Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)
Volume 7-Issue 1, January 2024
Paper: 66

Comparative analysis on Classification efficiency of Deep Learning Models on Amyotrophic Lateral Sclerosis Patients using speech signals

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

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

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

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

***Abstract*—Amyotrophic lateral sclerosis (ALS) is an irre- versible neurological disorder that affects speech and swallowing abilities, makeing it difficult for both human specialists and automated technology to detect vocal problems in ALS patients at an early stage. Our research suggests non-invasive deep learning models for speech assessment that can tell healthy people apart from ALS patients to address this problem. In order to detect ALS, we evaluate the continuous production of the vowel sounds /a/ and /i/ using the wavelet time scattering transform. Our study compares the effectiveness of four different deep learning models: Deep Neural Networks (DNN), Long Short- Term Memory (LSTM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) for categorization. Our findings indicate that DNN performs the best with an accuracy of 80.4%, while CNN also achieves similar results.**

***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].At some point, about 80% of ALS patients develop dysarthria, a speech disability brought on by neurological conditions. [2]. Clinical observations are now the main ALS diagnosis method but due to the lack of specific disease indicators,the procedure can take up to a year due to the ambiguous diagnostic criteria. [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 due to the fact that speaking needs a number of complex motions that must becoordinated precisely and on time, making it incredibly vul- nerable to neurological system disruptions. [6,7].A potential biomarker for the remote monitoring and diagnosis of ALS patients is the examination of voice and speech acoustics. [8,9]. One advantage of utilizing voice/speech signals is that patient-home recordings may be done using a smartphone or tablet, doing away with the need for a clinical setup. These observations form are the foundation of our study.Our study attempts to create an automated method that can identify bulbar anomalies in ALS patients. Sustained Vowel Phonation (SVP) dataset offers a consistent and homogeneous collection of voice data for study. SVP test produced excellent findings and was helpful in identifying those with Parkinson's disease. [10]Our research is motivated by these aims and objectives. The sustained phonation task is frequently used to test the phonatory speech subsystem and may examine a number of vo- cal characteristics, including pitch, loudness, and hoarseness. [11]. Although through extended vowels are frequently used in clinical settings, they could miss some vocal irregularities in continuous speech [12].Early research has also demonstrated that individuals with ALS are still capable of phonating continuously with normal vocal quality despite having aberrant voice acoustics. The glottic narrowing sign of ALS can also be looked for with the SVP test. The automated ALS patient screening method used in our investigation, SVP testing, is supported by these elements. Parkinson's, Alzheimer's, and dystonia are just a few of the neurological disorders that may be diagnosed with the SVP test. For instance, research have shown that a classifier based on data collected from the SVP test can accurately and consistently distinguish between people with Parkinson's disease and healthy people, with an over- all classification accuracy of almost 99%. [13].Early studies used SVP and other speech tests to categorize dysarthria,

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7-Issue 1, January 2024
Paper: 66

but diadochokinetic activities or running speech tests were mostly used to diagnose ALS. Though less attractive than non-invasive speech testing, kinematic sensors have also been employed in studies. In order to accurately identify ALS patients via prolonged phonation testing, the aim of this work is to investigate a novel feature extraction method, develop and compare deep learning models as classifiers, and then extract features. Although the standard vowel used in this test is the /a/ vowel, we have opted to include the /i/ vowel in our analysis because of the good results from previous studies. [14].

Our research aims to explore how acoustic analysis tech- niques 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 pre- vious 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 is essential for producing speech, but ALS can harm it and affect speech. The bulbar system's respiratory, phonatory, articulatory, and resonant properties are controlled by many subsystems. On the basis of physiological information and auditory characteristics, machine learning and signal processing approaches are being investigated for the classification of ALS patients.

For instance, In [15] researchers proposed the use of acous- tic 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 tech- niques like MFCC, Jitter, Shimmer,HNR and many more were used.LASSO and Relief were also used as feature selection techniques [15].

