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Enhancing Robot Feeding Efficiency for Children with Cerebral Palsy Using Facial Recognition Algorithms

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Abstract

Feeding difficulties are one of the most significant concerns of children with cerebral palsy. Their poor posture, muscle tone, and movement control make them more susceptible to choking and highly reliant on caregivers during feeding time.

Current feeding solutions include gastrostomy and nasogastric tube insertions. These have relieved a good number of symptoms but are associated with risk in the form of infection, skin irritation, and inhibited mobility for the child. Some studies have reported that as many as 35% of children with CP suffered from these complications. Thus, there is an immediate need for a safer, non-invasive feeding solution that enhances autonomy while maintaining caregiver oversight.

To solve these problems, the paper introduces a new robotic feeding assistant for children suffering from CP, FeedEase, through which facial landmarks can be detected and analyzed by using MediaPipe computer vision technology to establish, in real time, if the child's mouth is open or closed. FeedEase is controlled by the Arduino Nano and fed by precise NEMA 17 stepper motors through DRV8825 drivers, and it dispenses food automatically only when the mouth is open, thus reducing the chances of choking significantly and thus hands-on intervention by a caregiver or caregiver. In initial simulations, FeedEase has shown impressive accuracy as pointed out during in-mouth-state detection measures exceeding 95% precision and applicable both in home care scenarios and places like institutional care.

The system is designed so that the caregivers will hardly intervene, allowing the young ones with CP to be more independent during meals. Earlier simulations performed quite well, achieving over 90% accuracy on mouth-state detection, thus making FeedEase applicable for both domestic and institutional care. This investigation adds on to the avowal nursing care by feeding efficiency via facial expression recognition, and also provides a novel way of recognizing hunger cues .Effectively, combining and involving machine learning approaches with computer vision in real time, FeedEase offers an easier and non-invasive mode of feeding, hence increasing independence, minimizing the caregiver's burden and enhancing the quality of life for a child suffering from cerebral palsy.

Keywords: Facial Expression Recognition, Robotic Arm, Raspberry Pi Integration, Arduino Nano, RealTime Monitoring, Deep Learning Algorithms

1. Introduction

For children with cerebral palsy there are specific difficulties in feeding because this disease affects the posture, movement and muscle tone of the child. Cerebral palsy, caused by non-progressive brain injury has neurological abnormalities such as spasticity, ataxia, and dystonia that limit the ability to coordinate muscle movements and even simple acts like feeding are very dangerous. Hence, children with CP are likely to choke on their food and need support at every meal time or while being fed. Catheterization includes gastrostomy (G-tubes) and nasogastric (NG) tubes for central and peripheral nutrition, respectively; however, these procedures bear numerous complications: infections, local irritation, and limited mobility. These challenges call for the need to develop safe, effective and non-invasive feeding techniques which retains the spirit of independence among children with CP in order to have an optimum comfort.

To address this need, the present study presents FeedEase, a new developed robotic arm aimed at helping children with CP feed. Using MediaPipe, FeedEase implements a mouth-state detection algorithm that helps it determine when a child has opened their mouth and then dispense food with the help of a robotic spoon built with an Arduino Nano board.Utilizing predetermined coordinates, the robotic arm feeds the user, finishing the current feeding cycle regardless of any changes in the mouth's state later on. This entails using computer vision, which in turn is associated with real time feedback as a way of reducing the human interface which is supposed to have enhanced a rather safer and independent feeding system for children. The initial best-only simulation results indicated that FeedEase has excellent accuracy and precision, suggesting it can be used in home and institutional care.

This research moves towards the improvement of feeding efficiency by incorporating facial expression recognition systems with special attention to the hunger signal. By correctly determining mouth-based facial landmarks with the help of computer vision methods and machine learning algorithms, the system can independently detect hunger signals and start feeding if no additional signals are needed. This approach seeks to design a robotic arm for children with CP for delivering their midday meal, as well as for learning human motions and feelings to enhance assistive technology and augment the burden on carers.

2. Literature Review

The work of **María-Luisa et al. (Martín-Ruiz et al.) p**resents a bi-level development framework that is designed for collaboratively participating non-disabled and disabled children, drawn from techniques created for challenge based games. The major components of the virtual environment SONRIE framework, which is targeted for children with some sort of cerebral palsy and also incorporates interactive serious games, proved able to assist in monitoring oral-facial difficulties in children thanks to the SONRIE system.

The study by **Vladimir Robles-Bykbaev et al. (Robles-Bykbaev and Vladimir)** presented the low-cost robotic assistant to help with various tasks during speech-language therapy sessions for children. The pilot study involved the participation of 73 therapy sessions with 29 disabled children. The outcome of this experimental study has shown that children react positively to the robotic assistant within a short period after starting therapy. Further studies should be conducted to improve the functionality of the robotic assistant as well as expanding its use in various therapeutic settings thereby benefiting more children suffering from communication disorders.

The paper by **Mohammad Najafi et al. (Najafi)**proposes a robotic assistance framework which aims to aid the execution of position-following play behaviors like pick-and-place activities. In this task which is carried out by means of a master–slave tele-operation system where a child is the master and holds the master robot while the other slave robot completes the assigned task in its environment. The activity consists of two main phases: Demonstration Phase include A therapist or helper restrains the slave robot in the play environment while the child manipulates the master robot. Robotic Assistance Phase: After learning from the demonstration, the child and the robot work together, however, the robot adapts and helps the child based on what has been learned. The results proved that the robotic assistance helped the child more in doing the play activities than without it, such that it is a clear progression for assistive robots to render more effective and engaging play time even for physically impaired children.

