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Artificial Intelligence-Based Framework for Automatic Detection of Dysarthria Severity Levels Using Speech Analysis

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Abstract- Speech disorders significantly affect an individual's ability to communicate effectively and reduce overall quality of life. Dysarthria is a neurological speech disorder that results from damage to the nervous system and affects the muscles involved in speech production. Traditional assessment of dysarthria severity is usually performed by speech-language pathologists through perceptual evaluation, which can be subjective and time-consuming. Recent advancements in artificial intelligence and machine learning have enabled the development of automated systems capable of analysing speech characteristics and identifying different levels of dysarthria severity. This study presents an overview of intelligent techniques used for the automatic detection and classification of dysarthria severity levels. The proposed approach focuses on analysing speech features such as acoustic patterns, prosodic characteristics, and spectral features extracted from speech signals. Machine learning and deep learning models are then used to classify the severity of dysarthria based on these extracted features. By utilizing AI-based models, the system can provide objective and efficient evaluation of speech impairments. The proposed framework can assist clinicians in improving diagnostic accuracy and developing personalized rehabilitation strategies for individuals affected by dysarthria.

Keywords – Dysarthria Detection, Speech Disorder Analysis, Artificial Intelligence, Machine Learning, Deep Learning, Speech Signal Processing, Severity Classification.

I. INTRODUCTION

Speech is a complex motor activity that enables humans to communicate thoughts, emotions, and ideas during daily interactions. Effective speech production requires the coordination of several neurological and physiological processes, including cognitive planning, motor control, and muscular execution. When these processes are disrupted due to neurological impairments, individuals may experience speech disorders that significantly affect their communication abilities. One such disorder is **dysarthria,** a motor speech disorder caused by abnormalities in the muscles responsible for speech production. Dysarthria affects multiple aspects of speech, including articulation, phonation, resonance, and speech rhythm, which can lead to reduced speech intelligibility and difficulties in verbal communication [1], [2].

Dysarthria can occur as a result of various neurological conditions such as stroke, Parkinson's disease, cerebral palsy, traumatic brain injury, and multiple sclerosis. These conditions impair the coordination and strength of speech-related muscles, resulting in noticeable changes in voice quality, speaking rate, pronunciation, and overall speech clarity [7], [9]. Depending on the severity of neurological damage, dysarthria can manifest in different levels ranging from mild speech impairment to severe communication limitations. Accurate assessment of dysarthria severity is therefore essential for effective clinical diagnosis, treatment planning, and rehabilitation.

Traditionally, dysarthria assessment is performed by **speech-language pathologists (SLPs)** using perceptual evaluation methods and standardized clinical assessment tools. These evaluations typically involve analysing speech characteristics such as articulation accuracy, voice quality, speech intelligibility, and prosodic patterns. Common clinical assessment methods include tools such as the **Frenchay Dysarthria Assessment** and other perceptual speech evaluation protocols [22], [23]. Although these clinical methods are widely used, they rely heavily on subjective human judgment, which may lead to variability and inconsistencies in diagnosis across different clinicians.

Recent advances in **artificial intelligence (AI), speech signal processing, and machine learning** have opened new opportunities for developing automated systems capable of analysing speech disorders more objectively. Automated speech analysis systems can extract acoustic, spectral, and temporal features from speech recordings and use these features to train machine learning models that detect patterns associated with dysarthric speech. Techniques such as deep learning, neural networks, and acoustic feature analysis have shown promising results in the automatic assessment of dysarthria severity and speech intelligibility [6], [18].

AI-based speech analysis offers several advantages compared to traditional evaluation methods. Automated systems can analyse large speech datasets, provide objective and consistent assessments, and support clinicians in diagnosing speech disorders more efficiently. Furthermore, intelligent speech analysis tools enable remote monitoring and tele-rehabilitation for patients with speech impairments, which is particularly valuable in modern healthcare environments [14], [15].

