Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

Automatic Speech Assessment System for Aphasia Speech Disorder

Dr. K. R. Jothi, Priyanka Yawalkar, V L Mamatha
Vellore Institute of Technology, Tamil Nadu, India
jothi.kr@vit.ac.in
priyanka.yawalkar2019@vitstudent.ac.in
mamathav.l2019@vitstudent.ac.in

ABSTRACT

Aphasia is a language impairment disorder that affects speech production or speech comprehension. Person face difficulties in communication due to long pauses, repetitions and fillers which makes an unstructured and stuttering utterances. Speech disorder of an Aphasia patient is divided into two types such as fluent speakers and non-fluent speakers. Identification of the severity level in the early stage is very important in order to take appropriate treatment therapy. For this, Speech Assessment System plays a vital role. This work focuses on building an Assessment system which is based on Ensemble Machine Learning classifier such as AdaBoost, AdaBoost (SVM), XGBoost, Bagging and Neural Network based Categorical model for the classification of the severity level. Depending on textual and acoustic features, aphasia severity level will get classified into 3 classes such as Low-AQ, Mild-AQ and High-AQ.

Keywords
Aphasia, Speech Assessment System, Ensemble Learning, AdaBoost, XGBoost, Bagging Classifier and Neural Network Categorical Model

Introduction

Aphasia is a language impairment disorder that affects speech production or speech comprehension and also affects the reading and writing capabilities. Aphasia disorder can be majorly severe which makes communication with the individuals nearly impossible. According to NIDCD survey, In US approx. 1,000,000 cases and in India more than 3,000,000 cases of aphasia disordered. Among 240 people, one person is affected by this disorder. This disorder mostly seen in children’s and above 65 age [5]. Aphasia disorder is always cause due to damage to the brain, mostly due to a stroke. This disorder majorly seen in older aphasia individuals. This disorder generally causes due to injury to the brain, tumor and neurological diseases. These causes are of Aphasia disorder. Non-Fluent speeches are effortful, contains pauses and stuttering speeches, while fluent speakers can speak spontaneously but they make unstructured utterances. Aphasia individual produces long pauses, repetitions and fillers, makes unstructured and stuttering utterances. Aphasia disorder has different types that depends on fluency, comprehension and repetition. These types of aphasia related to location of brain damage. Aphasia types are global aphasia, Broca aphasia, Conduction aphasia, anomic aphasia, Trans motor aphasia and Wernicke aphasia. Fluent classified intoBroca, Global and Trans motor type, where non-fluent types of aphasia are Wernicke, conduction and anomic aphasia.
This disorder affects the individual’s capability in communication skills such as listening, reading, writing and reading skills etc. these individuals experience social isolation and unable to convey their thoughts, feelings and ideas. Language is very important function are supported by neuron’s network. To diagnose severity level in the early stage is very important to take the appropriate treatment therapy [5]. The treatment must be taken at a consistent period of time which are very costly. This disorder only affects language skills but not their intelligence. So, individuals may have innovative ideas.
This motivates to make Speech Assessment System that evaluates the speech spoken by aphasia individuals. For this speech assessment system, ensemble machine learning classifier and the Neural network based categorical model are used to differentiate between severity level. Machine learning classifier learns from past data, classified newer data set. Ensemble learning algorithms are used for this system are Adaptive Boosting, Adaptive Boosting (Support Vector Machine), Extreme Gradient Boosting (XGBoost) and Bagging classifier. In this paper, Ensemble learning algorithms and the Neural Network based Categorical model are used to evaluate individual speech using acoustic and textual features. Depending on these features, aphasic speech will get classified into 3 classes such as high-AQ, mild-AQ and low-AQ.

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

Literature Review

In the previous years of research study had been work on Automatic Detection of aphasia severity.For this assessment system, Aachen aphasia data set were used and this data set comprises of audios and transcript. [6]

Le et al., research work on paraphasia protection using aphasia bank data set. Data set contains recordings approx. of the 126 hours. In this paper automatic speech recognition system had been proposed. For the acoustic features, force alignment method was used. For the classification of paraphasia, algorithm as SVM, logistic regression and decision tree algorithms used. [7]

Silva et al., [8] proposed Semi-Auto Aphasia Diagnosis for audio processing using Feature Extraction. For this diagnosis 3 features were mostly considered such as confrontations naming, word repetition and comprehension etc. In this paper linear predictive cepstral coefficient Mail frequency cepstral coefficient techniques were used for the extraction of acoustic features. and also DTW that is dynamic warping method used for pattern matching that helps to determine the difference between original signal and the aphasia speech signal. [8]

