Narrative Review Article

Speech-Based Machine Learning for Neurological Disorders: Applications and Limitations in Parkinson's Disease, Amyotrophic Lateral Sclerosis, Huntington's Disease, and Vascular Dementia

Jayant Namburi

Van Alstyne High School, 700 Collin McKinney Pkwy, Van Alstyne, TX 75495, United States

ABSTRACT

Parkinson's disease (PD), amyotrophic lateral sclerosis (ALS), Huntington's disease (HD), and vascular dementia (VaD) all share a common feature of speech impairment. Recent advances in machine learning (ML) have allowed researchers to analyze speech patterns using acoustic features such as pitch variability, articulation rate, jitter, shimmer, and prosody. These measurable speech abnormalities can provide insight into neurological dysfunction and disease progression. This review evaluates the hypothesis that artificial intelligence (AI)-based machine learning of speech patterns can help recognize neurological impairment associated with PD, ALS, HD, and VaD by analyzing the pathophysiology, clinical symptoms, and speech characteristics of each disease, followed by an analysis of current speech-based ML approaches used in neurological research. Because most existing evidence comes from classifying speech in patients with an established diagnosis, this review distinguishes disease classification in diagnosed patients from genuine early-stage detection when interpreting the available evidence.

Keywords: speech analysis; machine learning; Parkinson's disease; amyotrophic lateral sclerosis; Huntington's disease; vascular dementia; digital biomarkers

INTRODUCTION

Speech impairment is a common feature of neurological disorders such as Parkinson's disease (PD), amyotrophic lateral sclerosis (ALS), Huntington's disease (HD), and vascular dementia (VaD). These conditions have many overlapping symptoms that affect both brain systems involved in motor control and cognition, leading to measurable changes in speech production (1, 2).

In recent years, machine learning (ML) has been used to analyze speech and identify patterns associated with neurological disease. Acoustic features such as pitch variability, articulation rate, and prosody can be measured and used to distinguish between patient groups in research settings (3, 4). Because speech is non-invasive and easy to collect, it has gained attention as a potential digital biomarker to aid clinical diagnosis and monitoring.

While most ML studies are based on datasets where patients already have a confirmed diagnosis, there is interest in leveraging these models for earlier diagnosis and classification. This review evaluates the hypothesis that speech-based machine learning can help recognize

Corresponding author: Jayant Namburi, E-mail: Jaynamburi62@gmail.com.

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neurological impairment associated with PD, ALS, HD, and VaD, while distinguishing disease classification in already-diagnosed patients from genuine early-stage detection across the studies reviewed. This review examines the pathophysiology, clinical symptoms, and speech characteristics of these four disorders, followed by an evaluation of current speech-based ML applications and their key limitations.

PATHOPHYSIOLOGY

The pathophysiology or mechanisms of disease between Parkinson's disease, amyotrophic lateral sclerosis (ALS), Huntington's disease, and vascular dementia have significant overlap as well as major differences, as seen in Table 1. One major similarity across these neurodegenerative conditions is progressive neuronal degeneration, meaning that neurons become more damaged over time and eventually die, leading to loss of neurological function. Although all of these diseases result in loss of neurological function, they differ in their underlying mechanisms. Parkinson's disease primarily involves protein misfolding and dopaminergic neuron loss; ALS involves excitotoxicity and motor neuron degeneration due to genetic mutations; Huntington's disease is caused by a single gene mutation leading to toxic protein accumulation; and VaD results from reduced blood flow and ischemic damage (1).

