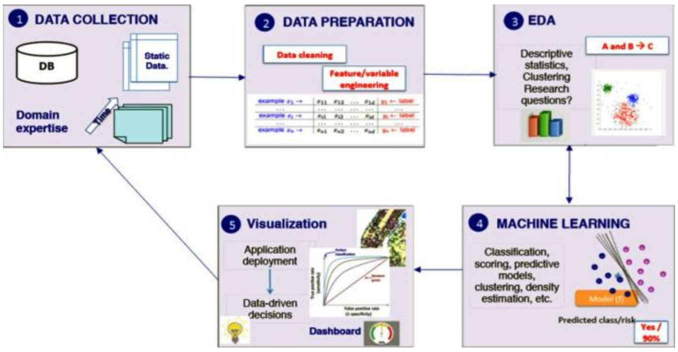

Fig 1. Machine Learning Steps

B. Importance of Machine Learning

Tasks cannot be well defined except by example; therefore, we can specify input/output pairs, but not concise relationships between inputs and desired outputs. We want machines to tune their internals to produce the correct output a sizable number of sampled inputs, constraining their input/output functions appropriately to approximate the relationships implied by the examples.

C. Training data

The training data includes both Inputs and Labels (Targets)
What are Inputs and Labels (Targets)?? for example addition of two numbers a=5,b=6 result =11, Inputs are 5,6 and Target is 11

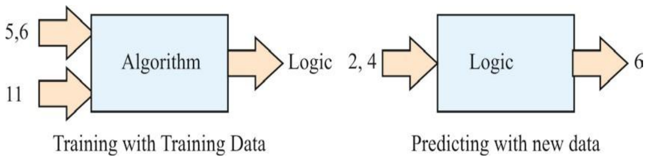

Fig 2. Training and Predicting Data

First we train the model with a large training data (input and target), then with new data and the logic we got before predicting the output (note: we don't get the exact 6 as the answer, based on the training data and the algorithm value close to 6) This process is called supervised learning and it is very fast and accurate.

D. Neural Network Neural Network Definition

A neural network is multiple algorithms, loosely modeled after the human brain, designed to recognize patterns. They interpret sensory data through a form of machine perception, labeling or grouping raw input. The patterns they identify are digital and encapsulated All real-world data, including images, sounds, texts, and time series, must be transformed into vectors.

Neural networks help us group and classify. You can think of them as a grouping and classification layer on top of the data you store and manage. They help group unlabeled data based on similarity between sample inputs and classify data when trained on labeled datasets. (Neural networks can also extract features that feed other algorithms for classification and clustering, so you can think of extensive neural networks as components of larger machine learning applications involving reinforcement learning, classification, and regression algorithms).

Proposed work

In this experiment, a framework for predicting seizures was created and tested. As a demonstration of the presented method, a first trial was performed using a tonic-clonic seizure case provided by the Krembil Neuroscience Center in Toronto. The activity of a tonic-clonic seizure is usually easy to visualize on the EEG, as the signal amplitude begins to peak and a different set of frequencies predominates. This serves as a simple indicator of the the seizure prediction system's effectiveness. Since there is no measurable gold standard of unique states to differentiate for seizure pattern recognition, an initial hypothesis of 7 states was defined. This guess was made by visually identifying the most distinctive parts of the EEG signal. To keep confounding variables constant, the training and test data used were taken from the same seizure cases, with 80% used for training and 20% used for testing (a new random permutation for each class). The initially defined states are shown in Table 1. The distinction between ictal and preictal is to determine if there is a more gradual transition between the preictal and ictal states.

Table 1. Initially defined epileptic states

State	Epileptic State
1	Normal, Calm EEG
2	Seizure Onset Period
3	Preictal
4	Ictal
5	Ictal (Full seizure state)

The outcome of this experiment were able to show the efficiency of state decision neurons in performing state transitions and decision fusion for improved classification. Additionally, a module was created to segment the multi-channel EEG signal, apply a window function and pass it to the system at appropriate time intervals. This makes it possible to simulate more realistic scenarios

EXPERIMENTAL RESULTS

A. Dataset preparation

The first dataset presented is an illustration of a severe seizure (possibly tonic-clonic) and the second dataset is the hemispheric complex partial seizure followed by a generalized seizure a few minutes later. Both datasets were sampled at 500 Hz The third and fourth datasets contain a few minutes of "baseline" interictal EEG data, both followed by bouts of ictal activity. These two datasets are sample data 250Hz.

Seizure type: SP, partially simple; CP, partially complex; GTC, generalized tonic-clonic seizures of origin. In this proposed work, a system is presented that can predict the onset of epileptic seizures using multi-channel real-time EEG signals. The system receives a selected number of EEG channels as input and reports the corresponding seizure status every second. In this system, ranking is done as a simulation of real-time dynamic predictions and depends on previously made predictions. Therefore, the perception must be controlled so that seizures are not predicted to occur more often than they actually do.

B. Feature Extraction

Among the most important steps in creating a signal classification system is to generate a mathematical representation and reduction of the given data so that the input signals can be correctly differentiated into their respective categories. In a sense, the mathematical representation of these signals is a mapping from a multidimensional space (the input signal) to a space with fewer dimensions. This dimensionality reduction is called "feature extraction". Ultimately, the extracted function set should only preserve the most important information from the original signal.

