Machine Learning Approaches in the Detection of Amyotrophic Lateral Sclerosis Disease Using Orofacial Gestures

Mara Hajdu Măcelaru[a], Rareş Chiuzbăian and Petrică Pop[b]
Department of Mathematics and Informatics, Faculty of Sciences, North University Center of Baia Mare, Technical University of Cluj-Napoca, Victoriei 76, Baia Mare, Romania
{Mara.HAJDU, Petrica.POP}@mi.utcluj.ro, chiuzbaian.vi.rares@student.utcluj.ro

Keywords: Machine Learning, Amyotrophic Lateral Sclerosis Disease, Orofacial Gestures.

Abstract: Amyotrophic lateral sclerosis (ALS) is a progressive neurodegenerative disease that affects nerve cells in the brain and spinal cord, specifically the motor neurons. As far as we know, there is no single test that can definitively diagnose ALS, and the diagnosis is often based on a integration of clinical findings, medical history, physical examination and various tests to rule out other possible conditions and confirm the diagnosis. The present work proposes four machine learning (ML) algorithms: K-Nearest Neighbors, the Iterative Dichotomizer 3, Naive Bayes and Logistic Regression to help the diagnosis of early signs of ALS disease. In order to test the proposed ML algorithms, we used the only existing data set, created by the Sunnybrook Research Institute in Toronto. Using the extracted images from the videos of the participants, we developed a system of recognition based on orofacial gestures of the early signs of ALS. The achieved experimental results show that the described ML techniques enable accurate ALS predictions and can be easily integrated into healthcare system for diagnostic use.

1 INTRODUCTION

Amyotrophic Lateral Sclerosis (ALS), also known as Lou Gehrig's disease, is a progressive and irreversible neurodegenerative disease that progressively paralyzes people because the brain loses the ability to send signals to the body's muscles, that we typically have the ability to move at will. Gradually, as the body's muscles deteriorate, someone living with ALS will lose the capability to walk, talk, eat, swallow, and eventually breathe.

The exact cause of most ALS cases remains unknown. Researchers have been investigating various factors potentially associated with ALS, such as genetics and environmental influences. Additionally, studies have explored connections with diet and injuries. While the cause for most ALS cases remains elusive, several inherited factors have been identified as causing familial ALS.

Over 250,000 individuals globally are affected by ALS. Until now, there have been limited published studies aimed at projecting the quantity and dispersion of ALS cases in future years. The research performed by (Arthur et al., 2016) indicated a projected rise in ALS cases around the world, from 222,801 in 2015 to 376,674 in 2040, marking a 69% increase. They mentioned that the primary reason for this rise is the aging population, especially in developing countries.

Although ALS is a very serious disease, it is crucial not to lose hope in the battle against it. Timely diagnosis is imperative for comprehensive treatment in the earliest stages. With advancements in science and technology, many patients have the opportunity for substantial improvement. Proper treatment can significantly enhance quality of life and extend the lifespan of the patients.

(Bandini et al., 2020) described the only available dataset containing videos showcasing orofacial gestures executed by individuals with orofacial impairment due to neurological disorders, such as ALS and stroke. Their experiments revealed that even in case of standardized experimental setup and mild to moderate orofacial impairment due to neurological diseases, a bias in the face alignment accuracy persisted.

Machine learning (ML) is an area of study in artificial intelligence (AI) focused on creating and examining statistical algorithms capable of learning from data, generalizing to new data, and executing tasks without explicit instructions. ML techniques have

[a] https://orcid.org/0000-0003-3135-1244
[b] https://orcid.org/0000-0002-0626-9284

Măcelaru, M. H., Chiuzbăian, R. and Pop, P.
Machine Learning Approaches in the Detection of Amyotrophic Lateral Sclerosis Disease Using Orofacial Gestures.
DOI: 10.5220/0013282000003890

In *Proceedings of the 17th International Conference on Agents and Artificial Intelligence (ICAART 2025) - Volume 3*, pages 1132-1139
ISBN: 978-989-758-737-5; ISSN: 2184-433X

been applied successfully to many fields including natural language processing, computer vision (Khan et al., 2021), speech recognition (Madanian et al., 2023), cybersecurity (Cosma et al., 2021), agriculture (Meshram et al., 2021), medicine (Chakraborty et al., 2023; Sudharsan and Thailambal, 2023), etc.

