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Eye Controlled Wheelchair Using Transfer Learning

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***Abstract*—** Freedom of mobility affects an individual's sense of prominence and confidence. Because of diseases injuring the nervous system like Amyotrophic Lateral Sclerosis (ALS) and Parkinson disease, people lose their ability to move outmoded wheelchairs. This paper presents a novel technique to control a wheelchair by using eye movements. Eye controlled chair comprised of an electric wheelchair, a webcam in front of the user's eye capturing eyeball movements with a low-cost Raspberry pi system, serially communicating with Arduino microcontroller to drive wheelchair in the desired direction. The transfer learning approach was adopted instead of traditional image processing techniques, making wheelchair more reliable and accurate. Keras deep learning pre-trained VGG-16 model led us to achieve excellent performance, with very little training dataset. Unlike conventional wheelchairs, presented methodology makes this wheelchair equally suitable for people wearing eye glasses.

***Keywords*—**eye motion, wheelchair control system, transfer learning, convolution neural network, VGG-16

I.INTRODUCTION

The present-day technological evolutions in the field of smart mobility-aided systems turn the scientists' minds towards innovation for Quadriplegic (four limbs paralysis) people. A study [1] conducted to investigate the quality of life of individuals suffering from spinal cord injury reveals the fact that quadriplegic patients suffer more in terms of physical functionality, well-being and independence than other paraplegic individuals. Monoplegia, Hemiplegic & Paraplegic persons can use joystick or gesture controlled wheelchairs which are easily available in the market. Quadriplegic persons suffer from Parkinson disease and

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Amyotrophic Lateral Sclerosis in which the nervous system of a person is damaged, fallouts in dearth of their capability to move their voluntary muscles [2]. According to a clinical survey [3], 9-10% of patients find it extremely difficult to operate power wheelchairs even after being trained with it. 85% of clinicians pointed out the tiring necessity of autonomous wheelchairs (eye & brain control) in those patients' life. Scientists across the world have worked hard for the development of such smart systems which are helpful for the control mechanism of rehabilitative autonomous devices. Utilization of bio-signals to detect corneo-retinal potential has been a key function to bring out an EOG (Electrooculography) based autonomous wheelchair. An important feature of this research is that the eye is used as a mouse to run many other graphical user interfaces [4]. Another research on the same technique has developed an EOG signal acquisition system [5]. EOG is limited to use because eye blinks produce problematic alterations in the dipole potential of cornea & retina, which reduces the efficiency of the technique [6]. Different systems have been developed related to the abovementioned problem. According to [7], eye blinks and head tilt movements can steer the wheelchair. It could give more independence to a disabled person without using electrodes. Infrared radiation (IR) sensors were used to mount three proximity sensors onto the eye frame to track the eyeball movement. Eye movements created a sequence of digital bits which were then processed by microcontroller IC prior to the control of motors accordingly [8]. IR radiations of wavelength 760nm to 1400nm are generally transmitted through ocular media and focus on the retina. In this spectral region, thermal effects dominate and extreme exposure of the retina and the choroid causes enzyme denaturation due to critical temperature rise. As regenerative capabilities of the retina are very limited. Therefore, such exposures cause visual acuteness [9]. Real time eye-gaze control can ease such hitches mentioned above. In view of that, Scientists developed an eye-controlled wheelchair based on Tobii eye tracker which converts eyeball movements into gazing point coordinates [10]. Kalman filter is applied to extract the coordinate's data in order to optimize data. This data is sent to the microcontroller for controlling the wheelchair. The performance of Tobii eye trackers varies from user to user and only