In Parkinson's disease, damage to dopaminergic neurons occurs because these neurons are especially vulnerable due to their calcium handling and their tendency to accumulate α-synuclein. These vulnerabilities ultimately lead to the degeneration of dopaminergic neurons in the basal ganglia (5). Alpha-synuclein is a protein that is primarily found at the presynaptic terminal of neurons, where it is involved in regulating synaptic vesicles and neurotransmitter release. Because of this role, α-synuclein functions as an active part of neuron communication rather than as a structural component. It is normally found in neurons, where it helps control the release of neurotransmitters. However, when the protein folds incorrectly, it begins to aggregate and form clumps inside the neuron called Lewy bodies. These clumps interfere with important cellular processes, including energy production and protein recycling. Dopaminergic neurons in the substantia nigra also depend heavily on calcium channels to maintain their regular electrical activity, and this constant calcium movement increases stress on the cell, making these neurons more likely to develop α-synuclein buildup and eventually degenerate (5).

ALS is caused by genetic mutations that may be inherited (familial ALS) or occur sporadically (de novo), with the majority of ALS cases being sporadic rather than directly inherited. This genetic mutation leads to dysfunction within neurons, including protein buildup and impaired RNA processing, which ultimately leads to a buildup of glutamate release, causing excitotoxicity and cell death (6). Several specific genetic mutations have been linked to ALS, including mutations in the SOD1, C9orf72, TARDBP, and FUS genes (6). These mutations can cause proteins to accumulate in motor neurons or disrupt normal RNA processing inside the cell. Because of these problems, neurons release excessive amounts of the neurotransmitter glutamate, and nearby support cells are unable to remove it properly, causing it to accumulate around motor neurons. Excess glutamate overstimulates nearby neurons and triggers a large influx of calcium into the cell. This process, known as excitotoxicity, damages mitochondria, increases cellular stress, and ultimately leads to motor neuron death. This death of motor neurons occurs in upper motor neurons within the motor cortex and lower motor neurons within the brainstem and spinal cord (6).

In Huntington disease, expanded CAG repeats in the HTT gene produce mutant huntingtin protein that disrupts cellular processes, which causes progressive neuron degeneration (7). The expanded CAG repeats in the HTT gene cause the huntingtin protein to contain an abnormally long chain of glutamine amino acids. This abnormal protein can misfold and accumulate inside neurons. Mutant huntingtin interferes with several important cellular processes such as gene expression, mitochondrial function, and the removal of damaged proteins. Because neurons depend heavily on these systems, this disruption eventually causes neurons, especially in the striatum, to degenerate over time (7).

In vascular dementia, chronic cerebral hypoperfusion and small vessel inflammation ultimately cause white matter destruction (8). Chronic cerebral hypoperfusion occurs when regions of the brain receive less blood flow than they normally should over a long period of time. This can result from conditions such as high blood pressure, small vessel disease, or atherosclerosis. When brain tissue does not receive sufficient oxygen and glucose through sclerotic arteries, cells cannot generate enough energy to function properly. This energy deficit can trigger inflammation and damage the blood-brain barrier. Over time, these processes specifically tend to damage the brain's white matter, which is essential for communication

between different regions of the brain (8), ultimately leading to VaD. Overall, although Parkinson's disease, ALS, Huntington's disease, and vascular dementia all involve progressive neurological dysfunction, each disease arises from distinct biological mechanisms that produce different patterns of neuronal injury.

CLINICAL SYMPTOMS

Although Parkinson's disease, amyotrophic lateral sclerosis (ALS), Huntington's disease, and vascular dementia are all neurological disorders, they present with different clinical symptoms depending on the areas of the nervous system that are affected (1). Some diseases mainly cause problems with movement and muscle control, while others primarily affect memory, thinking, behavior, or executive function. Despite these differences, all four conditions are progressive and can significantly impact a patient's ability to perform everyday activities. Understanding the similarities and differences in their clinical presentations is important for accurate diagnosis and management.

Parkinson's disease is commonly identified by symptoms of resting tremor, rigidity, bradykinesia, and postural instability. Patients frequently also develop a shuffling gait, stooped posture, reduced arm swing, masked facial expression, micrographia, and loss of smell. Together, these symptoms show the progressive loss of normal motor control and are important in the clinical diagnosis of Parkinson's disease (9).

