

Automation Detection Of Stuttering Using MFCC In Conjunction With CSO

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Abstract: Over 79.5 million people throughout the world suffer with stuttering, which is typified by prolongations, quiet pauses, and repeating noises. It stems from a neurological mismatch between speech intention and production, with idiopathic cases being common. This paper discusses the connection between stuttering and mental health issues, particularly social isolation, which is worsened by anxiety but not directly caused by it. Diagnosis involves speech-language pathologists assessing disfluencies through specific tests. Treatment aims to minimize the impact of stuttering using techniques like stuttering modification and fluency shaping therapies. The paper also explores enhancing stuttering detection using Mel-Frequency Cepstral Coefficients (MFCC) coupled with Cuckoo Search Optimization (CSO), emphasizing the methodology to improve diagnosis accuracy. The paper is about research gaps that exist in effective detection, diverse datasets, and the investigation of multimodal aspects to enhance detection systems, even with high accuracy metrics.

Keywords: Cuckoo Search Optimization (CSO), Mel-Frequency Cepstral Coefficients (MFCC), Stuttering Detection etc.

1. Introduction

Over 80 million people globally experience stuttering, a speech disorder more common in men, characterized by silent pauses, sound prolongations, and involuntary repetitions [1]. It arises from a neurological disconnect between the intent to speak and actual speech, not due to physical vocal cord issues [2]. Most cases are idiopathic, beginning in childhood and potentially leading to long-term mental health challenges, including social isolation and suicidal thoughts [3]. While acute anxiety and stress do not cause stuttering, they can exacerbate it; thus, stuttering is primarily a neurobiological condition influenced by anxiety. Stigma surrounding stuttering contributes to increased psychological strain, although there's no evidence linking stress directly to a predisposition to stuttering [4].

Stuttering is indicated by observable speech disfluencies, which can vary in strength depending on the context and include sound repeats, prolongations, and blocks. Stuttering can cause a great deal of anxiety in people, which commonly leads to stiff muscles or avoidance techniques [5-6]. Emotional consequences include negative feelings like embarrassment or shame. These feelings could be made worse by discrimination, which could result in social anxiety and a drop in self-esteem [8]. Stuttering can co-occur with dyslexia and Attention-Deficit/Hyperactivity Disorder (ADHD), suggesting a complex interplay between neurological and hereditary factors. Stuttering is understood through various theories, such as the "capacities and demands model," and differences in auditory processing, alongside research linking certain genes to the disorder. It encompasses more than just its visible symptoms [7].

Stuttering is a difficult speech problem that requires a diagnosis from a trained speech-language pathologist (SLP). A comprehensive case history must be obtained, and speech habits, including the types, frequency, and severity of disfluencies, must be examined in order to make a diagnosis [9]. Assessments may employ a range of tests, such as the Disfluency Type Index and Riley's Stuttering Severity Instrument. Additionally, to evaluate the potential social, psychological, or emotional impacts of stuttering, SLPs

employ tests for anxiety, attitudes, and quality of life[10]. Clinical psychologists can also diagnose stuttering using Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) codes, which categorize developmental and adult-onset fluency disorders, albeit it is unclear why the language was changed from Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV). This thorough evaluation aims to determine the presence and severity of stuttering in order to guide future treatment decisions [11].

Although there is no known cure for stuttering, there are customized treatment options available, such as stuttering modification therapy, which attempts to lessen stuttering rather than completely eradicate it, and fluency shaping therapy, which is not considered best practice because of the possible risks [12]. Joyful communication and self-acceptance are the main goals of avoidance reduction therapy for stuttering. Although they are not U.S. Food and Drug Administration (FDA)-approved, electronic fluency devices and certain drugs, such as dopamine antagonists, exhibit promise. The prognosis varies and self-help group support is essential. In early childhood, spontaneous recovery rates are high, but they drastically decline with later onset and longer duration of stuttering [13].

