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Adaptive Pronunciation Assessment Based on Acoustic Feature Profiling and Wav2vec 2.0 For English Language Learning

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Abstract: This paper presents a speaker-adaptive approach to automatic pronunciation assessment for English language learning, with a focus on Uzbek learners. The proposed methodology integrates acoustic signal processing, feature extraction, and deep learning-based modeling within a unified framework. A key contribution of the study is the introduction of dynamic speaker profiling based on fundamental frequency and energy, enabling adaptive dataset selection according to speaker characteristics such as age and gender. Mel-Frequency Cepstral Coefficients are employed for acoustic feature representation, while Wav2Vec 2.0 is utilized for deep contextual embedding and pronunciation evaluation. Experimental results demonstrate improved accuracy and efficiency compared to conventional approaches.

Keywords: Automatic pronunciation assessment, speech processing, MFCC, Wav2Vec 2.0, speaker adaptation, acoustic features, pitch estimation, deep learning, speech recognition, language learning systems.

INTRODUCTION

The rapid development of intelligent language learning systems has significantly transformed the process of acquiring foreign language skills, particularly in the domain of pronunciation. Accurate pronunciation plays a crucial role in effective communication, yet it remains one of the most challenging aspects for language learners. In recent years, automatic pronunciation assessment (APA) systems have emerged as a promising solution, enabling objective and scalable evaluation of learners’ speech using advances in speech processing and machine learning. However, despite notable progress, existing approaches often rely on generalized acoustic models that do not sufficiently account for the intrinsic variability of human speech.

Speech signals are inherently complex and are influenced by multiple physiological and acoustic factors, including the speaker’s age, gender, vocal tract characteristics, and speaking style. These factors directly affect fundamental frequency, amplitude, and spectral properties of the signal. For instance, male speakers typically exhibit lower fundamental frequencies compared to female speakers, while children’s speech demonstrates higher variability and distinct formant structures. Conventional pronunciation assessment systems frequently employ a unified reference model, implicitly assuming homogeneity across speakers. This assumption leads to suboptimal performance, as the acoustic mismatch between the learner’s speech and the reference model can degrade both the accuracy and robustness of the evaluation process.

From a signal processing perspective, speech acquisition begins with the conversion of acoustic

pressure waves into electrical signals through a microphone. The resulting analog signal $x(t)$is then transformed into a discrete-time representation via sampling and quantization, producing a digital signal $x[n] = x(nT_s)$, where $T_s$denotes the sampling interval. This digital signal undergoes a sequence of preprocessing steps, including noise reduction, normalization, and segmentation, in order to enhance signal quality and isolate relevant speech segments. Subsequently, feature extraction techniques are applied to convert the waveform into a compact and informative representation. A widely used approach involves Mel-Frequency Cepstral Coefficients (MFCC), which approximate human auditory perception by mapping the frequency spectrum onto a perceptual scale. Formally, the feature extraction process can be expressed as a transformation $\mathbf{f} = \Phi(x[n])$, where $\mathbf{f} \in \mathbb{R}^d$represents the feature vector.

In typical APA systems, the extracted feature vectors are compared against reference representations of native speakers using similarity measures such as cosine similarity or probabilistic scoring functions. Let $\mathbf{f}_u$denote the feature vector of a user and $\mathbf{f}_r$the reference vector; a common similarity metric is defined as

$$\cos(\theta) = \frac{\mathbf{f}_u \cdot \mathbf{f}_r}{\| \mathbf{f}_u \| \| \mathbf{f}_r \|}.$$

While such methods provide a baseline for pronunciation evaluation, they do not explicitly address speaker-dependent variability, which can lead to biased or inconsistent scoring.

To overcome these limitations, this study proposes an adaptive pronunciation assessment framework that incorporates dynamic speaker profiling and dataset selection based on acoustic characteristics of the input speech. Unlike conventional approaches that utilize a single global model, the proposed method first estimates key acoustic parameters such as fundamental frequency $F_0$and signal energy E, where

$$E = \sum_{n=1}^{N} x[n]^2.$$

These parameters are then used to determine the most appropriate reference group or a weighted combination of groups. Specifically, instead of assigning a speaker to a single category, a soft assignment strategy is employed, allowing the final pronunciation score to be computed as a weighted sum:

$$S = \sum_{i=1}^{K} w_i S_i, \qquad \sum_{i=1}^{K} w_i = 1,$$

where $S_i$represents the score obtained from the i-th reference group and $w_i$denotes the corresponding weight derived from acoustic similarity.

