A Systematic Review of Machine Learning based Automatic Speech Assessment System to Evaluate Speech Impairment

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Abstract— **Aphasia is a communication disability that falls under the category of neurological speech disorder. The main cause of the aphasia individual speech impairment damages certain portion of the cerebrum. The aphasic speech impairment ranges from mild level to the extreme level of severity in which the individual will not be able to communicate. The aphasia individuals face difficulties on the different communication categories like some individual have difficulty in formation of the clear and meaningful sentence, some have problem with understanding and some have trouble in the reading process. The aphasic speech impairment experience will be unique for each individual. It purely depends on the portion of the impairment in the cerebrum, position of the impairment in brain, degree of the severity and also individual age factor. This research work focuses on the assessment of speech impairment in the aphasia patients, basically in order to evaluate the communication aptitude of the aphasia individual. The assessment approach is based on the analysis of factors related to speech such as articulation, phonation, prosody and intelligibility. Through the assessment approach, degree of the severity level of patient will be identified through the automatic speech recognition (ASR) methodologies. This work helps the medical examiners namely neurologists and speech therapists to perform the effective speech analysis for the individuals with aphasia speech disorder.**

Keywords— Aphasia, speech assessment, automatic speech recognition, speech analysis

I. INTRODUCTION

Aphasia is a communication disability caused because of the damage in certain portion of the cerebrum which basically deals with the individual's language capability. Neurological disorder is related to the nervous system of human being. Due to damage in nervous system results in neurological disorder. Aphasia comes under the neurological disorder which is caused by stroke, paralysis, damage to the part of cerebrum where the language skills are associated. This kind of disorder takes time to recover. Aphasia speech disorder affect approximately 1,000,000 people in United States of America and also as per the survey 180,000 are estimated to acquire stroke every-year in 2020. Various types of aphasia such as anomic, broca, conduction, wernicke, global etc. Each type has different cause. Therefore, speech disorder individual face problems in communication. This disorder affects the communication skills such as reading, difficulty in formation of sentences, expressing thoughts or feelings, problem in pronunciations, to convey ideas in professional life etc.

The aphasic speech impairment experience remains unique for each individual. It purely depends on the portion of the impairment in the cerebrum, position of the impairment in brain, degree of the severity and also individual age factor. This work focus on assessment of the speech impairment in the aphasia patients, basically in order to evaluate the communication aptitude of the aphasia individual. The assessment approach is based on the analysis of factors related to speech such as articulation, phonation, prosody and intelligibility. Through the assessment approach, degree of the severity level of the patient will be identified through the automatic speech recognition (ASR) methodologies. Speech analysis plays an important role in the assessment process of the aphasia patient.

This motivated us to work on assessment system, which will help the medical examiners namely neurologists and speech therapists to perform the effective speech analysis of the individual with aphasia speech disorder to identify the degree of the severity level of the aphasia patient.

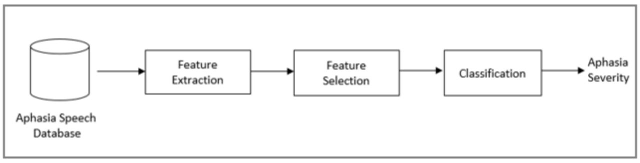

Fig 1: Abstract model of automatic speech assessment system

Various techniques are used in the development of assessment systems such as feature extraction; feature selection and classification, which is used in the identification of severity level in the aphasia individual.

In this survey work, different approaches used for the Automatic assessment system has been reviewed in which speech analysis of the aphasia individual is done by considering the speech evaluation parameters.

II. BACKGROUND RELATED WORK

A lot of research works have been undergone in the area related to the automatic assessment system for the aphasia individual. Previously work has been carried out on identification of the severity level for the aphasia patient by

C. Kohlschein et al. (2017), An automatic assessment system for the evaluation of the aphasic speech, which benefits medical examiners namely neurologists and speech therapists to perform the effective speech analysis of the individual with aphasia speech disorder is proposed. In order to recognize the aphasic speech vocal, biomarkers are used. A database is required to map aphasic speech to the type of aphasia and its severity level by using aphasia individual speech recording. SVM is considered for the classification of the aphasic speech [1].

Le et al. (2015), proposed an automated assessment system to help rehabilitation for an aphasia individual which has potential to provide feedback with respect to the verbal production of the aphasia patient. Extraction of the features and rhythm from the aphasia individual speech sample is done through the introduction of the powerful method which is with respect to the template match. The draw out features are combined with the GOP metrics and the previous draw out features set helps the system to achieve the performance equal to the human in classification of the speech quality of the aphasia patient [2].

Fraser et al. (2013), demonstrated diagnosing progressive aphasia and the two subtypes of it namely semantic variant primary-progressive-aphasia (PPA) and progressive-non-fluent-aphasia (PNFA) from the recorded speech samples and the analysis of the transcripts. Three classifiers are applied namely NB, SVM and RF. Two approaches of selection of features are compared, one according to the statistical relevance and other according to the minimum Redundancy Maximum Relevance (mRMR). After the optimization of the classifier, PPA classified correctly 75.6% of time and other two subtypes are classified correctly 87.4% of time [3].

