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COGNITIVE IMPAIRMENT DETECTION USING GRU

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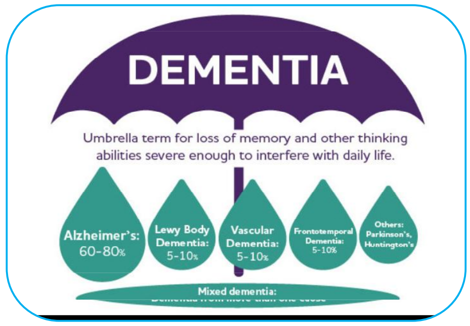
ABSTRACT:

Cognitive Impairment, like dementia, will impact speech, language, and therefore the capability of communication. A recent study to boost the dementia detection accuracy studied the usage of CA (Conversation Analysis) of interviews among patients and neurologists to differentiate among progressive ND (Neurodegenerative Memory Disorders) patients & those with (non-progressive) Functional Memory Disorders (FMD). Manual CA, on the other side, is costly & complex to scale up for frequent medical usage. Many studies reviewed did not utilize a sequence or random selection of a sample but selected a patient sample and a corresponding control group sample. Although this is not a major problem, it has several issues and may be a source of bias. Due to appropriate testing, the majority of studies have a low bias value for reference standards. In instances designated as uncertain, insufficient information about the tests utilized was given.



An early dementia detection system has been presented using speech recognition and analysis based on NLP technique and acoustic feature processing technique apply on multiple feature extraction and learning using GRU. In this work, Dementia dataset is taken from an audio file which is converted to text based on speech analysis. Then created the data frame with the help of the plan ACQ library. Text annotation, correction, and cleaning are done on the second features data frame. From this get some sentence and clean data as well as for dementia label and follow the process of dataset Tokenization and generated the full interview feature file then perform sentiment analysis on the data frame.

KEYWORDS: *Dementia Detection, GRU, Speech Analysis, features extraction.*

INTRODUCTION

Trust in mild cognitive impairment (MCI) & Alzheimer's disease (AD) diagnosis remains uncertain. Evidence shows that doctors are not adequately attentive to signs of cognitive impairment or early dementia, which is being attacked by the demand for care due to increased numbers of medical problems and the therapy available [1]. A major source of impairment and dependence among older people is AD and linked dementia illnesses globally and among the most expensive illnesses of society. By 2030, the worldwide cost of dementia is anticipated to be US$2 trillion, which may overwhelm the systems of health & social care. AD is an unalterable brain condition that gradually reduces the cognitive function of a person. The important risk aspect for AD is age, and the elderly consequently have the greatest prevalence. However, with proper treatment, if identified early, we can slow down or stop the deterioration. At now, long medical examinations, involving long questionnaires, normally include techniques of diagnosis. Cost-effective and scalable techniques are urgently required, which can detect AD early in the process. Researchers worldwide thus attempt to locate non-invasive techniques and therapies for the early identification of such illnesses [2].

Dementia is a brain condition that may be produced by a variety of illnesses including AD. One of the most recognized signs is memory difficulties, and from the beginning, they impact the language of an individual and their ability to hold a normal conversation- Neurologists frequently notice anything when beginning a regular history section during their evaluation.

In an analysis of conversation, this thesis examines the skills of a dementia individual in a variety of home and community environments communicating with a range of interlocutors. Dementia affects cognition, language, thinking, and executive functions; language may be impacted in several aspects, ranging from word-finding to articulation, but mainly language reveals the problems of dementia [3] by conveying confusion and repetitiveness, for instance.

In new research, a conversation analysis (CA) was used to such physician-patient communications and a set of 6 linguistic features may be utilized for differentiating between (ND) and (FMD) patients (not dementia-related). The survey has shown good diagnostic power findings, but depended on Manual CA to find out the patterns of interactions in the conversation; this includes audio recording, transcription of the meetings, and qualitative analysis performed by a qualified trained expert. It is consequently excessively costly, time usage & not practical for widespread usage. It works towards an automated CA-based dementia diagnosis method, where software specialized in speech technology analyses the audio conversations.

