Alternative Communication System for People with Severe Neuromotor Disorders using Artificial Neural Networks

1st Carolina Souza Floriano
School of Electrical, Mechanical and Computer Engineering
Federal University of Goiás
Goiânia, Goiás, Brazil
carolina.floriano@gmail.com

2nd Leonardo da Cunha Brito
School of Electrical, Mechanical and Computer Engineering
Federal University of Goiás
Goiânia, Goiás, Brazil
leonardo_brito@ufg.br

3rd Adson Silva Rocha
Goiano Federal Institute of Science and Technology
Trindade, Goiás, Brazil
adsonrocha@gmail.com

***Abstract*—Communication difficulties are frequent for many people with severe motor disabilities, making it difficult for them to interact with their families, caregivers and society in general. Augmentative and Alternative Communication (AAC) then aims to compensate for the communication deficit of these people, providing the individual with a better quality of life. However, these individuals with severe neuromotor disorders who have severe movement restrictions find great challenges in the use of several current assistive technologies. In this context, the objective of this article is to present an Alternative Communication System based on Artificial Neural Networks with a user-centered approach and their needs, for use by this public. The input and processing of signals is performed by reading the facial reference points, using the MediaPipe FaceMesh library, and the development of the classifier of gestures/facial expressions is carried out by implementing a Recurrent Neural Network Model, using long memory units term (LSTM) and dense layers. Real-time experimental results indicate that the proposed system has a good performance, with an average accuracy of 91.8%, demonstrating recognized results in the recognition of registered gestures.**

***Index Terms*—artificial neural networks, alternative communication, augmentative communication, neuromotor disorders, assistive technology**

I. Introduction

Communication difficulties are common for many individuals with severe motor disabilities, making it difficult for them to interact with their families, caregivers, and society in general.

The development and innovation of technology are responsible for providing society with a range of benefits, such as improvements in quality of life, ease and speed of access to information and knowledge, simplification of communication mechanisms, optimization, and automation of processes, and a significant contribution to healthcare.

Moreover, technology plays an essential role in promoting social inclusion, introducing the concept of assistive technology, whose goal is to assist in resolving functional problems encountered by people with disabilities, or to expedite and promote essential daily skills for these individuals [1]. To fulfill the interaction needs of some individuals with restrictions on movement and motor activities with communication devices, the use of new modalities of interaction such as gesture or tangible object input, voice commands, and various other types of sensors is becoming increasingly common [2].

Currently, there is a large number and variety of assistive interfaces, and recent studies related to Augmentative and Alternative Communication (AAC) seek to optimize existing devices, looking to reduce visual fatigue, increase typing speed and find more efficient ways to input information through eye movements or gaze direction [2].

II. An overview of augmentative and alternative communication in severe neuromotor disorders

A. Assistive Technology

The term Assistive Technology was officially created in 1988 as an important legal element within US legislation, known as Public Law 100-407, which, along with other laws, comprises the American with Disabilities Act (ADA). This set of laws regulates the rights of citizens with disabilities in the US and provides the legal basis for funding the resources they need. There was a need for legal regulation of this type of technology, and with this definition and legal support, the US population of people with disabilities began to have access to specialized services, as well as the full range of resources they need to lead a more independent, productive, and socially included life [3].

According to ADA, assistive technology is defined as "a wide range of equipment, services, strategies, and practices designed and applied to alleviate functional problems encountered by individuals with disabilities" [4].

The legislation of the United States registers assistive technology as resources, considering any item, equipment or part thereof, product or system manufactured in series or tailored to increase, maintain or improve the functional capabilities of people with disabilities. Services are defined as those that directly assist a person with a disability in selecting, purchasing or using the above-defined resources [1].

In the national context, on November 16th, 2006, the Technical Aids Committee (CAT) was established through ordinance n^o142 by the Special Secretariat for Human Rights of the Presidency of the Republic (SEDH/PR), composed of specialists and representatives from government agencies responsible for presenting proposals for policies related to assistive technology sector [4].