The field of medicine and healthcare has undergone rapid evolution and advancement in the last years (Chakraborty et al., 2023), especially driven by the adoption of robust and efficient ML and deep learning (DL) technologies. ML applications in the medical sector are swiftly developing, leading to fast improvement, reshaping the practice of medicine, and enhancing the experiences of clinicians and patients alike. Among the many benefits of ML and DL in medicine, according to Aslam et al. (Aslam et al., 2022), both streams of techniques can support clinicians in several key ways:

1. In predicting individuals susceptible to diseases, enabling timely alerts to avoid triggers.
2. In early and accurate disease diagnosis, leading to the use of therapeutic agents known to delay disease progression and enhance patient life quality.
3. In forecasting disease transformation by analyzing various markers such as blood, cerebrospinal fluid, radiological data, etc.
4. In predicting the efficacy of specific medications in halting disease deterioration and enable effective treatment monitoring.

ML significantly enhanced the reliability, performance, predictability, and accuracy of diagnostic systems for numerous diseases, such as Alzheimer's disease (Sudharsan and Thailambal, 2023), Parkinson's disease (Govindu and Palwe, 2023), etc, but as far as we know, this is the first work that uses ML approaches in the detection of amyotrophic lateral sclerosis disease using orofacial gestures.

1.1 Main Contributions

The scope of our paper is to develop predictive models through ML methods for early ALS detection using orofacial gestures. As far as we know, there are no studies sought to predict ALS development. This research fills this gap by focusing on the development of ML models able to handle clinical data from ALS patients, facilitating the accurate classification of the presence or absence of ALS. Through our approach, we plan to assist in the early detection and management of this irreversible neurodegenerative disease.

Our main contributions are outlined in the following:

1. From medical perspective, as far as we know, it is the first appoach to use ML techniques for early ALS detection using orofacial gestures.
2. From the perspective of algorithm design, we designed four ML techniques: K-Nearest Neighbors (KNN), the Iterative Dichotomizer 3 (ID3), Naive Bayes and Logistic regression for predicting individuals susceptible to ALS disease.
3. From the perspective of empirical evaluation, computational experiments were performed to assess the performance of the considered ML techniques on the only existing clinical dataset from ALS patients provided by the Sunnybrook Research Institute from Toronto. The achieved results were analyzed, evaluated and interpreted.

The remainder paper is structured as follows: the second section describes in details the data set from ALS patients provided by the Sunnybrook Research Institute from Toronto and the used data preprocessing, Section 3 describes the proposed ML techniques: K-Nearest Neighbors, the Iterative Dichotomizer 3, Naive Bayes and Logistic Regression, for detection of ALS using orofacial gestures. In Section 4, we report the achieved experimental results based on computational experiments on the clinical dataset from ALS patients. The achieved results were analyzed, evaluated and interpreted. Finally in Section 5, we formulate some conclusions and outline further research directions.

2 DATASET DESCRIPTION AND PREPROCESSING

The Toronto NeuroFace dataset (Bandini et al., 2020) comprises data from 36 participants, including 10 with ALS, 15 who have experienced a stroke (post-stroke), and 11 healthy individuals forming the control group. The data for each group is organized into separate folders, each containing:

- **Videos:** recordings of orofacial actions in .avi format, with filenames indicating subject ID and action ID. Actions include: repeating the sentence "Buy Bobby a Puppy" (BBP_NORMAL), repeating the syllable /pa/ rapidly (DDK_PA), repeating the syllables /pataka/ rapidly (DDK_PATAKA), pursing the lips like blowing out a candle (NSM_BLOW), pressing lips like a kiss (NSM_KISS), maximum mandible opening (NSM_OPEN), smiling with closed lips (NSM_SPREAD), big smile (NSM_BIGSMILE), raising eyebrows (NSM_BROW).

