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Application of Artificial Intelligence in Assessing Speech, Language, and Voice Disorders: A Scoping Review

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Abstract: **To identify the characteristics and outcomes of peer-reviewed literature on the application of Artificial Intelligence (AI) in assessing speech, language, and voice disorders (SLVDs) published in English from 2000 to 2024, we conducted a scoping review following the Arksey and O'Malley framework. Several databases were searched for peer-reviewed journal articles using the terms "artificial intelligence," "language," "speech," and "voice disorders" in their abstract or title. A total of 21 articles were included. Key findings are as follows: 1. All papers were published within the past five years. 2. Each of the 21 reviewed articles found AI to be an efficient tool for assessing SLVDs. 3. Notably, geographical and research design gaps were identified. 4. It was observed that AI has not been applied to evaluate some aspects of speech-language disorders (SLDs). Additionally, the review underscores advancements and limitations in utilizing AI for diagnosing SLVDs. It stresses the necessity for more extensive research, especially in underrepresented regions and disorders. The review advocates for inventive strategies in crafting culturally sensitive AI models and broadening the AI research scope to maximize its potential in comprehending and assessing communication challenges.**

Keywords: **Assessment, Artificial Intelligence, Language Disorders, Speech Disorders, Voice Disorders.**

I. INTRODUCTION

Communication is significantly impacted by speech, language, and voice disorders (SLVDs), as illustrated through various conditions. Aphasia, for instance, poses challenges in understanding, expressing oneself in both written and verbal forms, and reading. This highlights the intricate interconnections within the brain's language networks (Kohlschein et al., 2017). Apraxia of speech similarly affects the precise and consistent production of speech sounds. Another disruptive communication disorder is fluency disorders, exemplified by stuttering, which interferes with the natural flow of words, causing disruptions in rhythm and pace (American Speech-Language-Hearing Association [ASHA], n.d). Furthermore, language disorders, such as expressive and receptive issues that hinder effective communication and understanding of language rules (Albudoor & Peña, 2022). Conversely, dysarthria arises from neurological damage, manifesting as unclear speech, characterized by slurring or slowing down of speech (Song et al., 2022). Additionally, vocal cord issues contribute to voice disorders, marked by pitch variations, heightened volume, or hoarseness, complicating effective communication (Compton et al., 2022). Collectively, these disorders curtail personal expression and hinder participation in social and professional activities, underscoring the crucial need for precision in assessing SLVDs.

The traditional assessment of SLVDs usually relies on subjective evaluation methods grounded in clinical expertise. Speech-Language Pathologists (SLPs) commonly employ observational techniques, standardized tests, and patient interviews for diagnosis and treatment planning. Despite their widespread use, these methods have limitations, including variability in subjective evaluations among clinicians, resulting in potential diagnostic inconsistencies (Pravin & Palanivelan, 2022). Additionally, traditional assessments can be labor-intensive due to time-consuming processes and may not entirely capture an individual's condition in dynamic or real-world scenarios (Al-Banna et al., 2022).

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Artificial intelligence (AI), particularly in the field of machine learning, is transforming the assessment of SLVDs. Machine learning algorithms, through the analysis of extensive data, can identify patterns and anomalies associated with specific disorders. This approach offers an objective and data-driven method for evaluations, addressing challenges inherent in traditional assessments (Justice et al., 2019). The technology provides a level of precision and impartiality previously unattainable. AI's capacity to scrutinize and interpret nuanced speech, language, and voice features equips professionals with invaluable insights, significantly enhancing diagnostic accuracy (Compton et al., 2022; Day et al., 2021; Justice et al., 2019). The integration of AI in this domain signifies a noteworthy advancement, leveraging state-of-the-art technology to enhance assessment precision, efficiency, and depth.

II. METHODS

This study employed a scoping review to fulfill its objectives, recognizing the necessity for methodological rigor in such endeavors. Scoping reviews, as outlined by Arksey and O'Malley (2005), aim for a systematic and comprehensive process with a focus on broad and extensive goals, in contrast to the narrow research questions of systematic reviews (Tricco et al., 2016). The choice of a scoping review aligns with the study's need to extensively survey the literature to effectively address its objectives. The author adhered to the methods proposed by Arksey and O'Malley (2005), which guided the conduct of the scoping review.

