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Research Article

An Internet of Medical Things-Based Model for Real-Time Monitoring and Averting Stroke Sensors

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In recent years, neurological diseases have become a standout amongst all the other diseases and are the most important reasons for mortality and morbidity all over the world. The current study's aim is to conduct a pilot study for testing the prototype of the designed glove-wearable technology that could detect and analyze the heart rate and EEG for better management and avoiding stroke consequences. The qualitative, clinical experimental method of assessment was explored by incorporating use of an IoT-based real-time assessing medical glove that was designed using heart rate-based and EEG-based sensors. We conducted structured interviews with 90 patients, and the results of the interviews were analyzed by using the Barthel index and were grouped accordingly. Overall, the proportion of patients who followed proper daily heart rate recording behavior went from 46.9% in the first month of the trial to 78.2% after 3–10 months of the interventions. Meanwhile, the percentage of individuals having an irregular heart rate fell from 19.5% in the first month of the trial to 9.1% after 3–10 months of intervention research. In T5, we found that delta relative power decreased by 12.1% and 5.8% compared with baseline at 3 and at 6 months and an average increase was 24.3 ± 0.08. Beta-1 remained relatively steady, while theta relative power grew by 7% and alpha relative power increased by 31%. The T1 hemisphere had greater mean values of delta and theta relative power than the T5 hemisphere. For alpha ($p < 0.05$) and beta relative power, the opposite pattern was seen. The distinction was statistically significant for delta ($p < 0.001$), alpha ($p < 0.01$), and beta-1 ($p < 0.05$) among T1 and T5 patient groups. In conclusion, our single center-based study found that such IoT-based real-time medical monitoring devices significantly reduce the complexity of real-time monitoring and data acquisition processes for a healthcare provider and thus provide better healthcare management. The emergence of significant risks and controlling mechanisms can be improved by boosting the awareness. Furthermore, it identifies the high-risk factors besides facilitating the prevention of strokes. The EEG-based brain-computer interface has a promising future in upcoming years to avert DALY.

1. Introduction

A third of patients with acute ischemic stroke will suffer an early worsening of neurological symptoms, termed as stroke-in-evolution, which is commonly linked to poor clinical outcomes [1, 2]. As a result, detecting such signs early is essential in the management of acute stroke [3]. Stroke, on the other hand, is considered to affect the autonomic nervous system, resulting in cardiovascular responses [4, 5]. In the days following an ischemic stroke, heart attack, cardiac arrest, congestive heart failure, and other abnormal heart rhythms such as atrial fibrillation are all considered to be one of the leading causes of morbidity and even mortality [6]. According to a few studies [7], a

reduction in heart rate variability (HRV) is an indicator of general illness, including acute stroke. According to studies, cardioembolic strokes account for around 30% of all strokes, with atrial fibrillation (AF) being the single most important risk factor [8]. Heart rate (HR) monitoring and maintaining a normal heart rate are critical aspects of stroke unit therapy [9, 10]. The monitoring of the brain's electrical activity, known as electroencephalography (EEG), has been explored as a diagnostic and predictive method in stroke [11, 12]. Abnormalities such as a decrease in rapid frequencies are found when cerebral blood flow (CBF) is diminished during ischemia [13]. In stroke patients, EEG power is significantly impacted, with an increase in delta (1–4 Hz) power accompanied by decreases in alpha (8–14 Hz) and beta (14–30 Hz) power, resulting in a diffuse slow-wave EEG pattern. Recently, few studies have emphasized on the usability of EEG to support and understand brain changes at rehab centers. These tools can help identify changes in EEG biomarkers and parameters during therapy that might lead to improved therapy methods and functional prognoses [14]. Thus, we have made an attempt to have a real-time monitoring of few of the parameter with the use of an IoT-based system.

Over the past few decades, Internet of things (IoT) has proved to have a strong use in interlinking various sensor-based medical devices and healthcare professionals to provide quality medical services reaching to rural locations as well. This has improved patient health safety while also lowering healthcare expenditures, improving accessibility to healthcare services, and improving operational efficiency in the healthcare sector [15].

IoT devices (sensors, actuators, and so on) have also been incorporated in a few physical objects, allowing for real-time monitoring and data exchange over various communication protocols like Bluetooth and Wi-Fi [15]. In the healthcare field, such sensors are used to gather vital physiological data from a patient's body, such as an electroencephalograph (EEG), heart rate, and ECG [16], utilizing either an embedded or wearable mode on the human body. Aside from that, environmental data such as humidity, temperature, date, and time may be captured. This illustrates the use and potential of IoT, particularly in the healthcare sector. Nowadays, everyone in society is so preoccupied with coping with their life that their health is being neglected. With the introduction of smart sensors, it is now feasible to continually monitor an individual's actions and save data as well as anticipate the occurrence of a heart attack before the patient experiences the effects of a heart attack. As a result, it is critical to select and use the right sensors.

1.1. Related Work. In the healthcare industry, there are a variety of gesture-controlled systems available that have been created by various businesses and include built-in GSM modules to inform users without the need for an online database and remote access capability.

