Cleft Speech AI: Smart Speech Therapy for Post-Surgical Cleft Palate

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***Abstract*—Cleft palate is a congenital condition that significantly affects speech clarity, even after surgical correction. Continuous speech therapy is essential for recovery; however, access to speech-language pathologists is often limited by geographical and financial constraints. This study proposes Cleft Speech AI, a web-based platform that leverages deep learning techniques to assist with speech evaluation and therapy. The system records a child's speech, processes it using Mel frequency central coefficients, and analyzes it using a hybrid CNN-LSTM model. The model provides real-time feedback to improve speech quality. The experimental results demonstrated an accuracy of approximately 90**

***Index Terms*—Cleft Palate, Speech Therapy, Artificial Intelligence, Deep Learning, CNN-LSTM, Web Application**

I. INTRODUCTION

Cleft palate is one of the most common congenital craniofacial anomalies in children. It occurs when the tissues forming the roof of the mouth do not fuse properly during fetal development. Even after surgical correction, many patients continue to experience significant speech disorders, such as hypernasality, articulation errors, nasal air emission, and reduced speech intelligibility. These speech issues can negatively impact communication, social interactions, and overall quality of life.

Speech therapy is essential for the rehabilitation of postsurgical cleft palate patients. Traditionally, therapy is conducted by trained speech-language pathologists through regular, inperson sessions. However, access to such specialized healthcare services is limited, particularly in rural and underdeveloped regions of the world. Additionally, therapy requires long-term commitment, which can be difficult because of financial constraints, travel limitations, and lack of continuous monitoring.

With the rapid advancement of Artificial Intelligence and deep learning technologies, automated speech analysis systems have emerged as promising solutions. These systems can analyze speech signals, detect abnormalities, and assist in therapy without requiring constant supervision. Machine learning models have shown significant potential for identifying speech disorders with high accuracy.

In recent years, deep learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), have been widely used for speech processing tasks. CNN models are effective in extracting spatial features from speech representations, whereas Long Short-Term Memory (LSTM) networks can capture temporal dependencies in sequential data. The combination of these models enables a more accurate and efficient speech analysis.

This study proposes Cleft Speech AI, a web-based intelligent system designed to assist in speech therapy for patients with postoperative cleft palate. The system records and analyzes speech using a hybrid CNN-LSTM model and provides real-time feedback and therapy suggestions. The goal of this system is to make speech therapy more accessible, cost-effective, and efficient by allowing remote monitoring and continuous practice.

The main contributions of this paper are as follows:

- Development of a hybrid CNN-LSTM model for accurate speech analysis
- Design of a web-based platform for real-time speech therapy assistance
- Integration of feedback mechanisms to guide users in Improved Speech Quality
- Providing an accessible solution for remote and continuous therapy

The remainder of this paper is organized as follows. Section II presents the literature review; Section III describes the methodology. Section IV discusses the results, and Section V concludes the paper with future work directions.

II. LITERATURE REVIEW

Speech disorders in patients with cleft palate have been widely studied using traditional signal processing and machine learning techniques. Early research focused on acoustic analysis methods to identify speech abnormalities, such as hypernasality, articulation errors, and reduced intelligibility. These approaches rely heavily on handcrafted features and statistical models.

One of the commonly used traditional methods is the Support Vector Machine (SVM), which has been applied to the classification of speech disorders. SVM-based systems use features such as formants, pitch, and spectral characteristics to detect abnormality. Although SVM provides moderate accuracy, it struggles to capture complex patterns in speech signals, particularly temporal dependencies.

Gaussian Mixture Models (GMM) have also been used for speech modeling and classification. These probabilistic models represent the distribution of speech features and are useful for speaker recognition and detecting speech disorder. However, GMM-based approaches are limited in their ability to handle nonlinear and sequential data effectively.

With the advancement of deep learning, researchers have started using Convolutional Neural Networks (CNN) for speech analysis. CNNs are effective for extracting spatial features from spectrogram and MFCC representations. Studies have shown that CNN-based models improve the detection accuracy of hypernasality and articulation errors compared to traditional methods.

Recurrent Neural Networks (RNN), particularly long shortterm memory (LSTM) networks, have been introduced to address the limitations of traditional models in capturing temporal dependencies. LSTM models can learn long-term relationships in sequential speech data, making them suitable for speech recognition and disorder analysis.