Table 2. Dataset for different age groups

Patient	Sex	Age	Foci	Type	Cases
1	F	15	Frontal	SP,CP	4
2	M	38	Temporal	SP,CP,GTC	3
3	M	14	Frontal	SP,CP	5
4	F	26	Temporal	SP,CP,GTC	5
5	F	16	Frontal	SP,CP,GTC	5
6	F	31	Temp./Occ.	CP,GTC	3
7	F	42	Temp	SP,CP,GTC	3
8	F	32	Frontal	SP,CP	2
9	M	44	Temp./Occ.	CP,GTC	5
10	M	46	Temporal	SP,CP,GTC	5
11	M	11	Parietal	SP,CP,GTC	5
12	M	43	Temporal	SP,CP,GTC	4
14	F	41	Front./Temp.	CP,GTC	2
15	M	31	Temporal	SP,CP,GTC	4
16	M	49	Temporal	SP,CP,GTC	5
17	M	29	Temporal	SP,CP,GTC	5
18	M	24	Frontal	SP,CP	5
19	F	28	Frontal	SP,CP,GTC	4
20	M	34	Temp./Par.	SP,CP,GTC	5
21	M	13	Temporal	SP,CP	5

Table 3. Feature Extraction

Set	Mathematical Transform	Feature Number
1	Linear Predictive Coding Taps	1-4
2	Fast Fourier Transform Statistics	5-10
3	Fast Fourier Transform Subbands	17-75
4	Power Spectra Analysis	11-16
5	log(FFT) Analysis	76-81
6	Mel Frequency Cepstral Coefficients	82-85
7	Wavelet Decomposition	86-89
8	Enveloping & Peak Analysis	90-99
9	1^{st}, 2^{nd}, & 3^{rd}Derivatives	100-102
10	Phase Shift Correlation	103-108
11	Shannon/Log Entropy	109-110
12	Coherence Estimate	111-128
13	Hilbert Transform Statistics	129-138
14	Auto-Regressive Parameters	139-145
15	Lyapunov Exponents	146-151

C. Feature Optimization

To find the features with the greatest potential, an algorithm was implemented to estimate the strength of a single feature relative to all other features. The metrits of the feature depends on the accuracy of classifying the preictal state as an average of multiple classifications. Similar to cross-validation by elimination (explained in Section 3.3.2.1), the algorithm repartitions the feature set, performs a set of sorts, finds the best feature set to discard, and then adjusts the feature space so that only improved features are included quality and accurate.

Algorithm 1: Stepwise Feature Optimization

- Evaluate classification accuracy using all K feature sets.
- Discarding a group of operations at a time, partition the function space into function subsets K, K-1, and store the precision of each subset in location Kinvector Õ along with the resulting precision.
- Denote the index of Õ with maximum precision as Á, and remove all features of Õ listed in Á to K from the final feature space.

The precision of the resulting feature set Õ is similar to the precision at position Á in Õ. Undertraining and overtraining still require be considered as they have an impact on the accuracy of predictions.

D. Fusion of Classification Methods

The seizure prediction system proposed in this work uses a series of different classifiers at each moment to predict the current condition of epileptic disorder. Using multiple classifiers requires a way to combine predictions for final classification. Each sample is fed to four classifiers: LDA, KNN, SVM and NCVM. The method used here involves an initial voting system followed by a decision tree to generate a prediction for the current state.

Table 4. Performance evaluation of proposed work

Algorithms	Performance Metrics	All features set (%)	Performance set (%)
LDA	Sensitivity	97.33	98.1
	Specificity	97.66	98.7
	Accuracy	97.19	98.1
	Elapsed Time (Sec)	7.451	6.903
KNN	Sensitivity	96.1	97.9
	Specificity	97.3	98.12
	Accuracy	96.88	97.92
	Elapsed Time (Sec)	8.663	7.933
SVM	Sensitivity	97.13	98.72
	Specificity	97.86	98.11
	Accuracy	97.45	98.45
	Elapsed Time (Sec)	6.226	5.439
NCVM	Sensitivity	98.33	98.88
	Specificity	98.66	99.17
	Accuracy	98.45	99.16
	Elapsed Time (Sec)	5.955	5.308

CONCLUSION

The LDA and KNN classifiers are then run with their described training and test sets, and their predictions are passed to the decision fusion module. The decision-merging module then decides whether to use the NCVM or the SVM classifier to obtain a majority vote for status epilepticus. Tabulate these predictions and feed the initial predictions to the LDA. This fusion of prediction methods is then fed to the decision state neurons, which use the last 32 predictions (for this system, each neuron population contains 32 neurons) to determine the final prediction for the current status epilepticus and do The decision about when to make a state transition is depend on the defined weight matrix. Each test case assumes that all other cases of the same patient have occurred, and the average of the best weights for each case is used for the test case. The simulator received data from 9 seconds before impact to 2 seconds after impact and tested to determine how accurately each state transition was performed.

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