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Research Article

Technique of User-Computer Interface to Form the Movement Orientation of Virtual Objects within Virtual Reality Applications

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ABSTRACT

The machine-user interface is a dynamic technique for many applications precisely those associated with the motion of robots. The electrical signals generated in the brain pass through the nerves leading to the activities of the mixture on the scalp. Magnetic activates extracts to reflect a specific brain state and can be used to control the device. Robot motion control is achieved using brain waves that are classified by deep learning techniques namely AlexNet (CNN) in this paper that has been compared to another front-feeding neural network (ANN). The proposed case resulted in a forecast accuracy of more than 95%.

Keywords: Deep Learning, LMS, Brain Waves, Features, Classification.

INTRODUCTION

Because it invests in many technologies that use brain waves to guide and move applications, the bio-electrical signal produced by neurons in the brain, which is responsible for initiating human movement, helps test a variety of human movements.[1]. Human-computer interaction (HCI) applications are used extensively nowadays. Control interfaces such as a control stick are commonly used to operate wheelchairs, drones, and arm robots. However, if the user believes that the control sticks are not a good substitute, the Brain Computer Interface (BCI) technology is used.

The BCI system offers a different approach to solving this issue. Since electrical signals are used by the human brain to communicate with one another, it is conceivable to connect the brain to technological devices. Analyzing and documenting these processes is now feasible with the correct methods and the latest developments in cognitive neuroscience and brain imaging technologies. The market for BCI systems has grown quickly due to the devices' ability to use every signal and movement the brain produces to run them. These systems are intended to assist individuals with spinal injuries or loss of motor function in doing daily tasks [2]. To use the programs, people only need to think while they move.

Electroencephalography (EEG) is one technique used in neuroimaging to assess brain waves. It invests in developing and designing sensor systems that are based on BCI systems. The current study uses the BCI system application to create an interface between the human brain and the computer that controls a drone using the EEG method. The sensing device uses a range of frequency bands to record data based on EEG rhythm patterns.

A single channel dry electrode that comes with the NeuroSky gadget is used in this study to extract and collect brain waves from the user's scalp. Numerous features are included in the NeuroSky mindwave 2 device, including signal processing and digitization prior to Bluetooth transmission, including signal processing and digitization prior to Bluetooth transmission and other features as mentioned by Motlagh, et. al [3].

TUNES OF BRAINWAVES

There are more than 86 billion neurons in the human brain are responsible for controlling muscle movement and the formation of thoughts in the head. These active neurons operate at specific frequencies, these frequencies are captured using an electroencephalogram (EEG) by reading the electrical activity produced by these cells. Frequencies are classified into different bands depending on the mental state of the human being. The following table No. 1 shows these frequencies and the comparison between them.

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Table 1: Ranges of brain waves and detection status.

Particle	Frequency Range (Hz)	Brain situation
Delta wave	0.1 – 3	Deep sleep without dreams
Theta wave	(4 – 7)	Meditation and high relaxation
Alpha wave	(8 – 12)	Through relaxation
Beta wave	12 – 30	During concentration
Gamma wave	30 – 100	During information processing

ELECTROENCEPHALOGRAM

One of the most important methods used to track and record brain waves is an electroencephalogram (EEG). Brain activity can be monitored and evaluated through an electroencephalogram, where the nerve ion currents produced in the brain trigger electrical waves detected by the EEG by inserting electrodes installed in the headset, and nowadays the EEG is considered one of the most common non-invasive BCI methods [4] , with its many advantages such as fast response, ease and low cost with the possibility of implementation in different applications [5]. In contrast, the EEG headset retrieves and collects waves in different frequency bands according to the scalp locations of the map sensing of the electrodes. The EEG signals pass through many layers (skull, scalp, etc.) and so they have weak accuracy [6]. The EEG signal to noise ratio are disturbed as a result of factors affecting them, such as light sensitivity, noise, and others. EEG signals may be divided into three categories According to their electrical activity [7].

