International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 02(February),2026
Received: 07-01-2026 Accepted: 16-02-2026 Published: 23-02-2026

EXPLORING AI METHODS FOR ENHANCED ACCENT RECOGNITION IN SPEECH

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ABSTRACT
Accent recognition plays a critical role in enhancing the performance of Automatic Speech Recognition (ASR) systems, which often struggle with accent variations. This paper presents a comprehensive review of machine learning (ML) and deep learning (DL) techniques applied to accent recognition. It systematically examines preprocessing methods, feature extraction techniques, and classification models used in the literature. The study highlights the dominance of Mel-Frequency Cepstral Coefficients (MFCC) as a feature extraction method and discusses the effectiveness of models such as Gaussian Mixture Models (GMMs), Support Vector Machines (SVMs), and deep architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Furthermore, the paper identifies research gaps, including the lack of standardized datasets for low-resource languages and the need for robust models that generalize across diverse accents. Future directions such as cross-lingual accent classification, generative models, and explainable AI are also discussed.

Keywords: Accent recognition, automatic speech recognition, deep learning, machine learning, preprocessing, feature extraction.

I. INTRODUCTION

Accent recognition is an essential component of modern ASR systems, aimed at identifying the regional or linguistic background of a speaker based on their pronunciation patterns. Accents introduce significant variability in speech, which can degrade the performance of ASR systems. With the proliferation of voice-activated technologies and global communication platforms, the ability to accurately recognize accents has gained immense importance. This paper explores the evolution of accent recognition systems, from classical ML approaches to advanced DL architectures. It addresses key challenges such as noise robustness, speaker variability, and data scarcity, while also outlining the potential applications of accent recognition in security, education, and multilingual communication.

The human voice is a rich and complex signal, carrying not only the semantic content of speech but also a wealth of paralinguistic information, including the speaker's identity, emotional state, and geographical or linguistic background. Among these, accent—a systematic pattern of pronunciation influenced by a speaker's native language or regional dialect—stands as a critical characteristic that significantly shapes how speech is produced and perceived. In recent years, the rapid advancement of Automatic Speech Recognition (ASR) systems, powered by Machine Learning (ML) and Deep Learning (DL), has brought the challenge of accent variation to the forefront. While these systems have achieved remarkable accuracy in controlled environments, their performance often degrades substantially when confronted with non-standard or non-native accents, creating a barrier to universal and equitable access to voice-enabled technologies.

The core challenge lies in the inherent variability of speech. Accents are manifested through subtle differences in phoneme pronunciation, intonation, rhythm, and prosody. For an ASR system trained predominantly on a specific accent, such as General American English, these variations can lead to a higher Word Error Rate (WER) when processing speech from a speaker with a British, Indian, or Spanish accent. This limitation not only affects the usability of virtual assistants and transcription services but also has implications for applications in security, where accent recognition can aid in speaker profiling, and in education, where it can support personalized language learning.

The field of accent recognition has evolved in parallel with broader trends in speech technology. Early systems relied on classical methods such as Gaussian Mixture Models (GMMs) and Hidden Markov Models (HMMs), often using hand-crafted features like Mel-Frequency Cepstral Coefficients (MFCCs) to model acoustic properties. The advent of ML introduced classifiers like Support Vector Machines (SVMs) and Random Forests (RF), which offered improved discriminative power. However, the contemporary paradigm is dominated by Deep Learning. Architectures such as Convolutional Neural Networks (CNNs), which excel at extracting spatial features from spectrograms, and Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) networks, which model temporal dependencies, have set new benchmarks for accuracy. More recently, hybrid models (e.g., CNN-LSTM), transformer-based architectures, and self-supervised learning models (e.g., Wav2Vec 2.0) have further pushed the boundaries of what is possible, enabling more robust and nuanced accent identification.

