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Eye Controlled Electric Wheelchair: Proof of Concept Using an Arduino Robotic Car

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Abstract

This research aims to develop an electric wheelchair that can be controlledby using eye gestures, providing an intuitive and accessible interface for individuals with mobility impairments. The eye gesture is captured with the help of a camera and the live image is then preprocessed and fed to a CNN-based model for classification. The gesture is classified into 4 classes, namely, forward, left, right, and stop. Based on the classification, a signal is sent to the wheelchair through Bluetooth and the control system of the wheelchair operates as per the instruction. For the model training, the datasethas been collectedwith image frames of eye movement representing different control commands. The dataset is then trained using a ResNet-18-based CNN model. The model is then deployed on a mobile device which takes the image of the user's eyes from the camera and inferences the image to find the eye movement. The movement is then recognized, and appropriate control signals are generated and transmitted to the wheelchair through Bluetooth. The receiver in the wheelchair maps the transmitted signal to the specific movement and turns the actuators in the appropriate directions.Hence, the wheelchair can interpret eye movement captured by the camera, accurately recognize pupil movement, and translate them into control signals mapped from the predicted values given by the model, ultimately empowering users with improved mobility and independence. On testing the system under various lighting conditions and with different users, the control system showed 90.25% accuracy and the overall movement of the system showed an excellent result in following the user's eye movement in real-time. But when tested on very low light conditions, especially during night time, the system cannot perform as expected and often predicts random and false values.

Keywords: ResNet-18, Eye-control, Deep Learning, improved mobility

1. Introduction

LIS (Locked-in syndrome) is a very rare condition where almost all muscles are paralyzed except for the eyes. People with this syndrome are awake and aware but cannot move or speak. A study published in 1986 identified 139 cases. A recent 2023 national population-based study from Norway reported 16 cases living with LIS in a population of approximately 5.425 million which is 1 out of 339,000 individuals (orphanet, 2023). This condition can be caused by injuries to the brain, strokes, or problems in the brainstem. Because of this, they face many challenges in their daily lives and rely heavily on special technologies to communicate and interact with the world.

To assist people with Locked-in syndrome, it is important to develop solutions that meet their specific needs. This includes creating better wheelchairs and assistance devices. Such technologies are crucial for improving their mobility, independence, and overall quality of life. Focusing on the unique challenges faced

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by such individuals, this research aims to improve their mobility.

Traditional assistive technologies often fail to adequately address their needs, leaving them isolated and relying on caregivers for every basic task (orphanet, 2023). These researches provide the ability for individuals to be mobile without the need fora caretaker. The research uses the eye movement of the user as the input and translates it into commands for the movement. As such, this research allows individuals to be independent by providing a method to control the wheelchair without the need for an external caretaker.

2. Related Works

Research on eye-controlled electric wheelchairs has been continuously made for assisting people with mobility impairments. The research by Bai et. al. introduced an innovative prototype using an infrared camera and Kalman filter algorithm to monitor eye movements and control the wheelchair. The research uses a wired system and the eye-tracking algorithm faces issues with robustness in varying environments. Hence, a robust algorithm like machine learning can improve performance and a wireless medium can reduce device constraints (Bai, 2016).

Kohei Arai and team developed a prototype of an electric wheelchair controlled solely by the user's eye movements for paralyzed individuals. The system employs a camera to track the user's eye position and processes it using an image-processing-based pupil detection method. Then, it is translated into commands for controlling the wheelchair's direction and speed. The method is accurate even in low lighting conditions but has limitations in high lighting. Also, the project implements obstacle detection using ultrasonic sensors. Still, the prototype lacks robustness due to the use of image processing which can be solved by using a deep learning model (Arai, 2011).

Gneo et. al. proposed an eye-gaze tracking system with the combination of EEG to facilitate safer control over the movement of wheelchair. The eye-gaze tracking system is translated into commands and the EEG signal is interpreted by a brain-computer interface to confirm the motion. The research is, however, a proposal and correct analysis of EEG is itself an issue. Although the confirmation of command surely promotes safety, the accuracy of the brain interface alone can suffice for the movement too, replacing the eye-gaze tracking system. Still, the analysis of EEG and its correctness is an issue (Gneo, 2011).