(1) Self or Spontaneous activity: This activity type is employed in this consideration of the scalp and illustrates the states of alpha, beta, delta, gamma and theta of brain waves. (2) Induced potential: This EEG item measures the electrical activity of the brain in response to a certain stimulus, like an auditory, electrical, or visual stimulus, which stimulates sensory neural pathways.

(3) Bioelectrical actions. this type of EEG activity refers to single neurons. This activity is recorded by implanting microelectrodes in the brain.

STRUCTURE and RESOURCES

The purpose of ERS is to establish a relationship between distinct emotional states and related traits. Anger, fear, sadness, happiness, disgust, and surprise are six emotional states widely used in the identification process.

Audio, images, videos, and statistics are just a few of the data sources that ERS uses to do emotional recognition [8]. The most advanced and reliable automated emotion recognition systems are manufactured using deep learning and machine learning (ERSs) approaches. The two most common ways to express emotions are through sound and image. The picture may indicate a variety of characteristic emotional elements. Since the face is the only organ capable of clearly expressing human emotions, it may be used for the same purpose more successfully. Although images consist of rows and colors of pixels, each with a unique number, they are essentially two-dimensional (2D) data.

Information visible to the human eye is created by the contrast in the pixel values in the image. It is difficult to extract features from an image that correspond to emotional state or any other biometric information because image data is nonlinear and non-static [9]. These manifests itself in the fact that traits change in response to external environmental or physical stimuli. More specifically, it takes practice to recognize the same traits in the image of the same person. Aging is considered a main problem in image recognition systems (IRS) [10]. Other issues include poor lighting, face wear and alignment [11], and dust noise also reduces the effectiveness of ERS. However, in previous research, sounds were important as raw materials and were essential for the development of ERS. Activity recognition is a crucial technique for identifying emotions. This procedure looked at the movements of the patient's limbs and used image data to determine how they were feeling. Image processing techniques can be used to extract some features.

There are many uses for the great way to monitor brain activity, including the ability to recognize emotions. Several previous studies, notably [9], which used EEG data, have been effective in achieving this goal. This information can be recorded using a set of electrodes implanted above the skull. Nanoelectrodes can be implanted under the skull to collect EEG data either surgically or noninvasively. EEG data is repeatedly recorded using an international electrode from 10 to 20 [12]. Data from many channels is used to record information from different brain regions in order to distinguish emotions depending on their location and level of

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effort. In a similar way to how audio signals are converted into data, ADC is mostly used to convert electroencephalogram impulses into electrical form. To ensure that the recognition method works with each of the above types of emotional input, pre-treatment is required. The above data can be cleaned of noise and other interference using the commonly used wavelet conversion technology.

The development of machine learning algorithms has made it possible to use the latest technologies that have improved learning efficiency and prediction accuracy. Neural networks are inspired by the structure and functioning of the human nervous system [7 & 9]. Artificial algorithms are part of the smart generation of machine learning technology. The two basic stages of running the neural network are learning and testing.

Neural networks analyze data, their goals, and the relationships between input and output data throughout the learning phase (or expected outcomes). During the training phase, the following passengers can be taken into account.

The three basic parts of the neural network are the input, hidden, and output layers. According to the design requirements, the hidden part may be one or several layers. Figure 1 shows the construction of a single neural network from the hidden layer.

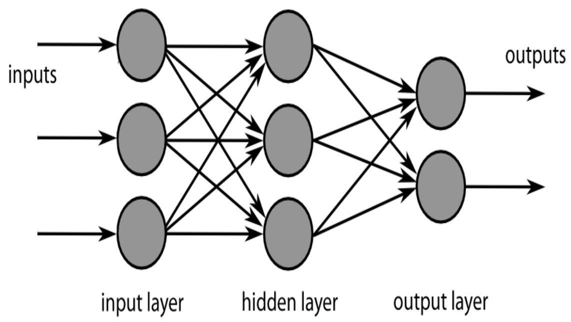

Fig. 1. The structure of the neural network shows the layers of the model.