- **Frames:** the extracted frames from the videos, saved in .jpg format, and utilized for the analyses presented in both the original article (Bandini et al., 2020) and in our work. Each frame retains the filename of the corresponding video. The frames used for analysis were extracted uniformly from each video based on a fixed frame rate, ensuring consistent representation across all actions and participants.
- **Landmarks_gt:** These files, formatted in .txt, encompass 68 points (or landmarks) delineating the facial features of each participant within the aforementioned frames. Each video corresponds to a .txt file bearing the same name. Within each file, the landmarks are presented in a standard CSV (comma-separated values) format, with the initial column denoting the annotated frame number. We employed these landmarks comprehensively, augmenting them with an extra 2D series and a set of 3D landmarks for each frame.
- **Bbox_gt:** These .txt files contain bounding boxes, which are rectangles encompassing all the points or the entire face, derived from the 68 landmarks. Each video corresponds to a .txt file bearing the same number. Within each file, the coordinates of the top-left (x_1, y_1) and bottom-right (x_2, y_2) corners are presented in CSV format, with the initial column indicating the annotated frame number. However, these data were not utilized in our study.
- **VideoInfoFile Spreadsheet:** file that contains additional information about videos, such as duration (in seconds), frame rate (fps), number of frames, format, and image size.
- **VID_DATASET_Clinical Information Spreadsheet:** file that describes the demographic (age, sex) and clinical information (duration of condition, etc.) of the specific groups.
- **SLP_Assessment Spreadsheet:** This document records the evaluations of two trained speech therapists (SLP1 and SLP2) who rated each video based on a scale from 1 (indicating normal functioning) to 5 (reflecting severe dysfunction) across various parameters including symmetry, range of motion (ROM), variability, and fatigue induced by orofacial movements. The total of these five scores was aggregated as ”All”.

To conduct this investigation, we examined various factors influencing the incidence of amyotrophic lateral sclerosis (ALS). Notably, race emerged as a significant factor, as highlighted by (Rechtman et al., 2015), while gender and age played comparatively lesser roles. According to the report from (Rechtman et al., 2015), 93% of ALS patients are of white ethnicity, with males comprising 60% of the cases.

The original dataset included age and gender information for participants but omitted race. To rectify this aspect, we had two options. The first involved manually attributing race based on participant images, a feasible task given the dataset's modest size of 36 participants. However, we opted for a more automated approach to ensure future scalability. Consequently, we utilized deep learning, specifically employing the DeepFace module for race detection.

For accurate race detection, we analyzed all images in the dataset. Results from analyzing all frames for each participant were saved in a .csv file, considering that single-frame analysis could yield inaccurate results. Subsequently, we collated the results from all files and identified the most frequently occurring race, validated against participant images, as the correct race.

Among the 10 ALS participants, 6 were identified as white, 3 as Hispanic Latino, and 1 as Asian, aligning with prior studies despite the limited sample size. Conversely, only 3 out of 10 ALS participants were male, with the majority of ALS patients being over 60 years old at the time of the study.

Since the original article on the Toronto NeuroFace dataset mentioned the use of the FAN model for landmark extraction, we applied the same model to our dataset. Both the 2D and 3D FAN algorithms (Bulat and Tzimiropoulos, 2017) were utilized on each frame.

Although we used the same model, our results diverged slightly from those of the original dataset. However, upon comparing variants against analyzed pictures, we found negligible discrepancies between the results and reality, attributing any differences to variations in the deep learning model across runs.

In our research, we used the 3D detection. A major advantage of using three-dimensional landmarks is that each one of the 68 orofacial landmarks is represented by three coordinates, which results in 204 features (compared to 136 in the two-dimensional case). This means that the data frame used has a total of 208 columns (204 landmark data, the age, race and the group of the subject) and 6229 rows (one for each frame).