Table-1: Literature Survey

S. No	Title	Year & Author	Summary
1	Audio-Visual Speech Dysfluency Detection Using Deep Multimodal Fusion	2023, Zhang et al., IEEE Access	Proposes Convolutional Neural Network (CNN)-based feature extraction from audio and facial video streams with early and late fusion strategies. Demonstrates improved dysfluency detection compared to audio-only systems.
2	Multimodal Learning for Speech Disorder Assessment Using Facial and Acoustic Features	Raghavendra et al., IEEE Transactions on Affective Computing, 2023.	Integrates facial landmark dynamics with acoustic features to assess speech disorders, highlighting the diagnostic importance of visual tension and articulation behavior.
3	Transformer- Based Audio- Visual Modeling for Speech Fluency Analysis	2024, Li et al., IEEE ICASSP	Introduces cross-modal transformer attention to jointly model temporal audio and visual speech dynamics. Achieves improved fluency classification under moderate acoustic noise.
4	A Multimodal Dataset and Benchmark for Speech Dysfluency Detection	Kourkounakis et al., IEEE Access, 2024.	Presents a synchronized audio-video dysfluency dataset with baseline multimodal models and standardized evaluation protocols.
5	Distance- Based and Lightweight Models	Elgalaly et al, 2024	Explores k-Nearest Neighbors (KNN)-based classifiers with Principal Component Analysis or Linear Discriminant Analysis (PCA/LDA) and distance metrics for stuttering classification. Effective on small datasets but limited by noise sensitivity and lack of temporal modeling.

6	Attention- Based Neural Models	Miyahara et al, 2025	Applies self-attention mechanisms to capture long- range temporal dependencies in dysfluent speech. Outperforms Convolutional Neural Networks and Recurrent Neural Networks (CNN-RNN) models but requires large datasets and consistent annotations.
7	T5-based NLP models, and TDNNs	Shaikh et al., 2025	Integrates acoustic and linguistic representations using Whisper, Text-to-Text Transfer Transformer (T5)-based Natural Language Processing (NLP) models, and Time-Delay Neural Network (TDNNs). Enhances robustness and accuracy at the cost of higher architectural and computational complexity.
8	Data Augmentation and Speech Disfluency Manipulation	Bouslah et al., 2025	Uses synthetic disfluency generation and removal to address dataset scarcity. Improves model generalization but risks introducing unnatural or biased speech patterns.

2.Related Work: The present Cuckoo Search Optimization (CSO) stuttering detection algorithm has demonstrated encouraging outcomes, with high sensitivity, specificity, and accuracy. However, there may be places for development and Research Gaps:

- Current system may be limited in its dataset size, potentially failing to encompass the full variety of stuttering patterns.
- Other optimization algorithms, such as particle swarm optimization and genetic algorithms, could potentially enhance the system's performance beyond what has been achieved with CSO.
- Current systems may lack design for real-time stuttering detection, crucial for practical applications.

2.1. Research Opportunities:

- Incorporating multimodal features like audio, video, and physiological signals can enhance the accuracy of stuttering detection.
- The performance of stuttering detection is being improved by Mel Frequency Cepstral Coefficients (MFCC).
- To utilize the treatment programs for stuttering are tailored to each patient's unique needs and traits.
- To improve stuttering detection systems, cross-linguistic analysis looks into stuttering patterns in different languages and cultures.

The development of a real-time stuttering detection system that provides users with instant feedback, the collection of a sizable dataset of stuttering samples to improve system robustness, and the comparison of the CSO algorithm's performance with other optimization algorithms to identify the most efficient approach. Researchers can further enhance the functionality and performance of stuttering detection systems by filling up these research gaps and investigating novel ideas.

3.1. Mel Frequency Cepstral Coefficients (MFCC): A speech condition known as stuttering is characterized by repetitions, prolonged sounds, and involuntary pauses (blocks) in speech. Repetitions may manifest as "I-I-I" or "b-b-ball," while prolongations

extend sounds (e.g., "Sssssssaturday"), and blocks involve tense pauses with no sound. Automatic stuttering identification in speech signal processing enables scalable evaluation using Mel-Frequency Cepstral Coefficients (MFCCs), which are utilized as low-level acoustic features for detecting disfluencies. The MFCC-based approach captures significant spectrum characteristics to detect dysfluencies, employing rule-based systems or machine learning models to extract acoustic features such as pitch and energy contours from audio signals, thereby classifying repetitions, prolongations, and blocks [14-15].