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The amount of input determines the number of nodes (combination) used to build each layer of the neural network, and more nodes usually lead to a longer network execution time. Weights, used to connect nodes, perform similar functions to neurons of the human nervous system. When inputs move from layer to layer, these weights, each represented by a number, measure them. Let's imagine that x[n], a one-dimensional matrix containing n rows and one column, provides input to the neural network model. The output of the hidden layer, denoted by y[n], appears as follows:

$$y[n] = \sum_{n=1}^{n=N} x[n].w_i \qquad (1)$$

In turn, the product of the hidden layer can be described by the value of the variable z [n], as expressed in equation (2)

$$z[n] = \sum_{n=1}^{n=N} y[n].w_h \qquad (2)$$

The weight of the three layers are the three different weight factors that the network will use. However, the following equation, denoted by m [n], can be used to express the final result of the network model.

$$m[n] = \sum_{n=1}^{n=N} z[n].w_o \qquad (3)$$

In this step, the neural network is first trained on a specific set of data with the aim of providing it with all the knowledge about the structure and nature of the data – more specifically, how its components relate to each other and to the target. The neural network cannot function without this mechanism. The goal of the neural network is determined by the correctness of the weight distribution. The primary goal of weight assignment is to process formula (3). Weight is a key element in the process of allocating inputs to a particular category, or in other words, output production. The equation below shows the result after applying the weight, assuming W is the general weight formula, x[n] is the input, and y[n] is the result:

$$W = \frac{x[n]}{y[n]} \qquad (4)$$

Recognize that the size of a weight vector can range from a few hundred to thousands of weights, depending on the amount of elements in the data set. LM technology, which is typical for determining weights in neural network models, is likely to be used to weigh the neural network model.

CONVOLUTIONAL NEURAL NETWORK (CNN)

The climax of Alex Kryzhevsky's incredible academic career was marked by his victory in the 2012 ImageNet competition (Krizhevsky, A., Sutskever, I., & Hinton, G. E. 2012). With outstanding performance in both machine learning and traditional

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computer programming techniques, AlexNet is the market leader in computer vision. During a period of growing interest in this topic, deep learning has quickly become critical to classification in machine learning and visual recognition. Figure 2 shows how AlexNet is organized (Figure 2). After the initial transformation and standardization of the local response, a set of 96 distinct layers is produced. The signal may be present using 11 × 11 tiles. Two separate step scales - one smaller and one larger - are used by three-by-three filters. Five filters are used five times to do the same filtering activities as the second layer. The consecutive warp layers the third, fourth, and fifth, respectively, include a map of 384, 384, and 296 related filter types, each consisting of three and three filters. The two completely threaded layers of the network terminate the softmax layer after pulling. This model consists of two networks of equal excellence and two organizations. Dropout and LRN are integrated into this network. There are two additional applications for LRN. First, patch maps or features N to N are useful when normalizing a single channel using neighborhood values. Second, character sets, keyboards, and on-screen displays can be used to expand the LRN (the neighborhood of the third dimension with pixels or just one location).

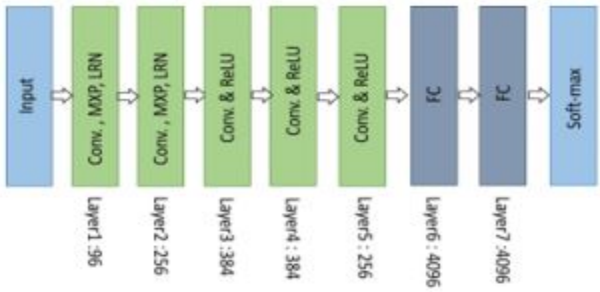

Fig. 2 layers used in AlexNet's architecture.

