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Eldo-care: EEG with Kinect sensor based telehealthcare for the disabled and the elderly

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ABSTRACT

Telehealthcare systems are nowadays becoming a massive daily helping kit for elderly and disabled people. By using the Kinect sensors, remote monitoring has become easy. Also, the sensors' data are useful for the further improvement of the device. In this paper, we have discussed our newly developed "Eldo-care" system. This system is designed for the assessment and management of diverse neurological illnesses. The telemedical system is developed to monitor the psycho-neurological condition. People with disabilities and the elderly frequently experience access issues to essential services. Researchers today are concentrating on rehabilitative technologies based on human-computer interfaces that are closer to social-emotional intelligence. The goal of the study is to help old and disabled persons with cognitive rehabilitation using machine learning techniques. Human brain activity is observed using electroencephalograms, while user movement is tracked using Kinect sensors. Chebyshev filter is used for feature extraction and noise reduction. Utilizing the autoencoder technique, categorization is carried out by a Convolutional neural network with an accuracy of 95% and higher based on transfer learning. A better quality of life for older and disabled persons will be attained through the application of the suggested system in real time. The proposed device is attached to the subject under monitoring.

1. Introduction

The number of elderly and disabled persons is rising daily in this period [1]. Many conditions, including amyotrophic lateral sclerosis, disabled, and older people, make it difficult for people to carry out simple daily tasks [2]. Scientists have attempted to solve the issue of the elderly and disabled people in their everyday routines by integrating some of the latest communication technologies associated with human brains as support of smart homes. A brain-computer interface (BCI) is a method that transforms brain movement into a numeral form that may be applied to read a user's thinking and carry out the intended task without requiring the user to move any bodily parts. Researchers are interested in the field of cognitive rehabilitation because of the rising population, the lack of qualified therapists, the expanding scientific potential, and the need for new technologies [3]. It is challenging for an older and disabled person to get by daily because of physical and mental health issues. According to a study conducted in China, more than 9% of the population was over 65 in 2015, and it is predicted that this number will rise to 20% between 2017 and 2037 [4]. According to a survey conducted in India, 8.4% of adults over 60 had cognitive impairment in the year 2020 [5]. Cognitive rehabilitation is a group of interventions designed to treat disabilities and enable people to carry out previously learned tasks. The terminology "neurorehabilitation" was first used in the modern world, and it is now widely utilized in clinical practice instruments for rehabilitation treatment [6]. This technique uses brain-computer interaction to deliver real-time data while monitoring brain activity by implanting electrodes on the scalp of the subject (BCI) [7–9]. EEG is a simple wearable device. The face, voice, finger, iris, and gesture are among the characteristics that the Kinect sensor detects and identifies [10]. For early-stage disability detection and subsequent rehabilitation, Kinect sensors efficiently separate human skeletal data from gesture and posture patterns [11].

To accumulate data from the brain and gestures, the proposed work combines hybrid sensors based on EEG and Kinect sensors. A Chebyshev filter is also employed to filter out noise. The next step is a learning-based convolution neural network for classification, which is followed by a feature extraction and feature selection auto-encoder. The proposed technique is especially beneficial for helping the elderly and disabled with their cognitive rehabilitation.

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1.1. Motivation

The elderly and those with disabilities were selected for the proposed scheme for the following reasons:

i) A neurological illness is one in which the symptoms frequently affect how the brain processes feelings and emotions.
ii) The therapy for the handicapped is being processed as soon as possible.
iii) Rehabilitation is severely constrained by the current system.

1.2. The originality of the suggested remedy and contribution

Comparing the suggested system to conventional approaches [12], numerous obstacles have been solved. The suggested approach will be used in the medical field. The suggested system offers the following benefits: The following describes the planned work's innovation and the current system's contribution:

i) To extract features from EEG and Kinect data more efficiently than with conventional approaches, the suggested work uses an autoencoder [12].
ii) Transfer learning is used to categorize disability since it improves upon existing methods in terms of performance.
iii) The feature extractor and classifier that combined autoencoder and transfer learning outperformed the techniques described in the recent literature.

The suggested approach makes healthcare more accessible to people with limited mobility, hence the proposed work will be applied to autonomous electronic healthcare. People living in smart cities and rural areas will benefit from the present planned system in other ways, such as reduced pathogen exposure, lower overall medical costs, and ease of use.

