# Classification of Amyotrophic Lateral Sclerosis Patients Using Speech Signals

Om Prakash Kurmi, Manasi Gyanchandani, Nilay Khare and Arvind Pillania



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1st Om Prakash Kurmi
*Computer Science and Engineering*
*Maulana Azad National Institute Of Technology*
Bhopal,India
kurmiom17@gmai.com

2nd Manasi Gyanchandani
*Computer Science and Engineering*
*Maulana Azad National Institute Of Technology*
Bhopal,India
mansigyanchandani@manit.ac.in

3rd Nilay Khare
*Computer Science and Engineering*
*Maulana Azad National Institute Of Technology*
Bhopal,India
nilay.khare@rediffmail.com

4th Arvind Pillania
*Computer Science and Engineering*
*Maulana Azad National Institute Of Technology*
Bhopal,India
arvind.pillania@gmail.com

***Abstract*—The neurological condition known as Amyotrophic lateral sclerosis (ALS), which progresses and is irreversible,starts with early signs including speech and swallowing difficulties. The early acoustic presentation of speech and voice problems can be difficult to identify for both human experts and automated systems. In order to address this challenge we developed a non-invasive machine learning model for ALS diagnosis, this study proposes a voice assessment approach for an automatic system that can distinguish between healthy individuals and ALS patients. Specifically, our work focuses on analyzing continuous production of the vowel sounds /a/ and /i/using a feature extraction technique known as the wavelet time scattering transform which is not yet explored for ALS disease detection. In order to select the most relevant features from the extracted set of 84 features, we employed a correlation-based feature selection approach, using which we identified features with a correlation coefficient lower than 0.75. The selected features were then subjected to principal component analysis (PCA) to reduce the dimensionality of the dataset, resulting in a final set of 10 features.. The resulting PCA-based model achieved an accuracy of 84.2% using support vector machine (SVM) for classification, with a sensitivity and specificity of 77.8% and 90%, respectively.**

***Index Terms*—Amyotrophic lateral sclerosis(ALS),sustained vowel phonation, wavelet time scattering transform , non-invasive**

## I. Introduction

Amyotrophic lateral sclerosis (ALS) is a lethal condition that impacts both the upper and lower motor neurons, resulting in degeneration of neurons. The disease comes in two basic forms: bulbar and spinal, each with a unique pattern of onset. Speaking and swallowing problems are typically the first signs of the Bulbar form of ALS [1].Almost 80% of people with ALS experience dysarthria at some stage, a speech impairment caused by neurological disorders [2]. Due to the lack of precise disease indicators, clinical observations are now the primary ALS diagnosis technique. Due to the unclear diagnostic criteria, the process can take up to 12 months [3] . In order to identify early indications of neurological illnesses, objective evaluations of voice and speech signals have become more popular in recent years [4,5].This is because speaking requires a series of intricate actions that need to be coordinated precisely and timely, making it extremely susceptible to disturbances of the neurological system [6,7].The analysis of voice and speech acoustics has emerged as a possible biomarker for the remote monitoring and diagnosis of individuals with ALS [8,9]. One benefit of employing voice/speech signals is that recordings can be made using a smartphone or tablet at the patient's home, eliminating the requirement for a clinical set up. Our research is built around these observations.Our research aims to develop an automated system to detect bulbar abnormalities in patients with ALS. We opted to utilize the Sustained Vowel Phonation (SVP) dataset because it offers a consistent and uniform collection for voice data for analysis. SVP test was useful to identify people with Parkinson's disease and obtained great results [10]. Our study is guided by these goals and motives. The phonatory speech subsystem is typically assessed using the sustained phonation task, which may evaluate a variety of voice attributes as pitch, volume, and hoarseness [11]. Although through extended vowels are frequently used in clinical settings, they could miss some vocal irregularities in continuous speech [12].Early studies have also shown that ALS patients may continuously phonate with normal vocal quality despite having abnormal voice acoustics. The SVP test can also be used to check for glottic narrowing, a symptom of ALS. These components support SVP testing, the automated ALS patient screening technique employed in our study . The SVP test is a frequently employed technique for identifying a number of neurological conditions, including Parkinson's, Alzheimer's, and Dystonia. For example, studies have demonstrated that a classifier based on features retrieved from the SVP test can reliably identify between Parkinson's disease patients and healthy persons with approximately 99% overall classification accuracy [13]. However just a few studies have particularly looked into the application of the SVP test for