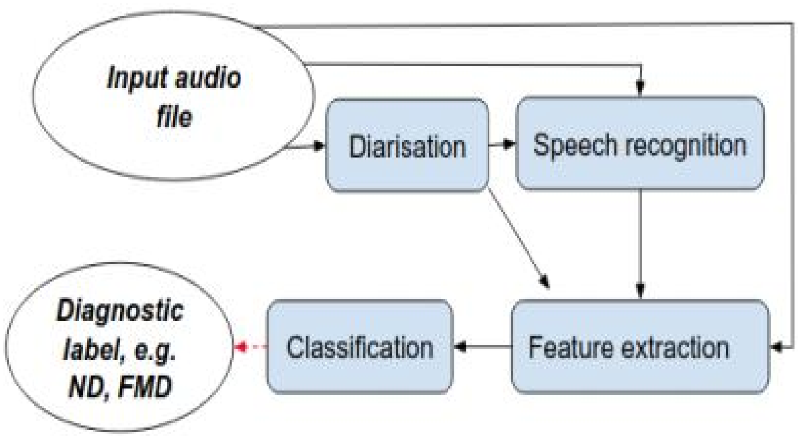


Figure 1 Automatic detection scheme for dementia

Automatic conversation analysis is a new and difficult field in which study involves many disciplines, including Automatic Speech Recognition (ASR), spoken diarization, and classificatory, to automate all stages of the CA process [4]. In addition, the newest methods and tools created for NLP & ML must be used to create an automated system for identifying dementia. A block diagram of an automated dementia detection scheme including a diarizing toolkit is shown in figure, followed by speech acknowledgment, feature removal, & categorization units [5].

The remaining article is systematized as follows: Section II. Literature Review work III. Section The proposedGRU model .algorithms are presented in Section III followed by the Problem Statement. Section IV. Presents and discusses the results of simulation. Finally, in section V, conclusions and suggestions are given for future work.

1. Literature Review

In current years there has been a growing interest in dementia care, like how professionals, service providers, & society, in general, could assist people to live with this situation effectively. In this context, guidance is essential to ensure conversation partners properly assist people with dementia in conversations.

Define the literature review linked to Dementia Detection, AD, automated conversation analysis, and the neurodegenerative memory disorder ND, including several methods to categorization and improvement strategies.

Zaini, S. S. M., et al. A decompression method is presented in this article to retrieve the data contained in a MySQL database. In Malaysian (AD) patients, the database contains genetic information. The data have been compressed for efficient storage due to the magnitude of the data. A decompression technique is provided in this article to retrieve the data and show it to the customer. PHP was used to build the decompression technique. The outcomes indicate that technique has been implemented successfully [6].

Obin, N. et al. The article presents new paradigms for speech-to-syllable segmentation. The primary thrust of the suggested technique is the utilization of description of the speech signal by time-frequency & fusion of intensity and speech-response measurements via different frequency zones for the automated selection of relevant segmentation info. Depending on the frequency area, the time-frequency description is utilized to exploit the speech properties. This presentation measures intensity profiles to give information in different frequency areas and measures voicing profiles to identify the frequency areas relevant to segmentation. The suggested approach exceeds traditional methods for detecting syllable landmarks and limits on the American-English TIMIT database and offers a promising paradigm for speech segmentation into syllables [7].

Zhu, Q. et al. 1-D Locally binary patterns (LBP), in conjunction with the hidden Markov model (HMM), is suggested for advanced speech recognition for the application in speech signal segmentation & voice activation detection (VAD). Adaptive Empirical Model Decomposition (AEMD) de-noises speech first and is then processed utilizing VAD depending on LBP. Lastly, the short-term energy identified from VAD in the speech activity is decreased and used as an input for the HMM identification process. Compared with existing VAD methods in various SNRs, from 15 dB to a strong noise condition -5 dB, the higher performance of the proposed system for voice recognition [8].

