An internet of things-based automatic brain tumor detection system

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ABSTRACT

Due to the advances in information and communication technologies, the usage of the internet of things (IoT) has reached an evolutionary process in the development of the modern health care environment. In the recent human health care analysis system, the amount of brain tumor patients has increased severely and placed in the 10th position of the leading cause of death. Previous state-of-the-art techniques based on magnetic resonance imaging (MRI) faces challenges in brain tumor detection as it requires accurate image segmentation. A wide variety of algorithms were developed earlier to classify MRI images which are computationally very complex and expensive. In this paper, a cost-effective stochastic method for the automatic detection of brain tumors using the IoT is proposed. The proposed system uses the physical activities of the brain to detect brain tumors. To track the daily brain activities, a portable wrist band named Mi Band 2, temperature, and blood pressure monitoring sensors embedded with Arduino-Uno are used and the system achieved an accuracy of 99.3%. Experimental results show the effectiveness of the designed method in detecting brain tumors automatically and produce better accuracy in comparison to previous approaches.

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1. INTRODUCTION

Nowadays, the network of physical objects embedded with electronics devices, sensors, and software known as the internet of things (IoT) is becoming popular around the world. IoT has achieved greater value and service by trading information and data with the manufacturer, operator, and/or other connected devices. In today’s modern healthcare, IoT has attracted much attention recently for its potential to ease the management and interoperability of patient-related and device information. Wearable devices like wristwatches, bracelets, and rings are now widely used for remote healthcare to monitor the physiological parameters of patients. In recent years, researchers have attracted a lot in this field to address the potential of IoT in the healthcare system. In the medical environment, the brain tumor has now become a dangerous problem and placed in 10th position as the leading cause of death [1], [2]. It is estimated that approximately 700,000 people are living with a brain tumor in America, among them 80% are benign and 20% are malignant [3]. In recent years, approximately 78,980 adults are diagnosed with a brain tumor, among them 55,150 are benign and 23,830 are malignant [3]. It is also estimated that approximately 16,700 adults will die from a brain tumor, among them 9,620 are male and 7,080 are female [4]. Also, about 4,830 children 0-19 years of age will be diagnosed with a brain tumor. According to the annual data in the United States, about 34% of men and 36% of females survive at least 5-years with brain tumors.

The IoT and information technologies now revolutionized the development of the healthcare system which has reduced the risk and cost of monitoring and evaluating patients' health conditions. Many researchers presented different methods for the segmentation and detection of brain tumors. A model for individualizing the texture of tumors in brain magnetic resonance imaging (MRIs) are proposed in [5]. To testify the accuracy of their proposed technique, they used more than 300 MRIs of 14 patients and compare their automatic segmentation of brain tumors using the MRIs technique to other segmentation of brain tumor works. Using the K-means algorithm and normalized histogram segmentation technique, a brain tumor detection technique is developed in [6]. They used the support vector machine (SVM) and Naïve Bayes classifier for the classification and accuracy of their method. Authors in [7] suggest an automatic detection and segmentation of brain tumors through the conditional random field in MRI images and obtained 89% accuracy on average. A modified mean-shift-based fuzzy c-mean segmentation technique for the detection of brain tumors is proposed in [8] which is fast to provide segmentation results. In [9], the authors proposed an SVM and rough K-means-based brain tumor detection algorithm, which classify MRI images and claimed almost 99.05% of accuracy. Authors in [10] convert MRI images into OtsoBinarization followed by K-means clustering segmentation in brain tumor detection and classification. They used the discrete wavelet transform technique to extract the features and SVM for classification of high accuracy. A better technique than artificial neural network (ANN) and SVM techniques is proposed in [11] which includes k-means clustering segmentation, high concentration slurry disposal (HCSD) method, extraction of features, and k-nearest neighbors (KNN) classifier. Authors in [12] proposed IoT based malignant tumor prediction system, where they used only three physical symptoms and their accuracy is not good. A hybrid feature extraction method was used based on discrete wavelet transform and principal component analysis to identify the brain tumor [13]. Based on the compression of MRI brain images an automatic tumor region extraction system was proposed in [14]. Principle component analysis and ANN techniques were used to detect and recognize the brain tumor [15], but that system used only 20 MRI images for training purposes and 45 MRI images for testing purposes.