The other sections of the study are segment 2 for the review of works, segment 3 for a planned experiment, segment 4 for a discussion of the results, and section 5 for a conclusion and suggestions for future research.

2. Literature survey

The rehabilitation workouts using Kinect expertise have remained us about the health-care motivational determinants for elderly persons as AAL research has grown and reinforced [13]. We may discover similar works in the rehabilitation sector as "MIRA" [14], a medical therapy device that attempts to help the patient's physical convalescence procedure, for example, for arm rehabilitation, to reduce the hazard of falls, over elder people's exercise games. This function includes managing patients, physicians, and physical therapists, and it keeps patient files and statistical information gleaned from rehab sessions using the 3D Kinect game. "GameUp" [15] for balance, flexibility, and leg strength is another such suggestion. This project combines seven mini-games into three distinct training levels that may be completed while standing, walking, and sitting, allowing affordance modifications based on the particular player's balance prowess. The problem discovered was that using Kinect makes you tired because the game required you to stand on one foot and raise your arms above your head. Additionally, 3D games are employed similarly for the rehabilitation of neuropsychiatric illnesses. The game is managed automatically by a multiagent system [16], minimizing the requirement for human participation to oversee the execution of software activities.

Another study [17] uses Kinect techniques and a low-cost inertial measurement unit to analyze the motions in the upper limb and enhance body coordination. The literature on gesture detection has described a variety of methods for identifying human body movements using video cameras over the years. From the psychological standpoint of how people recognize and use gestures to the kinesiology viewpoint of how gestures function mechanically, the computer graphics were focused on how to characterize high-level tasks and spatial interactions for human models. At this time, the greatest solution for improving identification is a 3D camera i.e., Microsoft Kinect [18]. Additionally, this sensor includes a Green, Red, and Blue camera, a four-microphone array, and a depth sensor allowing for the processing of full-body 3D motion capture as well as the recognition of human faces and voices. The 25 body joints are calculated in 3D space by the Kinect sensor using skeletal tracking. Codifying all the procedures from the raw sensor data is required to identify a basic gesture. A collection of characteristics and thresholds on joint location are used in the rule-based technique to track motions [16]. Based on this framework method, it is feasible to design a set of rules that specify the motions to recognize at a high level of abstraction. One such framework is FAAST [16], which enables full-body natural interaction to control arbitrarily programmed by adjusting gesture sensibility via threshold values and mapping these gestures to key and mouse events.

Another example is FUBI [19], which allows you to specify a set of motions by setting more specific choices in a specification language based on XML. Unfortunately, these frameworks don't take into account variations in user heights and positions inside the Kinect recognition field, as well as in user movement speeds and skill levels. Additionally, the detection of complicated gestures turns into a categorization issue. In this situation, supervised machine learning algorithms are used to convey information about the issue by classifying or labeling a gesture. This is why every gesture is tagged to create a classifier that uses training sets of the gestures and assesses how similar a new motion is to each taught gesture. Therefore, utilizing the skeletal data from Kinect, various frameworks employed Dynamic Time Warping, Decision Trees, and Support Vector Machines (SVMs) for motion recognition. Additionally, EasyGR [17] is a tool tested on seven gesture recognizers that aid in lowering the work required in the development of gesture recognition and improves the performance and accuracy of gesture recognition. With and without EasyGR support, metrics including code size, time spent, and the standard of the built gesture recognizers were compared. The outcomes demonstrated that the strategy was workable and decreased the effort needed to implement a gesture classifier using Kinect. Studies on the positive and negative impacts of playing video games on the human brain are only beginning. Cognitive load is a mental process used to gauge a person's mental state at any given time. When brain complexity rises, the cognitive burden rises as well, and vice versa.