Amira B. R. et al. In this article, suggest a technique for diagnosing AD that is dependent on a description of hippocampal volume. The average filter is used as a eliminate noise filter, the active shape model (ASM) is used to identify the hippocampus area, and an effective performance technique of categorization is used [9].

Krashenyi,I. et al. This study used a fuzzy logic technique to create an Automated method for differentiating among patients with AD and normal control. The fuzzy inference method utilizes core statistical moments in MRI voxel intensities in 24 of the most discriminating regions of interest (ROIs) as input features. As a feature of classification performance, the AUC was projected utilizing k-fold cross-validation. It is established that using 1^{st}, 2^{nd}, and 3^{rd} statistical moments in FIS at the same time yields the best AUC=0.895 [10].

Zhu, G. and Yang, P. The T-test technique is used in this article to find significant variations in gene expression among healthy individuals and three stages of AD patients. In this study 90 genes were observed, 5 of which were validated for other sources to be connected to AD, and 10 are connected to nerve cell tissue and signaling. AD-related genes have been identified, at least in some cases, according to this finding [11].

Anuradha, G. et al. This article is aimed towards identifying EEG dementia in MCI patients. A contrast of normal and MCI individuals involves the prevailing frequency, dominant frequency variability, and dominant frequency prevalence. This article shows the very desired use of EEG-based identification of disease for medical practice [12].

Chien, Y.W., et al. Proposed a new representation of the feature sequence and used a recurrent neural network to perform classification in this article. To confirm their approach, an experiment has been carried out using 150 speakers, with a rating of 0.95, which may surpass existing state-of-the-art techniques in terms of a region under the receiver operating feature curve.[13]

2. Proposed Work

Problem Identification

Whereas automated interaction analysis is a relatively new area of study & technology that was not used for differential memory diagnosis, important research was undertaken using ML methods to detect dementia symptoms in patients' speech & language. Manual CA for frequent clinical use is expensive & difficult to scale. Automatic classification is a new and difficult field of study that has produced some promising results. Automatic Speech Analysis of Conversations using data analytics (like Machine Learning and Deep Learning) is a critical task with NLP because it generally uses Text annotation, correction, and cleaning are done on the second features data frame which is complex. As with the descriptive studies, the primary issues were with patient selection.

Proposed Methodology

Dementia dataset is used, in which the audio file is used for speech recognition analysis, and data is generated based on that data, which is predefined in the dementia data databank. Based on speech analysis, that audio file is transformed into text.

The data frame is then created using the Pylang AQC library. Counting how many Utterances there are in the data frame. Then they identify participants to define the part of speech, calculate the number of words, and then use the part of speech to determine the tagged word. Extraction of Reg-Ex and UTF-8 encoding from participant information. After all of the processing, label the dataset to indicate which file or information belongs in which section: Control or Dementia. To construct tagged conversations, shuffle both label data into one data frame and use the spacy audio model "en-core-web-sm." Finally, make a dictionary including terms such as interjection, pronoun, noun, proper noun, and so on. Regular expressions were used to create a data frame with nine features: label, sentence, text, pos text, pos text complete, pos complete, new text, and text for pos. We're getting some sentence and clean data, as well as dementia label information. Tokenize the dataset before producing the full interview feature file and running sentiment analysis on it. Then, for the training, load the data.

Data Preprocessing

The Pylang ACQ library is used to create the data frame. PylangAcq is a language acquisition research library written in Python. Other TalkBank datasets can be accessed quickly. Python data structures with intuitive interfaces for flexible data manipulation and access. There are a variety of standard developmental tests available: TTR (Type-Token Ratio), MLU (Mean length of utterance), &IPSyn (index of productive syntax)

This library is used to identify the number of Utterances from the data frame and perform audio processing on the control label's Files. After that, we identify participants to define the part of speech as well as calculate the number of words, after which they use the part of speech to identify the tagged word. To avoid misunderstanding, create tagged sentences from parts of speech, compute the total number of sentences, and then grope them. Then, with the Dementia label, repeat the procedure. Utilizing Reg-Ex and UTF-8 to encode the tokenized data, which consists of the tokenized list and tokenized id, to produce a data frame using text, level, and id in the dementia list.