In this paper, an IoT-based automatic brain tumor detection system is designed and developed. Different symptoms of brain tumors are classified to extract their internal characteristics and measured by using sensors. Portable wristband Mi Band 2, temperature, and blood pressure monitoring sensors are used in the experiments to monitor the different symptoms of patients from time to time. Patients' information is stored in a developed mobile application via a third-party server. A comparison study has been made between sick and healthy people based on their extracted physiology information to testify the effectiveness of the developed brain tumor detection system.

The paper is organized as follows. In section 2, the methodology of the proposed brain tumor detection technique is discussed. The classifications and measurement of different symptoms related to brain tumors are explained in this section. The experimental data collection and data transfer techniques are discussed in section 3. Section 4 shows the result and discussion part of this system including the extracted experimental dataset. Section 5 shows the accuracy and comparison part of the system while section 6 provides the conclusion.

2. PROPOSED METHOD

For detection of brain tumor, 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, we will classify those symptoms and corresponding information. Then we will sense that information using sensors.

2.1. Symptoms analysis

Since there is no wearable sensor for capturing all the symptoms data correctly, we use classification in those symptoms. Based on the classification information, we will collect data by using our proposed device. The classifications of symptoms are shown in Table 1.

2.2. Measurements of classification symptoms

For every classification symptom (CS), a defined value is set to compare with the observed value. For example, 140/90 is the defined value of blood pressure. To measure the CS, in (1) is proposed which can be stated.

$$CS\ value = \begin{cases} 1, observe\ value \geq high\ defined\ value \\ 1, observe\ value < low\ defined\ value \\ \qquad\qquad -1, otherwise \end{cases} \tag{1}$$

In (1), observe value is the sensor's sensed value, and the high defined value (HDV) is such kind of symptoms values that will be always greater than or equal to the defined value if a person has that symptom. Similarly, a low defined value (LDV) is such a kind of symptoms value that will be always less than the defined value if a person has that symptom. In this research, HDVs are high blood pressure, increased body temperature, high heart rate, and a large amount of awake time in between sleep. Similarly, LDVs are a low heart rate, a fewer number of steps, lower deep sleep, and insomnia.

Blood pressure has two values- systolic and diastolic. Table 2 shows the chart of blood pressure. If the measured blood pressure becomes higher than HVD, the computer science (CS) value becomes equal to 1 according to (1), otherwise, CS becomes -1. Table 3 shows the normal body temperature for people aged 3 or above. Body temperature 98° Fahrenheit is considered as the HDV for 'increased body temperature' symptoms [16]. On the other hand, HDV for high heart rate is considered as 101, and LDV for low heart rate is chosen as 60 as shown in Table 4.

Table 1. Classification of brain tumor symptoms

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

Table 2. Blood pressure chart

Blood Pressure	Systolic (top number)	Diastolic (bottom number)
High Blood Pressure	Systolic ≥ 140	Diastolic ≥ 90
Normal Blood Pressure	90 ≤ systolic < 140	60 ≤ systolic < 90
Low Blood Pressure	Systolic < 90	Diastolic < 60

Table 3. Body normal temperature

Age	Fahrenheit	Celsius
3 to 5 years	98.6 to 99.0	37.0 to 37.2
7 to 9 years	98.1 to 98.3	36.7 to 36.8
Age ≥ 10 years	97.8	36.6

Table 4. Heart rate and average sleep chart

Age	Heart Rate	Average Sleep (Hours)
0 to 2 months	120 to 160	12 to 18
3 months to 1 year	80 to 140	14 to 15
1 to 3 years	80 to 130	12 to 14
3 to 5 years	80 to 120	11 to 13
6 to 12 years	70 to 110	10 to 11
Age ≥ 13 years	60 to 110	8.5 to 10

During insomnia known as sleeplessness, people may experience daytime sleepiness, a low level of energy, and always get depressed [17]-[19]. Table 4 shows the hours of average sleep required for some particular age groups. During insomnia, people may experience less sleep than normal people. Therefore, the

LDV for ‘insomnia’ is considered as 4 hours or 240 min. If anyone sleeps less than this LDV value for a long time, then he/she may have insomnia. The sleep stages for adults are given in Table 5 where the amount of deep sleep is observed to be as around 50 to 60 minutes. Therefore, for the CS “Less amount of deep sleep,” the LVD is set at 40 minutes. As observed, the average awake time for adults is 25 minutes. Therefore, the HDV is considered as 35 minutes for the CS “Large amount of Awake time in between Sleep”.