Qin et al 2018., proposed technique for the textual feature extraction from Acer system. For this experiment, Cantonese aphasia data set were taken from aphasia bank. In this paper, caustic and textural features were combined for classification assessment. The caustic features were extracted using HMM DNN architecture. The features where selected using FMLLR that selects about 440 dimensions of the features. Binary classification was applied on a Aphasia bank data set machine learning algorithm where used for the classification purpose. The algorithms are random forest, decision tree and SVM algorithm that classify low-AQ and high-AQ target labels the overall S ER are estimated for aphasia participant where 48.08%. [9]

Balaji V el al 2019, explained analysis of speech disorder from audio waveforms with the help of feature extraction. the factors we are considered for comparison are frequency, time, duration ATC. The audio signal generally analyzes in windows sequence between 10 to 20 ms. HMM, SVM - HMM hybrid and SVM model were used [10]. Qin et al , proposed a method for OVV words classifying between weak and strong speech recognizer. Using this approach, SER rate were 16.73% that classify between mild aphasia and severe of aphasia. The F1 score attain by the CNN classifier is 89% [11].

Adam et al., 2020 introduced acoustic feature analysis for prosody that depends on the data set. Acoustic measures were considered for this system are Phrase lengthening, Speech duration and word duration etc..[12]

[13], In this paper, dysarthric Japanese spoken data set were used for this system. The features were extracted using mfcc technique, TDNN deep learning algorithm applied on data set as a caustic classifier.

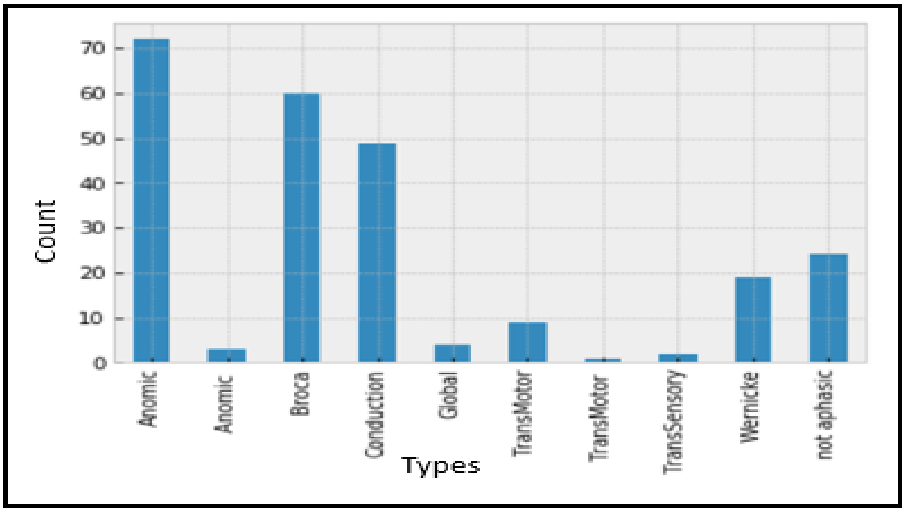
DNN - HMM approach was used for feature extraction for ASR system [14]. These features generally used for recognition of patterns. SVM model classify these features into two target labels. [14]

Wilson et al., 2018, describe about aphasia battery. Research contains 3 major features i.e., time efficiency, sound, multidimensional features. This research reduces gap between comprehensive battery which requires more time [15]. For auto evaluation, Aphasia Battery can be used to revaluate PPA. The main aim of this research paper where to evaluate PPA diagnosis and clinical variant to keep track of aphasia recovery over time period [16].

APHASIABANK DATASET

English is an Influential and crucial language that are spoken all over the world. Aphasia bank contains large collection of speech data set. Aphasia bank is multimedia database for communication study in aphasia. Dataset were collected from different websites across Canada and United States. Aphasia bank contains speech recordings that are accessible to aphasia bank members and it is password protected. Speaker narrated on free speeches, narration of stories, procedural description task, description of pictures etc [1]. these recordings were Transcribed manually using CLAN (Child language analyses) program. Western aphasia battery is a Standardized process applied on aphasic speech [2]. The WAB Comprised of comprehension, fluency, object naming test repetition of subject. Test results are numeric that are given by speech language pathologist with respect to criteria. The resulted score of the whole test is known as AQ (Aphasia Quotient). Data set consists of speech recordings from 244(Female:98, Male:145) [4]. Aphasia speakers are selected, that includes 60 Broca, 75 Anomic, 49 Conduction,10 Trans motor, 19 Wernicke and 24 not aphasic [4], Graphically shown in below figure.

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.



. Figure 1: Types of Aphasia

Aphasia quotient score are between 0 – 100 That indicates language impairment severity [2]. The aphasia quotient score ranges Between 17.0 to 95.0. Low-AQ shows higher level of aphasia severity and High-AQ shows lower level of Aphasia severity [19].