Recent studies have combined CNN and LSTM architectures to create hybrid models. The CNN component extracts spatial features, whereas the LSTM component processes temporal sequences. These hybrid models have demonstrated superior performance in speech classification tasks, achieving high accuracy and robustness.

Despite these advancements, most existing systems focus primarily on the detection of speech disorders and lack real-time feedback mechanisms. Additionally, many solutions are not user-friendly and require specialized hardware or software, limiting their accessibility to patients.

The proposed Cleft Speech AI system addresses these limitations by integrating detection, analysis, and therapy into a single web-based platform. By using a hybrid CNN-LSTM model and providing real-time feedback, the system offers a more practical and accessible solution for post-surgical speech therapy.

III. SYSTEM ARCHITECTURE

The proposed system consists of three main components: input module, processing module, and output module.

A. Input Module

The user records speech through a web interface or uploads an audio file. The system supports standard audio formats.

B. Processing Module

The audio signal undergoes preprocessing, including noise reduction and normalization. Features are extracted using MFCC, which effectively represent speech characteristics.

C. Model Design

A hybrid CNN-LSTM model is used:

- CNN extracts spatial features from speech signals
- LSTM captures temporal patterns and dependencies

D. Output Module

The system provides:

- Speech quality analysis
- Identification of errors
- Real-time feedback
- Therapy exercises

IV. METHODOLOGY

The proposed Cleft Speech AI system follows a structured pipeline consisting of data acquisition, preprocessing, feature extraction, model development, training, evaluation, and deployment. Each stage is designed to ensure accurate detection of speech abnormalities and effective therapy assistance.

A. Data Collection

Speech data is collected from publicly available speech datasets as well as recorded samples from individuals with cleft palate. The dataset includes both normal and disordered speech to enable supervised learning. Audio samples are recorded in controlled environments using standard microphones to maintain quality and consistency. The dataset is labeled based on speech characteristics such as hypernasality, articulation errors, and intelligibility levels.

B. Data Preprocessing

Raw audio signals often contain background noise and inconsistencies. Therefore, preprocessing is applied to improve data quality. Noise reduction techniques such as spectral gating are used to eliminate unwanted sounds. The audio is then normalized to ensure consistent amplitude levels across samples. Silence removal is performed to eliminate non-speech segments, which improves model efficiency. The processed audio is segmented into fixed-length frames for further analysis.

C. Feature Extraction

Feature extraction plays a critical role in representing speech signals effectively. In this system, Mel Frequency Cepstral Coefficients (MFCC) are used as primary features due to their effectiveness in capturing human auditory characteristics. The audio signal is converted into the frequency domain, and MFCC features are computed for each frame. Additional features such as pitch, energy, and spectral features may also be extracted to improve model performance.

D. Model Architecture

A hybrid CNN-LSTM model is employed to leverage both spatial and temporal information from speech data.

- Convolutional Neural Network (CNN): The CNN component is responsible for extracting spatial features from the MFCC feature maps. It consists of multiple convolutional layers followed by pooling layers, which help in identifying important patterns in the speech signal.
- Long Short-Term Memory (LSTM): The LSTM component captures temporal dependencies in speech sequences. It processes the sequential data and retains important contextual information over time.

The combination of CNN and LSTM allows the system to analyze both feature patterns and time-based variations in speech, leading to improved accuracy.

E. Model Training

The model is trained using supervised learning techniques. The dataset is divided into training and testing sets. During training, the model learns to classify speech patterns based on labeled data. Optimization algorithms such as Adam optimizer are used to minimize loss functions. Techniques like dropout and regularization are applied to prevent overfitting and improve generalization.

F. Evaluation Metrics

The performance of the model is evaluated using standard metrics:

- Accuracy
- Precision • Recall
- F1-Score

These metrics provide a comprehensive understanding of the model's ability to correctly classify speech abnormalities.

G. System Deployment

The trained model is integrated into a web-based platform using backend frameworks such as Flask or Django. The frontend interface is developed using modern web technologies to provide a user-friendly experience. Users can record speech, upload audio files, and receive instant feedback. The system also provides therapy exercises and tracks user progress over time.