Table 5. Sleep stages for adults

Sleep Stages	Minutes
Light sleep	252 to 324
REM sleep	84 to 108
Deep sleep	50 to 65
Awake	25

For detecting the CS “Less number of steps”, its previous data are used as LDV and compared to the present data as observe value and extract the result. Similar steps are also followed to find“ lack coordination in the arm or legs” which is presented in (2).

$$Lack\ coordination\ in\ the\ arms\ and\ legs = \frac{total\ number\ of\ steps\ per\ day}{total\ actvity\ time\ in\ minutes} \quad (2)$$

Around 30 minutes of average awake time in between sleep is considered normal. But if the awake time in between sleep is greater than or equal to 35 minutes, it will be considered HDV for a large amount of awake time in between sleep. Table 6 shows the HDV and LDV values for CS.

Table 6. HDV and LDV values for CS

CS	HDV	LDV
High Blood Pressure	140 & 90	-
Increase Body Temperature	98	-
High Heart rate	101	-
Low Heart Rate	-	60
Insomnia	-	240
Less amount of Deep Sleep	-	40
Less number of Steps	-	Depending on previous data
Lack of Coordination in the arm or legs	-	Depending on previous data
A large amount of Awake time in between Sleep	35	-

2.3. Measurements of symptoms

For measuring symptoms (SS) mentioned in Table 1, (3) is proposed based on the related CS values.

$$SS\ value = \begin{cases} 1, \sum_{1}^{p} CS\ value \geq 0 \\ -1, otherwise \end{cases} \quad (3)$$

In (3), ‘p’ is the total CS related to SS. Using (3), it is possible to identify the symptom of a brain tumor of any random person or patient. For example, vomiting or nausea (VN) related CSs are increased body temperature, high heart rate, and high blood pressure whose CS values could be either 1 or -1 according to (1). If the summation related three CS’s value of VN symptoms is greater than or equal to zero then SS becomes equal to 1 (means the selected person has VN symptoms), otherwise becomes -1.

2.4. Brain tumor prediction

After predicting all the SS values, the detection of a brain tumor can be done by using the proposed (4).

$$Posibility\ of\ brain\ tumor = \frac{1}{1+e^{-L}} \quad (4)$$

In (4), L is the sum of all SS values (*HA*+*VN*+*VC*+*SZ*+*WP*+*DS*+*FG*). The proposed (4) will show the probability of brain tumors between 0 and 1. The percentage of this probability of brain tumor is divided into a different class to make the decision shown in Table 7.

Table 7. Decision table of brain tumor

Percentage probability of brain tumor	Decision
70% or above	Brain Tumor
30% ≤ percentage probability <70%	Brain Tumor Candidate
Below 30%	Normal

3. EXPERIMENTAL SETUP

3.1. Data collection from sensors

In the experiment, Xiaomi "Mi Band 2" wrist band as shown in Figure 1 is used which includes an accelerometer, optical heart rate monitor, vibration engine, gyroscope, ambient light, and altimeter sensors [20], [21]. 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 as shown in Figure 2(a). Mi Fit stores those data and shows the average statistics and other information in terms of time (e.g., daily, weekly and monthly). Also, it can measure steps, distances, and different physical activities. Figure 2(b) shows the block diagram of the data transmission from sensors.