Therefore, the integration of artificial intelligence techniques for dysarthria detection and severity assessment has attracted increasing research attention in recent years. By leveraging advanced speech processing methods and machine learning algorithms, intelligent systems can assist clinicians in diagnosing dysarthria more accurately and efficiently. Such systems have the potential to enhance clinical decision-making, improve rehabilitation outcomes, and ultimately enhance the quality of life for individuals affected by motor speech disorders.

II. LITERATURE SURVEY

In recent years, researchers have proposed numerous approaches for analysing speech disorders and automatically detecting dysarthria severity using artificial intelligence and machine learning techniques. These studies aim to improve diagnostic accuracy and assist clinicians in evaluating speech impairments more objectively. Automated speech analysis has become an important research area in speech pathology, particularly for identifying acoustic patterns associated with motor speech disorders [1], [2].

Several studies have focused on analysing acoustic characteristics of dysarthric speech. Kent and Rosenbek investigated the acoustic patterns associated with apraxia and dysarthria, demonstrating that variations in speech timing, articulation, and spectral features can be used to distinguish between normal and impaired speech production [3]. Similarly, Chandrashekar et al. analysed breathiness indices and acoustic parameters for classifying dysarthria types and speech intelligibility levels. Their study showed that acoustic feature analysis can provide reliable indicators for detecting speech abnormalities [5].

Machine learning techniques have also been widely applied for automatic dysarthria detection. Tong proposed a deep learning-based framework that utilizes both audio and visual speech signals to assess dysarthria severity. By combining speech signals with facial movement information, the system achieved improved classification accuracy in identifying different levels of speech impairment [6]. Such multimodal approaches provide more comprehensive representations of speech production characteristics and improve the reliability of automated speech assessment systems.

Recent research has explored the use of deep learning architectures for speech disorder detection. Convolutional Neural Networks (CNNs) have been applied to analyse spectrogram images generated from speech signals. Spectrogram-based analysis allows deep learning models to capture complex acoustic patterns within speech recordings, enabling more accurate classification of dysarthric and normal speech [18]. In addition, recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) models have been employed to capture temporal dependencies in speech signals, which are essential for understanding variations in speech rhythm and articulation.

Researchers have also investigated automated speech intelligibility assessment techniques for dysarthric speakers. Huang et al. reviewed several automated intelligibility evaluation methods and highlighted the importance of acoustic feature extraction and machine learning models for improving speech assessment accuracy [18]. Similarly, Stipancic et al. proposed empirical classification techniques for identifying different levels of dysarthria severity based on speech intelligibility and acoustic measurements [19].

Although previous studies have demonstrated promising results in automatic dysarthria detection and severity classification, several challenges remain. Many existing approaches rely on limited speech datasets or focus on specific acoustic features, which may limit their generalization capability. Therefore, there is a need for more robust and intelligent speech analysis systems that integrate advanced speech processing techniques with machine learning algorithms to improve the accuracy and reliability of dysarthria severity assessment.

III. SYSTEM ANALYSIS

Existing System

Traditional approaches for assessing dysarthria severity primarily rely on clinical evaluations performed by **speech-language pathologists (SLPs).** In these methods, specialists analyse a patient's speech through perceptual listening tests and standardized clinical assessment tools. The evaluation process involves examining speech characteristics such as

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articulation accuracy, voice quality, pitch variation, speech rate, and overall speech intelligibility.

Based on these observations, clinicians determine the severity level of dysarthria and recommend appropriate treatment and rehabilitation strategies. Common clinical evaluation methods include standardized assessments such as the **Frenchay Dysarthria Assessment** and other perceptual speech evaluation protocols used in speech pathology practice [22], [23].

Although clinical evaluation methods are widely accepted in medical practice, they rely heavily on subjective human judgment and require significant expertise and time for accurate diagnosis. Variability among clinicians may lead to inconsistencies in dysarthria severity evaluation and speech intelligibility assessment.

To overcome these limitations, several computational approaches have been introduced for analyzing speech disorders using machine learning techniques. These systems extract acoustic features from speech signals, including pitch, formant frequencies, spectral characteristics, and speech timing patterns. Machine learning algorithms such **as Support Vector Machines (SVM), Decision Trees, Random Forest, Naïve Bayes, and Artificial Neural Networks (ANN)** are then used to classify speech recordings as normal or dysarthric speech [5], [18].