The authors **Dimitrios Sakkos et al. (Sakkos)** suggest a novel deep learning approach for assessing infant's movements, namely the GMA, based on the pose-features, derived from RGB video stream. They also present a method of visualization to show which body parts the localization algorithm attributes most to the classification decision, thus improving on interpretability. The other methods from the literature are then compared to the proposed framework using two independent datasets. The use of the proposed framework with the visualization capability provides higher classification consistency and robustness over the authors' earlier pose-based approaches and other related methods. The visualization part improves interpretability, which is valuable when it comes to its implementation in the medical domain. Unfortunately, the authors do not generalize the size and variety of the outlined dataset used for evaluation in the paper.

The research by **Clark et al. (Clark and Nicole) in**troduced an independent SAR for home, intervention, and companionship, for children with CP of young age. This tool is designed to get the targeted therapeutic dose needed for optimum developmental functioning in non-clinical environments. The SAR was created in a finalised iterative design process in consultations with clinicians, parents and children with CP. It uses changes in machine learning for the recognition of the multiple expressions on one's face making communication possible. This led to the conclusion that the design of the SAR fulfills certain core needs and is interesting to children with disabilities. Furthermore, the study on the feasibility of face recognition as a way of improving the SAR-child interaction indicated that the feature may hold promise in SARs to improve child-interaction online or in clinics. Therefore, the study does not present longitudinal and developmental data or effects of SAR on developmental milestones and such studies should be conducted in the future.

The research by **Ryan Cunningham et al. (Cunningham) su**ggested the utilization of convolutional neural networks (CNNs) for the indicator of the head's position and the eyes as well as the multi-segmented trunk and arms from SATCo videos. This would be very helpful in the scenario, in that it would make it easy to classify trunk posture and upper limb support without the help of annotation. There are 177 short videos with the duration of 5-10 s and the frequency of 25 Hz containing the images of 12 children with cerebral palsy during the SATCo testing Images of children's body hard-of and were manually annotated by three expert operators in 13 point-features using the SC Bent Words. To annotate the rest of the images, linear interpolation was applied on them and thus, there were 30825 images annotated in total. All children had hold-out test results for CNNs which were trained cross-validation. Despite this the CNNs were able to estimate the postural point-features with an error of 4. 4 ± 3. 8 pixels at, roughly, 100 images per second. More studies with more participants of different cases of cerebral palsy are required in order to compare the effectiveness of the CNN-based approach in general.

The study by **Manli Zhu et al. (Zhu)**proposes a channel attention module that can be embedded into diagnostic deep learning models for better CP prediction with infants' body motion. This model reveals features such as body joints where the model finds appropriate and this gives guidance on their rationale while coming up with the outcomes. The researchers then tested the system with actual data of infants' movements. CNNs was trained with the channel attention module and assessed the model accuracy in considering CP. The finding proved that to an accuracy of 91 the system was able to learn and generalize well. approximately 67% accuracy, which was reported to be better than other state of the art deep learning methods. The channel attention module was useful in visualizing the important joints and the outcomes of the model was much easier to interpret especially for clinicians.

The research by A **Meyer-Heim1 et al. (Meyer-Heim) ai**ms to measure the functional gait improvements of robotic-assisted locomotion training in children with CP.This study employed a single-case experimental A-B design, with participants receiving 3 to 5 sessions of 45–60 minutes per week for a 3–5-week period of driven gait orthosis training and was conducted at two settings: The inpatient group consists of the Rehabilitation Centre Affoltern am Albis, Children's University Hospital Zurich, Switzerland and the outpatient group consists of Neurology department of the Dr von Haunersches Children's hospital Munich, Germany. These included twenty-two children with CP Mean age 8. 6 years, range 4. 6–11. 7 with GMFCS level II-IV. These were the 10 metre Walk Test (10MWT) the Six Minute Walk test (6MinWT), the Gross Motor Function Measure (GMFM-66) dimensions D for standing and E for walking, and the Functional Ambulation Category (FAC). The results retrieved also indicated the enhanced mean maximum gait velocity: from 0. 0. 61 m/s; t (70) = -4. 91, p < [.01); the percent median dimension D of the GMFM-66 improved from 31. 6% (28. 7%); p<0. 05) after the interventional period.

The study by **L. Wallard et al. (Wallard)**examines the impacts of the application of the robotic-assisted gait training (RAGT) on the control of dynamic equilibrium in children with bilateral spastic cerebral palsy. Through the help of robotic devices, the therapy seeks to change faulty posture patterns and also help in achieving adaptive postural control during walking.

Biofeedback data were obtained with the Vicon® motion analysis system to assess full-body kinematics in both the sagittal and frontal planes. These changes were measured using the scales of Gross Motor Function Measure (GMFM) to reflect on the changes in standing and walking skills the children had. The results revealed a considerable change toward a more favorable condition of the Treated Group after the intervention, in the aspects of kinematic data covering the entire body and the GMFM dimensions D and E, which concern standing and walking, respectively. Also, the study did not consider other possible impacts that RAGT may have on other functioning domains apart from gait and balance.

The research by **Tanzim Mashrur et al. (Mashrur) c**oncentrates on the development of a personal care robotic assistive system that helps people who cannot self-feed due to upper limb disabilities, thus improving their independence and quality of life. Six degrees of freedom robotic manipulator, two depth cameras, and an electric gripper are employed in the use of the robotic feeding system, which aims at the method for food acquisition as opposed to the food itself, thus simplifying the feeding process. Testing yielded good results with few identification failures, high success rates for food reaching and delivering and good safety response time. The software is segmented into three parts; the first focuses on the identification of the food, the second on the acquisition of the food, and the last on the delivery of the food. Assistive robotics can help improve the quality of life of the disabled by enhancing the day to day activities of these individuals. A possible area of future improvement would be in the interaction with the user and also the use of advanced computer vision systems, and as for the design of tools, the use of 3D printing allows for the possibility of more efficient assistive devices.