Electroencephalography, which involves applying electrodes to the head in a variety of settings, can be used to measure cognitive stress [20]. For the assessment and management of diverse neurological illnesses, a telemedical system is being developed to monitor the psycho-neurological condition. People with disabilities are not a homogeneous group, and they deal with a variety of issues daily. People with disabilities and the elderly frequently experience access issues to essential services. Researchers today are concentrating on rehabilitative technologies based on a human-computer interface that is closer to social-emotional intelligence. The goal of the study is to help old and disabled persons with cognitive rehabilitation using machine learning techniques. Human brain activity is observed using electroencephalograms, while user movement is tracked using Kinect sensors [12]. The "ReHomation" system for electronic automatic control and monitoring of household characteristics, activity, and applications is inexpensive, simple to use, energy-saving, and minimal maintenance. Within a 20-meter radius, access to the system is possible. The 433 MHz radio, the HT12E encoder integrated chip, the 1 M ohm resistor, the switch, the PCB board, the 9 V battery, the HT12D decoder integrated chip,

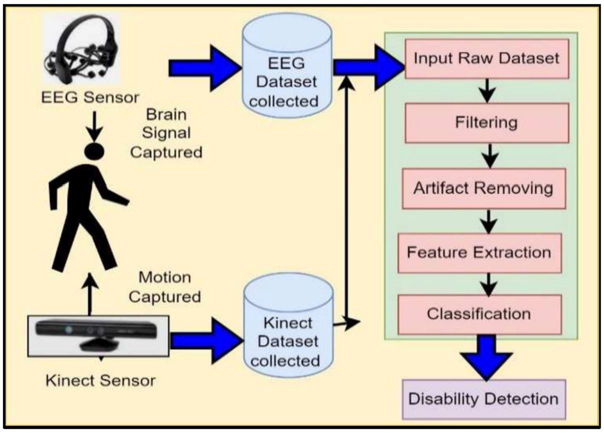

Fig. 1. Proposed method for Eldo care.

the 7805 V regulator, the 0.1uF ceramic capacitor, the 33 k ohm resistor, the bulb, the BC547 resistor, the 1N4007 diode, the 5 V relay, the 2 pins terminal block, the 220 V AC power It is simple for the end user to use the 433 MHz radio frequency, which is employed as both a transmitter and a receiver to capture signals [21]. The major goal of our chapter is to operate healthcare and home appliances using two types of automation: command-based using Telegram Bot and EEG-based brain-computer interfaces. The brain-computer interface uses EEG to gather data, a bandpass filter to filter data between 12 and 100 Hz, independent component analysis to remove artifacts, the Fast Fourier theorem to extract and select features, and command recognition to translate the data. The circuit is developed using the ESP8266 Node MCU and Relay on the microcontroller after all processes have been optimized. Another method is to use the available Telegram Bot to handle the home automation system. This method is just for people who are physically fit and can use the Bot for controlling home automation [22]. Completely-locked-in-syndrome (CLIS) is caused due to some illness i.e., amyotrophic lateral sclerosis (ALS), a type of motor neuron disease. This problem was addressed utilizing the EEG signals when a human thinks about some specific feelings and imagination. ANN was used for this work, where the dataset was split with 5, 4, and 3 imaginations in the pre-processing step. An overall accuracy of 80–100% was achieved for recognizing five imaginations using LVQ and FFNN classifiers [23].

The "Eldo-care" recommended study collects brain and gesture data while decreasing noise by combining EEG and Kinect Sensor. For feature extraction and selection, the Chebyshev filter, autoencoder, and classification, transfer learning-based convolution neural network is applied.

3. Proposed work

The three stages of the suggested approach are mostly used to identify speech disorders. First, two sensors—a Kinect sensor and an electroencephalogram—have been used to gather the data. The functionality of the system's sensors is initially described in this section.

The suggested method in Fig. 1 illustrates how the EEG sensor and the Kinect sensor can both capture data from the scalp of the human brain. Noise is eliminated using a Chebyshev filter. Using an autoencoder, which also extracts side features from the raw Kinect dataset in terms of distance and angle, significant features from the raw EEG dataset are obtained.

The most crucial stage is classification, which comes after data collection, noise reduction, and feature extraction. Convolutional neural networks are used for categorization; mental activity, physical activity, and identifying the problematic region in the brain is a frequent deep learning strategy. Following the identification of the disability, therapy might be recommended to improve the patient's quality of life.