Table 1: AphasiaBank Dataset for assessment

Aphasia Severity	Low	Mild	High
Participants	67	89	87

Western Aphasia Battery-R's AQ breakdown into 27.45% Low, 35.65% High and 36.4% mild. Each recording is approx. 30 min. The recordings can transcribe using CLAN program.

Proposed Approach

The proposed method is to discriminating person with Aphasia from Low to High AQ (Aphasia Quotient > 90). The proposed are shown in figure 2 below,

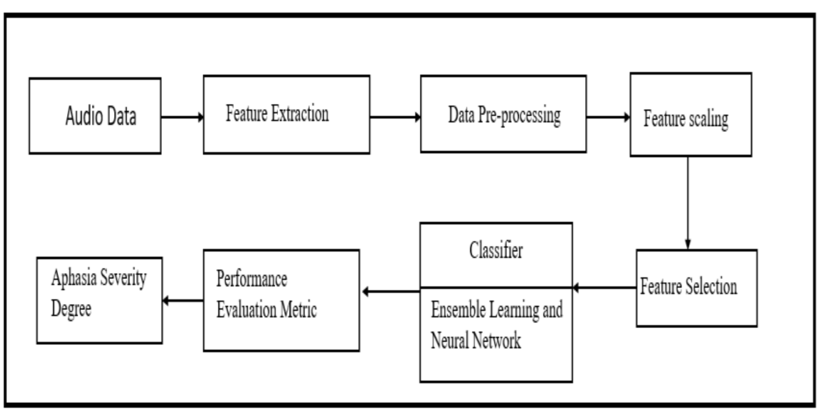


Figure 2: proposed architecture for Assessment System

Input to the system is audio recording. MFCC is used for acoustic feature extraction from spectrogram. Further feature selection method is applied to reduce overfitting. Finally, Ensemble Learning models such as Adaboost,

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

Adaboost (Support Vector classifier), Extreme Gradient Boosting (XGBoost), Bagging classifier and the Neural Network based categorical model are applied for 3-class classification

Methodology

Feature extraction

In machine learning, most popular Feature extraction technique for audio is MFCC (Mel-Frequency Cepstral Coefficient). MFCC provides most usable enough channel frequency for audio analysis. The features extract from audio data set and that creates dense presentation of data. Provided audio raw data as input, converted into 3-dimensional spectrogram. In this experiment, 25 ms sliding window are used to extract features. Spectrogram are estimated by calculating FFT across overlapping windows series which were extracted from audio signal. The audio data were splitted into NFFT and then each section from spectrum is calculated. Further window function applied on every segment. Overlapping amount of every segment are particularly specified with non-overlapping function. The sliding window width are enough to get the information. signal then down sampling to 16 kHz and extracted 6 MFCC and energy features. using MFCC, 6 features are extracted such as STFT, rmse, spectral centroid, spectral bandwidth, roll off and zero crossing rate. Generated Spectrogram image from audio using feature extraction are shown in figure 3,

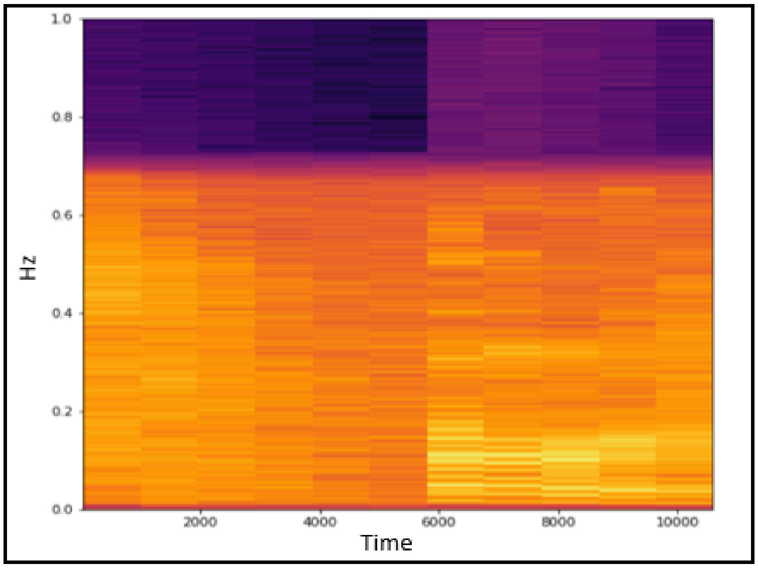


Figure 3: Spectrogram of audio signal using MFCC

Feature Selection

Dimensionality reduction method is used to reduce overfitting, so that the dataset can be minimized to a smaller number of data entries. Since data set comprises of 244 participants, so Feature Space reduced from 45 to 22 feature set. For feature selection, ANOVA F-VALUE statistic method is used. ANOVA is Analysis of Variance that helps for best feature selection. Variance measures the number from mean and each numeric value in that variable. Low variance shows no impact or less impact on response features. Since in dataset, all features are numeric, so ANOVA method will compute the scores by grouping quantitative feature by output vector, Then the means for every collective group are slightly vary. Then calculate model summary for F-test such as p-value, Log-Likelihood, residuals, F-statistics. F- statistics = 80.31, The ranking was given to each feature according to best high score and considered only n top best feature from rank list [5].