The research by **Qinyuan Fang et al. (Fang) pro**posed a system that exploits an RGB-D camera in an attempt to alleviate the difficulties of autonomous robotic feeding by tracking and recognizing the mouth of the human subject with precision. This is aimed at enhancing the feeding accuracy by the use of vision in control and feeding. The mouth as one of the 2D facial landmarks is identified using a modern face detection system. These two-dimensional images are subsequently used to estimate their three-dimensional locations using depth data allowing accurate mouth localization. The results demonstrated the effectiveness of the system in following the mouths of various subjects enabling the robot to pour water accurately. This indicates the usefulness of enhancing the robot feeding system for physically impaired persons. Additional developments could work towards embedding more complex machine learning strategies to suit different users and food types.

3. Methodology

The approach taken in this research is divided into several important phases that ensure the integration of facial recognition and a robotic feeder for children with cerebral palsy is effective. Real-time video input capturing, facial landmarks detection, mouth status identification, control signals transmission to the robotic arm, and feeding actions are all included in the process. Special attention is paid to utilizing facial expressions to improve the system's performance and make the feeding process as natural as possible and corresponding to the child's actual needs at a certain moment.

3.1 3D Design For Robotic Arm

To start with the development of the Robotic arm in the first step R-P-P Arm was developed using the CAd software. The dimensions of the arm were decided based on the real-time data collection from the NGO. The design was developed in such a way that it is self-balanced and doesn't need any external support to stand itself. To make it low cost all the parts were 3D printed and other standard parts were considered in manufacturing to keep easy interchangeability. Figure 1 shows the 3D design of the actual prototype. The design is made in such a way that at the place of the end gripper one can add the spoon for the feeding purpose.

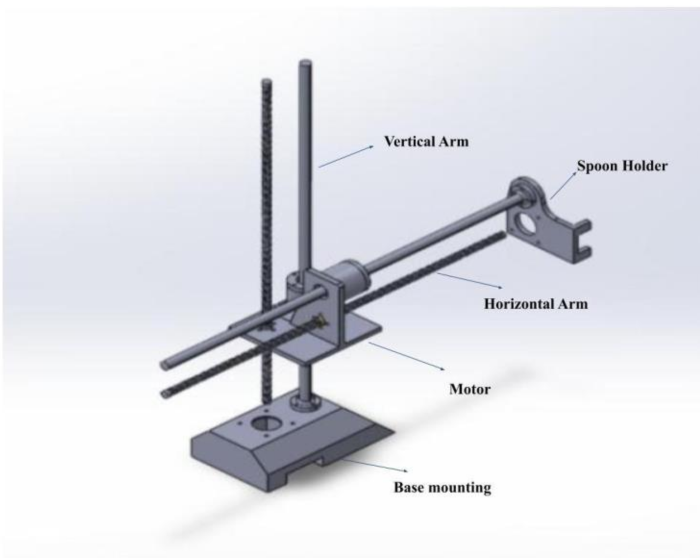


Fig. 1. Isometric View of Robotic Arm

3.2 Selection of Electronic Components-

4. Microcontroller- Arduino Nano

The above Fig 2 shows Arduino Nano which becomes an essential part because it plays the role of a control unit for the two NEMA 17 stepper motors which provide motion with the help of two DRV8825 motor drivers. This tiny, multi-purpose Arduino Nano proves very important to the design because it can fit within the minimal dimensions of the robotic feeding system. Despite the small size of the Nano, it contains all the power that enables the stepper motors to be controlled to such precise levels that movements by the robot arm are smooth and stable. The Arduino Nano further has support for multiple input/output operation capabilities, making it suitable for coordination with other constituents of the system.

Fig. 2. Fig 2. Arduino Nano (Fang)

This Nano will ensure compatibility with DRV8825 motor drivers to have proper communication and control over motors, which is going to be pretty important for delivering food at a safe consistent speed and position. Also, an added must in the project that focuses on assisting kids with Cerebral Palsy is fine control over movement because it promises a dependable and gentle feeding mechanism adapted to each user's specifics.

5. Motor Driver - DRV 8825

The DRV8825 motor driver shown in Fig 3, has been selected due to its high current capability of up to 2.2A. This driver will provide motor movement in small. The DRV8825 module connects directly to Arduino Nano through digital pins to precisely control the movement of the motor. The STEP and DIR pins determine the position of the motor and the rotation direction. Arduino Nano tells the motor to rotate the required number of steps by sending a pulse through the STEP pin and determines the rotation as being either clockwise or anticlockwise by the DIR pin. Authority is given to the motor to function by bringing down the ENABLE pin. The DRV8825 can also use the pins M0, M1, and M2 to enable microstepping. Setting these pins up allows the driver to work on a wide range of step resolutions from full-step to 1/32 microstepping, giving a more finer control over the motor. With all these properties of current regulation, microstepping, and with seamless integration into the Arduino Nano, DRV8825 happens to be an optimal choice for this prototype.