Y. Liu et al. (2019), demonstrated an investigation on application of ASR based technology to the speech disorder assessment system for the individual who speaks Cantonese. The ASR technology based on DNN is trained with the continual utterances of normal speaker who speaks Cantonese which is phonetically abundant in nature. It is observed that the obtained phonetic posterior at frame level from ASR is firmly correlated with speech disorder degree of severity. For the categorization of disorder into low, medium and high severity level an SVM classifier is utilize to categories the speaker utterances. Accuracy obtained for the low and high severity level disorder is 90.3% and also there is an observation of confusion with respect to the low and medium level of severity. In some cases related to the severe level disorder classification outcome is more inconsistent [4].

R. Gupta et al. (2016), This work focus on reviewing the machine learning application and the techniques of signals processing for the pathological speech and also precisely focus on the three divergent aspects. Firstly, challenges are listed such as supervising subjectivity with respect to assessment of the pathologic speech and implementation of ML-SP techniques and tools to domain specific in accordance with the patients' variability. Secondly, discussion on ML algorithms and design of extraction of feature are done [52]. Lastly discussion on few case study with respect to the analysis of pathologic speech [5].

D. Huang et al. (2016), demonstrated identification of the pathological speech. A novel method is proposed for representation of every utterance of speech using three types of representation with respect to signal namely Gaussian distribution, linear subspace and covariance matrix. In order to measure difference and similarity. Variants of kernel is applied on representations. Classifiers namely KNN, LR, SVM, Kernel partial-least-squares are explored for the comparison of the classifiers efficiency with respect to classification. Finally in order to enhance the performance a combinational learning classifier from various acoustic representation is carried at the score level decision. The proposed model achieved a accuracy of 78.0% on test set [6].

D. Le et al. (2016), demonstrated investigation of the practicality of the assessment system with respect to 3 aspects namely fluidity, prosody and clarity of the aphasia individual speech intelligibility. Corpus for the aphasia disorder is introduced which contains the speech samples related to the interaction of the aphasia individuals. An Application based on tablet is also designed for the therapy purpose. The classification efficiency of the system is investigated under 2 conditions: one based on transcripts labelled by human and the other based on transcripts generated automatically. The acoustic model based on DNN is applied. Thus this assessment system demonstrated the groundwork to bridge gap in between the human and the automatic assessment speech intelligibility system for the aphasia individual [7].

Assessment of speech plays a very comprehensive action for the aphasia individual. Y. Qin et al. (2018), proposed an automatic Assessment System for the aphasia patient who speaks Cantonese. Through word embedding approach feature extraction from the erroneous Automatic Speech Recognition system output is carried out. The texts feature which is extracted is used to differentiate stories narrated by unimpaired person from impaired person. The Automatic Speech Recognition system follows the architecture namely DNN-HMM. The supra segmented time span features are also extracted from the syllable level which is obtained as a outcome of the automatic speech recognition system used to distinguish the prosody of the aphasia individual speech. In the proposed system the extracted text features and the time span features are evaluated in the classification investigation along with the prediction of the score of the assessment. Thus the result shows both the extracted features is very useful in the assessment process for the aphasia individual [8].

Y. Qin et al. (2016), proposed an automatic Assessment System which is based on automatic speech recognition approach for the aphasia patient who speaks Cantonese. The ASR is built to aid acoustic and language analysis of the aphasia individual who speaks Cantonese. The performance of the ASR is analyzed based on severity level of the aphasia individual speech samples. The assessment system performance is investigated using two acoustic models GMM-HMM and DNN-HMM [9].

The rehabilitation of the speech disorder in aphasia individual requires a practice which is followed by a proper feedback. D. Le et al. (2014), in the proposed system feedback is provided to the aphasia individual through by giving description of pictures and the sentence formation. The classifiers are developed to estimate the quality of speech automatically. The performance of the classifiers is assessed in association to the evaluation done by human in an average level [10].

Lee et al. (2016), presented investigation on the assessment of voice using continual utterances of individual's speaking Cantonese is demonstrated. An ASR system based on DNN-HMM is undergone training with the speech of the unimpaired individual voice. As the severity level of the disorder is increased there is a slight decrease in the accuracy with respect to recognition. The obtained phonic posteriors for the continual speech through the low, medium and the severe level are more distinctive, this helps in diagnosis of the severity level [11].

The extraction of the MFCC feature is the very important step in the recognition application which is based on speech. This feature is wildly utilize in lot of applications. Trang et al. (2015), proposed recognition application which is based on speech using three methods for the extraction of the MFCC-Feature and the HMM model built in embed system successfully with matlab and ARM base A8. The accuracy of the recognition depicts effect of extraction approaches on entire system. Combination of the extraction approach of the MFCC-Feature and PCA approach demonstrated high performance with respect to the accuracy of the recognition and also with respect to the speed calculation [12].