A research by Jun Wang demonstrated the potential for diagnosing ALS automatically using pre-symptomatic speech samples. When using data from various subjects, the study Novotny´ presents a study on the effectiveness of deep neural network (DNN) based speech signal enhancement for improv- ing robustness of speaker recognition systems. He focussed on the use of DNNs for reducing noise and reverberation in speech signals and their impact on speaker recognition performance.The authors evaluate the performance of various DNN-based enhancement methods on a dataset of speech signals with different levels of noise and reverberation.He further demonstrated that DNNs is capable of learning from unstructured data making them ideal for applications such as computer vision and natural language processing [21]

produced encouraging results, and including articulatory infor- mation can improve detection performance. Cross-validation and k-fold approaches were used in the investigation. [16].

When it comes to related work on wavelet-based feature extraction N.mei proposed a two-stage procedure in which the quality of the heart sounds is first assessed before features are extracted and the heart sounds are then classified using a wavelet scattering transform (WST). A decision tree-based method is used to evaluate the quality while taking the spectral flatness and kurtosis of the heart sounds into account. The WST is then used to obtain high-dimensional properties from the heart sounds. Prior to training a support vector machine (SVM) classifier, the obtained features are minimized using principal component analysis (PCA). [17].

Liu Zem uses the wavelet scattering method to classify electrocardiogram (ECG) beats in his research. He used wavelet time scattering transform, a non-invasive diagnostic technique for identifying the electrical activity of the heart, to examine the ECG data. He then used a support vector machine (SVM) classifier to identify the ECG beats after ext

racting properties from them using the wavelet scattering technique. They evaluate the effectiveness of their method and contrast it with other cutting-edge methods using an ECG dataset that is available to the general public. The results show that the wavelet scattering transform-based method achieves excellent classification accuracy while excelling in terms of sensitivity and specificity [18].

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7-Issue 1, January 2024
Paper: 66

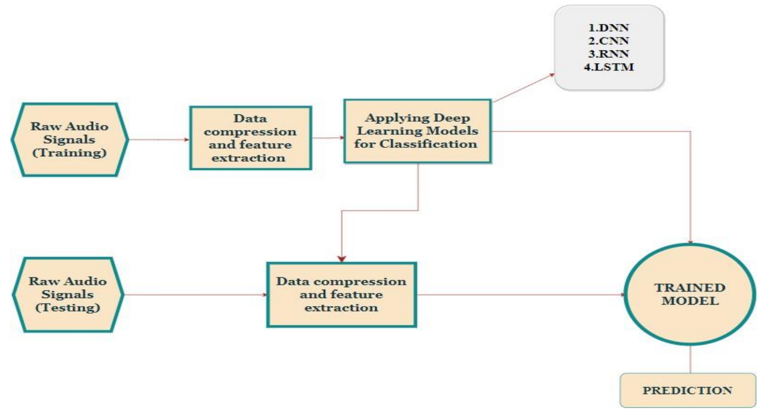


Fig. 1: Workflow of the model

Ding Liu focused on using deep learning methods to remove noise from speech signals. The authors compared various deep learning models, including CNNs, RNNs, and autoencoders, with traditional signal processing techniques like Wiener fil- tering and spectral subtraction.The authors evaluate the per- formance of these models on several datasets, including the NOISEX-92 dataset and the CHiME-3 dataset. The study found that deep learning models, especially CNNs and RNNs, performed better than traditional methods in denoising speech signals [20].

III. WORKFLOW OF OUR MODEL

The objective of our research is to assess the performance of various deep learning models as classifiers for distinguishing between individuals with ALS and those without it. To achieve this, we implemented a data compression technique to create a lightweight model that could produce accurate results while utilizing less computational power. Furthermore, we used the Wavelet Time Scattering (WTST) transform method for feature extraction, which allowed us to extract 84 informative fea- tures from the speech signals.After extracting 84 informative features using the WTST method, we have evaluated the classification abilities of four different deep learning models. Specifically, we tested Deep Neural Networks (DNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) to determine their suitability for processing speech signals.We carefully compared the results obtained from each model to understand their respective strengths and weaknesses.

Overall our research evaluated and compared the perfor- mance of different deep learning models, including DNN, LSTM, CNN, and RNN, for classifying individuals with ALS based on features extracted using WTST. We utilized a series of rigorous and sophisticated steps to ensure the development of a precise and simple classification model. By combining data compression, feature extraction, and classification using deep learning models, we obtained a comprehensive analysis that yielded comparative results. Our findings provide insight into the suitability of each model for distinguishing between ALS and healthy patients based on speech signals.