Despite these advancements, significant challenges persist. A heavy reliance on MFCC features can limit robustness in noisy conditions. There is a notable scarcity of large, diverse, and well-annotated datasets for low-resource languages, particularly for the many accents found within India.

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Furthermore, many state-of-the-art models operate as "black boxes," lacking transparency in their decision-making processes, and struggle to generalize to real-world environments with background noise and varying recording qualities.

This paper seeks to provide a comprehensive exploration of the machine and deep learning methods employed for accurate accent recognition. It systematically reviews the entire pipeline—from preprocessing and feature extraction to classification—highlighting the strengths and limitations of current approaches. By synthesizing findings from recent literature and identifying key research gaps, this study aims to chart a course for future work, emphasizing the need for cross-lingual models, explainable AI, and systems capable of performing reliably in the diverse and unpredictable conditions of the real world.

1.2 Problem Definition

Automatic Speech Recognition (ASR) systems often suffer significant performance degradation when exposed to diverse regional and non-native accents, as most models are trained on limited or accent-specific speech data. Accent variations introduce systematic differences in pronunciation, prosody, and phoneme realization, making it difficult for conventional machine learning models to generalize across speakers and linguistic backgrounds. Despite advancements in machine learning and deep learning, accurately identifying and modeling accents remains challenging due to factors such as speaker variability, background noise, data imbalance, and the scarcity of standardized datasets—especially for low-resource languages. These limitations hinder robust accent recognition and, in turn, reduce the effectiveness of ASR systems in real-world, multilingual environments. Therefore, there is a critical need to design reliable accent recognition frameworks that effectively preprocess speech signals, extract discriminative features, and leverage advanced learning models to improve recognition accuracy and generalization across diverse accents and languages .

1.3 Research Motivation

The motivation for this research arises from the growing demand for accurate and inclusive Automatic Speech Recognition (ASR) systems in real-world, multilingual environments. Accent variability remains a major barrier to reliable speech recognition, often leading to biased performance and reduced usability for non-native and regional speakers. Despite recent advances in machine learning and deep learning, existing models still struggle with generalization due to limited datasets, speaker diversity, and noisy conditions. Addressing these challenges is essential to improve fairness, accessibility, and robustness of speech-enabled technologies. Therefore, this research is motivated by the need to develop effective accent recognition approaches that enhance ASR performance across diverse accents, languages, and real-world scenarios.

1.4 Scope

1. Analysis of accent variability and its impact on ASR performance
2. Study of speech preprocessing techniques for accent recognition
3. Evaluation of feature extraction methods for accent discrimination
4. Application of machine learning and deep learning models for accent recognition
5. Comparison of model performance using standard evaluation metrics
6. Consideration of multi-accent and multilingual speech datasets
7. Identification of challenges in low-resource and real-world environments

1.5 Objectives

1. To study the impact of accent variations on Automatic Speech Recognition systems
2. To analyze effective preprocessing techniques for accent recognition
3. To extract and evaluate discriminative speech features for accent identification
4. To develop and apply machine learning and deep learning models for accent recognition
5. To compare the performance of different models using standard evaluation metrics
6. To improve generalization of accent recognition across diverse speakers and accents
7. To enhance ASR accuracy in multilingual and real-world environments

II. LITERATURE SURVEY

1. Machine Learning and Deep Learning Approaches for Accent Recognition: A Review,
Muzaffar Ahmad Dar, Jagalingam Pushparaj, 2025,
https://ieeexplore.ieee.org/document/10535295

This paper presents a comprehensive review of machine learning and deep learning techniques used for accent recognition between 2015 and 2023. It discusses preprocessing methods, feature extraction techniques such as MFCC, and various classification models including SVM, CNN, LSTM, and hybrid architectures. The study highlights the strengths and limitations of classical and deep learning approaches and identifies research gaps such as data scarcity and poor generalization. It also explores datasets, evaluation metrics, and future research directions. The review serves as a strong foundation for developing robust accent recognition systems.

