PERTIENCE OF IoT IN BIOMEDICAL DIAGNOSTIC SYSTEM – A REVIEW

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ABSTRACT

In Morden era of technology and science we have achieve success in many areas of biomedical field to elongate the life span of human beings but still we are struggling to achieve superior solutions for diseases like cancer, neuronal disorders, genetical disorder etc.The available treatments, diagnostic methods, instruments used, drugs or medicines used for these diseases have many shortfalls and need to improve the way of treatments. This review article summaries application of IOT for better and early detection of diseases to impact positively on the treatment in early stage of diseases to save the life of patients

Keyword : - IoT , OMRES Model, Sensors,

1. INTRODUCTION

In condition of bileganance or malignance early-stage diagnosis is very important to restrict the speed of spread of disease in the body. Internet of things commonly known as IOT plays a vital role in early fast detection of diseases.[1] These tools help us for localize specific detection of tumour cell and area around it which helps to come on final conclusion. This has also impact on line of treatment to save the life of patient. This paper includes few listed tools used to detect the cancer cells and related growth [2]. Similarly neurological disorders hamper regular routine of patients. In diseases like depression, scizophinia and child seizure [5] early detection is much needed to avoid panic situation. There are many psychological methods and line of treatments available to treat patients who are in various stages of depression [6]. But it has been observed that many patients move on next stage of diseases. To avoid this pathic situation we need to focus on detection and diagnosis systems to avoid the negative progress of the disease. IOT plays key role here to detect the disease in shorter span. Biomedical monitoring is becoming a tool which can improve reliable and accurate medical diagnostic and health state evaluation.[4] Mobile software and platforms are hosts for advanced health state monitoring systems and recently are moving towards decision support tools. The analytical process must be supported by sensing equipment selected to evaluate specific symptoms (and preferably their intensity) of a given disease. This paper summarizes application of IOT in disease diagnostic system.

2. IoT BASED BODY TUMOUR MONITORING (MOBILE APPLICATION FOR BRAIN TUMOUR)

The proposed IoT-based enhanced machine learning algorithm was structured, even within the molecular subtype of a particular cancer symptom, and the tumour genetic profile of each individual is different and unique[3].The genetic analysis of cancer DNA provides information on the major genetic abnormalities (mutations) that drive the disease, and many of these contain specific drugs designed to inhibit their action.The abnormalities of cancer DNA

help to better understand the basic mechanisms by which the cancer cell uses its continuous and rapid growth and proliferation and to discover new and more targeted drugs. Therefore, in the case of a disease such as cancer, which is associated with morbidity and mortality, every piece of information that helps to understand the cancer characteristics of the individual will be useful. Listed as follows are the first three reasons why patients should order their DNA and consult a specialist with their results.
Grade 1: cancer cells look like normal cells and do not grow.
Grade 2: cancer cells do not look like normal cells. At this level, cancer cells grow rapidly.
Grade 3: cancer cells look abnormal. And, those cells are likely to grow or spread aggressively to other organs.

Genetic Sequencing of Cancer HLPs to Identify an Individual Treatment Option. For many cancer patients who do not respond to the standard of maintenance chemotherapy treatment, tumour sorting can help better identify major abnormalities that can then be treated with more recently developed target drugs and used only in specific cases. It has the required attribute. In stubborn, recurrent, and resistant cancers, the genetic specification of the tumour DNA will facilitate access and inclusion in clinical trials testing new and innovative target drugs or finding unique alternative and customized drug options (treatments) based on cancer characteristics. The grade of cancer is determined by the appearance of the cancer cells seen under a microscope. A low grade indicates slow-growing cancer, while a high grade indicates fast-growing cancer cells.