ALS screening but it was observed that SVP test when used for classification after using proper feature extraction techniques have given great results [10]. SVP and other speech tests have been employed in some earlier studies to classify dysarthria, while diadochokinetic activities or running speech tests has been mostly used to identify ALS. Kinematic sensors have also been used in research, however they are intrusive and less appealing than non-invasive speech testing. The goal of this study is to explore a new feature extraction technique to extract features and create a classifier that can successfully identify ALS patients using sustained phonation testing. While the /a/ vowel is the conventional vowel utilized in this test, we have chosen to include the /i/ vowel also in our analysis due to the encouraging findings from other research [14].

Our research aims to explore how acoustic analysis techniques can be used to classify voice data. The paper is organized as follows: Section 2 provides an overview of the existing literature on voice data classification and previous studies, while Section 3 presents a critical analysis of methodologies and techniques. Section 4 and section 5 presents our experiments and experimental results, including our evaluation of classifiers and feature selection techniques, and the influence of various factors on classification accuracy. Finally, in Section 6, we summarize our findings and discuss potential future research directions.

## II. Related Work

The bulbar system plays a crucial role in speech production, but ALS can damage it and cause speech impairments.Different subsystems of the bulbar system are responsible for respiratory, phonatory, articulatory, and resonant characteristics.Machine learning and signal processing techniques are being explored for classifying ALS patients based on physiological data and acoustic features.

For instance, a study by M. Vashkevich and Yu. Rushkevich proposed the use of acoustic analysis of sustained vowel phonations of a and i for the classification of ALS patients .In this paper they used various feature extraction techniques concatenated them in order to get the best result. Primitive feature extraction techniques like MFCC, Jitter, Shimmer,HNR and many more were used.LASSO and Relief were also used as feature selection techniques [15].

Jun Wang conducted a study that showed the possibility of identifying ALS automatically through pre-symptomatic speech samples. The study yielded promising results when using data from different individuals, and incorporating articulatory information can enhance the detection performance. The study employed cross-validation and k-fold techniques [16].

Regarding related work on wavelet-based feature extraction N.mei suggested a two-stage method that evaluates the heart sounds' quality first before extracting features and classifying them using a wavelet scattering transform (WST). The spectral flatness and kurtosis of the heart sounds are taken into consideration during the quality evaluation utilizing a decision tree-based approach. Then, high-dimensional characteristics are extracted from the heart sounds using the WST. Principal component analysis (PCA) is used to minimize the collected features before training a support vector machine (SVM) classifier [17].

The wavelet scattering technique is used by Liu zem in his work to categorize electrocardiogram (ECG) beats. He employed wavelet time scattering transform to analyze the ECG data, which is a non-invasive diagnostic method for determining the electrical activity of the heart. He further employed the wavelet scattering transform to extract characteristics from ECG beats, and then a support vector machine (SVM) classifier to categorize the beats. Using a publicly accessible ECG dataset, they assess their method's performance and compare it to other cutting-edge techniques. The findings demonstrate that the wavelet scattering transform-based technique excels in terms of sensitivity and specificity and achieves high classification accuracy [18].