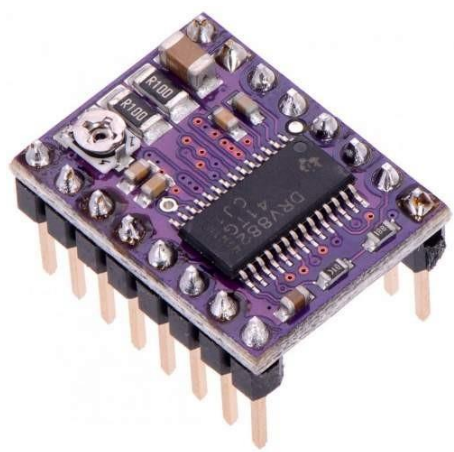


Fig. 3. Fig 3. DRV8825 Motor driver ()

6. Stepper Motor - Nema 17

Fig. 4. Fig 4. NEMA 17 Stepper Motor ()

Fig 4 shows the NEMA 17 which is used to attain the exact and controlled movements required by the robotic feeding system, one of the crucial elements is the NEMA 17 stepper motor. The NEMA 17 motor requires a step angle of 1.8° per step, allowing accurate positioning and delivering necessary incremental movements to deliver food safely and steadily. Internally, it has the stator, the stationary part, and the rotor, the moving part. The stator of the motor is composed of multiple windings. Through the windings, once current is passed through them, they develop magnetic fields.

This motor is driven by a DRV8825 motor driver, getting step pulses from the Arduino Nano, which allows for precise control of the rotation of the motor. The DIR pin controls the rotation.

6.1 Hunger Expression Detection Algorithm

The above Fig 5 describes a system for enhancing robotic feeding for children with cerebral palsy using face recognition. It starts by capturing video frames on the webcam followed by conversion to RGB format. MediaPipe recognizes facial landmarks, particularly the mouth region. In the face, the system computes the distance between the upper lips and lower lips to check whether the mouth is open or closed.

When the mouth is open, through an electrical connection to the Arduino Nano, the robotic arm feeds the captive using coordinates that have been provided. Once a feeding cycle starts based on the mouth state predicted by the mouth state detection program, even if there is a change in the mouth state prediction sent by the program during the feeding cycle, the robotic arm completes its current feeding cycle and then stops, until the mouth state is detected as open again indicating hunger. This approach helps minimize the recovery time and improve its safety because feeding is automated based on real-time face recognition.

7 Model Loading and Setup:

The process of developing a system starts with loading a model for face detection in MediaPipe. MediaPipe, an advanced real-time face tracking framework, well qualifies the facial areas and locates facial features with great precision. This enables the bringing to focus of these areas especially the mouth region that is important for the expression analysis.In this case, the mouth region is followed to categorize between ‘mouth open’ and ‘mouth closed’ expressions. When it comes to analyzing mouth position, MediaPipe’s FaceMesh model conveniently identifies the positioning of key points around the mouth, and displays the mouth position in terms of coordinates that has been derived based on distance measurements.

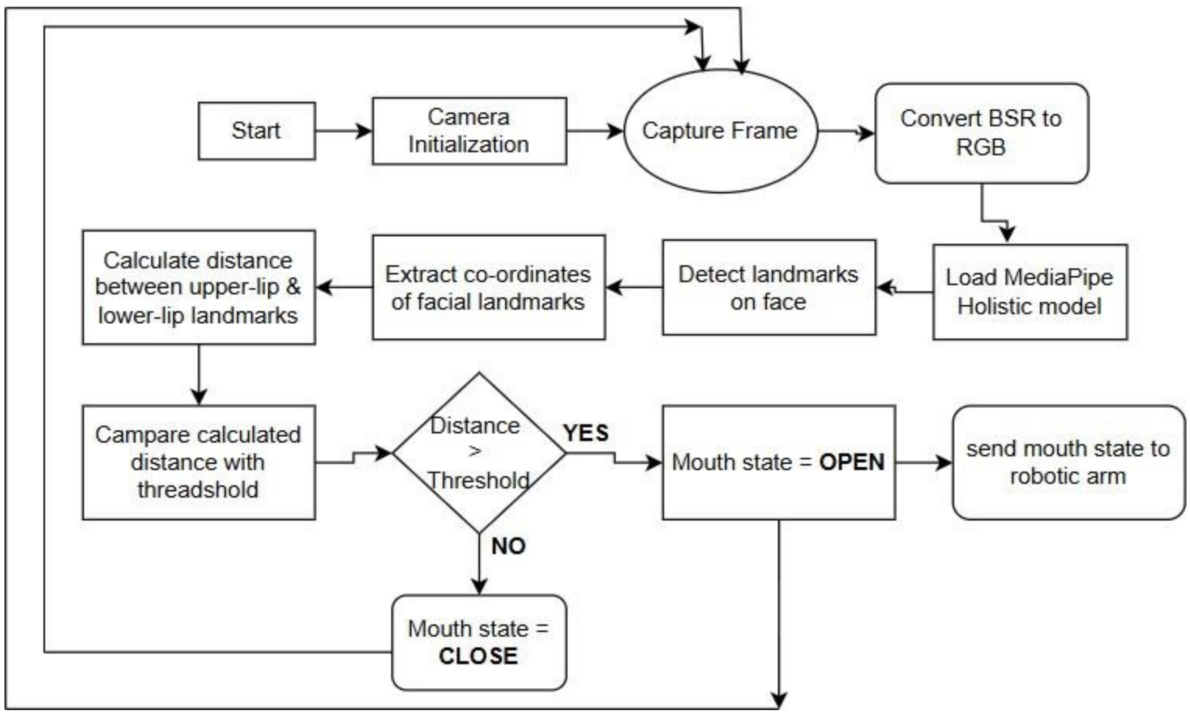


Fig. 5. Flowchart Depicting the Logic for Detecting Mouth State from User

8 Real-time Data Acquisition

Real time facial data is used through the webcam. To fit into the model best, each of the frames in the video is reduced to a standard size of 300 pixels in width which is quite standard. This resizing step helps to rectify this aspect and equally facilitate efficiency in image processing and model inference. OpenCV is used to capture live video streams and use it to process each frame of video to the grayscale that helps the face detection.

