STM JOURNALS

Journal of
Computer Technology & Applications
https://journals.stmjournals.com/jocta

ISSN: 2229-6964 (Online)
ISSN: 2347-7229 (Print)
Volume 15, Issue 2, 2024
May–August
DOI (Journal): 10.37591/JoCTA

Research JoCTA

Automatic Stroke Recovery Rate Prediction System Based on Movement Analysis During Computer Interaction

Chethan P.J.[1,*], Aishwarya B.R.[2], Amitha G.S.[2], Ananya V.K.[2], Anjali C.R.[2]

Abstract

Stroke is a major health concern worldwide, often resulting in impaired motor functions and affecting the quality of life for affected individuals. This research introduces an innovative approach for predicting stroke recovery rates by leveraging movement analysis during computer interaction. The proposed system aims to provide a non-invasive and automated solution to assess the rehabilitation progress of stroke survivors. The system utilizes advanced motion tracking technologies to capture and analyze the fine-grained movements exhibited during computer-based tasks. Machine learning algorithms are employed to correlate these movement patterns with established indicators of stroke recovery, allowing for personalized predictions tailored to individual patients. This approach offers a more dynamic and responsive assessment compared to traditional methods.

Keywords: AIML, computer vision, CNN, rehabilitation, movement analysis

INTRODUCTION

Stroke is a medical disorder that damages the brain by rupturing blood arteries in the area. It may also happen if the brain's supply of blood and other nutrients is cut off. The World Health Organization (WHO) states that stroke is the primary cause of death and disability worldwide. The majority of research has been done on heart stroke prediction, but relatively little has been done on brain stroke risk. In light of this, numerous machine learning models are developed to forecast the likelihood of a brain stroke. Numerous machine learning algorithms are developed to forecast the likelihood of a brain stroke. Stroke is a destructive illness that typically influences individuals over the age of 65 years. Since stroke prediction takes a lot of time, the project's primary goal is to use newly developed machine learning algorithms to estimate the likelihood of a stroke occurring. The goal is to develop an application with an intuitive user interface that makes it simple to explore and enter data. Machine Learning has made it possible to anticipate the likelihood of a stroke thanks to advancements in medical technology. The algorithms used in machine learning are helpful in providing accurate analysis and accurate predictions. The majority of the earlier research on stroke focuses on heart stroke prediction. Very less works have been performed on Brain stroke. This study is based on predicting the occurrence of a brain stroke using Machine Learning. The most important aspects of the methods and outcomes are that Naïve Bayes outperformed the other five classification algorithms, achieving a better accuracy measure.

***Author for Correspondence**
Chethan P.J.
E-mail: chethan.petkar@gmail.com

[1]Assistant Professor, Department of Computer Science and Engineering, People's Education Society Institute of Technology and Management, Shivamogga, Virupina Koppa, Karnataka, India
[2]Student, Department of Computer Science and Engineering, People's Education Society Institute of Technology and Management, Shivamogga, Virupina Koppa, Karnataka, India

Received Date: May 03, 2024
Accepted Date: July 22, 2024
Published Date: August 01, 2024

Citation: Chethan P.J., Aishwarya B.R., Amitha G.S., Ananya V.K., Anjali C.R. Automatic Stroke Recovery Rate Prediction System Based on Movement Analysis During Computer Interaction. Journal of Computer Technology & Applications. 2024; 15(2): 76–82p.