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works for one display at a time. Also, it mounts permanently Bond to display so the user has to choose wisely [11]. Rather webcam/cellphone-cam based eye tracking is a more reliable. So, researchers introduced a Recursive Circular Hough Transform (RCHT) scheme for pupil detection. Pupil images were captured through very lowresolution cell phone camera [12]. Researchers made use of more advanced image processing functions to detect eye movements. They developed an eye-controlled wheelchair system which was running on raspberry pi computer [13]. Eye directions were subjected onto the screen to run the wheelchair. Eyeball movement is being tracked through the use of eyeball coordinates. Ultrasonic sensors have also been implemented for obstacle detection to avoid accidents. In the context of most recent human intelligence based deep learning neural networks [14], scientists again have functioned the EOG and EEG (Electroencephalography) based technology for driving a wheelchair through the classification of artificial neural networks. They used NeuroSkyMindWave headset to measure EEG and wet superficial electrodes to measure EOG. Principal components analysis method and wavelets transform are used for the further processing of these bio-signals. The wheelchair model is being developed through a circular Hough transform approach [15]. Deep learning neural networks have been used with open source computer vision where they can work comparable to the human brain. Some deep learning models are highly inspired by image processing of biological nervous systems like convolutional neural network (CNN). These networks have attained inordinate power for image classification tasks. The exceptional learning potentials of CNN remain to be further studied for untwisting real-world problems. Transfer Learning has also proved to be a powerful method by catching pre-trained models as their starting point. The rest of the paper is organized as follows; section II describes the proposed system with applied methodology. Section III shows the hardware implementation and results are discussed in section IV.

II.PROPOSED SYSTEM

The design of the proposed system involved a camera placed in front of the user, which continuously read the current position of the eyeball. This information was sent to the raspberry pi/laptop, which made a decision

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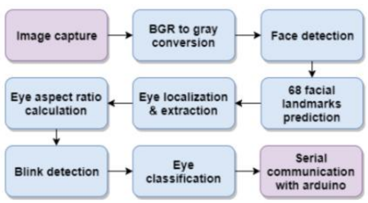
by classifying the image input. Eyeball classification was done using the pre-trained deep convolutional neural network. Based on the specific eyeball position, a unique character was encoded to Arduino, which moved the wheelchair in the desired direction. Fig. 1 shows the algorithm of the system.



A. Implementation Algorithm The webcam continuously took input from the user, resized it, converted it from BGR (Blue, Green, Red) format to gray scale. 1) Face detection: Face detection could be done in many ways. We used OpenCV's Haar cascade as well as Dlib's face detector. It was found that Dlib's face detector was more accurate as compared to the other. The Dlib library uses a pre-trained face detector which is based on a modification to [16] for object detection. 2) Facial Landmarks detection: We detected salient facial structures on the face region to extract eye position from the face. This task was accomplished through facial landmark predictor included in Dlib library. Dlib facial structure detector is an implementation of [17]. Dlib pretrained facial points detector was then used to map 68 (x, y)- coordinates on the face.Dlib facial landmark predictor was trained on iBUG 300-W dataset [18]. The indexes of the 68 points can be seen from Fig.

3

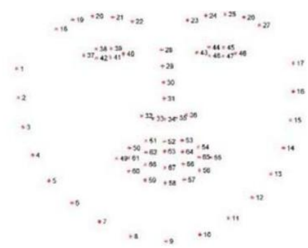


Fig. 3. Visualization of the 68 Coordinates from the iBUG 300-W Dataset [18]

3) Eye localization: The facial landmarks produced by Dlib function follows an indexable list. Each eye was represented by 6 x-y coordinates. As the index values were known, eyes were extracted effortlessly.

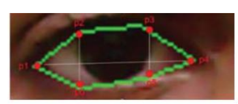


Fig. 4. Visualizing 6 x-y coordinates of eye

4) Blink detection: Unlike traditional eye blink detectors, we used algorithm of eye aspect ratio (EAR) deveoped by Soukupová, Tereza, and Cech [19] for eye blinks detection. The vertical and horizontal distances between the coordinates of an eye were useful for the purpose. The eye aspect ratio was calculated