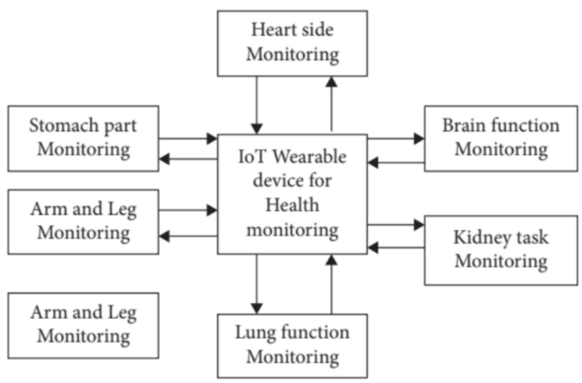

Fig -1 : IoT based body tumour monitoring

If diagnosed more accurately, the delay in calculating the size of the tumour and sending the tumour to the doctor will further increase the patient’s risk. (e state-of-the-art model with IoT further enhances time management by analyzing the size and type of tumours and making it possible to send the results immediately to the doctor without compromising accuracy. The proposed IoTEML was getting good accuracy, better precision, great recall rate, fine F1-score, and low computation duration compared with the existing HFBSO, MTE, CSFCC, and HFEM. Hence, the proposed IoT-based enhanced machine learning method was very accurate to identify the tumours with low time consumption [10]. At a saturation point, the proposed IoT- EML model achieved 94.56% of accuracy, 94.12% of precision, 94.98% of recall, 95.12% of F1-score, and 1856ms of execution time. These computations are very important in the medical field to diagnose the types of tumours in patients. It is especially helpful for physicians to obtain information about the nature of patients and their health from the place where IoT procedures were performed. The future enhancements of the proposed system include IoT-based consultation with the doctor and guided clinical examination, finding out the details of cancer and helping to get better treatment.

3. AUTOMATIC BRAIN TUMOUR DETECTION SYSTEM (WEARABLE DEVICE FOR BRAIN TUMOUR)

For detection of brain tumour, seven common symptoms including- headache, vomiting or nausea, vision change, seizures, walking problem (consider normal people who can walk), drowsiness or sleeping problems are fatigue considered. Firstly, classify those symptoms and corresponding information [9]. Then sense that information using sensors. Since there is no wearable sensor for capturing all the symptoms data correctly, use classification in those symptoms. Based on the classification information, collect data by using our proposed device.

3.1 Data collection from sensors

Xiaomi “Mi Band 2” wrist band is used which includes an accelerometer, optical heart rate monitor, vibration engine, gyroscope, ambient light, and altimeter sensors. The pedometer of MI Band 2 used an improved algorithm to measure steps more accurately. The high-precision accelerometer measures the number of steps and tracks the total activity time for a total number of steps. This device measures the heart rate by using an optical heart rate monitor sensor and tracks deep sleep records. This device tracks the sleep pattern (deep and light sleep) of human and awake time in between sleep by using a heart rate sleep assistant, which measures the heart rate when a human is asleep. Using this wearable wristband, most of the CS symptoms can be measured. Another two individual sensors are used to get the body temperature and blood pressure. All these sensors and the wristband are associated with Arduino Uno to get the results. The wristband connects with the android smartphone using the Mi Fit app to collect data from devices. Also, it can measure steps, distances, and different physical activities.

Symptoms (SS)	Classification Symptoms (CS)	Time
Headache (HA)	○ High Blood pressure ○ Increase body temperature ○ Accompanied by vomiting	○ Usually, steady pain after waking in the morning ○ Get better within a few hours
Vomiting or Nausea (VN)	○ Increase body temperature ○ High heart rate ○ High blood pressure	○ Maybe occur in the morning ○ Or when change the position
Vision changes (VC)	○ Low heart rate ○ High blood pressure ○ Headache ○ Nausea and vomiting	○ After waking from sleep ○ Double or triple vision in one eye ○ Suddenly change posture
Seizures (SZ)	○ Increasing heart rate (High heart rate) ○ Increasing blood pressure (High blood pressure)	○ Any time ○ Blood pressure, heart rate get normal after 30 minutes of seizures
Walking problem (WP)	○ Less number of steps (compare to normal) ○ Lack coordination in the arms or legs	○ Any time of the day, face difficulties to walk
Drowsiness or sleeping problem (DS)	○ Insomnia (less sleep than normal people) ○ Less amount of deep sleep	○ Falling asleep during the day ○ Sometimes not sleeping until 5 or 6 am
Fatigue (FG)	○ Difficulty sleeping (Insomnia) ○ Headache ○ A large amount of Awake time in between Sleep ○ Vision changes	○ Whole day patient experiences this symptom