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

Models for Classification

I. Machine Learning Based Models for The Prediction of Severity Level

a) Adaptive boosting and Adaboost (Support Vector Classifier)

AdaBoost or Adaptive boosting uses Decision Tree as a base classifier. This model creates various sequence models and corrects the error from previous one. Weights are assigned to every instance in dataset. Algorithm estimates the error based on actual and predicted values. It updates the weights based on error data and repeats the process till function error not changed. For this algorithm, estimators assigned to 10 which is total base learner. In other model, Base Estimator are support vector classifier, with total estimators were 50 and learning rate =0.1.

b) Extreme Gradient Boosting(XGBoost)

Extreme Gradient Boosting is based on Decision Tree which is an Ensemble learning algorithm and also uses Gradient Boosting Algorithm. This method also called as Regularized Boosting method and provides parallel processing functionality. XGBoost based on gradient Boosting that reduces errors in sequence models. For this algorithm, estimators were assigned to 200, learning rate = 0.01. XGB can be used for multiclass classification. Model prunes the tree when gain is negative (gamma > loss). So, objective parameter is multi: softprob i.e. specifically for multi class. Maximum depth of the tree were 7 and minimum_child_weight = 2, describes summation of all the weights of the observation in child. On threshold = 0.088, giving classification accuracy to 89.04%.

c) Bagging Classifier (Decision Tree)

It is an ensemble learning algorithm use to make predictions and used for classification i.e. baggingclassifier. Steps in this algorithm are, using real dataset, it creates random small dataset. Subset takes all the features from dataset. Further, base learner is fitted on smaller subsets. All the predictions are combined and gives result. Default base learner for this classifier is decision tree. Parameters for hyperparameter are Estimators =10 and base learner is decision tree. Accuracy for this algorithm is 87%. This algorithm classifies 64 datapoints correctly.

Neural Network Based Categorical Model for The Prediction Of Severity Level

Artificial Neural Networks (ANN) is a supervised approach which is built based on number of elements called neurons or perceptron. Each of the neuron make decision and feeds the decisions into another neuron which is organized in an interconnected layer. A NN (Neural Networks) used to classify the provided data into labled classes. This work focuses on the prediction of Aphasia Individual severity level using the neural network. Aphasia patients are classified based on severity level. In this current work dataset of aphasia patient speech samples is utilized. The dataset required is accessed from the AphasiaBank English datasets. In total there are 244 participants and 22 parameters for classification. Dataset is stratified splitted into train 80 percent of total available data and test 20 percent of total available data. Feature wise normalization is carried out through subtracting the mean of input feature and then dividing it by standard deviation so the input feature is centre around zero and have a unit standard deviation. The accuracy achieved by the categorical model for the classification of the aphasia severity level is 87.75%.

Result and Analysis

I. Result Analysis of the Machine Learning based Models for The Prediction of Severity Level

Multi-Classification results are taken out with four algorithms such as AdaBoost, AdaBoost (Support Vector classifier), Extreme Gradient Boosting (XGBoost), Bagging classifier. Total 22 features are selected using ANOVA F-test technique. F1-score calculates weighted average between recall and precision. AUC-ROC score is an Area Under Receiver Operating

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

Characteristic Curve are used for metric. F1- score and AUC score are shown in following figure 4.