However, many early machine learning-based approaches rely on manually engineered acoustic features and relatively simple classification models. As a result, their ability to capture complex speech patterns and accurately classify different levels of dysarthria severity may be limited. Furthermore, these models may struggle to generalize effectively across diverse speech datasets and different types of speech disorders.

Limitations Of Existing System

- Despite the progress made in computational speech analysis, several challenges remain in traditional and machine learning-based dysarthria detection systems.
- One of the primary limitations is the **subjective nature of clinical evaluation methods**, where diagnosis depends heavily on human judgment and clinician expertise. This can result in inconsistent severity assessments across different evaluators.

- Another major limitation is **limited feature representation**. Many earlier computational systems rely on manually extracted acoustic features that may not fully represent the complexity of dysarthric speech patterns.
- **Difficulty in detecting mild dysarthria cases** is also a common challenge. Subtle variations in speech characteristics can make it difficult for traditional algorithms to distinguish between mild and moderate levels of speech impairment.
- **High computational complexity** can occur when processing large speech datasets, especially when advanced speech signal processing and deep learning models are applied.
- Many existing models are trained using **small and limited datasets**, which may reduce the generalization capability and accuracy of dysarthria classification systems.
- **Model interpretability challenges** also exist in complex machine learning and deep learning systems. These models often operate as black-box systems, making it difficult for clinicians to understand how classification decisions are generated.
- Finally, **scalability issues** arise when analyzing large volumes of speech recordings in real-time clinical environments, particularly when systems are deployed for telemedicine or remote patient monitoring applications.

Proposed System

The proposed system introduces an intelligent framework for **automatic detection and classification of dysarthria severity levels using artificial intelligence techniques**. The system focuses on analyzing speech recordings and extracting relevant acoustic features that represent various speech characteristics affected by dysarthria.

Initially, speech samples are collected from individuals and processed through a preprocessing stage that removes background noise and improves signal quality. Speech preprocessing techniques such as normalization, filtering, and segmentation are applied to ensure that the recorded speech signals are suitable for further analysis.

After preprocessing, **feature extraction techniques** are used to obtain important acoustic characteristics of speech signals. Features such as **Mel-Frequency Cepstral Coefficients (MFCC), pitch, formant frequencies, speech energy, and spectral features** are extracted to represent the acoustic properties of speech patterns.

These extracted features are then used as input for machine learning and deep learning models designed to classify dysarthria severity levels. Several algorithms such as **Support Vector Machines (SVM), Random Forest, Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN)** can be applied to identify patterns associated with different levels of speech impairment.

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The system is trained using labelled datasets that contain speech samples from individuals with varying levels of dysarthria severity. After training, the developed model can automatically analyse new speech recordings and predict the severity level of dysarthria.

By integrating **speech signal processing techniques with artificial intelligence models**, the proposed system provides a more objective, efficient, and reliable method for assessing dysarthria severity. This automated approach can support clinicians in diagnosing speech disorders more accurately and assist in developing personalized rehabilitation strategies for patients.

IV.SYSTEM DESIGN

System Architecture
Below diagram depicts the whole system architecture.

