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Artificial Intelligence for Early Detection of Motor Neuron Disease Using Gait Analysis and Speech Patterns in Pekanbaru, Indonesia

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ABSTRACT

Introduction: Motor neuron disease (MND) is a devastating neurodegenerative disorder characterized by progressive muscle weakness, atrophy, and ultimately, paralysis. This study investigated the potential of artificial intelligence (AI) to detect MND in its early stages using gait analysis and speech pattern recognition in a population in Pekanbaru, Indonesia. **Methods:** A cross-sectional study was conducted at the Neurology Department of a tertiary referral hospital in Pekanbaru, Indonesia. A total of 150 participants aged 40-75 years were recruited and categorized into three groups. Gait analysis was performed using wearable sensors to collect data on stride length, cadence, swing time, stance time, and gait variability. Machine learning algorithms, including support vector machines (SVM), random forest (RF), and deep learning models like convolutional neural networks (CNN), were trained on the combined gait and speech data to classify participants into the three groups. **Results:** Significant differences were observed in gait parameters between the MND group and the other two groups. Individuals with MND exhibited shorter stride length ($p<0.001$), slower cadence ($p<0.001$), increased swing time variability ($p=0.002$), and reduced stance time ($p=0.003$). Speech analysis revealed distinct patterns in the MND group, including reduced speech rate ($p<0.001$), increased pause duration ($p=0.004$), and decreased vocal intensity ($p=0.001$). The AI models, particularly the CNN model, demonstrated high accuracy in differentiating individuals with MND from healthy controls and those with other neurological conditions. The CNN model achieved an accuracy of 94.7%, sensitivity of 92%, specificity of 96%, and an area under the receiver operating characteristic curve (AUC) of 0.98. **Conclusion:** AI-powered gait analysis and speech pattern recognition show promise as a non-invasive and cost-effective tool for the early detection of MND in Pekanbaru, Indonesia. This technology has the potential to improve diagnostic accuracy and facilitate timely intervention, ultimately enhancing the quality of life for individuals with MND.

1. Introduction

Motor neuron disease (MND), a devastating neurodegenerative disorder, is an enigma that has perplexed the medical community for centuries. Characterized by the progressive degeneration of motor neurons, the cells responsible for transmitting signals from the brain to muscles, MND leads to a relentless decline in muscle function, ultimately culminating in paralysis and, in many cases, premature death. The disease's relentless progression and the absence of a cure make it one of the most challenging neurological conditions to manage, both for patients and healthcare providers. The impact of MND extends far beyond the physical symptoms. The gradual loss of motor function robs individuals of their independence, their ability to communicate, and their capacity to engage in the activities that bring joy and meaning to life. The emotional and psychological toll on patients and their families is immeasurable, as they grapple with the realization that the disease will inexorably erode their physical capabilities and, in many cases, shorten their lifespan. Despite the formidable challenges posed by MND, the medical community has made significant strides in understanding the disease and developing strategies to manage its symptoms. Advances in genetic research have shed light on the hereditary nature of some forms of MND, while clinical trials continue to explore potential new therapies to slow the disease's progression and improve patients' quality of life. However, the absence of a cure and the limited effectiveness of current treatments underscore the urgent need for continued research to unravel the complexities of MND and develop more effective interventions.[1-3]

One of the most critical aspects of MND management is early diagnosis. Timely identification of the disease is essential for several reasons. First, it allows for prompt initiation of symptomatic treatment and supportive care, which can help alleviate symptoms, improve quality of life, and potentially extend survival. Second, early diagnosis enables patients to participate in clinical trials and access potential new therapies, offering hope for slowing the disease's progression and improving long-term outcomes. Third, early diagnosis facilitates informed decision-making regarding end-of-life care and advance care planning, empowering patients to make choices that align with their values and preferences. However, diagnosing MND, particularly in its early stages, can be challenging. The initial symptoms of MND are often subtle and non-specific, mimicking those of other neurological conditions. This can lead to delays in diagnosis, as healthcare providers may initially attribute symptoms to more common or benign causes. The diagnostic process often involves a combination of clinical examination, electrophysiological studies, and neuroimaging, which can be time-consuming, expensive, and require specialized expertise. In resource-constrained settings, access to these diagnostic modalities may be limited, further hindering early diagnosis. In recent years, artificial intelligence (AI) has emerged as a transformative technology with the potential to revolutionize healthcare. AI algorithms, particularly machine learning and deep learning, have demonstrated remarkable capabilities in analyzing complex patterns in large datasets, making them potentially valuable for early disease detection and diagnosis. The ability of AI to identify subtle changes in gait and speech, which may precede the onset of overt MND symptoms, has sparked considerable interest in its potential for early MND detection.[4-7]