IV. DESCRIPTION OF DATABASE:

A. Database

In [15]researchers provided the voice database utilized in this investigation. The collection contains recordings of pro- longed 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 ± 7.7 and in women it was 57.3 ± 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.

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7-Issue 1, January 2024
Paper: 66

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.

V. Proposed Methodology

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 compres- sion is a crucial process in reducing storage requirements and bandwidth usage while maintaining the quality of thedata. 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 incorpo- rates time-translation invariance by applying the wavelet filters to multiple time-shifted versions of the signals.For a variety of signal processing tasks, such as voice recognition, picture classification, and medical image analysis, the Wavelet Time Scattering Transform (WTST) has shown to be a very efficient tool. The WTST has a number of noteworthy benefits, but one that makes it particularly helpful in most applications is its capacity to extract time-frequency information from signals while preserving translation invariance. The WTST has been used to extract features from speech signals for a variety of speech recognition tasks, including speaker identification, emotion detection, and speech recognition, improving perfor- mance in these tasks.Na Mei and Hongxia Wang in their work showed that wavelet scattering performed better than traditional methods when SVM was used for classification [17]. This inspired our research's goal to use the WTST's capability to create a classification model that can discriminate between ALS patients and healthy people, a field that has not yet been studied using this method to extract 84 features.The analysis of wavelet features graphical plot showed of ALS and healthy subjects showed distinct differences in terms of pitch fluctuation.ALS patients had a significant loss of throat muscle strength, resulting in noticeable fluctuations in their feature value . 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. Mathematical formulae:

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

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

where α and β are scale and time shift parameters, respec- tively, and $\langle , \rangle$ denotes inner product. Next, the wavelet coef- ficients are convolved with another set of wavelets, yielding a second set of wavelet coefficients:

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

Volume 7-Issue 1, January 2024
Paper: 66

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

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

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

Moving on to the next aspect of our study, we will now discuss the results obtained from the various deep learning models used as classifiiers and comparison among them

C. Classification using deep learning models

Deep learning models are essential for classifying speech signals as they can capture non-linear correlations between the target variable and input characteristics, particularly in complex datasets.Our study employed Deep Neural Networks (DNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) to compare their results for this specific classification task.

1) Deep Neural Networks (DNN): A Deep Neural Network (DNN) is a type of artificial neural network with multiple hidden layers situated between the input and output layers. DNNs are capable of capturing complex, non-linear relation- ships between input and output variables. In our work, we constructed a DNN model with three dense layers; the first with 64 neurons, the second with 32 neurons, and the final output layer with a single neuron and a sigmoid activation function. Dropout layers were employed to prevent overfitting. The model was compiled with binary cross-entropy loss and optimized using the Adam optimizer. We trained the DNN model using the training data for 50 epochs with a batch size of 30 and a validation split of 0.3.On training the DNN on the ”a” dataset, we achieved an accuracy of 81.5%, with the highest accuracy of the model being achieved on epoch 37. Similarly, while training the DNN on the ”i” dataset and then applying it to a combined dataset containing recordings of both ”a” and ”i”, we achieved accuracies of 82.1% and 80.4% respectively, with the highest accuracies of the models being achieved on epoch 26 and 47 respectively.

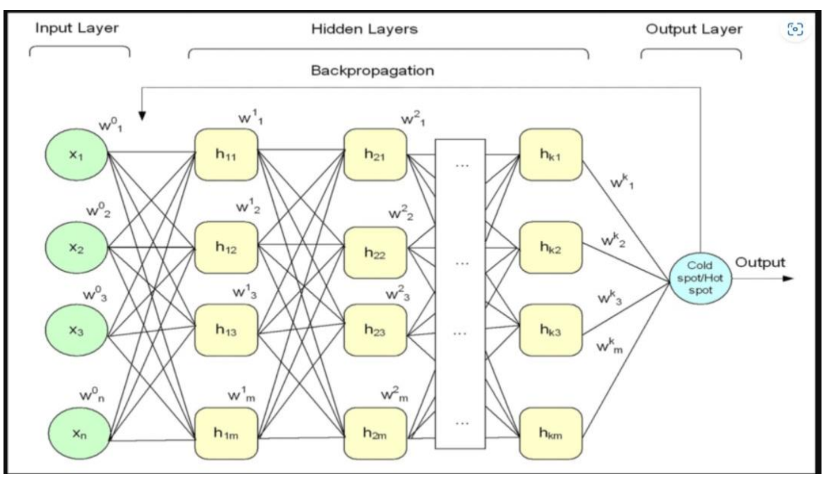


Fig. 2: Architecture of DNN

DNN architecture consists of multiple layers of intercon- nected nodes for learning complex representations of input data. It has been successfully used in various applications like

speech recognition, image recognition, and natural language processing.