Research questions addressed by this scoping review were:

1. What are the characteristics of the studies included?

2. What are the outcomes of utilizing AI for the assessment of SLVDs?

In conducting this scoping review, Arksey and O'Malley recommended the following crucial steps:

1. Systematic Search: This involved systematically searching electronic databases, including PubMed, CINAHL, ERIC, PsychInfo, and Google Scholar from 2000 through 2024. It encompassed a range of keywords such as AI, Speech and Language Pathology (SLP), Assessment, Evaluation, Articulation Disorders, Voice Disorders, Speech Sound Disorders, Apraxia of Speech, Fluency Disorders (Stuttering, Cluttering), Dysarthria, Language Disorders, and Aphasia. These keywords were chosen specifically to comprehensively cover all AI applications in assessing SLVDs. Each database utilized tailored subject headings to ensure a thorough and accurate literature search. Additionally, the reference lists of the selected articles were examined to identify additional relevant studies.

2. Study Selection Criteria: The study selection criteria employed in this scoping review were specifically tailored to the application of AI in the assessment of SLVDs. Papers were selected based on the following inclusion criteria:

- Language/Specific Focus: Articles must be in English and exclusively employ AI approaches for assessing SLVDs. The review includes only those discussing AI's role in evaluating individuals with SLVDs. Papers related to AI interventions in SLVDs are excluded, unless they explicitly involve the assessment of individuals with SLVDs using AI.

- Research Design: The review exclusively examined empirical articles presenting evidence from quantitative, qualitative, or mixed-method research designs. Non-empirical studies, including policy papers and review articles, did not fall under this criterion. The emphasis lies on selecting studies focused on practice-oriented and evidence-based applications within the domain of SLVDs.

The selection approach employed ensures a concentrated and pertinent analysis of AI's role in the assessment of SLVDs.

3. Data Charting: Data gathered from the reviewed studies encompassed details such as article authors, study country, participant demographics, research design, type of AI used, disorders assessed, and key findings. This information was specifically chosen for its relevance in addressing the research questions of this scoping review. All collected data were systematically organized in a Microsoft Excel spreadsheet.

4. Summarizing the Results: The extracted data were thoroughly processed in Excel, facilitating the generation of graphs and diagrams for improved trend and pattern visualization. This iterative approach ensured an effective summary of findings, directly addressing research questions while highlighting both limitations and potential future directions in AI for assessing SLVDs. The outcome was a succinct, illuminating overview of the research literature.

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III. RESULTS

Q1. What are the characteristics of the studies included?

The 21 articles reviewed originated from a diverse range of 11 distinct countries. Articles from the United States and Italy were the most common, each representing approximately 19% of the total (4/21). India followed with about 14% of the articles (3/21), while Canada and China each accounted for roughly 9.5% (2/21). Articles from Greece, Cyprus, Brunei, Australia, the United Kingdom, and South Korea each made up approximately 4.8% of the total (1/21).

The scoping review indicates that Machine Learning is the most common AI technology used to determine SLVDs, as mentioned in all 21 articles, marking its occurrence at a rate of 100% (21/21). In this group, Support Vector Machine has scored the highest, representing about 28 percent (6/21) of the dataset. Convolutional Neural Networks follow closely with five cases, translating into close to 24 percent (23.8%) frequency rate in terms of appearance rather than individual prominence factors. Meanwhile, Artificial Neural Networks and Random Forests accounted for three entries each, reaching 14 percent (14.3%) each. This distribution highlights exemplified specialized sub-varieties related to machine learning, such as Boosted Trees and Automatic Speech Recognition, among others, as shown through various algorithms adopted by these branches. It also reveals that a particular type pattern dominates over other alternatives available within machine learning itself; boosted trees or some kind of automatic recognition system would be an example here. More information on these types can be found in Table 1 below.

In the AI-supported assessment of SLVDs, the scoping review revealed that language disorders were the most prevalent, representing 28.57% (6/21) of the cases. Following closely was dysarthria at 23.81% (5/21), with fluency disorders also noteworthy at 19.05% (4/21). Aphasia and voice disorders each constituted 14.29% (3/21) of the studies. For a detailed breakdown of these findings, please refer to Table 1.

The scoping review revealed a wide range of participant characteristics. The age range of participants covered in the articles was extensive, spanning from three-year-old children to adults over 74 years old. Additionally, the studies ranged in size, with the smallest focusing on 17 bilingual children with Specific Language Impairment, while the largest involved 2,003 respondents with healthy pathological voices. The younger demographic, particularly second graders, commonly received diagnoses for Developmental Language Disorder, whereas adults were often evaluated for dysphonia and aphasia. The participants' conditions also varied, ranging from typically developing individuals to those with severe/profound cognitive impairment.