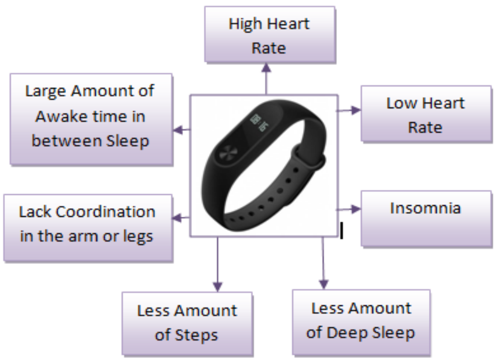

Figure 1. CS symptoms measured by MI Band 2

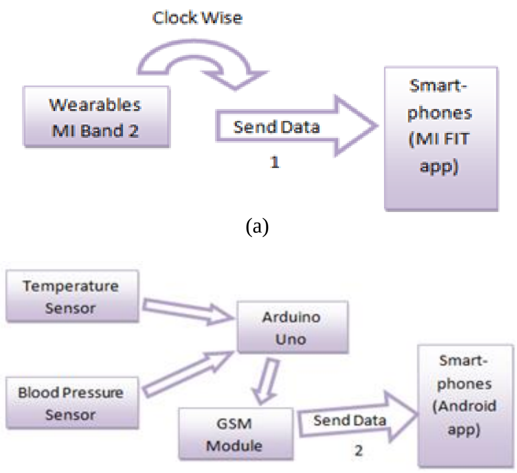

Figure 2. Data transmission through, (a) Mi band to Mi Fit app and (b) sensors to android app

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. Figure 2 illustrates the data flow of wearable bands and sensors via indirect access. As shown, 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.

4. EXPERIMENTAL RESULTS

4.1. Datasets collections

The experimental data were extracted from two groups of people: one is from brain tumor patients and the other is from normal people. Brain tumor patient data were collected from a renowned hospital in Bangladesh through the clinical trial method. Total 375 brain tumor patient data are collected and used in this system. Normal people's data were collected from university and college students, and staff. Total 625 normal person data were collected and used in this system for validation. In this paper, randomly selected 10 data from each group are used. Tables 8 and 9 show the data of the brain tumor patient and the normal person used in this paper, respectively.

Table 8. Experimental data of brain tumor patient

Sample info		Blood Pressure		Body Temperature	Heart Rate	Total Sleep	Total Deep Sleep	Total Awake Time	Total Steps	Total Activity Time of Steps	Previous Total Steps	Previous Total Activity Time of Steps
#	Age	Systolic mmhg	Diastolic mmhg	F	bpm	min	min	min		min		min
1	41	162	94	100.1	51	230	38	34	5646	73	5644	75
2	47	156	90	99.1	55	249	51	66	6586	82	5739	80
3	52	140	89	98.5	101	198	31	59	5611	78	4235	56
4	56	145	96	99	108	237	42	30	4983	64	5415	71
5	49	138	110	99.2	102	241	43	53	5967	68	5613	64
6	53	133	92	97.8	101	217	36	47	4017	61	4768	66
7	44	157	101	98.5	112	234	39	32	4511	57	5241	65
8	31	152	104	99.2	57	298	31	47	3554	45	3922	47
9	42	143	96	98.7	52	211	43	64	5546	65	4132	56
10	39	148	98	98.7	96	179	29	71	4658	70	3219	63

Table 9. Experimental data of normal person

Sample info		Blood Pressure		Body Temperature	Heart Rate	Total Sleep	Total Deep Sleep	Total Awake Time	Total Steps	Total Activity Time of Steps	Previous Total Steps	Previous Total Activity Time of Steps
#	Age	Systolic mmhg	Diastolic mmhg	F	bpm	min	min	min		min		min
1	23	108	72	97.8	45	291	57	12	8723	101	8313	99
2	23	138	92	98.1	98	350	105	2	5993	66	5098	59
3	57	125	87	98	47	274	33	3	9329	97	10213	109
4	23	136	90	97.9	93	475	114	5	7921	88	8111	96
5	23	126	81	97.9	77	463	108	20	11310	112	12512	117
6	51	130	89	97.9	100	363	62	12	3527	43	3409	42
7	23	121	83	97.8	97	475	119	4	3120	39	3411	41
8	24	107	72	97.9	89	393	132	2	2739	36	2711	36
9	23	123	81	97.9	95	465	127	12	1857	28	1927	31
10	46	118	86	97.9	101	367	97	1	4614	55	4973	56

4.2. Experimental analysis

The measured data are analyzed in two scenarios to detect brain tumors. The experimental data of brain tumor patients given in Table 8 are considered as scenario-1 and the data of the normal person as shown in Table 9, are considered as scenario-2. The required CS symptoms are measured by using (1). These measured values of CS are used to find the SS values via (3) shown in Table 10. Later, in (4) is used to calculate the probability of brain tumor based on the measured SS values which are graphically depicted in Figure 3. As observed, the designed system gives almost 99% of the probability of brain tumor except for sample number 6 having the probability of 73.11%, who may not experience all the mentioned symptoms.

