Investigating Differences in Language Processing with Aphasia Disorder Using Graph Convolutional Networks

Kailash Nath Tripathi[1], Sudhakar Tripathi[2], Ravi Bhushan Mishra[3], and Anand Bihari[4]

ARTICLE INFO

Article history:
Received: 8 December 2023
Revised: 27 February 2024
Accepted: 25 March 2024
Online: 31 March 2025

Keywords:
Aphasia affected patients
Healthy person
Graph Convolutional Network
Functional magnetic
Resonance imaging
RETROICOR

ABSTRACT

Aphasia Affected Persons (AAPs) often get annoyed due to the dearth of a link between their internal monologue, which is also known as inner speech, and external words or overt speech. The main objective of this research is to classify the manners in which people with aphasia caused by stroke relate to themselves and others. This paper proposes a model employing a Graph Convolutional Network (GCN) aimed at achieving specific research objectives. Utilizing functional Magnetic Resonance Imaging (fMRI) data from 20 subjects, including individuals diagnosed with Aphasia Affected Persons (AAP) and Healthy Persons (HP), the study encompasses a balanced dataset of 11 females and 9 males. The methodology is designed to investigate elusive properties or relationships, thereby providing an enhanced understanding of the mechanisms underlying language processing in the brain. Data is pre-processed thoroughly using methods like Retrospective Image Correction (RETROICOR) and spatial smoothing is applied to eliminate physiological noise as well as enhance data quality. The GCN is trained on how patients judge words (JoW) and synonyms (JoS) so that it makes predictions about them after partitioning its data among different models. Evaluation of the proposed model's performance included metrics such as patient accuracy and response time. As compared to age-matched controls, AAP shows greater inter-subject variations in brain activity between concrete and abstract words possibly due to an increased concreteness effect. In contrast, HPs reach their maximum accuracy in an abstract condition where it amounts to 99.65% at reaction time equaling 1981.33 milliseconds whereas AAPs whose control condition records 100% with reaction time around 1642.56 milliseconds.

1. INTRODUCTION

The intricate fundamental cognitive function of language has been of great interest in neuroscience [1]. Understanding how language is generated by the brain has huge therapeutic implications because it is a basic scientific question [2]. Aphasia has been one area that this endeavor has focused on; this is a condition where a person loses the ability to understand or produce speech after sustaining brain injury [3]. Caused by either a stroke or an injury to the brain, it affects communication language comprehension, and production abilities of a person leading to poor quality of life as well [4].

Investigating the neural basis of language processing in aphasic persons is critical for effective rehabilitation and treatment approaches apart from its scientific significance [5]. A general decoding model of the text modality for AAPs is shown in Figure 1.

The neuroimaging techniques over time particularly fMRI have revolutionized the understanding of how the human brain works [7]. Using fMRI researchers can capture dynamic neural processes accompanying various cognitive functions such as language processing [8],[9].

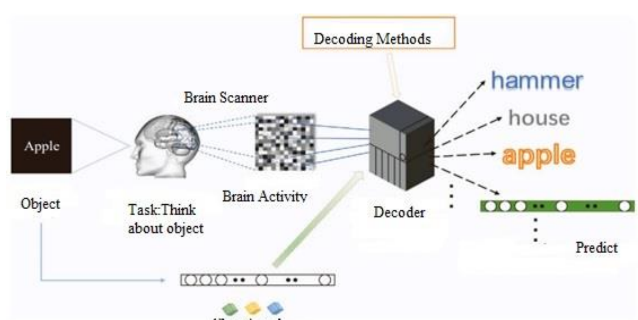


Fig. 1. A general decoding model of the text modality [6].

In addition, advances in machine learning and deep learning techniques have provided novel strategies to analyze complex brain data and figure out intricate patterns

[1]*ISBM College of Engineering, Pune, Maharastra, India.*
[2]*Department of Information Technology, R. E. C. Ambedkar Nagar ,U. P., India.*
[3]*Department of Computer Science & Engineering, IIT(BHU)(Retd.), Varanasi, U. P., India.*
[4]*Department of Computational Intelligence, School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, Tamil Nadu, India.*
**Corresponding author*: Anand Bihari; Email: anand.bihari@vit.ac.in, csanandk@gmail.com.

of neural connectivity across areas that are difficult to connect [10].

This current research attempts to merge neuroscience with machine learning using GCNs to investigate neural connectivity patterns related to language processing among people who experience aphasia. GCNs which are a form of neural network designed specifically for graph-structured data have proven impressive performance modeling relationships between elements within complex systems [11]. Therefore, they provide promising approaches to study connections facilitating linguistic activity within the context of brain research.

1.1 Language Processing in the Brain

Language processing is a complex cognitive function that involves a distributed network of brain regions [12-13]. This networking encompasses areas in the left and right hemispheres with specific regions dedicated to different linguistic functions [14]. Language processing, in general, can be classified as receptive language (comprehension) and expressive language (production) [15].

In terms of receptive language, the Superior Temporal Gyrus (STG) and middle temporal gyrus (MTG) are important regions for auditory word recognition and comprehension [16]. The back part of the Superior Temporal Sulcus (STS) deals with prosody, rhythm, and melody of speech. On the other hand, semantic processing which links words to their meanings takes place at the angular gyrus (AG) [17].

On the other hand, expressive language includes regions such as Broca’s area located at the posterior frontal gyrus that is responsible for speech production and syntactic processing [18]. Phonological processing and word retrieval take place within the left inferior frontal gyrus (IFG). As well as motor function through articulation occurs at the precentral gyrus.

However, this connectivity does not mean that these regions exist in isolation but rather they are interconnected within them. A considerable number of inter-regional connections form a highly complex neural network that enables seamless merging of differing types of linguistic processes. To explain this better it is important to put fMRI data under consideration where it is determined how connected most regional parts are to one another during the execution of certain cognitive tasks - experiments [19].

1.1.1 Aphasia: Disruption of Language Processing

Aphasia refers to any kind of impairment in normal communication brought about by disturbances in cortical circuits involved in language [20]. Aphasia can manifest differently depending on lesion location and extent [21]. Consequently, if Broca's area has been damaged then it can result in Broca’s aphasia characterized by the inability to produce grammatically correct sentences while Wernicke's area sounds fluent but meaningless when it gets damaged [22].

Knowledge of aphasia presents a unique opportunity to understand how the brain is organized for language processing [23]. Researchers have made significant progress in mapping the brain regions critical for various aspects of language by correlating specific brain lesions with language deficits [24]. However, this understanding would need to go beyond individual regions and look at how they are connected [25].

1.1.2 Advances in Neuroimaging and Connectivity Analysis

Recent advancements in neuroimaging, particularly functional magnetic resonance imaging (fMRI), have allowed us to examine the connectivity of the human brain during cognitive tasks [26]. It can be used to track changes in blood flow and oxygenation resulting from neural activity therefore helping researchers infer patterns of connectivity within the mind.