LITERATURE SURVEY

The machine-learning model designed to detect compensatory movements in stroke patients during rehabilitation exercises. The model analyzes movement data collected from patients and provides real-time feedback on their performance, helping them avoid unwanted compensatory patterns and focus on proper movement techniques [1]. A novel method for assessing motor function in stroke patients using a bi-lateral virtual reality (VR) task and machine learning. The VR task involves catching balls with both hands, while movement data is collected and analyzed. This data is then used to train a machine learning model that estimates the patient's level of impairment [2]. A novel method for analyzing and classifying motor impairment in stroke patients using data from inertial measurement units (IMUs) worn on data gloves. The method uses functional data analysis to model the trajectory of the IMUs during hand movements, and extracting features that capture key characteristics of the data. These features are then used to train machine learning models to classify the patients' level of motor impairment [3]. The use of functional data analysis (FDA) to accurately assess hand function in stroke patients. The method involves collecting data from inertial measurement units (IMUs) worn on data gloves during various hand movements. This data is then modeled using FDA techniques to extract key features that characterize the movement patterns. Finally, machine learning models are trained on these features to classify the patients' level of motor impairment [4]. The use of a soft robotic glove controlled by a Steady-State Visually Evoked Potential (SSVEP) based Brain-Computer Interface (BCI) for post-stroke hand function rehabilitation. The BCI allows patients to control the robotic glove movement through visual stimuli, potentially offering an alternative to traditional methods [5]. A system called AREEN was developed to detect SN in stroke survivors using EEG and augmented reality (AR). EEG was used to measure brain activity, and AR was used to display visual stimuli in the patient's field of view. The system was able to detect neglected targets with high accuracy [5]. A novel method for automatically detecting compensatory movement patterns in stroke patients with hemiplegia. These patients often experience limited arm movement and rely on compensatory movements from other body parts to achieve tasks. The method uses a pressure distribution mattress and machine learning algorithms to identify these compensatory movements [6]. A real-time hand motion detection system designed for unsupervised home training in rehabilitation settings. The system combines a convolutional neural network-based hand motion detection module with a gesture recognition system, offering several functionalities [7].

METHODOLOGY

Artificial Intelligence and Machine Learning

Automating accident detection and analysis is made possible in large part by Artificial Intelligence and Machine Learning (AIML) approaches. To find accident trends, these algorithms use real-time data from surveillance cameras and traffic sensors. They examine pictures and videos using computer vision techniques to identify crashes and abrupt changes in vehicle movement. The capacity of AIML to use deep learning algorithms to learn from big datasets makes it possible to accurately detect and classify a variety of accident types, including collisions and events involving pedestrians. As a result, AIML greatly enhances traffic flow, improves emergency response in urban contexts, and increases road safety [8].

Computer Vision

One of the most important applications of artificial intelligence is computer vision, which is used to automate accident investigation and detection. Computer vision algorithms use the analysis of visual input from sensors or surveillance cameras to identify accidents by extracting relevant patterns and characteristics. In order to identify accident indications such as abrupt changes in vehicle trajectories or accidents, real-time or recorded visual data is evaluated. Furthermore, by the extraction of pertinent data from photos or video, such as vehicle locations, speeds, and contextual elements, computer vision makes extensive accident analysis possible. Real-time event recognition, quicker emergency response times, and insights for better road safety and traffic management decision-making are all made possible by the use of computer vision as shown in Figure 1. In the end, computer vision enables automatic analysis and identification of accidents, improving traffic flow and road safety [9].

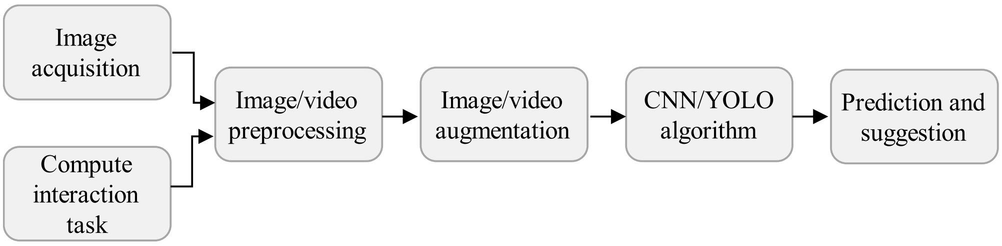

Figure 1. Flow chart of computer vision.

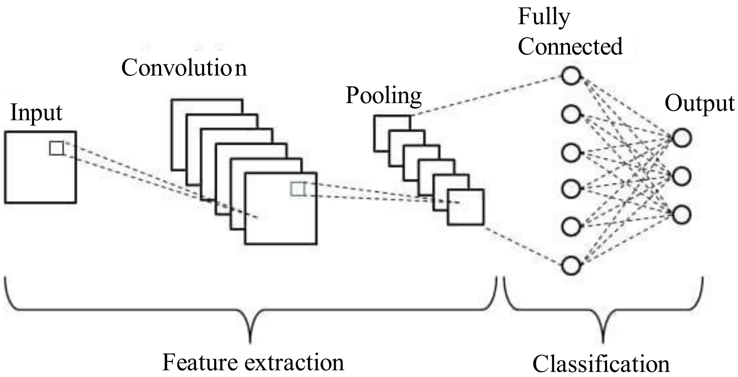

Figure 2. Convolutional neural network flow chart.