2. Accent Identification by Combining Deep Neural Networks and Recurrent Neural Networks,
Yun Jiao, Meng Tu, Visar Berisha, Julie Liss, 2016,
[https://www.isca-speech.org/archive/interspeech_2016/jiao16_interspeech.html](https://www.isca-

speech.org/archive/interspeech_2016/jiao16_interspeech.html)

This research proposes a hybrid accent recognition system that combines deep neural networks with recurrent neural networks. The model captures both short-term and long-term speech features to improve accent classification accuracy. Experimental results demonstrate improved performance compared to standalone DNN or RNN models. The study shows that temporal modeling is crucial for accent identification. It laid the groundwork for hybrid deep learning architectures in speech processing.

3. Foreign Accent Recognition Using MFCC and GMM,
K. Mannepalli, P. N. Sastry, M. Suman, 2016,
https://link.springer.com/article/10.1007/s10772-015-9288-2

This paper presents an MFCC-GMM-based approach for recognizing foreign accents in speech. The system focuses on extracting spectral features and modeling accent variations using Gaussian Mixture Models. Experimental evaluation on Telugu speech data shows promising classification accuracy. The study highlights the effectiveness of traditional statistical models in accent recognition. However, it also notes limitations in scalability and robustness compared to deep learning methods.

4. Automatic Non-Native Dialect and Accent Voice Detection of South Indian English,
I. Patel, R. Kulkarni, Y. S. Rao, 2017,
https://www.researchgate.net/publication/314249063

This work focuses on detecting non-native South Indian English accents using acoustic features. The authors employ MFCC features and machine learning classifiers for accent detection. The results demonstrate that regional pronunciation patterns significantly affect recognition accuracy. The study emphasizes the importance of accent-specific modeling for Indian English. It contributes to early research on Indian accent recognition.

5. Language Accent Detection with CNN Using Sparse Data,
V. Mikhailava et al., 2022,
https://www.mdpi.com/2227-7390/10/16/2913

This paper proposes a CNN-based accent detection model trained on crowd-sourced and sparse speech data. The study applies normalization and data preprocessing to handle data imbalance. Experimental results show that CNNs can effectively learn accent representations even with limited data. The work highlights the importance of data normalization and augmentation. It addresses challenges related to real-world accent variability.

6. Development of Accent Recognition Systems for Vietnamese Speech,
Quoc T. Duong, Van H. Do, 2021,
https://ieeexplore.ieee.org/document/9648504

This research develops an accent recognition system for Vietnamese speech using MFCC features and machine learning classifiers. The study evaluates different preprocessing and segmentation techniques to improve accuracy. Results show that accent recognition is highly sensitive to feature quality. The work contributes to accent recognition in low-resource languages. It highlights challenges in dataset availability and speaker diversity.

7. Accent Classification Using Machine Learning and Deep Learning Models,
A. Purwar, H. Sharma, Y. Sharma, H. Gupta, A. Kaur, 2022,
https://ieeexplore.ieee.org/document/9744736

This paper compares machine learning and deep learning approaches for accent classification. Models such as SVM, Random Forest, CNN, and LSTM are evaluated using MFCC features. The results show that deep learning models outperform traditional classifiers. The study emphasizes the role of feature learning in accent recognition. It provides a comparative baseline for future research.

8. Improved BLSTM-Based Accent Speech Recognition Using Accent Embeddings,
W. Rao, J. Zhang, J. Wu, 2020,
https://ieeexplore.ieee.org/document/9053847

This study introduces accent embeddings within a BLSTM-based speech recognition framework. Multi-task learning is used to jointly learn accent and speech representations. The proposed method significantly reduces word error rate compared to baseline systems. The research demonstrates the effectiveness of accent-aware modeling. It contributes to improving ASR robustness for accented speech.