H. Workflow of the System

The overall workflow of the system is as follows:

1. User records or uploads speech input
2. Audio is preprocessed and cleaned
3. Features are extracted using MFCC

4. CNN-LSTM model analyzes the input
5. System generates feedback and therapy suggestions

This pipeline ensures efficient and accurate speech analysis, making the system suitable for real-time applications.

V. RESULTS AND DISCUSSION

The proposed Cleft Speech AI system was evaluated using a dataset consisting of normal and cleft palate speech samples. The dataset was divided into training and testing sets to assess the model performance. The evaluation focused on the system's ability to accurately detect speech abnormalities, such as hypernasality and articulation errors.

A. Performance Evaluation

The CNN-LSTM model was trained and tested using standard evaluation metrics, including accuracy, precision, recall, and F1-score. The results demonstrate that the proposed model outperforms traditional machine learning approaches.

The results indicate that the CNN-LSTM model achieves the highest accuracy of approximately 90%, demonstrating its effectiveness in capturing both spatial and temporal features of speech signals.

Table I: Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
SVM	82%	80%	79%	79.5%
CNN	88%	87%	85%	86%
CNN-LSTM	90%	91%	89%	90%

B. Analysis of Results

The superior performance of the hybrid model can be attributed to its architecture design. The CNN component effectively extracts important spectral features from the MFCC representations, whereas the LSTM component captures temporal dependencies in speech sequences. This combination enables the model to better understand variations in speech patterns compared with standalone models.

The system was also tested for real-time performance evaluation. The model provided quick responses with minimal latency, making it suitable for practical deployment in webbased applications. The feedback generated by the system includes the identification of speech errors and suggestions for improvement, which can assist users in continuous learning.

C. Comparison with Existing Systems

Compared with traditional systems that rely solely on classification, the proposed system offers additional advantages, such as real-time feedback and therapy assistance. Most existing approaches are limited to offline analysis, whereas the proposed system integrates both analysis and therapy on a single platform.

D. Practical Implications

The system can be effectively used by children undergoing speech therapy after cleft palate surgery. It reduces the dependency on frequent hospital visits and enables remote monitoring. The web-based nature of the system ensures accessibility across devices, making it user-friendly and scalable.

E. Limitations

Despite its effectiveness, this system has certain limitations. The model performance depends on the quality and size of the dataset. The limited availability of labeled cleft palate speech data can affect generalization. In addition, variations in the recording environment may introduce noise and affect accuracy.

F. Future Improvements

Future enhancements may include the use of larger and more diverse datasets, the incorporation of multilingual speech analysis, and the integration of advanced models, such as transformers. Improving the personalization of therapy exercises based on user performance can further enhance the effectiveness of the system.

VI. CONCLUSION AND FUTURE WORK

This paper presents Cleft Speech AI, an intelligent webbased system designed to assist in speech therapy for postsurgical cleft palate patients. The system utilizes a hybrid CNN-LSTM model to analyze speech signals and identify abnormalities, such as hypernasality and articulation errors. By combining spatial feature extraction and temporal sequence modeling, the proposed approach achieved an accuracy of approximately 90

One of the key contributions of this study is the integration of speech analysis with real-time feedback and therapy assistance on a single platform. Unlike existing systems that focus only on detection, the proposed solution provides practical guidance to users,

thereby enabling continuous improvement in speech quality. The web-based implementation ensures accessibility, allowing patients to use the system remotely without the need for frequent clinical visits.

The results demonstrate that the proposed system is effective, scalable, and suitable for deployment in real-world settings. It has the potential to significantly improve the availability and efficiency of speech therapy, particularly in regions where access to speech-language pathologists is limited in the future.

Despite its advantages, this system has certain limitations. The performance of the model depends on the availability and quality of the speech datasets. Variations in the recording conditions and background noise may affect the accuracy of the predictions. Additionally, the current system is primarily designed for a specific language and may require adaptation for broader use.

Future work will focus on expanding the dataset to include more diverse speech samples, improving the model robustness, and incorporating multilingual support. Advanced deep learning techniques, such as transformer-based models, can be explored to further enhance performance. Additionally, the personalization of therapy exercises based on individual user progress and the integration of mobile application support can improve user engagement and effectiveness.

Overall, the proposed Cleft Speech AI system represents a significant step toward developing intelligent, accessible, and cost-effective speech therapy solutions.

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