M. Shahin et al. (2020), presented assessment approaches used in analysis of the speech of children having different types of speech disorders. Investigation is carried on the usage of paralinguistic feature-extraction in order to reduce the necessity for the low annotation level. The anomaly-detection approach performance was better than DNN-GOP based approach with F1 accuracy score 0.83. Demonstration of the usage of pre-trained deep-learning-network for the extraction of embeddings from the segments of therapy session [13].

V. Balaji et al. (2019), this work aim is to bridge the communication barriers faced by the dysarthric individual. This is achieved through the mapping severe dysarthric speech sample audio signals to the normal people speech signal or with less severity speech signal. The investigation is carried out through the comparison of speech signal waveforms of individuals having no communication speech disorder and the individuals having communication speech disorder. Then the features are extracted from audio signal. The features are processed using HMM which is followed by decoding features to phonemes and the mapping of phonemes are done. GMM-HMM model is generated in order to observe the probability of state transition as HMM is non deterministic machine [14].

Povey et al. (2011), presented description on Kaldi, an open source and freely available toolkit for recognition of speech. Toolkit is supported by modeling the phones which is context dependent in nature having different context length and also general used approaches is estimated through max likelihood. It also supports SGMM (subspace-Gaussian-mixture-models) and also standard GMM (Gaussian-mixture-models). It is written in C++. Release of Kaldi is under Apache v2.0 license and it is available for wide users' community as it is non-restrictive [15].

In order to modeling emission-distribution of HMM for the recognition of speech task, Gaussian-mixture-models considered as one of the most dominant approach. Mohamed et al. (2012), demonstrated that a better recognition of phones on TIMIT datasets will be achieved through replacement of GMM by DNN(Deep-neural-networks) which contains layers of feature and also contains many parameters which are pre-trained in an generative method. This approach is used in the training of language-models and also acoustic-model with the usage of complete utterance instead of frames window. After the pre-training fine tuning is performed through backpropagation for the better predictions [16].

T. N. Sainath et al. (2011), this work focus on application of DBNs (Deep-Belief-Networks) for the LVCSR (Large-Vocabulary-Continuous-Speech-Recognition) system. In this work the performance of DBNs over the HMM and MLPs has been improved through pre-training of the weights in DBNs for the variant feature expansions. And also an approach is demonstrated in this work for parallel-training of the DBNs in order to make it more feasible with respect to computational aspect for LVCSR work without influencing WER [17].

Assessment of the Speech plays a very important role in the rehabilitation for aphasia patients. Analysis of the factors related to speech such as articulation, phonation, prosody and intelligibility has larger impact on the clarity of aphasic speech. S. Mahmoud et al., proposed Automatic assessment system. The proposed system adopts the Convolutional neural network approach in order to map the association in between the degree of severity of the aphasia patient speech and three factors related to speech such as fluency, articulation tone frequency. The proposed system predicts the degree of severity of aphasia individual speaking mandarin with the good accuracy level [18].

To perform the Assessment of the speech basically two steps are involved feature extraction and classification of the features extracted. Y. Qin et al. (2018), proposed automatic assessment system for the aphasia individual speaking Cantonese. The main working principle of this system is to classify the aphasia individuals based on the severity level. In order to map the speech samples to classification outcome, Convolutional neural network and Gated Recurrent Unit-Recurrent Neural Network models are implemented. Convolutional neural network (CNN) model performance is better in comparison with Gated Recurrent Unit-Recurrent Neural Network model [19].

Y. Qin et al. (2019), demonstrated investigation of the application of ASR in assessment of speech of the aphasia individual. The unique characteristics of aphasia patient speech sample is paraphasia. Paraphasia refers to the occurrence of phonemic errors, unplanned words, occurrence of non-verbal sound. With the inspiration from the research work on OOV words detection. The paraphasias in the aphasic speech is captured through the comparison of phonic posteriorgrams with respect to weakly and strongly constrain speech recognizers. Dual channel CNN and Siamese models utilized for classification of the posteriorgrams and also for the prediction of the degree of severity. The F1 accuracy achieved on the classification is about 0.891 [20].

J. K.R et al. (2019), this work focuses on bridging communication barriers for an aphasia individual. Based on the degree of severity the intelligence system will perform analysis of the words pronounced, which are unstructured in nature and transform it to prediction. The recognition system is based on CNN. The system interprets the aphasia individual spoken speech to the text format with the accuracy of 85.10% [21].

Kohlschein et al. (2018), developed an assessment system to predict the aphasia type using the transcripts which is obtained from the aphasia clinical data. The utterance of the aphasia patient is converted into words list and the model word2vec is trained. The classifier is trained by converting training utterances into 20 dimension word vectors and then padding to the thirty vectors length. The LSTM layer is trained with the lists which has designated aphasia type label. The performance and the challenges are both depicted for the aphasia clinical data [22].