The following are some examples: (1) smart healthcare monitoring system using IoT and Android by Chesti Altaff Hussain. The aim of the mentioned project is monitoring and gradually improving the quality of care of people in rural location and providing data about the people for making better health maintaining decisions in drastically bad situations and to minimize the regular checkup and expenditure of the very old aged people [17]; and (2) IOT-based heart rate, temperature, and heart attack detection monitor by Gowrishankar et al. [18].

Keeping in mind the promising features of IoT, we have made an attempt to have a real-time monitoring of few of the parameters with the help of the Internet of things (IoT)-based system for earlier stroke prediction, thus averting its repercussions through early intervention. The present study aims to test the designed glove-wearable technology that could detect and analyze the heart rate and EEG for better management and avoiding stroke consequences.

2. Materials and Method

2.1. Study Design, Setting, and Patients

2.1.1. Ethical clearance. The Institutional Committee and a partnered hospital approved the data collection format and experimental techniques to prospectively gather detailed information on acute stroke patients in order to conduct this study. A signed informed consent form was required of each patient. The complete data collection procedure was carried out in accordance with the approved methodology and standards.

2.2. Participants. As this is a retrospective study, the inclusion and exclusion criteria are framed keeping in mind the objective of the study, which are as follows.

Inclusion criteria: Those patients that were currently enrolled in a rehabilitation plan, as well as those who were neuropsychological and clinical investigations, were only included. Second, individuals with acute stroke, who were admitted in hospital within 24 hours from January 2021 to June 2021, were also studied prospectively ($n = 90$).

Exclusion: Patients with symptomatic heart failure, inability to collect heart rate signals within 48 hours after consideration, or heart rate signals of very poor quality or artifacts were not included in the study.

2.3. Data Acquisition. For descriptive study, data pertaining to age, gender, education, and marital status of volunteers were collected. Along with it, the Barthel index was calculated for all the patients.

It is an ordinal scale that is most widely used to quantify the functional independence in the domains of personal care and mobility in patients with chronic, disabling conditions, especially in the rehabilitation settings [19].

It is mostly utilized to determine the severity of a stroke and cognitive function [20]. The composite BI is a 100-point scale, with 100 indicating complete independence, 60–99 suggesting little reliance, 40–59 indicating moderate reliance, 20–39 indicating severe reliance, and 0–19 indicating total reliance. The functional independence of the patients was assessed using the measure [21]. It was ensured that all

patients received routine critical care, which included blood pressure, heart rate, and EEG monitoring. Here, the glove measures the heart rate and blood pressure, whereas EEG was measured with a portable EEG machine. In the future, we plan to prepare a smart glove that carries out real-time EEG.

2.4. Heart Rate and EEG. Heart rate and EEG sensors were used to design the gadget. Arduino Uno was incorporated for control action, whereas the GSM module looked over communication control. The heart rate and EEG sensors timely sense individuals' heart rate. The block diagram of our glove-based heart rate and EEG monitoring system is shown in Figure 1. The microcontroller compared the sensed vitals with the threshold value on a regular basis. The supplied electrodes were distanced from each other by 10% or 20% of the reference distance, according to the usual technique. When the sensed vitals change, the microcontroller recognizes the change and sends an automatic barcoded ID message to the patient's doctor or family through the standard GSM module connected to the controller unit (this feature is currently under some minor changes). The other benefit of it is there is a provision where the doctors can easily access the updated patient's record from the database, thus deciding further intervention. As we all know, the heart rate sensor senses our pulse and converts it into electrical data, which are acquired from Arduino connected to it, and this Arduino sends the processed data to another Arduino using the Wi-Fi module that is connected to home appliances. Here, the second Arduino processes the data based on the data received from the first Arduino, and the second Arduino will be programmed such that it automatically controls the home appliances based on the processed data. In the transmitter part of the circuit, the accelerometer sensor senses the movement of hand and records the signals and converts the signals into electrical data that are then processed and analyzed by the Arduino found at the receiver end, and these data are transmitted to the receiver circuit. The heart rate sensor and accelerometer are implemented in hand gloves or a watch, which is wearable by any person. Data representation was carried out by a UI where on request the data are first retrieved from the cloud database, and if needed it is further processed, and then it is displayed for further either analysis or interpretation. In order to get feedback of system failure, the glove was also equipped with LEDs (acquisition or transmission).

2.5. Statistical Analysis. The demographics of the groups were studied using the goodness-of-fit test (based on Barthel index scores). The statistical mean of the aberrant heart rate was validated using ANOVA. The complexity index results were given as a percentage standard error on graphs. P0.05 was chosen as the significant threshold. For all analyses, SPSS, version 20.0, was utilized.

Our study aim is to test the designed glove-wearable technology that could detect and analyze the heart rate and EEG for better management and avoiding stroke consequences. The demographics of the groups (based on Barthel index scores) were studied based on the goodness-of-fit test. ANOVA was used to validate the statistical mean of the abnormal heart rate. Graphs were plotted, and complexity index values were presented as the percentage ± standard error. A significant level was set at $p < 0.05$. The SPSS, version 20.0, was used for all analyses.