The formation of CAT established the following objectives: to present proposals for governmental policies and partnerships between civil society and public agencies regarding assistive technology; structure guidelines in this area of knowledge; conduct surveys on human resources currently working with this topic; identify regional reference centers aiming at forming an integrated national network; encourage federal, state and municipal spheres to create reference centers; propose courses creation in assistive technology area as well as other actions aimed at training qualified human resources and proposing studies and research related to assistive technology theme [5].

It was then that on December 14th, 2007 members approved concept definition for Assistive Technology which is defined as an interdisciplinary field characterized by products, resources methodologies strategies practices services aimed at promoting functionality related activity participation people with disabilities impairments mobility reduced seeking their autonomy independence quality life social inclusion [6].

Therefore, the objective of assistive technology is to provide greater independence to people with disabilities, promoting improvements in their quality of life and social inclusion by facilitating or expanding their communication, mobility, independence, and skill development.

Considering the main objective of Assistive Technology is the use of technology that helps overcome the functional limitations of human beings in a social context, it is extremely important to identify not only the purely technological aspects but also the factors related to human and socioeconomic issues. A model of education and training in assistive technologies should be based on a human development model that takes into account the problems people with disabilities face when trying to adapt to an adverse environment [6].

In [5], a classification of assistive technologies for educational purposes was developed, encompassing products, devices and services, subdivided into: Aids for daily living and practical life; AAC - Augmentative and Alternative Communication; Accessibility resources for computers; Environmental control systems; Architectural projects for accessibility; Orthoses and prostheses; Postural adequacy; Mobility aids; Aids to enhance visual function and resources that translate visual content into audio or tactile information; Aids to improve auditory function and resources used to translate audio content into images, text, and sign language. Mobility in vehicles, sports, and leisure.

Assistive technology and its resources should be distinguished from other technologies applied in medical and rehabilitation fields, as assistive technology should be understood as the ”user's resource” in contrast to the ”professional's resource,” since its purpose is to promote autonomy and efficiency in the execution of daily tasks for users [5].

B. Augmentative and Alternative Communication Systems

Augmentative and Alternative Communication (AAC) is a subfield of Assistive Technology that encompasses a broad range of strategies, methods, and tools aimed at increasing communicative capacity for individuals who are unable to use verbal communication in a functional and effective way.

AAC has been described by the American Speech-Language-Hearing Association (ASHA) as ”the effort to study and, when necessary, compensate for temporary or permanent disabilities, activity limitations, and participation restrictions of people with severe disorders in production and/or comprehension of spoken or written language” [7].

In general, AAC has two main purposes with two different target audiences: (a) to improve the communicative capacity of individuals with unintelligible or non-fluent speech, and (b) to provide an alternative form of communication for individuals who cannot speak or are unable to develop a language capable of efficiently [4].

The use of AAC resources is typically recommended for individuals with unlimited or no speech capacity, with this loss being caused by a variety of medical and disability conditions (congenital, acquired, progressive, or temporary) [4].

Among congenital conditions that may be related to complex communication needs are cerebral palsy, intellectual disability, aphasia, and autism. As for acquired disorders, the progression or severity of some diseases may lead their carriers to need to use AAC mechanisms to communicate, such as amyotrophic lateral sclerosis (ALS), motor neuron disease, locked-in syndrome, among others. In progressive conditions, muscular dystrophy can be cited, and in temporary conditions, the use of AAC can occur in post-surgical moments or even in situations that cause temporary loss of speech.

C. Neuromotor Disorders

Neuromotor disorders represent any pathological condition where there is loss of function or disruption of nerve cells, and can be referred to as neuromotor disorders or even neuromuscular disorders [8]. These disorders can cause severe communication restrictions, including verbal communication and body language.

Among the most severe neurodegenerative disorders are Amyotrophic Lateral Sclerosis (ALS), cerebral palsy, quadriplegia, and Locked-in Syndrome, which represents the most extreme case, as the individual loses virtually all motor functions, except for eye movement [9].

a) Amyotrophic Lateral Sclerosis (ALS): is a degenerative and progressive disease that affects the nervous system, leading to irreversible motor paralysis. As the disease progresses, its carriers gradually lose their functional capacity, including the ability to perform basic self-care [10]. One of the possible complications resulting from ALS progression is the inability to speak. Its initial symptoms vary among carriers; however, a pattern usually becomes evident. Initially, speech rate decreases, progressing with moderate reductions and then severe reductions in intelligibility, impairing overall communication effectiveness and ultimately resulting in total loss of functional speech [11].

b) Locked-In Syndrome (LIS): a rare neurological disorder first described in 1966 [12], is characterized by complete paralysis of all voluntary muscles except those responsible for controlling eye movement. The cognitive function of LIS patients is not affected; they remain conscious and awake but unable to move (except for eye movement) or communicate (aphonia) [13].