Fig -2: Classified Information for Collection of Data

3.2 Data transfer and store in the server

An indirect access technique where an intermediate system works to collect data from the source to the third party is used to transfer data from smartphone to server. Wearable MI Band 2 captures data clockwise and sends those captured data to smartphones using the Mi Fit app termed as Send data 1. Arduino Uno transfers the captured data from sensors through the global system for mobile communication (GSM) module to android phones. This data sending process is termed here as Send data 2. Finally, the stored data in these smartphones are transferred to the third-party server.

A portable wristband device, and temperature and blood pressure sensors are used to track the daily activities of both brain tumour patients and normal people. Different symptoms of brain tumours are analysed and classified as the selected common symptoms [10]. The experimental dataset for both the brain tumour patient and normal people groups testify to the accuracy of the proposed method for automatic detection of brain tumours using IoT. This system achieved an accuracy of 99.3%. Compared to other existing techniques, the designed system shows a better precision in detecting the probability of brain tumours and does not require MRI which reduces the computational complexity. Moreover, the proposed portable system is cost effective and easy to use in comparison with other systems.

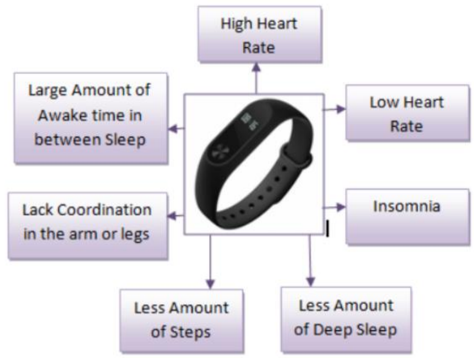

Fig.3: CS Symptoms Measured by MI Band

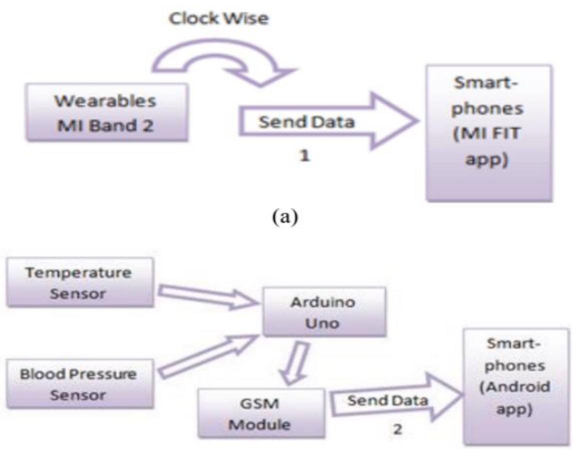

Fig.4: Data Transmission Through (a) MI band to MI Fit App (b)sensors to android app.

4. OMERAS MODEL (FOR BRAIN TUMOUR)

Brain tumours are a serious health issue that affects many people's lives. Such a tumour, which is either benign or malignant, can be fatal if malignant cells are not correctly diagnosed [8]. According to the most recent human health care analysis system, the number of brain tumour patients has climbed dramatically and is now the 10th top cause of death. As a result, detecting brain tumours in their early stages can considerably improve the patient's prospects of complete recovery and therapy.

This scenario presents an IoT-based framework that adopts a multiuser detection system by sending the images to the cloud for early detection of brain tumour, which makes the system accessible to anyone and anywhere for accurate brain tumour categorization. Two key hyper-parameters are used to fine-tune the OMRES model, firstly different optimizers are tested using different learning rates, batch sizes, and a constant number of epochs, and secondly, the impact of changing dropout rates is made. The suggested model achieves superior improvement with the highest rated accuracy of 98.67% compared to the conventional CNNs.