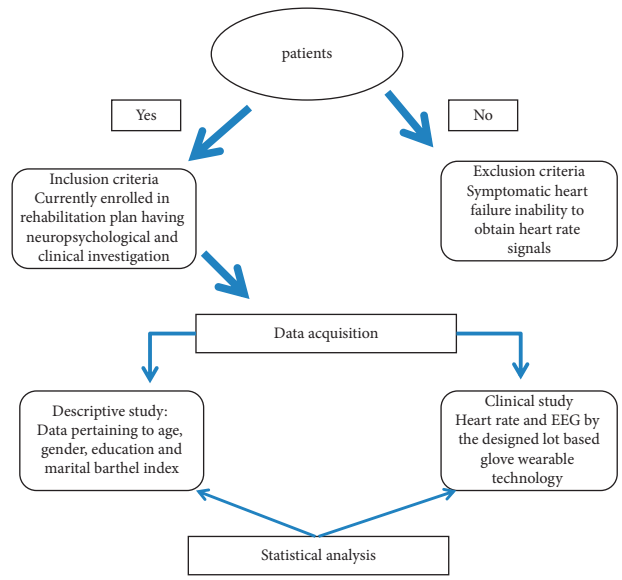

Figure 1: Overview of work process.

3. Results

3.1. Model Configuration. We can track and monitor everything in a distant healthcare facility at any time and from any remote place across the world, thanks to the Internet of things revolution. Our study's objective is to develop an infrastructure that will enable real-time patient monitoring, whether online or offline. Different layers have been utilized since the communication paradigm demands end-to-end data delivery. The layers should be interconnected since they are made up of data extraction, collection, and sending from the patient to the healthcare authority.

3.2. Working Mechanism of the Model. Figure 2 represents the working prototype of the model designed for remote patients' health monitoring. There are 5 separate layers, namely data acquirement stage, data collecting and recoding stage, data sensing and data transmission stage, application stage, and analytics and data visualization stage.

All of the sensors are physically connected to the data collecting and recoding layer of a specific microcontroller via wires. Individual sensing activities are performed by connecting the sensors to different pins on the microcontroller. Following data collection from the microcontroller, the network layer offers a forwarding mechanism for transferring data across the network using numerous protocols and different length network packet sizes. The network layer uses Wi-Fi technology for packet formatting, forwarding, and routing. The cloud storage service keeps data safe, manages it, and backs it up remotely. The storage layer platform

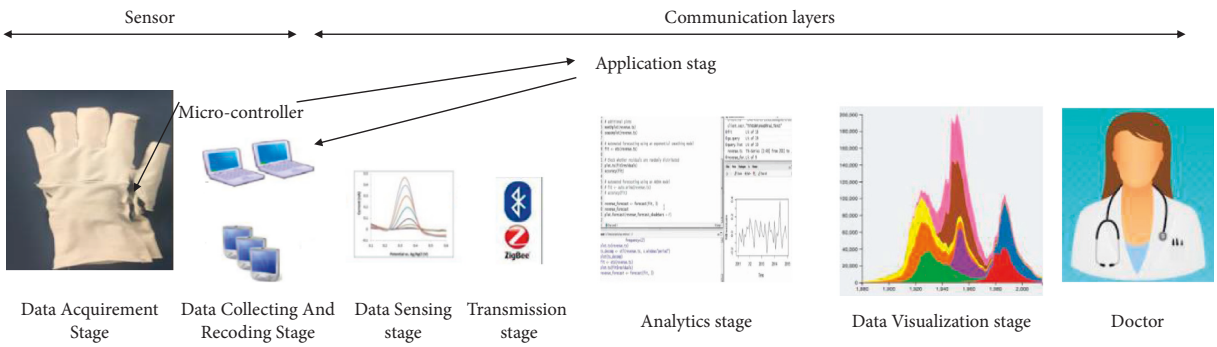

Figure 2: Concept of infrastructure developed for the remote CNS patient monitoring system.

enables patients' data records to be uploaded to the Internet and assembles every essential information available and accessible from any location over the Internet. Relocating data storage to the cloud benefits both patients and clinical institutions since it allows portability and on-demand access. Cloud hosting and processing, when combined with analytics and visualization (detailed in the following sections), can help healthcare organizations save money while also providing improved diagnostic information. The energy competent detecting devices have been used in context of wireless sensor networks (WSNs). The suggested energy competent detecting practices focus on assigning sensing duties to networks dependent on the relative distance in order to detect the most amount of physical information while decreasing energy consumption by removing redundant sensing chores. Smart phones, laptops, and other devices are used for transmission of data. Machine learning techniques are employed for data analytics, which might potentially discover correlations between sensor observations and therapeutic diagnostics and improves clinical diagnostics by using these databases over longer periods of time and aggregating across a broad user base. The output is expressed in an intuitive format in the visualization layer, so that a physician or doctor may quickly grasp the interrelationships between values and begin using sensory information in their clinical settings.

Table 1 shows a summary of the participants who took part in the study. The entire valid population was 65.4 years old on average. There were only a few distinctions between the genders (males accounted for 72.2 percent and females accounted for 57.8 percent of the study population). The majority of the study participants (self, 46.6%) stated that they did not receive financial assistance from other family members. Only 5.5 percent of the research respondents lived alone, and 50 percent completed their education. According to the Barthel index, which measures functional independence, 33.3 percent of the individuals have total independence (a score of 100), whereas 8.8% have total dependency (Barthel index scores ranging from 0 to 19). According to the goodness-of-fit test, neither study participant's demographics exhibited statistical differences.