Amyotrophic lateral sclerosis (ALS) is mainly identified by progressive muscle weakness caused by degeneration of both upper and lower motor neurons. Common clinical signs include muscle wasting, fasciculations, cramps, limb weakness, stiffness, spasticity, and difficulty with fine motor tasks such as writing or buttoning clothes. As the disease advances, weakness can spread to other muscle groups and can eventually affect breathing because the respiratory muscles become weak. These combined upper and lower motor neuron findings are a major part of the clinical picture of ALS (10).

Huntington's disease is characterized by involuntary movements along with cognitive and psychiatric changes. Patients commonly develop chorea, abnormal body postures, clumsiness, and problems with coordination. Patients can also experience decline in thinking, judgment, and concentration, as well as depression, irritability, impulsivity, anxiety, or socially inappropriate behavior. Because Huntington's affects movement, behavior, and cognition at the same time, the diagnosis often depends on recognizing this combination of symptoms rather than only one feature by itself (11).

Vascular dementia often presents with problems in executive function before memory becomes the main issue. Patients display difficulty with planning, decision-making, attention, organization, and processing speed. In addition, they can show focal neurological deficits related to prior strokes, such as weakness, sensory loss, abnormal reflexes, or visual field deficits, and many also develop gait disturbance or falls. A stepwise decline in function is another common clinical clue that helps distinguish VaD from other dementias (12). In summary, while all four disorders progressively impair daily functioning, their clinical presentations differ according to the specific motor, cognitive, and behavioral systems affected.

SPEECH CHARACTERISTICS

These neurological disorders affect speech through both shared and disease-specific mechanisms, and speech symptoms are often indicators of disease severity and progression (2), as seen in Table 1. As discussed, these diseases have different biological causes, yet they often produce speech symptoms that are difficult for the examining clinician to distinguish. Therefore, specific speech deficits or patterns are often not used as diagnostic criteria, and clinicians rely on different symptoms for diagnosis.

As a result of loss of dopamine-producing neurons in the substantia nigra, Parkinson's patients have difficulty coordinating the muscles used for speech. These patients therefore exhibit speech changes that include reduced vocal loudness, monotone pitch, and imprecise articulation. Some studies show that speech impairment can worsen even when other motor symptoms appear stable (4). This suggests that speech analysis can detect subtle disease progression that is not always captured in standard clinical tests, making it a potentially useful tool for disease monitoring and supporting clinical diagnosis (4).

ALS studies have shown that the disease can strongly affect speech patterns including speaking rate and intelligibility. This is because ALS causes degeneration of both the upper and lower motor neurons, leading to patients losing control over the muscles used for speech. Bulbar-onset ALS patients often show faster declines in speech performance than spinal-onset patients (13). Speech often becomes slurred, slower, and less clear over time. Further studies show that ALS can also lead to

Table 1. Neurological mechanisms and speech patterns associated with selected neurological disorders. *Note. ALS = amyotrophic lateral sclerosis.*

Disease	Main Neurological Mechanism	Primary Speech Pattern
Parkinson's disease	Basal ganglia dysfunction affecting dopaminergic motor control	Hypokinetic dysarthria with reduced loudness and monoprosody
ALS	Degeneration of upper and lower motor neurons	Progressive mixed dysarthria with declining articulation and intelligibility
Huntington's disease	Degeneration of basal ganglia circuits affecting movement and timing	Hyperkinetic dysarthria with irregular rhythm and prosodic instability
Vascular dementia	Cerebrovascular injury causing variable disruption of frontal-subcortical circuits	Variable cognitive-linguistic and motor speech impairment depending on lesion location

strained or breathy speech patterns (13, 14). Because of this, speech analysis provides a useful and non-invasive way to monitor disease severity and progression (15). Dysarthria occurs in approximately 78% of ALS patients (16).