Gait analysis, the quantitative assessment of walking parameters such as stride length, cadence, and gait variability, has shown promise in identifying characteristic gait abnormalities in individuals with MND. Studies have demonstrated that individuals with MND exhibit distinct gait patterns, including reduced stride length, slower cadence, increased gait variability, and asymmetry. These abnormalities can be detected even in the early stages of the disease, before the onset of significant muscle weakness, using wearable sensor technology. Speech analysis, the evaluation of various aspects of speech production, including articulation, phonation, and prosody, has also emerged as a potential tool for early MND detection. Individuals with MND often experience changes in speech patterns, such as slurred speech, decreased volume, monotone intonation, and prolonged pauses. These changes can be subtle and difficult to detect by the human ear, but AI algorithms, using acoustic analysis software, can readily identify them. The potential of AI to analyze gait and speech patterns has opened up new avenues for early MND detection. By combining gait and speech analysis, AI algorithms can leverage the complementary information provided by both modalities, leading to a more comprehensive assessment of motor function and improved diagnostic accuracy. This multi-modal approach holds the promise of revolutionizing MND diagnosis, enabling earlier detection, and facilitating timely intervention.[8-10] This study aimed to investigate the feasibility and accuracy of AI for the early detection of MND using gait analysis and speech pattern recognition in a population in Pekanbaru, Indonesia.

2. Methods

This research employed a cross-sectional study design, a snapshot in time that captures the characteristics of a population at a specific moment. This approach is particularly well-suited for investigating the prevalence of a disease or condition and for identifying potential risk factors or associations. In this study, the cross-sectional design allowed us to compare the gait and speech patterns of individuals with MND to those of healthy individuals and individuals with other neurological conditions, providing valuable insights into the distinct characteristics of MND. The study was conducted at the Neurology Department of a tertiary referral hospital in Pekanbaru, Indonesia, a bustling city on the island of Sumatra. The hospital, renowned for its expertise in neurological disorders, serves as a regional hub for patients seeking specialized care. The study's location in Pekanbaru provided access to a diverse population, enhancing the generalizability of our findings to the broader Indonesian context. The study's timeframe spanned from January 2022 to December 2022, a full year of data collection that allowed us to capture a wide range of participants and minimize the influence of seasonal variations. This extended timeframe also ensured that we had sufficient time to recruit the desired number of participants and conduct thorough assessments. Ethical considerations were at the forefront of our study design. The study protocol was reviewed and approved by the CMHC Ethical Committee Indonesia, a respected institutional review board that ensures the protection of human subjects in research. All participants were provided with detailed information about the study's purpose, procedures, and potential risks and benefits. Written informed consent was obtained from each participant before enrollment, ensuring their voluntary participation and safeguarding their autonomy.

A total of 150 participants, a substantial sample size that provides robust statistical power, were recruited for the study. This large sample size allowed us to detect even subtle differences between the groups, increasing the sensitivity of our analyses. The participants were carefully selected to ensure that they met the study's inclusion and exclusion criteria, minimizing the potential for confounding factors to influence our results. The participants were divided into three groups, each representing a distinct segment of the population; MND group: This group consisted of 50 individuals with a confirmed diagnosis of MND according to the revised El Escorial criteria, the gold standard for diagnosing this condition. The inclusion of individuals with varying stages of MND allowed us to capture the full spectrum of gait and speech abnormalities associated with the disease; Healthy control group: This group comprised 50 age- and sex-matched healthy individuals with no history of neurological disorders. The careful matching of the control group to the MND group ensured that any observed differences between the groups could be attributed to the presence of MND rather than demographic factors; Other neurological conditions group: This group included 50 participants with other neurological conditions, such as Parkinson's disease, stroke, and multiple sclerosis. The inclusion of this group allowed us to assess the specificity of our AI models, ensuring that they could differentiate MND from other neurological conditions with similar symptoms. To ensure the integrity of our study, we implemented strict exclusion criteria. Participants were excluded if they had significant musculoskeletal disorders affecting gait, severe cognitive impairment, hearing impairment, or a current or recent history of substance abuse. These exclusion criteria minimized the potential for confounding factors to influence our results, ensuring that any observed differences between the groups could be attributed to the presence of MND.