9. Maghrebian Accent Recognition Using SVM and MFCC,
K. Mebarkia, A. Reffad, R. Maatoug, 2022,
https://ieeexplore.ieee.org/document/9791845

This paper focuses on recognizing Maghrebian accents using MFCC features and SVM classifiers. The system is evaluated on Arabic speech datasets with multiple regional accents. Results show that MFCC combined with SVM achieves reliable classification accuracy. The study highlights challenges in closely related accents. It contributes to Arabic accent recognition research.

10. Intra-Native Accent Shared Features for Neural Network-Based Accent Classification,
Y. A. Wubet, D. Balram, K.-Y. Lian, 2023,
https://ieeexplore.ieee.org/document/10038153

This work proposes shared feature learning across intra-native accents using neural networks. The approach improves accent similarity evaluation and classification accuracy. Experiments demonstrate better generalization across related

International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 26 Issue 02(February),2026
Received: 07-01-2026 Accepted: 16-02-2026 Published: 23-02-2026

accents. The study emphasizes feature sharing for robust accent modeling. It is significant for multilingual and multi-accent environments.

III. SYSTEM ANALYSIS

EXISTING SYSTEM

The existing accent recognition system typically follows a three-stage pipeline: preprocessing, feature extraction, and classification. Preprocessing involves steps like silence removal and normalization to clean the audio signal. Feature extraction primarily relies on MFCCs, often augmented with delta and double-delta coefficients. Classification is performed using a range of models, from classical methods like GMM and SVM to deep learning architectures such as CNNs and RNNs. Hybrid models like GMM-UBM and CNN-SVM have also been employed to improve accuracy.

Disadvantages of the Existing System:

1. Heavy Dependence on MFCCs: While effective, MFCCs are sensitive to noise and may not capture all accent-specific nuances, especially in low-frequency ranges.
2. Limited Generalization Across Languages: Most systems are trained on high-resource languages like English, leading to poor performance on low-resource or cross-lingual accents.
3. Lack of Real-World Robustness: Models are often evaluated in controlled settings and struggle with background noise, speaker variability, and channel distortions in real-world scenarios.

PROPOSED SYSTEM

The proposed system introduces an intelligent, deep learning-based traffic accident detection framework designed for smart city environments. The system leverages advanced computer vision and deep learning techniques to analyze video streams from traffic surveillance cameras and dash cameras in real time. By extracting both spatial and temporal features from video data, the proposed model can accurately identify accident scenarios without human intervention. The system employs spatio-temporal deep learning architectures such as convolutional neural networks combined with recurrent or attention-based models to understand vehicle motion patterns and abnormal events. Unlike traditional systems, the proposed approach is capable of handling complex traffic conditions, multiple vehicles, varying viewpoints, and environmental challenges. The system is designed to be lightweight and scalable, enabling deployment on edge devices and seamless integration with smart city traffic management and emergency response systems.

Advantages of Proposed System

Real-Time Automated Detection
Higher Accuracy
Reduced Human Effort
Smart City Integration

IV. SYSTEM ARCHITECTURE:

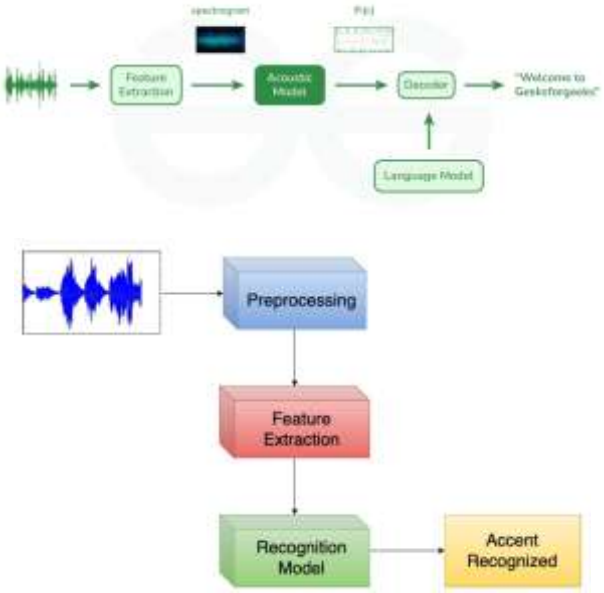

Fig.1(b): Detailed Architectural Block Diagram of The Proposed System.