After all of the processing, the dataset is labeled to indicate which file or information belongs in which section: Control or Dementia. Use the spacy audio model "en-core-web-sm" to construct tagged dialogues by combining both label data into one data frame.

For example, en-core-web-sm is a straightforward English language pipeline with vocabulary, vectors, and phrases, as well as entities trained on written web content (news, blogs, comments).

Finally, a dictionary including information such as noun, interjection, proper noun, pronoun, and so on will be created.

Replacing special tags by regular expression and they created a final data frame with nine features: label, sentence, text, pos_text, pos_, pos_text_complete, pos_complete, new_text, text_for_pos.

The second features data frame is used to undertake text annotation, correction, and cleaning. They're getting some clean data and sentences, as well as dementia labels. Tokenize the data before generating the whole interview feature file and running sentiment analysis on it. Then, for training purposes, load the data.

GRU

The architecture of Gated Recurrent Unit

Let's have a look at how GRU operates now. A GRU cell that looks similar to an LSTM or RNN cell may be found here.

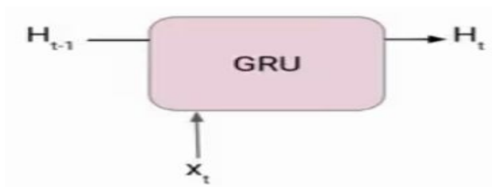


Figure 2: GRU Architecture

At every timestamp t, an X_t input & hidden state $H_{t-1}$from the preceding timestamp, t-1 is taken. It then releases a novel hidden state H_t, which is then transferred to the following timestamp.

In contrast to the three gates in an LSTM cell, a GRU typically has two gates. The 1st gate is a reset gate, while the second is an update gate.

- **Reset Gate (Short term memory)**

It gives a hidden state (H_t) of the network's short-term memory. The Reset gate equation is as follows.

$$r_t = \sigma(X_t * U_r + H_{t-1} * W_r) \quad (3.1)$$

It is quite similar to this if you remember the LSTM gate equation. Due to the sigmoid function, rt is between 0 and 1. U_r &W_r have reset gate weight matrices.

- **Update Gate (Long Term memory)**

They also have a long-term memory update gate, which is represented by the gate equation below.

$$U_t = \sigma(X_t * U_u + H_{t-1} * W_u) \quad (3.2)$$

Weight matrices such as U_u and W_u differ only.

1) Add Model layer

Input layer: input sentence to this framework.
Embedding layer: map every word into a lower dimension vector.
layers: Gated recurrent units (GRUs) were invented by Kyunghyun Cho et al. in 2014 as the gate mechanism in RNN. Gated recurrent units have a forgetting gate, but fewer parameters than LSTM because of the lack of an output gate.
Activation: To utilize activation function. Default: hyperbolic tangent (tanh). No activation (i.e. "linear" activation: a(x) = x) if you pass None is applied.
Dense: The word refers to the number of fully connected neurons in a network surface (dense). Every neuron on the surface collects data from all neurons on the surface before it, resulting in a highly

interconnected system. A dense surface, in other words, is a fully linked surface, implying that all neurons in one layer are linked to those in the next.

Algorithm

Step 1: Collect the Dementia Dataset of speech audio files (.cha).
Step 2: Audio file is considered for speech recognition and text data generation.
Step 3: After that Creating a data frame with the help of the pylang ACQ library.
Step 4: First, we process the control label's files, identifying the number of Utterance from the data frame.
Step 5: Then we identify participants for defining the part of speech and calculate the no. of the word then identify the tagged word.
Step 6: Then repeat the same process for the Dementia label.
Step 7: From participants' information, extracting RegEx and encoding them UTF-8.
Step 8: Now Encode the tokenized data using UTF-8 that consists of a tokenized list and tokenized id that creates a data frame using text, level, and id in dementia list.
Step 9: Shuffle both label data into one data frame, using the spacy audio model "en_core_web_sm" to create tagged dialogues.
Step 10: Replacing special tags with a regular expression and forming a final data frame with 9 features like label, sentence, text, pos_text, pos, pos_text_complete, pos_complete, new_text, text_for_pos.
Step 11: We are getting some things sentence and clean data as well as for dementia label.
Step 12: Tokenize the dataset, generate the full interview feature file then perform sentiment analysis on the data frame.
Step 13: Then load the data for the training.