D. *Artificial neural networks*

In technology, one of the most relevant and fascinating areas is the simulation of human cognitive abilities. Currently, machines are being designed to exhibit intelligent behavior similar to human reactions.

When it comes to intelligence, humans stand out as having the most advanced among all creatures, and the structure responsible for this intelligence is the brain. The basic entities of this structure are neurons that are interconnected in networks allowing for information exchange and creating biological intelligence. Artificial neural networks emerged from research aimed at understanding and mapping neuron intelligence in an artificial structure [14].

1) Artificial Neurons: The main characteristic of an artificial neuron is its ability to be trained from a set of previously labeled samples so that its internal configuration can generate a response consistent with its assigned objective [15].

The artificial neuron model [14] presented in Fig.1 seeks to simulate the biological realities that occur within a cell of the nervous system. The information provided by other neurons enters D input x_j into the processing neuron. Processing is performed from a linear combination of inputs, as in (1).

$$net = w_1x_1 + w_2x_2 + ... + w_Dx_D = \sum_{j=1}^{D} w_jx_j = w^Tx \quad (1)$$

Where each input is associated with a weight w_j that reflects the importance of input x_j. The result of this linear μ combination is the net value. If this value exceeds threshold μ, the neuron "fires" binary output $y = 1$, and otherwise, output remains passive at $y = 0$. Comparison between net and threshold μ is performed through Heaveside function (step function) $\Theta(x) = 1$ if $x \geq 0$ and $\Theta(x) = 0$ otherwise.

$$y = \Theta(\sum_{j=1}^{D} w_jx_j - \mu) \quad (2)$$

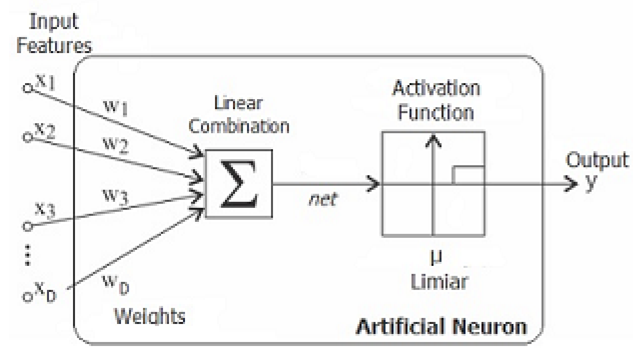

Fig. 1. McCulloch and Pitts model of a neuron [13] [14].

There are other activation functions capable of producing an output value for a neuron besides those demonstrated in model [13], such as linear function, step function and sigmoidal function [14].

In certain situations, only one neuron does not produce significant results in solving the problem at hand; therefore, a valid alternative would be to combine several neurons into a layered structure where each layer may present different numbers of neurons forming thus deep neural network called Multilayer Perceptron (MLP). In this network, vector values enter through initial layer while their outputs are connected to inputs on next layer until final outputs representing end result [15]. Thus it's possible to compose networks with multiple layers known as deep neural networks which can learn increasingly complex relationships.

Multilayer Perceptron (MLP - Multilayer Perceptron) incorporates one or more fully connected hidden layers between output and input layers so that hidden layer's output is transformed using an activation function. Some commonly used activation functions include ReLU (Rectified Linear Unit), step function, sigmoidal function softmax and hyperbolic tangent. Fig. 2 [15] represents scheme of a Multilayer Perceptron Network.

2) Convolutional Neural Networks (CNNs): are computational algorithms that follow feed-forward pattern where all layers connect to next layer, following path from input towards network output. One of their main applications is in processing and analyzing digital images, where converting images into numerical matrix space and assigning weights makes it possible to simulate synapses, providing algorithm with ability to retain knowledge acquired during learning [16].