The outlines methods in speech processing, focusing on speech acquisition and preprocessing through noise removal and normalization [16-17]. It discusses frame-based short-time signal analysis and the extraction of MFCC features from speech frames. Additionally, it highlights temporal modeling utilizing machine learning or deep learning classifiers, as well as the classification of fluent and stuttered speech segments [18]. The process generally follows several stages:

1. Input: Audio input refers to the raw speech signal captured from a microphone. Sound repetition involves the repetition of MFCC vectors, while syllable repetition is characterized by periodic MFCC patterns. Prolongation is represented by stable MFCCs over extended frames, and blocks consist of a sudden silence accompanied by a spectral jump.

2. Pre-Processing: Audio processing involves several key techniques: Framing & Windowing divides signals into short, overlapping frames (e.g., 15-20 ms) and employs functions like Hamming to reduce spectral leakage. Pre-emphasis enhances the magnitude of high-frequency components in a signal relative to lower frequencies. Voice Activity Detection (VAD) identifies segments containing speech versus silence or noise by analyzing the actual speech input captured from devices like microphones.

3. Feature Extraction: Feature extraction involves identifying relevant acoustic features from speech frames that characterize speech disfluencies. Key methods include Mel-Frequency Cepstral Coefficients (MFCCs) that capture the short-term power spectrum reflecting human voice characteristics, and Linear Predictive Coding (LPC/LPC-C) which provides additional features commonly used. Additionally, Pitch/Fundamental Frequency (F0) identifies variations, prolongations, or pitch breaks in speech.

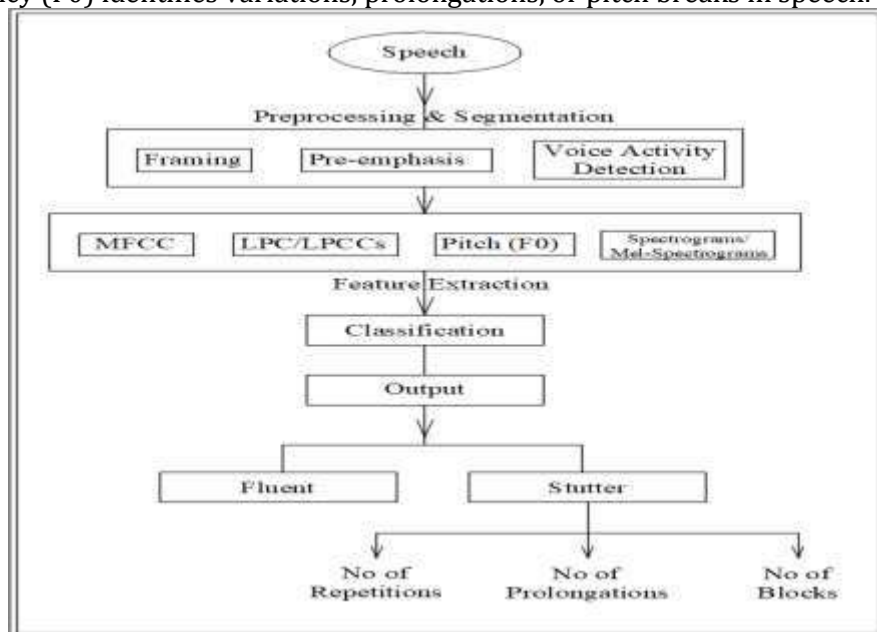


Figure-1: Automatic Stuttering Detection Block Diagram

4. Classification: Classification in machine learning and deep learning models involves categorizing features. Machine learning techniques. Deep learning methods. These approaches are prevalent in sequence modeling and identifying patterns such as repetitions, prolongations, and blocks.

5. Output: The system outputs a classification (stuttered vs. fluent) or identifies specific disfluency types (e.g., prolongation, block, repetition).

3.2. Stuttering detection using Mel-Frequency Cepstral Coefficients (MFCC): It can involve a standard speech-processing method where MFCCs serve as low-level acoustic features to identify disfluencies such as repetitions, prolongations, and blocks. MFCCs are effective due to their ability to capture the spectral envelope of speech, temporal instability from disfluencies, and variations in phonation and articulation. Stuttering events typically exhibit abnormal spectral continuity, repeated MFCC frame patterns, and extended stationary segments indicative of prolongations [19].