Transitioning from simple files to a more robust database management system, we migrated all information into a MongoDB database. This process encompassed three types of files: participant data (updated from the previous step), original dataset landmarks, and our generated landmarks. Each participant data file was read and added as a document to the database, while corresponding landmarks from each

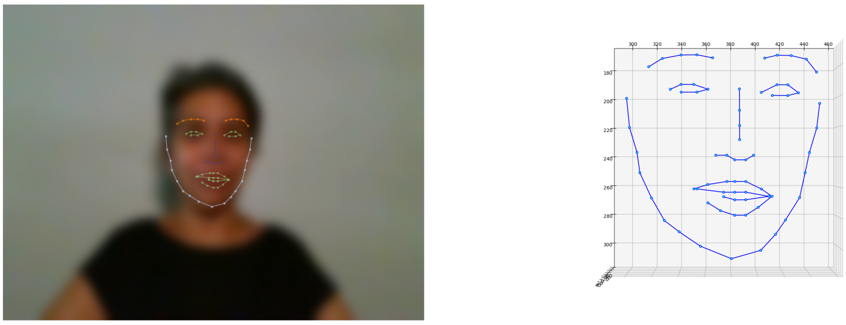

Figure 1: 2D and 3D orofacial point detection from a frame.png.

.txt file associated with the videos were also inserted into the database.

3 ML-BASED TECHNIQUES FOR DETECTION OF ALS USING OROFACIAL GESTURES

The proposed approach gathers information from the extended version of the Toronto NeuroFace dataset. The data is subjected to preprocessing, analysis, and the resulting attributes are stored in our database. Four models: K-Nearest Neighbors, the Iterative Dichotomizer 3, Naive Bayes, and Logistic Regression are trained using 80% of the data set. These models are trained to classify whether a patient has ALS based on the data provided. Afterwards, the models are tested on the remaining 20% of the data set and evaluated in terms of accuracy and prediction time. All frames from a single participant were used as the testing set, with the model trained on frames from the remaining participants. This ensured no overlap between training and testing data, allowing the evaluation to focus on the model's ability to generalize across different individuals rather than relying on participant-specific patterns. Figure 2 illustrates the overall implemented process.

3.1 K-Nearest Neighbors (KNN)

The K-Nearest Neighbors (KNN) algorithm classifies a point by checking the K nearest neighbors and assigning the most common class among them. It works best when data clusters are identifiable.

To use KNN, we converted all features to numerical values and plot them in an n-dimensional space, where n is the number of features. While effective for simple tasks, KNN has limitations. It requires significant computation for distance calculations and high memory usage, as it relies on the entire dataset for predictions, unlike logistic regression which uses specific records.

To implement the KNN algorithm, we used a function `euclidean_distance` that calculates the Euclidean distance. The *init* method sets the number of neighbors, usually to 5, and the *fit* method initializes the known data. To predict, the predict method uses the _predict helper to find the K closest points, determine their most common class, and return that class.

3.2 The Iterative Dichotomizer 3 (ID3)

The Iterative Dichotomizer 3 (ID3) algorithm constructs decision trees from labeled datasets. Each node in the tree represents an attribute, the links denote decision rules, and the leaves show outcomes. ID3 builds a decision tree from training data to classify new instances and can also be adapted for regression. To choose attributes for branching, ID3 calculates the entropy, measuring the quality of the splits. Zero entropy means complete homogeneity (all instances in the same class), while entropy of one indicates an even distribution among classes. The entropy is calculated in the method _entropy from the DecisionTree class, based on the following formula:

$$Entropy(S) = -\sum_{i=1}^{c} p_i log_2(p_i),$$

where S is the dataset, c is the number of classes in the dataset, in our case whether or not the subject has ALS and p_i is the probability of occurrence of class i in S. Since entropy measures the "lack of order", a lower value is better. However, leaf nodes with zero entropy can slow the algorithm for large datasets. To address this aspect, we used simultaneously the following stopping conditions: maximum tree depth reached, entropy change below a predefined threshold and node size falls below a minimum threshold. A `Node` class was designed for the decision tree structure with the following attributes:

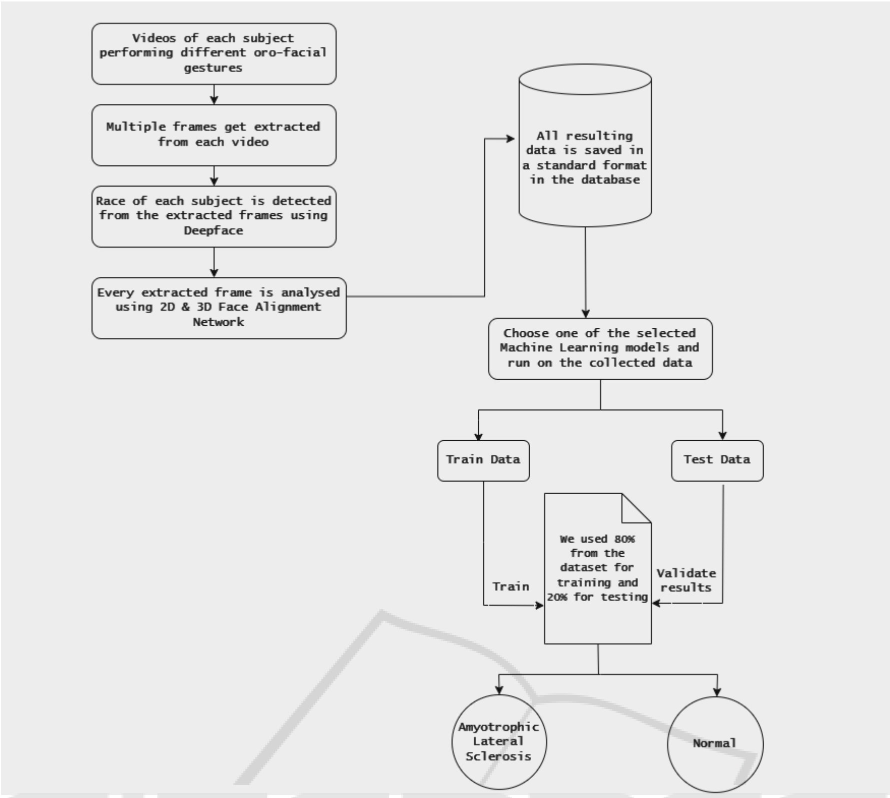

Figure 2: The developed architecture.

- `Feature`: Attribute for splitting.
- `Threshold`: Value dividing elements into two groups.
- `Left`: Indices of elements in the ”left” group.
- `Right`: Indices of elements in the ”right” group.
- `Value`: Majority category of elements in the node.

For leaf nodes, only `Value` is set, while non-terminal nodes use all attributes. The `is_leaf_node` method checks if a node is a leaf by verifying if `Value` is not None. The `DecisionTree` class manages the decision tree. Its `init` method sets stopping conditions and initializes the root node as None. We have two public methods: `fit` for training and `predict` for making predictions.

1. `fit` initializes the root node and builds the tree using `_grow_tree` method, updating node elements, checking stopping conditions, and splitting based on the best method.
2. `predict` traverses the tree to return the classification result for the input data.

3.3 Naive Bayes

Naive Bayes is a supervised classification model based on Bayes' Theorem. It calculates the conditional probability $p(C_l|x_1,x_2,...,x_n)$ for each class C_l given a vector $x = (x_1,x_2,...,x_n)$ of n features. Its key advantage is computational efficiency, especially with large datasets.

In our paper, we implemented this model in Python with the ”NaiveBayes” class, featuring:

1. The `fit` method trains the model by storing the number of samples and features, determining possible classes from unique values in y (the training results), and initializing the mean (self._mean), variance (self._var), and prior probabilities (self._priors). Then, it calculates the mean and variance of features for each class.
2. The `predict` method returns predictions for all elements. The _predict method classifies an element by calculating the product of probabilities for each feature, using the generalized Bayes Theorem. To handle very small probability products, it sums the logarithms of these probabilities.
3. The _prob_density method computes the probability of a feature indicating a final class using the Gaussian distribution.

3.4 Logistic Regression

Logistic Regression is used for binary classification tasks where the outcome is categorical with two possible values. It models the probability of an input belonging to a particular class. In Python, we implemented this model with a class that includes:

- `learning_rate` to adjust the speed of updating weights and bias, with low rates causing slow learning and high rates risking overshooting,
- `nr_iterations` for the number of training iterations,
- `weights` for feature weights,
- `bias` as the correction term.