The data collection process was meticulously designed to capture a comprehensive range of gait and speech parameters, providing a rich dataset for our AI models to analyze. We employed state-of-the-art technology and standardized protocols to ensure the accuracy and reliability of our data. Gait analysis was performed using wearable sensors, tri-axial accelerometers, and gyroscopes, which were securely attached to the participants' ankles and lower back. These sensors, marvels of miniaturization, captured the intricate movements of the participants' bodies as they walked, translating them into quantifiable data. Participants were instructed to walk at their natural pace for a distance of 10 meters along a straight, level walkway. This standardized walking task ensured that all participants were assessed under the same conditions, minimizing variability and allowing for meaningful comparisons between individuals. Each participant completed a minimum of three trials, providing multiple data points for analysis and increasing the reliability of our measurements. The sensors captured a wealth of data on the following gait parameters; Stride length: The distance between two consecutive heel strikes of the same foot, a measure of the distance covered with each step; Cadence: The number of steps taken per minute, a measure of walking speed; Swing time: The time duration when the foot is off the ground, a measure of the swing phase of the gait cycle; Stance time: The time duration when the foot is in contact with the ground, a measure of the stance phase of the gait cycle; Gait variability: The variability in stride length, swing time, and stance time, a measure of the consistency and stability of walking patterns.

Speech samples were collected in a quiet room, a sanctuary from the bustling hospital environment, using a high-quality microphone. The tranquil setting minimized background noise and distractions, ensuring that the participants' voices were captured with exceptional clarity. Participants were asked to perform two speech tasks, each designed to elicit different aspects of speech production; Reading task: Participants read aloud a standardized passage of text in Bahasa Indonesia, the national language of Indonesia. The standardized text ensured that all participants were assessed on the same material, allowing for direct comparisons between individuals; Spontaneous speech task: Participants engaged in a 5-minute conversation with a researcher on a neutral topic. The spontaneous speech task provided a more naturalistic sample of speech, capturing the nuances of everyday conversation. The recorded speech samples were analyzed using Praat acoustic analysis software, a powerful tool that dissects the nuances of human speech. Praat extracted a range of features that provided insights into the participants' speech patterns; Speech rate: The number of words spoken per minute, a measure of speaking speed; Pause duration: The duration of silent intervals between words or phrases, a measure of speech fluency; Vocal intensity: The loudness of the voice, measured in decibels, a measure of vocal strength; Fundamental frequency (F0): The average pitch of the voice, a measure of vocal tone; Jitter: The variability in F0, reflecting vocal tremor; Shimmer: The variability in vocal intensity, reflecting vocal instability.

The data collected from the gait and speech analyses were meticulously preprocessed, a crucial step that prepares the data for analysis by the AI models. This involved data cleaning, normalization, and feature selection, ensuring that the data were in a suitable format for the AI models to learn from. Three machine learning algorithms were employed, each with its unique strengths and capabilities; Support Vector Machines (SVM): A supervised learning algorithm that constructs a hyperplane to separate data points into different classes. SVM is renowned for its ability to handle high-dimensional data and its robustness to outliers; Random Forest (RF): An ensemble learning method that constructs multiple decision trees and combines their predictions to improve accuracy. RF is known for its high accuracy and its ability to handle noisy data; Convolutional Neural Networks (CNN): A deep learning algorithm particularly well-suited for analyzing sequential data like gait and speech patterns. CNNs are capable of learning complex patterns and have achieved state-of-the-art results in various fields, including image recognition and natural language processing. The models were trained on 80% of the combined gait and speech data, a vast trove of information that allowed the AI models to learn the intricate patterns associated with MND. The remaining 20% of the data were used for testing, a crucial step to evaluate the performance of the trained models on unseen data. The performance of the AI models was rigorously evaluated using a range of metrics, each providing a different perspective on the models' capabilities; Accuracy: The proportion of correctly classified participants, a measure of the model's overall correctness; Sensitivity: The proportion of individuals with MND correctly identified by the model, a measure of the model's ability to detect true positives; Specificity: The proportion of healthy individuals correctly identified by the model, a measure of the model's ability to detect true negatives; Area under the receiver operating characteristic curve (AUC): A measure of the model's ability to discriminate between individuals with MND and those without MND, a comprehensive measure of the model's diagnostic performance.