This is possible through weight adjustments during training using back-propagation algorithm. In this algorithm, calculation of error occurring in neural network's output layer is

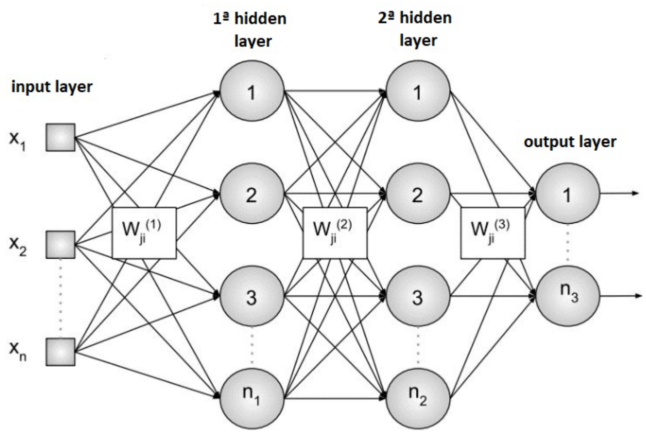

Fig. 2. Multilayer Perceptron Network [15]

used as basis for recalculating value of weights vector w for last layer of neurons (layer prior to output), proceeding thusly backwards through previous layers until reaching input layer while performing retropropagation of error obtained by neural network. This retropropagation aims at reducing the error obtained by the network making it more efficient.

E. High-Tech Augmentative and Alternative Communication Systems

The use of Augmentative and Alternative Communication (AAC) in all neuromuscular diseases is limited, but studies in Amyotrophic Lateral Sclerosis suggest that the use of an AAC system is usually well accepted and promotes improvements in quality of life [11]. Technological advances are making AAC systems more accessible, so they have great potential to extend access to communication even to the most severe patients with neuromuscular diseases.

A study conducted in [17] analyzed the applicability of AAC systems in Amyotrophic Lateral Sclerosis from the perspective of patients, caregivers, and healthcare professionals, demonstrating that the perception of the usefulness of these systems is high among them, and also identified some relevant factors that contribute to increasing the usefulness of these systems.

In [18], the authors conducted a study to analyze whether an eye-tracking device improves the quality of life of patients, and also to analyze whether this device affects the burden experienced by caregivers. The research showed that the eye-tracking assistive device significantly improved the quality of life of patients compared to patients who did not use the device ($p < 0.01$), and the assistive device also reduced the overload of caregivers ($p < 0.05$).

The development of an assistive virtual keyboard has been carried out in various studies such as in [2], [4], [6], [19], where, in addition to creating the assistive keyboard, these works aimed to optimize their results by improving typing speed, reducing errors, and minimizing user effort.

In [12], an evaluation was conducted between three methods of access to augmentative and alternative communication, electrooculography (EOG), an eye tracker, and a brain-computer interface (BCI) by an individual with locked-in syndrome. It was demonstrated that this person was able to use all three proposed interfaces, but would consider using only the BCI because of the loss of eye muscle control due to the disease. The authors concluded that user-centered approaches in the development of these systems increase the likelihood that they will be used as assistive technology in daily life.

The project, GazeSpeak [20], presented the development of an eye gaze gesture communication system, which operates on a smartphone and is designed to be low-cost, robust, portable, and easy to learn, with a higher communication bandwidth than an e-tran board (eye-gaze transfer). Its final evaluation demonstrated that GazeSpeak is robust, has good user satisfaction, and is capable of providing faster speed improvements than an e-tran board, as well as additional improvements such as low cost and effort.

In [8], a new Augmentative and Alternative Communication (AAC) system controlled by the user's eye movement integrated with a mobile app was presented to allow long-distance communication with caregivers and family members. The system was tested by 17 volunteers, who evaluated its usability, and the results showed that the system was rated excellent by users with an average score of 92.79 on the System Usability Scale (SUS).

III. The Proposed System

With the aim of promoting social inclusion for individuals with severe motor disabilities, a personalized facial gesture recognition system is proposed in this section, with a user-centered approach focused on their needs, in order to enhance the probability of assistive technology being used in their daily lives. The architecture of the proposed system is shown in Fig. 3.