One way fMRI data can be analyzed is through functional connectivity analysis that assesses temporal correlations between different areas of the brain [27]. This resulted in the definition of functional networks involved in diverse cognitive functions including Language. On the other hand, this method often treats every part as a separate node with no consideration for their interdependence in terms of connection complexity.

Network analysis based on graph theory provides a broader view of connectivity within the cerebral cortex [28]. Conceptually, the brains can be viewed as networks where each node represents a region and edges represent connections between them. By this structural organization, researchers could study the way it connects both locally and widely.

1.1.3 Graph Convolutional Networks: Bridging Neuroscience and Machine Learning

In the area of graph-structured data, there have been several advancements in machine learning such as GCNs [29]. For instance, these were initially developed for social network analysis and recommendation systems; however, they are now applied in various fields such as natural language processing and biology [30].

Wiring the brain (GCNs) is a branch of science in neuroscience that provides a robust model for simulating the brain’s connectivity [31]. With this, complex interactions among regions and how they relate to cognitive processes are captured by considering nodes as brain regions and edges as their connections in graphs known as GCNs [32]. This has provided an alternate approach to reveal language processing within the neural sphere in healthy individuals and those with aphasia.

1.2 Problem Statement

Language functions have various parts of the brain responsible for them. One such hypothesis suggests that grammar is contained within Broca's area which forms a network connected by nerves. However, this version of the hypothesis has been challenged. Simple grammatical patterns, such as word order and case inflections, can be learned even in languages with complex morphology, supporting the idea that language centers in the brain function as a switchboard connecting various areas that store linguistic information.

Aphasia, a language disorder resulting from damage to the brain region responsible for speech production and comprehension, primarily affects the Broca area. Individuals with aphasia lose the ability to engage in meaningful conversations. Many stroke patients also experience aphasia, a language disorder caused by the loss of the brain's ability to coordinate and manage linguistic capabilities due to a disrupted connection between the Broca area and other regions.

When a person has aphasia, their cerebellum is impaired, and they cannot produce speech because the Broca area fails to respond to the lingual gyrus, even though the speech comprehension and production mechanisms have been activated. This incorrect retrieval in the lingual gyrus can cause the cortex to lose its structure and become displaced.

1.3 Research Objectives

This section provides the objectives of the work as follows:

a. The primary objective of this research is to investigate the neural connectivity patterns associated with language processing, with a specific focus on individuals with aphasia.
b. This study aims to explore how different regions of the brain work together to generate language and sentences in both normal and aphasic individuals.
c. To develop a computer model or graph network that replicates brain language processing and shows how different brain regions are involved. Experimental data would underpin the model.

The remaining parts of this work are structured as described below. Previous research is analyzed and discussed in Section 2. In Section 3, the suggested framework is assessed, and its implications are examined. In the next part (section 4), the findings are reviewed, and a brief explanation is also provided for better comprehension. The study ends in Section 5, which also includes some thoughts on potential future work and the conclusion of the work.

2. RELATED WORK

This section discusses the previous study performed on investigating the differences in language processing with Aphasia disorder using GCN.

Teghipco et al. (2023) [33] explored the possibility that encoding spatial dependencies in the data could improve predictions by identifying unique individualized spatial patterns and tested the efficacy of using deep learning techniques with Convolutional Neural Network (CNN) on entire brain morphometry and lesion the human body to determine which individuals with chronic stroke have serious aphasia. Even when the Support Vector Machine (SVM) is nonlinear or blends both linear and nonlinear reduction of dimensionality approaches, the authors found that CNN obtains much greater accuracy of 77% and F1 scores of 0.7 than the SVM.

Shams et al. (2023) [34] employed machine learning techniques, and the researcher projected that patients with gliomas that had infiltrated the language network would suffer from aphasia. The Aachen Aphasia Test (AAT) was used to determine the severity of aphasia before surgery. The model used a random forest to choose features and then an SVM to analyze the data. Utilizing patient demographics, tumor World Health Organization (WHO) grade, tumor location, and relative tract volumes, the best model performance obtained 81% accuracy (specificity = 85%, sensitivity = 73%, and AUC = 85%).

Billot et al. (2022) [35] employed disconnectome maps, and authors searched for patterns of architectural disconnection that are associated with long-term language challenges. Support-vector regression disconnectome-symptom projection research was carried out to study the associations that exist between disconnectome maps (which indicate the likelihood of disconnection at each white matter voxel) and different language scores. In addition, research on lesion-symptom mapping was carried out, making use of support-vector regression, and the findings were analyzed qualitatively. Although there was a great deal of agreement between the results of the SVR with disconnectome-symptom mapping (SVR-DSM) and the SVR with lesion-symptom mapping (SVR-LSM) for scores such as aphasia severity and naming, it seemed that focal impairment at the level of the insular and central opercular cortices was the primary factor in explaining overall language abilities.

Smaïli et al. (A2022) [36] developed a strategy for improving a person with aphasia's ability to communicate with people around them. A machine translation system is presented that can assist a patient with aphasia to communicate more effectively by identifying and fixing any mistakes they make in their speech. In this paper, researchers have demonstrated the viability of the research for converting from aphasia data to normal language by demonstrating how authors construct a pseudo-aphasia database from genuine data. Based on these first findings, the authors can conclude that the deep learning algorithms that are used provide accurate translations with a BLEU of 38.6.

Moral et al. (2021) [37] analyzed the differences between non-fluent, semantic, and logopenic Primary progressive aphasia (PPA) patients and 20 healthy controls by using a cross-sectional design. Multinomial Naive Bayes, Decision Tree, Elastic Net, Support Vector Machines, Random Forest, K-Nearest Neighbours (KNN), and Gaussian Naive Bayes were among the seven machine learning algorithms tested. KNN algorithm's diagnostic ability to differentiate PPA from controls was strong (accuracy 75%, F1-score 83%). When comparing PPA variations, however, discrimination was less (58% accuracy and 60% F1-score for KNN).

Kristinsson et al. (2021) [38] employed machine learning techniques to analyze a multimodal neuroimaging dataset and make predictions about aphasia severity and language scores. Included in the neuroimaging data set were measurements of cerebral blood flow (CBF), lesion burden, and fractional anisotropy (FA) values derived from diffusion-based fMRI. The findings suggest that several neuroimaging modalities can be used to portray how brain injury and surviving brain function transfer better properly into language function in aphasia.