CNN

A thorough education Convolutional, pooling, and fully connected (FC) layers make up CNN's three layers. The FC layer comes last and is preceded by the convolutional layer. The CNN gets more sophisticated as it moves from the convolutional layer to the FC layer. Because of its escalating intricacy, the CNN is able to recognize more significant areas and intricate details of a picture until ultimately identifying the item in its whole as shown in Figure 2.

Layer of Convolution

The convolutional layer, the central component of a CNN, is where most calculations take place. The first convolutional layer may be followed by a second one. A kernel or filter inside this layer travels across the receptive fields during the convolution process.

DESIGN AND IMPLEMENTATION

System requirements are taken into consideration while translating system specifications into a software representation. The designer focuses on the following at this phase: software architecture, data structures, algorithms, etc. The programmer begins coding at the coding phase in order to provide a complete product sketch. Stated otherwise, the conversion of system requirements only results in machine-readable compute code. The real coding or programming of the software takes place during the implementation phase. Usually, the library, executables, user guides, and other software documentation are the results of this step. All models (programs) are merged and tested during the testing phase to make sure the system as a whole satisfies the software requirements. Validation and verification are the focus of testing. The longest stage of which is the maintenance phase as shown in Figure 3.

Training data: The information used to train the CNN algorithm is known as training data. It probably includes pictures of people's hands and legs in motion as well as illustrations of these two body parts.

CNN algorithm: An artificial neural network type that excels at identifying patterns in pictures is called a convolutional neural network. In this scenario, in order to categorize fresh data, the CNN algorithm would first be taught to identify movement patterns in the training set.

YOLO V8 algorithm: YOLOv8 is the latest iteration in the popular YOLO series of real-time object detection models. Developed by Ultralytics, it builds upon the success of its predecessors while introducing several enhancements to improve accuracy and speed.

New data: This is the information that the system will utilize to forecast a person's movements. It may be a single photo or a video of someone working out.

Classifier: The CNN algorithm will produce a categorization of the person's movements after processing the fresh data.

Prediction: The algorithm will then predict the next exercise the user should perform based on their categorization. This might depend on a number of things, including the individual's goals, degree of fitness, and any past ailments.

Exercise suggestion: The individual will receive a recommendation from the system for their next workout and a speedy recovery.

RESULT AND DISCUSSION

Figure 4 tells about the user interface which the patients can understand the usage of it.

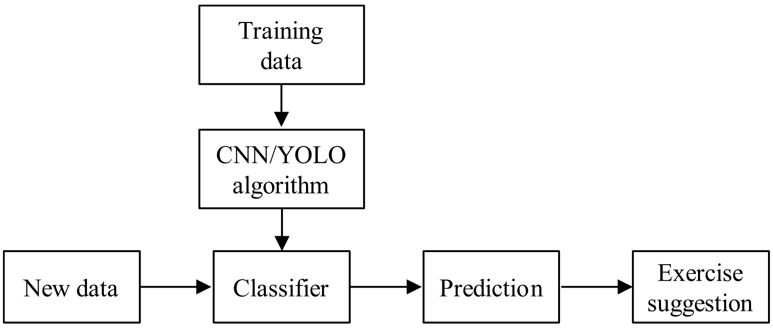

Figure 3. Design of the proposed model.