AlexNet consists of three convolutional layers, two of which are completely interconnected. Averaged all parameters in each AlexNet layer using an ImageNet dataset results in a starting point of 17.7 KB as a parameter. The output and input of 4 steps are 555596 and 2242243, respectively. The weight of the first layer was calculated to be 290,400 neurons (55 in total) and 364 weights, as stated earlier. The first torsion layer contains 105, 705, 600 parameters (290,400*364*105,705,600). Millions of parameters on each sheet are displayed in the second table. In total, the network contains 724 million MAC and 61 million weights.

RESULTS AND DISCUSSIONS

Experimental study was held for ten-fold numbers. Using the method of K-fold validation processing the performance employing ten different sets of data. Table 1 shows the measured accuracy for each fold.

Table 1: accuracy fold wise of prediction values.

Fold	CNN	ANN
1	97.3	96
2	96	94.2
3	5	94
4	97	94
5	91.7	94.5
6	98	98.1

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7	89.5	90.8
8	93.7	88
9	97.7	93.2
10	96.1	91.5

The same thing is shown graphically as in Figures 3 to 5. Prediction performance using NNNs appears to have a peak in fold No. 6 (refer to Figure 3) with an expectation accuracy of 98.1%. While in the case of the convolutional neural network, higher performance was noticed in fold No. 6 with a 98% (refer to Figure 4).

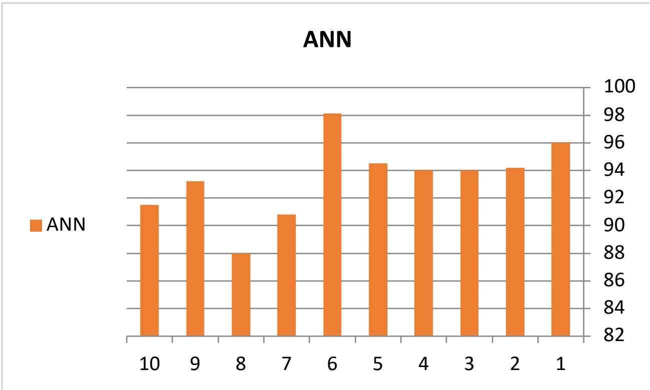

Fig. 3: Local network performance metric that shows the percentage of forecast accuracy.

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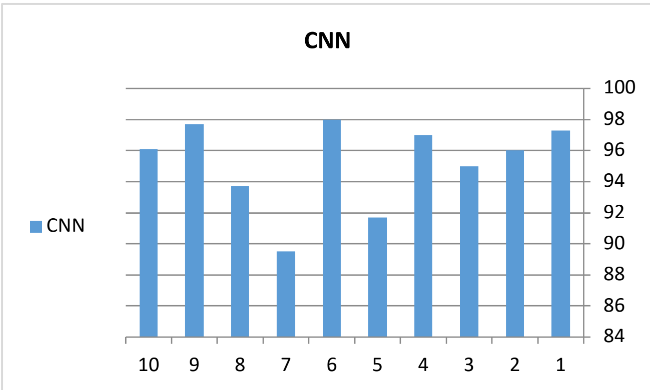

Fig. 4: CNN performance metric shows percentage of prediction accuracy.

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CNN's performance shows the best results in almost all folds as shown in Figure 5.

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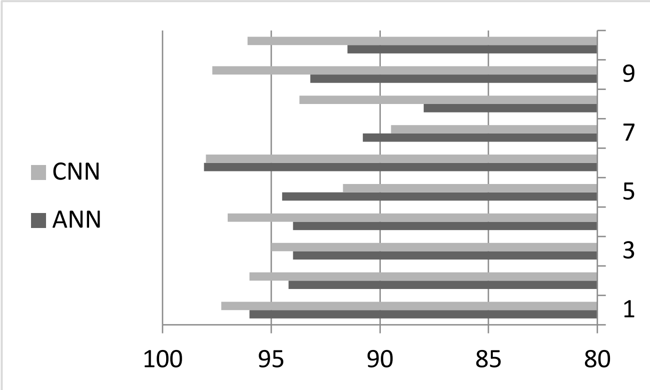

Fig. 5: Compare performance of ANN and CNN

Table 3 shows the average accuracy of ANN and CNN proposed models are shown in table 3 where the CNN model gives the best prediction performance of 95.2 percent. The same is shown in Figure 6.