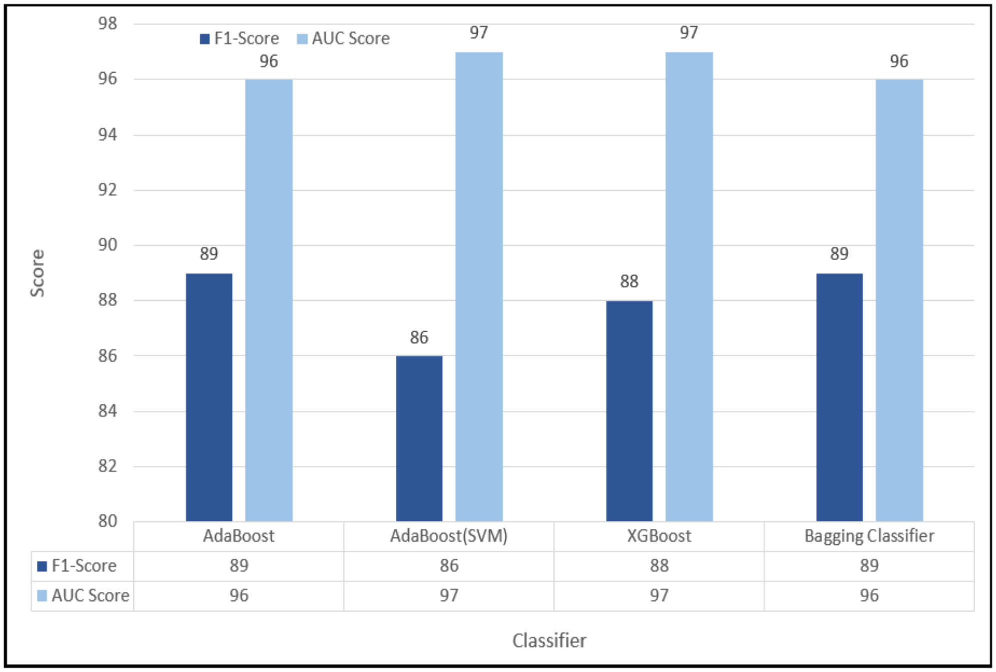


Figure 4: Performance Metrics (F1-score and AUC Score)

Form the above figure, XGBoost and AdaBoost (SVM) have high AUC score and F1-score is high in AdaBoost classifier.

Confusion Matrix for All Classifier

In Confusion Matrix, Low-AQ defines 0, Mild-AQ defines 1 and High-AQ defines 2.

1.AdaBoost Classifier

It classifies 65 datapoints correctly and 8 datapoints are missclassified. From matrix, Low = 19, Mild = 24 and High = 22 are correctly classified as per true and predicted values. Recalls using this classifier are Low-AQ, Mild-AQ and High-AQ are 95%(19/20), 89%(24/27) and 85% (22/26) respectively.

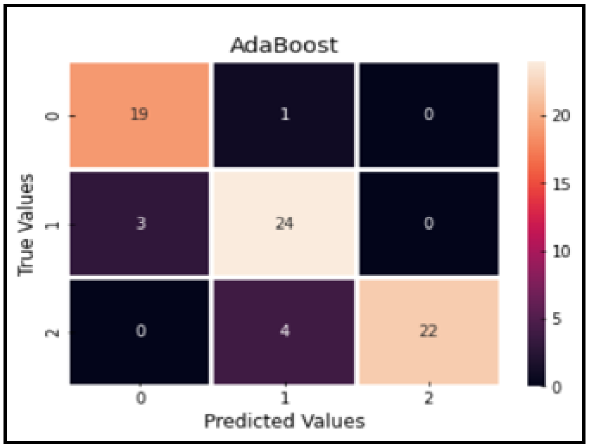


Figure 5: Confusion Matrix for AdaBoost

2.AdaBoost(SVM) classifier

This model Correctly clasifies 63 datapoints and 10 missclassifed. Weighted Average precision for this classifier is 0.86. From matrix, Low = 16, Mild = 22 and High = 25 are correctly classified as per true and predicted

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

values. Recalls using this classifier are Low-AQ, Mild-AQ and High-AQ are 80%(16/20), 81%(22/27) and 96% (25/26) respectively.

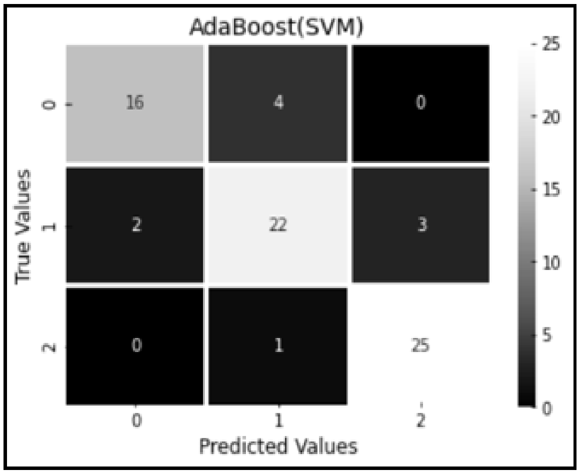


Figure 6: Confusion Matrix for AdaBoost(SVM)

3.XGBoost Classifier

This classifier Correctly clasifies 65 datapoints and 8 missclassifed. Weighted Average precision for this classifier is 0.89. From matrix, Low = 19, Mild = 22 and High = 24 are correctly classified as per true and predicted values. Recalls using this classifier are Low-AQ, Mild-AQ and High-AQ are 95%(19/20), 81%(22/27) and 92% (24/26) respectively.