Table 10. Measured SS value for scenario-1

Sample info		HA	VN	VC	SZ	WP	DS	FG	Sum All (L)
#	age								
1	41	1	1	1	1	-1	1	1	5
2	47	1	1	1	1	-1	-1	1	3
3	52	1	1	1	1	1	1	1	7
4	56	1	1	1	1	1	1	1	7
5	49	1	1	1	1	-1	-1	1	3
6	53	-1	-1	-1	1	1	1	1	1
7	44	1	1	1	1	1	1	1	7
8	31	1	1	1	1	1	1	1	7
9	42	1	1	1	1	-1	1	1	5
10	39	1	1	1	1	-1	1	1	5

In the case of scenario-2, data were collected from a normal person who regularly check-up their health and does not contain a brain tumor. Table 11 shows the corresponding experimental CS and SS values for scenario-2 which are measured in a similar way as for scenario-1. As shown in the case of the normal person dataset in Figure 3, the system provides nearly zero probability of brain tumor except the sample numbers 3 and 10 who may have walking and seizure problems that do not reflect the brain tumor symptoms.

Table 11. Measured SS value for scenario-2

Sample info		HA	VN	VC	SZ	WP	DS	FG	Sum All (L)
#	age								
1	23	-1	-1	-1	-1	-1	-1	-1	-7
2	23	-1	-1	-1	-1	-1	-1	-1	-7
3	57	-1	-1	-1	-1	1	1	-1	-3
4	23	-1	-1	-1	-1	1	-1	-1	-5
5	23	-1	-1	-1	-1	1	-1	-1	-5
6	51	-1	-1	-1	-1	-1	-1	-1	-7
7	23	-1	-1	-1	-1	1	-1	-1	-5
8	24	-1	-1	-1	-1	-1	-1	-1	-7
9	23	-1	-1	-1	-1	1	-1	-1	-5
10	46	-1	-1	-1	1	1	-1	-1	-3

5. RESULT ANALYSIS AND DISCUSSION

In our experiment, we divide our dataset into two scenarios and use 10 randomly taken samples for each scenario. For each scenario, our proposed methodology performs very efficiently. We have used the most popular and common metrics available to evaluate the results. We have also measured the accuracy using the following equation.

$$Accuracy\ Score = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

where TP = True Positive (actually positive and predicted positive), FP = false positive (actually negative but predicted positive), TN = true negative (actually negative and predicted negative), and FN = false negative (actually positive but predicted negative). The accuracy of the designed system with the proposed model is given in Table 12 for both scenarios 1 and 2. Figure 3 shows the graphical representation of our results.

Various techniques have been proposed to detect brain tumors. Most of them are image classification-based. To find the efficiency of our method, we have compared our accuracy with other state-of-the-art methodologies. Table 13 shows the accuracy table for various techniques.

Table 12. Accuracy of the proposed method for both scenarios

Dataset	# of sample	Identify correctly	Accuracy score
Scenario-1 (Brain Tumor patient's data)	375	375	100%
Scenario-2 (Normal person's data)	625	618	98.88%
Total (both scenarios)	1,000	976	99.3 %