The research by Patel, S.N and Prakash, V. uses methods similar to those of Arai K (Arai, 2011). They implement a camera to detect the pupils and use an image processing technique to differentiate the movement. The difference is that the processing is done using a Raspberry Pi and the entire system is mobile. However, the image processing technique used by Patel et. al. faces difficulty in changing environments. Lighting and noise can abrupt the system’s performance. So, a more robust system needs to be developed to avoid such problems. (Patel, 2015).

Djoko Purwanto and team proposed an electric wheelchair control system that utilizes gaze direction and eye blinking as input methods which was designed to improve mobility for individuals with severe physical impairments by allowing them to control the wheelchair with minimal physical effort. The wheelchair is equipped with sensors to detect the user's eye movements and blinks, which are translated into commands. Despite the system's potential to enhance user independence, has limitations such as the need for precise calibration of the sensors, susceptibility to errors due to involuntary eye movements or blinks, and potential difficulties in maintaining accurate control of the wheelchair in dynamic environments. (Purwanto, 2009.)

Bharat Thakur and K. Kulshrestha implemented comfortable wheelchair locomotion for severely disabled people. The estimation of the direction of movement is decided solely by the patient without stressing them physically. This is successfully achieved by investigating the user's natural gaze behavior using eyeball tracking in NI LabView. The prototype consists of a camera, image processing software, and a motor controller to drive the wheelchair. The tracking algorithm utilized is shape adapted mean shift algorithm in NI Vision Assistant. The eyeball tracking outcomes are then used to produce suitable wheelchair motion taking the user to the intended location (Thakur, 2014).

Marwa Tharwat et. al. proposed a hands-free wheelchair based on an eye-controlled system. The movement of eyeballs is used to control the wheelchair movements instead of hands. The infrared eye-tracking system was adopted in this project for several advantages. The head-mounted eye-tracking system uses infrared light emitters and sensors in gaze detection. By measuring the intensity of the infrared light reflected from the corneal. The changes in the reflected intensity can be translated into signals to determine an eye position. After the gaze direction is determined, it is used to steer the wheelchair accordingly. (Tharwat, 2022).

Walnut and team developed a smart wheelchair based on eye tracking which consists of four modules including an imaging processing module, a wheelchair-controlled module, an SMS manager module, and an appliance-controlled module comprised of a webcam installed on the eyeglass and C++ customized image processing software. The image processing is done using OpenCV to derive the 2D direction of the eyeball to control the movement of a wheelchair with two-dimensional rotating stages. The motion of the eyeball is also used as the cursor control on the Raspberry Pi screen to control the operation of some equipped appliances and send messages to the smartphone. (Wanluk, 2016).

Jun Xu, Zuning Huang, Liangyuan Liu, Xinghua Li, and Kai Wei designed a technologically intelligent wheelchair that consists of an electric wheelchair, a vision system, a two-dimensional robotic arm, and a main control system. Monocular camera as input and uses deep learning and an attention mechanism to calculate the eye-movement direction. Starting from the relationship between the trajectory of the joystick and the wheelchair speed to establish a motion acceleration model of the smart wheelchair with an AI controller. (Xu, 2023).

Anagha Dwajan B and team design technology in which Continuous image is captured with the help of a webcam which further undergoes several image processing techniques, to detect the position of eye pupil Haar cascade algorithm is being implemented with the resultant of the image processing technique wheelchair moves accordingly. DC motor is mounted to the wheels for easy motion of the wheelchair. The ultrasonic sensor is mounted to the wheelchair so that it detects any obstacles in the path of its movements and the wheelchair stops movement as per sensor command (Anagha Dwajan B, May 2020).

3. Methodology

3.1 System Block Diagram

The proposed system is shown in Figure 1. Initially, the laptop camera captures live video of the user in the wheelchair. Then, the image is extracted from the wheelchair at 12.73 frames per second and each image is processed for face detection using the Haar-Cascade face model. The extracted face is again processed using the Haar Cascade eye model and eye regions are extracted.