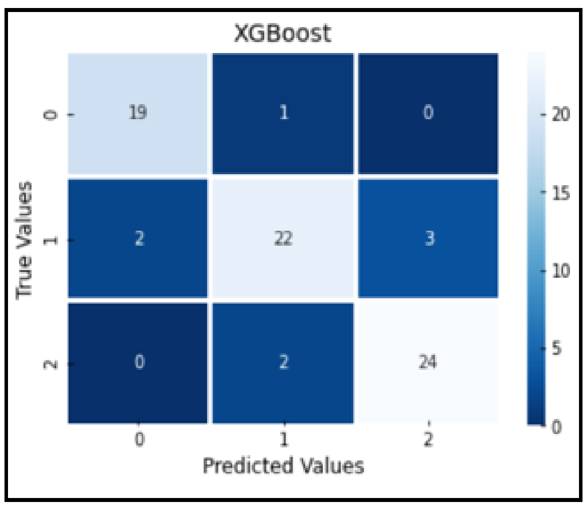


Figure 7: Confusion Matrix for XGBoost

4. XGBoost Classifier

This classifier Correctly clasifies 65 datapoints and 8 missclassifed. Weighted Average precision for this classifier is 0.86. From matrix, Low = 18, Mild = 22 and High = 25 are correctly classified as per true and predicted values. Recalls using this classifier are Low-AQ, Mild-AQ and High-AQ are 90%(18/20), 81%(22/27) and 96% (25/26) respectively.

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

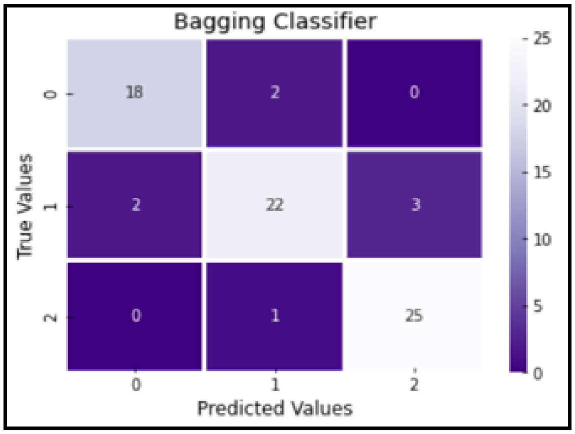


Figure 8: Confusion Matrix for Bagging Classifier

Other performance metric such as Cohen's Kappa, Matthews corrcoef and average recall and average precision are also measured. Matthews Correlation Coeficient measures multi class classification quality. All values from Matthew's Corrcoef are positive and above average random prediction. Cohen's Kappa values are between 1 to -1 and all are above 0.78 that shows complete agreement. Average Precision are the weighted precison mean reached at every threshold. All these measures are statistic measure shown in below table,

Table 2: Performance metrics of Cohen's Kappa, Matthews corrcoef, Average Recall:

Classifier	Matthews Corrcoef	Cohen's Kappa	Average Recall	Average Precision
AdaBoost	0.84	0.83	0.89	0.90
AdaBoost (SVM)	0.79	0.79	0.86	0.86
XGBoost	0.84	0.83	0.89	0.89
Bagging Classifier	0.83	0.83	0.89	0.87

II. Result Analysis of the Neural Network based Categorical Model for Prediction of Severity Level

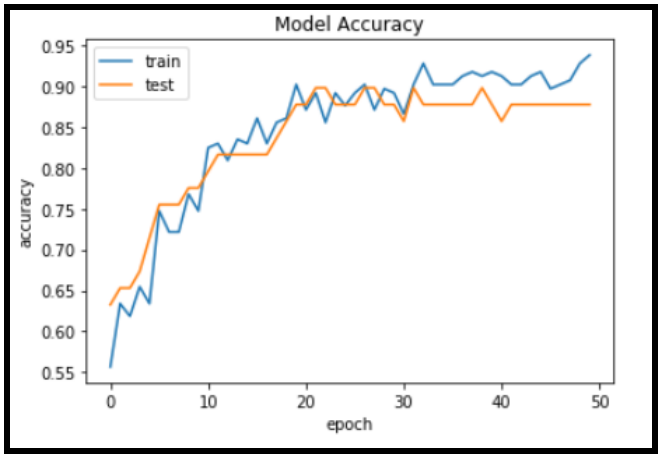
Classification of severity of aphasia is carried out using the neural network model. The python libraries are used such as numpy, pandas and matplotlib and also the machine learning related libraries such as keras and sklearn are used. The features are extracted from the audio speech samples. The neural network model is fed with the extracted features. The model is trained with the 80 percent of the data and the validation of the model is done on the 20 percent of the data. The model is trained with 194 participants samples and the validation of the model is done with the 49 participants samples. During training phase, the evaluation of the model is done through capturing the loss and the accuracy of the model in every iteration. During the testing phase validation of the model is done through the consideration of the accuracy of the model and the loss of the model on various iteration with the 49 samples.