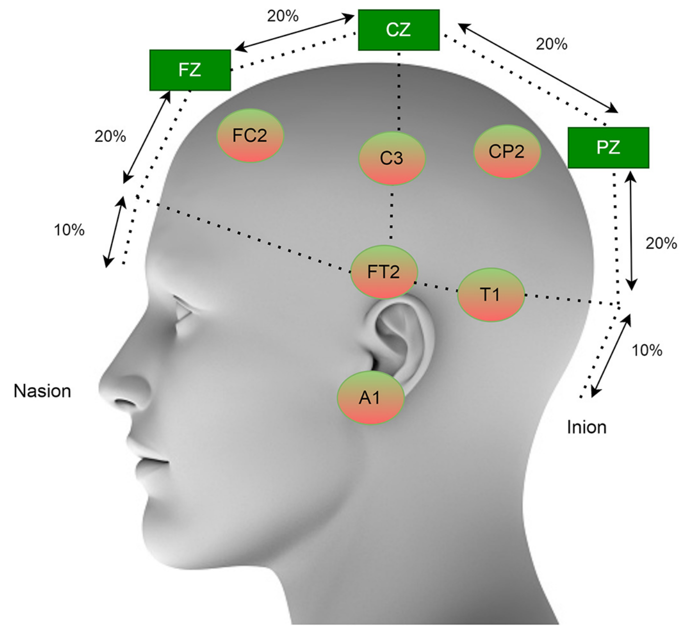

Fig. 2. Electrode placement of the standard 10–20 EEG system.

3.1. Data collection using electroencephalography

In the proposed system, data will be collected from the human brain scalp using a non-invasive device called BrainTech Traveler, and brain activity will be monitored using electroencephalography (EEG). As seen in Fig. 2, conventional 10–20 EEG systems gather information from various regions of the brain. After collecting the information, it transmits electrical impulses to the brain via a brain-computer interface.

3.2. Collected dataset using the Kinect sensor

25 body joints are tracked by the Kinect sensor, including the Neck, Head, Shoulders, Spine, Right and Left Elbows, Right and Left Wrists, Right and Left Thumbs, Right and Left Hands, Right and Left Hand Tip, Right and Left Hand Tip, Mid Spine, Base Spine, Right and Left Hips, Right and Left Knees, Right and Left Ankles, Left and Right Left Ankles, and Left and Right Left Ankles. The aforementioned 25 features are visible within a 4 m range, and two additional features—facial appearance and audial—are similarly employed to monitor subject activity to identify disabilities (Fig. 3).

3.3. Preprocessing

The methods for feature extraction and preprocessing are covered in this module.

3.3.1. Filtering

Filtering, the initial step for pre-processing, is used to take the noise out of the EEG signals. For cleaning in this investigation, a Chebyshev filter is used here. Fig. 4 illustrates that the band-pass filter for 6th order Chebyshev II filters with 30 dB band stop attenuation, stopband edge frequency is 100 Hz that corresponds to 0.6 rad per sample.

$$G(F_0, F_1) = \frac{1}{\sqrt{1 + E^2 T_n^2(\frac{F_0}{F_1})}} \tag{1}$$

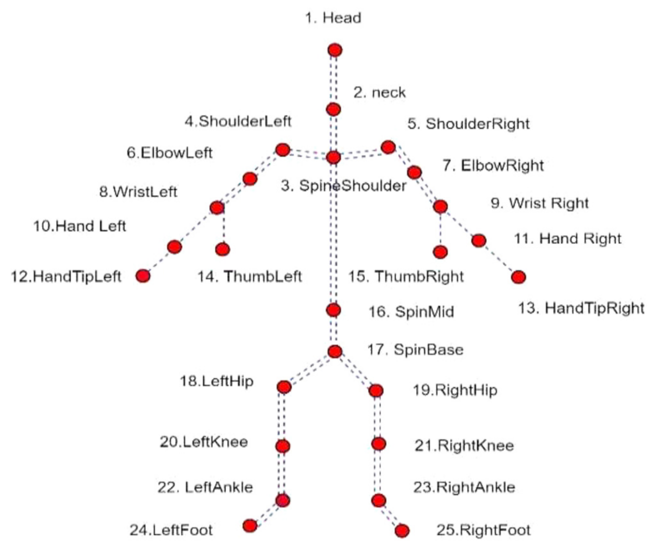

Fig. 3. Kinect sensor skeleton-tracker.

