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Epilepsy/Seizure Detection Using Machine Learning Through IOT

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Abstract: *Epilepsy is a condition that results from nervous system imbalance and can be fatal. The most typical signs of epilepsy are rapid changes in heart rate and uncontrollable muscle contractions (seizures). Only epilepsy patients are intended for usage of the wireless electronic diagnostic equipment in this instance. seizures that our system predicted would occur. This device enables the patient to live a healthy life. Leaving the patient alone will be challenging since seizures might happen at any time. the computerized technique for finding epilepsy that forecasts its onset. The signals produced by the human body are utilized to identify epilepsy disorder. The gadget sends a coded signal to create control signals for switching when it notices the symptoms. To pinpoint the patient's precise position, an alarm device, a doctor's or a family member's mobile phone employing wireless communication, a GSM modem, and GPS are employed.*

Key Word: *Accelerometer sensor, brain sensor, heart rate sensor, GPS, GSM.*

I. INTRODUCTION

According to the Epilepsy Foundation, epilepsy is a chronic neurological illness that affects more than 65 million individuals worldwide. It is accompanied by frequent, abrupt seizures that are brought on by a brief electrical disruption and excessive brain neuronal firing. Alterations in awareness or a full-body convulsion with uncontrollable movements are the results of epileptic seizures. Seizures are unpredictable and can raise the risk of catastrophic injury, especially if they happen when the patient is exercising, driving, or doing other activities. The medical profession has long held the view that epileptic seizures were sudden shifts that could not be anticipated. Research has found that patients' Electroencephalographic (EEG) signals, however, really represent the changes that occurred before the epileptic episodes. EEG is a record of brain activity that may be monitored with the use of implanted sensors. EEG is generally acknowledged and used for seizure monitoring and diagnosis. Evidence from EEG research demonstrates that seizures begin to manifest hours before any clinical symptoms. According to quantitative analysis of epileptic EEG recordings, there are three different stages of brain activity in epileptic subjects: ictal, preictal, and interictal. Preictal refers to the condition of the brain one or more hours before the commencement of a seizure, whereas ictal describes the state of the brain during real seizures. Interictal describes the state of the EEG recording when there are no seizures. The visual analysis recorded by the neurologist of the EEG has demonstrated and proven the ability to distinguish between ictal, interictal, and preictal phases. Engineering-wise, these three states may be separated using EEG data via pattern recognition methods. To identify seizures "after" they occur, a variety of techniques have been suggested. These retroactive techniques are crucial for automating the processing of EEG data and cutting down on the time and expense involved. They were created to replace visual seizure detection, which hasn't been shown to be particularly effective, especially for analyzing Big Data and long-term epileptic EEG recordings. Predicting or forecasting epileptic seizures before they happen, however, has considerably more promise as a use since it will enable patients to take the necessary safeguards (e.g., taking medication, pulling aside, etc.). Patients can benefit from portable, low-power gadgets with network access, especially with the development of the Internet of Things (IoT). It has been demonstrated that machine learning approaches are useful for creating seizure prediction systems. A model is developed utilizing a large number of labelled EEG signals and classification techniques like as neural networks, support vector machines, decision trees, logistic regression, etc. to determine if an EEG state is preictal or interictal. The majority of seizure prediction techniques have problems with low specificity (too many false alarms) and inconsistent patient performance. One of the causes, often referred to as imbalanced categorization, is the asymmetrical nature of seizure data (very infrequent ictal and preictal condition, while the patient is typically in the interictal state). In order to enhance the state-of-the-art in seizure prediction, the American Epilepsy Society, Epilepsy Foundation of America, and National Institutes of Health conducted a competition on Kaggle.com in 2014. For interictal and preictal EEG training signals, they supplied EEG data from seven participants. The competitors-built classifiers utilizing a variety of characteristics from the available training data using supervised machine learning techniques. The models, methods, and outcomes of the top contestants were published. Modern seizure prediction algorithms aren't suited or designed for portable, restricted IoT devices, though.

II. METHODLOGY

Figure 1 depicts an overview of a typical detection system for tracking bad health problems. There are frequently three primary processes that detecting systems take during training. Initially, there is a pre-processing stage where various filters are used to prepare the data for subsequent processing. Then, depending on the target system, distinct time-domain or frequency-domain properties of the processed signal are used to extract the features. In the last phase, the model is extracted and any bio-medical anomalies are detected using a machine learning algorithm that has been specifically chosen and trained for the target problem.

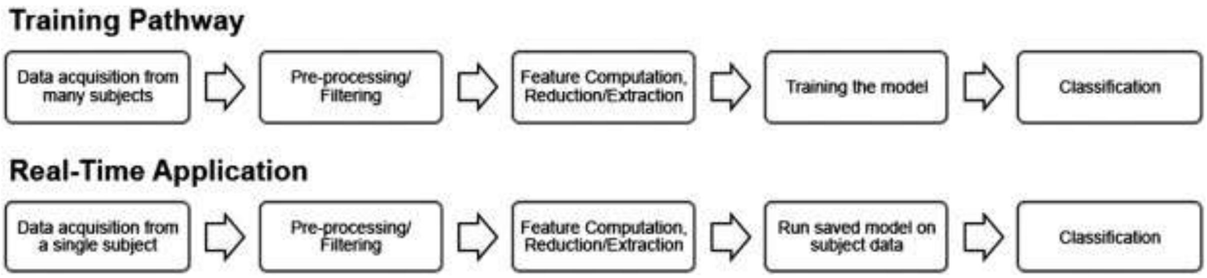

Fig 1: Overview of a typical detection for monitoring pathological health conditions