Classifying a brain tumour requires an accurate and prompt diagnosis of the tumour type because the selection of successful treatment methods depends mostly on the pathological type. However, the conventional method for the identification and classification of magnetic resonance imaging (MRI) brain tumours is through human observation that relies heavily on the expertise of radiologists who study and interpret image characteristics and usually give a non-accurate diagnosis. Computer-aided diagnostic methods are highly desirable for these issues.

Accurate and timely detection of brain tumour grade has a serious influence not only on earlier stage brain tumour diagnosis but also on treatment decisions and tumour growth evaluation for the patient. The classification of the tumour is one of the more complicated jobs due to the variances in size, shape, contrast, and location of tumour cells. MRI, ultrasound, computed tomography (CT), X-rays, and other medical pictures play a significant part in disease diagnosis and therapy. CT and MRI are the most often utilized modalities for evaluating and diagnosing brain malignancies. MRI is considered the primary modality due to its higher level of resolution, especially in brain imaging.

First, most brain datasets contain images of varying sizes, so the image is loaded and resized to 224×224 pixels to ensure that all images in the dataset have the same size to be inserted into CNN. After that, the preprocessing procedure raises the picture quality of brain tumour MR images and prepares them for further analysis by clinical experts or imaging modalities. It also aids in the enhancement of MR image characteristics. Improving the signal-to-noise ratio and visual appearance of MR images, removing irrelevant noise and unwanted background portions, smoothing internal portion areas, and preserving relevant edges are among the essential parameters in the image preparation process. Then, the process of obtaining quantitative information from an image, such as color properties, texture, shape, and contrast, is known as feature extraction. Here, the deep feature extraction method is then carried out using CNNs. Finally, the classifcation algorithm determines whether the input image is normal or abnormal based on the fnal feature descriptor. The input data are converted into a 1D vector by the fully connected layer. The SoftMax layer then computes the class scores.

For the suggested model, four main optimizers will be tested-

4.1 Stochastic Gradient Descent with Momentum (SGDM)

It is one of the most widely used optimizers where the SGD optimizer has been improved. The momentum in each dimension is estimated using the current gradient and previous momentum. It also adds up the gradient of previous steps to determine which way to travel.

4.2 Adaptive Moment (ADAM)

It is a Stochastic Optimization Method where momentum and RMSprop are combined in ADAM. Exponential weighted moving averages (also called leak averages) are a fundamental component of ADAM, as they estimate both the gradient's momentum and second-order moment.

4.3 Root-Mean-Square Propagation (RMSProp)

The RMSprop is another optimizer that uses the average exponential decay of squared gradients to break the learning rate. To decrease the loss function relatively faster, it is dependent on momentum. The RMSprop, like momentum, uses a different way to reduce oscillations. It adjusts the learning rate automatically by selecting a new one for each parameter. The mean square error is used to determine the running average.

4.4 Adaptive Scheduling of Stochastic Gradients (ADAS)

ADAS is an adaptive optimization method for scheduling a CNN network's learning rate during training. ADAS is substantially faster than other optimization techniques at achieving convergence. ADAS showed generalization features (low test loss) comparable to SGD-based optimizers, outperforming adaptive optimizers' poor generalization characteristics. ADAS adds new polling metrics for CNN layer removal in addition to optimization (quality metrics).

For the OMRES model, the probability of the normal class being correctly identifed as normal is 38.7%, while the probability that an abnormal class is correctly identifed as abnormal is 60%. Besides, the probability that the normal class is incorrectly identifed as abnormal is 1.3% and the probability that an abnormal class is incorrectly identifed as normal is 0% which means that the proposed model is more efcient in predicting abnormal tumours.

OMRES scheme is the best one for correct recognition of the tumour cases with accuracy of 98.67%, Recall of 94.66%, Specifcity of 100%, and F1-Score 98.3%.