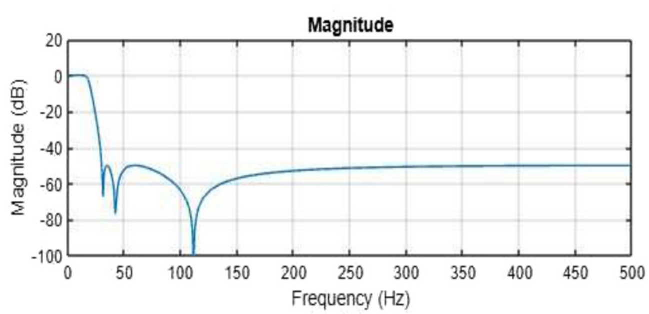

Fig. 4. Filtering making use of the Chebyshev filter II.

Here, E is the ripple factor, F_0 and F_1 are the cutoff frequencies, and T_n is the Chebyshev polynomial, which is of nth order, and G is the gain. A gain in the range between -1 and 1 typically refers to a proportional change in the amplitude or magnitude of a signal.

since T_n alternates between -1 and to $\dfrac{1}{\sqrt{1+B^2}}$.

$$\text{Here } B = \frac{1}{\sqrt{10^{\frac{s}{10}} - 1}} \tag{2}$$

In equation (2), y is the stop band attenuation and B is the band pass filter.

3.3.2. Feature extraction

Using Euclidean geometry and the joint angles of human bodies, Kinect sensor characteristics are employed to calculate distance. EEG characteristics are measured using an autoencoder. Equation (3) demonstrates that the distance (D) connecting the two locations in the Euclidean space is equal to the "norm of the translation from one-point X to Y".

$$D(R,S) = \left||\overrightarrow{RS}|\right| \tag{3}$$

the angle between R and S, two non-zero vectors, as calculated by the formula in equation (4).

$$\theta = \left(\frac{RS}{||R||||S||}\right) \tag{4}$$

Fig. 5 illustrates the five processes involved in the feature extraction process utilizing the autoencoder. Step 1 begins with input at the input layer, followed by an encoder in step 2, a code generator in step 3, a decoder in step 4, and output in step 5, which is stored on output nodes.

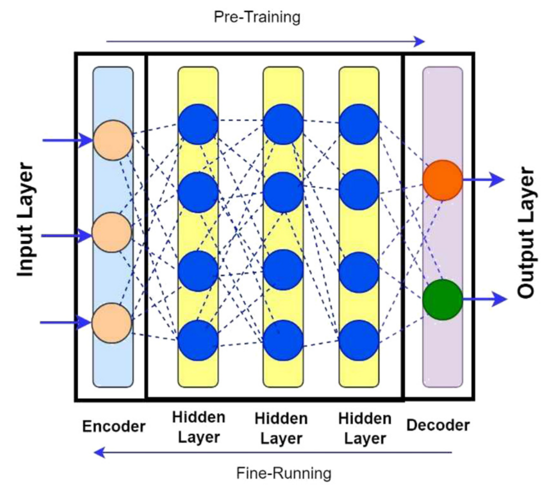

Fig. 5. Extraction of features using an auto encoder.

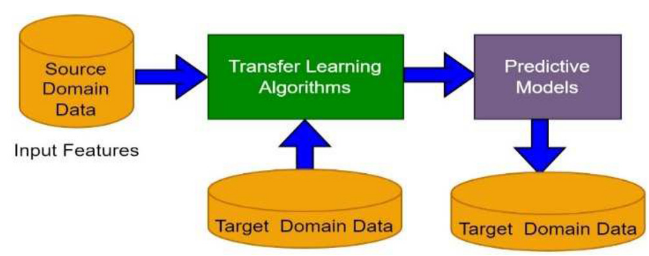

Fig. 6. Utilizing transfer learning as a classification mechanism.

3.4. Classification

To address related new problems, classification is a pre-trained deep learning technique, as shown in Fig. 6.

$$T = \{t_1, t_2, t_3 \ldots T_n\} \in T. \tag{5}$$

$$Z = \{T, P(T)\} \tag{6}$$

Target domain C_t, source domain C_s, learning task D_s, and learning task D_t, where $C_s > C_t$.

$$D_s \neq D_t$$

Fig. 6 demonstrates how the input attributes are gathered and forwarded to the origin using a source model before learning information is transferred and the source is sent to a target model. Equation (5) indicates that F is the feature space, while equation (6) demonstrates that C is indicating to the domain and P is indicating to the marginal probability distribution (T).