The `init` method initializes these fields, and the `fit` method trains the model using data x and outcomes y. It stores the number of samples in `nr_samples` and features in `nr_features`. During training, predictions are made by multiplying input data by weights and adding the bias. These linear predictions are then converted into probabilities using the sigmoid function:

$$S(x) = \frac{1}{1+e^{-x}}.$$

The sigmoid function is crucial in logistic regression, converting linear combinations of input features into probabilities between 0 and 1. The `predict` method uses the trained model to predict outcomes for new data, following the same process as during training, and rounds results to 0 or 1.

4 EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

The aim of our paper was to develop an efficient method of detecting amyotrophic lateral sclerosis (ALS) disease using orofacial gestures. We used the Toronto NeuroFace dataset (Bandini et al., 2020) which contains data from 36 participants, including 10 with ALS, 15 who have experienced a stroke (post-stroke), and 11 healthy individuals who make up the control group. We compared four different ML techniques and how they affected our models. Specifically, we used the following ML algorithms: KNN, ID3, Naive Bayes and logistic regression. We divided the sample into two categories of data in order to assess the performance of the suggested strategy utilizing the Toronto Neuro Face dataset (Bandini et al., 2020). The first group is made up of the training samples, which consists of 80% of the total samples. The system will be tested, validated, and its accuracy will be verified using the remaining samples.

4.1 Implementation

The experimental study has been executed on one desktop PC running Windows 11 Pro 23H2, AMD Ryzen 7 7700 CPU, 32 GB RAM DDR5 RAM and one NVIDIA GeForce GTX 1060 with 6 GB GDDR5 VRAM. The algorithms and models were implemented in Python programming language. We have also used the DeepFace library for the extraction of other relevant data in the prediction of amyotrophic lateral sclerosis. Specifically, we used this library to detect a person's age, gender, current emotion, and race from images.

4.2 Performance Evaluation

Assessment of classifier performance involves the use of evaluation metrics. In our study, we used both the confusion matrix and the classification report that shows the accuracy, precision, recall, and F1-score.

The confusion matrix organizes actual class instances along rows and predicted class occurrences along columns. It outlines four potential outcomes: True Positives (TP), i.e. the number of instances accurately classified as belonging to the positive class; True Negatives (TN), i.e. the number of instances accurately classified as belonging to the negative class; False Positives (FP), i.e. the number of instances that are incorrectly classified as belonging to the positive class, and False Negatives (FN), i.e. the number of instances that are incorrectly classified as belonging to the negative class. For further details, see (Jayaswal, 2021).

Accuracy is a metric that measures the frequency with which a ML model correctly predicts the outcome. Accuracy is computed based on the following formula:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision can be seen as a metric that reflects the exactness of a classifier. It is calculated for each class as the ratio of true positives to the sum of true positives and false positives.

Recall is a metric that measures the thoroughness of a classifier, indicating its ability to correctly identify all positive instances. These metrics are computed according to the following formulas:

$$Precision = \frac{TP}{TP+FP}, \quad Recall = \frac{TP}{TP+FN}$$

F1-Score represents the harmonic mean of precision and recall, taking into account both false positives and false negatives.

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall}.$$

4.3 Experimental Results

Table 1 illustrates the results achieved by our considered ML models for detection of ALS disease using orofacial gestures on the Toronto NeuroFace dataset (Bandini et al., 2020). For each considered ML model we provide the the accuracy, precision, recall, F1-score, training time and prediction time. Both computational times were measured in seconds.

Both traditional ML ID3 and Naive Bayes algorithms achieved the best results, achieving an accuracy of 100%. But the training time in case of ID3 is much higher than the corresponding training time of the Naive Bayes. Therefore, the Naive Bayes model seems to be the better one based on the accuracy results and computational times.