3.3. Systematic Observation. Our proposed model's efficacy is being evaluated in terms of data quality connected to heart rate and error accuracy in EEG bands (delta, theta, alpha, and beta).

The variation in the percentage for normal and abnormal heart is reported in Figure 3 (T1–T5). Overall, the proportion of patients who followed proper daily heart rate recording behavior went from 46.9% in the first month of the trial to 78.2% after 3–10 months of the interventions, as shown in Figure 3. Meanwhile, the percentage of individuals having an irregular heart rate fell from 19.5% in the first month of the trial to 9.1% after 3–10 months of intervention research. The highest deviation observed in Figure 3 (T5) was recorded for the total independence patients. The patients whose records were already measured are separated into five groups based on their follow-up times, and ANOVA was performed to validate the statistical meaning of the aberrant heart rate. The T1 group included participants who have total dependency as per the Barthel index (BI) for longer than 1 month and participated in this intervention study around 3 months' period; the T2 group included patients who have severe dependency; and T3 group have gathered those patients who take part in the mediation trial before 6 months and they had moderate dependence. Participants from the T4 (slight dependence) and T5 (total independence) groups were involved in this research trial before 6 months likewise the T3 group. Among the five groups, there was a significant multivariate impact (p-value 0.001), and the aberrant heart rates decreased significantly with follow-up time ($p < 0.001$ in every stage).

Figure 4 shows the accuracy percentage of delta, theta, and alpha electroencephalographic (EEG) bands and correlation with heart rate. The relative and absolute EEG intensities in the delta, theta, alpha, and beta bands indicate fluctuations in the temporal-temporal leads of the group of handicapped people over the course of 6 months of recording (Barthel score: more than 60). The mean delta relative power of the T1 (total dependence) hemisphere fell by 20.1 percent and 21.5 percent, respectively, after 3- and 6-month recordings, compared with baseline; theta relative power increased by 48.90% and 55.70%, alpha relative power climbed by 60.10% and 64.80%, and beta-1 relative power increased by 55.80% and 72.50% percent, respectively. In T5 (total independence), we found that delta relative power decreased by 12.1% and 5.8% compared with baseline at 3 and at 6 months and the average increase was 24.3 ± 0.08. Beta-1 remained relatively steady, while theta relative power

Table 1: Demographic details of the studied participants.

Items	Syllogistic sample	Null and void sample	p Value	Items	Syllogistic sample	Null and void sample	p Value
No. of participants	90	30	0.533				
Age	65.4 ± 13.1	64.3 ± 9.8		**Financial support basis**			0.821
Female	25	12		Self	42	4	
Male	65	18		Domestic partner	11	5	
Level of education			0.411	Children	32	14	
10th–12th Std.	33	8		Community help	5	4	0.230
Graduate	45	13		**Family size**			0.528
Postgraduate	12	9		Alone	5	1	
Marital status			0.929	2–3 members	53	11	
Unmarried	2	0		>4 members	32	18	
Married	77	21		**Initial Barthel index**			0.339
Widowed	11	9		T1: total dependence	8	6	
				T2: severe dependence	6	2	
				T3: moderate dependence	18	8	
				T4: slight dependence	28	4	
				T5: total independence	30	10	

The Barthel index (BI) is a regularly used index by doctors, nurses, and rehab therapists to assess patients. It is primarily used to assess the severity of a stroke and cognitive functioning (18). The composite BI is a 100-point rating, with 100 indicating entire independence, 60–99 indicating modest dependency, 40–59 indicating moderate dependence, 20–39 indicating severe dependence, and 0–19 indicating total dependence.

grew by 7% and alpha relative power increased by 31%. In T5, the highest variation on 10th interval was achieved at 84%. The T1 hemisphere has greater mean values of delta and theta relative power than the T5 hemisphere. For alpha ($p < 0.05$) and beta relative power, the opposite pattern was seen. The distinction was statistically significant for delta ($p < 0.001$), alpha ($p < 0.01$), and beta-1 ($p < 0.05$) among T1 and T5 patient groups.

4. Discussion

Central nervous system diseases have come to the top of the global list of main causes of death and disability [22]. The autonomic nervous system (ANS) deals with the physiological and pathological states [23–25], where changes are typically reflected in the rhythm of the heart beat and the brainwaves that can communicate via regulatory central nervous system (CNS) signals. As it is known that EEG alterations affect the physiological response pattern, it has been proposed to use in practical applications for the evaluation of various physiological responses, not only this, but it is a methodology for identifying relaxing states based on patterns from the heart rate, and skin conductance has been investigated over the past decade [26–28]. However, medication and environmental factors may interfere with the results obtained for the skin conductance and heart rate.