2) Long Short-Term Memory (LSTM): The model presented here utilizes Recurrent Neural Networks with Long Short- Term Memory (LSTM) capabilities, which are ideal for tasks such as sentiment analysis, language translation, and speech recognition. Our model is developed using the Keras Se- quential API to train an LSTM neural network for a binary

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7-Issue 1, January 2024
Paper: 66

classification task. The first layer of the model consists of an LSTM layer with 128 units and ReLU activation, followed by a Dropout layer with a rate of 0.2 to address overfitting, and a Dense layer with a sigmoid activation function that produces a binary classification output. The model is built using Adam optimizer and binary crossentropy loss. A batch size of 30 is utilized for 50 training epochs, and a validation split of 0.3 is used to monitor the model's performance.During the training of the Long Short-Term Memory (LSTM) neural network on the "a" dataset, we obtained a classification accuracy of 70.4%. The highest accuracy of the model was recorded during epoch 41, indicating the point where the model achieved the most efficient training progress.Similarly, when we trained the LSTM on the "i" dataset and then tested it on a combined dataset containing recordings of both "a" and "i", we achieved classification accuracies of 64.3% and 67.8%, respectively. The highest accuracies of the models were achieved on epoch 42 and 43, respectively, which indicated the point where the models achieved the most efficient training progress.

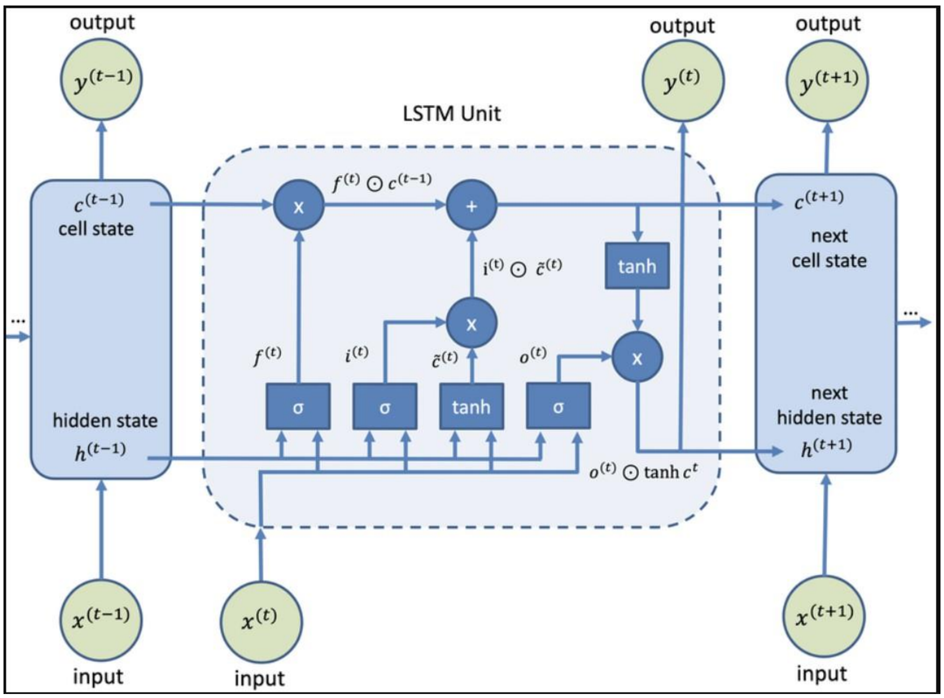


Fig. 3: Architecture of LSTM

LSTM (Long Short-Term Memory) is a type of recurrent neural network that is capable of handling sequential and time-series data. It uses memory cells and gates to selectively store and retrieve information, allowing it to overcome the vanishing gradient problem and learn long-term dependencies.