Huntington's disease also produces measurable speech abnormalities due to degeneration in the basal ganglia and the effects of mutant huntingtin protein. Huntington's disease is associated with irregular rhythm and variability in speech rate due to impaired motor coordination (17). Patients also show irregular timing, articulation difficulties, and reduced coordination between speech muscles (18). These changes occur because the disease disrupts normal motor control and coordination. As the condition progresses, speech can become less controlled and more unpredictable (18). Patients also experience cognitive decline that affects language processing. These patterns can be measured using acoustic analysis techniques, allowing researchers to track changes over time and better understand disease progression (18).

Vascular dementia can affect speech in different ways depending on the location and extent of the underlying brain injury. Repeated cerebrovascular damage can gradually affect brain regions involved in language and cognition, and because different regions control different aspects of speech, symptoms can vary widely between patients. VaD commonly results from chronic vascular injury that causes white matter damage and disrupts frontal-subcortical circuits (8). Because these pathways contribute to higher-level thinking and language processing, patients can develop slowed verbal fluency and word-finding difficulty (12).

Although each condition has characteristic features, many speech abnormalities, such as slowed rate or reduced clarity are not unique to a single disease. Instead, they reflect broader disruptions in motor and cognitive systems, making differentiation during a physical exam by a clinician quite challenging. Overall, these disorders produce both shared and disease-specific speech abnormalities, creating measurable patterns that can aid monitoring but often remain difficult to distinguish clinically (2).

SPEECH-BASED MACHINE LEARNING APPLICATIONS

Speech has several advantages as a digital biomarker that can be analyzed via machine learning approaches for diagnostic utility. It is non-invasive, fast, scalable, and can capture subtle changes over time (3, 19). Digital acoustic analysis allows for the incorporation of multiple variables including motor changes, coordination, and respiratory function; Table 2 summarizes the key acoustic features and speech tasks most commonly used in the studies reviewed for each disorder.

In Parkinson's disease, speech-based machine learning has demonstrated promising performance in distinguishing patients with established Parkinson's disease from healthy controls and may have future potential for earlier identification; however, current evidence for genuine early or pre-symptomatic detection remains limited. Researchers use speech features like pitch changes, jitter, shimmer, and Mel-frequency cepstral coefficients to find patterns linked to Parkinson's. Little *et al.* reported 91% classification accuracy using a support vector machine (SVM) model analyzing dysphonic speech features to distinguish Parkinson's disease patients from healthy controls (3).

In amyotrophic lateral sclerosis (ALS), speech-based

Table 2. Key acoustic features and speech tasks commonly used in the machine learning literature across neurological disorders.
Note. ALS = amyotrophic lateral sclerosis; MFCCs = Mel-frequency cepstral coefficients.

Disease	Key Acoustic/Linguistic Features	Commonly Used Speech Tasks in the Literature
Parkinson's disease	Jitter, shimmer, reduced pitch variability, MFCCs, decreased vocal intensity	Sustained vowel, reading passage, spontaneous speech
ALS	Articulation rate, pause duration, vocal intensity, formants, intelligibility measures	Reading passage, sentence repetition, spontaneous speech
Huntington's disease	Speech rate variability, pause patterns, pitch instability, abnormal prosody	Reading passage, syllable repetition, spontaneous speech
Vascular dementia	Response timing, pause duration, verbal fluency, lexical diversity, speech rate	Verbal fluency tasks, picture description, spontaneous speech

machine learning is mostly being used to detect bulbar involvement and measure how serious speech problems are. Simmatis *et al*. showed that acoustic speech analysis could tell ALS patients apart from healthy controls quite well, and it could also separate patients with earlier bulbar changes from those with more advanced speech impairment (20). Tena *et al*. found very strong results when classifying bulbar versus non-bulbar ALS (21). Together, these findings suggest that speech analysis could be a useful, non-invasive way to catch bulbar decline earlier and to track disease progression over time.

In Huntington's disease, speech-based machine learning seems especially useful for telling apart different stages of the disease. Kouba *et al*. found that automated speech analysis could distinguish pre-symptomatic, prodromal, and manifest Huntington's disease from healthy controls, with performance getting stronger as the disease became more advanced (22). Nunes *et al*. further showed that a machine learning model analyzing speech features such as pausing, pitch variation, and intelligibility could help predict clinical status in Huntington's disease patients (23). These findings suggest that speech analysis appears useful for disease classification and staging in patients with established Huntington's disease and may contribute to future early-detection strategies as additional longitudinal evidence becomes available (23).