As a result, we have combined the ideas of wireless sensor networks, Internet of things, and real-time health care in this study to create a framework that can track a patient's heart rate and temperature, as well as environmental factors, from any location at any time [29]. All of the data were successfully entered in the database and can now be utilized to analyze the patient's performance in order to provide medical advice. As a result, the prototype may be used to monitor patients in a range of contexts, including ICUs, homes, ambulances, and even during a sporting event. Because the computed and communicated error rates are so low, anyone may be followed in real time to avert a fatal stroke using this technique. According to the findings of the study, this approach may significantly increase the time efficiency of emergent delivery [30]. During the study period, 90 individuals with conditions such as T1 (total reliance) and T2 (severe dependence) were evaluated. Patients with recurrent stroke were classified as T3 (moderate dependence), T4 (slight dependence), and T5 (total independence). They were enrolled in the intervention model, and we determined the suitable heart rate measurement fraction. This study is inspired with the previous study by Green et al. (2008) [29]. According to Green et al. (2008), a "Web-based health monitoring with a pharmacy-intervened healthcare model" offers people with thorough self-care information and assists them in accomplishing the objectives of proper heart rate and blood pressure regulation [31, 32].

In stroke, electroencephalography (EEG), or monitoring the electrical activity of the brain, has been investigated as a diagnostic and predictive tool [11, 33]. Abnormalities such as decreases in rapid frequencies are noticed when cerebral blood flow (CBF) lowers during ischemia [34]. In stroke patients, EEG power is significantly impacted, with an increase in delta power (1–4 Hz) accompanied by a drop in alpha (8–14 Hz) and beta (14–30 Hz) power, resulting in a diffuse slow-wave EEG pattern. The importance of these frequency bands led to the development of a quantitative index known as the delta/alpha ratio (DAR), which measures global delta activity in comparison with normative alpha

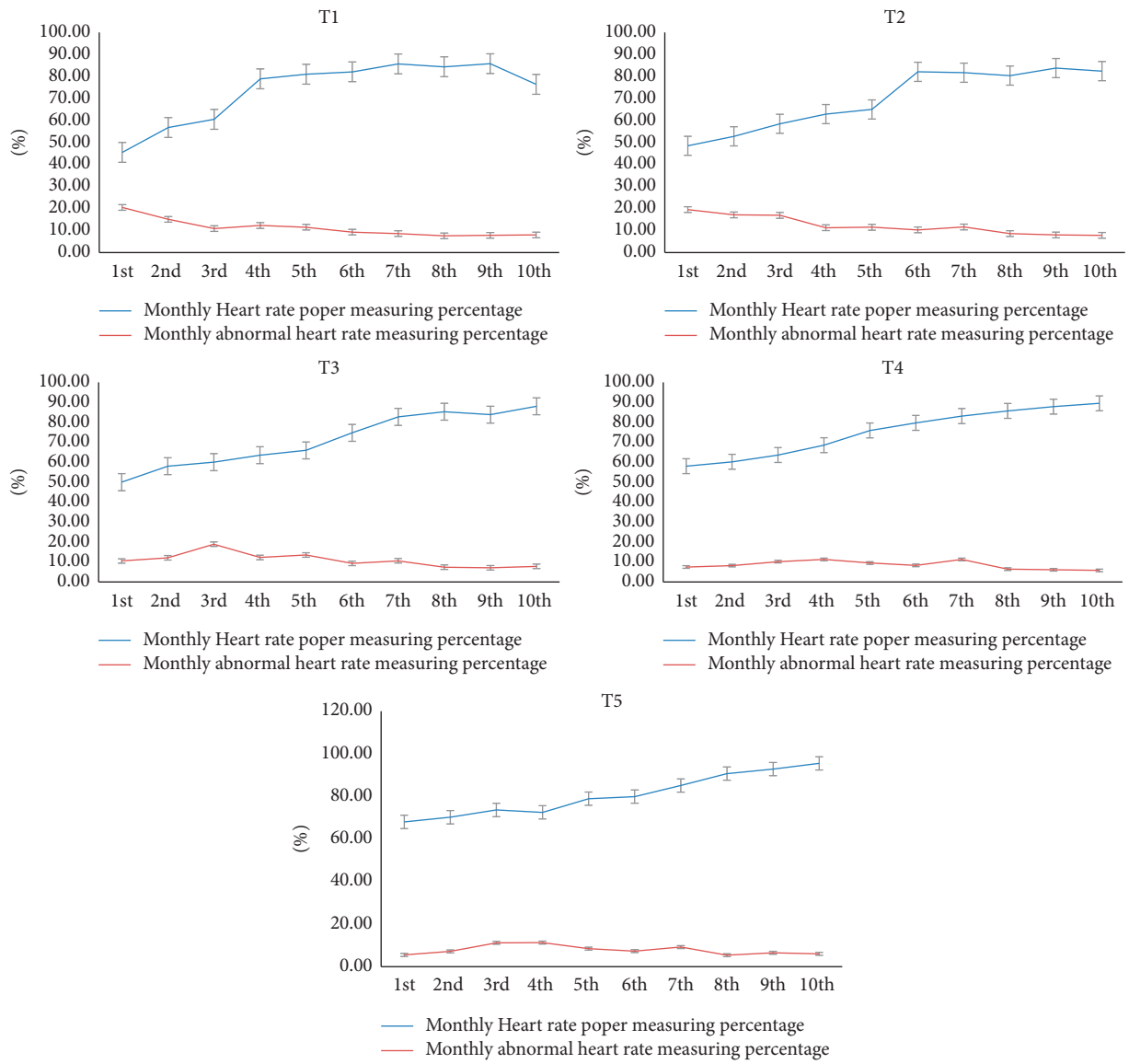

Figure 3: T1–T5: percentage efficacy of monitoring normal and anomalous heart rates, as evaluated in an intervention study.