Aphasia is speech disorder which affects the language skills of the individual which is caused due to the cerebrum damage resulting difficulty in communication. The Aphasia individual spoken speech is often distinguished by the error called as paraphasia's. The Investigation of this will be helpful to decide the relevant treatment for the aphasia patient and also it is helpful in determining improvement in recovery if the aphasia individual. Le et al. (2017), a study on identifying neologistic paraphasias and phonemic detection from the aphasia individuals' speech samples is done. An ASR system has been proposed with the task-oriented language model to reproduce speech of aphasia individual automatically. The DBLSTM-RNN is used for the prediction of monophone and senone labels. The Deep Learning algorithms are very effective for accurate predictions [51]. The extracted features are analyzed based on the metrics namely DUR, GOP, DIST, DTW. For the classification of paraphasia SVM, DT and LR classifiers are implemented. Thus proposed system outlines the demonstration of the feasibility of paraphasia automatic detection [23].

The Speech Recognition models based on the feed forward and the recurrent neural network has be used from many years. The recent work have shown LSTM-RNN performance is better than DNN as an acoustic model for the ASR System. Sak et al. (2015), in this work the performance of the LSTM-RNN based model is upgraded through the application of improvised techniques for the huge vocabulary. Stacking of frames and reduction in the rate of frame leads to the quick decoding and also building accurate model. Performance improvement in the model is due to the introduction of the CD (Context Dependent) phonetic model units. Without the usage of language models, training of the acoustic model in the word degree can be carried in order to achieve good accuracy on intermediatory average vocabulary ASR is depicted in this work [24].

Automatic recognition of the speech of an aphasia individual is a challenging task due to the shortage of availability of the training datasets appropriate of the aphasia individuals. To perform investigation on the aphasia individual AphasiaBank is used by the Clinicians. AphasiaBank act as a most promising data source for the neural network model. First continuous huge vocabulary for the speech recognition is standard on AphasiaBank. Le et al. (2016), depicts the usage of AphasiaBank can leverage to enhance the recognition accuracy. Two approaches are followed to distinguish the aphasia severity level. Discriminative pre-training offers benefits for the individual having less aphasia severity on the other hand i-vectors benefits for the individual having more aphasia severity [25].

D. Antkowiak et al. (2016), proposed an application which focus on providing the favorable approach for the therapy of the aphasia individual with respect to the language through augmented-reality-application. With this application assist appropriate exercises can be made available for the aphasia patients at home as a part of therapy. Assistance to the aphasia individual is provided through 3D scan, tracking activities on mobile, feedback support and editor to annotate scanned images. Bounded therapy is designed for the complex therapy exercise within rehabilitation linguistic process. Thus augmented-reality-application contribute an outstanding opportunity for therapy for the aphasia individual without much financial load [26].

Y. Liu et al. (2018), in this work assessment of the disordered Speech is done using the Kullback Leibler divergence (KL). The distortion in terms of the phone level between the impaired and unimpaired speakers is measured using KL divergence. Combination of the impaired speech and the normal speech corpus is used to train the ASR for the Cantonese. Acoustic model which incorporates multi task approach of learning is utilized to include various characteristics of speech. The proposed Kullback Leibler divergence with acoustic model experimental outcome depicts that it is more effectual in continual speech assessment systemof different types of pathologies [27].

Stephanie Gillespie et al. (2018), presents investigation on identification of the acoustic estimated measures which is relate to the affective change of state in the aphasia individual adult's speech. The results demonstrates that Machine Learning disclosed moderate level success in classification of depression in aphasia adults, minimal level success in prediction of the stress scores and the depression and finally minimal level success in the classification of the changes related to the affective change of state category between beginning speech and the end speech. The result obtained from this work are promising and assist in the development of the clinical-tools to help clinicians in diagnosis of the depression, stress and the affective change of state in the adults with the aphasia disorder [28].

C. Shih et al. (2013), proposed the Assistive Therapeutic Speech System for the aphasia individual to provide therapy at the home and also build few experiments in order to improve effectiveness with respect to Taiwan. The procedure to perform experiments adopted classic strategy called as ABA investigational design. For the treatment purpose at the home thirty words were found. The final result depicts the improvement with respect to reaction timespan and correctness. Thus, it is concluded that the usage of assistive therapeutic program for the treatment at the home is useful and also it going to increase treatment density for the outpatients [29].

G. Teodoro et al. (2013), proposed virtual clinicians in opposition to the real actual clinician. Initially test were carried using an VirtualClinician avatar accompanied with the human driver. To compare the efficiency of aphasia individual's speech production with real actual clinician collection of data was done. The outcome of the results depicted that the aphasia individual's respond suitably to VirtualClinician [30].