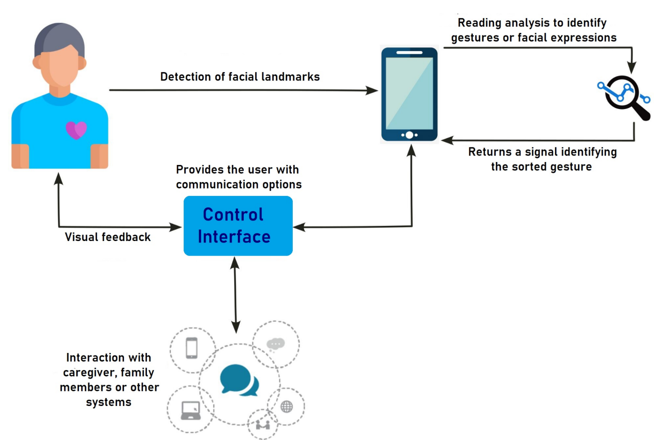

Fig. 3. Proposed system architecture.

The proposed AAC system will be divided into the following modules:

- Signal Input and Processing: performed through a smartphone, where facial landmark detection will be carried out using the MediaPipe Face Mesh library;
- Reading Analysis: then, reading analysis will be performed to identify gestures or facial expressions. Next, the identified gesture/expression is compared with registered gestures/expressions, and the classification of the sent signal is sent to the control interface.
- Control Interface: available through a smartphone, providing users with options for interacting with caregivers, family members or other systems. It receives from the reading analysis module the identified gesture/expression and is able to determine which action should be executed. Example represented in the Fig. 4.

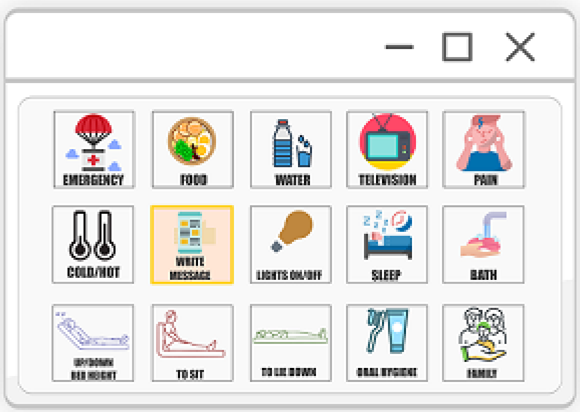

Fig. 4. Control Interface

A. Data acquisition

In order for the user to be able to use the proposed system, they must first register the gestures/expressions that represent the basic actions of the system: Yes/Confirm, No/Return and Neutral/Continue.

The registration of these gestures will be done by recording ten samples for each action so that after training, the neural network is capable of recognizing each gesture when performed. For each sample, information regarding 20 frames is stored, thus constituting the movement of the gesture/expression; however, this value can also be customized.

B. Signal Input and Processing

The proposed system was developed following the steps shown in Fig. 5 These steps correspond respectively to inputting the original video into the algorithm, processing of image (detection and selection of user's face, detection of specific facial points), and then having processed video containing information on expressions recognized during image processing by software.

The first step in detecting and selecting a user's face occurs with FaceMesh library combined with OpenCV usage. Then for detection of facial points solution FaceMesh was used which aims at mapping 468 real-time 3D facial points that can be used for identification purposes such as eyes, nose and mouth structures.

For our proposed solution aiming at mapping as many expressions as possible some key points from facial structures were utilized: eyes, eyebrows,nose,mouth,and contouring around face. Finally after detecting selected points distance between pairs are calculated (previously established according to possible facial expressions to detect)and then these values are saved in a characteristic vector to be used as a training set by neural network or prediction identified gesture.