Chen et al. (2021) [39] explored the use of resting-state fMRI to characterize global and nodal facets of functional networks in individuals with aphasic stroke. A 3-T fMRI scan was performed on 24 right-handed stroke patients with aphasia and 19 healthy controls (HC). Patients with aphasia were shown to have lower-than-average levels of local efficiency (Eloc), normalized clustering coefficient (gamma), and small-worldness (sigma). Patients with aphasia also showed an improvement in their language skills, recollection, naming, and understanding after using Eloc. The findings show that aphasic stroke patients had changes to both global and local topological features as a consequence of their injuries.

Nissim et al. (2020) [40] intended to rigorously analyze the effectiveness of transcranial direct current stimulation (tDCS) and transcranial magnetic stimulation (TMS) in enhancing linguistic outcomes in PPA; explored the size of effects across stimulation modalities and investigated possible modifiers that can impact treatment results. Changes in performance on language-related activities were measured as standard mean differences before and after stimulation. Research has shown that tDCS is mostly responsible for the observed improvement in naming skills after brain stimulation.

Shain et al. (2020) [41] used fMRI in a realistic comprehension paradigm; it was shown both (1) that predictive coding in the brain's response to language is domain-specific and (2) that these predictions are susceptible to both local word co-occurrence sequences and to a hierarchical framework. Large prediction effects in the linguistic network were shown by the fact that the model caught over 37% of the explainable variance on held-out data. These findings show that brain processes sensitive to hierarchical structure and specialized for the processing of language are responsible for creating predictions about future words in human sentence processing mechanisms rather than input from high-level executive control mechanisms.

Johnson et al. (2020) [42] analyzed to distinguish patients who responded most favorably from those who did not (i.e., responders and nonresponders) and to ascertain whether network measures anticipated naming enhancements, researchers are used worldwide (i.e., network-wide) and local (i.e., regional) graph theoretical measures of functional connectivity before treatment. Several areas involved with various cognitive processes showed group differences in local measurements. Based on these findings, it seems that the features of a patient's functional network are related to how well they respond to naming treatment, which can have predictive implications.

Chien et al. (2019) [43] used a data-driven approach to categorization by proposing a new Feature Sequence format and using a recurrent neural network. It is also shown that the system is automated, which bodes well for its ease of widespread deployment. The findings of the research have been verified by a battery of studies using a total of 120 speech samples, with the best possible score being a 0.838 area under the receiver's operating characteristic curve.

Angelopoulou et al. (2018) [44] examined the relationship between aphasia and pause characteristics and their relationships with language components. Eighteen individuals were recruited with left hemisphere stroke-related persistent aphasia. Transcriptions of speech samples were analyzed for silence using ELAN, an animation tool. Based on The data, researchers can say that the distribution of pause durations in both groups follows a log-normal bimodal model, with thresholds that are different enough to classify pauses into two groups in each population. Brief and extensive.

Friederici, Angela D (2011) [45] highlighted the fact that many analogies can be drawn between the human brain and a machine. Like how a digital computer processes data to generate conclusions and ideas, so does the human brain. Human memory, on the other hand, does not have the same spatial arrangement as digital storage. It seems that some regions of the brain provide crucial contributions to the operation of neural networks. The use of both deterministic and emergent models has been shown. Syntactic activities have been shown to rely on left temporal-frontal networks, whereas semantic processes rely on right-lateralized networks.

3. PROPOSED IMPLEMENTATION MODEL AND DESCRIPTION

Researchers outline the process for classifying brain images of individuals with aphasia and healthy individuals, encompassing data collection, preprocessing, modeling, and evaluation. The journey begins with the collection of two distinct sets of brain images, one featuring individuals affected by aphasia and another composed of images from healthy individuals. Subsequently, data preprocessing through the application of RETROICOR, a method used to remove physiological noise from the brain images, and Spatial Smoothing, which enhances image quality through convolution. The preprocessed data is then thoughtfully split into training and testing sets to facilitate model development and validation. A Graph Convolutional Neural Network (GCN) is implemented to construct a robust classifier. Classification is achieved by deploying the trained GCN model on the testing dataset, thereby distinguishing between Aphasia-affected and healthy individuals based on brain images. Finally, the performance of the model is assessed by calculating accuracy and, if relevant, measuring reaction time, while the study concludes with a summary of key findings and potential future research avenues.

This study aims to examine the collaboration of various brain regions in the formation of language and sentences under normal conditions, as illustrated in Figure 2, and under abnormal circumstances, as depicted in Figure 2.

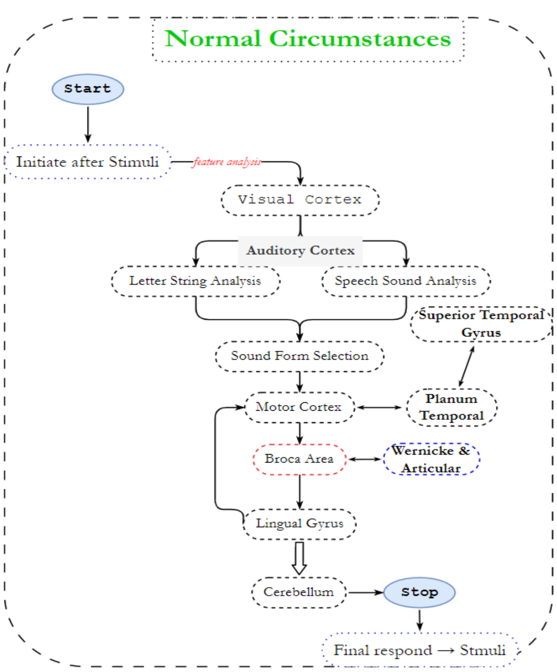


Fig. 2. Block Diagram of language processing inside the brain (normal).

Normal Circumstances

- Initiate the processing mechanism.
- First, the data obtained from external stimuli is processed by the visual cortex. This primary region of the brain's cortex is responsible for receiving, integrating, and processing visual information, primarily through feature analysis.
- Next, the response is sent to the auditory cortex. Located in the temporal lobe, the auditory cortex in humans is responsible for decoding auditory data such as letter and speech analysis. The response is then sent to an appropriate selection mechanism before reaching the motor cortex.
- The motor cortex serves as the final arc, receiving the external agent's request and generating the mechanism to respond to the stimuli. The motor cortex, located in the frontal lobe's precentral gyrus of the posterior parietal lobe and anterior to the central sulcus, is thought to be responsible for initiating, regulating, and executing voluntary actions. It first sends a response to the planum temporal for analysis and then receives a signal from the superior temporal gyrus regarding auditory processing management.
- Ultimately, the motor cortex sends a response to Broca's area for speech and Wernicke's area for memory formation and retrieval. The Broca's and Wernicke's areas are connected through sensory nerves, primarily responsible for communication analysis, which aids in grammar analysis and proper reading and metaphor classification. The response is then sent to the lingual gyrus.
- The lingual gyrus, also known as the medial occipitotemporal gyrus, is a visual processing area of the brain that generates output responses about input stimuli, specifically in the context of letter and score reading.
- Finally, the response is sent to the cerebellum to react to external stimuli. The cerebellum is responsible for coordinating movement and completing language analysis within the brain. It assesses expressive and receptive grammar processing, the ability to recognize and correct language errors, writing skills, and responsiveness to input.