## III. Proposed Methodology

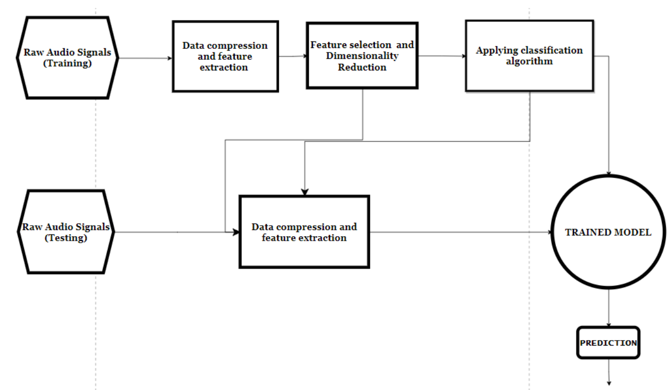


Fig. 1: Workflow of the model

The aim of this study is to create a precise model that can classify and differentiate between individuals who have Amyotrophic Lateral Sclerosis (ALS) and those who do not, in order to diagnose presence of the disease.To achieve this goal, several steps were undertaken. Firstly, data compression was performed to create a lightweight model that could produce the results with less computational power. Following this, feature extraction was performed using the Wavelet Time Scattering (WTST) transform, a relatively new technique in this field. This method resulted in the extraction of 84 features, which had the potential to cause overfitting. To address the above mentioned issue, we adopted the Correlation-based Selection (CFS) approach to identify a subset of features that exhibit a correlation coefficient of less than 0.75, resulting in the selection of 50 optimal features. In order to further reduce the dimensionality of the data, we employed Principal Component Analysis (PCA), a widely used technique known for its resilience to noise and ability to effectively handle outliers.. Lastly, classification algorithms were used to classify the patients using Support Vector Machine (SVM).

Overall, the proposed methodology involved a series of rigorous and sophisticated steps to ensure that a precise and simple classification model is developed. The combination of data compression, feature extraction, feature selection, dimensionality reduction and classification using machine learning and deep learning models provided a comprehensive approach that yielded promising results for distinguishing between ALS and healthy patients

### *A. Data Compression using Pydub*

Pydub is a Python library designed for manipulating audio files in various formats. Its functionality includes reading, editing and writing audio files, and it also provides the ability to compress audio data using various codecs. Data compression is a crucial process in reducing storage requirements and bandwidth usage while maintaining the quality of the data. Several compression algorithms exist for compressing audio data. In this study, the compression technique used was resampling the data with a new sampling rate of 22050 and adjusting the bit depth to 16. This approach was adopted to improve the cost-effectiveness of the model, considering that the feature extraction techniques employed in this study required a significant amount of computational resources.

### *B. Wavelet Time Scattering Transform*

Wavelet Time Scattering Transform can capture time-frequency information in signals. This transform decomposes the signal using a set of wavelet filters at multiple scales, similar to the original scattering transform, but also incorporates time-translation invariance by applying the wavelet filters to multiple time-shifted versions of the signals. The Wavelet Time Scattering Transform (WTST) has emerged as a highly effective tool in signal processing for various applications, including speech recognition, image classification, and medical image analysis. One of the most significant advantages of the WTST is its ability to capture time-frequency information in signals while maintaining translation invariance, making it particularly useful in most applications. In speech recognition, the WTST has been employed to extract features from speech signals for a range of tasks such as speaker identification, emotion recognition, and speech recognition, leading to improved performance in these tasks.Na Mei and Hongxia Wang in their work showed that wavelet scattering performed better than traditional Motifs, MFCCs, Motifs and temporal when SVM was used for classification [17]. This motivated our research aim to leverage the potential of the WTST to develop a classification model to distinguish between ALS patients and healthy individuals, an area that has not been explored using this approach.We utilized the Wavelet Time Scattering (WTST) technique to extract features from audio files of ALS patients, which were labeled as level 0. The same technique was applied to healthy subjects, and the extracted features were labeled as level 1. Concatenating both the lists of features generated two levels for our classification model. The resulting feature matrix contained 84 columns, representing the features generated by WTST.We further applied feature selection techniques to avoid overfitting and improve the performance of our classification model.The analysis of wavelet features graphical plot showed distinct differences between ALS and healthy subjects in terms of pitch fluctuation.ALS patients had a significant loss of throat muscle strength, resulting in noticeable fluctuations in their pitch. Healthy subjects sustained their pitch better with fewer fluctuations.These findings may have implications for early detection and diagnosis of ALS using non-invasive methods. The Wavelet Time Scattering Transform (WTST) can be formulated mathematically as follows: First, the signal is convolved with a mother wavelet $\psi(t)$ and a scaling function $\varphi(t)$, both of which are functions of time. This results in a set of wavelet coefficients