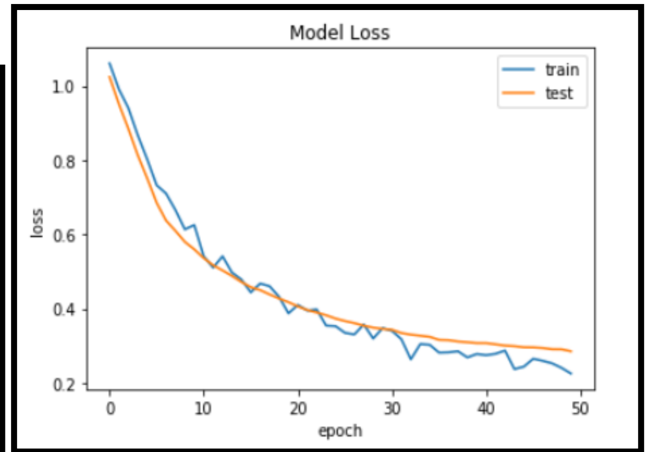
Using the machine learning library keras, a neural network is built which incorporates hidden layer. Categorical classification approach is used. For the better performance of the model regularization technique is

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

applied through dropout. For the hidden layer relu activation function is used and for final layer of neural network, softmax function is used.

During training period of model, categorical_crossentropy loss and other various parameters are taken into consideration, namely learning rate, total number of iterations, val_loss, val_accuracy, batch size. In order to achieve





the best accuracy, the weights are learned through the backpropagation model. The metrics of validation relatively closed to the training phase. The obtained model accuracy and the model loss is depicted in the figure below

Figure 9 : Epoch Vs AccuracyFigure 10: Epoch Vs Loss

The Classification report of the categorical model is illustrated in the below figure:

```
Results for Categorical Model
0.8775510204081632
              precision    recall  f1-score   support

           0       0.80      0.92      0.86        13
           1       0.88      0.78      0.82        18
           2       0.94      0.94      0.94        18

    accuracy                           0.88        49
   macro avg       0.87      0.88      0.88        49
weighted avg       0.88      0.88      0.88        49
```

Figure 11: Classification report

Discussions

The proposed methodology shows effective results in discriminating severity from low to high level disorder. Comparative study on accuracy for different models are as follows:

I. Accuracy Comparative Study on the Machine Learning Based Models for the Prediction of Severity Level

Model A: For three class classification, one vs one strategy has used. The dataset was classified as in three classes such as mild, moderate and severe. For this classes, Recalls are 60%, 53.1% and 82.7% [3]. For this classification

SVM (Kernel = Quadratic) were used. However, model shows difficulty in classifying moderate and mild severity [3].

Model B: In this experiment, four Ensemble learning algorithms are used. All the algorithms giving closed accuracy among all algorithms. Recalls using XGBoost classifier are Low-AQ, Mild-AQ and High-AQ are 95%(19/20), 81%(22/27) and 92% (24/26) respectively. This model can classify datapoints among all classes

.

II. Accuracy Comparative Study on the Neural Network based Categorical Model for the Prediction of Severity Level

Model A: The DNN model trained with children speech corpus dataset. Achieved accuracy for severity detection is 0.83. As the severity increases the performance of the model decreased [17].

Model B: DNN model is trained with AphasiaBank Cantonese Speech dataset. The model predicts the severity such as mild, moderate and severe level. Achieved accuracy for severe case is 39.35% for SER and 24.03 for PER [18].

Model C: In the current work, Neural Network based categorical model is trained with AphasiaBank English Speech dataset. Prediction of the severity is done using the Categorical model. Achieved accuracy by the Categorical model for the classification of the severity level is 87.75%

Conclusion and Future Work

Automatic speech AQ classification system have significant importance in Real Application in medical. In this paper, different classifier are used for aphasia severity classification. This paper presents the feature extraction, feature selection ,ensemble learning technique and the Neural Network Categorical model applied on AphasiaBank English dataset for the classification of the severity level of aphasia speech disorder. All algorithms classifies dataset well. This system can be helpful and efficient for saving manual task.

Future work of this system is to increase the dataset for more improved results. More accoustic features are required for analysis. This Assessment System can implement on different languages.

References

[1] Y. Qin, T. Lee, Y. Wu and A. P. H. Kong, "An End-to-End Approach to Automatic Speech Assessment for People with Aphasia," 2018 11th International Symposium on Chinese Spoken Language Processing (ISCSLP), Taipei City, Taiwan, 2018, pp. 66-70, doi: 10.1109/ISCSLP.2018.8706690.

[2] Y. Qin, T. Lee and A. P. Hin Kong, "Automatic Speech Assessment for Aphasic Patients Based on Syllable-Level Embedding and Supra-Segmental Duration Features," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, 2018, pp. 5994-5998, doi: 10.1109/ICASSP.2018.8461289.