The cropped image is then referenced using a CNN model which classifies whether the eye is in left (L), right (R), or closed (C). Each of the frames is classified and a sequence-based analysis is done to determine the movement of the eye based on previous eye positions. The values are represented as -1, 0, 1, and 2 for L, R, C,and no action respectively.

The value is then transmitted to the wheelchair witha Bluetooth receiver, HC-05. The command is interpreted by an Arduino which regulates the motor's speed and direction by sending appropriate signals to the motor driver. Hence, the wheelchair is driven in the required direction.

The initialization of the eye-controlled electric wheelchair system involved integrating a high-resolution camera that captures the user’s face and processes it in the real-time eye. Figure 2 presents the actual workflow of the overall system. The system is divided into two parts: The transmission side and the Receiver side. The transmission side deals with the detection of the face from which the eye is extracted and classified based on the position. The result is then transmitted using Bluetooth. At the receiver side, the detected command is converted to equivalent control signals for the motor, and the required movement is performed.

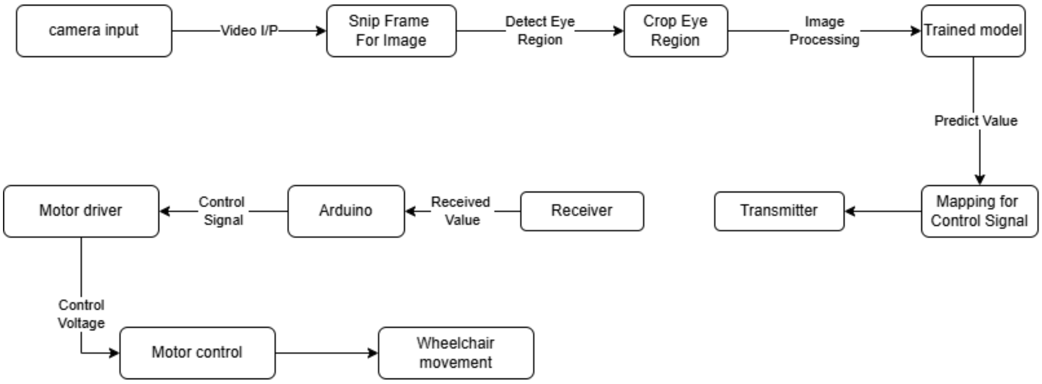

Figure 1. System block diagram

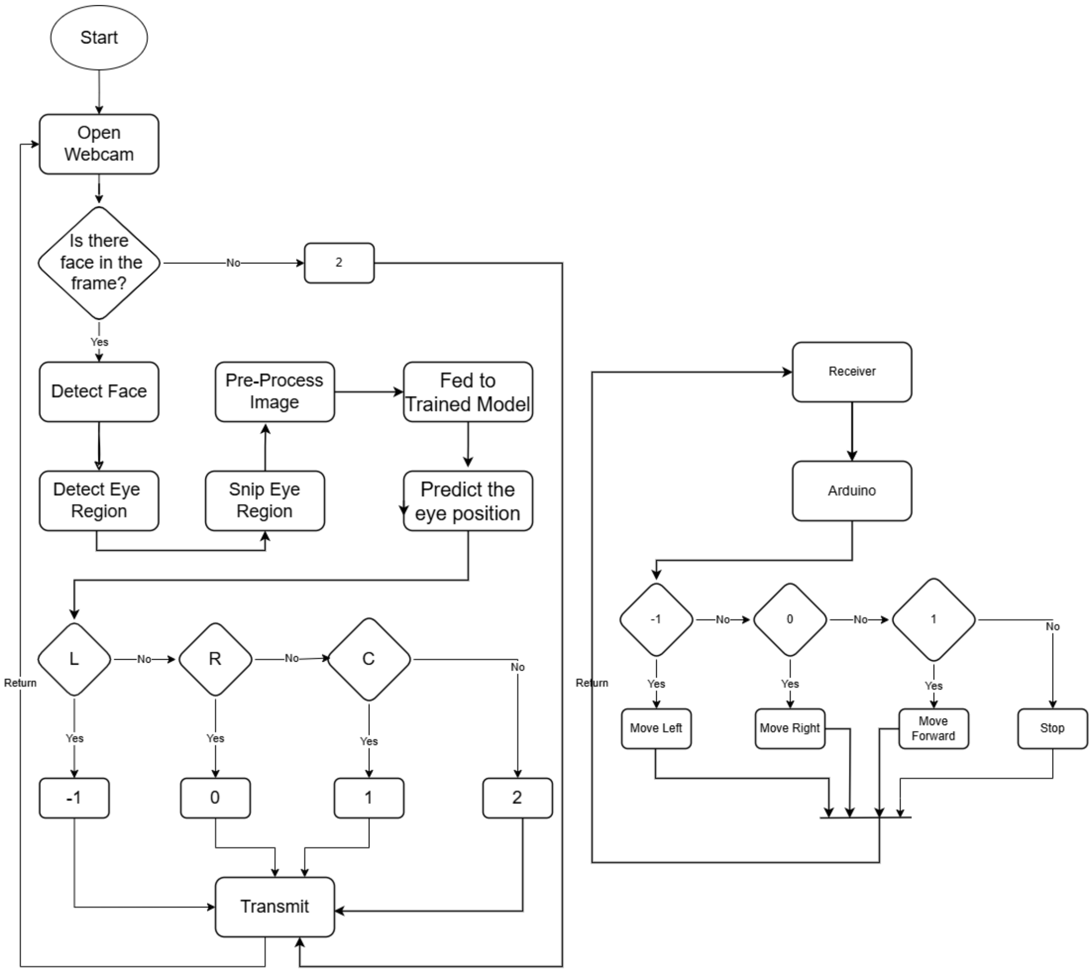

Figure 2. System flowchart

3.2 ModelTraining

3.2.1 Dataset:

The research utilizes both primary and secondary data sources. For primary data, a total of 9593 images of different people were collected and labeled manually as shown in Table 1. Kaggle was used as the secondary source, from where almost 22,000 face images were collected with an average of 5,500 images in each position of the eye (i.e. left, right, forward, and eye closed) collected as shown in Table 2. The data was then split into 70% for training, 20% for testing, and 10% for the validation of the model.

The collected data were pre-processed and resized to 224x224 before feeding into the model.For the data preprocessing, normalization, and color spacing were performed.The following table shows the collected data summary.

Table 1. Created Dataset

S.NO.	Data Label	Data Count
1	Closed Eye Data	2580
2	Forward Looking Data	2029
3	Right Looking Data	2048
4	Left Looking Data	2936

Table 2. Dataset (Source: Kaggle)

S.NO.	Data Label	Data Count
1	Closed Eye Data	5484
2	Forward Looking Data	5511
3	Right Looking Data	5374
4	Left Looking Data	5341

Normalization is done before being fed into the model. All images undergo pre-processing steps to ensure uniformity and facilitate model training. This includes resizing all images to a fixed size of 224x224 pixels.

All the original images are converted into grayscale, effectively doubling the number of images sourced from the custom dataset. By integrating data from both Kaggle and custom sources, the dataset offers a diverse array of images capturing various eye positions. This comprehensive dataset enables the model to learn robust features and generalize well to unseen data, ultimately enhancing the model's accuracy and effectiveness in classifying human eye positions.