M. Khan et al. (2017), developed a framework which does Aphasia disorder diagnosis and the classification which is semi-automatic in nature which incorporates extraction of feature and the pattern match techniques of DSP- Digital Signal Processing. Evaluation of the time taken, characteristics of the speech and acoustic property for the language components such as repetition, comprehension and naming are carried out in the proposed system. DSP methods are utilized in repletion and the naming tasks. Scores are calculated for the language components through mathematical associations. Then the framework determines diagnosis with respect to the obtained scores and also the accuracy and efficiency is increased through the consistent and correct diagnosis conclusion. Thus, it diagnose sub-types of the aphasia disorder namely Anomic and Wernicke's with good accuracy [31].

Christensen et al. (2014), demonstrated investigation of training of accurate models for the Dysarthric individual speech recognition system which is speaker dependent through choosing carefully which speaker to be involve in speaker dependent models which is adjust to targeted speaker data. Acoustic proximity between the speakers is investigated and also it is ranked accordingly using various approaches on measuring the closeness on UA Speech database. The result depicts improvements in terms of accuracy on an average of 11.5% in comparison with SI and SD standards and also in comparison against system model which has undergone training using CMLLR-SAT (which is a excellence mechanism to deal with the huge inter speaker variance in data [32].

Jokel et al. (2014), presented review of PPA impairment treatment. The main aim of this work is to provide assistance to the clinicians for selecting the mediation approaches for the PPA individuals to bridge the communication barriers. Transcranial-Magnetic-Stimulation (TMS) is the most effective tool which has got very interesting therapeutic capability. It also observed that approaches for the treatment of PPA which is based on computer are viable option. Thus exposing PPA individuals to current advanced technologies help them in staying connected with their surroundings [33].

Henry et al. (2018), This paper focus on reviewing the assessment which is utilized in the examination of the cognition and communication in the PPA which includes ProgressiveAphasia , common aphasia battery which is designed for the stroke and also tests of linguistic function under cognitive domain which includes repetition, production of speech, sentence and word understanding, written speech, motor-speech. Thus evaluation of the speech allows the medical examiners to assist the PPA individuals and also families of the PPA individual with the proper recommendations [34].

Hall et al. (2013), the result of this work recommends that the Telepractice is the most productive way in delivering service to the aphasia individuals. The delivered assistance includes appraisal, interventions, diagnosis and the consultation. The evaluation of the review work is evaluated with respect to the participants' characteristics, technologies, services provided through telepractice, methodology applied in the research work, and finally the research outcome and conclusions of study. The Telepractice is used by the medical examiners and pathologists to provide assistance while delivering services [35].

David et al. (1982), This work focus on reviewing on multicenter-trial on therapist of speech and the volunteers who are untrained on the recovery form speech disorder aphasia after stroke. The study results depict the patients in both the treatment class improved. The improvement in the communication after treatment due to the proper stimulation and also because of encouragement and support provided through therapy session [36].

Roger et al. (2000), presents report survey result of the treatment and assessment practices considered by the pathologists on language-speech for the aphasia patient in Australia. The research study also reveals that lot of pathologists on language-speech wished to enhance their knowledge and the skills which is appropriate to the work which they carry with the individuals coming from different cultural and language background. Thus this work also gives information on various ways to carry the treatment and assessment in an effective way [37].

Le et al. (2018), this work focus on performing expansive study on quantitative investigation of the aphasia speech which is spontaneous in nature. The proposed model approach is BLSTM-RNN based and the utterance i-vectors degree sets the standard for the speech recognition based on aphasia on the AphasiaBank. With the assist of feature calibrations the proposed quantitative investigations are more powerful against errors obtained from ASR and also it can be possibly used in clinical diagnostic assistance. At last the efficiency of the quantitative investigations are demonstrated in the prediction of WAB-R AQ which results in good accuracy [38].

Clark et al. (2019), demonstrated investigation on WAB-R Western-Aphasia-Battery-Revised for the classification of variants PPA (Primary-Progressive-Aphasia). The secondary goal is to investigate metrics of WAB-R in the individual with PPAOS (Primary-Progressive-Apraxia-of-Speech. The classification of PPA/PPAOS are determined through review of the speech, cognitive profile and language. Obtained scores on WAB-R tests are used in deriving AQ (Aphasia-Quotient), three ratios depicting the sub-tests performance and WAB-R profile of aphasia. The result depicted that the AQ mean was high in PPAOS category in comparison with all variants of PPA [39].

Wilson SM et al. (2018), presented description of the development and evaluation of QAB (quick-aphasia-battery) which can be administered in small duration and also provide profiles of the aphasia patient in multidimensions specifying the weakness and strength across language domain. The assessment in this work is carried with the help of items selection carefully, graded-scoring method, and also summary-measures considered with respect to the underlying functions of language [40].

Detection of Intelligibility of pathological voice has got a significant importance in medical sector. Huang et al. (2014), proposed An ASKPLSC (Asymmetric-sparse-kernel-partial-least-squares-classifier) is proposed in order to detect intelligibility of pathological speech. The accuracy achieved by the proposed systemis about 74.0% [41].