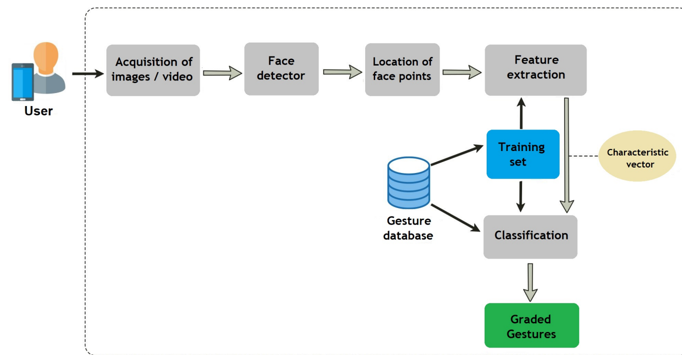

Fig. 5. Flowchart of the proposed system.

To train the neural network, the control group samples for each registered gesture were divided into two groups. The first set, intended for network training, was composed of seven elements from the sample. The second set, intended for validation of training, was composed of three elements from the sample. In total, as three gestures were considered, the first set consisted of twenty-one elements and the second set consisted of nine elements.

C. Gesture/Facial Expression Classifier

In developing the gesture/facial expression classifier, a Recurrent Neural Network (RNN) model is implemented using Long Short-Term Memory (LSTM) units and dense layers. LSTM-type neural networks are a special type of RNN capable of learning connections in sequences of information. An LSTM layer (illustrated in Fig. 6), first described by [21], has two state outputs: Hidden State (which basically represents observed state in RNNs) and Cell State which functions as "memory".

LSTM cells can retain or manipulate information through gates that control information flow between cells. LSTM networks have three types of gates: forget gate responsible for determining which information should be forgotten by memory cell; input gate responsible for adding new information to memory cell state; output gate whose function is to extract useful information from current memory cell state and pass it on to next memory cell [22].

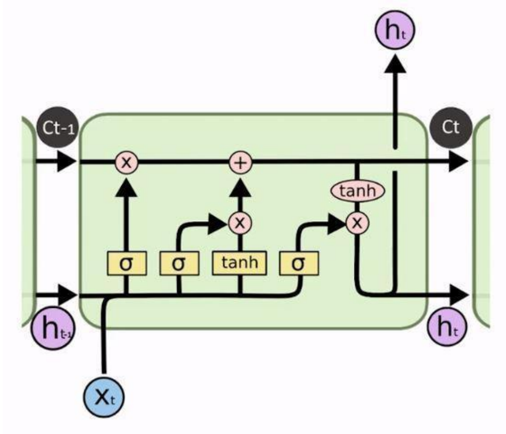

Fig. 6. LSTM network architecture [17].

IV. Results and discussion

Using LSTM-based RNNs, the model was trained including a set of 3 gestures/facial expressions, with a total of 30 samples, where each gesture has 10 samples. For each gesture, 7 samples are used for training and 3 samples for validation.

Fig. 7 and Fig. 8 demonstrate the accuracy and loss of the model during training.

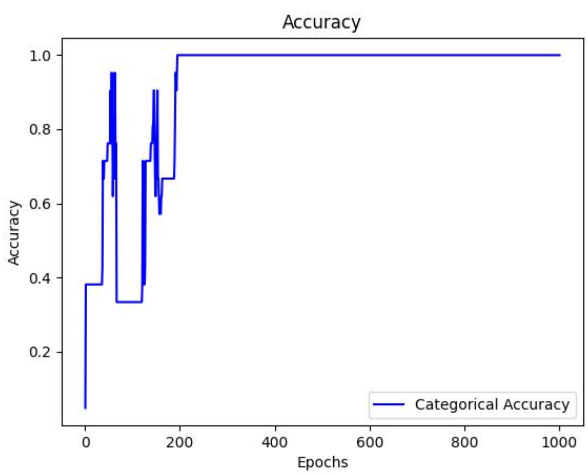

Fig. 7. Model accuracy during training.

Based on the confusion matrix presented in Fig. 9, it can be noticed that the classifier is well-trained, correctly recognizing gesture samples, especially for the Neutral/Continue gesture. The recognition results of the proposed classifier are good due to its high accuracy and good generalization, so that facial expressions are correctly recognized in 95 out of a total of 100 samples with an accuracy rate of 95%.