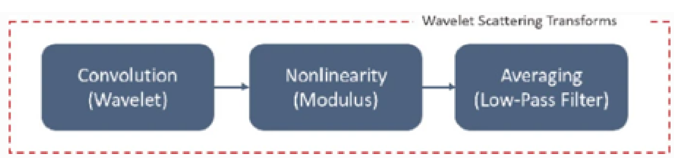


Fig. 2: Wavelet Scattering Transform Steps

$$W_x(\alpha, \beta) = \langle x, \psi_{\alpha,\beta}(t) \rangle \quad (1)$$

$$V_x(\alpha, \beta) = \langle x, \varphi_{\alpha,\beta}(t) \rangle \quad (2)$$

where $\alpha$ and $\beta$ are scale and time shift parameters, respectively, and $\langle , \rangle$ denotes inner product. Next, the wavelet coefficients are convolved with another set of wavelets, yielding a second set of wavelet coefficients:

$$W_{2x}(\alpha, \beta, \gamma) = |Wx \cdot \psi_\gamma| \cdot \varphi_{\alpha,\beta} \quad (3)$$

$$V_{2x}(\alpha, \beta, \gamma) = |Wx \cdot \varphi_\gamma| \cdot \varphi_{\alpha,\beta} \quad (4)$$

where $*$ denotes convolution, and $|\,|$ denotes the modulus operation. This process can be repeated iteratively to obtain higher-order wavelet coefficients. Finally, the resulting coefficients are aggregated to obtain the scattering coefficients, which capture the time-frequency structure of the signal.

$$S_x(\alpha, \beta_1, ..., \beta_n) = |W_{n,x} * ... * W_{2,x} * W_x| \cdot \varphi_{\alpha,\beta_1,...,\beta_n} \quad (5)$$

where $n$ is the order of the scattering transform and $\beta_1, ..., \beta_n$ are time shifts.

### *C. Correlation Based Feature Selection*

Correlation analysis-based feature selection removes highly correlated features to improve model performance and reduce dimensionality. It prevents overfitting by eliminating redundant features.In this study, we applied wavelet time scattering transform to generate 84 features for our analysis. To address the issue of overfitting, we experimented with different threshold values of correlation coefficient and found that a correlation coefficient below 0.75 yielded the best results. Consequently, we selected 50 optimal features based on this criterion.We used these 50 features in our analysis. Our findings indicate that using all 84 features resulted in suboptimal results, presumably due to the large number of features. Overall, our results suggest that selecting a subset of relevant features based on the correlation coefficient threshold can improve the performance of our analysis.The study used a heatmap of correlation coefficients to identify redundant features by analyzing the relationship between generated features, with the aim of improving the analysis by eliminating highly correlated features that do not significantly contribute to the analysis.