Vanbellingen et al. (2011), This paper focus on reviewing the subtypes of the apraxia namely ideomotor and ideational apraxia and also the impact of the apraxia disorder on the daily activities of the individual with the focus on features related to clinical, its diagnosis and the association to the aphasia. Its influence on functional capability of patient been talk about and the significance of assessment and also the treatment procedures are mainly focused [42].

T. Barman et al. (2017), developed application based on android which assist the speech impaired individuals. It's an Augmentative-and-Alternative-communication (AAC) mobile system which generates speech in the form of output which is in English and Assamese languages [43].

Armstrong et al. (2006), this work focus on investigating the conversation of aphasia individuals which helps in providing the effective treatment for the aphasia patient. A framework called Speech-Function-Analysis is proposed in this work in order to incorporate conversation principles to therapy session. The analysis is performed by considering the impact of syntactic and lexical limitations and also the context of the dialogue [44].

The association between the cognitive function and language, namely executive-function (EF) has an important impact on individual with communication disorder. Gonçalves et al. (2018), this work focus on investigation of components of EF. The working-memory (WM) is considered the most cognitive-measure while performing the evaluation through different tasks. Basically the association between the narrative ability, writing ability and grammatical understanding was identified [45].

C. Sorna et al. (2009), this work focus on investigation of application of NLP techniques to enhance the efficiency of assistance for aphasia patient. In this work contextual-information is utilized in prediction of word process. The AAC (Augmentative-and-Alternative-communication) devices provides recognizable progress in the assistive system for the aphasia individual. Description of words are based on strategy of System-functional-grammar which includes both contextual and syntactic analysis and also its capability in providing production of language in the assistive system [46].

Carstoiu et al. (2013), developed innovative platform which is computer based for aphasia individual rehabilitation which is devoted to romanian individual. Integration of computer based application as the treatment preference provides lot of benefits with respect to social, technical and medical perspective. AFARom System is web based which interconnects two main individuals: therapist and patient for the rehabilitation task [47].

Nakase-Richardson et al. (2005), this work focus on validation of MAST (Mississippi-Aphasia-Screening-Test) which incorporates nine measuring expressive sub-scales and the language receptive ability. The collection of data to perform the review includes MAST administration. Analysis depicted that validity of MAST in differentiating impairments with respect to language among the collected samples [48].

Lahiri et al. (2020), presents the summarized predictions of the severity level of aphasia disorder after stroke. An instrument called BWAB (Bengali-version-of-western-aphasia-battery) used for the examination of language. The degree of severity estimated through Aphasia-Quotient (AQ) and also considering scale of severity with respect to BWAB. Statistical examinations were made while analyzing the collected datasource. Using Linear regression predictions were made on severity level with the predictive-value of 90.4% [49].

Pustina et al. (2017), this work focus on estimation of severity level of the post stroke aphasia individual and the recovery potential prediction. Multimodal architecture developed in order to build unimodal-predictions array to feed in the final framework which creates STAMP (Stacked-multimodal-predictions). Aphasia-scores namely sentence understanding and repetition, image naming, and the degree of severity is considered while performing predictions. The result depicted the accurate prediction for aphasia-scores. Thus the multimodal prediction is more accurate compared to single modal prediction [50].

III. Comparative Based Gap Analysis

TABLE I. Summary of Literature Survey Based on Dataset, Feature extraction, Classification and Gap Analysis

Author name	Dataset	Feature extraction	Classification	Gap Analysis
Kohlschein et al. (2017) [1]	AAT	openSMILE toolkit	SVM	Future work is to include non-fluent speech samples and also usage of CNN model
Le et al. (2014) [10]	UMAP	Features extracted from transcripts based on 4 categories: Non-speech, Vague-speech, Filler-words, Clear-speech	Decision Tree, Logistic Regression, Naive Bayes, Random Forest, and SVM.	Future work on consideration of more parameters on phone level
Fraser et al. (2015) [3]	Speech Pathology Dept., University of Toronto	1)Lu's L2 Syntactic Complexity Analyzer 2)Stanford tagger[for POS-tag extraction] 3)SUBTL[for word frequency count]	naïve Bayes, random forest and SVM	Future work is on analyzing effects of more features during classification process.
Qin et al. (2018) [8]	Aphasia Bank	MFCC Syllable-level Embedded features	Decision tree, Random forest, SVM	Future work is to incorporate more speech samples of aphasia individuals with different severity levels
Qin et al. (2016) [9]	Aphasia Bank	MFCC	DNN-HMM, GMM-HMM	Future work has to be carried to improve performance on the non-fluent speech
Le et al. (2016) [25]	UMAP, Aphasia Bank	for acoustic features MFCC and	HMM-DNN, HMM-	Based on diagnosis adaption