4. Results of experiments

The present model was created by MATLAB 2021B and stimulated by it. We will concentrate on the categorization findings in this section.

4.1. Feature extraction

The label and attributes from the brain signals that were collected using electrode placement for a typical 10–20 EEG system are shown in Table 1. Additionally, it shows the feature values.

Table 1
The features and labels of the electrodes collected from the EEG sensor.

Electrodes	Mean	Median	Standard Deviation	Entropy	Power	RMS
C1	31.23	51.03	35.12	80.23	74.02	0.20
C2	3.95	5.69	6.13	76.32	65	0.53
C3	7.76	9.01	8.09	65.89	93.25	0.65
P1	79.32	91.2	21.12	90.30	62.31	0.38
CP1	61	45.36	20.04	75	68.03	0.21
CP2	32. 62	41.23	23.50	22	8	0.81
CP3	79.86	60	36	83	57.36	0.89
FT2	8.2	24	4.26	85	90	0.6
T1	54.96	48	46.32	62	75.36	0.75
FC2	30	31	3.96	34	90	0.52

Table 2
The features and labels from the Kinect sensor.

The categories of prerequisite	Number of samples	Mental features and movements
Asleep	175	drained arm, behind the cheek
Upright	200	welcoming arms and vivacious
Strolling	182	Continue with purpose.
Thirsty	150	Finger with lips close by and thirsty
Chew	156	Finger with its mouth open and a hungry
excretion	192	moving my hands and urgently urinating
Pee	70	Urge to urinate quickly and head movement
Calling the Physian	200	rapid hand motion and urgency
Relax	200	Nothing

Here, the mean value is calculated using Equation (7). Whereas, the median value is calculated using equation (8). The standard deviation is computed using equation (9) and entropy calculation is done by equation (10). The power is computed using equation (11). We enumerate the root mean square value (RMS) using equation (12). Using cross-validation and autoencoder, all the 1600 records are arranged for neural training by the requirements.

$$\text{Mean} = \frac{Sum\ of\ all\ numbers\ of\ the\ dataset}{The\ numbers\ of\ elements} \tag{7}$$

$$\text{Median} = \text{Middle value of the dataset} \tag{8}$$

$$\text{Standard Deviation} = \sqrt{\frac{\sum(Each\ value\ from\ dataset - Mean)}{The\ size\ of\ the\ dataset}} \tag{9}$$

$$\text{Entropy} = \text{Signal randomness} \tag{10}$$

$$\text{Power} = \frac{Signal\ Value}{Signal\ Length} \tag{11}$$

$$\text{RMS} = \sqrt{\frac{\sum(Each\ value\ from\ dataset)^2}{The\ numbers\ of\ the\ dataset}} \tag{12}$$

Fig. 3 displays Kinect sensor skeleton tracker structure. The composed of training features from the Kinect sensor are displayed in Table 2. The types of needs, sample sizes, and in this regard, motions and mental traits are covered in the table.

4.2. Classification

The participant was classified as being in a sleeping condition for the first trial, standing for the second trial, walking for the third trial, drinking for the fourth trial, eating for the fifth trial, urinating for the sixth trial, calling for a doctor for the eighth trial, and resting for the last trial, as shown in Fig. 7.

Fig. 7 demonstrates that four non-identical algorithms determine accuracy, precision, recall, and mean error rate 20 times for every epoch. Accuracy, precision, recall, F1-Score, mean error rate are shown in equations (13), (14), (15), (16), and (17). In this case,

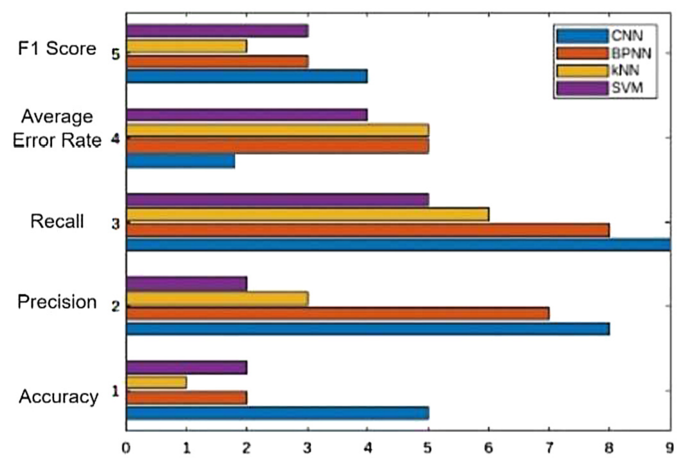

Fig. 7. Evaluation of performance for the proposed system.