Abnormal (Aphasia) condition

Aphasia is a language disorder caused by damage to the brain region responsible for both producing and comprehending speech. Individuals with aphasia struggle to communicate meaningfully with others. Aphasia is a common outcome of stroke, affecting numerous people.

Primary issue in this disorder lies in language processing:

- Aphasia primarily impacts Broca's area, rendering the brain incapable of managing language coordination and abilities. This disrupts the sensory nerve mechanism between the Broca's and Wernicke's areas.

- Due to aphasia, Broca's area cannot respond to the lingual gyrus, resulting in improper reading and a disrupted output response mechanism. This affects the responsive output to the cerebellum, which in turn is unable to generate an output.
- The improper response retrieval in the lingual gyrus affects the cortex, causing it to deviate from its original form and position, as depicted in Figure 3.

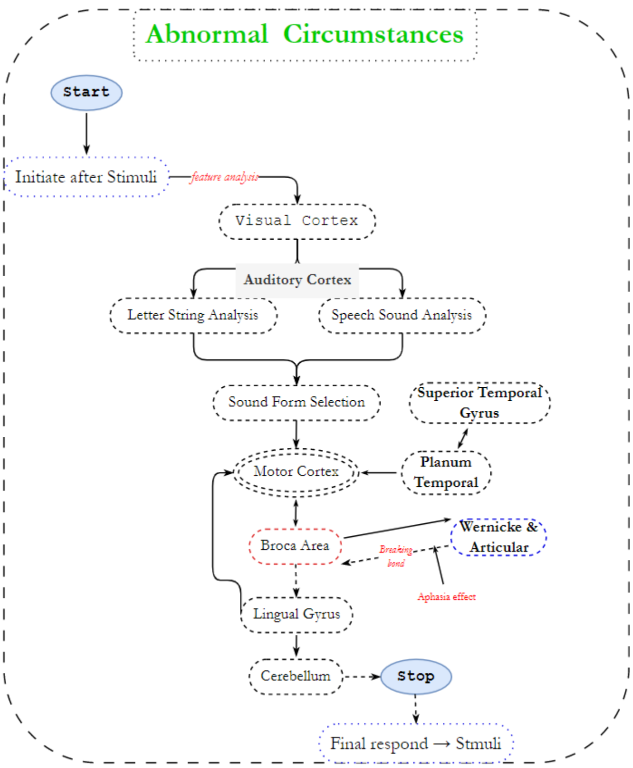


Fig. 3. Block diagram of language processing in an abnormal condition.

3.1 Dataset Description

In this work, the dataset taken into consideration is a primary dataset. It consists of details of some aphasia-affected Patients (AAP) and some healthy persons (HP) means persons who are not affected by aphasia. The parameters that describe the information of these individuals are gender, age, education, and aphasia type. In this, researchers take data of 11 females and 9 males, in which 6 females are AAP and the rest are HP. Also, out of 9 males, 4 are AAP, and the rest are HP. A short description of this dataset is described in Table 1, which is provided below.

3.2 Technique Used

This section describes the techniques below, which are taken into consideration in the methodology.

Table 1. Dataset Description

Parameters	**AAP**	**HP**
No. of Samples	10	10
Age	Between 50-65	Between 50-65
Education	Graduation and above	Graduation and above
Aphasia Type	Anomic, Transcortical Motor	---

3.2.1 RETROICOR

RETROICOR is a preprocessing method for fMRI that addresses physiological noise, like cardiac and respiratory fluctuations. It involves Fourier analysis to identify the fundamental frequencies of these physiological signals. The mathematical representation typically involves creating noise regressors, denoted as R(t), to capture the timing and amplitude of these physiological fluctuations. These regressors are then included in the general linear model (GLM) analysis of fMRI data, where they are regressed out to improve data quality and enhance the sensitivity to neural activity [46]. The mathematical expression for RETROICOR might look like:

$$Y(t) = X\beta + R(t) + \varepsilon \tag{1}$$

where, $Y(t)$ represents the fMRI signal at time t; X represents the design matrix for the experimental task; β is the parameter estimate for the task-related activity; $R(t)$ represents the physiological noise regressors; ε is the error term.

3.2.2 Spatial Smoothing

Spatial smoothing in fMRI involves applying a Gaussian smoothing filter to the data. The mathematical formula for Gaussian smoothing is:

$$S(x,y,z) = \Sigma\Sigma\Sigma\, I(i,j,k) * G(x - i,y - j,z - k) \tag{2}$$

where, S(x,y,z) is the smoothed value at voxel (x,y,z); I(i,j,k) is the original intensity value at voxel (i,j,k); G(x - i,y - j,z - k) is the Gaussian function that determines the weights for the nearby voxels.

The operation involves a weighted average of the intensities of neighboring voxels based on their spatial distance. This process reduces noise and enhances the signal-to-noise ratio in fMRI data. The degree of smoothing is controlled by the parameters of the Gaussian function, such as the standard deviation.

3.2.3 Graph Convolutional Network

A GCN is a type of neural network architecture designed specifically to operate on graph-structured data [47,48]. Graphs are mathematical structures composed of nodes (also known as vertices) connected by edges (also known as links). GCNs extend the traditional convolutional neural networks (CNNs) to handle graph data by incorporating a notion of node connectivity. The graph convolutional layer typically follows these steps:

Initialization: Each node is assigned an initial feature vector.

Aggregation: The feature vectors of a node's neighbors are aggregated to obtain a combined representation. This aggregation step is like the neighborhood pooling operation in CNNs.

Transformation: The aggregated representation is transformed using a trainable weight matrix.

Update: The transformed representation is combined with the node's current representation, often through element-wise addition or concatenation.

Activation: An activation function is applied to the updated representation to introduce non-linearity.