		LDA methods with i-vector	GMM	techniques has to be incorporated
Lee et al. (2016) [11]	CUSENT , CanPEV	MFCC, LDA + MLLT , SAT + fMLLR	DNN-HMM, Language model: syllable bi-gram	For the Continual speech samples ASR used to produce dysphonia features and phone alignments
Balaji V et al. (2019) [14]	UASPEECH Database	MFCC	GMM-HMM	Limited to the supervised closed-set vocabulary task recognition, future work is to build the recognizer which can work on open-set vocabulary
Christensen et al. (2014) [32]	UA SPEECH	-	triphones with GMM (Gaussian Mixture model), state clustered	Future work is automatic way of arriving at optimal-set of speakers for SI model.
Qin et al.(2018) [19]	Aphasia Bank	MFCC	GRU-RNN, CNN	Future work focus on incorporation of more neural network layers for the characterization of language-impairment

Table 1: Comparison based on Dataset,Feature extraction,Classification

TABLE II. Summary of Literature Survey based on Language features, Acoustic Features and Metrics used for analysis

Author name	Language feature set	Acoustic Feature set	Metrics used for analysis
Qin et al. (2016) [9]	Number of chunks, syllables, speeches and pauses Duration of speech chunks, syllables and pauses	Filler-words, Non-speech, Repeated-words, Non-speech sounds	Syllable error rate (SER), Aphasia Quotient(AQ)
Fraser et al. (2015) [3]	Lexical features and syntactic features:58	Acoustic features:23	-
Le et al. (2015) [2]	Mean, variance, skewness, zero crossing-rate, correlation function	Non-Speech and Clear-Speech, duration of Filler, total duration, voiced duration, speech duration, Vague-Speech, start time of first speech activity, pause rate and phonation, Clear-Speech rate	Word-Error-Rate(WER)
Le et al. (2016) [19]	-	Speaker level features	Phone error rate (PER), Aphasia Quotient(AQ)
Le. et al. (2014) [7]	Mean, correlation function, skewness, kurtosis, zero-crossing rate	Non-Speech, Filler, Vague-Speech, Clear-Speech	Aphasia Quotient(AQ), Syllable-Error-Rate(SER)
Lee et al. (2016) [11]	Word level features	Phone level features	Phone error rate (PER), Syllable error rate (SER), phone matching rate (PMR)
Qin et al. (2018) [8]	Syllable level features	Supra segmental duration features	Aphasia Quotient(AQ) SER

Table. 2. Comparision based on Feature extraction, Acoustic and Language models.

TABLE III. Summary of Literature Survey based on Dataset, Methodology, Merits and Limitations

Author name	Dataset	Methodology	Merits	Limitations
Le et al. (2014) [10]	UMAP	1) For each utterance's features are extracted from transcripts namely Non-speech duration, Vague-speech, Filler-words, Clear-speech, voice duration etc. 2) For each voice-segment in utterance transcript acoustic features are extracted namely mean, variance, skewness, zero-crossing-rate, kurtosis etc. 3) For classification, Decision Tree, Logistic Regression, Naive Bayes, Random Forest, and SVM classifiers are utilized	1)The Accuracy achieved by this system is comparable with the human-evaluator-scoring and also the feature-selection output provides insights to factors which influence human-evaluation	1)Dependency on the manually-labelled-transcripts needs to be lifted 2)Future work focus on lifting manually-labelled-transcripts through categorization of the time-segments automatically
Fraser et al. (2015) [3]	Speech Pathology Dept., University of Toronto	1)Audio samples and Transcripts are the information sources available for every participant 2) From these sources 81	1)The performance of the naïve Bayes method is very promising 2)Usage of both	1)For PPA subtyping, fluency acts as a poor marker for discrimination because of word finding difficulties

		features are extracted .In which 58 are syntactic and lexical features extracted from transcript and 23 are acoustic-features which is extracted from audio samples 3)Feature selection is performed to select a feature to minimize redundancy and to maximize relevance 4)For classification, naïve Bayes, random forest and SVM classifiers are utilized	acoustic and text features have significant impact on classification accuracy	
Qin et al. (2018) [19]	Cantonese Aphasia Bank	1)Frame level features extraction from utterance are done first and then it is feed into the classifier which is based on neural network 2)Through sigmoid function of neural network severity-score is obtained for every utterance 3)Speaker-level-score calculation is done by taking average 4)For classification of utterance CNN and sequence-to-one GRU-RNN are considered	1)Features specific to pathology are extracted automatically through the usage of CNN and sequence-to-one GRU-RNN for classification which improves the assessment system efficiency by reducing manual work 2)The CNN model performance for severity classification is better in comparison with GRU-RNN model	1)The model concentrates mainly on acoustic impairments and fails in learning content of the utterances 2) Future work focus on incorporation of more neural network layers for the characterization of language-impairment
Qin et al. (2016) [9]	Cantonese Aphasia Bank	1)Pronunciation -lexicon, language-models and acoustic-models are important components of ASR system 2)Investigation of acoustic modeling is done through GMM-HMM and DNN-HMM	Advantage of the DNN-HMM over the GMM-HMM is noticeable	1)Performance of the model decreases in case of severely-impaired speech samples 2) Future work has to be carried to improve performance on the non-fluent-speech sounds and also on filler-words
Balaji V et al. (2019) [14]	UASPEECH Database	1)In this work statistical-pattern-matching approach is considered 2)features are decoded to phonemes using HMM model and the mapping of phonemes to words are done 3)undesirable noise is identified and removed through the application of normalization and clustering techniques	The accuracy of the recognition is improved through identification and removal of the alike feature-vectors corresponding to repetition of phonemes	1)The implementation is closed-set vocabulary and supervised task where testing phase data are the words which system is trained initially 2) future work is to build the recognizer which can work on open-set vocabulary
Le et al. (2017) [23]	Aphasia Bank	1)DBLSTM-RNN is utilized for the prediction of correct monophone and senone labels 2)Goodness-of-Pronunciation GOP is the metric used in the pronunciation assessing 3) combining acoustic-model with language-model automatic-transcription of utterances is performed 4)For classification Decision tree, SVM and Logistic regression is used as classifiers	1) proposed system outlines the demonstration of the feasibility of paraphasia automatic detection 2)Automatic detection of neologistic and phonemic paraphasia's from aphasia speech samples is done with the usage of ASR techniques	The proposed model is limited to the classification of neologistic paraphasia's from the known-transcripts 2)The recognizer fails to detect in the free form environment