"True Positive," is indicated as TP, "True Negative," as TN, "False Positive," as FP and "False Negative" as FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{14}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{15}$$

$$\text{F1 Score} = \frac{Precision * Recall}{Precision + Recall} \tag{16}$$

$$\text{Mean Error Rate} = \frac{1}{n}\sum_{t=1}^{n}\frac{(AV_t - FC_t)}{AV_t} \tag{17}$$

Fig. 8 displays the confusion matrix table for the convolution neural multiclass classifier which classifies as healthy, medium healthy, and not healthy. The prediction of confusion matrix shows 53.3% positive prediction and decreased in the false positive prediction as not healthy low as 40% and medium health prediction is increased to 46.7%, where the not healthy percentage is also increased in the false positive 26.7% compared to true positive 13.3%.

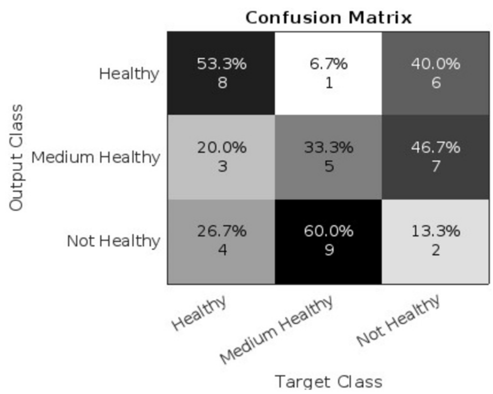

Fig. 8. Confusion matrix table for Convolution Neural Multiclass Classifier.

5. Conclusion and future work

The suggested project is referred to as a telehealth care system for monitoring patients' psycho-neurological conditions during the rehabilitation process and is used for elderly and disabled people. This is a good outcome and would be highly beneficial in today's society. In the proposed study, brain activity is monitored using an EEG to look for signs of mental illness, seizure disorders, cognitive strain, etc. The Kinect Sensor is used to record whole body 3D motion, recognize gestures, and faces. Transfer learning is a safe method that may manage numerous jobs concurrently. Here, Convolutional neural networks along with the transfer learning method performed classification with an accuracy of 95% and higher. To improve the memory and lower the stress level, the patient will benefit from an early diagnosis of cognitive disorders. The proposed study would result in a novel form of the cognitive rehabilitation benefit for the aged and disabled, also it will serve as a telehealth care and monitoring system for tracking patients' psycho-neurological conditions as they undergo rehabilitation.

In the future, brain, body, and heart surveillance will combine Kinect sensors with ECG, EEG, EMG, and PPG sensors. We are also proposing some IOT sensors to record and store the sensor data in the cloud. This will give us the advantage of availability. For better outcomes, the proposed model will be tested on a wider range of subject populations.

Human and animal rights

The authors declare that the work described has been carried out in accordance with the Declaration of Helsinki of the World Medical Association revised in 2013 for experiments involving humans as well as in accordance with the EU Directive 2010/63/EU for animal experiments.

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Author contributions

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.

Declaration of competing interest

The authors declare that they have no known competing financial or personal relationships that could be viewed as influencing the work reported in this paper.