Some reasons for this decision are further explained below: It reduces the computational work and enhances the detection rate when using grayscale images. Grayscale conversion reduces data dimensions as the remainder of the color data is a distraction to the needed facial structure differentiation. This streamlined data helps identify the facial features correctly and alongside this the detection of the faces is done in real time.

9 Face Detection and Region of Interest Extraction

The MediaPipe FaceMesh solution then localizes face landmarks in each frame after considering each video frame in grayscale. This detection process just finds particular positions on the face, indicating some major zones such as the mouth. They provide reference so that it is possible to define regions of interest (ROI), for instance, the mouth region in expression analysis. It poses some parameters of the head where major features that define the mouth segment are discovered such as the upper and the lower lip points. These coordinates are used to come up with the state of the mouth through the Euclidean distance of landmarks of upper and lower lips. A certain limit is set by which, lip distance defines whether the mouth is open or not. After that, the mouth region is used as the ROI for the other further classification.

10 Displaying Mouth Status in Real Time

Upon recognition and measurement of the facial landmarks, the system shows the mouth position (either open or closed) on the video stream in real time. If the mouth is open, there should be a label written “Mouth is open.” Ready to feed!" as shown in Fig 6, and at the top of the frame there is an annotation all the time. This gives users a chance to see the response of the system in real-time, after showing the appropriate facial expression.

As figure 7 illustrates, the message “Mouth is closed” is displayed on the screen when the mode is closed; the color is totally confrontational and unambiguous. These dynamic interface values change dynamically as new frames are processed, providing the interaction in real time based on the Facial Expressions detected. Through the static and dynamic updates of the mouth status, the state and result of classification are well shown, which increases the user’s perception of the analysis of the system.

11 Performance and Considerations

The effectiveness of mouth landmark detection using MediaPipe FaceMesh is influenced by several factors, including webcam feed quality, ambient lighting, and variations in facial