Additionally, this review outlines the research designs employed in the 21 selected articles. The vast majority, accounting for 20 (95.2%) articles, utilized quantitative research designs. Among these, experimental types constituted the highest proportion, comprising 52.4% (11/21) of the studies. Observational studies were also notable, representing 14.3% (3/21). Each design occurred once in the 21 articles, constituting 4.76% per design. Examples encompassed various methodologies such as mixed method with both quantitative and qualitative data analysis, non-experimental quantitative secondary data analysis, comparative cross-sectional design, controlled prospective cohort study, predictive modeling, exploratory study, and diagnostic accuracy study. These diverse methodologies illustrate the varied approaches within this field, detailed in Table 1.

Q2. What are the outcomes of utilizing AI for the assessment of SLVDs?

Out of the 21 studies (28.6%), six explicitly focused on the use of AI in assessing language disorders. Remarkably, all these studies reported positive results, with AI demonstrating high accuracy (ranging from 0.92 to 0.98) in detecting language disorders, particularly in children. Additionally, AI proved effective in distinguishing between individuals with and without language disorders across diverse age groups, as indicated by various survey findings.

Three articles (14.3%) specifically focused on the application of AI in diagnosing voice disorders. All three studies consistently reported a high level of effectiveness in AI algorithms for accurate diagnosis. Milani et al. (2020) achieved the highest classification accuracy at 87.5% using the Artificial Neural Network (ANN) classifier. In contrast, Decision Trees (DT) and Support Vector Machines (SVM) demonstrated lower accuracies of 62.5% and 50%, respectively. Notably, Compton et al.'s AI models outperformed general practitioners and otolaryngologists in predicting vocal cord pathologies, showcasing superior diagnostic efficiency (Compton et al., 2022). For instance, Verde et al. (2019) highlighted the effectiveness of the Boosted Trees algorithm in diagnosing voice disorders across both adults and children.

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Within the context of aphasia evaluation, three out of 21 studies (14.3%) in our review incorporated AI. These studies collectively revealed that AI improves diagnostic accuracy and predicts aphasia severity more effectively. Convolutional Neural Networks (CNNs) demonstrated superior accuracy in identifying aphasic patients compared to traditional machine learning methods. Concerning aphasia severity prediction, neural networks and random forests proved effective, with neural networks achieving low mean absolute errors and random forests attaining a classification accuracy of 73%. Additionally, DALL-E 2, an advanced AI, exhibited a remarkable 94.5% success rate in generating images for assessment purposes, underscoring the potential of AI in developing assessment tools.

In four studies (19% of the 21 total studies) investigating stuttering. A consistent discovery emerged: the notable efficacy of AI methodologies in accurately identifying and categorizing stuttering. Each study utilized diverse AI models, including Random Forest classifiers, Convolutional Neural Networks, and Deep Neural Decision Trees, renowned for their high accuracies. Notably, certain cases achieved success rates as high as 95% in detecting stuttering behaviors through these models. Collectively, these findings underscore that, irrespective of the model employed, AI stands out as the most precise tool for evaluating stuttering, surpassing traditional diagnostic approaches.

Five out of the 21 articles (23.8%) in this research field focused on dysarthria detection through AI. These articles commonly highlighted the remarkable accuracy of AI in diagnosing dysarthria, with some models achieving precision rates as high as 93.97%. AI applications have demonstrated the ability to enhance speech intelligibility classification and can also be applied when evaluating the severity of dysarthria in terms of speech capabilities. Additionally, these studies illustrated the capability of AI to identify various types within dysarthria.

IV. DISCUSSION AND FUTURE RESEARCH

The major findings of a scoping review on research utilizing AI to assess SLVDs include: 1. All papers were published within the past five years. 2. Each of the 21 reviewed articles found AI to be an efficient tool for assessing SLVDs. 3. Notably, geographical and research design gaps were identified. 4. It was observed that AI has not been applied to evaluate some aspects of speech-language disorders (SLDs).