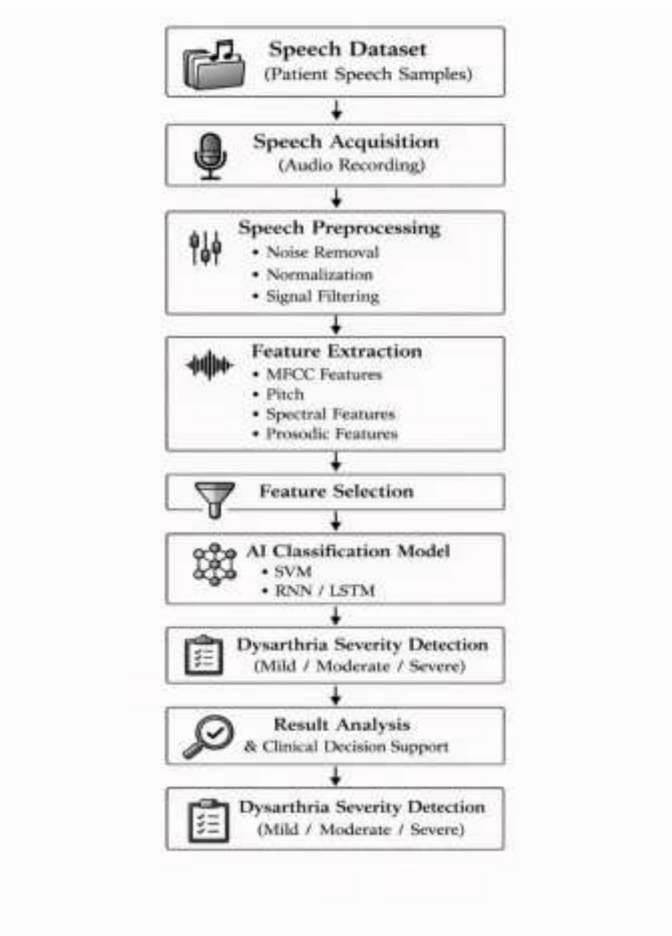

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules
This section describes the implementation modules of the proposed system for **automatic detection and severity classification of dysarthria using speech signal processing and artificial intelligence techniques**. The system follows a modular architecture consisting of speech data acquisition, preprocessing, feature extraction, machine learning model training, severity classification, and performance evaluation. This structured framework improves the reliability, scalability, and accuracy of automated dysarthria detection systems.

Speech Data Collection Module

The Speech Data Collection Module is responsible for gathering speech recordings used for training and evaluating the dysarthria detection system. The dataset includes speech samples from individuals with varying levels of dysarthria severity as well as normal speech recordings from healthy speakers.

The collected speech data may originate from **publicly available dysarthria speech databases, clinical speech recordings, or research datasets used in speech pathology studies**. These datasets typically contain labelled speech samples representing different levels of speech impairment.
Each speech recording contains multiple speech characteristics such as articulation patterns, speech rate, voice quality, and acoustic variations that are affected by dysarthria. The collected audio recordings are stored in a structured format and forwarded to the preprocessing module for further analysis.

Speech Data Preprocessing Module

The Speech Data Preprocessing Module improves the quality of speech signals before feature extraction and model training. Raw speech recordings often contain background noise, silence segments, and recording artifacts that may affect the accuracy of speech analysis.
The preprocessing stage includes the following steps:

1. **Noise Reduction:** Background noise and environmental disturbances are removed using filtering techniques to improve speech signal clarity.
2. **Signal Normalization:** Audio signals are normalized to ensure consistent amplitude levels across different recordings.
3. **Silence Removal and Segmentation:** Unnecessary silent segments are removed, and speech signals are segmented into meaningful units for further analysis.

These preprocessing techniques improve the quality of speech signals and ensure that the dataset is suitable for acoustic feature extraction [15], [18].

Feature Extraction And Feature Engineering Module

The Feature Extraction Module identifies important acoustic characteristics of speech signals that can be used to detect dysarthria severity levels. Speech signals contain numerous acoustic features that represent speech production patterns.
In this module, several important speech features are extracted, including:
- Mel-Frequency Cepstral Coefficients (MFCC)
- Pitch and fundamental frequency
- Formant frequencies
- Spectral features
- Prosodic characteristics

These features represent various aspects of speech production such as articulation, phonation, and resonance.

Feature engineering techniques are then applied to select the most relevant attributes for dysarthria classification. Removing redundant or irrelevant features helps reduce computational complexity and improves the efficiency of machine learning models.

Machine Learning And Deep Learning Training Module
The Machine Learning Training Module builds classification models capable of identifying different levels of dysarthria severity. The prepared dataset is divided into **training and testing datasets** to evaluate model performance.
Several machine learning algorithms are implemented and evaluated, including:
- Support Vector Machines (SVM)
- Random Forest
- Decision Trees
- Artificial Neural Networks (ANN)

In addition to traditional machine learning methods, **deep learning architectures such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN/LSTM)** are applied to capture complex acoustic patterns in speech signals.