3) Recurrent Neural Networks (RNN): A recurrent neural network (RNN) is a type of artificial neural network designed for processing sequential data. It achieves this through the use of a hidden state, which allows the network to retain a "memory" of past inputs. to define the architecture of RNN,

the Keras Sequential API is often employed.The model we used has 3 layers .In order to prevent overfitting, a dropout layer is also added to our RNN model. The model itself typically includes a single SimpleRNN layer with 64 units, as well as a Dense layer with a single output unit and ReLU activation.When training the RNN model, a batch size of 32 and a validation split of 0.2 are often used. The model is typically trained on the training set for a specified number of epochs. in this case, 55 epochs were used.The classification accuracy we achieved with the Recurrent Neural Network (RNN) during training on the "a" dataset was 72.0%. The model's best accuracy was noted in epoch 38, indicating the time at which it made the most effective training progress. Similar to this, we attained classification accuracy rates of

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

65.3 % and 62.9 %, respectively, when we trained the RNN on the ”i” dataset and subsequently tested it on a combined dataset including recordings of both ”a” and ”i.” The models' best accuracy was attained at epochs 25 and 30, respectively. RNN (Recurrent Neural Network) is a type of neural network

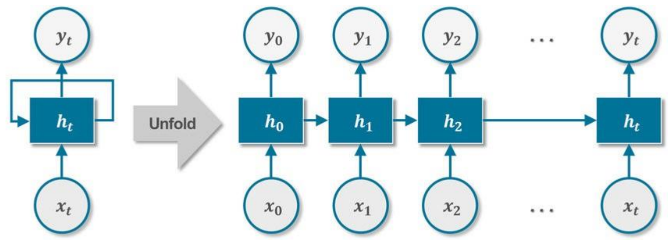


Fig. 4: Architecture of RNN

that is designed to process sequential and time-series data. It uses recurrent connections to allow information to persist across time steps, enabling it to learn dependencies between inputs and outputs.

4) Convolutional Neural Networks (CNN): CNNs are used for audio analysis tasks, such as speech recognition, music genre classification, and sound event detection, by extracting useful features and patterns from spectrograms.It suits well for image data but can also perform well with voice data.In our model input data is reshaped to 3D for compatibility with the CNN architecture. The CNN is defined using the Sequential API from Keras, and it consists of two convolutional layers, max pooling layers, dropout layers for regularization, and two fully connected layers. The model is compiled with binary crossentropy loss and the Adam optimizer.The classification accuracy we achieved with during training on the ”a” dataset was 78.6%. The model's best accuracy was noted in epoch 41, indicating the time at which it made the most effective training progress. Similar to this, we attained classification accuracy rates of 76.7 % and 76.3 %, respectively, when we trained the CNN on the ”i” dataset and subsequently tested it on a combined dataset including recordings of both ”a” and ”i.” The models' best accuracy was attained at epochs 50 and 49 respectively.

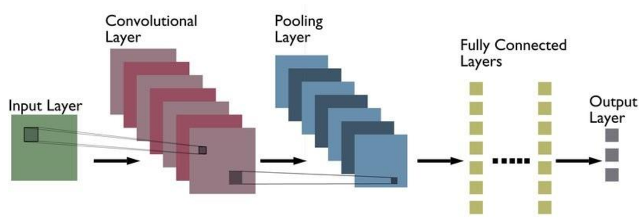


Fig. 5: Architecture of CNN

CNN (Convolutional Neural Network) is a type of neural network designed for image processing and audio tasks which uses convolutional layers to extract features and pooling layers to reduce their dimensionality. These features are then fed into fully connected layers for classification or regression

VI. Simulation and Results

A. Simulation

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7-Issue 1, January 2024
Paper: 66