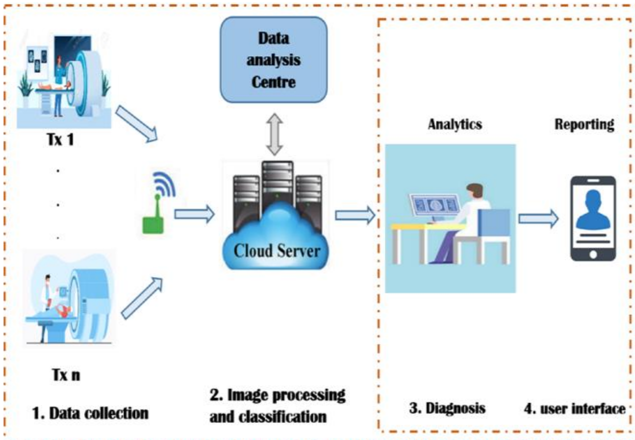

Fig. 5: OMRES Model

5. NERVE MOBILE APPLICATION(FOR CHILD SEIZURE)

NERVE is a mobile wearable-based system composed of miniature biomedical multisensor (actigraph, electromyograph), a mobile emergency and treatment application, and a central knowledge base[13]. The central part of the system - mobile app – provides functions for seizure and disease monitoring, diagnosis and assessment of drug therapy effectiveness via detailed recording and reporting of seizure characteristics. The app coordinates continuous seizure monitoring with its alarm sequence, which consists of two main steps[7]. First, when suspicious muscle activity is detected, the preliminary alarm is activated. It lasts for pre-set time (the default value is 15 seconds) and can be deactivated when the muscle activity does not turn out to be a seizure.

NERVE’s users can help doctors by using app’s dedicated screens and entering various informations about the illness such as: details about medications being taken (name, dosage, time of taking), eaten food (time of meal, and approximate amount of calories, fats and carbohydrates), and mood of the child. All data provided by the user are stored in the app’s memory and can be displayed in it’s calendar. Each event type has it’s own colour – seizures are red, meals are blue, and medicines are purple. Details about them can be accessed simply by clicking on a date in the calendar. In the Day View user can browse through answers to after-seizure questionnaire. That way either parents or doctors can easily access all gathered informations. The app correlates seizure frequency with other events it gathered (such as taken medicines) and provides a histogram that shows trends in number seizures in conjunction with medicines that are being taken. This summary is designed to help with determining the effectiveness of therapy - just by looking at it doctor can see if a medicine (or diet) he prescribed reduces or increases the number and frequency of seizures.

In order to be able to detect seizures, it was necessary to select a sensor that would collect appropriate biomedical signals of appropriate quality. Myo armband is an 8-channel electromyograph with inertial sensors and Bluetooth standard. The choice was made for this sensor because it provides high accuracy of EMG data. Another reason is the straightforward to use of all channels as well as a single one, if we turn the bracelet to the left side we can put any channel to any muscle to get a record of its activity in the form of a sEMG signal.

Unfortunately Myo armband provides only built-in filtering capabilities without any possibilities to modify behaviour for algorithmic data analysis. even in the initial phase, it only sends a raw signal to the phones using

Bluetooth, which means that the analysis of the signal lies entirely on the side of the application. This generates a serious problem, because when for some reason the sensor disconnect from the phone, it is not possible to determine whether the seizure took place.

Epileptic seizures can consist of different stages such as aura, clonic, tonic and postictal. Each stage differs from another in various ways – we are most interested in changes in muscle activity there for NERVE's reasoning algorithm is focused on tonic and clonic stages which have the biggest impact in muscle tension and changes in other signals used in the project (collected by accelerometer and gyroscope).

The algorithm collects data from Myo for t seconds. For each incoming packet, based on readings they contain, we calculate the arithmetic average which is then added at the end of the appropriate list (EMG, ACC or GYRO). After t seconds three created lists are passed to the parameter calculator which calculates the values of individual features. Next, this set of parameters is passed to appropriate classifiers. Based on obtained classification results a decision is made if the window is qualified as normal, tonic or clonic, moreover for the windows to be qualified as normal, tonic or clonic at least k algorithms must qualify them as such (where k is from one to the number of AI domain algorithms).