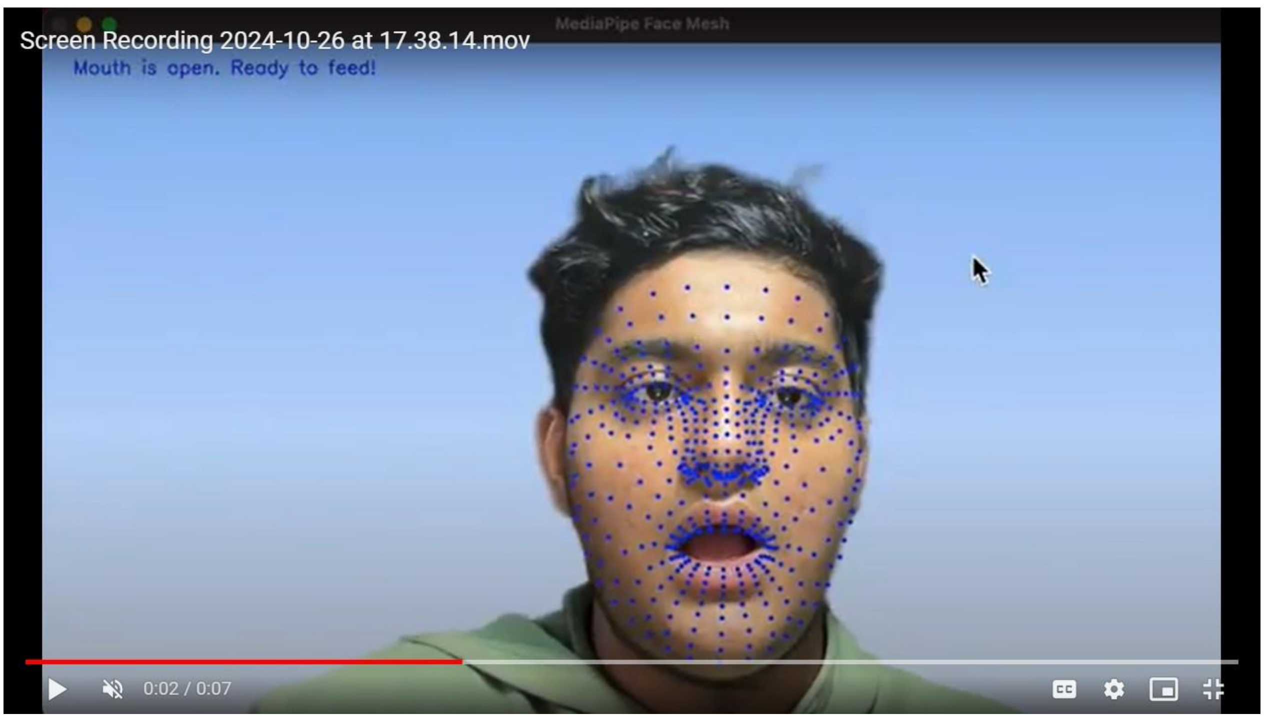


Fig. 6. Mouth State Detection Foropen Lips

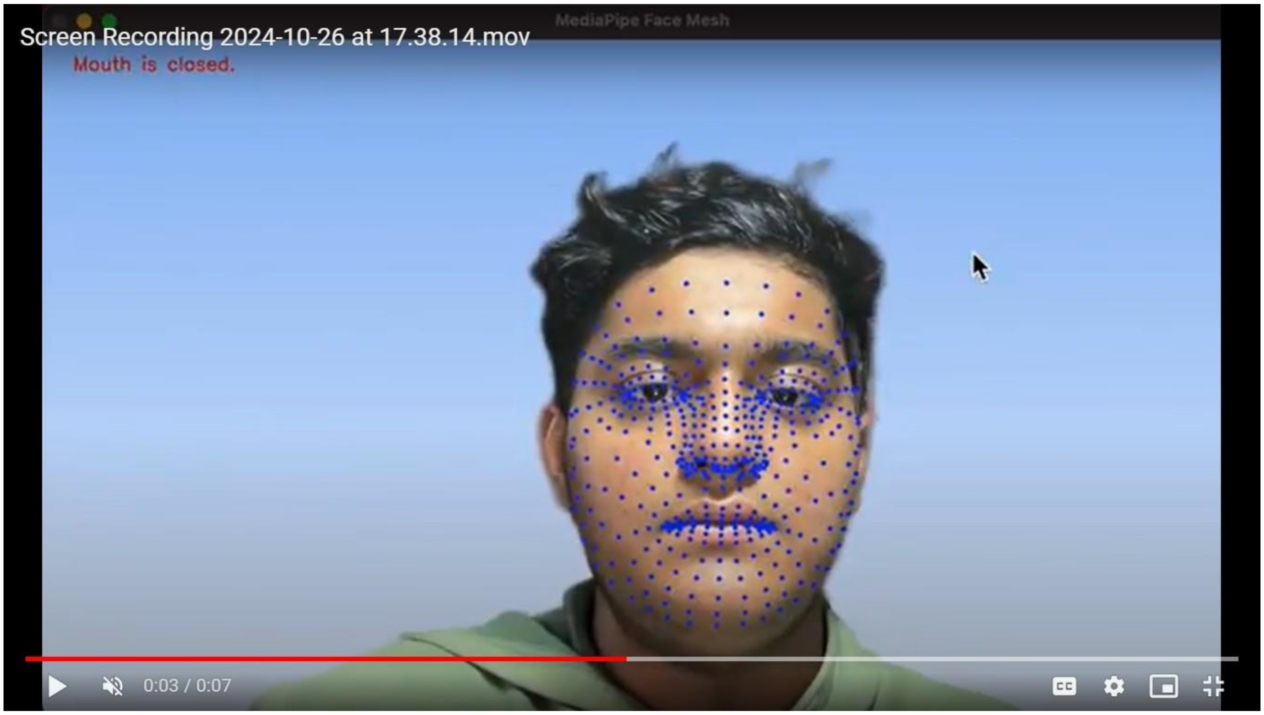


Fig. 7. Mouth State Detection For close Lips

orientation. FaceMesh is generally capable of accurately tracking mouth movements, even with slight changes in face angle and lighting conditions. However, extreme camera angles or low-light environments can significantly reduce the accuracy of detecting whether the mouth is open or closed.Real-time performance is achieved by maintaining a high frame rate, ensuring smooth interaction without noticeable lag. The detection of lip distance is precise enough to support accurate recognition of dynamic mouth expressions. Nonetheless, certain limitations remain, especially in scenarios involving occlusions caused by facial hair, glasses, masks, or hands. These factors can obstruct landmarks and reduce detection accuracy, depending on their density.To ensure reliable classification in various environments, adjustments and preliminary setup may be required, such as optimizing camera placement, enhancing lighting conditions, and minimizing obstructions around the face.

Another form of consideration is to allow the motor at the spoon end of the prototype to have a wider range of movements to allow the children with cerebral palsy to be fed effectively, irrespective of their position or posture of sitting.

11.1.1 Integration of Hunger Detection Algorithm with the Prototype

The above Fig 8 is showing an example of an automated feeding system for cerebral palsy children using face recognition technique. The process starts with the webcam capturing frames, which are then processed to RGB and have facial landmarks predicted by MediaPipe. It measures the distance between the upper and lower lips to determine if the mouth is open or closed.For open a signal is sent to an Arduino Nano which in turn moves a current robotic arm to feed using coordinates that seem suitable. The robotic arm finishes one cycle, and it doesn’t consider the mouth status changes any more to guarantee its unobstructed work. Mentioned that if the mouth is closed the arm does not change its position and remains in the starting position. This system supports feed with real facial indications without hand-aided feeding assistance.