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by (1) $\text{EAR} = \frac{|P_2 - P_6| + |P_3 - P_5|}{2|P_1 - P_4|}$ Where P1,P2,P3,P4,P5,P6 are facial landmarks detected in Fig. 2. We used blink detection for initializing our system so that it start to take directive commands from the user.Fig. 5 shows a complete flow chart of the system. A webcam was placed in front of the user to read images that were converted into grayscale for face detection. Eyes were then localized in the image. When two blinks were detected, the system initializes to read eye movements as directive commands for the hardware system. B. Classification Algorithm To allow wheelchair to move in a specific direction, we have implemented a technique based on the latest research area i.e. deep learning. Deep learning has dominated the computer vision field over the last few years. Our wheelchair operates by getting a signal from the system as it classifies the user's eye into its respective position i.e. left, right, up, or middle. Deep learning models require training data and their performance is strongly correspondent to the amount of training data. To achieve desirable accuracy, the availability of a huge amount of data related to our problem was an issue. To avoid this problem, we didn't build our model from scratch rather we used the transfer learning design approach to tackle this issue. Transfer learning allowed us to reuse a pre-trained model which has been already trained on millions of images. By leveraging the pre-trained model for the classification of the eye, we have avoided the need of large training dataset. Transfer learning approach saved a lot of time and computational resources without affecting decision accuracy.

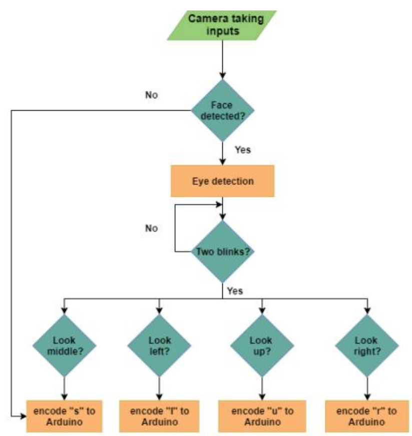

Fig. 5. Flow chart of system

1) Training Data: Inputs from a user, by looking in the left-right middle and upward direction, were taken and placed in respective folders for the training dataset. Directories were made with Keras functions. Those functions helped to create a directory structure where the image of each class was saved on a subdirectory in the training and validation dataset. Images were then split into 175 (for training) and 75 (for validation).

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2) Pre-trained model: Visual Geometry Group (VGG16) model pretrained on ImageNet dataset has 13 convolutional layers followed by 3 fully connected layers. VGG-16 was introduced by Simonyan and Zisserman [20]. VGG-16 model was selected as it showed excellent performance in terms of classification accuracy and flexibility for all types and levels of distortion as compared to other networks [21]. Fig. 6 shows the complete model architecture. This network is characterized by smaller (3x3) convolutional layers stacked on each other with increasing depth, using rectified linear unit (ReLU) function in between convolutional layers, introducing non-linearities which makes decision functions more discriminative. Volume was reduced in successive layers by max pooling. The idea was to remove fully connected layers of the network and the remaining portion of the model was used as a feature extractor for the smaller dataset. VGG-16 model was initialized without the final fully connected layers. A data generator was created for training the images and was run on VGG-16 model to save all the features for training purpose, then a small fully connected model was trained on those extracted features to get classified output.

3) Convolutional neural network: Convolutional neural network is a class of artificial neural networks that deals with the two-dimensional inputs i.e. images and has efficiently been applied to the analysis of visual images. A convolutional neural network is made up of one or more convolutional layers followed by one or more fully connected layers. It is easier to train and requires fewer parameters as compared to other fully connected neural networks. The first layer of many hidden layers may learn local edge pattern. Then each successive layer may learn some other complex patterns or representations. The last final layer classifies the images.

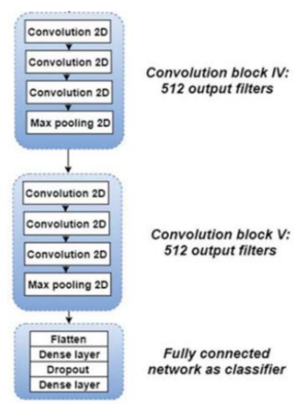

Fig. 6. Proposed model architecture

C. Classification Algorithm

The neural network was initialized as a sequential network followed by flattening the previous VGG-16 layers. Flattening was

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used to convert all the two-dimensional arrays into a single continuous vector.

1) Dense layer: This layer was imported to make full connections of the neural network with 256 neurons.