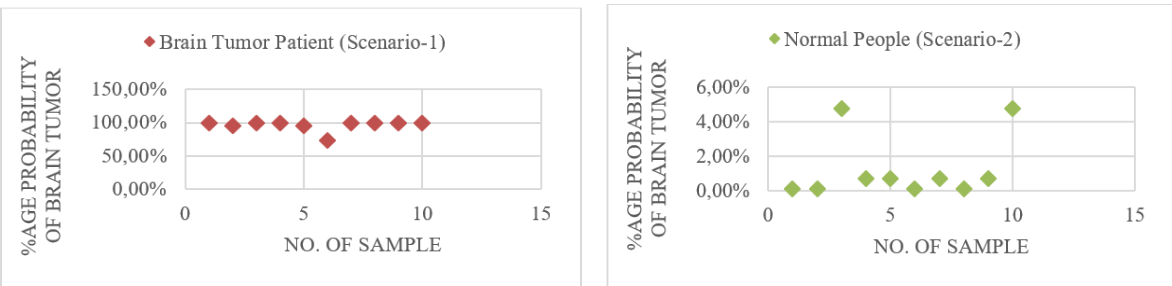

Figure 3. Probability of brain tumor for brain tumor patient's dataset and normal people's dataset

Table 13. A comparison study of the proposed method with other existing techniques

System	Accuracy
Naïve Bayes Classifier [6]	87.23%
Rao *et al.* [7]	89%
Dandil *et al.* [22]	90.79%
SVM classifier [6]	91.49%
Devasena and Hemalatha [23]	98.8%
El-Dahshan *et al.* [24]	99%
Halder and Dobe [9]	99.05%
Arakeri and Reddy [25]	99.09%
Proposed Method	99.3%

6. CONCLUSION

In this paper, a stochastic method for the automatic detection of brain tumors based on IoT is proposed. A portable wristband device, and temperature and blood pressure sensors are used to track the daily activities of both brain tumor patients and normal people. Different symptoms of brain tumors are analyzed and classified as the selected common symptoms. The experimental dataset for both the brain tumor patient and normal people groups testify to the accuracy of the proposed method for automatic detection of brain tumors 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 tumors 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. Although the proposed system is easy to use and cost-effective, our proposed system cannot detect the position and size of brain tumors. In the future, we will add more functions to our system such that it can detect the position and size of the tumor as well.

REFERENCES

[1] C. Narmatha, S. M. Eljack, A. A. R. M. Tuka, S. Manimurugan, and M. Mustafa, “A hybrid fuzzy brain-storm optimization algorithm for the classification of brain tumor MRI images,” *Journal of Ambient Intelligence and Humanized Computing*, pp. 1-9, 2020, doi: 10.1007/s12652-020-02470-5.

[2] J. L. Longe, “Brain Tumor, third ed.,” Gale Encyclopedia of Medicine, 2018.

[3] Brain Tumor: Statistics, https://www.cancer.net/cancer-types/brain-tumor/statistics (Last accessed: 23 January, 2021).

[4] Quick Brain Tumor Facts-National Brain Tumor Society, (2021). http://braintumor.org/brain-tumor-information/brain-tumor-facts (Last accessed: 23 January, 2021).

[5] A. A. Alshehri, T. Daws, and S. Ezekiel, “Medical Image Segmentation Using Multifractal Analysis,” *International Journal on Advanced Science, Engineering and Information Technology*, vol. 10, no. 2, pp. 420-429, 2020, doi: 10.18517/ijaseit.10.2.11011.

[6] G. Singh and M. A. Ansari, "Efficient detection of brain tumor from MRIs using K-means segmentation and normalized histogram," *2016 1st India International Conference on Information Processing (IICIP)*, 2016, pp. 1-6, doi: 10.1109/IICIP.2016.7975365.

[7] C. H. Rao, P. V. Naganjaneyulu, and K. S. Prasad, "Brain Tumor Detection and Segmentation Using Conditional Random Field," *2017 IEEE 7th International Advance Computing Conference (IACC)*, 2017, pp. 807-810, doi: 10.1109/IACC.2017.0166.

[8] G. A. Kumar and P. V. Sridevi, “Brain Tumor Segmentation Using Chi-Square Fuzzy C-Mean Clustering,” *Innovative Product Design and Intelligent Manufacturing Systems*, pp. 857-865, 2020, doi: 10.1007/978-981-15-2696-1_83.

[9] A. Halder and O. Dobe, "Rough K-means and support vector machine based brain tumor detection," *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*, 2017, pp. 116-120, doi: 10.1109/ICACCI.2017.8125826.

[10] S. K. Shil, F. P. Polly, M. A. Hossain, M. S. Ifthekhar, M. N. Uddin, and Y. M. Jang, "An improved brain tumor detection and classification mechanism," *2017 International Conference on Information and Communication Technology Convergence (ICTC)*, 2017, pp. 54-57, doi: 10.1109/ICTC.2017.8190941.