activity. Anomalies such as slackening (amplified delta-to-alpha ratio (DAR) or increased (delta + theta)/(alpha + beta) ratio (DTABR)) and changes in brain regularity are recognized in the acute pyelonephritis. The power spectrum returns to normal in the first three months after a stroke, but quantitative EEG (qEEG) may still indicate abnormalities, such as reduced symmetry, that persist after satisfactory motor recovery [35]. Previous research has demonstrated that qEEG indices like DAR could be useful for both diagnosis and prediction of clinical outcomes in ischemic stroke [32, 34, 36, 37].

In addition, compared with the hospital-wide rate of 26.5%, this analysis revealed a comparatively substantial accuracy percentage of delta, theta, and alpha electroencephalographic zones, as well as a low ER revisit rate of 16.8%. [38]. Our findings corroborate previous studies on the effectiveness of IoT-based solutions. (This technique may also be used to efficiently assess the risk of stroke when patients are at home and provide an emergency transport.) Furthermore, we developed an IoT-based remote health monitoring service that allows healthcare practitioners to intervene, as opposed to service models that merely provide passive information [39].

4.1. Limitations and Future Work. First, the sample size was limited and it was not a multicenter study. Second, due to our exclusion and inclusion criteria, there was limited degree of freedom for the generalizability of our results. Third, we did not group out the individuals based on their stroke.

4.2. Future Scope of Improvement. For future development of our model, we are also attempting to add some sophisticated security features to encrypt the data in order to make it a comprehensive device and manage vital parameters such as SpO_2 and glucose level. In addition, the system will be

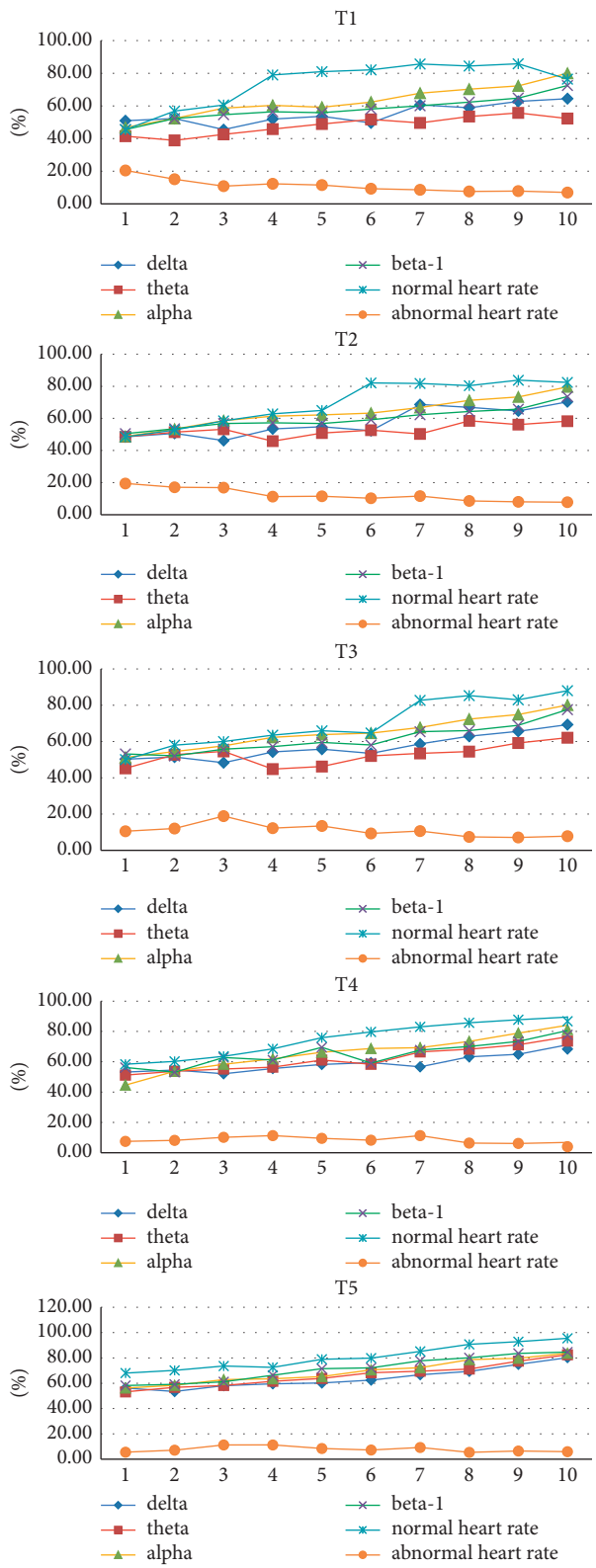

Figure 4: Graphs showing the accuracy percentage of delta, theta, and alpha electroencephalographic (EEG) bands and correlation with heart rate (T1–T5).

downsized into a tiny, portable, wearable device that can continuously monitor all critical parameters.