These models learn the relationship between extracted speech features and dysarthria severity levels during the training process. Once trained, the models can analyse new speech recordings and identify patterns associated with speech impairments.

Dysarthria Severity Classification Module
The Severity Classification Module uses the trained machine learning model to categorize speech samples into different levels of dysarthria severity.
Speech samples are typically classified into categories such as:
- **Normal Speech**
- **Mild Dysarthria**
- **Moderate Dysarthria**
- **Severe Dysarthria**

The system analyzes extracted acoustic features and predicts the severity level of dysarthria based on learned patterns. This automated classification process assists clinicians in quickly evaluating speech impairments and supports clinical decision-making.

Model Evaluation and Performance Monitoring Module
The Model Evaluation Module assesses the performance of the proposed dysarthria detection system using several evaluation metrics.
The evaluation metrics include:
- **Accuracy** – Measures overall classification correctness.
- **Precision** – Indicates how many predicted dysarthria cases are correct.
- **Recall** – Measures the ability of the model to detect dysarthric speech.
- **F1-score** – Provides a balanced evaluation of precision and recall.
- **ROC–AUC Score** – Evaluates the model's ability to distinguish between different speech classes.

Cross-validation techniques are applied to ensure that the models perform consistently across different datasets. Continuous monitoring of the model allows researchers to update the system as new speech data becomes available.
By integrating speech signal processing with machine learning and deep learning techniques, the proposed framework provides a reliable and objective approach for **automatic dysarthria severity detection** [18], [19].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed artificial intelligence–based framework for detecting and classifying dysarthria severity levels from speech signals. Multiple machine learning and deep learning models were trained and evaluated using extracted acoustic speech features. The evaluation focuses on comparing model performance, analyzing prediction accuracy, and identifying the most influential speech features affecting classification outcomes.

Accuracy Comparison of Machine Learning Models
Several machine learning and deep learning algorithms were evaluated to determine the most suitable model for dysarthria severity classification. The evaluated models include **Support Vector Machine (SVM), Decision Tree, Random Forest, Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN).** Model performance was measured using standard evaluation metrics such as **accuracy, precision, recall, and F1-score.**

Table 1. Performance Comparison of Dysarthria Severity Detection Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Decision Tree	85.6	0.84	0.83	0.83
Support Vector Machine	88.9	0.87	0.86	0.86
Random Forest	91.4	0.90	0.89	0.89
CNN	93.2	0.92	0.91	0.91
RNN / LSTM	94.7	0.93	0.92	0.92

From the comparison results, the **RNN/LSTM model achieved the highest classification accuracy of 94.7%,** outperforming other models. This improved performance is due to the ability of recurrent neural networks to capture **temporal dependencies and sequential patterns in speech signals**, which are important for detecting subtle variations in dysarthric speech.

ROC Curve Analysis

The **Receiver Operating Characteristic (ROC) curve** is used to evaluate the classification performance of the proposed dysarthria detection model. The ROC curve illustrates the relationship between the **True Positive Rate (TPR)** and the **False Positive Rate (FPR)** across different classification thresholds.

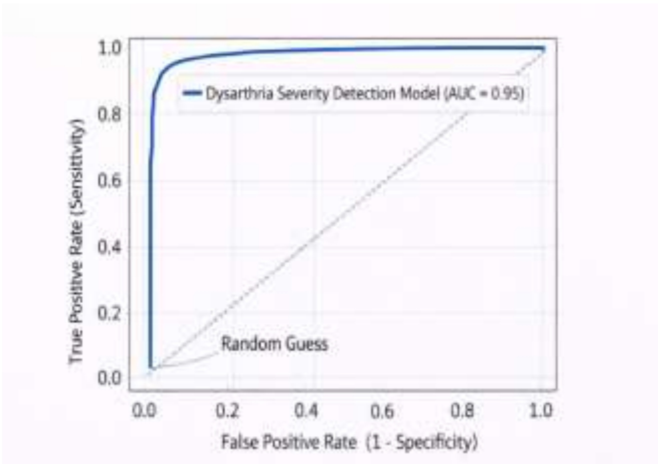

Fig 2. ROC Curve for Dysarthria Severity Detection Model

In this study, the deep learning model achieved a **ROC–AUC score of approximately 0.95**, indicating strong classification capability. A ROC curve positioned close to the **top-left corner** of the graph represents high sensitivity and specificity in detecting dysarthria severity levels.