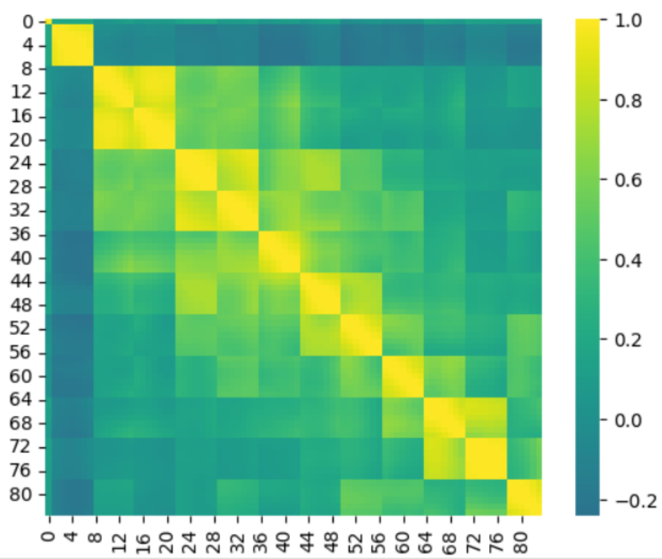


Fig. 3: Heatmap of pairwise correlation coefficients

The heatmap revealed a stronger correlation as yellow color and weaker corellation as green color shades, The analysis indicates that more than 50% of the features meet the 0.75 correlation threshold.

### D. Dimensionality Reduction

This study utilized Principal Component Analysis (PCA) to reduce the dimensionality of a dataset consisting of 84 features selected using a correlation-based feature selection technique. The aim was to create a more efficient and accurate classification model for medical diagnosis. The optimal number of principal components was determined to be 10, resulting in improved interpretability, computational efficiency, and model accuracy. PCA was found to be a robust technique that could handle noisy and variable data.. Centering the data, calculating the covariance matrix, calculating the eigenvectors and eigenvalues of the covariance matrix, sorting the eigenvectors by the corresponding eigenvalues, selecting the k eigenvectors corresponding to the k largest eigenvalues to form the reduced subspace, and projecting the data onto the reduced subspace are the steps involved in PCA.

## IV. Description of Experiments and Database:

### A. Database

The Republican Research and Clinical Center of Neurology and Neurosurgery in Minsk, Belarus, provided the voice database utilized in this investigation. The collection contains recordings of prolonged vowel sounds with comfortable pitch and volume from 64 speakers, including 33 healthy controls and 31 people with ALS. The average age of ALS patients in men was $61.1 \pm 7.7$ and in women it was $57.3 \pm 7.8$.. The recordings were done using cellphones and common headphones, and they were stored as 16-bit uncompressed PCM files with a 44.1 kHz sampling rate. [15]

TABLE I: Collected Voice Dataset Information

| Parameters | Values | Description |
|---|---|---|
| Vowel Signal | 128 | 64 of vowel $/i/$ and $/a/$ |
| People | 64 | Almost balance (52% : 48%) |
| Healthy people | 33 (13 M and 20 W) | Age range: $(34, 80)$ |
| ALS patients | 31 (17 M and 14 W) | Age range: $(39, 70)$ years. |

### B. Classifier Validation

For classification and regression problems, Support Vector Machines (SVMs) have become a strong machine learning technique.due to its ability to handle high-dimensional data In our research, we employed SVM as a classification algorithm to classify the extracted data. One of the key advantages of SVM is its robustness to outliers ,this makes it appropriate for a variety of applications.. However, the performance of SVM is highly dependent on the choice of kernel and hyperparameters, necessitating careful tuning of these parameters to optimize its performance on our dataset. In our experiments, we found that the regularization parameter C played a crucial role in achieving optimal SVM performance. C manages the trade-off between reducing training error and increasing testing error., and we found that a value of C=1 yielded the best results when combined with the ‘rbf’ kernel. The choice of kernel function, which determines the type of decision boundary that the SVM model will learn, was also an important hyperparameter. We experimented with different kernel functions such as ’poly’ and ’linear’ ,but found that the ’rbf’ kernel provided the best performance in our work, possibly due to our dataset’s non-linear nature. Additionally, we experimented with different values of the gamma parameter, which is used in the ‘rbf’ kernel and controls the width of the kernel function. We found that gamma=1 was optimal for our dataset. Finally, we utilized the test data to evaluate the performance of our SVM model after successfully training it. First we aimed to classify a dataset using features extracted from wavelet time scattering transform. Initially, we used a feature set consisting of 84 features and achieved an accuracy of 78.9%, with sensitivity and specificity values of 80% and 77.8%, respectively. We then employed a CSF-based feature selection method to identify an optimal subset of 50 features, which resulted in an improvement in accuracy to 80%, while sensitivity and specificity values increased to 90% and 70%, respectively.To further improve the performance of the classification model, we applied PCA to reduce the dimensionality of the dataset . As a result, the feature set was reduced to 10 features, and the resulting model showed an increase in accuracy, sensitivity, and specificity values to 84.2%, 90%, and 77.8%, respectively