The cumulative total of publications in the last five years on utilizing AI to assess SLVDs indicates a notable increase in research during this period. This trend can be attributed to various factors, with progressive developments in AI technologies, such as machine learning and natural language processing, playing a crucial role in assessing SLVDs. Consequently, these advancements have resulted in more objective measures for evaluating SLVDs, addressing the limitations of traditional approaches that heavily rely on subjective assessments involving clinicians' expertise (Toki et al., 2023). According to ASHA (2016), progress in science and technology has expanded possibilities for communication disorder assessments. ASHA points out that SLPs are actively engaged in developing new technologies, utilizing advanced tools, and employing techniques to enhance service quality in their profession. This technological orientation aligns with broader trends in the field. The significant increase in AI-related publications over the past five years indicates a progressing domain where sophisticated AI technologies are essential for evaluation. Additionally, the demand for improved diagnostic methods in SLVDs has spurred more studies on AI applications.

An astonishing discovery has also been made: all 21 articles in the scoping review unanimously endorse AI as an effective tool for assessing SLVDs. This consistent support validates AI's effectiveness and suggests a potential paradigm shift in SLVDs. Such a shift calls for a critical evaluation of the field's readiness to fully integrate AI into standard practices. Given that AI can provide more detailed, nuanced, and personalized assessments, complete integration could transform patient evaluation methods. The overall consensus among researchers on this issue indicates an increasing reliance on AI to address the intricacies and fluctuations found in SLVDs, signaling a movement towards more advanced, data-driven assessment techniques. Pravin and Palanivelan (2022) emphasize that AI is indispensable for conducting speech-language assessments, primarily due to its ability to adapt to variations in speaking rates and accents. The accuracy in distinguishing dysfluency types aligns with the findings of this review. These shared perspectives lay the groundwork for future research, potentially opening up new frontiers for the application of AI in SLVDs.

Furthermore, the present study has identified gaps in the current literature on utilizing AI for diagnosing childhood SLVDs within Gulf countries, including Saudi Arabia, Bahrain, Kuwait, and others globally. This gap underscores the need to broaden research scope to encompass a more extensive range of linguistic and cultural contexts, enhancing global applicability and effectiveness of AI-driven assessments in SLP. Therefore, incorporating regions with diverse speech patterns, languages, or dialects would be valuable in addressing current blind spots in available academic literature on these aspects. The table above provides a comprehensive summary of locations where studies on the use of AI for children with communication problems, such as hearing difficulties or autism spectrum disorder (ASD), have been conducted. Therefore, it is essential for the research site selection process to be all-inclusive, facilitating universal application in AI solution development. By addressing this gap, we can enhance the diagnostic capacity of AI models for diverse populations through increased cultural sensitivity and linguistic accuracy.

In terms of research design, the scoping review notably identified a deficiency in longitudinal and predictive modeling approaches within the included studies. For instance, Albudoor and Peña (2022) utilized language assessment data originally collected in a longitudinal study to evaluate the development of children's language skills over time. However, despite being part of a longitudinal design, their analysis was conducted using a comparative cross-sectional framework, limiting the full exploitation of its longitudinal potential. This gap is particularly evident in the context of applying AI to assess SLDs, as there is no evidence of its involvement in such longitudinal or predictive modeling approaches. Hence, it is recommended that combining these techniques would significantly enhance our understanding of speech disorders, leveraging AI's capability to decipher complex, evolving patterns. This can be achieved by analyzing data across various phases at specific intervals. In other words, AI-supported longitudinal studies could provide an in-depth examination of the individual progression of SLDs. This approach would yield information illuminating the dynamics of these conditions, as exemplified by the following statement.

In addition to showcasing promise in AI applications within speech-language pathology, significant gaps persist across various areas. Certain conditions, such as cluttering—an example of a disfluency disorder—and acquired apraxia of speech among adults, have received little attention despite the potential impacts that AI might have in these areas. Furthermore, there is limited knowledge about articulation disorders among Arabic speakers, particularly in the context of AI identifying specific types of errors, such as distortions, deletions, substitutions, or additions to sounds. This knowledge gap necessitates the use of AI, especially when compared to phonological issues. Identifiable rule-based mistakes, like fronting, stopping, and final consonant deletion, are more predictable. In essence, the lack of use cases for AI-driven assessments in these domains underscores the need for dedicated research to enhance diagnostic accuracy for these specific speech and language impairments.

Compton et al.'s study (2022) highlights challenges in diagnosing voice disorders in primary care, mainly due to a lack of effective tools. According to their findings, they suggest addressing this issue by introducing AI, potentially reducing diagnosis time and minimizing the burden of dysphonia. The capability of AI to accurately distinguish between various vocal cord pathologies indicates the potential for precise and time-saving diagnostic methods. This underscores the growing importance of AI in SLVDs, offering promising prospects for significant advancements in clinical assessment strategies.