In vascular dementia, speech-based machine learning research remains far more limited than for the other three disorders, and no dedicated study was identified in this review that applies speech-based machine learning to a diagnosed vascular dementia population in the way the other disorders have been studied. The closest related evidence comes from Martínez-Nicolás *et al*., who used speech analysis to predict vascular risk factors, including diabetes, hypertension, hypercholesterolemia, and heart disease, in people with mild cognitive impairment; these conditions are known predictors of vascular dementia rather than markers of the disease itself (24). Their discriminant analysis achieved accuracies above 95% for diabetes and hypertension and above 80% for hypercholesterolemia and heart disease using speech frequency and rhythm parameters. However, because this study measures risk factors for future vascular dementia rather than diagnosing existing disease, it does not directly address whether speech-based machine learning can detect or monitor vascular dementia once it has developed. This represents a clear gap in the current literature and a direction for future research.

Early ML studies showed strong performance in distinguishing patients with neurological disorders from healthy individuals using speech features. These models used measures such as jitter, shimmer, and speech rate and performed well under controlled conditions (3). More recent studies have expanded data collection using smartphones and remote monitoring, suggesting that speech analysis can be applied outside the clinic (4). However, most of this research focuses on separating patients from healthy controls rather than distinguishing between different neurological disorders. While this demonstrates that speech contains useful diagnostic information, it does not address the more difficult clinical challenge of determining which specific neurological disorder a patient has.

Some studies, including Kang *et al*., have attempted to classify multiple disorders, including PD, ALS, HD, and progressive supranuclear palsy (PSP), a related disorder not otherwise covered in this review, and reported balanced classification accuracies of 83% for a four-class model and 77% for a five-class model that

also included healthy controls (25). These findings suggest that speech analysis can help distinguish among several neurological conditions. However, these studies are based on patients with established diagnoses, often at more advanced stages of disease. As neurological disorders progress, speech abnormalities generally become more noticeable and easier to detect. Therefore, some of the reported accuracy may reflect the model's ability to recognize different stages of disease severity rather than disease-specific speech characteristics alone. This is an important finding because early diagnosis is often the greatest clinical challenge, and patients in the earliest stages may have more subtle and overlapping speech abnormalities. Overall, machine learning models show promise for identifying neurological disorders using speech. However, additional research is needed to determine how accurately these models can distinguish between different disorders, particularly during the early stages of disease when diagnosis is most difficult. Taken together, current evidence suggests that speech-based machine learning can detect neurological impairment and disease progression, although its ability to reliably differentiate among disorders remains limited.

Beyond these performance metrics, several methodological limitations affect how confidently these findings can be interpreted. Many of the studies described above enrolled relatively small, single-site samples, which limits statistical power and increases the risk that reported accuracies reflect patterns specific to that dataset rather than generalizable disease signatures. Dataset composition is also a concern, since studies often do not report disease severity, age range, sex distribution, or medication status, making it difficult to know whether models are learning disease-related speech changes or incidental characteristics of the sample studied. Overfitting is a related risk: several of these models are trained and evaluated using cross-validation on the same dataset rather than tested on an independent, external cohort, so reported accuracies may not generalize to new patients or recording conditions. Differences among machine-learning algorithms further complicate comparisons across studies, since support vector machines, random forests, and other classifiers vary in how they handle high-dimensional acoustic features and small sample sizes. Deep learning approaches may capture more complex speech patterns but generally require substantially larger datasets to minimize overfitting and achieve robust external validation. Direct comparison of accuracy figures across studies that use different algorithms, feature sets, and validation strategies should therefore be interpreted with caution. Table 3 summarizes the study population, methodology, and key limitations of the machine-learning studies discussed above.