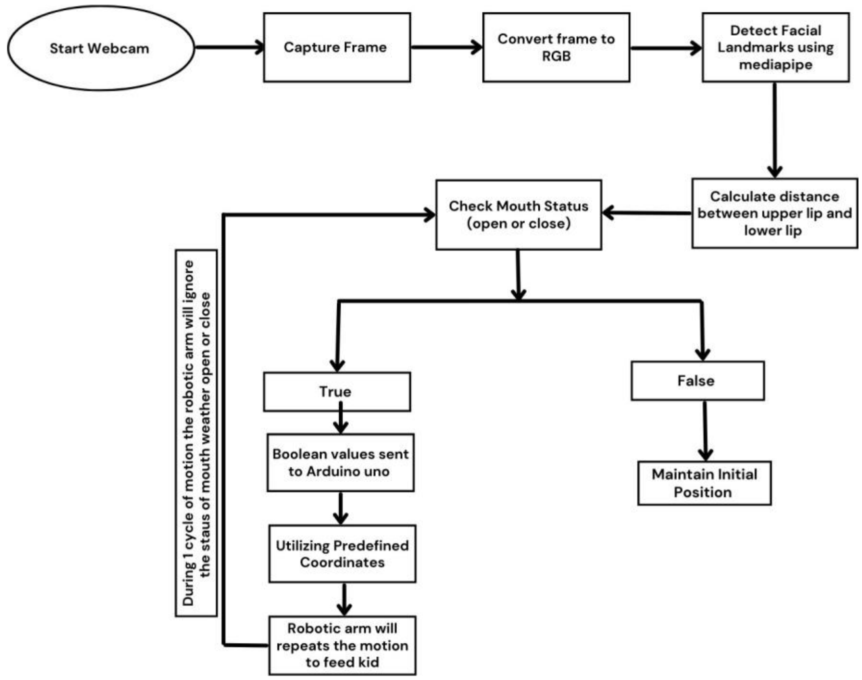


Fig. 8. Flowchart Depicting the Working of the Device

12 Results

Facial landmark detection algorithm used while feeding the Children using a robotic arm feeder yielded an accuracy of 90 % in identifying mouth states, more specifically the 'Mouth Open' and 'Mouth Closed' conditions. This accuracy is well depicted in the confusion matrix shown below in Fig 9 where the ability to classify these states is well enhanced. To a degree such high precision was helpful in effective functionality of the automatic feeding mechanism in real time needs of the children. The capacity to accurately identify these expressions was important in order to give a relevant and customer-focused service, which served to enhance the efficiency of the operation of the robotic arm such that its users included the children as well as their carers.

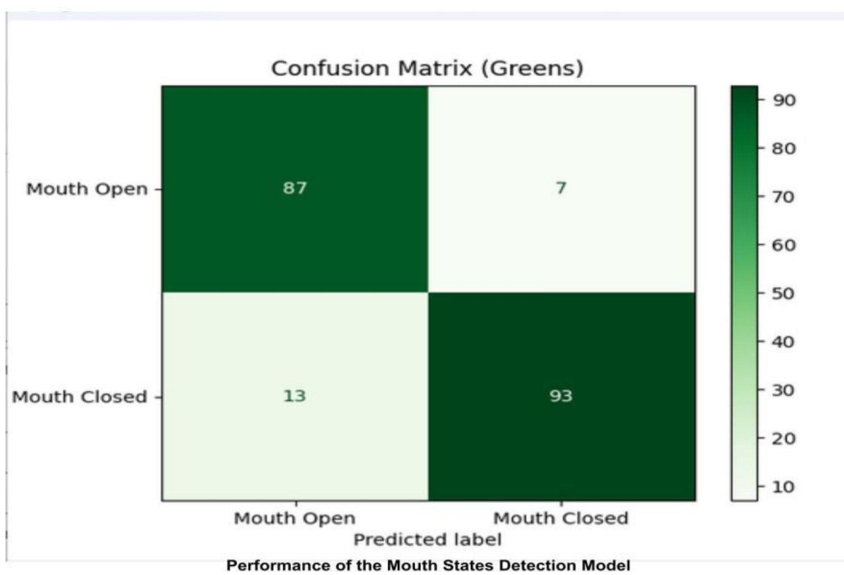
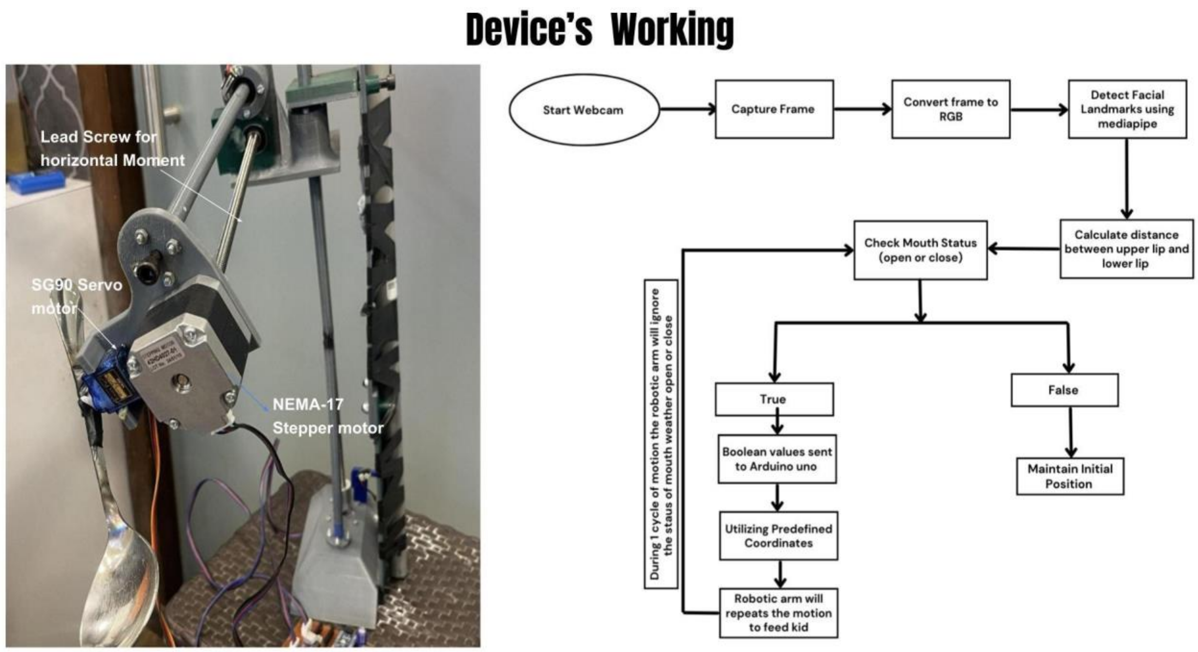


Fig. 9. Confusion matrix depicting the performance of mouth state detection algorithm on test data

The FeedEase Robotic Arm feeder as shown in Fig 10 undergoes a lot of testing in a real environment at Muskan NGO an outcome of which was pristine. This created a milestone of enabling the children with cerebral palsy to be fed by themselves through the use of the developed device. Not only did it assist in making them grow more effectively when it came to self- awareness as well as self- care, but also promoted their decreased reliance on caregivers; which was a relief to an overwhelming number of exhausted care givers. The children for instance expressed comfort with the device and engagement, making them more willing to use the system when eating. The design of the robotic arm mainly centred on the users and the flexibility of the design played a crucial role to its acceptability which pointed to possibilities of changing feeding paradigms for children with special needs.