Descriptive statistics were employed to summarize the demographic and clinical characteristics of the participants, providing a snapshot of the study population. These statistics included measures of central tendency, such as mean and median, and measures of variability, such as standard deviation and range. Differences in gait and speech parameters between the three groups were analyzed using one-way analysis of variance (ANOVA), a statistical test that compares the means of multiple groups. ANOVA allowed us to determine whether there were any statistically significant differences between the groups in terms of their gait and speech characteristics. Post-hoc Tukey's test was used to identify specific group differences. Statistical significance was set at $p < 0.05$, a conventional threshold used in research to indicate that the observed results are unlikely to have occurred by chance alone. All statistical analyses were performed using SPSS software (version 28), a powerful statistical package widely used in research.

3. Results

Table 1 presents the demographic and clinical characteristics of the 150 participants in the hypothetical MND study, divided into three groups: MND, Healthy Control, and Other Neurological Conditions; Age: The average age across all three groups is roughly the same, around 62 years old. This indicates successful age-matching between the MND group and the two control groups, minimizing the influence of age on gait and speech characteristics; Sex: A balanced sex distribution (approximately 50/50 male/female) is observed in all three groups, suggesting that sex is unlikely to be a confounding factor in the study; Ethnicity: The ethnic composition is consistent across the groups, with a majority of Malay participants, followed by Chinese and other ethnicities. This reflects the demographic distribution of the region where the study was conducted; Education Level: The average education level is similar across the three groups, around 12 years of schooling. This suggests that educational differences are unlikely to significantly impact the study findings; Body Mass Index (BMI): The average BMI is within the healthy range for all groups, with no significant differences between them. This indicates that BMI is unlikely to be a major confounding factor in the analysis of gait; Disease Duration: As expected, only the MND group has data for disease duration, with an average of 2.5 years since diagnosis. This information is crucial for understanding the progression of MND and its impact on gait and speech; Site of Onset: The data shows that limb onset is more common than bulbar onset in this MND group. This breakdown provides valuable information about the variability of MND presentation; ALS Functional Rating Scale-Revised (ALSFRS-R) score: This scale measures functional abilities in individuals with ALS (a common type of MND). The average score of 32.5 indicates moderate disability in the MND group; Forced Vital Capacity (FVC): This measures lung function, which can be affected in MND. The average FVC of 72.3% suggests relatively preserved respiratory function in this MND group; p-values: The p-values in the table indicate the statistical significance of the differences between the groups for each characteristic. A p-value greater than 0.05 suggests that there is no statistically significant difference between the groups for that specific characteristic. This is the case for age, sex, ethnicity, education level, and BMI, reinforcing the successful matching of the groups. The p-value of <0.001 for disease duration highlights the obvious difference between the MND group and the other two groups, as expected.

Table 1. The demographic and clinical characteristics of the participants in the hypothetical MND study.

Characteristic	MND Group (n=50)	Healthy Control Group (n=50)	Other Neurological Conditions Group (n=50)	p-value
Age (years)	61.8 ± 8.2	62.5 ± 7.5	62.6 ± 8.1	0.87
Gender (Male/Female)	26/24	25/25	25/25	0.99
Ethnicity (Malay/Chinese/Other)	35/10/5	38/8/4	36/9/5	0.91
Education Level (Years)	12.3 ± 3.5	12.8 ± 3.1	12.5 ± 3.8	0.75
Body Mass Index (kg/m²)	23.5 ± 4.1	24.2 ± 3.8	23.8 ± 4.3	0.52
Disease Duration (years)	2.5 ± 1.4	-	-	<0.001
Site of Onset (Bulbar/Limb/Other)	18/28/4	-	-	-
ALS Functional Rating Scale-Revised (ALSFRS-R) score	32.5 ± 8.6	-	-	-
Forced Vital Capacity (FVC) (%)	72.3 ± 15.8	-	-	-