2) Dropout layer: A dropout of 50% was added after dense layer. Dropout layers have a very specific function in neural networks. It ignored 50% connections to the final layer to avoid overfitting of data. It made sure that the network is not getting too "fitted" to the training data. This layer was proceeded by a dense layer having 4 output nodes (equal to the number of classes), with a sigmoid activation function represented by (2) $f(x) = \frac{1}{1 + exp(x)}$ A call to the training function was made to train the model. This step took 30 minutes on a laptop and 60 minutes on raspberry pi 3. The training was required only for once. After the classification task, appropriate characters were serially sent to Arduino for driving the wheelchair in the respective direction. The hardware architecture of the proposed system model is shown in Fig. 7. This system was based on real time data acquisition operating system. Python based eye classification algorithm was successfully implemented both on laptop and raspberry pi 3 i.e. a low power consumption computer board providing with input and output pins with four USB ports. Raspberry pi supports 32 GB of memory card. RAM of raspberry pi 3 is 1 GB with ARM based controller. A small webcam mounted on a wheelchair took input from the user. After the processing, results were sent to Arduino nano. Python Bridge is a python application that is used to communicate with Arduino via pyserial function. Arduino nano, a small compact microcontroller based on ATmega 328p, took serial input from raspberry pi/laptop and provided PWM (Pulse width modulated) outputs to two IBT-2 motor driver modules. A potentiometer was connected to the analog input of Arduino to vary the speed of the left and right motor. A buck converter module was also used to step down 24V from batteries to 5V to power other components. The proposed wheelchair

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system is shown in Fig. 8.

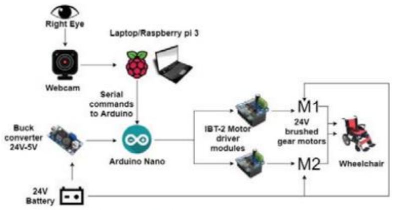


Fig. 7. Proposed model architecture

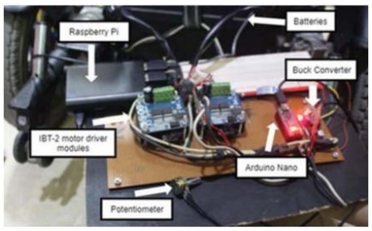
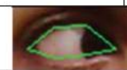


Fig. 8. Hardware implementation

III.RESULTS

The model was trained on 250 images of different eye positions in 50 epochs with a batch size of 16. The model extraordinarily achieved an accuracy of 99% on training data and 98% on validation data. Proposed architecture outperformed many eye motion controlled wheelchairs as it is also suitable for people wearing eye glasses. The execution of code (for the left side and stop the wheelchair) is shown in Fig. 9. Table 1 shows the eye's movements which sent appropriate characters to Arduino making the wheelchair to move in respective direction.

TABLE I. IRIS POSITION FOR WHEELCHAIR MOVEMENT

Eye Movement	Wheelchair Movement
	Left
	Right
	Stop
	Forward

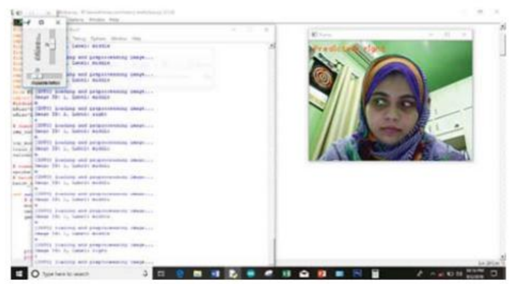


Fig. 9. Display after execution of code

IV.CONCLUSIONS

This proposed system has led us to conclude that people suffering from motor neuron disorders can use their only part in which they have full control over i.e. their eyes to propel a wheelchair in the desired direction. Using image classification with the help of pre-trained model VGG-16, it is possible to achieve high accuracy of 98% for classifying different iris positions. The predicted position of the eyeball is encoded to Arduino microcontroller which further sends the appropriate command to the motor drivers so that the wheelchair can move according to the user's input.

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