A. Real-Time Experimental Results

For real-time tests, frame-by-frame prediction was initially applied. However, for sequential identical gestures (for example, a long blink and two quick blinks), the model could not

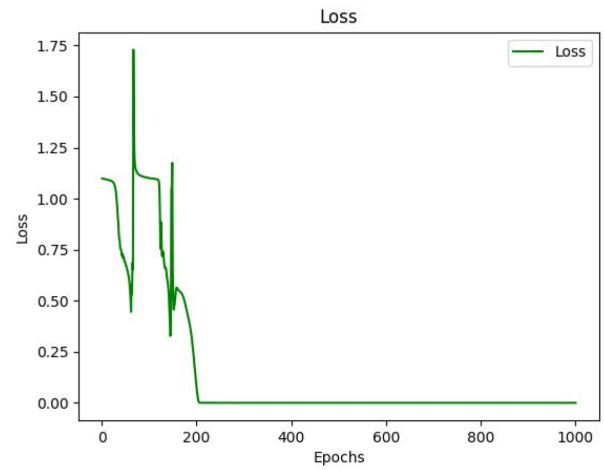

Fig. 8. Model loss during training.

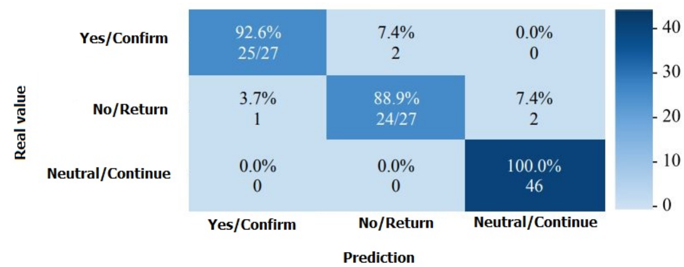

Fig. 9. Confusion matrix of the classification results of the proposed model.

distinguish them. Therefore, it was necessary to adapt to the sliding window technique.

The sliding window technique was then implemented to ensure greater accuracy in detecting gestures in real-time, especially due to the presence of sequential identical gestures. However, this technique takes longer to make predictions because it requires scanning multiple frames before detecting the performed gesture, thus demonstrating a certain disadvantage.

During real-time testing, the average accuracy rate for Yes/Confirm gesture dropped from 92.6% to 87.5%, and the average accuracy rate for No/Return gesture dropped from 88.9% to 87.8%. On the other hand, Neutral/Continue gesture maintained an average precision of 100%, representing an overall average precision of 91.8%. Considering that Yes/Confirm and No/Return gestures are similar - with one represented by a long blink and another by two quick blinks -the implemented model achieved satisfactory accuracy.

B. Real-Time System

To demonstrate usability of proposed method,a simple module for recognizing facial expressions/gestures was implemented. The Fig. 10 illustrates how this module works in real time where user performs a gesture which is recognized satisfactorily by system.

Fig. 10. Real-time model.

V. CONCLUSIONS

The development of systems that capture movements or gestures in a personalized way aims to contribute to the innovation of assistive technologies used by users with severe neuromotor disorders that cause serious and varied movement restrictions.

Real-time experimental results have shown that the proposed system has good performance, with an average accuracy of 91.8%, demonstrating satisfactory results in recognizing registered gestures. Therefore, it represents an intelligent, adapted, efficient and robust solution capable of transforming the lives of individuals with restricted mobility, providing them with a better quality of life.