Accuracy(Ac):$\frac{TP+TN}{TP+TN+FP+FN}$

Sensitivity(Sen): $\frac{TP}{TP+FN}$.
Specificity(Spe): $\frac{TN}{TN+FP}$.
where true positive,true negative,false negative and false positive are represented by TP,TN,FN,FP respectively.

Our results suggest that the combination of CSF-based feature selection and PCA can effectively enhance the performance of classification models based on features extracted from wavelet time scattering transform

## V. Simulation and Results

### A. Simulation

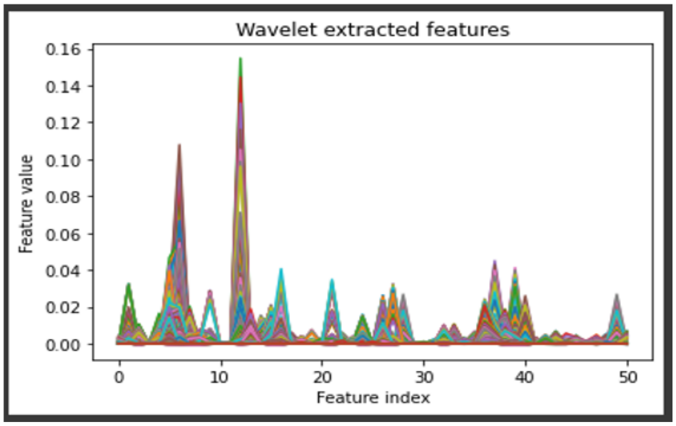


Fig. 4: Wavelet Scattering Transform of Healthy Patients

X axis of the plot represents feature index while y axis represents feature value of healthy patients.It can be easily observed that the fluctuation in the feature index implies the change in pith and frequency of the speech spectrum .

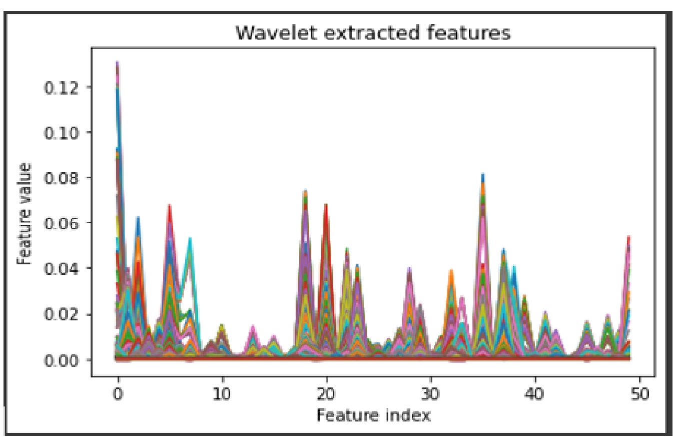


Fig. 5: Wavelet Scattering Transform of ALS Patients

The analysis of wavelet features showed distinct differences between ALS and healthy subjects in terms of pitch fluctuation .ALS patients had a significant loss of throat muscle strength, resulting in noticeable fluctuations in their pitch resulting in a very inconsistent feature value at different feature indexes.Healthy subjects sustained their pitch better with fewer fluctuations.With these plots highlighted differences can be observed on impact of ALS in speech production.