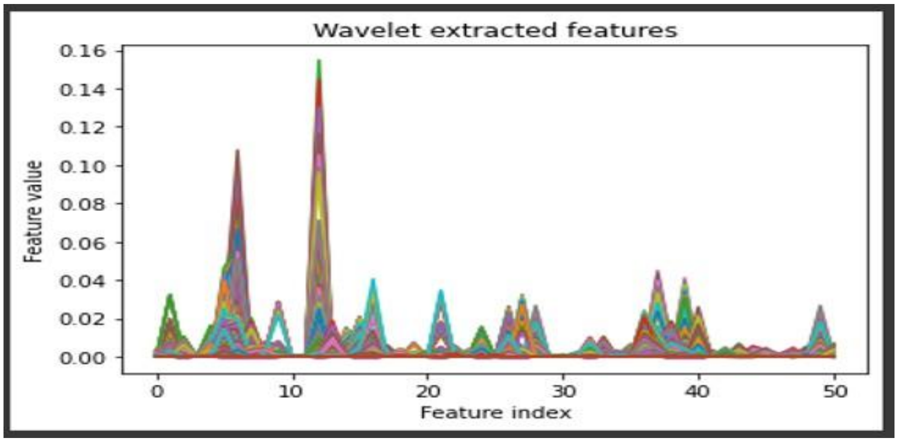
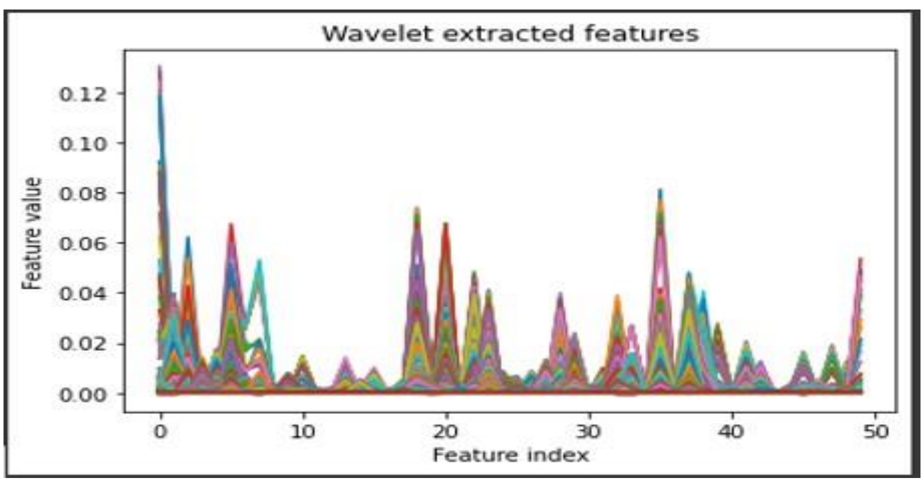


Fig. 6: Wavelet Scattering Transform of Healthy Patients

Fig. 7: Wavelet Scattering Transform of ALS Patients The plot's X axis depicts the feature index, and the Y axis the feature value of healthy patients.It is clear that changes in the feature index correspond to changes in the frequency and intensity of the speech spectrum.As a result, variations

in feature value may be seen.The analysis of wavelet features showed distinct differences between ALS and healthy subjects in terms of pitch fluctuation.ALS patients had a 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: Comparison of Deep Learning Models with SVP Test on ”a”

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7-Issue 1, January 2024
Paper: 66

Deep Learning Model	Batch Size	Epooch for best accuracy	Accuracy of SVP Test on ”a”
DNN	30	37	81.5%
RNN	36	38	72.0%
LSTM	32	43	67.8%
CNN	30	41	78.6%

TABLE III: Comparison of Deep Learning Modelsn with SVP test on ”i”

Deep Learning Model	Batch Size	Epooch for best accuracy	Accuracy of SVP Test on ”i”
DNN	32	26	82.1%
RNN	28	25	65.4
LSTM	30	42	64.3%
CNN	30	50	76.7%

TABLE IV: Comparison of Deep Learning Models with SVP Test on ”a” and ”i”

Deep Learning Model	Batch Size	Epooch for best accuracy	Accuracy of SVP Test on ”a” and ”i”
DNN	26	47	80.4%
RNN	28	30	62.9%
LSTM	30	43	67.8%
CNN	32	49	76.3%

In our work we have compared the classification accuracy of four deep learning models Deep Neural Networks (DNN), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) when applied on the features extracted from wavelet time scattering transform.The performance of these features are compared in above table and it was observed than DNN performed the best with 80.2 percent accuracy while CNN also obtained similar resultsOverall, these findings provide evidence that WTST can be a useful technique for speech- related data and offer insights for future research in this field.And other feature extraction techniques can be added in convulation to it in order to increase the efficiency of the model.