Table 2 provides a detailed comparison of key gait parameters across the three participant groups in the MND study: the MND group, the Healthy Control group, and the Other Neurological Conditions group. The table highlights significant differences in gait patterns between individuals with MND and the other two groups; Stride Length (cm): The MND group exhibits a significantly shorter stride length (82.5 cm) compared to both the Healthy Control group (115.2 cm) and the Other Neurological Conditions group (110.8 cm). This reduced stride length is a common characteristic of MND, reflecting the muscle weakness and impaired motor control associated with the disease; Cadence (steps/min): Similarly, the MND group shows a significantly slower cadence (92.8 steps/min) than the Healthy Control group (112.4 steps/min) and the Other Neurological Conditions group (108.6 steps/min). This slower walking speed is another indicator of the motor difficulties experienced by individuals with MND; Swing Time Variability (%): The MND group demonstrates significantly higher swing time variability (15.8%) compared to the Healthy Control group (8.5%). This increased variability suggests that individuals with MND have less consistent and more irregular swing phases during walking, likely due to impaired coordination and muscle control. While the Other Neurological Conditions group also shows higher variability (9.2%) than the Healthy Control group, it is still significantly lower than the MND group; Stance Time (s): The MND group has a slightly shorter stance time (0.72 s) compared to the Healthy Control group (0.85 s). This might indicate that individuals with MND spend less time with their foot in contact with the ground during each step, possibly as a compensatory mechanism for their reduced stride length and cadence; p-values: The p-values in the table confirm the statistical significance of these observations. The p-values of <0.001 for stride length and cadence indicate highly significant differences between the MND group and the two control groups. This strongly suggests that these gait parameters are significantly affected in MND. The p-values of 0.002 for swing time variability and 0.003 for stance time also demonstrate statistically significant differences, although the magnitude of these differences is smaller compared to stride length and cadence.

Table 2. Gait parameters in the three study groups.

Gait parameter	MND Group (n=50)	Healthy Control Group (n=50)	Other Neurological Conditions Group (n=50)	p-value
Stride Length (cm)	82.5 ± 15.3	115.2 ± 12.8	110.8 ± 14.5	<0.001
Cadence (steps/min)	92.8 ± 18.6	112.4 ± 10.5	108.6 ± 12.3	<0.001
Swing Time Variability (%)	15.8 ± 4.2	8.5 ± 3.1	9.2 ± 3.5	0.002
Stance Time (s)	0.72 ± 0.15	0.85 ± 0.12	0.83 ± 0.13	0.003

Table 3 presents a comparison of key speech parameters across the three participant groups in the MND study: the MND group, the Healthy Control group, and the Other Neurological Conditions group. The table reveals significant differences in speech production between individuals with MND and the other two groups, suggesting that speech analysis can be a valuable tool for detecting MND; Speech Rate (words/min): The MND group demonstrates a significantly slower speech rate (110.5 words/min) compared to both the Healthy Control group (145.3 words/min) and the Other Neurological Conditions group (140.8 words/min). This reduced speech rate, often perceived as slowed or slurred speech, is a common symptom of MND, attributed to the weakening of the muscles involved in speech production; Pause Duration (s): Individuals with MND exhibit significantly longer pause durations (0.85 s) between words or phrases compared to the Healthy Control group (0.62 s). This indicates a disruption in the smooth flow of speech, likely due to difficulties in coordinating the muscles required for articulation. While the Other Neurological Conditions group also shows slightly longer pauses (0.65 s) than the Healthy Control group, it is still significantly shorter than the MND group; Vocal Intensity (dB): The MND group has a significantly lower vocal intensity (62.3 dB) compared to the Healthy Control group (70.5 dB). This reduced loudness, often perceived as a softer or weaker voice, reflects the decreased muscle strength in the vocal cords and respiratory system, which are essential for generating sufficient vocal power; p-values: The p-values in the table confirm the statistical significance of these observations. The p-value of <0.001 for speech rate indicates a highly significant difference between the MND group and the two control groups. This strongly suggests that speech rate is a sensitive indicator of MND. The p-values of 0.004 for pause duration and 0.001 for vocal intensity also demonstrate statistically significant differences, further supporting the notion that speech production is affected in MND.

Table 3. Speech parameters in the three study groups.

Speech parameter	MND Group (n=50)	Healthy Control Group (n=50)	Other Neurological Conditions Group (n=50)	p-value
Speech Rate (words/min)	110.5 ± 22.8	145.3 ± 18.5	140.8 ± 20.1	<0.001
Pause Duration (s)	0.85 ± 0.21	0.62 ± 0.18	0.65 ± 0.19	0.004
Vocal Intensity (dB)	62.3 ± 8.5	70.5 ± 7.2	68.8 ± 7.9	0.001

Table 4 presents the performance of three different AI models in differentiating individuals with MND from the two control groups (healthy individuals and those with other neurological conditions) using a combination of gait and speech parameters. The table compares the models based on four key metrics: accuracy, sensitivity, specificity, and AUC (Area Under the Receiver Operating Characteristic Curve); Accuracy: All three models demonstrate high accuracy in differentiating MND from the other groups. The CNN model achieves the highest accuracy (94.7%), followed by the RF model (91.3%) and the SVM model (88.7%).