Several important areas show significant gaps in the use of AI in SLDs, despite its potential. Others, such as acquired apraxia of speech in adults, cluttering, or other forms of dysarthria, have been generally overlooked. Additionally, beyond that, AI may have the capacity to revolutionize assessments for different Arabic-speaking individuals with articulation disorders, capturing specific pronunciation errors, for example, deletion, addition, substitution, and distortion of speech sounds. On the other hand, future research can capitalize on the use of AI technology to distinguish between the different types of dysarthria, including flaccid, hypokinetic, hyperkinetic, ataxic, unilateral upper motor neuron, and spastic. In this particular context, it seems necessary to apply AI techniques to improve diagnostic accuracy when handling difficulties with articulation and distinguishing among dysarthrias. The absence of AI-driven assessments in these domains underscores a significant gap in the literature, calling for studies that focus on utilizing AI's analytic capabilities to enhance diagnostic precision for specific speech and language impairments.

V. CONCLUSION

In conclusion, the review of AI in diagnosing communication disorders demonstrates both progress and identifies gaps. The collective findings from the reviewed studies highlight the transformative impact of AI on SLVDs, as evidenced by the shift towards more refined and data-driven assessment techniques observed in numerous recent research studies focusing on AI applications in assessing SLVDs. However, the lack of literature in specific parts of the world, such as Saudi Arabia, and on other aspects like cluttering disorder, acquired apraxia, and different types of dysarthria, indicates the need for a wider and more inclusive research agenda. A significant gap exists between the use of predictive modeling techniques and

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longitudinal approaches, limiting the effective harnessing of AI analytic capacities. Consequently, addressing these shortcomings through cutting-edge research designs targeting little-studied speech disorders and language illnesses is essential to achieve optimal AI benefits. This approach holds potential for refining the diagnostic framework with highly personalized, culturally sensitive models derived from AI while concurrently exploring new territories for future investigations into possible roles for AI within clinical language sciences. As technology evolves, expanding the scope of AI research to cover other disorders using different methods becomes paramount for realizing comprehensive advantages in understanding and evaluating communication difficulties via speech science, given its advanced nature.

VI. SUMMARY OF RESEARCH FINDINGS

Table 1: Summary of Research Findings

Author	Country	Research Design	Participants' Characteristics	AI Technologies	Type of Disability being Assessed	Summary of Findings
Justice et al. (2019)	United States	Quantitative research design: non-experimental, quantitative secondary data	Age Range: 3–5 Number of Participants: Not specified Diagnoses and Characteristics: 54% with language disorders; 46% typically developing (without specified disorders) 10% with severe/profound cognitive impairment	Machine learning: Least Absolute Shrinkage and Selection Operator	Language disorders	The study demonstrated that machine learning can effectively differentiate children with/without language disorders.
Albudoor & Peña (2022)	United States	Quantitative research design: comparative cross-sectional design	Age: Second graders (7–8 years old) Participants: 84 Diagnosis and Characteristics: 25 with Developmental Language Disorder 59 with Typical Language Development Bilingual (Spanish-English)	Machine learning: Automatic Speech Recognition	Language disorders: developmental language disorders	The study demonstrated that ASR technology could moderately agree with human scoring in identifying developmental language disorders in bilingual children. Further, it suggested that careful item selection could improve its classification accuracy.
Parsa et al. (2021)	Canada	Quantitative research design: comparative cross-sectional design	Age: Not specified. Participants: 22 Diagnosis: 9 with dementia 13 without dementia	Machine learning: including Convolutional Neural Networks (CNN) and Support Vector Machines (SVM)	Language disorders	The research demonstrated that traditional machine learning classifiers could accurately detect language impairment in older adults with better performance when employing the Picture Description dataset and phone-based recordings.
Toki et al. (2023)	Greece	Quantitative research design: experimental	Age Range: Average of 9 Number of Participants: Not specified	Machine learning: 1. BFGS (Broyden–Fletcher–Goldfarb–Shanno)	Language disorders	The research demonstrated that the Integer-bounded Neural Network outperformed other AI algorithms in the