5. Conclusion

The revolution in IoT technology helps us to monitor and track anything in a remote healthcare center at any given time from any location. The purpose of this study was to test the designed glove-wearable technology that could detect and analyze the heart rate and EEG for better management and avoiding stroke consequences. The percentage of individuals having an irregular heart rate decreased from 19.5% in the very first month of the trial to 9.1% after 3–10 months of intervention research. Beta-1 remained relatively steady, while theta relative power grew by 7% and alpha relative power increased by 31%. The T1 hemisphere had greater mean values of delta and theta relative power than the T5 hemisphere. For alpha ($p < 0.05$) and beta relative power, the opposite pattern was seen. The distinction was statistically significant for delta ($p < 0.001$), alpha ($p < 0.01$), and beta-1 ($p < 0.05$) among T1 and T5 patient groups. In conclusion, our single center study found that such IoT-based real-time medical monitoring devices significantly reduce the complexity of real-time monitoring and data acquisition processes for a healthcare provider and thus provide better healthcare management.

Data Availability

The data are made available on request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] P. Seners, G. Turc, C. Oppenheim, and J.-C. Baron, "Incidence, causes and predictors of neurological deterioration occurring within 24 h following acute ischaemic stroke: a systematic review with pathophysiological implications," *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 86, no. 1, pp. 87–94, 2015.

[2] L. Chen, V. Jagota, and A. Kumar, "Research on optimization of scientific research performance management based on BP neural network," *International Journal of System Assurance Engineering and Management*, vol. 12, 2021.

[3] C.-H. Chen, P.-W. Huang, S.-C. Tang et al., "Complexity of heart rate variability can predict stroke-in-evolution in acute ischemic stroke patients," *Scientific Reports*, vol. 5, no. 1, Article ID 17552, 2015.

[4] F. Ajaz, M. Naseem, S. Sharma, M. Shabaz, and G. Dhiman, "COVID-19: challenges and its technological solutions using IoT," *Current Medical Imaging, Formerly: Current Medical Imaging Reviews*, vol. 17, 2021.

[5] P. Sörös and V. Hachinski, "Cardiovascular and neurological causes of sudden death after ischaemic stroke," *The Lancet Neurology*, vol. 11, no. 2, pp. 179–188, 2012.

[6] M. A. Samuels, "The brain-heart connection," *Circulation*, vol. 116, no. 1, pp. 77–84, 2007.

[7] B. Graff, D. Gąsecki, A. Rojek et al., "Heart rate variability and functional outcome in ischemic stroke," *Journal of Hypertension*, vol. 31, no. 8, pp. 1629–1636, 2013.

[8] P. A. Wolf, R. D. Abbott, and W. B. Kannel, "Atrial fibrillation as an independent risk factor for stroke: the Framingham Study," *Stroke*, vol. 22, no. 8, pp. 983–988, 1991.

[9] D. Leys, E. B. Ringelstein, M. Kaste, and W. Hacke, "The main components of stroke unit care: results of a European expert survey," *Cerebrovascular Diseases*, vol. 23, no. 5-6, pp. 344–352, 2007.

[10] European Stroke Organisation (ESO) Executive Committee, ESO Writing Committee, "Guidelines for management of ischaemic stroke and transient ischaemic attack 2008," *Cerebrovascular Diseases*, vol. 25, pp. 457–507, 2008.

[11] A. Agius Anastasi, O. Falzon, K. Camilleri, M. Vella, and R. Muscat, "Brain symmetry index in healthy and stroke patients for assessment and prognosis," *Stroke Research and Treatment*, vol. 2017, pp. 1–9, 2017.

[12] K. G. Jordan, "Emergency EEG and continuous EEG monitoring in acute ischemic stroke," *Journal of Clinical Neurophysiology*, vol. 21, no. 5, pp. 341–352, 2004.

[13] S. Finnigan, A. Wong, and S. Read, "Defining abnormal slow EEG activity in acute ischaemic stroke: delta/alpha ratio as an optimal QEEG index," *Clinical Neurophysiology*, vol. 127, no. 2, pp. 1452–1459, 2016.

[14] M. Sebastián-Romagosa, E. Udina, R. Ortner et al., "EEG biomarkers related with the functional state of stroke patients," *Frontiers in Neuroscience*, vol. 14, p. 582, 2020.

[15] M. Shabaz and U. Garg, "Predicting future diseases based on existing health status using link prediction," *World Journal of Engineering*, vol. 18, 2021.

[16] S. Gowrishankar, M. Y. Prachita, and P. Arvind, "IOT based heart attack detection, heart rate and temperature monitor," *International Journal of Computer Application*, vol. 170, no. 5, pp. 26–30, July 2017.

[17] C. V. Granger, L. S. Dewis, N. C. Peters, C. C. Sherwood, and J. E. Barrett, "Stroke rehabilitation: analysis of repeated Barthel index measures," *Archives of Physical Medicine and Rehabilitation*, vol. 60, pp. 14–17, 1979.

[18] F. I. Mahoney and D. W. Barthel, "Functional evaluation: the Barthel index. Md," *Statistics in Medicine J.*vol. 14, pp. 61–65, 1965.