Table 3. Comparison of representative speech-based machine-learning studies, including study population, speech task, machine-learning approach, reported performance, and major methodological limitations affecting clinical translation. *Note. PD = Parkinson's disease; ALS = amyotrophic lateral sclerosis; HD = Huntington's disease; VaD = vascular dementia; PSP = progressive supranuclear palsy. Entries marked "not specified in cited source" reflect methodological details that were not reported in the studies as described in this review.*

Study	Disorder	Speech Task / Data	ML Method	Reported Performance	Key Limitation
Little *et al*. (3)	PD	Sustained phonation / reading speech tasks	Support vector machine (SVM)	91% accuracy vs. healthy controls	Diagnosed-patient classification, not early detection; external validation not reported
Simmatis *et al*. (20)	ALS	Reading of standardized 99-word passage; 119 ALS, 22 controls	Bayesian LASSO logistic regression	AUROC 0.85 (ALS vs. control); 0.78 (early ALS vs. control); 0.70 (early vs. late ALS)	Small clinical sample; validation approach not detailed: single center sample
Tena *et al*. (21)	ALS	Sustained vowel phonation (voiceprint analysis)	Multiple classifiers compared (Random Forest, SVM, neural network, LDA, logistic regression); Random Forest performed best	Up to 92.4% accuracy (Sensitivity 83.3%, Specificity 97.5%) distinguishing bulbar involvement stages; >93% accuracy overall after corpus curation	Single-center sample; external validation not reported

Continued Table 3. Comparison of representative speech-based machine-learning studies, including study population, speech task, machine-learning approach, reported performance, and major methodological limitations affecting clinical translation.
Note. PD = Parkinson's disease; ALS = amyotrophic lateral sclerosis; HD = Huntington's disease; VaD = vascular dementia; PSP = progressive supranuclear palsy. Entries marked "not specified in cited source" reflect methodological details that were not reported in the studies as described in this review.

Study	Disorder	Speech Task / Data	ML Method	Reported Performance	Key Limitation
Kouba *et al*. (22)	HD	Acoustic speech analysis across HD stages (premanifest, prodromal, manifest)	Acoustic feature-based discrimination models (specific classifier not named in source)	AUC 0.97 (manifest HD vs. control, 90% accuracy); AUC 0.92 (prodromal HD vs. control, 83% accuracy); AUC 0.74 (premanifest HD vs. control, 60% accuracy)	Cross-sectional design; performance declines substantially at the premanifest stage; external validation not reported.
Nunes *et al*. (23)	HD	Passage reading, counting forward/ backward; 36 participants (18 HD, 7 prodromal HD, 11 control)	Random forest classifier	73% balanced accuracy, AUC 0.92 (predicting clinical status)	Small sample; single dataset; generalizability not established
Martínez-Nicolás *et al*. (24)	VaD (risk factors, not diagnosis)	Reading-aloud speech in MCI patients	Discriminant analysis	>95% (diabetes, hypertension); >80% (hypercholesterolemia, heart disease)	Predicts vascular risk factors, not diagnosed VaD; no dedicated speech-ML study of diagnosed VaD patients identified
Kang *et al*. (25)	PD, PSP, ALS, HD (multi-class)	Brief structured speech assessment (30.88–60.02 s duration)	Elastic Net regression	83% balanced accuracy (four-class model); 77% balanced accuracy (five-class model including controls)	Small sample size; diagnosed, often advanced-stage patients; accuracy may reflect disease severity rather than disease-specific patterns

Collectively, these methodological limitations indicate that reported classification accuracies should be interpreted cautiously, as performance observed under controlled research conditions may not directly translate to routine clinical practice.

Overall, although speech-based machine learning has demonstrated encouraging performance across several neurological disorders, differences in study design, dataset characteristics, feature extraction methods, machine-learning algorithms, and validation strategies currently limit direct comparison between studies. These methodological issues should be addressed through standardized multicenter studies before speech-based machine learning can be considered for routine clinical implementation.