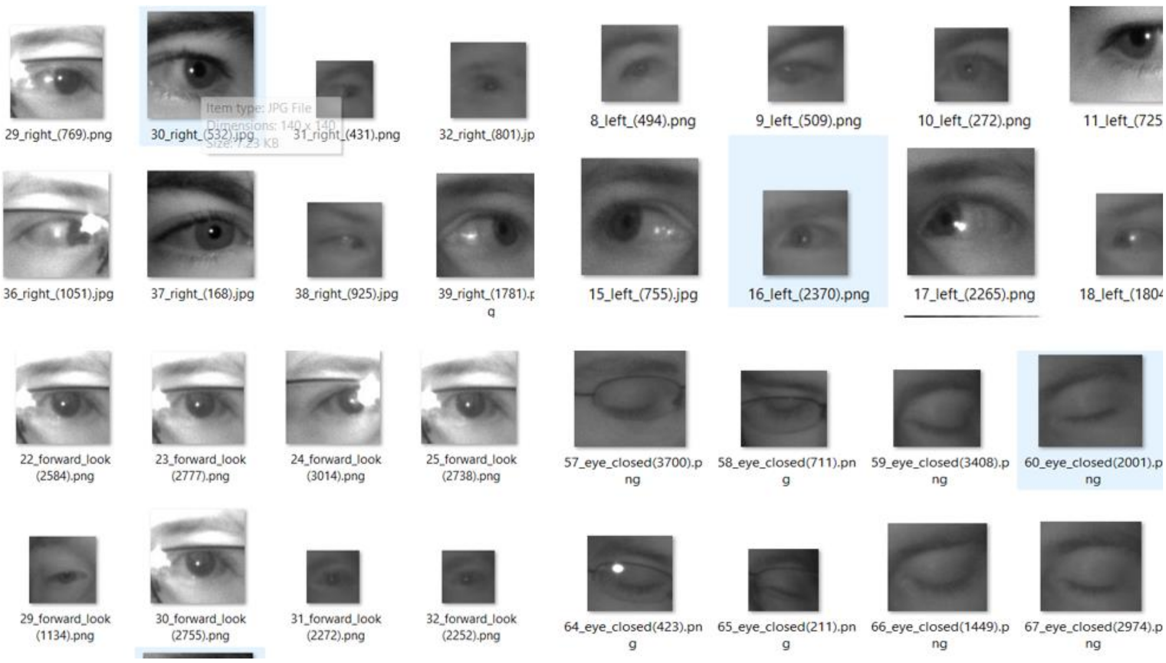

Figure 3: Dataset Samples

3.2.2 Model Architecture

The model architecture is rooted in the ResNet18 framework as shown in Figure 4 due to its proven performance in image recognition tasks. Specifically, the model consists of several convolutional layers followed by residual blocks. These residual blocks enable the model to learn features while resolving the vanishing gradient problem, which can perform training in deeper networks. The ResNet18 architecture also incorporates max-pooling layers to down sample feature maps, reducing computational complexity and increasing the receptive field. (He, Zhang, Ren, & Sun, 2016). The final layer of the ResNet18 architecture is replaced with a linear layer for the classification of the eye position.

The training process begins with importing the images from this layer. In this, images are imported from the directory, and images are saved inthe image folder. Then, the images are transformed and resized into 224X224 image size, then converted to tensor and finally normalized. When the normalized images were obtained, they were classified into train, test, and validation which were distributed in the ratio of 7:2:1. The initial Convolution layer where the resized image was converted into 64 channel 112X112 sized image, and spatial dimension was reduced to half. Then the residual layer with 4 blocks where sampling is done in each layer reduces the dimension by half and down-sampling occurs in each block. The ResNet-18 applies global average polling over 512 channel 14x14 sized images and the feature map results in a single value per channel and thus results in 512 channel 1X1 sized images. This process is followed by a fully connected layer that adapts the output to specific classification tasks. And on the final layer, each image batch is passed through the neural network through 32 epochs. This layer saves the model onto the root directory for further use.