References

[1] P. Dommaraju, Perspectives on old age in India, in: Contemporary Demographic Transformations in China, India and Indonesia, 2016, pp. 293–308.
[2] S. Desai, S.S. Mantha, V.M. Phalle, Advances in smart wheelchair technology, in: 2017 International Conference on Nascent Technologies in Engineering, ICNTE, IEEE, January 2017, pp. 1–7.
[3] D. Webster, O. Celik, Systematic review of Kinect applications in elderly care and stroke rehabilitation, J. NeuroEng. Rehabil. 11 (1) (2014) 1–24.
[4] X. Wang, J. Ellul, G. Azzopardi, Elderly fall detection systems: a literature survey, Front. Robot. AI 7 (2020) 71.
[5] A.B. Khanna, C.S. Metgud, Prevalence of cognitive impairment in elderly population residing in an urban area of Belagavi, J. Fam. Med. Prim. Care 9 (6) (2020) 2699.
[6] H. Nakano, EEG measurement as a tool for rehabilitation assessment and treatment, in: Electroencephalography – From Basic Research to Clinical Applications, IntechOpen, 2020.
[7] R. Inoue, T. Sugi, Y. Matsuda, S. Goto, H. Nohira, R. Mase, Recording and characterization of EEGs by using wearable EEG device, in: 2019 19th International Conference on Control, Automation and Systems, ICCAS, IEEE, October 2019, pp. 194–197.
[8] S. Das, L. Ghosh, S. Saha, Analyzing gaming effects on cognitive load using artificial intelligent tools, in: 2020 IEEE International Conference on Electronics, Computing and Communication Technologies, CONECCT, IEEE, July 2020, pp. 1–6.
[9] A. Ghosh, S. Das, S. Saha, Stress detection for cognitive rehabilitation in COVID-19 scenario, 2020.
[10] S.M.H. Mousavi, A. Ilanloo, Seven staged identity recognition system using Kinect V. 2 sensor, in: 2022 9th Iranian Joint Congress on Fuzzy and Intelligent Systems, CFIS, IEEE, March 2022, pp. 1–7.
[11] S. Kapgate, P. Sahu, M. Das, D. Gupta, Human following robot using Kinect in embedded platform, in: 2022 1st International Conference on the Paradigm Shifts in Communication, Embedded Systems, Machine Learning and Signal Processing, PCEMS, IEEE, May 2022, pp. 119–123.
[12] S. Das, P. Bhowmick, N.C. Giri, K. Minakova, O. Rubanenko, D. Danylchenko, Telemedical system for monitoring the psycho-neurological state of patients in the process of rehabilitation, in: 2022 IEEE 3rd KhPI Week on Advanced Technology, KhPIWeek, Kharkiv, Ukraine, 2022, pp. 1–6.
[13] W. Meekes, E.K. Stanmore, Motivational determinants of exergame participation for older people in assisted living facilities: mixed-methods study, J. Med. Internet Res. 19 (7) (2017) e238.
[14] A. Calin, E. Stanmore, Exergames, how to make physiotherapy fun, https://www.software.ac.uk/blog/2016-09-26-exergames-how-make-physiotherapy-fun. (Accessed 14 July 2017).
[15] GameUp, Game-based mobility training and motivation of senior citizens, http://www.aal-europe.eu/projects/gameup/. (Accessed 14 July 2017).
[16] Cristina Roda, Arturo Carlos Rodriguez Cobo, A multi-agent system for acquired brain injury rehabilitation in ambient intelligence environments, Neurocomputing 231 (2017) 11–18.
[17] Yushuang Tian, et al., Upper limb motion tracking with the integration of IMU and Kinect, Neurocomputing 159 (2015) 207–218.
[18] Evan A. Suma, Belinda Lange, Albert A. Rizzo, David M. Krum, Mark T. Bolas, FAAST: the flexible action and articulated skeleton toolkit, in: IEEE Virtual Reality Conference, 2011.
[19] Rodrigo Ibañez, Álvaro Soria, Alfredo Teyseyre, Marcelo Campo, Easy gesture recognition for Kinect, Adv. Eng. Softw. 76 (2014) 171–180.
[20] S. Das, A. Ghosh, S. Saha, A review on gaming effects on cognitive load for smart healthcare and its security, https://doi.org/10.4018/978-1-6684-5741-2.ch001, 2022.
[21] S. Das, S. Saha, Home automation system combining internet-of-things with brain–computer interfacing, https://doi.org/10.1007/978-981-19-1408-9_11, 2022.
[22] S. Sima, N.C. Giri, S. Nayak, S. Routray, D. Tamboli, R. Gajjar, ReHoMation: low cost, RF based remotely home automation without microcontroller, Indian J. Nat. Sci. 13 (2022) 42235–42241.
[23] S. Majumdar, A. Al-Hababibeh, A. Omurtag, B. Shakmak, M. Asrar, A novel approach for communicating with patients suffering from completely locked-in-syndrome (CLIS) via thoughts: brain computer interface system using EEG signals and artificial intelligence, Neurosci. Inform. (2023) 100126.