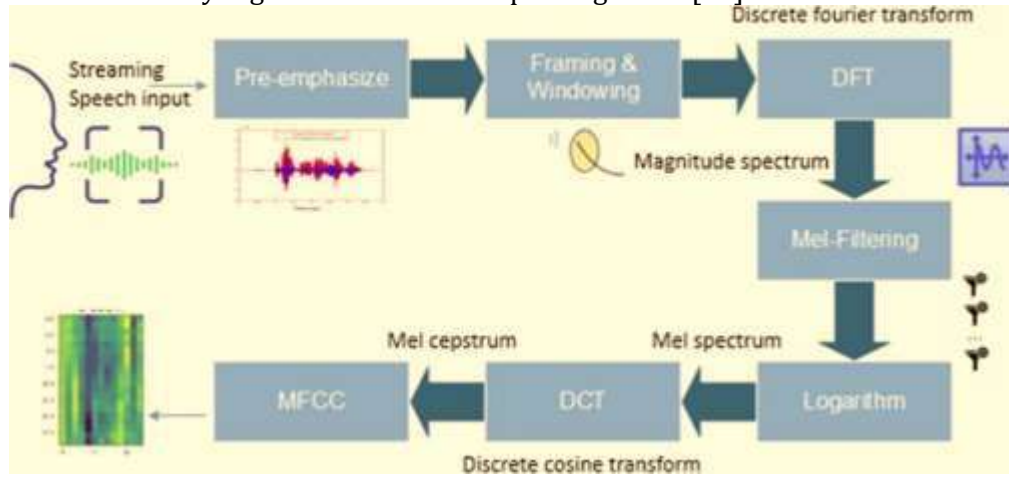


Figure-2: Process Stages of Stuttering Detection

1. Pre-emphasis: Since human voice usually has less energy at higher frequencies, this layer increases high-frequency components to balance the spectrum.

$$y(n) = x(n) - \alpha \cdot x(n-1) \quad (1)$$

where α is the pre-emphasis coefficient, typically between 0.9 and 1.0.

2. Framing: To make the continuous audio signal stationary, it is split into short, stable overlapping frames (usually 20–40 ms). Frame Length (N): 256 or 512 samples are typical. Frame Stride (M): Usually overlaps between 100 and 160 samples.

3. Windowing: To lessen spectral leakage at the boundaries, a Hanning or Hamming window is applied to every frame.

$$\text{Hamming Window: } w(n) = 0.54 - 0.46 \cdot \cos\left(\frac{2\pi n}{N-1}\right) \quad (2)$$

(2)

where n =Sample index within the frame, N = Length of the frame.

4. Processing of Mel Filter Banks: A bank of triangle filters is used to map the power spectrum onto the Mel scale. The non-linear human ear's sensitivity to frequencies is roughly represented by this scale.

$$\text{Frequency to Mel Convention: } M(f) = 2595 \cdot \log_{10} \left(1 + \frac{f}{700} \right) \quad (3)$$

Filter Bank Application: $S(m) = \sum_{k=0}^{N-1} P(k) \cdot H_m(k)$ (4)
 where $H_m(k)$ is the weight of the m^{th} triangular filter at frequency k .

5. Logarithm: In order to simulate how loudness is perceived by humans, the logarithm of the Mel filter bank energies transforms the multiplicative relationships of sound into additive ones.

$$L(m) = \ln(S(m)) \quad (5)$$

6. The DCT, or Discrete Cosine Transform: In order to simulate how loudness is perceived by humans, the logarithm of the Mel filter bank energies transforms the multiplicative relationships of sound into additive ones.

$$C(n) = \sum_{m=1}^M L(m) \cos\left(\frac{\pi n(m-0.5)}{M}\right) \quad (6)$$

where $C(n)$ is the n^{th} MFCC and M is the number of filters.