[3] Yuanyuan Liu, Tan Lee, Thomas Law, and Kathy Yuet-Sheung Lee. 2019. Acoustical Assessment of Voice Disorder With Continuous Speech Using ASR Posterior Features. IEEE/ACM Trans. Audio, Speech and Lang. Proc. 27, 6 (June 2019), 1047–1059. DOI: https://doi.org/10.1109/TASLP.2019.2905778

[4] MacWhinney, B., Fromm, D., Forbes, M. & Holland, A. (2011). AphasiaBank: Methods for studying discourse. *Aphasiology*, *25*,1286-1307.

[5] K. R. Jothi, S. S. Sivaraju and P. J. Yawalkar, "AI based Speech Language Therapy using Speech Quality Parameters for Aphasia Person: A Comprehensive Review," 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2020, pp. 1263-1271, doi: 10.1109/ICECA49313.2020.9297591.

Annals of R.S.C.B., ISSN: 1583-6258, Vol. 25, Issue 5, 2021, Pages. 5382 - 5392
Received 15 May 2021; Accepted 20 May 2021.

[6] C. Kohlschein, M. Schmitt, B. Schüller, S. Jeschke and C. J. Werner, "A machine learning based system for the automatic evaluation of aphasia speech," 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom),Dalian,2017,pp.1-6 ,doi:10.1109/HealthCom.2017.8210766.

[7] Le, Duc & Licata, Keli & Mower Provost, Emily. (2017). Automatic Paraphasia Detection from Aphasic Speech: A Preliminary Study. 294-298. 10.21437/Interspeech.2017-626.

[8] M. Khan, B. N. Silva, S. H. Ahmed, A. Ahmad, S. Din and H. Song, "You speak, we detect: Quantitative diagnosis of anomic and Wernicke's aphasia using digital signal processing techniques," , 2017IEEE International Conference on Communications (ICC), Paris, 2017, pp. 1-6, doi: 10.1109/ICC.2017.7996967.

[9] Y. Qin, T. Lee and A. P. Hin Kong, "Automatic Speech Assessment for Aphasic Patients Based on Syllable-Level Embedding and Supra-Segmental Duration Features," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, 2018, pp. 5994-5998, doi: 10.1109/ICASSP.2018.8461289.

[10] V. Balaji and G. Sadashivappa, "Waveform Analysis and Feature Extraction from Speech Data of Dysarthric Persons," 2019 6th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2019, pp. 955-960, doi: 10.1109/SPIN.2019.8711768.

[11] Y. Qin, T. Lee and A. P. Hin Kong, "Combining Phone Posteriorgrams from Strong and Weak Recognizers for Automatic Speech Assessment of People with Aphasia," ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Brighton, United Kingdom, 2019, pp. 6420-6424, doi: 10.1109/ICASSP.2019.8683835

[12] Dergipark.org.tr. 2020. [online] Available at: <https://dergipark.org.tr/en/download/article-file/104812> [Accessed 14 September 2020].

[13] R. Takashima, T. Takiguchi and Y. Ariki, "Two-Step Acoustic Model Adaptation for Dysarthric Speech Recognition," ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Barcelona, Spain, 2020, pp. 6104-6108, doi: 10.1109/ICASSP40776.2020.9053725.

[14] Y. Liu, T. Lee, T. Law and K. Y. Lee, "Acoustical Assessment of Voice Disorder With Continuous Speech Using ASR Posterior Features," in IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 27, no. 6, pp. 1047-1059, June 2019, doi: 10.1109/TASLP.2019.2905778.

[15] Henry ML, Grasso SM. Assessment of Individuals with Primary Progressive Aphasia. *Semin Speech Lang*. 2018;39(3):231-241. doi:10.1055/s-0038-1660782

[16] Wilson SM, Eriksson DK, Schneck SM, Lucanie JM. A quick aphasia battery for efficient, reliable, and multidimensional assessment of language function [published correction appears in PLoS One. 2018 Jun 15;13(6):e0199469]. PLoS One. 2018; 13(2):e0192773,, .Published, 2018 Feb 9. doi:10.1371/journal.pone.0192773

[17] M. Shahin, U. Zafar and B. Ahmed, "The Automatic Detection of Speech Disorders in Children: Challenges, Opportunities, and Preliminary Results," in IEEE Journal of Selected Topics in Signal Processing, vol. 14, no. 2, pp. 400-412, Feb. 2020, doi: 10.1109/JSTSP.2019.2959393.

[18] Lee, Tan & Yuanyuan, Liu & Yeung, Yu & Law, Thomas & Lee, Kathy. (2016). Predicting Severity of Voice Disorder from DNN-HMM Acoustic Posteriors. 97-101. 10.21437/Interspeech.2016-1098.

[19] Fraser, Kathleen & Rudzicz, Frank & Rochon, Elizabeth. (2013). Using text and acoustic features to diagnose progressive aphasia and its subtypes