Table. 3. Comparision based on Dataset, Methodology, Merits and Limitations

IV. Discussion

As per the survey work rehabilitation and assessment for the aphasia individuals with the higher degree of the severity be difficult in case of usage of words and also in case of fluent speech. Normally, Feature extraction based on MFCC along with the machine learning algorithms were utilized for the ASR. According to the survey the standard techniques has provided good accuracy, but performance of the machine learning based techniques mostly depends on the extracted feature which constitutes underlying traits of dataset. Conversely conversion of ASR issue to image-classification issue enables the usage of CNN, leads to the automatic identification of features and it also provides a good classification result compared to machine learning algorithms.

Assessment strategies such as WAB-R Western-Aphasia-Battery-Revised [39], QAB (quick-aphasia-battery) [40], BWAB (Bengali-version-of-western-aphasia-battery) [49] and Aachen-Aphasia-Test (AAT) are used by the medical examiners worldwide for assessment purpose. The assessment approaches consume more time and also it requires expertise in order to perform the assessment.

The Speech Recognition models based on the feed forward and the recurrent neural network has be used from many years. The recent work have shown LSTM-RNN performance is better than DNN as acoustic model for the ASR System. The LSTM based classifiers were built. The performance of the LSTM-RNN based model is upgraded through the application of improvised techniques for the huge vocabulary. The DBLSTM-RNN is used for the prediction of monophone and senone labels. The extracted features are analyzed based on the metrics namely DUR, GOP, DIST, DTW. For the classification of paraphasia SVM, DT and LR classifiers are implemented. With respect to articulation features sometimes aphasia individuals will be having poor synchronization among the organs related to the speech which going to adversely affect pronunciation of initial consonants and the finishing consonants, this leads to the incorrect meaning. In the same way with respect to the features related to the tone, incorrect word pronunciation sounds like some other word. Because of importance of features like articulation, tone the assessment technique related to speech should focus on speech features related to lucidity individually.

The association between the cognitive function and language, namely executive-function (EF) has an important impact on individual with communication disorder. The working-memory (WM) has considered the most cognitive-measure while performing the evaluation through different tasks. Basically, the association between the narrative ability, writing ability and grammatical understanding was identified [45]. Integration of computer-based application as the treatment preference provides lot of benefits with respect to social, technical and medical perspective. Thus, exposing aphasia individuals to current advanced technologies help them in staying connected with their surroundings [33].

V. CONCLUSION

The primary objective of this work is to survey previous work which has undergone in the area related to the automatic assessment system for the evaluation of the speech impairment in the aphasia patient. Various techniques used in the development of assessment system such as feature extraction; feature selection and classification has been reviewed in this work, which is used in the identification of severity level in the aphasia individual. Analysis on language features, acoustic features and also the metrics used for the speech analysis is also incorporated in this paper work.

Aphasia individual speech holds numerous abnormalities like incorrect pronunciation, fillers, repetition of words, erroneous starts etc. In order to identify these typical patterns specialized language and acoustic models is required. During the assessment phase the aphasia individual needs a feedback for the effective assessment process. Thus, in future additional work needs to be carried to support the classification output to generate genuine feedback which can be utilized by aphasia individuals in order to improve speech and also there is a need for the development of applications based on user interface, which is engaging and user friendly. The prime challenge faced in the work related to the assessment system is due to the aphasic speech, which is non-spontaneous in nature in which the impairment related to the language could be confused easily with the unproficiency speaking skills

Still there is lot of scope for further work in this area. As per the survey most of the work were limited to fluent aphasic speech samples and closed-set vocabulary. In future, this research work will investigate on non-fluent speech and also to build a recognizer, which works on open-set vocabulary.

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