Table 3: Scale of average accuracy of the proposed models

Model	Accuracy (mean)
ANN	93.43
CNN	95.2

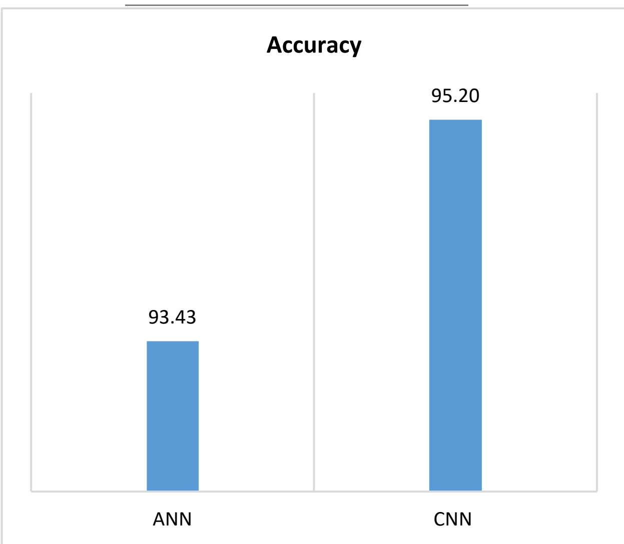

Fig. 6: the accuracy of the proposed models

On the other hand, the mean squared error (MSE) of both algorithms is measured and the results are presented in Figure 7.

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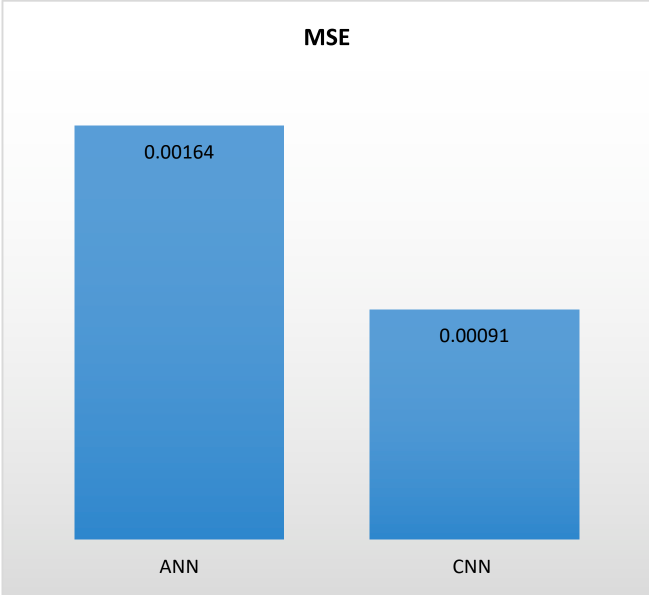

Fig. 7: Mean square error measures of ANN & CNN models

CONCLUSION

Controlling a robot through computer interface technique depends on recognizing the emotional state of human brain. The four primary sources of primary data for emotional recognition were speech signal, brain activity (EEG), facial image, and individual activity (such as limb movement). All assessment methods are aimed at grouping emotions into six categories (sadness, anger, fear, disgust, happiness, and surprise). To create ERS, deep learning and machine learning can be applied separately or jointly (mixed). Deep learning workbooks are difficult to work with due to the multiplicity of formats and dimensions that the data reaches. The workbook settings that the researchers modified by including additional filters or layers had an impact on the classification accuracy they could achieve. When combined with additional data sources, including speech and EEG, for the purpose of emotional recognition, filtering and noise reduction techniques may enhance the ERS payload. The two models used are convolutional neural networks (CNN) and artificial neural networks (ANN) (ANN). Accuracy and average squared error are calculated as performance measures when training models. The CNN has been shown to have the best accuracy (95.2%) and the lowest loss mean square error.

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