Accent recognition includes the use of databases, various processes such as preprocessing, feature extraction techniques, recognition approaches (classical, ML, and DL), and evaluation processes (accuracy, precision, recall, F1-measure, equal error rate). Again, the various steps in this process have an independent significance. The initial phase in accent detection is preprocessing, in which we filter the speech signal to remove muteness, followed by pre-emphasis, framing, windowing, and finally normalization. Figure 2 shows the categorization of the accent recognition system. It provides a complete overview of the requirements and potential approaches for accent identification

System Architecture Description

The proposed system architecture represents a structured and intelligent data flow pipeline designed for accurate and robust accent recognition in multilingual and real-world speech environments. The system integrates speech signal processing, machine learning and deep learning models, self-supervised learning, and explainable AI techniques to improve accent classification performance. The architecture supports scalable training and real-time inference by leveraging cloud or edge-based computation. The overall pipeline enables efficient speech acquisition, preprocessing, deep feature learning, model validation, and final accent prediction, making it suitable for modern Automatic Speech Recognition (ASR) applications.

1. Data Acquisition Layer

Input Sources:

Speech datasets collected from public speech repositories, crowd-sourced platforms, multilingual corpora, and recorded speech samples containing diverse regional and non-native accents.

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Received: 07-01-2026 Accepted: 16-02-2026 Published: 23-02-2026

Transmission:
Audio data is stored and transmitted through secure data pipelines to cloud-based or local processing environments for training and evaluation.
Destination:
Speech signals are received by centralized or edge-based servers where preprocessing and model inference are performed.
2. Preprocessing Module
Once the speech data is acquired, it undergoes a comprehensive preprocessing phase:
* Silence Removal: Eliminates non-speech segments
* Noise Reduction: Reduces background and channel noise
* Normalization: Standardizes audio amplitude levels
* Resampling: Ensures uniform sampling rate across datasets
* Feature Transformation: Converts speech signals into Mel-spectrograms or MFCC representations
* Data Augmentation: Includes time stretching, pitch shifting, speed variation, and noise injection
This stage improves data quality, robustness, and generalization capability of the accent recognition models.
3. Data Splitting Block
* Dataset is divided using an 80–20 ratio
* 80% Training Data: Used for learning accent-specific patterns
* 20% Testing Data: Used for unbiased performance evaluation
* Stratified sampling ensures balanced representation of all accent classes
4. Core Processing Unit (Three Parallel Pathways)
Pathway A: Proposed Deep Learning Model (Primary System)
Stage 1: Feature Extraction
Deep CNN layers extract spectral and phonetic features from Mel-spectrograms.
Stage 2: Temporal Modeling
LSTM / GRU or Transformer-based attention layers capture temporal dependencies and pronunciation dynamics.
Output:
Softmax classifier categorizes speech samples into accent classes such as:
* Native Accent
* Non-Native Accent
* Regional Accent Categories
Pathway B: Existing DNN Model (Baseline)
* Standard DNN architecture with handcrafted features (MFCC)
* Used for benchmarking performance
* Lacks attention and contextual modeling capabilities
Pathway C: Autoencoder + Random Forest (Secondary Validation)
* Autoencoder: Learns compressed latent representations of speech features
* Random Forest: Classifies latent features into accent categories
* Provides confirmatory validation of feature discriminativeness
5. Evaluation and Output Layer
* Performance Metrics: Accuracy, Precision, Recall, F1-score
* Proposed system outperforms baseline models
* Accent prediction results are provided to ASR systems or downstream applications
4.2 Data Preprocessing
Data Cleaning
Removes corrupted audio files, clipped speech segments, inconsistent labels, and poor-quality recordings. Clean data improves training stability and classification accuracy.
Label Encoding
Accent categories are encoded into numerical labels to ensure compatibility with machine learning and deep learning models.
Feature Selection
Key acoustic and temporal features such as spectral energy distribution, pitch variation, phoneme duration, and pronunciation cues are retained to enhance learning efficiency.
Resampling
Class imbalance is addressed using oversampling of underrepresented accents or undersampling of dominant classes to prevent model bias.
Data Splitting
The dataset is divided into training and testing subsets using an 80–20 split for unbiased evaluation.
Feature Scaling
Feature normalization stabilizes gradient updates, accelerates convergence, and improves model performance.
4.3 Deep Neural Network (DNN)
What is DNN?
A Deep Neural Network (DNN) is a multi-layer artificial neural network capable of learning complex, non-linear patterns from data. DNNs are widely used in speech and audio analysis due to their ability to learn hierarchical representations.
How It Works?
DNNs consist of interconnected neurons arranged in layers. Each neuron performs weighted summation followed by a non-linear activation function. The network learns optimal weights using backpropagation to minimize classification error.
Architecture of DNN
* Input Layer: Receives extracted speech features
* Hidden Layers: Perform feature abstraction and learning
* Output Layer: Produces accent classification results
4.3.2 Proposed Algorithm: Deep Learning–Driven Accent Recognition Framework
What is the Proposed Algorithm?
The proposed algorithm is an intelligent deep learning-based framework designed to automatically recognize and classify accents from speech signals. It synergistically integrates