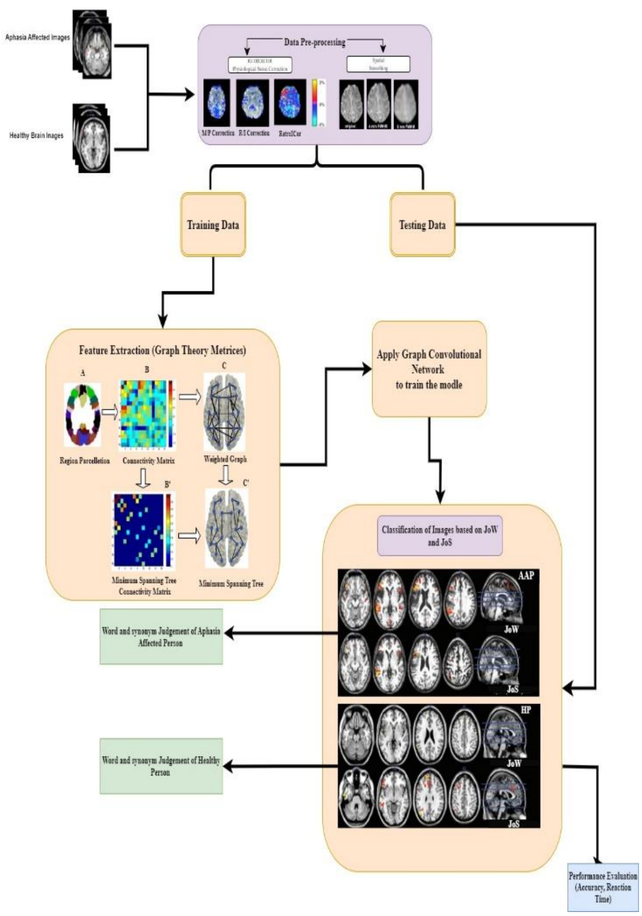


Fig. 4. Proposed Architecture.

The process of aggregation, transformation, update, and activation is repeated for each layer in the network. The final output of the GCN is typically used for various downstream tasks, such as node classification, link prediction, or graph-level tasks. The graph convolutional operation in a GCN can be defined as:

$$H = \sigma(A * X * W) \tag{3}$$

where, H is the output matrix of size NxF, where N is the number of nodes, and F is the number of output features per node; σ is the activation function, such as the ReLU function.

* *Denotes matrix multiplication.*

W is the learnable weight matrix of size DxF, where D is the number of input features, and F is the number of output features.

An approach that combines an Artificial Neural Network (ANN) with a Back Propagation (BP) algorithm, further enhanced by a Genetic Algorithm (GA), to develop load shedding strategies for power systems. The GA helps train the BP Neural Networks (BPNN), aiming to enhance regression abilities, minimize errors, and reduce training duration [49].

3.3 Proposed Architecture

The proposed architecture of the work is shown in Figure 4.

3.4 Proposed Algorithm

Data Collection:

- Let $\boldsymbol{X_{aphasia}}$ $\rightarrow$ the set of brain images from Aphasia-affected individuals.
- Let $\boldsymbol{X_{healthy}}$ $\rightarrow$ the set of brain images from healthy individuals.

Data Preprocessing:

4 RETROICOR:

- Apply RETROICOR to remove physiological noise:
- For each voxel i in $\boldsymbol{X_{aphasia}}$ **and** $\boldsymbol{X_{healthy}}$:
  - Perform regression to remove physiological signals:
  - $\boldsymbol{X_{aphasia\_retroicor[i]}} = \boldsymbol{X_{aphasia[i]}} - \sum_j \beta_{aphasia[j]} \cdot P_j$
  - $\boldsymbol{X_{healthy\_retroicor[i]}} = \boldsymbol{X_{healthy[i]}} - \sum_j \beta_{healthy[j]} \cdot P_j$

5 Spatial Smoothing:

- Apply spatial smoothing with a Gaussian kernel:
- $\boldsymbol{X_{aphasia\_\mathrm{smooth}}} = Convolve(\boldsymbol{X_{aphasia-retroicor,}}\text{Gaussian kernel})$
- $\boldsymbol{X_{\mathrm{healthy\_smooth}}} = Convolve(\boldsymbol{X_{healthy-retroicor,}}\text{Gaussian kernel})$

Data Splitting:

- Split the data into a training set $\boldsymbol{X_{train}}$ and a testing set $\boldsymbol{X_{test}}$ For both Aphasia-affected and healthy individuals.

Model Training:

- Implement a Graph Convolutional Neural Network (GCN) model represented as a function **GCN_Model**.
- The simplified mathematical representation of the GCN can be expressed as follows:
- $H' = \sigma(A \cdot H \cdot W)$
- Here, H represents the node features, which in this case are the image data. A is the adjacency matrix of the graph, where each brain image serves as a node, and W stands for the weight matrix. The activation function (σ), typically ReLU or Sigmoid, is applied to the result. This model is trained to capture features and relationships within the brain image data.

Classification:

- Apply the trained GCN model for classification:
- $\boldsymbol{Y_{pred}} = \boldsymbol{f_{GCN}}(\boldsymbol{X}_{\mathbf{test}})$.
- Where $\boldsymbol{Y_{pred}}$ → the predicted labels for the test data.

Performance Evaluation:

- Calculate accuracy:
- $\boldsymbol{Accuracy} = \frac{(\boldsymbol{Number\ of\ Correct\ Predictions})}{(\boldsymbol{Total\ Number\ of\ Predictions})}$.
- Measure reaction time.

Abbreviation used:

- $\boldsymbol{X_{aphasia}}$: Set of brain images from Aphasia-affected individuals.
- $\boldsymbol{X_{healthy}}$: Set of brain images from healthy individuals.
- RETROICOR: A method for removing physiological noise from brain images.
- P_j: Physiological signals.
- Convolve: The process of applying convolution, often used in image processing.
- $\boldsymbol{X_{aphasia\_retroicor[i]}}$: Brain images from Aphasia-affected individuals after RETROICOR processing for voxel i.
- $\boldsymbol{X_{healthy\_retroicor[i]}}$: Brain images from healthy individuals after RETROICOR processing for voxel i.
- $\boldsymbol{X_{aphasia\_\mathrm{smooth}}}$: Brain images from Aphasia-affected individuals after spatial smoothing.
- $\boldsymbol{X}_{\mathrm{healthy\_smooth}}$: Brain images from healthy individuals after spatial smoothing.
- $\boldsymbol{X_{train}}$: Training set of data.
- $\boldsymbol{X}_{\mathbf{test}}$: Testing set of data.
- H': Updated node features after applying the GCN model.
- σ : Activation function (commonly ReLU or Sigmoid).
- $\boldsymbol{f_{GCN}}$: Function representing the GCN model.
- $\boldsymbol{Y_{pred}}$: Predicted labels for the test data.

END

4. RESULTS AND DISCUSSION

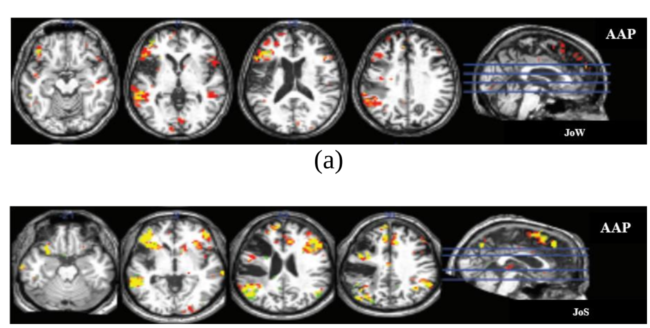
This section gives a summary of the results.

