Open Brain AI: An AI Research Platform

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Abstract

Language assessment is pivotal in identifying therapeutic interventions for speech, language, and communication disorders stemming from neurogenic origins, developmental or acquired, and student performance in the classroom. Traditional assessment techniques, however, are predominantly manual, necessitating extensive time and effort for administration and scoring. Such procedures can exacerbate the stress experienced by patients. In response to these inherent challenges, we introduced Open Brain AI (https://openbrainai.com). This state-of-the-art computational platform leverages advanced AI methodologies, encompassing machine learning, natural language processing, large language models, and automated speech-to-text transcription. These capabilities enable Open Brain AI to autonomously analyze multilingual spoken and written language productions. This work aims to present the development and evolution of Open Brain AI, elucidating its AI-driven language processing components and the intricate linguistic metrics it employs to evaluate the overarching and granular discourse structures. Open Brain AI significantly reduces the workload on researchers, clinicians, and teachers by facilitating rapid and automated language analysis. It allows healthcare and education professionals to optimize their operational processes, reallocating precious time and resources to more personalized user interactions. Moreover, Open Brain AI provides clinicians, researchers, and educators the autonomy to undertake essential data analytics, freeing up more bandwidth to focus on other vital facets of therapeutic intervention and care.

Keywords

Open Brain AI, Large Language Models, NLP

1. Introduction

Assessing speech, language, and communication is critical for clinicians and researchers. It informs clinicians about the neurologic functioning of their patients, provides early linguistic biomarkers of conditions, such as Mild Cognitive Impairment (MCI), and guides treatment (1-7). Furthermore, speech and language assessments are critical for evaluating the classroom performance of first and second-language students. Nevertheless, the manual evaluation of speech, language, and communication is cumbersome, time-consuming, and subjective, as it depends on the expertise and training of those who perform the evaluation. Moreover, manual assessments, such as the Boston Naming Test (BNT; 8), Western Aphasia Battery-Revised (WAB-R Kertesz (9)), Boston Diagnostic Aphasia Examination (BDAE; 10), and Psycholinguistic Assessment of Language Processing in Aphasia (PALPA; 11) often focus on a single language domain, such as confrontational naming and fluency, and do not offer an ecological depiction of speech, language, and communication. Therefore, it is critical to provide tools to enable researchers, clinicians, and educators to conduct assessments of speech, language, and communication informed by ecologically reliable data. Currently, machine learning models, natural language processing techniques, signal processing methodologies, and advanced statistics collectively named Artificial Intelligence can easily automate language assessment and offer the means for more robust, accurate, and quantitative language assessments that can generalize for speakers with different linguistic backgrounds.

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In our previous research, we demonstrated that a computational system with four computational pipelines for performing automated acoustic analysis, speech-to-text transcription, automatic morphosyntactic and linguistic analysis of transcripts, and machine learning could enable the identification of Swedish patients with Mild Cognitive Impairment and Alzheimer's Disease from healthy controls (12-17) and the subtyping of patients with Primary Progressive Aphasia into variants (nonfluent PPA, semantic PPA, and logopenic PPA) (18). The machine learning model of the classification of patients with PPA was based on deep neural networks (DNN), and its performance was better than that of Random Forests, Support Vector Machines, Decision Trees, and expert clinicians' classifications (18). We have also employed morphological and syntactic evaluation to analyze transcripts using natural language processing (NLP) and to provide automated part-of-speech (POS) tagging and syntactic parsing. For example, Themistocleous, Webster (19) analyzed connected speech productions from 52 individuals with PPA using a morphological tagger and showed differences in POS production in patients with non-fluent Primary Progressive Aphasia (nfvPPA), logopenic variant of Primary Progressive Aphasia (lvPPA), and the semantic variant of Primary Progressive Aphasia (svPPA). Also, we have employed machine learning to identify speakers with different dialects, from speech acoustics, namely prosody (20-22), vowels (23, 24), and consonants (21, 25-28). Machine learning was used to track the learning of L1 dialectal learners of the standard language variety in classrooms (29), showing the implication of using machine learning applications in diverse populations. The end-to-end automated machine learning approaches we developed for these works inspired the development of Open Brain AI to enable clinicians and researchers to provide an easy, quick, and inexpensive assessment of speech, language, and communication.