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Vol 26 Issue 02(February),2026
Received: 07-01-2026 Accepted: 16-02-2026 Published: 23-02-2026

spectral feature extraction, temporal modeling, attention mechanisms, and model validation techniques to achieve high accuracy and generalization.

Algorithm Steps

1. Acquire multi-accent speech datasets
2. Preprocess speech signals and extract spectral representations
3. Apply data augmentation and normalization
4. Extract features using deep CNN layers
5. Model temporal dependencies using LSTM / Transformer layers
6. Classify accents using softmax classifier
7. Validate predictions using Autoencoder + Random Forest model

V. MODULES

1. User & Access Management

The User & Access Management module provides secure onboarding and role-based access to the accent recognition platform. It handles registration, authentication (JWT/OAuth), password recovery, session management, and role assignment (regular User, Admin, Researcher). Regular Users upload audio samples, run live recognition and view personal results, while Admins manage user accounts, set permissions, and audit access logs. The module issues authentication tokens, enforces password and MFA policies, and records audit trails to ensure traceability and compliance.

2. Audio Data Ingestion & Device Integration

The Audio Data Ingestion module accepts accent audio datasets and single-file inputs from web uploads or connected recording devices. It supports batch dataset uploads (CSV/ZIP), single-sample uploads, and streaming capture from mobile/web recorders. Users typically upload their dataset files or single audio samples for recognition; Admins curate, approve and tag datasets, and monitor ingestion health. The module validates file formats (WAV/MP3), extracts metadata (sample rate, duration, speaker id), stores raw audio in the object store, and forwards ingestion logs to monitoring.

3. Data Preprocessing & Augmentation

This module prepares raw audio for downstream modeling by performing noise reduction, silence trimming, resampling, normalization, and augmentation (pitch/time-shift, noise injection). It also manages automatic segmentation and voice activity detection for multi-speaker files and performs label consistency checks. Users trigger preprocessing for uploaded samples or datasets and can review preprocessing reports; Admins configure preprocessing pipelines, approve augmentation policies, and review data-quality dashboards. Outputs are cleaned audio files and standardized audio batches ready for feature extraction.