Flowchart

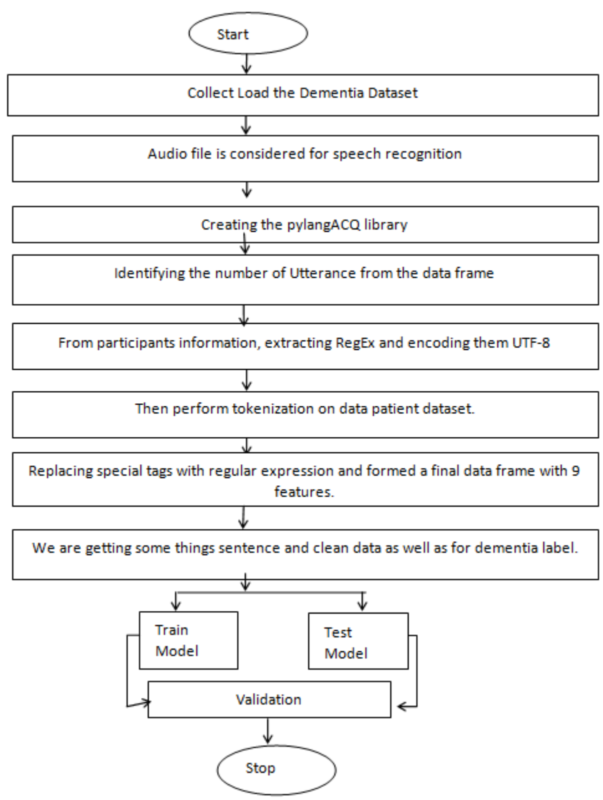


Figure 3: Flow chart

The LSTM cell state allows information to move between units while maintaining interactions. To add or delete data, each unit has a cell state with input, output, and a forget gate. The forget gate uses a sigmoid function to select information from the previous cell state that must be forgotten. The input gate controls information flow into the current cell state using the 'tanh' and 'sigmoid' multiplication operations. Finally, the output gate selects the data that will be transferred to the next hidden state.

3. RESULTS & DISCUSSION

This study was performed utilizing the Python programming language and a Jupyter notebook as the platform (version 6.3.1). here, we have used the Dementia dataset. Experiment. The description of such dataset and achieved results of the proposed model has given below.

A. Dataset description

The survey uses the biggest freely available database of transcripts and Dementia bank (Boller and Becker,2005), and

Figure 4. The explanation task of a Boston cookie theft. All activities in the picture were asked from participants

Patient interviews with audio recordings (and control). 1 Patient was requested to carry out a variety of tasks; for example, patients were shown an image in the description of 'Boston Cookie Theft' (See Figure 4). The "recall test" also includes recalling the features of a story that was previously told to the patients. Each Dementia bank transcript has an automatic syntactic morph analysis, like standard part-of-speech tagging, tense descriptions, & repetition markers. 2 Note that these characteristics are generic linguistic properties that are automatically extracted and are not AD-specific. To utilize as data samples, we have broken every transcript into separate statements. Note that we have also removed utterances without POS tags. This balance lowered the number of details but made sure that the models were compared with tagged and non-tagged parameters.

The transcripts and audio files have been acquired under the greater protocol of the University of Pittsburgh School of Medicine, overseen by Alzheimer and Related Dementia studies. NIH grants AG005133 and AG003705 to the University of Pittsburgh were funded in the first gathering of the Dementia Bank data. Elderly controls, individuals with likely and potential Alzheimer's disease were included. Longitudinally, the data were collected annually.
https://dementia.talkbank.org/access/English/Pitt.html.