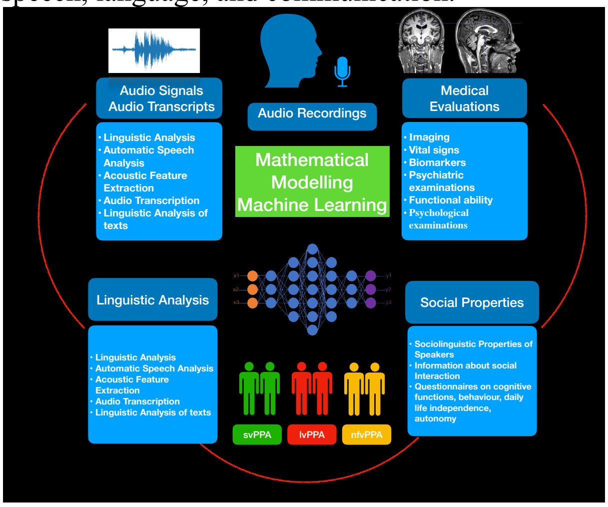

Figure 1. Multimodal Analysis of speech, language, cognition, the brain, and sociolinguistic properties in Open Brain AI.

2. Open Brain AI

Open Brain AI (http://openbrainai.com) is online computational platform application that aims to provide automated linguistic and cognitive assessments and tools that can be employed by researchers, clinicians, and educators to inform their daily practice and automate their tasks (30). Open Brain AI relies on Artificial Intelligence (AI) methods and tools for assessing speech, language, and communication. Clinicians can use Open Brain AI to automate spoken and written language analysis and provide informative linguistic measures of discourse and conversation to support diagnosis, prognosis, therapy efficacy evaluation, and treatment planning. Teachers can use Open Brain AI to analyze the speech and language of their students and elicit meaningful markers from essays and other materials, estimate student performance, and assess the efficacy of teaching methodologies. Researchers can produce quantitative measures of speech, language, and communication, provide results that can be compared across studies, collaborate, share ideas, and evaluate novel technologies for patient care and student learning.

3. Technologies

Open Brain AI assesses written text, speech recordings, neurolinguistic assessments, and other documents researchers, clinicians, and teachers use. These documents are first pre-processed and analyzed depending on the application. A speech-to-text component enables the multilingual transcription of speech recordings into texts. Texts are subsequently parsed using large language models, morphological taggers/parsers of the analysis of grammar, and semantic analysis tools. These tools also provide quantitative measures of the linguistic domains, such as phonology, morphology, syntax, semantics, and lexicon. Additional tools incorporate IPA transcription and acoustic analysis tools. *Open Brain AI* enables end-to-end spoken and written speech production analysis by combining the different computational pipelines to provide automated and objective linguistic measures (1, 16, 18, 19, 24, 26, 31, 32).

To achieve this Open Brain AI, incorporate language-specific Natural Language Processing (NLP) tools for analyzing written and oral texts (33, 34). These include tokenizers, which split texts into individual tokens, such as words, punctuation marks, and numbers; stemmers, to analyze words to their stems, which are the primary forms of words; lemmatizers, to identify the lemmas of words, which are the canonical or dictionary forms of words; part-of-speech (POS) taggers to assign a POS tag to each word in a sentence; named entity recognizers (NERs), to identify and classify named entities, such as people, dates, places, and organizations; parsers, to analyze the grammatical/syntactic structure of sentences; semantic role labelers to assign semantic roles to the constituents of a sentence, such as agent, patient, and recipient; and coreference resolvers: Identify and resolve coreferences in text, which are expressions that refer to the same entity (33, 34). Open Brain AI also incorporates state-of-the-art language models used to analyze texts in specific Open Brain AI applications, such as the discourse analysis of texts.

Open Brain AI provides acoustic analysis to enable the transcription of texts. Sound is first passed to Open Brain AI's acoustic analysis modules and Speech-to-Text for automatic transcription. Then, it segments speech into words and speakers and extracts acoustic measures, such as prosody and voice quality. An independent component allows the acoustic analysis tools to plot sound waveforms, spectrograms, and F0.

Machine Learning and statistical models, especially Deep Neural Network architectures, are employed to find patterns from texts and characterize language impairment. The computational can be integrated with multimodal data for research, clinical, and educational applications (Figure 1).

4. Principles

First, Open Brain AI provides access to language assessment to all individuals independently of language. For this reason, Open Brain AI offers multilingual support in different languages and language varieties (e.g., dialects). It offers automatic transcription and comprehensive grammar analysis in English, Norwegian, Swedish, Greek, and Italian. The complete grammar analysis extends to Danish, Dutch, Finnish, French, German, Portuguese, and Spanish, whereas other tools work with a wider range of languages and language varieties. Additional language varieties will be supported over time. The ability of Open Brain AI to scale concerning new languages and language variety support highlights a critical difference between computational models and traditional manual assessment techniques, which require expert knowledge for translation, standardization, and evaluation to maintain crosslinguistic psychometric properties, such as the reliability and validity of tests. The Open Brain AI platform offers access to these trained models for clinicians and teachers and makes them available.