[19] L. Ferrucci, C. Koh, S. Bandinelli, and J. M. Guralnik, "Disability, functional status, and activities of daily living," *Encyclopedia of Gerontology*pp. 427–436, Elsevier, Amsterdam, Netherlands, Second Edition, 2007.

[20] G. Jorge, V. Byron, and Z. Emilio, "Patient monitoring system based on internet of things," in *Proceedings of the 7th International Conference on Ambient Systems, Networks and Technologies (ANT 2016)*, vol. 83, pp. 90–97, Madrid, Spain, 2016.

[21] S. P. Nayak, S. Das, S. C. Rai, and S. K. Pradhan, "SIMAS: smart IoT model for acute stroke avoidance," *International Journal of Sensor Networks*, vol. 30, no. 2, pp. 83–92, 2019.

[22] W. Li and S. Kara, "Methodology for monitoring manufacturing environment by using wireless sensor networks (WSN) and the internet of things (IoT)," *Procedia CIRP*, vol. 61, pp. 323–328, 2017.

[23] H.-C. Chiu, Y.-H. Lin, M.-T. Lo et al., "Complexity of cardiac signals for predicting changes in alpha-waves after stress in patients undergoing cardiac catheterization," *Scientific Reports*, vol. 5, no. 1, p. 13315, 2015.

[24] S. D. Kreibig, "Autonomic nervous system activity in emotion: a review," *Biological Psychology*, vol. 84, no. 3, pp. 394–421, 2010.

[25] R. A. Calvo and S. D'Mello, "Affect detection: an interdisciplinary review of models, methods, and their applications," *IEEE Transactions on Affective Computing*, vol. 1, no. 1, pp. 18–37, 2010.

[26] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 2, pp. 186–197, 2010.

[27] D.-K. Kim, K.-M. Lee, J. Kim et al., "Dynamic correlations between heart and brain rhythm during Autogenic meditation," *Frontiers in Human Neuroscience*, vol. 7, pp. 1672–1687, 2013 Jul 31.

[28] M. Ako, T. Kawara, S. Uchida et al., "Correlation between electroencephalography and heart rate variability during sleep," *Psychiatry and Clinical Neurosciences*, vol. 57, no. 1, pp. 59–65, 2003.

[29] B. B. Green, A. J. Cook, J. D. Ralston et al., "Effectiveness of home blood pressure monitoring, web communication, and pharmacist care on hypertension control: a randomized controlled trial," *Journal of the American Medical Association*, vol. 299, no. 24, pp. 2857–67, 2008.

[30] A. L. Schneider and K. G. Jordan, "Regional Attenuation WithOut Delta (RAWOD): a distinctive EEG pattern that can aid in the diagnosis and management of severe acute ischemic stroke," *The Neurodiagnostic Journal*, vol. 45, no. 2, pp. 102–117, 2005.

[31] R. V. A. Sheorajpanday, G. Nagels, A. J. T. M. Weeren, M. J. A. M. van Putten, and P. P. De Deyn, "Quantitative EEG in ischemic stroke: correlation with functional status after 6months," *Clinical Neurophysiology*, vol. 122, no. 5, pp. 874–883, 2011.

[32] S. Giaquinto, A. Cobianchi, F. Macera, and G. Nolfe, "EEG recordings in the course of recovery from stroke," *Stroke*, vol. 25, no. 11, pp. 2204–2209, 1994.

[33] C. Fanciullacci, F. Bertolucci, G. Lamola et al., "Delta power is higher and more symmetrical in ischemic stroke patients with cortical involvement," *Frontiers in Human Neuroscience*, vol. 11, 2017.

[34] R. A. L. Macdonell, G. A. Donnan, P. F. Bladin, S. F. Berkovic, and C. H. R. Wriedt, "The electroencephalogram and acute ischemic stroke: distinguishing cortical from lacunar infarction," *Archives of Neurology*, vol. 45, no. 5, p. 520, 1988.

[35] J. I. Doerrfuss, T. Kilic, M. Ahmadi, M. Holtkamp, and J. E. Weber, "Quantitative and qualitative EEG as a prediction tool for outcome and complications in acute stroke patients," *Clinical EEG and Neuroscience*, vol. 51, no. 2, pp. 121–129, 2019.

[36] A. Aminov, J. M. Rogers, S. J. Johnstone, S. Middleton, and P. H. Wilson, "Acute single channel EEG predictors of cognitive function after stroke," *PLoS One*, vol. 12, no. 10, Article ID e0185841, 2017.

[37] E. H. Wagner, B. T. Austin, and M. Von Korff, "Organizing care for patients with chronic illness," *The Milbank Quarterly*, vol. 74, no. 4, pp. 511–44, 1996.

[38] J. M. Walsh, K. M. McDonald, K. G. Shojania et al., "Quality improvement strategies for hypertension management: a systematic review," *Medical Care*, vol. 44, no. 7, pp. 646–57, 2006.

[39] C. Sharma, B. Amandeep, R. Sobti, T. K. Lohani, and M. Shabaz, "A secured frame selection based video watermarking technique to address quality loss of data: combining graph based transform, singular valued decomposition, and hyperchaotic encryption," *Security and Communication Networks*, vol. 2021, Article ID 5536170, 19 pages, 2021.