7. Optional Delta and Delta-Delta: The first-order (delta) and second-order (delta-delta) derivatives are frequently computed to represent temporal dynamics, or trajectories over time.

$$\text{Delta } d_t = \frac{\sum_{n=1}^N n(C_{t+n} - C_{t-n})}{2 \sum_{n=1}^N n^2} \quad (7)$$

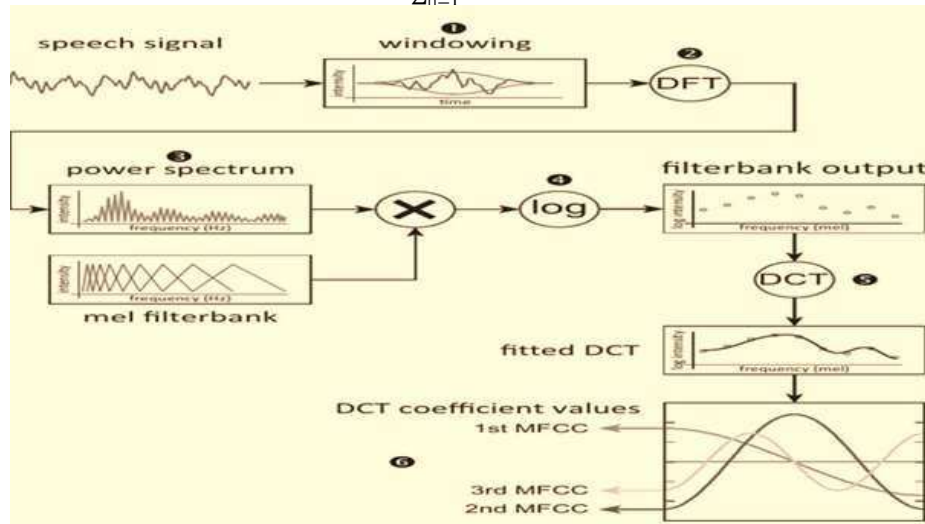


Figure-3: MFCC Block Diagram

Different Waveforms Showing the Scale, Spectrogram Uses Linear Spaced Frequency Scale and MFCC Uses a Quasi-Logarithmic Spaced Frequency Scale shown in Figure-5.

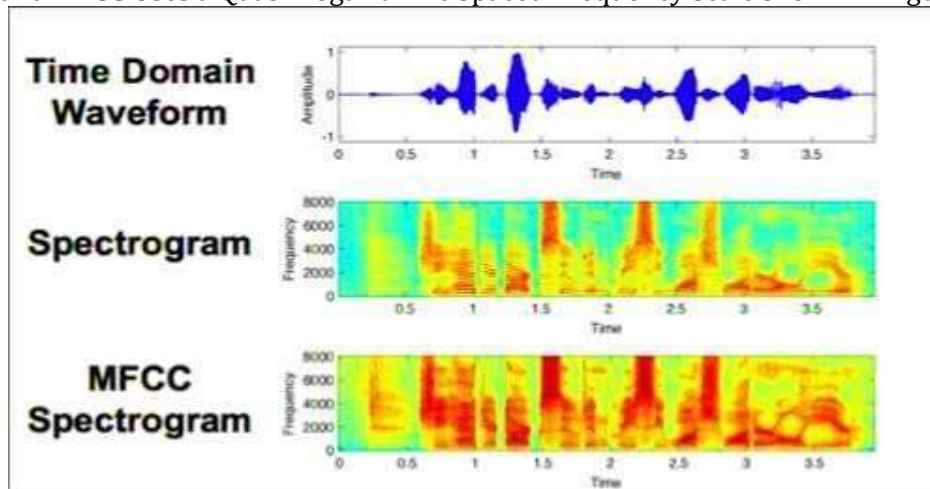


Figure-4: Diverse Waveforms Showing the Scale, Spectrogram

Mel-frequency cepstral coefficients (MFCC) effectively model human auditory perception via the Mel frequency scale. They provide compact features that minimize data size while maintaining speech characteristics. MFCCs are extensively validated in speech recognition and disorder detection, and their computational efficiency supports real-time stuttering application.

Disadvantages of MFCC include sensitivity to background noise and channel variations, loss of temporal information from its emphasis on short-term spectral features, reliance on careful parameter selection, and insufficient robustness for highly emotional or pathological speech without additional features [21].

MFCC has limitations including the assumption of stationary speech signals over short frames, which does not suit disfluent speech like stuttering. It captures prosodic features inadequately and is not effective for cross-language or cross-speaker variability without normalization. To improve accuracy, MFCC must often be combined with other features such as Δ -MFCC or deep features.