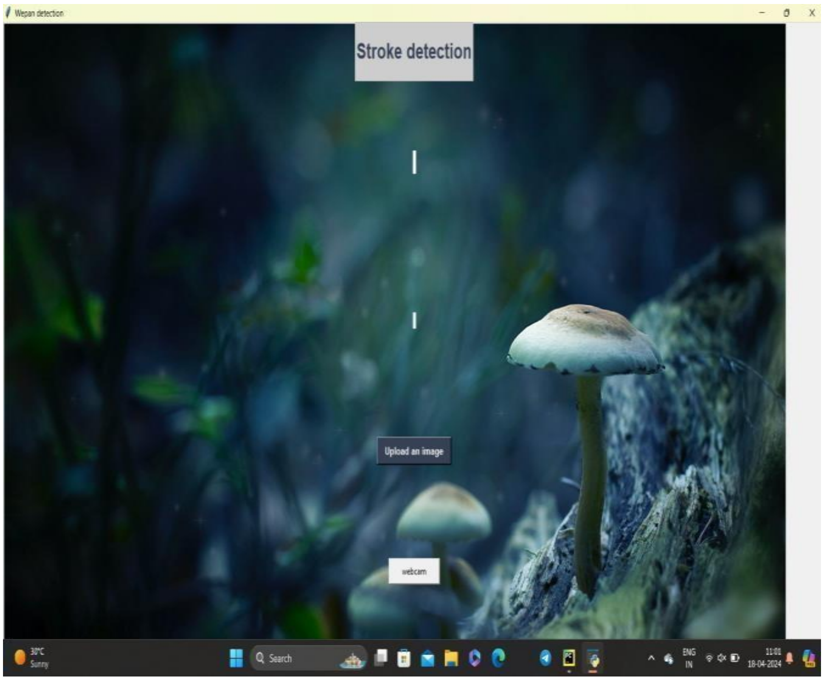

Figure 4. User Interface for stroke detection.

In the Figures 5–7 the user can upload the image of the hand and it can detect the hand along with the recovery rate prediction.

In the Figures 8–10 the user can upload the image of the arm and it can detect the arm along with the recovery rate prediction.

Figure 5. Detection of hand and recovery rate predict at 100%.

Figure 6. Detection of hand and recovery rate predict at 75%.

Figure 7. Detection of hand and recovery rate predict at 0%.

Figure 8. Detection of arm and recovery rate predict at 50%.

Figure 9. Detection of arm and recovery rate predict at 0%.

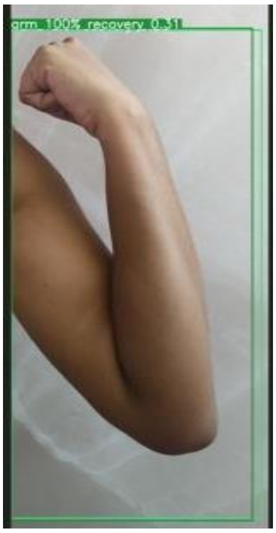

Figure 10. Detection of arm and recovery rate predict at 0%.

In Figure 11 the user can upload the image of the leg and it can detect the leg along with the recovery rate prediction.

In the Figures 12–14 the user uses webcam for the image of the hand and it can detect the hand along with the recovery rate prediction.

Figure 11. Detection of leg and recovery rate predict at 0%.

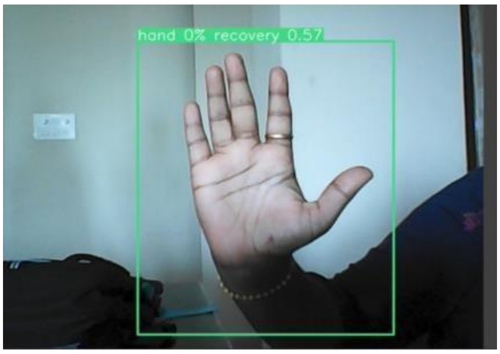

Figure 12. Detection of Hand and recovery rate predict at 0%.

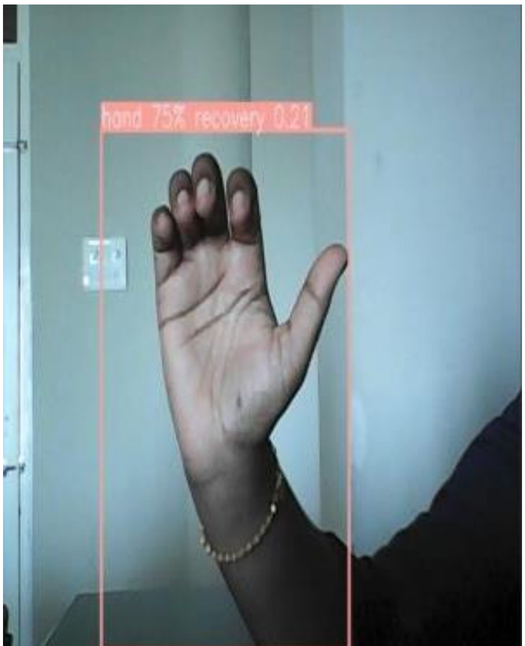

Figure 13. Detection of Hand and recovery rate predict at 75%.