[11] C. P. S. Raj and R. Shreeja, "Automatic brain tumor tissue detection in T-1 weighted MRI," *2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*, 2017, pp. 1-4, doi: 10.1109/ICIIECS.2017.8276094.

[12] M. L. Rahman, S. H. Shehab, Z. H. Chowdhury, and A. K. Datta, "Predicting the Possibility of Being Malignant Tumor based on Physical Symptoms using IoT," *2020 IEEE Region 10 Symposium (TENSYMP)*, 2020, pp. 26-30, doi: 10.1109/TENSYMP50017.2020.9230941.

[13] D. M. Toufiq, A. M. Sagheer, and H. Veisi, “Brain tumor identification with a hybrid feature extraction method based on discrete wavelet transform and principle component analysis,” *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 10, no. 5, pp. 2588-2597, 2021, doi: 10.11591/eei.v10i5.3013.

[14] V. Singh, “Compression of MRI brain images based on automatic extraction of tumor region,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 5, pp. 2088-8708, 2021, doi: 10.11591/ijece.v11i5.pp3964-3976.

[15] Z. Faisal and N. K. El Abbadi, “Detection and recognition of brain tumor based on DWT, PCA and ANN,” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 18 no. 1, pp. 56-63, 2020, doi: 10.11591/ijeecs.v18.i1.pp56-63.

[16] M. Sund-Levander, C. Forsberg, and L. K. Wahren, “Normal oral, rectal, tympanic and axillary body temperature in adult men and women: a systematic literature review,” *Scand J Caring Sci.*, vol. 16, pp. 122-128, 2002, doi: 10.1046/j.1471-6712.2002.00069.x.

[17] N. Binti Zaini, “What Is Insomnia,” *e-Jurnal Medika Udayana*, vol. 2, pp. 2061-2076, 2013.

[18] T. Roth, “Insomnia: definition, prevalence, etiology, and consequences,” *Journal Clin Sleep Med.*, vol. 3, no. 5, S7, 2007, doi: 10.5664/jcsm.26929.

[19] A. R. Punnoose, R. M. Golub, and A. E. Burke, “Insomnia,” *JAMA*, vol. 307, no. 24, p. 2653, 2012, doi: 10.1001/jama.2012.6219.

[20] Xiaomi Mi Band 2. https://arstechnica.com/gadgets/2016/06/xiaomis-mi-band-2-is-its-first-tracker-with-a-screen-but-remains-affordable/ (Last accessed: 18 January, 2021).
[21] XiaomiMi Band 2 – CNET, 2016. http://www.cnet.com/news/xiaomi-unveils-mi-band-2-fitness-tracker-for-23 (Last accessed: 18 January, 2021).
[22] E. Dandıl, M. Çakıroğlu, and Z. Ekşi, "Computer-Aided Diagnosis of Malign and Benign Brain Tumors on MR Images," In: *Bogdanova A., Gjorgjevikj D. (eds) ICT Innovations 2014, ICT Innovations 2014. Advances in Intelligent Systems and Computing*, vol. 311, Springer, Cham, 2014, doi: 10.1007/978-3-319-09879-1_16.
[23] C. L. Devasena and M. Hemalatha, "Efficient computer aided diagnosis of abnormal parts detection in magnetic resonance images using hybrid abnormality detection algorithm," *Centr. Eur. J. Comp. Sci.*, vol. 3, pp. 117-128, 2013, doi: 10.2478/s13537-013-0107-z.
[24] E. S. A. El-Dahshan, H. M. Mohsen, K. Revett, and A. B. M. Salem, "Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm," *Expert Syst Appl.*, vol. 4, no. 11, pp. 5526-5545, 2014, doi: 10.1016/j.eswa.2014.01.021.
[25] M. P. Arakeri and G. R. M. Reddy, "Computer-aided diagnosis system for tissue characterization of brain tumor on magnetic resonance images," *Signal Image Video P.*, vol. 9, pp. 409-425, 2015. doi: 10.1007/s11760-013-0456-z.

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