4. Stuttering Detection Using Cuckoo Search Optimization: Cuckoo Search Optimization (CSO) is a metaheuristic algorithm inspired by cuckoo birds' brood parasitism, introduced in 2009 by Yang and Deb. Important elements of the method include nests (search space), eggs (solution quality), cuckoos (possible solutions), and Le'vy flights (random walks for exploration). Initializing nests, assessing their quality, creating new solutions through Le'vy flights, replacing subpar solutions, and iterating continuously until termination requirements are satisfied are how CSO works. Its ability to optimize globally, adaptability to different issues, and resilience in noisy conditions are some of its main benefits. CSO is used in engineering problems, optimization activities, and machine learning model tuning. Multi-objective CSO for conflicts between several objectives and Binary CSO for discrete problems are examples of variations [20]. **The CSO algorithm updates the cuckoos' locations using the following mathematical formulas:**

$$1. \text{levy Flight: } x^{(t+1)} = x^t + \alpha \cdot \text{Levy}(\beta) \quad (8)$$

where x^t is the current position, α is the step size, and $\text{Levy}(\beta)$ is a random step drawn from a Levy distribution.

$$2. \text{Le'vy Distribution: } \text{Levy}(\beta) = \frac{u}{|v|^{\frac{1}{\beta}}} \quad (9)$$

where u and v are normally distributed random variables, and β is the Levy index.

$$3. \text{New Solution Generation: } x^{(t+1)} = x^t + \alpha \cdot \text{Levy}(\beta) \cdot (x^t - x_{\text{best}}^t) \quad (10)$$

where x_{best}^t is the best solution found so far.

$$4. \text{Discovery Probability: } P_{\text{augmentation}} = (1 - (t/T_{\text{max}})^2) \cdot p_a \quad (11)$$

where p_a is the discovery probability, t is the current iteration, and T_{max} is the maximum number of iterations.

Pseudocode for CSO:

1. Start the nest populations
2. Assess each nest's fitness.
3. While the requirements for termination were not fulfilled
 1. Make use of the levy flights to generate new solutions.
 2. Assess the suitability of the novel solutions.
 3. Find and swap out subpar solutions
 4. Update the optimal solution.
4. Give back the best response.

To detect stuttering in speech, this approach combines Mel Frequency Cepstral Coefficients (MFCC) for feature extraction with Cuckoo Search Optimization for classification. MFCC extracts acoustic features from speech signals, while Cuckoo Search Optimization enhances feature selection and classification, leading to improved accuracy in detecting stuttering trials.

5. Experimental Result: The stuttering, a speech disorder marked by disruptions in flow, including repetitions and silent blocks, commonly beginning in childhood and more frequent in boys. Symptoms include involuntary repetitions and silent pauses, with possible physical struggle behaviors. Causes are linked to genetics, neurobiological factors affecting speech, and stress. Management involves speech therapy, parent-assisted programs, support groups, and techniques to reduce anxiety. Analyzing stuttering detection results using CSO involves a dataset consisting of speech samples classified as stuttering or non-stuttering, with features such as MFCC, pitch, and energy. The CSO-optimized model employs classifiers, with optimized parameters including features, C, and gamma, evaluated using metrics such as accuracy and F1-score.

The following is the experimental outcome of the Cuckoo Search Optimization (CSO)-based stuttering detection system: Stuttering is a speech disorder marked by interruptions in speech flow, including repetitions of sounds or syllables, elongations, and silent pauses. Performance metrics are shown in Table-1 and Graph-1.

CSO Parameters:

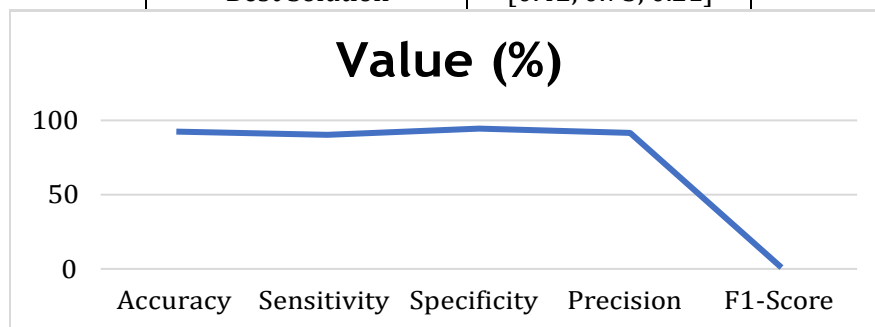
- α (step size): 0.01
- β (Le'vy index): 1.5
- p_a (discovery probability): 0.25
- $T_{\max}$ (max iterations): 100