LIMITATIONS OF APPLYING MACHINE LEARNING TO CLINICAL DIAGNOSIS

In clinical practice, patients do not present with a clear diagnosis. Instead, they may have general speech changes such as reduced clarity, altered fluency, or monotone voice, which can be caused by different neurological conditions.

Early-stage disease makes this more difficult. Parkinson's disease can appear similar to another neurodegenerative disease, progressive supranuclear palsy (26), and ALS can begin with only speech involvement before other symptoms develop. Stroke can also produce speech patterns that resemble similar neurodegenerative disorders depending on the affected

brain region (27).

Diagnosis is not based on a single test. Clinicians consider multiple factors, including patient history, neurological examination, imaging, and how symptoms change over time. This process often involves uncertainty, especially early in the disease course. Most ML studies do not reflect this reality because they rely on clearly labeled datasets and controlled conditions.

A key issue is how model performance is interpreted. Many acoustic features used in ML models reflect general neurological impairment rather than disease-specific patterns.

This means a model can perform well by identifying that something is abnormal, without accurately determining the underlying condition.

As a result, strong performance in research settings does not necessarily translate into reliable diagnosis. Models can distinguish between healthy and affected individuals or between different levels of severity, but still struggle to identify the exact disease.

From a clinical perspective, this distinction is important. Detecting impairment is useful, but effective treatment depends on correctly identifying the condition. Overall, the greatest challenge for clinical implementation is that speech abnormalities often reflect general neurological dysfunction rather than disease-specific characteristics, reducing diagnostic accuracy in real-world settings.

CONCLUSION

Speech-based machine learning has emerged as a promising approach for the objective assessment of neurological dysfunction and disease progression in PD, ALS, HD, and VaD. As a non-invasive, low-cost, and scalable digital biomarker, speech offers a way to assess patients remotely and repeatedly, which is difficult to achieve with imaging or other invasive testing, and can be particularly valuable for monitoring disease progression and treatment response outside specialized clinical settings.

However, most current studies are conducted in controlled settings with small, single-site samples and do not fully reflect the complexity of clinical diagnosis. Models that perform well in separating predefined groups may not reliably distinguish between different neurological disorders in practice, and reported accuracies often come from cross-validation on the same dataset rather than independent external validation, raising concerns about overfitting and generalizability. Differences in acoustic features, speech tasks, and machine-learning algorithms across studies further limit direct comparison of results, as summarized in Table 3.

Returning to the hypothesis that speech-based machine learning can help recognize early symptoms of PD, ALS, HD, and VaD, the evidence reviewed here only partially supports this claim. Current studies demonstrate that speech-based ML can reliably distinguish patients with an established diagnosis from healthy controls and, in some cases, differentiate between related disorders or disease stages. However, because nearly all of this evidence comes from patients with confirmed, often moderate-to-advanced disease, it does not directly demonstrate genuine early or pre-symptomatic detection. The hypothesis is therefore best considered partially supported for disease classification and monitoring, but not yet confirmed for early detection.

Future research should focus on more clinically relevant study designs, including multiple diseases, earlier stages of illness, and more diverse populations such as stroke. Combining speech analysis with other clinical data and tracking patients over time may improve its usefulness. Overall, speech-based ML is likely to be more effective for detecting neurological impairment and monitoring changes than for making specific diagnoses at this stage. Further research is needed before it can be used reliably in clinical decision-making.

Despite these challenges, speech-based digital biomarkers have the potential to transform neurological care by enabling objective, non-invasive, and scalable assessment of disease-related changes. As advances in artificial intelligence, digital health technologies, and multimodal biomarker integration continue, speech analysis may become an important component of personalized neurological assessment, complementing rather than replacing conventional clinical evaluation. Continued collaboration among neurologists, speech-language pathologists, engineers, and data scientists will be essential to translate these promising research tools into reliable clinical applications.

CONFLICT OF INTEREST

The author declares no conflicts of interest related to this work.

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