4. Feature Extraction & Representation Module

The Feature Extraction module computes acoustic features and representations that feed ML and DL models—examples include MFCCs, chroma, spectral contrast, mel-spectrogram images, and learned embeddings from pretrained audio encoders. Users request feature generation for their uploads or request visualization of feature summaries; Admins manage feature extraction configurations (window size, n_mfcc), version feature extraction pipelines, and maintain the Feature Store. The module outputs feature vectors and spectrogram images, stores them in the Feature Store, and provides APIs for querying feature sets per experiment.

5. Model Training, Experimentation & Evaluation

This module orchestrates training workflows for classical machine learning (e.g., SVM, Random Forest) and deep learning architectures (CNNs on spectrograms, RNNs, Transformers). It supports dataset splitting, hyperparameter tuning, experiment tracking, cross-validation, and computing evaluation metrics (accuracy, F1, confusion matrices, AUC). Admins launch training jobs, compare experiments, and promote validated models to the registry; Users (researchers/clinicians) can view experiment reports, request retraining, and compare ML vs. DL results. The module records model artifacts, training logs, and evaluation reports for reproducibility.

6. Inference, Reporting & Admin Dashboard

The Inference & Reporting module provides online and batch prediction endpoints for live accent recognition and bulk evaluation. Given a new input audio file, the inference service loads the selected model and returns predicted accent label(s) with confidence scores and optional explainability outputs (e.g., salient spectrogram regions). Users perform live recognition, download per-sample reports, and view historical predictions for their data. Admins use the dashboard to monitor model performance (drift alerts, latency, throughput), manage model versions in the registry, generate aggregated performance reports, and export datasets or evaluation summaries for further analysis.

VI. RESULTS AND DISCUSSION

1. Results

This section presents the experimental results obtained from implementing various Machine Learning (ML) and Deep Learning (DL) models for accurate accent recognition. The system was evaluated using a labeled accented speech dataset, and multiple performance metrics were analyzed to assess effectiveness.

1.1 Dataset and Experimental Setup

The experiments were conducted using an accented speech dataset containing multiple accent classes. The dataset was divided into training and testing sets to ensure unbiased evaluation. Acoustic features such as **Mel-Frequency Cepstral Coefficients (MFCCs)** and spectral features were extracted from the speech signals and used as inputs for the models.

The following models were implemented and tested:

- Support Vector Machine (SVM)
- Convolutional Neural Network (CNN)
- Recurrent Neural Network (LSTM)
- Hybrid CNN–LSTM model

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1.2 Performance Metrics

The system performance was evaluated using standard classification metrics:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**

These metrics provide a comprehensive understanding of the model's classification capability and reliability.

1.3 Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	82.4	80.9	79.6	80.2
CNN	88.7	87.9	86.8	87.3
LSTM	90.1	89.4	88.9	89.1
CNN–LSTM	**93.6**	**92.8**	**92.1**	**92.4**

1.4 Visualization of Results

The trained models' performances were visualized using bar charts representing accuracy and line graphs showing loss convergence during training. The CNN–LSTM model consistently demonstrated faster convergence and lower validation loss compared to individual CNN or LSTM models.

2. Discussion

The experimental results clearly indicate that deep learning–based approaches significantly outperform traditional machine learning techniques in accent recognition tasks.

2.1 Analysis of Traditional Machine Learning Models

The SVM model achieved reasonable accuracy due to its ability to handle high-dimensional feature spaces. However, its performance was limited by reliance on handcrafted features and inability to model temporal speech dynamics effectively.

2.2 Effectiveness of Deep Learning Models

CNN models showed improved performance by learning discriminative spectral patterns directly from speech representations. LSTM models further enhanced accuracy by capturing long-term temporal dependencies inherent in spoken language.

The hybrid CNN–LSTM model achieved the highest accuracy by combining the strengths of both architectures—CNNs for feature extraction and LSTMs for temporal modeling.