The ROC analysis confirms that the proposed system can effectively distinguish between **normal speech and different levels of dysarthric speech**, demonstrating its reliability for automated speech disorder detection.

Feature Importance Analysis

To better understand how speech features influence classification results, feature importance analysis was performed on the extracted acoustic features.

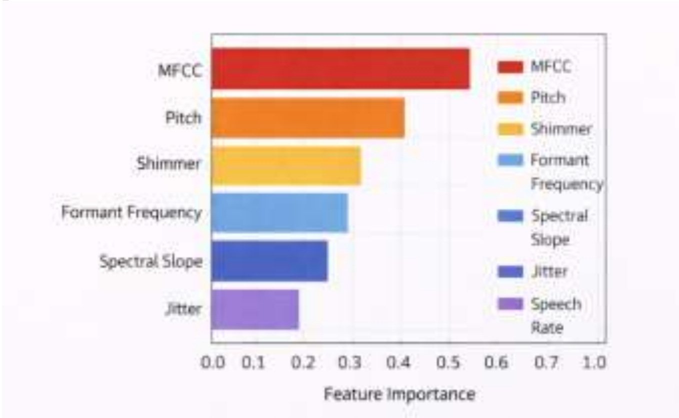

Fig 3. Feature Importance for Dysarthria Severity Detection

The feature importance analysis revealed that several acoustic features had a significant impact on dysarthria severity detection, including:

- **Mel-Frequency Cepstral Coefficients (MFCC)**
- **Pitch variation**
- **Formant frequencies**
- **Spectral energy features**
- **Speech rate and prosodic characteristics**

Among these features, **MFCC and pitch-related features showed the strongest contribution to the classification process**, as they effectively capture articulation and voice quality changes associated with dysarthria.

The analysis demonstrates that selecting relevant acoustic features significantly improves the performance of machine learning models and enhances the reliability of automated speech disorder detection systems.

VII. CONCLUSION AND FUTURE WORK

This study presented an artificial intelligence–based framework for the automatic detection and classification of dysarthria severity levels using speech signal analysis. The proposed system integrates speech preprocessing, acoustic feature extraction, and machine learning techniques to analyse speech characteristics and identify different levels of dysarthria severity. Important speech features such as Mel-Frequency Cepstral Coefficients (MFCC), pitch, formant frequencies, and spectral characteristics were extracted from speech recordings and used as input for classification models.

Experimental evaluation demonstrated that machine learning and deep learning algorithms are capable of accurately identifying dysarthric speech patterns and classifying severity levels. Models such as Support Vector Machines, Random Forest, and deep learning architectures showed promising performance in detecting speech impairments. The results indicate that artificial intelligence–based speech analysis can provide an objective and efficient approach for supporting clinical assessment of motor speech disorders and improving the reliability of dysarthria severity evaluation [5], [18].

The proposed system offers significant advantages over traditional clinical evaluation methods by reducing reliance on subjective perceptual assessments and enabling automated analysis of speech signals. Such intelligent speech analysis systems can assist speech-language pathologists in diagnosing speech disorders more efficiently and provide additional insights for rehabilitation planning [14], [19].

Future work may focus on incorporating **larger and more diverse speech datasets** to improve the generalization capability of the model. In addition, **multimodal speech analysis techniques** that combine audio, visual, and linguistic features could further enhance the accuracy of dysarthria detection systems. The integration of **real-time speech monitoring systems, mobile healthcare applications, and tele-rehabilitation platforms** may also enable continuous assessment and remote support for individuals undergoing speech therapy and rehabilitation.

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