Data from each participant were analyzed using the proposed algorithm at the individual level, corrected with $p < .05$. Two tasks were used to elicit specific semantic processing for abstract and concrete words: JoW and JoS. Accuracy and reaction time were the primary objectives of the research's statistical analysis, which aimed to uncover and evaluate relevant data. Nonparametric statistical tests, including the Mann-Whitney U and Kruskal-Wallis tests, were used because of the research's small sample size. The paper included a control, concrete, and abstract condition.

No statistically significant variations were found between AAPs and HPs concerning reaction time (p-values of 0.51 for both tasks) or accuracy ($p = 0.82$ for the JoW task). However, when looking at the JoS task, a clear difference showed up: HPs showed more accuracy than AAPs ($U = 3.86$, $p = 0.05$). This result indicates that compared to HPs, AAPs had a more difficult time with the JoS assignment. Separate analyses were run on AAP data and HP data to investigate the unique impacts of each circumstance.

4.1 AAP

Most significantly, all AAP had consistent activation patterns (Figure 5 (a) and (b)). First, the left inferior frontal gyrus was consistently the most active region in all AAP, irrespective of task or word type. The second finding was that all AAP showed bilateral activation, and this was true independent of task or word category. When compared to concrete nouns, abstract nouns elicited more neural activity in all AAP.



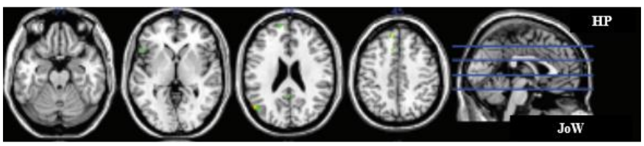
(a)

(b)

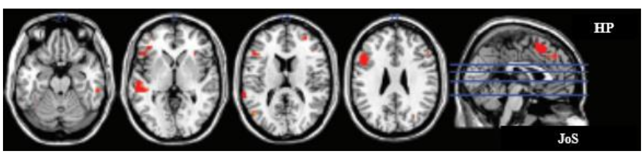
Fig. 5. Activations for AAPs. Activation is shown at p < .05 for contrasts abstract > control (red) and concrete > control (green). Yellow = overlap between contrasts.

4.2 HP

Similar activation patterns could be seen in HPs, as well as in AAPs (Figure 6 (a) and (b)). To begin, left IFG activation was found in every HP. This activation appears to be task- and word-mediated, in contrast to AAPs. Second, as compared to AAPs, HPs exhibited less overall brain activity, with language areas mostly located in the left hemisphere. However, there are noticeable outliers, such as bilateral activations that seem to be driven by task and word type. Third, task mediation seemed to be at work, as all HPs exhibited greater stimulation for abstract than tangible terms.



(a)



(b)

Fig. 6. Activations for HPs. Activation is shown at p < .05 for contrasts abstract > control (red) and concrete > control (green). Yellow = overlap between contrasts.

In summary, no statistically significant variations were found between AAPs and HPs concerning reaction time (p-values of 0.51 for both tasks) or accuracy ($p = 0.82$ for the JoW task). However, when looking at the JoS task, a clear difference showed up: HPs showed more accuracy than AAPs ($U = 3.86$, $p = 0.05$). This result indicates that compared to HPs, AAPs had a more difficult time with the JoS task.

Table 2. Values of performance evaluation parameters

	Synonym Judgment		Word Judgment	
	HP (N=10)	**AAP (N=10)**	**HP (N=10)**	**AAP (N=10)**
Abstract				
Accuracy	90.95% (6.84%)	86.52% (6.50%)	98.99% (3.33%)	82.67% (16.15%)
Reaction time (in milliseconds)	1854.38 (421.84)	2120.27 (137.50)	1517.23 (210.33)	1507.07 (358.85)
Concrete				
Accuracy	99.65% (1.98%)	96.04% (3.54%)	95.89% (2.98%)	98.99% (1.02%)
Reaction time (in milliseconds)	1981.33 (66.78)	1878.23 (43.54)	1654.87 (543.34)	1432.98 (66.22)
Control				
Accuracy	98.90% (1.08%)	99.92% (0.23%)	96.45% (1.09%)	100% (0.00%)
Reaction time (in milliseconds)	1345.54 (654.21)	2114.43 (34.87)	1987.21 (321.43)	1642.56 (352.36)

Table 2 shows the obtained values of both parameters, which are accuracy and reaction time for all three conditions, i.e., abstract, concrete, and control for both types of individuals (AAP and HP).

The graphs for accuracy and response time, which are shown below in Figures 7 and 8, respectively, correspond to the information presented in Table 2.

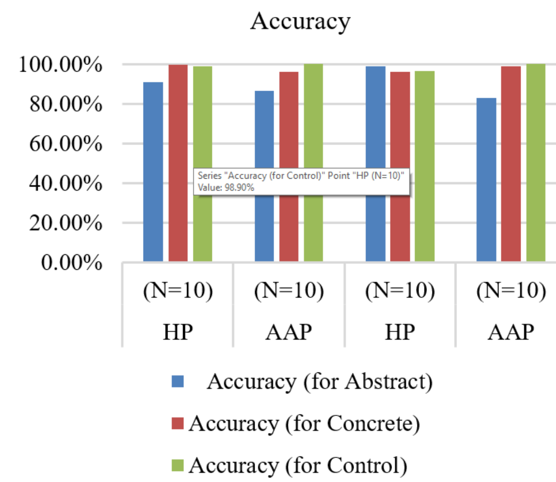


Fig. 4. Accuracy.

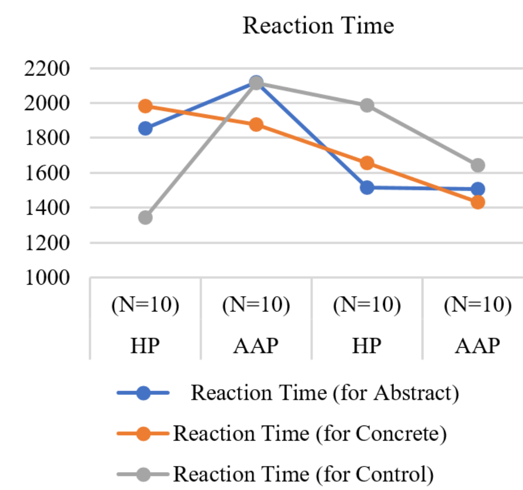


Fig. 5. Reaction Time.