			Diagnoses and Characteristics: Both typical and neurodevelopmental disorders, with both genders represented.	2. Genetic Algorithms 3. Particle Swarm Optimization 4. Integer-bounded Neural Network 5. Adam optimizer 6. K-Nearest Neighbors 7. Support Vector Machine		detection of speech and language deficiencies.
Georgiou & Theodorou (2023)	Cyprus	Quantitative research design: experimental	Age Range: 7 years 10 months–10 years 4 months Number of Participants: 30 Diagnoses and Characteristics: Balanced for gender, with and without Developmental Language Disorder, no cognitive impairments, normal hearing, and vision.	machine learning: Feed-forward neural network	Language disorders: Developmental Language Disorder	The study revealed that the AI model demonstrated high accuracy (0.92–0.98 for various metrics) in identifying Developmental Language Disorder in children using language data, thereby indicating its potential for early and efficient DLD assessment.
Beccaluva et al. (2023)	Italy	Quantitative research design: experimental	Age Range: Not specified Number of Participants: 47 Diagnoses and Characteristics: With and without Developmental Language Disorder	Machine Learning: convolutional neural networks	Language disorders: Developmental Language Disorders	The study found differences in the rhythmic vocal patterns between children with and without Developmental Language Disorder, suggesting that their tool, MARS, could be effective in early assessment of DLD.
Milani et al. (2020)	Brunei	Quantitative research design: experimental	Age or Age Range: Not Specified Number of Participants: 40 Diagnoses and Characteristics: Hyperkinetic Dysphonia: 10 Hypokinetic Dysphonia: 10 Reflux Laryngitis: 10 Healthy Individuals: 10	Machine learning: Decision Tree (DT), Support Vector Machine (SVM), Artificial Neural Network (ANN).	Voice disorders, specifically: Hyperkinetic dysphonia, hypokinetic dysphonia, reflux laryngitis.	The study found that the ANN classifier achieved the highest accuracy in classifying voice disorders at 87.5%. The DT algorithm had a classification accuracy of voice disorders at 62.5%, while SVM showed the lowest classification accuracy of voice disorders, at 50%.
Compton et al. (2022)	Canada	Quantitative research design: Controlled Prospective Cohort Study	Age or Age Range: Over 18 Number of Participants: Not Specified Diagnoses and Characteristics: Dysphonia Able to follow instructions in English	Machine learning: Artificial Neural Network	Voice disorders and vocal cord pathologies, specifically: Mass lesions -Inflammatory disorders -Normal voice -Unilateral paralysis	The study demonstrated that the AI model accurately predicts vocal cord pathologies, outperforming general practitioners and otolaryngologists in diagnostic accuracy. Standardized data

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			No prior treatments for dysphonia/surgery on the larynx		-Adductor spasmodic dysphonia	collection is crucial for improving the model's performance.
Verde et al. (2019)	Italy	Quantitative research design: experimental	Age or Age Range: Not Specified Number of Participants: 2003 Diagnoses and Characteristics: Healthy Voices: 796 Pathological Voices: 1207	Machine learning; Boosted Trees	Voice disorders	The study found that the Boosted Trees algorithm accurately identified voice disorders, outperforming other algorithms in the study.
Mahmoud et al. (2021)	China	Quantitative research design: experimental	Age or Age Range: Healthy Subjects – Average 21.5 years; Aphasic Patients – Average 61.8 years Number of Participants: 46 Diagnoses and Characteristics: Healthy Subjects: 34 (11 Females) Aphasic Patients: 12 (7 Males, 5 Females)	Machine learning: Convolutional Neural Networks	Aphasia	The study revealed that Convolutional Neural Networks were more accurate than classical machine learning techniques in identifying healthy individuals versus aphasic patients.
Day et al. (2021)	United States	Quantitative research design: predictive modeling study	Age or Age range: 61.84 (average) Participants Numbers: 238 Diagnoses and Characteristics: Various types of aphasia	Machine learning: Natural Language Processing	Aphasia	The study demonstrated that neural networks and random forests effectively predicted aphasia severity, with mean absolute errors of 0.067 and classification accuracies of 73%, respectively.
Pierce (2024)	Australia	Quantitative research design: exploratory study	No human participants	Machine learning: DALL-E 2, developed by OpenAI	Aphasia	The study revealed that the DALL-E 2 achieved a 94.5% success rate in generating aphasia assessment images.
Das et al. (2020)	United States	Quantitative research design: experimental	Age or Age range: Not specified Participants Numbers: Not specified Diagnoses and Characteristics: Adult males with stuttering	Machine learning: Convolutional Neural Network Architecture A, Convolutional Neural Network Architecture B, Random Forest classifier	Stuttering	The study demonstrated that Convolutional Neural Network Architecture A accurately predicts stuttering from pre-speech facial movements, outperforming other models.
Al-Banna et al. (2022)	United Kingdom	Quantitative research design: experimental	Age or Age range: Not specified (pre-existing datasets) Participants Numbers: Not specified Diagnoses and Characteristics: Data derived from FluencyBank dataset and SEP-28K dataset	Machine learning: 1. Support Vector Machine 2. Random Forest 3. Decision Trees 4. AdaBoost 5. k-Nearest Neighbors (k-NN)	Stuttering	The study revealed that the Random Forest classifier outperformed other classifiers in prediction accuracy for stuttering disfluency detection on the SEP-28K and FluencyBank