### B. Obtained Results

TABLE II: Calculation of Model parameters

| Model Parameters | SVP Test(a) | SVP Test(i) | SVP Test(a and i) |
|---|---|---|---|
| 1.Accuracy | 83.33% | 85.7% | 84.2% |
| 2.Sensitivity | 52% | 68.7% | 90.0% |
| 3.Specificity | 97.3% | 96.3% | 77.8% |

In our work we have calculated model parameters for acoustic analysis for subjects with vowel phonation of a ,and for i. Further we have calculated the same for a and i together and got above model parameters.The findings obtained from our study indicate that the Wavelet-based Time Scattering Transform (WTST) feature extraction technique can be effective for speech-related data.Our results suggest that WTST can be used as a standalone technique or in conjunction with other feature extraction techniques to achieve superior outcomes.These outcomes support the notion that WTST can be a valuable tool for researchers and practitioners in the speech and audio processing domain, enabling them to optimize feature selection and improve the accuracy of their models.

Overall, these findings provide evidence that WTST can be a useful technique for speech-related data and offer insights for future research in this field.

### C. Comparison wih other Models

In this section we are analyzing our work with respect to other similar works in the field of ALS disease classification based on speech signals.Although running speech was used predominantly as speech signals for this purpose but researchers also used vowel phonation for this purpose and obtained good results [15].

TABLE III: Compaarison of Proposed model

| **Contributors** | **R.Norel [8]** | **M.Kim [19]** | **Proposed Model** |
|---|---|---|---|
| Feature Extraction Technique | Open-SMILE toolkit | filterbank energies + its deltas | WTST+CFS |
| Database | 67 ALS, 66 HC on running speech | 13 ALS and 13 HC on running speech | 31 ALS, 33 HC, SVP test |
| Classifier | Linear SVM | CNN | Radial Basis SVM |
| Model Parameters | for male: Ac=79%, Sen=76%, Spe=70%; for female: Ac=83%, Sen=78%, Spe=88% | Ac=76.2%, Sen=71.5%, Spe=80.9% | Ac=84.2%, Sen=90.0%, Spe=77.8% |

The research conducted by M. Vashkevich on the detection of ALS using sustained vowel phonation has shown promising results. However, the study involved the use of multiple feature extraction techniques, and concatenation was used to obtain the final results [15]. In contrast, the model proposed in our research utilizes only one feature extraction technique, yet we were able to achieve comparable results.

The significance of our model lies in its simplicity and effectiveness in detecting ALS. Furthermore, we were able to outperform the RelieFF model used in Vashkevich's research using our model [15].This indicates the potential of WTST as a useful tool for researchers working on speech signals.

Our findings suggest that future research on speech signals can explore the combination of WTST with other feature extraction techniques to yield even better results in detecting ALS. Overall, the simplicity and effectiveness of our model demonstrate the potential for WTST to be a valuable tool in detecting ALS and other speech-related disorders.

## VI. Conclusion

This research presents an unexplored approach using wavelet time scattering transform for diagnosing of Amyotrophic Lateral Sclerosis (ALS) using machine learning on real-world audio signals. Our proposed model is non-invasive that offers a promising alternative to current diagnostic methods that can be problematic and time-consuming for patients. We used wavelet time scattering transform for feature extraction and PCA for dimensionality reduction , followed by careful model tuning to obtain accuracy ,specificity and sensitivity of 84.2%,77.8% and 90% respectively.Future research in audio signal processing could explore combining multiple feature extraction techniques with wavelet time scattering transform to enhance classification performance.This approach may lead to a more comprehensive representation of the signal and provide a more robust and reliable classification model.

## Acknowledgment

We are grateful to the Republican Research and Clinical Center of Neurology and Neurosurgery in Minsk, Belarus for generously sharing their dataset with the wider community. Their selfless act is a testament to their commitment to advancing knowledge and improving healthcare outcomes. We extend our sincere appreciation for their valuable contribution.

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