Table 2. Comparison of the proposed model with the previous state-of-the-art methods

Author [Reference]	Model used	Accuracy
Sharma et al., [34]	RF+SVM	81%
Rubio et al., [37]	KNN	75%
Proposed model	GCN	100%

4.3 Comparative analysis

In this section the evaluation of the proposed model is performed based on the comparison with previously developed state-of-the-art methods to prove the robustness of the proposed model. As seen in Table 3, the KNN model attains the lowest accuracy of 75% whereas the proposed GCN model achieves the highest accuracy of 100% which shows the superiority of the proposed model over other models.

5. CONCLUSION AND FUTURE WORK

AAPs often express frustration at the discord between their thoughts and the words that come out of their mouths (what is called "inner speech" and "overt speech," respectively). The fundamental goal of the work is to classify the self- and social-interaction patterns of people with stroke-related aphasia by using a GCN-based model. The GCN model uses fMRI scans from 20 people (both AAP and HP), with 11 female and 9 male nodes, to look for enigmatic qualities and relationships to better understand how the brain processes language. The data is preprocessed comprehensively to remove physiological noise and enhance its quality, using techniques such as RETROICOR and spatial smoothing. By segmenting data and training models, researchers teach the GCN to make predictions based on patients' past performance on JoW and JoS. Metrics like accuracy and patient reaction time are used to evaluate the proposed model's performance. There can be an increased concreteness effect in AAPs since they show greater differences in brain activity between concrete and abstract terms compared to age-matched controls. Maximum accuracy for HPs is 99.65%, with a response time of 1981.33 milliseconds in the abstract condition, whereas maximum accuracy for AAPs is 100% in the control condition, with a reaction time of 1642.56 milliseconds. Future research should focus on increasing the variety of participants, investigating the neurological bases of concreteness effects, and using the GCN model to create useful tools for assisting people with aphasia in their communication.

REFERENCES

[1] Thomas, M. S., Ansari, D., & Knowland, V. C. (2019). Annual research review: Educational neuroscience: Progress and prospects. *Journal of Child Psychology and Psychiatry*, *60*(4), 477-492.

[2] Laird, J. E., Lebiere, C., & Rosenbloom, P. S. (2017). A standard model of the mind: Toward a common computational framework across artificial intelligence, cognitive science, neuroscience, and robotics. *Ai Magazine*, *38*(4), 13-26.

[3] Doedens, W. J., & Meteyard, L. (2022). What is functional communication? A theoretical framework for real-world communication applied to aphasia rehabilitation. *Neuropsychology Review*,*32*(4) ,937-973.

[4] Montemurro, S., Mondini, S., Signorini, M., Marchetto, A., Bambini, V., & Arcara, G. (2019). Pragmatic language disorder in Parkinson's disease and the potential effect of cognitive reserve. *Frontiers in psychology*, *10*, 442793.

[5] Penaloza, C., Martin, N., Laine, M., & Rodríguez-Fornells, A. (2022). Language learning in aphasia: A narrative review and critical analysis of the literature with implications for language therapy. *Neuroscience & Biobehavioral Reviews*, *141*, 104825.

[6] Varma, S., & James, D. P. (2021). An efficient deep learning-based video captioning framework using multi-modal features. *Expert Systems*.

[7] Mueller, S. M., Hogg, S., Mueller, J. M., McKie, S., Itin, P., Reinhardt, J., ... & Kleyn, C. E. (2017). Functional magnetic resonance imaging in dermatology: the skin, the brain and the invisible. *Experimental dermatology*, *26*(10), 845-853.

[8] Salig, L. K., Valdés Kroff, J. R., Slevc, L. R., & Novick, J. M. (2021). Moving from bilingual traits to states: Understanding cognition and language processing through moment-to-moment variation. *Neurobiology of Language*, *2*(4), 487-512.

[9] Yen, C., Lin, C. L., & Chiang, M. C. (2023). Exploring the frontiers of neuroimaging: a review of recent advances in understanding brain functioning and disorders. *Life*, *13*(7), 1472.

[10] Patil, G., Patil, T., & Wagh, K. (2023, December). Bridging Neuroscience and Minds: Exploring Collective Intelligence through Brain Duplication using AI. In *2023 31st Irish Conference on Artificial Intelligence and Cognitive Science (AICS)* (pp. 1-4). IEEE.

[11] Zhou, W., Qu, A., Cooper, K. W., Fortin, N., & Shahbaba, B. (2023). A Model-Agnostic Graph Neural Network for Integrating Local and Global Information. *arXiv preprint arXiv:2309.13459*.

[12] Ding, K., Zhou, M., Wang, Z., Liu, Q., Arnold, C. W., Zhang, S., & Metaxas, D. N. (2022). Graph convolutional networks for multi-modality medical imaging: Methods, architectures, and clinical applications. *arXiv preprint arXiv:2202.08916*.

[13] Stefaniak, J. D., Halai, A. D., & Lambon Ralph, M. A. (2020). The neural and neurocomputational bases of recovery from post-stroke aphasia. *Nature Reviews Neurology*, *16*(1), 43-55.

[14] Fedorenko, E., & Varley, R. (2016). Language and thought are not the same thing: evidence from neuroimaging and neurological patients. *Annals of the New York Academy of Sciences*, *1369*(1), 132-153.

[15] Kronenberger, W. G., & Pisoni, D. B. (2019). Assessing higher order language processing in long-term cochlear implant users. *American Journal of Speech-Language Pathology*, *28*(4), 1537-1553.

[16] Bhaya-Grossman, I., & Chang, E. F. (2022). Speech computations of the human superior temporal gyrus. *Annual review of psychology*, *73*, 79-102.

[17] Elmer, S., Dittinger, E., & Besson, M. R. (2018). One Step Beyond: Musical Expertise and Word Learning 10.1 A Cortical Framework of Speech and Language Processing 10.1. 1 The Faculty of Language and its Neural Substrate. *Voices in the brain*.

[18] Flinker, A., Korzeniewska, A., Shestyuk, A. Y., Franaszczuk, P. J., Dronkers, N. F., Knight, R. T., & Crone, N. E. (2015). Redefining the role of Broca's area in speech. *Proceedings of the National Academy of Sciences*, *112*(9), 2871-2875.