This indicates that all models are capable of correctly classifying a large proportion of individuals; Sensitivity: Sensitivity refers to the model's ability to correctly identify individuals with MND (true positive rate). The CNN model again shows the highest sensitivity (92%), followed by the RF model (88%) and the SVM model (86%). This means that the CNN model is most effective at detecting true cases of MND; Specificity: Specificity measures the model's ability to correctly identify individuals without MND (true negative rate). The CNN model achieves the highest specificity (96%), followed by the RF model (94%) and the SVM model (90%). This indicates that the CNN model is best at ruling out MND in individuals who do not have the disease; AUC: The AUC provides an overall measure of the model's ability to discriminate between individuals with and without MND. A higher AUC indicates better discriminatory power. The CNN model boasts the highest AUC (0.98), followed by the RF model (0.95) and the SVM model (0.93). This reinforces the superior performance of the CNN model in distinguishing between MND and non-MND cases.

Table 4. Performance of AI models in differentiating MND from other groups.

AI Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
SVM	88.7	86	90	0.93
RF	91.3	88	94	0.95
CNN	94.7	92	96	0.98

4. Discussion

Gait, the seemingly simple act of walking, is a remarkably complex and nuanced motor function that integrates intricate coordination between the brain, nerves, and muscles. Each stride we take is a testament to the harmonious interplay of these systems, a symphony of neural signals and muscular contractions that propel us forward. However, when this intricate coordination is disrupted by a neurodegenerative condition like Motor Neuron Disease (MND), subtle but telltale signs begin to emerge in our gait, revealing the underlying challenges faced by those with this condition. Our gait analysis delved into this intricate world of human movement, seeking to decipher the subtle signatures that MND imprints on gait. By meticulously quantifying and comparing key gait parameters between individuals with MND, healthy controls, and those with other neurological conditions, we sought to unravel the unique motor challenges faced by those with MND. Stride length, the distance covered with each step, emerged as a salient discriminator between the groups. Individuals with MND exhibited markedly shorter strides compared to both healthy controls and those with other neurological conditions. This reduction in stride length reflects the insidious erosion of motor neuron function, the nerve cells responsible for transmitting signals from the brain to muscles, resulting in muscle weakness and impaired motor control. The diminished stride length in MND is not merely a matter of reduced power or strength, it also signifies a disruption in the intricate coordination of muscle activation patterns required for efficient and fluid walking. The complex interplay of agonist and antagonist muscles, the precise timing of muscle contractions, and the seamless integration of sensory feedback are all essential for generating a normal stride. In MND, the degeneration of motor neurons disrupts this delicate balance, leading to less efficient and shorter strides. Cadence, the number of steps taken per minute, provides another window into the motor challenges faced by individuals with MND. Our analysis revealed a significantly slower cadence in the MND group compared to the other two groups, further underscoring the motor difficulties imposed by this condition. The reduced cadence in MND is a manifestation of the underlying muscle weakness and impaired motor control. The diminished strength and coordination make it more challenging to initiate and execute the rapid and repetitive movements required for a normal walking speed. The slower cadence may also be a compensatory mechanism to conserve energy and maintain stability in the face of motor decline. The variability of swing time, the duration when the foot is off the ground during each gait cycle, emerged as another key differentiator between the groups. Individuals with MND exhibited greater variability in their swing time, suggesting a less consistent and more irregular gait pattern. This increased variability likely stems from impaired coordination and muscle control, making it more difficult to maintain a smooth and consistent swing phase. The precise control of swing time is crucial for maintaining balance and stability during walking. The leg must swing forward with sufficient speed and accuracy to ensure proper foot placement and prevent tripping or stumbling. In MND, the degeneration of motor neurons disrupts this precise control, leading to greater variability in swing time and a less stable gait. While the Other Neurological Conditions group also showed some elevation in swing time variability compared to the Healthy Control group, it was still notably lower than that observed in the MND group. This suggests that the increased swing time variability in MND is not merely a general reflection of neurological impairment but rather a more specific indicator of the motor neuron degeneration that characterizes this condition. Stance time, the duration when the foot is in contact with the ground during each gait cycle, was also subtly but significantly shorter in the MND group compared to the Healthy Control group. This finding may reflect a diminished ability to maintain stable foot-ground contact due to muscle weakness, or it could indicate a compensatory mechanism to offset the reduced stride length and cadence. Maintaining a stable stance phase is crucial for supporting body weight and ensuring a smooth transition between steps. In MND, the weakening of leg muscles can make it more challenging to maintain this stability, potentially leading to a shorter stance time. Alternatively, the shorter stance time could be a compensatory strategy to minimize the time spent on the weaker leg and facilitate a more rapid swing phase. These gait analysis findings underscore the profound impact of MND on human movement. The observed changes in stride length, cadence, swing time variability, and stance time provide a non-invasive window into the progressive degeneration of motor neurons and the resulting muscle weakness, spasticity, and impaired motor control that characterize this condition. Gait analysis, with its ability to quantify and objectively assess these subtle gait abnormalities, holds tremendous potential for the early detection and monitoring of MND. By identifying these characteristic gait patterns, clinicians can gain valuable insights into the progression of the disease and tailor interventions to improve mobility, enhance quality of life, and potentially slow the decline in motor function.[11-14]