In order to recognise a complex seizure, let's define window sequence as a sequence of time windows. Such a series of windows is considered as a whole. Each window in a sequence is classified separately, as previously described. Based on the information of how many windows were classified as normal, clonic or tonic the algorithm decides what is the state of the patient. The last (but not least important) thing to look out for is that the algorithm, like every other algorithm, isn't perfect so errors can occur.

NERVE multi sensor which will be tuned to child usage and capable of recording and recognising motion seizures, but most of all will allow us to move a part of analytical algorithms towards hardware sensor thus separating components responsibilities and optimising energy consumptions and making the system and detection more reliable. NERVE is electronic guidance tool with time-constraint support for monitoring and auditing drug intake, surveying and sensor tests. The classification algorithms for simulated seizure data reached – 78.275% accuracy only for ~50 datasets. Presented method evaluates the intensity of neurological disease symptoms for both epileptologii and PD based on the signal features and machine learning techniques. Electromyography and actigraphy based data fusion has proven to be a useful technique for seizure analysis. High accuracy of recognition of movement seizures can be achieved using energy efficient, proactive wearable sensors.

6. DEPRESSION MONITORING USING WEARABLE SENSORS (FOR DEPRESSION)

Depression is a non-communicable disease and can be cured with the correct dosage of medicines and sometimes lifestyle changes. Sensors with android applications are more of the new IOT can be utilized for creating a model that could help the people to detect depression and can hence visit the doctors and psychiatrists respectively [11,12]. In this proposed solution a mobile application is developed which is automated to display the detail of the health band information of the individual. The mobile app as well as sends the notification to the caretaker of the individual on emergencies.

Initially user will wear the health band and connect it to the android phone. The input in the form of signal data is obtained from the wearable (Health-Band) device. This inputted data is then sent to the smart phone using hc-05 Bluetooth module. The wearable device contains some sensors, like Temperature Sensor, BPM sensor, MPU 6050 Sensor and etc. The user can view the sensor data received from the wearable device through the system. Support Vector Machine (SVM) algorithm is applied on some features to make some decisions that mainly includes user's Position (Sitting, Standing) and detection of depressive disorders. If the individual is facing the depression, then the notification is sent to the guardian (caretaker) via android application. The android application is also useful for displaying the entire details of the individual.
List of Hardware required is:
1. Temperature Sensor
2. BPM sensor
3. MPU 6050 Sensor
4. HC-05 Bluetooth module

5.1 Temperature Sensor

The main purpose of the temperature Sensors is to measure the amount of heat energy or even coldness that is generated by an object or system, allowing us to "sense" or detect any physical change to that temperature producing either an analogue or digital output. Get current temperature value.

5.2 BPM sensor

The output in the form of the digital can be connected to microcontroller directly to measure the Beats Per Minute (BPM) rate. Get Blood Pressure value and coronary disease detection using block blood flow and oxygen rich level in blood.

5.3 HC-05 Bluetooth module

The HC-05 Bluetooth module is considered as efficient to apply on Bluetooth SPP (Serial Port Protocol) module, designed for transparent wireless serial connection setup. To send the data from wearable band to the smartphone.

5.4 MPU 6050 Sensor

The MPU 6050 is a 6 DOF (degrees of freedom) or a six-axis IMU sensor, which means that it gives six values as output: three values from the accelerometer and three from the gyroscope. The MPU 6050 is a sensor that relies on MEMS (micro electro mechanical systems) technology. To return sedentary, Idle and sitting positions.

4. CONCLUSIONS

After reviewing variety of papers related to integrated technology, IoT and diagnostic systems it has been concluded that IoT helps us to get the better pertinence in biomedical field for early detection of diseases to avoid further complications. These methods are more reliable, easy for detection, rapid with more accuracy in results but still day by day updatation is needed to improve the scope of diagnosis detection, rapid with more accuracy in results but still day by day updatation is needed to improve the scope of diagnosis.

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