[19] García, A. M. (2019). The neurocognition of translation and

interpreting.
[20] Hunter, P. (2020). Understanding the human language processor: Neurobiology's insights into the human brain's semantic processing of information could inform education and therapies for language disorders. *EMBO reports*, *21*(12), e52028.
[21] Song, S. E., Krishnamurthy, L. C., Rodriguez, A. D., Han, J. H., Crosson, B. A., & Krishnamurthy, V. (2023). Methodologies for task-fMRI based prognostic biomarkers in response to aphasia treatment. *Behavioural Brain Research*, *452*, 114575.
[22] Lima, L. F. (2021). Syntactic aspects of impaired speech in interface with prosody and information structure: data from Broca's and Wernicke's aphasia. *Signótica*, *33*, e62942-e62942.
[23] Streese, C. D., & Tranel, D. (2021). Combined lesion-deficit and fMRI approaches in single-case studies: unique contributions to cognitive neuroscience. *Current opinion in behavioral sciences*, *40*, 58-63.
[24] DeMarco, A. T., & Turkeltaub, P. E. (2018). *A multivariate lesion symptom mapping toolbox and examination of lesion-volume biases and correction methods in lesion-symptom mapping* (Vol. 39, No. 11, pp. 4169-4182). Hoboken, USA: John Wiley & Sons, Inc..
[25] Schumacher, R., Halai, A. D., & Lambon Ralph, M. A. (2019). Assessing and mapping language, attention and executive multidimensional deficits in stroke aphasia. *Brain*, *142*(10), 3202-3216.
[26] Warren, S. L., & Moustafa, A. A. (2023). Functional magnetic resonance imaging, deep learning, and Alzheimer's disease: A systematic review. *Journal of Neuroimaging*, *33*(1), 5-18.
[27] Zamani Esfahlani, F., Jo, Y., Faskowitz, J., Byrge, L., Kennedy, D. P., Sporns, O., & Betzel, R. F. (2020). High-amplitude cofluctuations in cortical activity drive functional connectivity. *Proceedings of the National Academy of Sciences*, *117*(45), 28393-28401.
[28] Fleischer, V., Radetz, A., Ciolac, D., Muthuraman, M., Gonzalez-Escamilla, G., Zipp, F., & Groppa, S. (2019). Graph theoretical framework of brain networks in multiple sclerosis: a review of concepts. *Neuroscience*, *403*, 35-53.
[29] Liu, Y., Wang, Q., Wang, X., Zhang, F., Geng, L., Wu, J., & Xiao, Z. (2020). Community enhanced graph convolutional networks. *Pattern Recognition Letters*, *138*, 462-468.
[30] Bhatti, U. A., Tang, H., Wu, G., Marjan, S., & Hussain, A. (2023). Deep learning with graph convolutional networks: An overview and latest applications in computational intelligence. *International Journal of Intelligent Systems*, *2023*, 1-28.
[31] Li, Y., Mateos, G., & Zhang, Z. (2022). Learning to model the relationship between brain structural and functional connectomes. *IEEE Transactions on Signal and Information Processing over Networks*, *8*, 830-843.
[32] Li, L., Jiang, H., Wen, G., Cao, P., Xu, M., Liu, X., ... & Zaiane, O. (2022). TE-HI-GCN: An ensemble of transfer hierarchical graph convolutional networks for disorder diagnosis. *Neuroinformatics*, 1-23.
[33] Teghipco, A., Newman-Norlund, R., Fridriksson, J., Rorden, C., & Bonilha, L. (2023). Distinct brain morphometry patterns revealed by deep learning improve prediction of aphasia severity. *Research Square*.
[34] Shams, B., Reisch, K., Vajkoczy, P., Lippert, C., Picht, T., & Fekonja, L. S. (2023). Improved prediction of glioma-related aphasia by diffusion MRI metrics, machine learning, and automated fiber bundle segmentation. *Human Brain Mapping*, *44*(12), 4480-4497.
[35] Billot, A., de Schotten, M. T., Parrish, T. B., Thompson, C. K., Rapp, B., Caplan, D., & Kiran, S. (2022). Structural disconnections associated with language impairments in chronic post-stroke aphasia using disconnectome maps. *Cortex*, *155*, 90-106.
[36] Smaïli, K., Langlois, D., & Pribil, P. (2022, September). Language rehabilitation of people with BROCA aphasia using deep neural machine translation. In *Fifth International Conference on Computational Linguistics in Bulgaria*.
[37] Moral-Rubio, C., Balugo, P., Fraile-Pereda, A., Pytel, V., Fernández-Romero, L., Delgado-Alonso, C., ... & Ayala, J. L. (2021). Application of machine learning to electroencephalography for the diagnosis of primary progressive aphasia: A pilot study. *Brain Sciences*, *11*(10), 1262.
[38] Kristinsson, S., Zhang, W., Rorden, C., Newman-Norlund, R., Basilakos, A., Bonilha, L., & Fridriksson, J. (2021). Machine learning-based multimodal prediction of language outcomes in chronic aphasia. *Human brain mapping*, *42*(6), 1682-1698.
[39] Chen, X., Chen, L., Zheng, S., Wang, H., Dai, Y., Chen, Z., & Huang, R. (2021). Disrupted brain connectivity networks in aphasia revealed by resting-state fMRI. *Frontiers in Aging Neuroscience*, *13*, 666301.
[40] Nissim, N. R., Moberg, P. J., & Hamilton, R. H. (2020). Efficacy of noninvasive brain stimulation (tDCS or TMS) paired with language therapy in the treatment of primary progressive aphasia: an exploratory meta-analysis. *Brain Sciences*, *10*(9), 597.
[41] Shain, C., Blank, I. A., van Schijndel, M., Schuler, W., & Fedorenko, E. (2020). fMRI reveals language-specific predictive coding during naturalistic sentence comprehension. *Neuropsychologia*, *138*, 107307.
[42] Johnson, J. P., Meier, E. L., Pan, Y., & Kiran, S. (2020). Pre-treatment graph measures of a functional semantic network are associated with naming therapy outcomes in chronic aphasia. *Brain and language*, *207*, 104809.
[43] Chien, Y. W., Hong, S. Y., Cheah, W. T., Yao, L. H., Chang, Y. L., & Fu, L. C. (2019). An automatic assessment system for Alzheimer's disease based on speech using feature sequence generator and recurrent neural network. *Scientific Reports*, *9*(1), 19597.
[44] Angelopoulou, G., Kasselimis, D., Makrydakis, G., Varkanitsa, M., Roussos, P., Goutsos, D., ... & Potagas, C. (2018). Silent pauses in aphasia. *Neuropsychologia*, *114*, 41-49.
[45] Friederici, A. D. (2011). The brain basis of language processing: from structure to function. *Physiological reviews*.
[46] Kassinopoulos, M., & Mitsis, G. D. (2021). Physiological noise modeling in fMRI based on the pulsatile component of photoplethysmograph. *NeuroImage*, *242*, 118467.
[47] Uoc, N. Q., Duong, N. T., Son, L. A., & Thanh, B. D. (2022). A novel automatic detecting system for cucumber

disease based on the convolution neural network algorithm. *GMSARN Int. J.*, *16*(3), 295-301.

[48] Kipf, T. N., & Welling, M. (2016). Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*.

[49] Phung, T. T., Le, N. T., Quyen, A. H., Pham, H. H., & Nguyen, A. T. (2020). A Hybrid Artificial Neural Network-Genetic Algorithm for Load Shedding in Power.GMSARN International Journal 14 ,21 – 28.