KNN has the lowest accuracy and the corresponding prediction time is high, therefore, we can conclude that this model is the worst of the considered ML models. The confusion matrix of this model is illustrated in Figure 3, and the classification of the outcomes into the four categories is: $TN = 1$, $FN = 1$, $TP = 4$ and $FP = 1$.

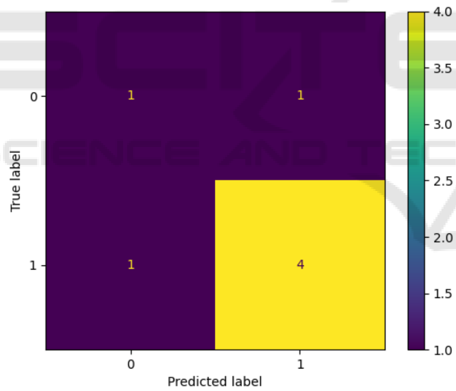

Figure 3: Confusion matrix for KNN.

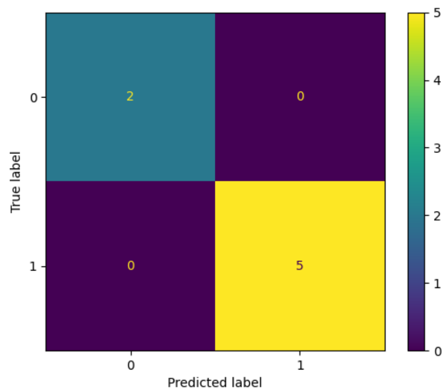

Figure 4: Confusion matrix for ID3.

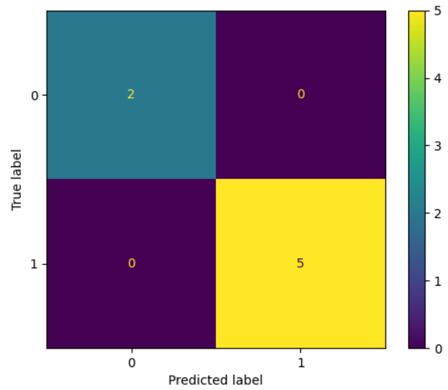

Figure 5: Confusion matrix for Naive Bayes model.

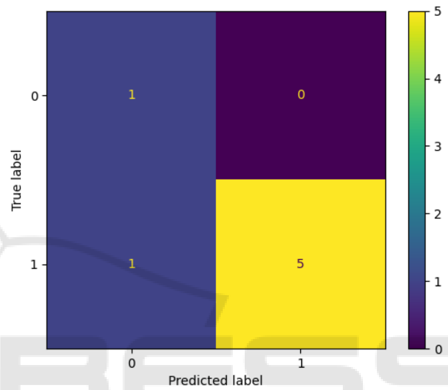

Figure 6: Confusion matrix for Logistic regression model.

ID3 has perfect accuracy but the training time is the worst from the investigated models. This model has a very good prediction time. The confusion matrix of this model is illustrated in Figure 4, and the classification of the outcomes into the four categories is: $TN = 2$, $FN = 0$, $TP = 5$ and $FP = 0$.

Naive Bayes model performs best for our dataset and has the higher accuracy. This model has the shortest training time and acceptable prediction time. The confusion matrix of this model is illustrated in Figure 5, and the classification of the outcomes into the four categories is: $TN = 2$, $FN = 0$, $TP = 5$ and $FP = 0$.

Logistic Regression has an accuracy of 85% and reasonable training and prediction times. The confusion matrix of this model is illustrated in Figure 6, and the classification of the outcomes into the four categories is: $TN = 1$, $FN = 1$, $TP = 5$ and $FP = 0$.

Table 1: Machine learning model's performance.

ML model	Accuracy	Precision	Recall	F1-score	Training time	Prediction time
KNN	71.42%	0.5	0.5	0.5	0.0029	17.8924
ID3	100%	1	1	1	85.4265	0.0025
Naive Bayes	100%	1	1	1	0.0025	0.0231
Logistic Regression	85.71%	1	0.5	0.66	0.4051	0.0023

5 CONCLUSIONS

In this paper, we proposed using machine learning approaches to diagnose the amyotrophic lateral sclerosis by using orofacial gestures.