VII. Conclusion

This research presents an unexplored approach using wavelet time scattering transform for diagnosing of Amy- otrophic Lateral Sclerosis (ALS) using deep learning models on real-world audio signals. Our proposed model is non- invasive that offers a promising alternative to current diag- nostic methods that can be problematic and time-consuming for patients. We used wavelet time scattering transform for feature extraction and used these features as for classification using the deep learning models after carefully selecting the model parameters.We then provided a comparative analysis among these models and observed that DNN performed best with an accuracy of 80.2% followed by CNN with 76.3% accuracy.RNN and LSTM also gave comparable results with 62.9% and 67.8% respectively.Our observations suggest that DNN can perform quite well for classification using the features extracted from WTST.

References

[1] J.R. Green, Y. Yunusova, M.S. Kuruvilla, J. Wang, G.L. Pattee, L. Synhorst, L. Zinman, J.D. Berry, Bulbar and speech motor assessment in ALS: challenges and future directions, Amyotroph. Later. Scler. Frontotempor. Degenerat. 14 (7–8) (2013) 494–500.
[2] J.R. Duffy, Motor Speech Disorders: substrates, Differential Diagnosis, and Management, Elsevier Health Sciences, 2013. .

Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 7-Issue 1, January 2024
Paper: 66

[3] Y. Iwasaki, K. Ikeda, M. Kinoshita, The diagnostic pathway in amy- otrophic lateral sclerosis, Amyotroph. Later. Scler. Other Motor Neuron Disorders 2 (3) (2001) 123–126
[4] J. Rusz, R. Cmejla, H. Ruzickova, E. Ruzicka, Quantitative acoustic measurements for characterization of speech and voice disorders in early untreated Parkinson's disease, J. Acoust. Soc. Am. 129 (1) (2011) 350–367.
[5] J.R. Orozco-Arroyave, F. Honig, J.D. Arias-London˜o, J.F. Vargas- Bonilla, K. Daqrouq, S. Skodda, J. Rusz, E. Noth, Automatic detection of Parkinson's disease in running speech spoken in three different languages, J. Acoust. Soc. Am. 139 (1) (2016) 481–500..
[6] P. Gomez-Vilda, A.R.M. Londral, V. Rodellar-Biarge, J.M. Ferrandez- Vicente, M. de Carvalho, Monitoring amyotrophic lateral sclerosis by biomechanical modeling of speech production, Neurocomputing 151 (2015) 130–138,
[7] E. Castillo Guerra, D.F. Lovey, A modern approach to dysarthria classification, in: Proc. of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 3, IEMBS, 2003, pp. 2257–2260
[8] R. Norel, M. Pietrowicz, C. Agurto, S. Rishoni, G. Cecchi, Detection of amyotrophic lateral sclerosis (ALS) via Acoustic Analysis, in: Proc. Interspeech, 2018, pp. 377–381.
[9] T. Spangler, N.V. Vinodchandran, A. Samal, J.R. Green, Fractal features for automatic detection of dysarthria, in: Proc. of IEEE EMBS Interna- tional Conference on Biomedical Health Informatics, BHI, 2017, pp. 437–440 in Medicine and Biology Society, Vol. 3, IEMBS, 2003, pp. 2257–2260
[10] A. Tsanas, M.A. Little, P.E. McSharry, J. Spielman, L.O. Ramig, Novel speech signal processing algorithms for high-accuracy classification of Parkinson's disease.
[11] A. Benba, A. Jilbab, A. Hammouch, Discriminating between patients with Parkinson's and neurological diseases using cepstral analysis, IEEE Trans. Neural Syst. Rehabil. Eng. 24 (10) (2016) 1100–1108
[12] J.A. Go´mez-Garc´ıa, L. Moro-Vela´zquez, J. Godino-Llorente, On the design of automatic voice condition analysis systems. Part I: Review of concepts and an insight to the state of the art, Biomed. Signal Process. Control 51 (2019).
[13] R.J. Baken, R.F. Orlikoff, Clinical Measurement of Speech and Voice, second ed. Singular Thomson Learning, 2000, p. 593. signal processing algorithms for high-accuracy classification of Parkinson's disease.