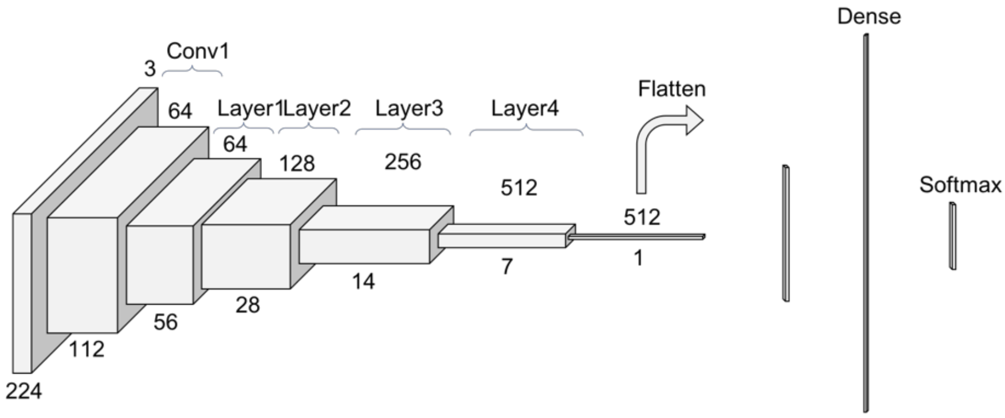

Figure 4. Model Architecture (K_05 Understanding of ResNet - EN)

For training, the hyperparameters used are listed in Table 4.

Table 4. Training Hyperparameters

Hyperparameter	Value
Batch Size	64
Epochs	32
Learning rate (initial)	0.001
Optimizer	ADAM
Activation Function	ReLU
Loss Function	Cross Entropy

Figure 5. Training and validation Accuracy

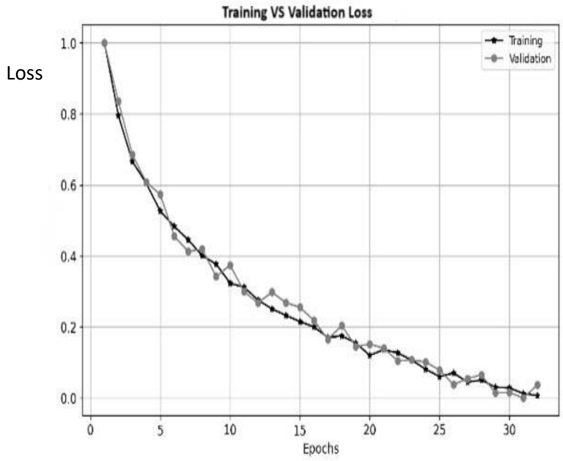

Figure 6. Training and validation loss

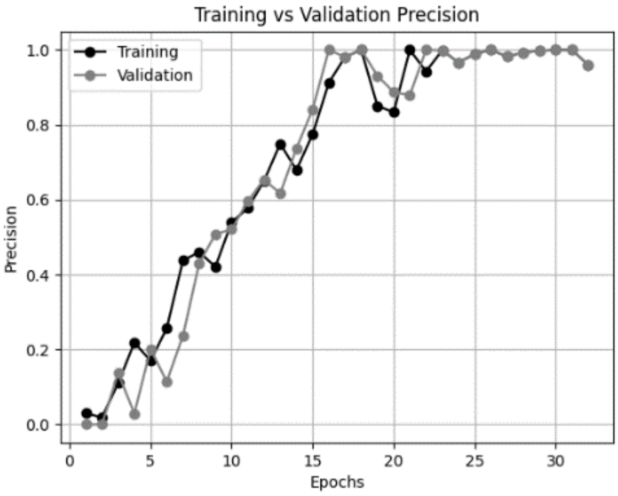

Figure 7. Training and validation Precision

The model is trained for 32 epochs with hyperparameters shown in Table 4. The training curves are shown in Figure 5, Figure 6, and Figure 7. With each epoch, the training accuracy increases, and the validation accuracy follows the training curve illustrating improved learning, with some fluctuations. Similarly, training and validation precision also increases with each epoch with a final validation accuracy of 89.76% and final training accuracy of 90.25%.

The accuracy graph in Figure 5 shows how accuracy changes over epochs of model training. Both training and validation accuracy increase, indicating model improvement.

Similarly, the loss graph in Figure 6illustrates how this model training and validation loss change over epochs during training. Both losses decrease, indicating learning improvement. The training loss consistently remains slightly lower than the validation loss, suggesting good generalization.

The precision graph, Figure 7 shows precision values over epochs during the training. Both training and validation precision increase as the number of epochs grows. The training precision exhibits more fluctuations, while the validation precision appears smoother. This trend suggests that the model is learning and improving over time, but it’s essential to monitor.