The same pre-processing and feature extraction steps are repeated for fresh data in the test phase, and the derived model from the training phase is then applied to identify the findings for the new data. Seizure prediction systems based on the EEG signal are newer systems that have a similar topology. The similar process is used on the ECG signal to identify obstructive sleep apnea on wearable sensors. In e-Glass, the same flow is shown for a detection system based on four EEG electrodes for the detection of epileptic episodes. As a result, the design of systems for detecting epileptic seizures is revisited in this paper as the major case study.Contrary to earlier systems, we will employ self-awareness to balance detection accuracy and power consumption by taking advantage of how epileptic convulsions interact noticeably with the autonomic nervous system (ANS) andalter sympathetic and parasympathetic neural activity. Alterations in cardiac and respiratory functioning are a result of these ANS changes. Ictal tachycardia, which frequently exceeds100 bpm,isthe most frequent cardiac alteration related to seizures, but ictal bradycardia < 50 bpm is uncommon. In addition to changing the sensation of breathing and fullness of breath (e.g., shortness of breath), seizures can also affect reflexes (e.g., coughing), quality (e.g., stridor), and secretions. It is also possible for neurogenic pulmonary enema to develop and to cause SUDEP. Monitoring of cardio-respiratory functions is used to analyze these cardiac and respiratory parameters. Our technique for detecting epileptic seizures is briefly detailed in the parts that follow.

A. Pre-processing

The ECG signal is initially divided into windows of one minute in duration with an 80% overlap (48-second length). The noise, which is often of a high frequency nature, is then reduced by applying a low-pass filter for each window in order to exclude frequencies over 60 Hz.

B. Feature extraction

The R-peak to R-peak interval (RRI) and ECG-Derived Respiration (EDR) time series are retrieved from the ECG signal in this initial stage of our wearable system design. The baseline from the ECG signal is removed, the R-peaks are located on the pre-processed signal, and the area included in the areas 100 msec beyond the R-peaks is calculated to produce the EDR time series. The RRI time series is used to compute the hearth-rate variability (which includes time-domain and frequency-domain components of hearth-rate) and Lorenz plot of RRI (to capture the dynamic fluctuation of the RR intervals).

C. Machine Learning

The collected features are now used to train a support vector machine (SVM) using the radial-basis function (RBF) kernel to classify seizure (ictal) and no-seizure (inter-ictal) segments. Along with being highly effective in accurately detecting seizures, SVM is also appropriate for use in embedded systems with limited resources.

Since long-term monitoring of patient signal changes is necessary for giving Real-Time feedback in health monitors, the key issue in monitoring systems is to provide good detection quality despite severe resource restrictions. By incorporating the idea of self-awareness into wearable technology, it will be possible to reduce the amount of energy used by the monitoring system and enable it to run in low-power mode when appropriate (energy-saving mode). On the other hand, utilizing freshly obtained data that the system has correctly categorized, the self-awareness idea can enhance the system's detection performance by enhancing the detection model.

III.LITERATURE SURVEY

- Epileptic seizures are brought on by an imbalance in the electrical activity of the brain. There are several types of epileptic seizures. Epileptic seizures can take many different shapes, according to research. About one-third of epilepsy sufferers are resistant to the medications that can manage these seizures, which happen with little to no warning. Machine learning approaches have been effective in the development of predictive seizure medicines, the Internet of Things (IOT), and patient-helping portable, low-power gadgets with network access. The electroencephalogram (EEG) data from a wearable cap or other portable device for collecting EEG information was interpreted by researchers using deep machine learning and a complicated analytical tool based on the data. As a result, the system could make predictions with a sensitivity of up to 81.4% and a false prediction rate as low as 0.06 per hour. While there is still some ambiguity, it is anticipated that as availability to seizure data expands, sensitivity rates will rise. Using a convolutional neural network that is very adept at monitoring changes in brain activity based on EEG measurements, the system can provide optimum features for everyone.

- Epilepsy is the most common ailment since there are actually close to 50 million cases worldwide. Nowadays, the majority of research is focused on diagnosing and preventing epilepsy. Here, we can identify epilepsy based on signal and image processing's ability to forecast, as well as a comparison of the effectiveness of various extraction techniques and classifiers. Using the multi model technique, which increases the system's specificity as soon as possible to prevent fault identification, we may learn more about the disease in the brain.
- Short Time Fourier Transform (STFT) and convolution neural network have been used to create an EEG signal (CNN). The two primary elements that confirm feasibility are the actual study data and parameter setup. Using a support vector machine, the signal's average accuracy is 86%, according to comparison (SVN). With an accuracy rise to 90%, the signal will be steady and perform well for epileptic seizure detection. The EEG signal has been a primary method for establishing a link between the EEG and epileptic seizures. EEG signal processing, signal re-processing, and time-frequency analysis are just a few of the applications for deep learning that are now being used.

IV.CONCLUSION

Modern technology is now on the cutting edge of numerous automations. Due to the relationship between epileptic seizures and the EEG, Signal is the primary methodology for epileptic seizure research. The signal processing or image processing is what determines the prognosis and diagnosis of epileptic seizures. Without the use of a multi model tool, there is a chance that a defect would be identified, which might result in a delay in treatment that could possibly result in death. Particularly, this technology, which is affordable and aids millions of epilepsy/seizure sufferers. The patient may walk about freely while wearing this equipment, just like a regular person. To avoid fatalities, epilepsy must be predicted before it occurs.

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