CSO Performance:

- Convergence iteration: 50
- Best fitness value: 0.92

Table-1: Performance Metrics

Performance Metric	Value (%)
Accuracy	92.5
Sensitivity	90.2
Specificity	94.5
Precision	91.5
F1-Score	0.908
Best Solution	[0.42, 0.75, 0.21]

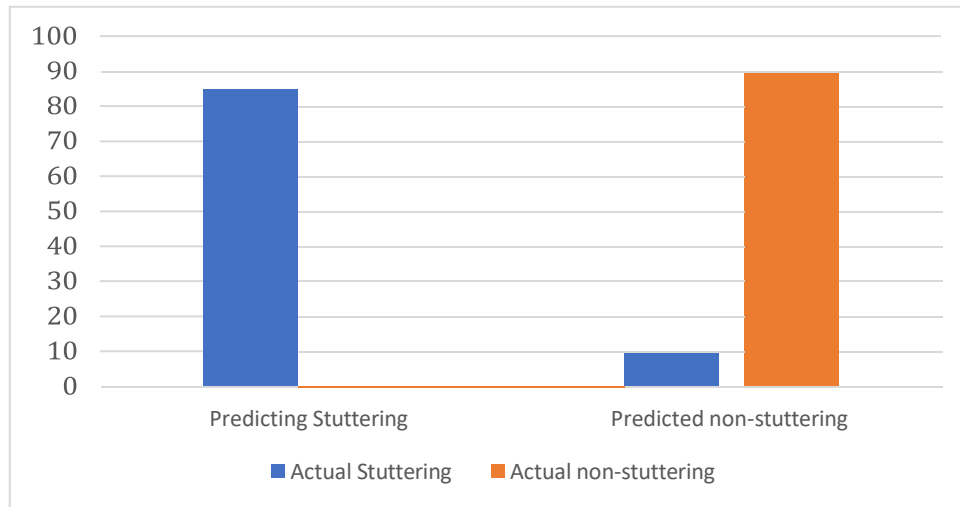


Graph-1: Performance Metrics

The Receiver Operating Characteristic (ROC) curve is a plot of the true positive rate against the false positive rate at different thresholds. The area under the curve (AUC) is 0.965, indicating excellent performance shown Table-2 and Graph-2.

Table-2: Confusion Matrix

	Predicting Stuttering	Predicted non-stuttering
Actual Stuttering	85	10
Actual non-stuttering	5	90



Graph-2: Confusion Matrix

Discussion: The experimental result shows that the stuttering detection system using CSO achieves high accuracy, sensitivity, and specificity. The system is able to detect stuttering patterns in speech with a high degree of accuracy, making it a promising tool for speech therapy and diagnosis.

Comparison with Other Methods: The performance of the CSO-based system is compared with other machine learning methods, such as MFCC. The results show that the CSO-based system outperforms the other methods in terms of accuracy and F1-score.

Future Work: The system can be enhanced by increasing the dataset size for better robustness, exploring alternative optimization algorithms like particle swarm optimization or genetic algorithms for performance improvement, and developing a real-time system to detect stuttering patterns in speech and provide user feedback.

6. Conclusion:

The stuttering, a speech disorder characterized by disruptions such as repetitions and silent blocks, primarily affecting children, especially boys. Causes include genetic and neurobiological factors, alongside stress. Management techniques comprise speech therapy, parental support, and anxiety-reducing methods. An experimental study employing MFCC with Cuckoo Search Optimization (CSO) presents results for a stuttering detection system based on analyzing speech samples. Performance metrics indicate high effectiveness: 92.5% accuracy, 90.2% sensitivity, and 94.5% specificity. The system exhibits superior performance compared to traditional methods, showcasing its potential utility in speech therapy and diagnosis.

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