3.3 Hardware Implementation

As proof of concept to our model simple Arduino robotic car was implemented. The robotic car control and movement by the eye movement of the user's eye was demonstrated and the scalability of the system was proved.

As shown in Figure 1, the Arduino acts as the hardware section's main controller. The received value by the receiver (Bluetooth) module was passed to the Arduino. The Arduino then uses a simple but powerful logical if...else statement function to convert those received signals into two-bit binary control signals. This control signal is then provided to the Motor Driver. The motor driver in the hardware section acts as a secondary controller. Upon receiving the proper control signal in its two input pins, it generates control voltage to individual motors. The motor rotates in the desired direction (clockwise or anti-clockwise) at a predefined speed, making the robotic car move in the desired direction. For wheelchair feedback, a buzzer was used to generate a beep sound upon engagement and disengagement of the system.

Using the same circuits and relays to convert the Arduino signal into higher voltage the real-world usable wheelchair can be implemented.

Table5 below shows the details of the hardware used in this project.

Table 5: Hardware listing and the model number used in project.

Component	**Model**
Arduino UNO	UNO R3
Bluetooth Module	HC-05
Motor Driver	L298N
Motor	TT Gear Motor
Buzzer	KPI-2210L

3.4.Wheelchair control and movement:

The model outputs the eye position which is in the range [-1,3]. If there exists a face in the image then the eye position is predicted the predicted output is mapped to -1, 0, 1, and 2 for left, right, looking forward and eye closed position of the user. If there is no image, a value of 3 is transmitted to the wheelchair.

The transmitted value is captured by the HC-05 Bluetooth module and transferred to Arduino. The Arduino controls the hardware section which converts the command toan appropriate motor driver signal. The motor driver powers the respective motors with the appropriate voltage level and finally motor rotates in the desired direction. In this way,the movement ofthe wheelchair is controlledby the eye movement of the user.

For practicality and usability of the system, it is equipped with some constraints and usage requirements:

1. ***Wheelchair Engagement and Disengagement(safety)*****:** It’s crucial to maintain the safety of the user, for this, we have added some usage constraints to when the system will react to the user's eye position.

a. ***Engagement*****:** The system is designed to react to the user's eye movement in his/ her concern, for engagement usershave to look at the right side for two to three seconds until a beep sound is heard.

b. ***Disengagement:*** When users want the model not to react to the eye movement, they can keep looking at the right side again in system system-engaged state until the beep sound is heard and this indicates the system is disengaged. Furthermore, for additional safety, if the user keeps looking at the sides for longer than usual or closes his/ her eye for a long time, the system will automatically disengage itself to protect the user from additional harm.

2. ***Battery swapping and Recharging:*** The system is equipped to be battery swapped on the go, with this feature users can carry extra batteries and keep moving without even needing to get out of the wheelchair. During the rest time, user can recharge their battery outside of the wheelchair. For safety and to protect the wheelchair from charging while the system is engaged, the system comes with charging outside the usage hour policy, this means the battery has to be disconnected before connecting to the charging outlet.

While designing this prototype proof, we have considered multiple communication alternatives including Bluetooth and WIFI technology. After thorough evaluation, Bluetooth was selected based on several key requirements:

The system needs to work on battery power, making energy efficiency a crucial requirement in design. The system needs to have low latency for real-time usage, which is essential for the safety and security of the use. As the transmitter and receiver are located close to each other, the communication system should work efficiently over short distances.

With these all constraints and design considerations, we come across Bluetooth technology as our ideal choice. Below is how Bluetooth helps mitigate our all requirements and was chosen for the project:

1. ***Low Power*:** Bluetooth is designed to operate in low power where power efficiency is crucial and high-power consumption may lead to frequent recharging or battery swapping requirements. Bluetooth Low Energy keeps the device in sleep mode whenever the transmission and reception are not required and wakes the device up only for the time of transmission or reception.

2. ***High D*ata *Rate:*** As compared to many wireless communications, Bluetooth can achieve a data rate of up to 2Mbps, which is more than what is demanded to transmit a control signal. While the control signal doesn't demand high bandwidth in our scenario, this extra data rate ensures multiple control signalsare transmitted within the same time frame for real-time operation, this leads to low latency in the system allowing for real-time usage.