Figure 14. Detection of Hand and recovery rate predict at 50%.

CONCLUSION

Predicting stroke recovery through computer interaction analysis unveils exciting possibilities. By analyzing patients' movements while using the computer, personalized therapy plans, convenient remote monitoring, and even reduced healthcare costs could become reality. However, challenges like ensuring data accuracy and addressing ethical concerns require careful consideration before this promising system can revolutionize stroke rehabilitation. By navigating these hurdles, we can unlock the immense potential of technology to empower patients and optimize their recovery journey. Movement analysis during computer interaction has the potential to be a valuable tool for monitoring stroke recovery. By tracking how people move their hands and fingers while using a computer, researchers can gain insights into their motor skills and overall recovery progress. Predicting stroke recovery rates can be challenging. There are many factors that influence recovery, and it is difficult to accurately predict how well someone will do. However, even if predictions are not perfect, they can still be helpful for guiding treatment and rehabilitation. More research is needed to validate and improve automatic stroke recovery rate prediction systems. As this field continues to develop, we can expect to see more accurate and reliable systems that can provide valuable information for patients and healthcare providers.

REFERENCES

1. Kashi S, Polak RF, Lerner B, Rokach L, Levy-Tzedek S. A machine-learning model for automatic detection of movement compensations in stroke patients. IEEE Trans Emerg Topics Comput. 2020 Apr 23; 9(3): 1234–47.
2. Powell MO. Machine Learning, Virtual Reality, and Biomechanical Simulation to Aid Physical Rehabilitation. Santa Cruz (CA): University of California, Santa Cruz; 2021.
3. Hwang YT, Lu WA, Lin BS. Use of functional data to model the trajectory of an inertial measurement unit and classify levels of motor impairment for stroke patients. IEEE Trans Neural Syst Rehabil Eng. 2022 Mar 25; 30: 925–35.
4. Gomez-Arrunategui JP, Eng JJ, Hodgson AJ. Monitoring Arm Movements Post-Stroke for Applications in Rehabilitation and Home Settings. IEEE Trans Neural Syst Rehabil Eng. 2022 Aug 10; 30: 2312–21.
5. Guo N, Wang X, Duanmu D, Huang X, Li X, Fan Y, Li H, Liu Y, Yeung EH, To MK, Gu J. SSVEP-based brain computer interface controlled soft robotic glove for post-stroke hand function rehabilitation. IEEE Trans Neural Syst Rehabil Eng. 2022 Jun 22; 30: 1737–44.
6. Mak J, Kocanaogullari D, Huang X, Kersey J, Shih M, Grattan ES, Skidmore ER, Wittenberg GF, Ostadabbas S, Akcakaya M. Detection of stroke-induced visual neglect and target response prediction using augmented reality and electroencephalography. IEEE Trans Neural Syst Rehabil Eng. 2022 Jul 4; 30: 1840–50.
7. Teixeira-Salmela LF, Parreira VF, Britto RR, Brant TC, Inácio ÉP, Alcântara TO, Carvalho IF. Respiratory pressures and thoracoabdominal motion in community-dwelling chronic stroke survivors. Arch Phys Med Rehabil. 2005 Oct 1; 86(10): 1974–8.
8. Bhatt A, Shah N, Horn M, Bhatt S, Yanushkevich S, Almekhlafi M. Assessment of Post-Stroke Motor Function Weakness using Pressure Sensor Data. In 2021 IEEE Symposium Series on Computational Intelligence (SSCI). 2021 Dec 5; 1–7.
9. Tang QP, Wang GQ, Huang XS, Yan ML, Han GD, Pu QQ, Ouyang CH, Zhan HL, Feng JH, Yang QD. The influence of different movements on ambulatory blood pressure in hypertensive subacute stroke patients. J Int Med Res. 2012 Apr; 40(2): 590–600.