Our results reveal that both traditional ID3 and Naive Bayes ML algorithms obtained the best results, achieving an accuracy of 100%. The training time in case of ID3 is much higher than the corresponding training time of the Naive Bayes. Therefore, we can conclude that the Naive Bayes algorithm obtained the best accuracy within a short computational time.

In the future, we plan to collaborate with medical institutions to expand the dataset by collecting videos from a larger and more diverse pool of patients. This will enhance the dataset's representativeness and support the development of more accurate and scalable prediction models using ML algorithms and DL techniques. As well, we plan to develop a web application accessible to anyone interested in assessing the presence of ALS symptoms. Such an application holds the potential to revolutionize screening and diagnosis efforts, leading to earlier detection of ALS.

Our research marks a major progress in the early detection of ALS, and we do hope that these findings will encourage the use of ML approaches in the detection of ALS disease using orofacial gestures.

REFERENCES

Arthur, K. C., Calvo, A., Price, T. R., Geiger, J. T., Chio, A., and Traynor, B. J. (2016). Projected increase in amyotrophic lateral sclerosis from 2015 to 2040. *Nature communications*, 7(1):12408.

Aslam, N., Khan, I. U., Bashamakh, A., Alghool, F. A., Aboulnour, M., Alsuwayan, N. M., Alturaif, R. K., Brahimi, S., Aljameel, S. S., and Al Ghamdi, K. (2022). Multiple sclerosis diagnosis using machine learning and deep learning: challenges and opportunities. *Sensors*, 22(20):7856.

Bandini, A., Rezaei, S., Guarín, D. L., Kulkarni, M., Lim, D., Boulos, M. I., Zinman, L., Yunusova, Y., and Taati, B. (2020). A new dataset for facial motion analysis in individuals with neurological disorders. *IEEE Journal of Biomedical and Health Informatics*, 25(4):1111–1119.

Bulat, A. and Tzimiropoulos, G. (2017). How far are we from solving the 2d & 3d face alignment problem?(and a dataset of 230,000 3d facial landmarks). In *Proceedings of the IEEE international conference on computer vision*, pages 1021–1030.

Chakraborty, C., Bhattacharya, M., Pal, S., and Lee, S.-S. (2023). From machine learning to deep learning: An advances of the recent data-driven paradigm shift in medicine and healthcare. *Current Research in Biotechnology*, page 100164.

Cosma, O., Macelaru, M., Pop, P. C., Sabo, C., and Zelina, I. (2021). A comparative study of the most important methods for forecasting the ict systems vulnerabilities. In *Computational Intelligence in Security for Information Systems Conference*, pages 224–233. Springer.

Govindu, A. and Palwe, S. (2023). Early detection of parkinson's disease using machine learning. *Procedia Computer Science*, 218:249–261.

Jayaswal, V. (2021). Performance metrics: Confusion matrix, precision, recall, and f1 score. towards data science.

Khan, A. A., Laghari, A. A., and Awan, S. A. (2021). Machine learning in computer vision: a review. *EAI Endorsed Transactions on Scalable Information Systems*, 8(32):e4–e4.

Madanian, S., Chen, T., Adeleye, O., Templeton, J. M., Poellabauer, C., Parry, D., and Schneider, S. L. (2023). Speech emotion recognition using machine learning—a systematic review. *Intelligent systems with applications*, page 200266.

Meshram, V., Patil, K., Meshram, V., Hanchate, D., and Ramkteke, S. (2021). Machine learning in agriculture domain: A state-of-art survey. *Artificial Intelligence in the Life Sciences*, 1:100010.

Rechtman, L., Jordan, H., Wagner, L., Horton, D. K., and Kaye, W. (2015). Racial and ethnic differences among amyotrophic lateral sclerosis cases in the united states. *Amyotrophic Lateral Sclerosis and Frontotemporal Degeneration*, 16(1-2):65–71.

Sudharsan, M. and Thailambal, G. (2023). Alzheimer's disease prediction using machine learning techniques and principal component analysis (pca). *Materials Today: Proceedings*, 81:182–190.