3. ***Frequency Hopping*:** Bluetooth uses a technique known as frequency hopping, this technique minimizes the chances of interference by other devices operating in the same frequency band, especially WIFI, this helps reduce the chance of system failure due to interference.

4.Results and Discussions

We found that our CNN model accurately recognized eye movements, such as closing eyes to stop, looking straight to move forward, and looking left to engage for moving backward. The system responded quickly to these commands, with minimal delay, making it suitable for real-time use.

Testing also showed that the model performed well under different lighting conditions and with various users, maintaining consistent accuracy. The confusion matrix is shown in Figure 8 whichdemonstrates a decent model with the maximum of data concentrated in the leading diagonal.

The evaluation metricsare shown in Table 6. The model has an accuracy of 90.25%. Also, the model illustrated a recall of 90.25% and a precision of 90.27%. Overall, the F1 score of the model is 90.26%.

This result concludes that the model performed pretty well in varying conditions. Due to the variance in datasets, the model is independent of the environment and can evaluate the data accurately in varying conditions.

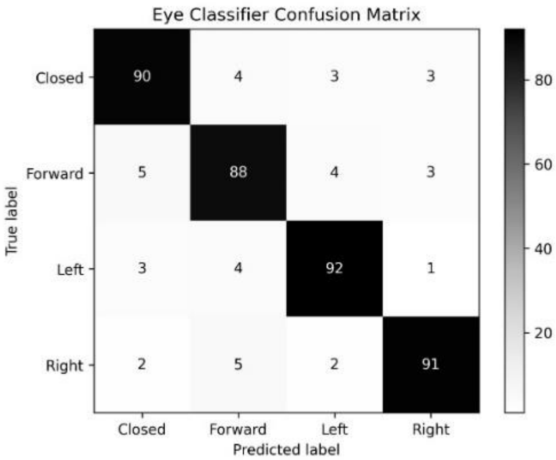

Figure 8. Confusion Matrix

Table 6. Evaluation metrics

Metrics	**Value**
Precision	90.27%
Recall	90.25%
F1 Score	90.26%
Accuracy	90.25%

An example of the demonstration is shown in Figure 9. Initially, the wheelchair is facing frontwards. When the user sees right, the image is processed and sent to the wheelchair which also rotates to the right. The camera detects and analyzes the eye movement at 12.73 frames per second.

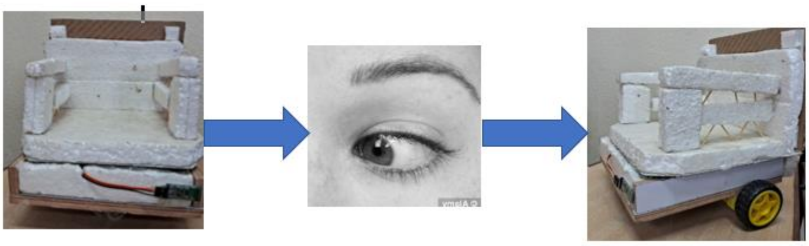

Figure 9. System Output

5. Conclusion

The research aimed to develop a robust system for detecting eye movement and controlling a wheelchair accordingly. For accurate and robust eye movement detection, a ResNet-18-based CNN model is trained which can detect eye movement with 90.25% accuracy. The model exhibits a precision of 90.27%, recall of 90.25%, and F1 score of 90.26%. The detected eye movement is then transferred to the wheelchair wirelessly and effective control is achieved. The use of CNN based model in this paper increases the effectiveness of the system in varying conditions, resulting in a more robust and adapting system. Overall, this research developed a machine learning-based model for controlling a wheelchair using eye movements.

In the future, the system can be improved by implementing accurate brain-computer interfaces. Also, an FPS of 12.73 is achieved in the current system which can be increased with the use of high-end processors.

This can effectively increase the effectiveness and response time of the system. For a practical implementation, safety sensors can also be employed in the wheelchair.

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