Second, Open Brain AI does not collect data provided for analysis. Data are analyzed on the server or locally on the user's machine. Data uploaded on the server for analysis are removed immediately after processing. Information provided in Open Brain AI for accessing the site is not shared with third parties. Open Brain AI takes data privacy and security very seriously and follows industry standards to protect the confidentiality and security of personal health information. However, no data transmission over the Internet is guaranteed to be completely secure. Therefore, Open Brain AI cannot guarantee the security of any information transmitted through the service, and you use the service at your own risk. Open Brain AI provided for healthcare purposes is not intended to replace or substitute for professional medical advice, diagnosis, or treatment.

5. Backend Infrastructure

Open Brain AI is developed using the Django framework in Python and SQL server. It is hosted on Google Cloud Run and utilizes several Google Cloud services, such as Cloud Run, Cloud Secret Manager, and Cloud Storage, to ensure consistent performance and scalability. Specifically, the system architecture includes an SQL database connection for user and post management, configurations for static file storage, email backend, and a template pack for front-end design and accessibility. The Django application of the project is deployed on Google Run, a serverless computing platform, allowing it to scale based on demand without manual server management. The application's secret key is maintained in the Cloud Secret Manager for security measures, and all static files are stored in Cloud Storage. Furthermore, the Open Brain AI backend supports the Natural AI text and sound processing models.

The backend design of Open Brain AI allows for scalability. Namely, the infrastructure supports automatic scaling depending on demand without server intervention. It provides security as secret keys are safeguarded in a dedicated location, and static files are retrieved from a scalable object storage service. The system ensures high reliability and availability.

Finally, it is flexible, as the configuration via Django settings and environment variables enables customization to address specific user requirements or scenarios. For example, the backend infrastructure allows users to access the online platform from different devices, e.g., Computers, Tablets, and Mobile phones, without specific configuration.

6. Applications

Open Brain AI offers applications for three distinct groups: researchers, clinicians, and teachers. Researchers may want to access raw data to analyze further, whereas applications for clinicians and teachers provide applications that can analyze the patients and students in clinical or teaching environments.

6.1. Research Applications

Computational Discourse Analysis Application. Discourse provides multidomain data and information on language production, perception, planning, and cognition *(35-38).* Thus, discourse can explain brain functioning and provide recommendations on whether there is evidence for a possible speech, language, and communication impairment. Open Brain AI's discourse module employs large AI language Models to analyze texts and metrics from discourse, semantics, syntax, morphology, phonology, and lexical distribution elicited using NLP and machine learning. Subsequently, it combines its internal knowledge of the world based on its training to provide a comprehensive analysis of speech, language, and communication for the textual transcripts based on quantified measures from part of speech analysis, syntactic phrase identification, semantic analysis (e.g., named entity recognition), and linguistic distribution.

Linguistic Measures Application. Open Brain AI provides objective measures of written speech production that clinicians, teachers, and researchers compare a patient with a targeted population concerning discourse, phonology, morphology, syntax, semantics, and lexicon *(18, 39-45)*. Specifically, this module analyzes the text or the transcripts from the speech-to-text module and conducts measures on the following linguistic domains:

1. Phonology: It elicits measures, such as the number and type of syllables and the ratio of syllables per word.
2. Morphology: It provides counts and their ratio of parts of speech (e.g., verbs, nouns, adjectives, adverbs, and conjunctions) concerning the total number of words.
3. Syntax: It provides counts and their ratio of syntactic constituents (e.g., noun phrases and verb phrases).
4. Lexical Measures: it provides measures such as the number of words, hapax legomena, and Type Token Ratio (TTR) measures.
5. Semantic Measures: It provides counts and their ratio of semantic entities in the text (e.g., persons, dates, and locations).
6. Readability Measures: It provides readability measures about the text and grammar.

Recordings are analyzed using different applications.

1. *Automatic transcription.* Open Brain AI employs Automatic Speech Recognition (ASR) to process audio files. The process begins by uploading an audio file on Open Brain AI. The transcription of the audio file is conducted using speech-to-text. The system is modular, so it employs different speech-to-text applications.
2. *Linguistic Analysis & AI Discourse Analysis.* The transcripts are further analyzed using the automatic morphosyntactic analysis and by a GPT3 Large Language Model. The module combines the text and metrics from discourse, semantics, syntax, morphology, phonology, and linguistic distribution.
3. *Acoustic Analysis.* The spoken speech assessment module provides transcription and grammatical analysis of these transcripts. The grammatical study replicates that of written speech productions. Namely, it offers total phonology, morphology, syntax, semantics, and lexicon scores.
4. *Speakers Segmentation.* The Open Brain AI platform allows splitting the audio, dividing patients from clinicians in the audio recordings. When there is more than one speaker in the audio file. The diarization output is exported as a coma delimited file or Praat TextGrid for researchers wanting to perform acoustic analysis.
5. *Word Alignment and Pause Detection.* The platform enables the alignment of words with the sound wave to allow further acoustic analysis for measures, such as word duration, and the elicitation of the specific acoustic measures on acoustic production. The automatically segmented sounds are exported in various formats, such as Praat TextGrids.