REFERENCES

[1] R. C. R. Bersch, "Design of an assistive technology service in public schools", Master's Dissertation, School of Engineering and Technology Faculty, Federal University of Rio Grande do Sul, Porto Alegre, 2009.
[2] R. A. Silva, A. C. P. Veiga, "Algorithm for decoding visual gestures for an assistive virtual keyboard", IEEE LAT AM T, vol. 18, no. 11, pp. 1909–1916, Mar. 2021.
[3] T. A. G. Filho, J. D. C. Garcia."National Survey of Assistive Technology". São Paulo: Institute of Social Technology - ITS BRASIL and Ministry of Science, Technology and Innovation - MCTI/SECIS, 2012, 68 p., ISBN: 978-85-64537-04-0.
[4] R. A. Silva. "Development of a virtual keyboard for communication through visual gestures". PhD Thesis, Faculty of Electrical Engineering, Federal University of Uberlândia, Uberlândia, 2021.
[5] R. C. R. Bersch, "Introduction to Assistive Technology", Porto Alegre, RS, 2018. Available at: www.assistiva.com.br
[6] Empowering Users Throught Assistive Technology (EUSTAT), "Education in assistive technologies for end-users: guidelines for trainers". European Commission, 1999. ISBN 88-85936- 29-6.
[7] American Speech-Language-Hearing Association (ASHA),2019. Available in: https://www.asha.org.
[8] Y. L. Coelho, et al., "A New Augmentative and Alternative Communication System Based on Eye Tracking" at the XXV Brazilian Congress of Biomedical Engineering, Foz do Iguaçu, Paraná, Brazil, p. 667-670, 2016. ISSN 23593164.
[9] L. F. B. Loja, "Assistive Technology: an evolutionary virtual keyboard for application in alternative and augmentative communication systems", Doctoral Thesis, Faculty of Engineering, Federal University of Uberlândia, Uberlândia, 2015.
[10] Ministry of Health (2021, Sep.), "Amyotrophic Lateral Sclerosis (ALS): what it is, causes, symptoms and treatment". Available in: https://antigo.saude.gov.br/saude-de-a-z/ela-esclerose-lateral-amiotrofica
[11] I. L. J. Ball, S. Fager, M. Fried-Oken, "Augmentative and alternative communication for people with progressive neuromuscular disease", in Phys Med Rehabil Clin N Am. 2012 Aug; 23(3):689-99. doi: 10.1016/j.pmr.2012.06.003. PMID: 22938882.
[12] Kübler e S. Halder, " Comparison of eye tracking, electrooculography and an auditory brain-computer interface for binary communication: a case study with a participant in the locked-in state", J. Neuroeng. Rehabil. 2015; 12: 76.
[13] W. S. Mcculloch, W. Pitts. "A logical calculus of the ideas immanent in nervous activity", Bulletin of Mathematical Biophysics 5, 115–133 (1943). https://doi.org/10.1007/BF02478259
[14] T. W. Rauber, "Artificial Neural Networks". Department of Computer Science - Federal University of Espírito Santo, 2005.
[15] J. J. Silva Júnior, "Deep neural networks for facial recognition in the context of public security", Master's Dissertation, Institute of Informatics, Federal University of Goiás, Goiânia, 2020.
[16] J. G. J. Silva, "Deep neural networks for automatic detection and counting of whiteflies in the agricultural context", Master's thesis, Institute of Informatics, Federal University of Goiás, Goiânia, 2021.
[17] A. M. F. Oliveira, "Augmentative and Alternative Communication Systems in Amyotrophic Lateral Sclerosis: Applicability and Usefulness for Patients, Caregivers, and Healthcare Professionals", Master's Thesis, Faculty of Medicine, University of Porto, Portugal, 2019.
[18] C. S. Hwang, H. H. Weng, L. F. Wang, C. H. Tsai, H. T. Chang, "An Eye-Tracking Assistive Device Improves the Quality of Life for ALS Patients and Reduces the Caregivers' Burden, Journal of Motor Behavior, 46:4, 233-238, 2014. DOI: 10.1080/00222895.2014.891970.
[19] R. S. Gomide, et al., "A new concept of assistive virtual keyboards based on a systematic review of text entry optimization techniques", in Research on Biomedical Engineering [online]. 2016, v. 32, n. 2, pp. 176-198. ISSN 2446-4740. https://doi.org/10.1590/2446-4740.01715.
[20] X. Zhang, H. Kulkarni, M. R. Morris (2017), "Smartphone-Based Gaze Gesture Communication for People with Motor Disabilities". 2878-2889. 10.1145/3025453.3025790.
[21] Hochreiter, S. Schmidhuber, J. Long short-term memory. Neural Computation, v. 9, n. 8, p. 1735–1780, 11 1997. Https://dl.acm.org/citation.cfm?id=1246450.
[22] Voigt, J. F.. Deep learning for hand gesture recognition using images and skeletons with applications in Libras. 2018. 92 f. Dissertation (Master's in Mathematics) - Institute of Mathematics, Graduate Program in Mathematics, Federal University of Alagoas, Maceió, 2018.