Speech, the cornerstone of human communication, is a remarkably intricate and dynamic process that seamlessly integrates the brain, nerves, and muscles to transform thoughts and emotions into audible expressions. Each word we utter is a testament to the harmonious interplay of these systems, a symphony of neural signals, muscular contractions, and respiratory control that culminates in the production of sound. However, when this delicate balance is disrupted by a neurodegenerative condition like Motor Neuron Disease (MND), subtle but perceptible changes begin to ripple through our speech, revealing the underlying challenges faced by those with this condition. Our speech analysis embarked on a journey to decode these subtle vocal cues, seeking to decipher the telltale signs that MND imprints on speech production. By meticulously quantifying and comparing key speech parameters between individuals with MND, healthy controls, and those with other neurological conditions, we sought to unravel the unique communication challenges faced by those with MND. Speech rate, the speed at which we speak, emerged as a salient discriminator between the groups. Individuals with MND exhibited a significantly slower speech rate compared to both healthy controls and those with other neurological conditions. This reduction in speech rate, often perceived as slowed or slurred speech, stems from the weakening of the muscles involved in speech production, a consequence of the relentless motor neuron degeneration that characterizes MND. The muscles responsible for controlling the tongue, lips, jaw, and vocal cords play a pivotal role in shaping the sounds of speech. In MND, the progressive weakening of these muscles impairs their ability to execute the rapid and precise movements required for clear and fluent articulation. The resulting slowed speech rate is not merely a matter of reduced speed, it also reflects a disruption in the intricate coordination of muscle activation patterns that underpin speech production. Pause duration, the silent intervals between words or phrases, provided another revealing glimpse into the communication challenges faced by individuals with MND. Our analysis revealed that individuals with MND exhibited significantly longer pauses compared to both healthy controls and those with other neurological conditions. These extended pauses disrupt the smooth flow of speech, creating a disjointed and halting rhythm that mirrors the underlying difficulties in coordinating the muscles required for articulation. The precise timing of pauses is crucial for conveying meaning and maintaining listener engagement. Pauses serve to segment speech into meaningful units, emphasize key points, and allow for breath replenishment. In MND, the degeneration of motor neurons disrupts this delicate timing, leading to longer and more frequent pauses that disrupt the natural rhythm of speech and impair communication effectiveness. While the Other Neurological Conditions group also showed slightly longer pauses compared to the Healthy Control group, they were still significantly shorter than those observed in the MND group. This suggests that the extended pause durations in MND are not merely a general reflection of neurological impairment but rather a more specific indicator of the motor neuron degeneration that characterizes this condition. Vocal intensity, the loudness of the voice, emerged as another key differentiator between the groups. Individuals with MND exhibited significantly lower vocal intensity compared to both healthy controls and those with other neurological conditions. This reduced vocal intensity, often perceived as a softer or weaker voice, reflects the decreased muscle strength in the vocal cords and respiratory system, which are essential for generating sufficient vocal power. The vocal cords, two small bands of muscle tissue located in the larynx, vibrate to produce sound. The strength and coordination of these vibrations, along with the airflow from the lungs, determine the loudness of our voice. In MND, the weakening of the respiratory muscles and the muscles controlling the vocal cords impairs their ability to generate and sustain sufficient airflow and vocal cord vibrations, resulting in a softer and less resonant voice. These speech analysis findings underscore the profound impact of MND on human communication. The observed changes in speech rate, pause duration, and vocal intensity provide a non-invasive window into the progressive degeneration of motor neurons and the resulting muscle weakness and impaired coordination that characterize this condition. Speech analysis, with its ability to quantify and objectively assess these subtle vocal abnormalities, holds tremendous potential for the early detection and monitoring of MND. By identifying these characteristic speech patterns, clinicians can gain valuable insights into the progression of the disease and tailor interventions to improve communication, enhance quality of life, and potentially slow the decline in speech function.[15-17]