6.2. Clinical Applications

The clinical toolkit provides scoring tools and comprises four primary tools:

Picture Description Task. A picture description task is a standard assessment tool for evaluating individuals with aphasia or other language disorders. In a picture description task, the patient is presented with a picture and is asked to describe it in as much detail as possible. The picture typically depicts a scene with multiple elements, actions, and interactions to allow for various linguistic constructions and vocabulary. The task assesses the patient's ability to produce spontaneous speech. It can reveal difficulties in forming grammatically correct sentences, using appropriate vocabulary, or maintaining coherence. Open Brain AI incorporates tools to conduct the picture description task and evaluate the content (what the patient says) and the structure (how they say it). This can provide insights into the type and severity of the aphasia. Patients with distinct types of aphasia (e.g., Broca's, Wernicke's, Global) may produce different patterns of errors and difficulties in the picture description task. Repeated assessments using Open Brain AI over time can track a patient's recovery and the effectiveness of therapeutic interventions.

Automatic conversion to the International Phonetic Alphabet. The tool converts words written in standard orthography into the International Phonetic Alphabet with extensive support to languages and language varieties and provides measures of their sounds in the transcribed texts.

Spelling Scoring App. The evaluation of spelling is a complex, challenging, and time-consuming process. It relies on comparing letter-to-letter, the words spelled by the patients to the target words, using the Levenshtein Distance. It processes both words and non-words (1). It specifically Themistocleous, Neophytou (1) developed a spelling distance algorithm that automatically compares the inversions, insertions, deletions, and transpositions required to make the target word and response identical (1, 46). To determine phonological errors in patients with aphasia, we have developed a phonological distance algorithm that quantifies phonological errors automatically.

Phonological Scoring Tool. The tool converts the target and response words into the International Phonetics Alphabet, compares their differences using the Levenshtein Distance, and provides scores changes, namely deletions, insertions, transpositions, and substitutions. It processes both words and non-words.

Semantics Scoring Tool. The semantic distance scoring tool employs embeddings to score naming tasks involving semantic memory access (47-49).

6.3. Educational Applications

Open Brain AI provides infrastructure for educational applications. The underlying system for automatic spoken and written language analysis is being employed to assess students' performances in different settings, to track students' performance over time, and to assess teaching methods' efficacy. The Open Brain Education platform incorporates phonology, semantics, spelling, and essay assessment scoring applications.

Essay Assessment. This application, powered by advanced language models, evaluates Content and Argumentation by examining the thesis statement's clarity and strength, logical argument progression, depth of analysis, and evidence backing claims. The tool reviews essays' structure, ensuring logical flow, cohesion, and the presence of a clear introduction, body, and conclusion. It checks for Grammar and Mechanics, including punctuation, spelling, sentence construction, verb tense adherence, style, and voice for uniqueness, consistency, and appropriateness. The tool provides feedback on essay clarity and precision, flagging ambiguous language or jargon. Lastly, it highlights potential grammatical and stylistic errors.

6.4. Offline Open Brain AI Applications

Accurate diagnosis and prognosis are vital for personalized intervention in speech, language, and communication disorders, enhancing the quality of life (50, 51). Prognosis involves predicting a patient's trajectory and outcomes (52). Offline Open Brain AI harnesses machine learning and multimodal data to distinguish patients with MCI from healthy controls (12, 15, 16), students with different learning needs (19, 53) , and speakers with contextualized speech patterns based on age, gender, and sociolinguistic factors (21, 23, 24, 26-28) (Figure 1). Computational tools offer a comprehensive analysis of patients and students (19) and can be extended to naturalistic speech analysis (54).

7. Conclusions

Speech and written language are distinct communication modalities, and accurate diagnosis and prognosis of speech, language, and communication disorders and student assessment in classroom settings require understanding their unique characteristics. Continued collaboration between experts in education, clinical research, computer science and AI will enhance our understanding and capabilities in assessing and treating neurocognitive disorders and support students learning, improving the lives of affected individuals. By considering the factors above and leveraging technological advancements offered by Open Brain AI, clinicians, educators, and researchers can develop effective intervention plans in the clinic and the classroom and make informed prognostic judgments. Ultimately, Open Brain AI empowers clinicians, educators, and researchers to deliver effective and inclusive support to patients with speech, language, and communication impairments and language students, improving their overall well-being and learning.

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