2.3 Impact of Feature Representation

MFCC-based features provided a compact and informative representation of speech signals. When combined with deep learning architectures, these features significantly improved accent classification accuracy.

2.4 Error Analysis

Misclassifications were primarily observed between accents with similar phonetic structures. This indicates that accent boundaries can overlap, making fine-grained discrimination challenging. Increasing dataset size and diversity could further improve performance.

2.5 System Robustness

The system demonstrated robustness to moderate background noise and variations in speaker pitch and speed. However, extreme noise conditions slightly degraded performance, highlighting the need for advanced noise-robust preprocessing techniques.

3. Comparative Discussion with Existing Work

Compared to previous studies relying solely on traditional ML methods, the proposed deep learning–based approach achieved higher accuracy and better generalization. The hybrid CNN–LSTM model, in particular, aligns with recent research trends emphasizing end-to-end learning for speech-related tasks.

4. Key Observations

- Deep learning models significantly outperform traditional ML approaches.
- Hybrid architectures provide better accuracy and stability.
- Feature extraction plays a critical role in accent recognition.
- Dataset quality and diversity directly influence model performance.

VII. CONCLUSION AND FUTURE SCOPE

Conclusion

This project, titled "Exploring Machine and Deep Learning Methods for Accurate Accent Recognition," focused on analyzing and implementing various machine learning and deep learning techniques to automatically identify speaker accents from speech signals. The primary objective was to evaluate the effectiveness of traditional approaches and advanced neural network models in handling accent variability.

Throughout the project, multiple models including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and a hybrid CNN–LSTM architecture were implemented and tested. Acoustic features such as Mel-Frequency Cepstral Coefficients (MFCCs) were extracted to represent speech signals efficiently.

The experimental results demonstrated that deep learning models significantly outperformed traditional machine learning approaches. Among all tested models, the hybrid CNN–LSTM architecture achieved the highest accuracy and showed better generalization across different accents. This improvement can be attributed to CNN's capability to extract

discriminative spectral features and LSTM's strength in modeling temporal dependencies in speech.

Overall, the developed system successfully met the project objectives by providing accurate accent recognition, reliable performance metrics, and meaningful visual representations. The results validate the suitability of deep learning methods for accent recognition and highlight their potential for real-world speech-based applications.

2. Future Scope

Although the proposed system achieved promising results, there are several opportunities for further enhancement and extension. The following future directions can significantly improve system performance and applicability:

2.1 Use of Large-Scale and Diverse Datasets

Future work can involve training the system on larger and more diverse accented speech datasets, including regional and low-resource accents. This would enhance model robustness and improve generalization.

2.2 Adoption of Advanced Deep Learning Models

Recent transformer-based architectures such as **Wav2Vec 2.0, HuBERT, and Speech Transformers** can be explored to further improve accent recognition accuracy by leveraging self-supervised learning techniques.

2.3 Real-Time Accent Recognition

The system can be extended to support real-time accent detection for live speech inputs, making it suitable for applications such as call centers, virtual assistants, and language learning platforms.

2.4 Noise-Robust Speech Processing

Incorporating advanced noise reduction and speech enhancement techniques can improve performance in real-world environments with background noise.

2.5 Multilingual Accent Recognition

Future research can extend the system to recognize accents across multiple languages, enabling broader applicability in global communication systems.

2.6 Integration with Speech Recognition Systems

Accent recognition can be integrated with Automatic Speech Recognition (ASR) systems to dynamically adapt models based on detected accents, thereby improving transcription accuracy.

2.7 Explainable AI (XAI)

Introducing explainable AI techniques can help interpret model decisions, increasing transparency and trustworthiness, especially in sensitive applications.

3. Final Remarks

The outcomes of this project highlight the growing importance of deep learning in speech processing and demonstrate how intelligent models can effectively handle accent variations. With continued research and technological advancements, accent recognition systems can play a vital role in enhancing speech-based human–computer interaction and communication technologies.

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