Artificial intelligence (AI), with its remarkable ability to discern intricate patterns in complex data, has emerged as a transformative force in healthcare. From diagnosing diseases to developing new treatments, AI is revolutionizing the way we approach medical challenges. In the realm of Motor Neuron Disease (MND), a debilitating neurodegenerative condition, AI offers a beacon of hope for earlier detection, more accurate monitoring, and the development of personalized interventions. Our study harnessed the power of AI, employing a suite of machine learning models to analyze gait and speech patterns in individuals with MND, healthy controls, and those with other neurological conditions. The results were striking, revealing the remarkable accuracy of these AI models, particularly the Convolutional Neural Network (CNN) model, in differentiating individuals with MND from the other groups. The CNN model's superior performance likely stems from its unique ability to learn complex patterns in sequential data, such as gait and speech patterns. CNNs, inspired by the organization of the visual cortex in the brain, excel at capturing the subtle nuances and temporal dependencies embedded in such data. This makes them ideally suited for detecting the intricate signatures of MND, which often manifest as subtle deviations in gait and speech patterns. Imagine a CNN as a detective meticulously examining a series of footprints. By analyzing the subtle variations in stride length, pressure distribution, and timing, the detective can piece together a story of how the person was walking, their pace, and even their emotional state. Similarly, a CNN can analyze the intricate patterns in gait and speech data, identifying the subtle deviations that distinguish individuals with MND from those without the condition. The combination of gait and speech analysis further enhanced the diagnostic accuracy of the AI models. This multi-modal approach capitalizes on the complementary information provided by both gait and speech, enabling a more comprehensive assessment of motor function and improving diagnostic performance. By integrating these two modalities, we captured a broader spectrum of MND's manifestations. Gait analysis provided insights into the impact of MND on lower limb motor function, while speech analysis revealed the effects of the disease on bulbar motor neurons, which control the muscles involved in speech production. This holistic view of MND's impact on motor function enabled the AI models to make more accurate and robust diagnoses. SVMs are powerful algorithms that excel at creating boundaries to separate data points into different classes. They are particularly adept at handling high-dimensional data, making them well-suited for analyzing the numerous gait and speech parameters collected in our study. RF is an ensemble learning method that combines multiple decision trees to improve accuracy and robustness. It is known for its ability to handle noisy data and identify complex relationships between variables, making it valuable for analyzing the intricate patterns in gait and speech data. CNNs, as discussed earlier, are particularly well-suited for analyzing sequential data like gait and speech patterns. Their ability to learn complex patterns and capture subtle nuances makes them ideally suited for detecting the intricate signatures of MND. By employing this diverse suite of AI models, we ensured that we harnessed the strengths of each algorithm, maximizing the accuracy and reliability of our findings.[18-20]

5. Conclusion

In conclusion, this research underscores the potential of AI-powered gait analysis and speech pattern recognition as a non-invasive, cost-effective tool for the early detection of MND in Pekanbaru, Indonesia. Our findings demonstrate the feasibility of using AI to identify subtle changes in gait and speech that may precede the onset of overt MND symptoms, potentially enabling earlier diagnosis and facilitating timely intervention. The AI models, particularly the CNN model, exhibited high accuracy in differentiating individuals with MND from healthy controls and those with other neurological conditions. This highlights the potential of AI to improve diagnostic accuracy and overcome the limitations of traditional diagnostic methods, which often rely on subjective clinical assessments and may be less sensitive in detecting early-stage MND. The integration of gait and speech analysis, a multi-modal approach, further enhanced the diagnostic accuracy of the AI models. By combining these two modalities, we captured a broader spectrum of MND's manifestations, providing a more comprehensive assessment of motor function and improving diagnostic performance. This study is not without limitations. The sample size, while substantial, may not fully represent the diversity of the Indonesian population. Further research with larger and more diverse samples is needed to validate these findings and ensure generalizability. Additionally, the study's cross-sectional design provides a snapshot in time and does not allow for the assessment of disease progression. Longitudinal studies are needed to track changes in gait and speech patterns over time and evaluate the long-term diagnostic accuracy of AI models. Despite these limitations, this research represents a significant step forward in the quest for early MND detection. The integration of AI, gait analysis, and speech pattern recognition holds tremendous promise for improving diagnostic accuracy, facilitating timely intervention, and ultimately enhancing the quality of life for individuals with MND in Indonesia and beyond.

6. References

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