B. Performance Matrix

1. Accuracy

Accuracy is a measure of how many predictions your model has done for the whole test dataset. The following formulation measures it:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

2. Recall

Recall – or the true positive rate – is the measure of how many true positive values of all the positive ones in the data set are expected. Sensitivity is also occasionally termed. The following formula collects the measurement:

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (2)$$

3. Precision

Precision is a measure of the accuracy of a positive forecast. In other terms, it signifies how positive you can be if a result is projected as good. The following formula is used for calculation:

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (3)$$

4. F-score

The F1-score is the F-score most frequently utilized. It is a combination of accuracy and memory, that is, its harmonic significance. The following formula allows you to compute the F1-score:

$$F1 = 2.\frac{Precision.recall}{Precision+recall} \qquad (4)$$

Table1: Comparison of performs Parameter between Existing Method and Table Base and Proposed GRU method

Parameter	Existing Method (LSVM)	GRU (Proposed)
Accuracy	0.77	0.71
Precision	0.76	0.77
Recall	0.83	0.94
F-Score	0.79	0.84

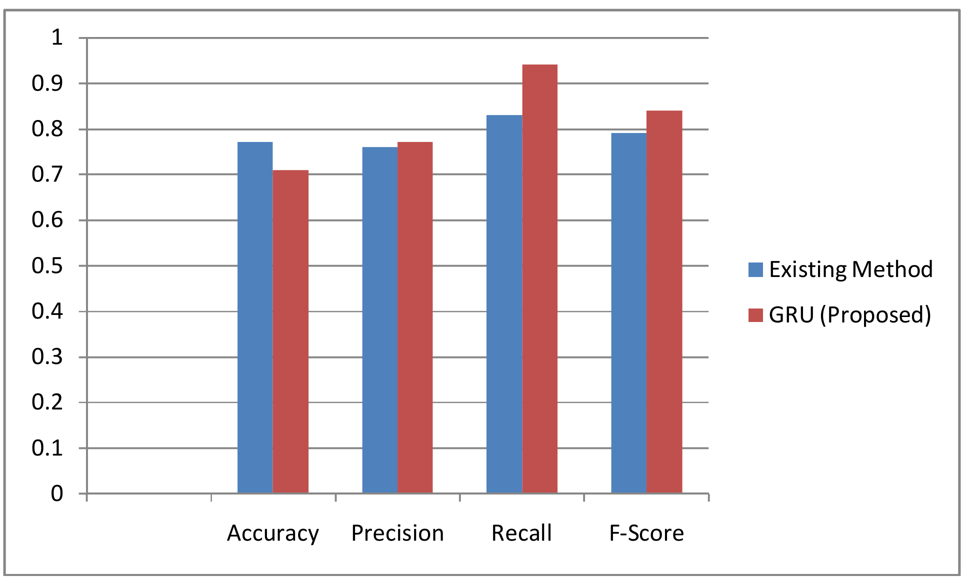


Figure 5: Comparison graph of existing methods with GRU

The comparison of several classification methods is represented in Table 1. It represents overall performance comparison output in contrast to several existing methods and GRU Method like Accuracy, Precision, Recall, and F-Score.

5. CONCLUSION

AD is an incurable brain illness that wreaks havoc on one's life quality. It most often affects older individuals plus eventually necessitates full-time care. Dementia can impair a person's ability to communicate verbally, linguistically, as well as in a conversational setting. In the early steps of neurodegenerative memory problems, persons with dementia's spoken communication might be impaired, plus expert analysis utilizing the qualitative approach of communication analysis of neurologist patient encounters can give diagnostic signals for doctors. Language changes might indicate that a patient's cognitive skills have been harmed, allowing for an earlier diagnosis. Using the Dementia Bank dataset, we apply NLP approaches to identify as well as evaluate the language features of AD patients.

Using sentence level GRU the accuracy (71%), precision (77%), recall (94%), and F1 scores of (84%) were obtained which enhanced state-of-the-art outcomes. There are pre-trained language frameworks accessible in a variety of languages. As a result, a technique in this study may be tested in languages other than English. Additionally, by using multilingual versions of these frameworks, information about AD prediction in one language may be translated to another language in the absence of a sufficiently large dataset.