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				6. Quadratic Discriminant Analysis 7. Gaussian Naïve Baye		datasets. However, it is suggested that deep learning and end-to-end ASR may yield better results for larger datasets.
Asci et al. (2023)	Italy	Quantitative research design: Observational study	Age or Age range: 7–30 Participants Numbers: 124 (53 + 71) Diagnoses and Characteristics: Individuals with and without stuttering	Machine learning: Support Vector Machine, Artificial Neural Networks	Stuttering	The study demonstrated that high accuracy was achieved in stuttering identification employing machine learning.
Pravin & Palanivelan (2022)	India	Quantitative research design: Experimental	Age or Age range: 5–7 (inclusive) Participants Numbers: 17 Diagnoses and Characteristics: Specific Language Impairment (SLI), dysphemia, and Bilingual children (Tamil-English speakers).	Machine learning: 1. Weight Decorrelated Stacked Autoencoder-Deep Neural Decision Trees 2. Multilayer Perceptron 3. Standalone Deep Neural Decision Trees	Stuttering	The study revealed that the Weight Decorrelated Stacked Autoencoder-Deep Neural Decision Trees model achieved the highest mean test accuracy of 95% for classifying speech fluency disorders.
Tartarisco et al. (2021)	Italy	Quantitative research design: diagnostic accuracy study	Age or Age range: 12 (average) Participants Numbers: 55 Diagnoses and Characteristics: Healthy controls: 18 Ataxia: 37 (21 Progressive, 16 Congenital non-Progressive)	Machine learning: Support Vector Machine, k-Nearest Neighbors (kNN), Decision Tree, Naïve Bayes	Dysarthria	The study revealed that the Hierarchical Machine Learning Model achieved 90% accuracy for dysarthria assessment in ataxic children.
Bhat & Strik (2020)	India	Quantitative research design: experimental	Not specified	Machine learning: Bidirectional Long-Short Term Memory neural network	Dysarthria	The study revealed that the Bidirectional Long Short-Term Memory enhanced dysarthric speech intelligibility classification by 6% over traditional machine learning methods.
Zhang et al. (2023)	China	Quantitative research design: observational cross-sectional analysis	Age: 22–40 for Controls and 19–46 for Wilson's Disease (Dysarthria) Participants: 65 each group Diagnoses: Controls - healthy, Wilson's Disease - diagnosed with dysarthria (subdivided: Mild and Moderate-Severe)	Machine learning: Random Forest	Dysarthria	The study demonstrated that the AI-powered acoustic analysis system effectively assessed dysarthria severity in Wilson's disease patients.
Joshy & Rajan (2022)	India	Quantitative research design: experimental	Not specified	Machine learning: 1. Deep Neural Network 2. Convolutional Neural Network	Dysarthria	The study demonstrated that the AI model achieved 93.97% accuracy in speaker-dependent

				3. Gated Recurrent Unit 4. Long Short-Term Memory Network		dysarthria severity assessment and 49.22% accuracy in speaker-independent scenarios.
Song et al. (2022)	South Korea	Quantitative research design: experimental	Age: Ataxic: 65.00 ± 8.46 Hypokinetic: 68.68 ± 9.40 None: 74.00 ± 5.77 Participants: 422 Diagnoses: Ataxic, Hypokinetic, None	Machine learning: Patch-wise Wave Splitting and Integrating AI System for audio classification	Dysarthria	The study demonstrated that the convolutional neural network AI model accurately differentiated between ataxic and hypokinetic dysarthria, showcasing high performance and potential for clinical application in dysarthria detection.

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