Major Components of the FeedEase Robotic Arm **Flowchart Depicting the Working of the FeedEase Device**

Fig. 10. eedease robotic arm feeder with all its components labeled

The extensive testing phase along with feedback from both children and caregivers lead to field tested results showing the FeedEase Robotic Arm to be a practical and efficient device to be incorporated into current caregiving processes and procedures as a way to decrease a caregiver's workload by feeding children independently and without assistance as shown in below Fig 11.

The approach was established to be user-friendly and flexible and the users recommend increasing the flexibility if modification suggestions are adopted. In particular, the caregivers disclosed the need to improve the range of motion of the arm and increase the work speed to target the plurality of needs that children feeding require, thus customizing the device to suit the child's feeding tendencies. In support of these observations, the findings presented here point to a potential path for continued advancement of the technology by way of feature upgrades with modularity in mind. In summary, the successful implementation of the FeedEase system in the real-world of course proves its benefit; additionally, such success paves the way for the further introduction of its utilization across the broader spectrum, for independent feeding for children with disabilities.

12.1 Conclusion

The Developed prototype is the first of its kind to help cerebral palsy-afflicted children with an adaptive robotic feeding system that uses real-time facial recognition to naturally respond to the child's needs. The design and implementation of this system take several stages working in concert to create a safe and efficient feeding process.

The primary steps involved would be video capture, facial landmark detection, mouth status identification, and controlling the movement of the robotic arm to make feeding as fluid as possible. The control system accurately operates the NEMA 17 stepper motors, which are driven by DRV8825 motor drivers, ensuring smooth, reliable movement of the robotic arm. This precision was vital for controlled feeding to ensure that food reached the user at a soft and safe speed, sensitive to every user's requirement.

Compact integration of the 3D design of the robotic arm and electronic components allows for putting together this system in such a way that it can be operated stably and securely. NEMA 17 stepper motors ensure that the adaptive feeding and fine control require the necessary level of torque. Micro-stepping is allowed by DRV8825 drivers to make very fine adjustments that can match the child's subtle mouth movements. MediaPipe's FaceMesh model can achieve the most critical facial landmark detection on the mouth areas, which will ultimately enable the system to distinguish an open mouth from a closed mouth. This online analysis allows the robotic arm to almost react immediately and to start action each time its mouth is open rather than when it is shut for safe interaction.

Currently, FeedEase is developed for increasing feeding independence of children with cerebral palsy, however it still has its limitations to its performance, flexibility as well as safety. Future revisions also incorporate machine learning in order to distinguish faint signals of hunger and discomfort, with inputs from a larger dataset. The mechanics of the robotic arm should be improved with very slim motors for their sizes as well as slim profile to make it more portable hence versatile for use in different settings by use of a slim profile arm that can be adjusted as necessary for different circumstances. Applying IoT capabilities such as remote tracking and data collecting might enhance provisions by recognizing feeding schedules and problems. Force sensors may be used to minimize chances of choking and voice or gesture control could enable more of the robot to be operated independently. Lastly, the FeedEase vision is to transform the system into a learning one which will utilize artificial intelligence in helping children with CP to feed themselves independently.

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Works Cited

. *DRV8825 Stepper Motor Driver Module. (n.d.). indiamart.com* ().

<https://www.indiamart.com/proddetail/drv8825-stepper-motor-driver-module- 2853587737888.html?mTd=1>.
. (). <https://www.indiamart.com/proddetail/4-8-kg-cm-nema17-stepper-motor- 23873626812.html?mTd=1>.
Clark, Cecilia and Nicole. *Intelligent Clinical Augmentation: Developing a Novel Socially Assistive Robot for Children with Cerebral Palsy* (2020).
Cunningham, Ryan. "Fully automated image-based estimation of postural point-features in children with cerebral palsy using deep learning". *Royal Society Open Science* 6 (2019): 191011–191011.
Fang, Qinyuan. "RGB-D camera based 3D human mouth detection and tracking towards robotic feeding assistance". *Proceedings of the 11th PErvasive Technologies Related toAssistive Environments Conference* (2018).
Martín-Ruiz, et al. "A virtual environment to improve the detection of oral-facial malfunction in children with cerebral palsy". *Sensors* 16 (2016): 444–444.
Mashrur, Tanzim. "Assistive feeding robot for upper limb impairment-Testing and validation".

International Journal of Advanced Robotic Systems 20 (2023):

17298806231183571–17298806231183571.

Meyer-Heim, Andreas. "Improvement of walking abilities after robotic-assisted locomotion training in children with cerebral palsy". *Archives of disease in childhood* 94 (2009): 615–620.

Najafi, Mohammad. "Robotic assistance for children with cerebral palsy based on learning from tele-cooperative demonstration". *International Journal of Intelligent Robotics and Applications* 1 (2017): 43–54.

Robles-Bykbaev and Vladimir. "Robotic assistant for support in speech therapy for children with cerebral palsy". *IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC)* (2016).

Sakkos, Dimitrios. "Identification of abnormal movements in infants: A deep neural network for body part-based prediction of cerebral palsy". *IEEE Access* 9 (2021): 94281–94292.

Wallard, Laura. "Robotic-assisted gait training improves walking abilities in diplegic children with cerebral palsy". *European journal of paediatric neurology* 21 (2017): 557–564.

Zhu, Manli. "Interpreting deep learning based cerebral palsy prediction with channel attention". *2021 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI)* (2021).