Future work will include expanding the size of our dementia dataset, developing additional GRU for dementia detection, and replacing manual annotation with automatic speech divarication and identification.

REFERENCES

[1] Sabbagh, M. N., Malek-Ahmadi, M., Kataria, R., Belden, C. M., Connor, D. J., Pearson, C., Jacobson, S., Davis, K., Yaari, R., and Singh, U. (2010), The Alzheimer's questionnaire: a proof of concept study for a new informant-based dementia assessment. Journal of Alzheimer's disease: JAD. 22(3): 1015–1021. https://doi.org/10.3233/JAD-2010-101185

[2] Wimo, A., Guerchet, M., Ali, G.-C., Wu, Y.-T., Prina, A. M., Winblad, B. and et al. (2017),The worldwide costs of dementia 2015 and comparisons with 2010. Alzheimer's Dement. 13, 1–7. doi: 10.1016/j.jalz.2016.07.150

[3] Mirheidari, B., Blackburn, D., Reuber, M. et al. (2016), Diagnosing people with dementia using automatic conversation analysis. In: Proceedings of Interspeech, San Francisco, CA. ISCA. 1220-1224

[4] Kindell, J., Sage, K., Keady, J., and Wilkinson, R. (2013), Adapting to conversation with semantic dementia: Using enactment as a compensatory strategy in everyday social interaction. International Journal of Language and Communication Disorders. 48(5):497–507.

[5] Oba, H., Sato, S., Kazui, H., Nitta, Y., Nashitani, T., and Kamiyama, A. (2018), Conversational assessment of cognitive dysfunction among residents living in long-term care facilities. International psychogeriatrics. 30(1):87–94.

[6] Zaini, S. S. M., et al. (2012), Implementation of decompression algorithm in Alzheimer's disease database. 2012 International Symposium on Computer Applications and Industrial Electronics (ISCAIE). 278-281. doi: 10.1109/ISCAIE.2012.6482112.

[7] Obin, N., Lamare, F. and Roebel, A. (2013), Syll-O-Matic: An adaptive time-frequency representation for the automatic segmentation of speech into syllables. 2013 IEEE International Conference on Acoustics, Speech and Signal Processing. 6699-6703. doi: 10.1109/ ICASSP.2013.6638958.

[8] Zhu, Q., Chatlani, N. and Soraghan, J. J. (2012), 1-D Local binary patterns based VAD used INHMM-based improved speech recognition. 2012 Proceedings of the 20th European Signal Processing Conference (EUSIPCO). 1633-1637.

[9] Amira, B. R. et al. (2014), Computer-assisted diagnosis of Alzheimer's disease. International Image Processing, Applications and Systems Conference. 1-4. doi: 10.1109/IPAS.2014.7043281.

[10] Krashenyi, I. et al. (2015), Fuzzy classification of Alzheimer's disease using statistical moments. 2015 IEEE 35th International Conference on Electronics and Nanotechnology (ELNANO). 409-412. doi: 10.1109/ELNANO.2015.7146921.

[11] Zhu, G.-Q. and Yang, P.-H. (2016), Identifying the candidate genes for Alzheimer's disease based on the rejection region of T test. 2016 International Conference on Machine Learning and Cybernetics (ICMLC). 732-736. doi:10.1109/icmlc.2016.7872979.

[12] Anuradha, G., Jamal, N. and Rafiammal, S. (2017), Detection of dementia in EEG signal using dominant frequency analysis. 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI). 710-714. doi:10.1109/icpcsi.2017.8391806.

[13] Chien, Y.-W., Hong, S.-Y., Cheah, W.-T., Fu, L.-C., & Chang, Y.-L. (2018). An Assessment System for Alzheimer's Disease Based on Speech Using a Novel Feature Sequence Design and Recurrent Neural Network. 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC). doi:10.1109/smc.2018.00557

[14] Alhanai, T., Au, R., & Glass, J. (2017). Spoken language biomarkers for detecting cognitive impairment. 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU). doi:10.1109/asru.2017.8268965