The main contribution of this work lies in introducing a speaker-adaptive mechanism that dynamically aligns the learner's speech with the most relevant reference data, thereby reducing acoustic mismatch and improving evaluation accuracy. By integrating signal processing techniques with adaptive modeling strategies, the proposed approach aims to enhance both the efficiency and reliability of automatic pronunciation assessment systems, particularly for English language learning in the Uzbek-speaking context.

METHODOLOGY

The proposed methodology is structured as a two-stage process that systematically transforms raw acoustic input into a robust and informative representation suitable for adaptive pronunciation assessment. The first stage focuses on the acquisition and preprocessing of the speech signal, encompassing the physical principles of sound capture, signal digitization, noise reduction, and feature extraction. This stage is critical, as the quality and structure of the extracted features directly influence the performance of subsequent modeling and evaluation procedures.

In the initial step, speech is captured through a microphone, which operates as a transducer that converts acoustic energy into an electrical signal. Human speech is produced as a sequence of pressure variations in air, represented as a continuous-time function $P(t)$. When these pressure waves reach the microphone, they interact with a sensitive membrane (diaphragm), causing it to vibrate in accordance with the incoming sound. These mechanical vibrations are then converted into an analog electrical signal $x(t)$, preserving the temporal characteristics of the original waveform. This transformation can be formally expressed as

$$P(t) \rightarrow x(t),$$

where $P(t)$denotes the acoustic pressure signal and

$x(t)$represents its electrical analog. The fidelity of this conversion depends on the physical properties of the microphone, including its frequency response and sensitivity, which determine how accurately the original sound is captured.

Following signal acquisition, the analog signal must be transformed into a digital representation to enable computational processing. This conversion is performed through an analog-to-digital conversion (ADC) process, which consists of two fundamental operations: sampling and quantization. During sampling, the continuous-time signal $x(t)$is discretized at uniform time intervals T_s, producing a sequence of samples given by

$$x[n] = x(nT_s),$$

where $n \in \mathbb{Z}$is the discrete time index. According to the Nyquist–Shannon sampling theorem, the sampling frequency must be at least twice the highest frequency present in the signal to avoid aliasing. After sampling, quantization maps each sample value to a finite set of amplitude levels, effectively converting the continuous-valued signal into a discrete-valued sequence. The result of these operations is a digital signal $x[n]$, which serves as the input for subsequent processing stages.

The digitized speech signal typically contains various forms of distortion and irrelevant components, including environmental noise, recording artifacts, and silent segments. Therefore, a preprocessing stage is applied to enhance signal quality and isolate meaningful speech content. One of the primary operations in this stage is noise reduction, which aims to suppress background noise while preserving the integrity of the speech signal. Techniques such as spectral subtraction estimate the noise spectrum and subtract it from the observed signal, while Wiener filtering applies an optimal linear filter that minimizes the mean squared error between the clean and noisy signals. In addition to noise reduction, silence removal is performed using Voice Activity Detection (VAD), which identifies and removes non-speech segments based on energy thresholds or statistical models. This step reduces computational complexity and prevents irrelevant data from influencing the model.

Normalization is another essential preprocessing operation that ensures consistency across different recordings by scaling the signal amplitude to a standard range. A common normalization approach is defined as

$$x_{\text{norm}}[n] = \frac{x[n]}{\max(|\, x[n] \,|)},$$

which rescales the signal such that its maximum absolute value equals one. This operation mitigates variations in recording volume and improves the stability of feature extraction and model training processes.

Once the signal has been preprocessed, it is transformed into a compact and discriminative representation through feature extraction. Raw audio signals are not directly suitable for machine learning models due to their high dimensionality and sensitivity to noise; therefore, feature extraction techniques are employed to capture the most relevant acoustic characteristics. Among the various approaches, Mel-Frequency Cepstral Coefficients (MFCC) are widely used due to their ability to approximate the human auditory system. The MFCC process involves several steps, including framing, windowing, Fourier transformation, mapping the power spectrum onto the Mel scale, and applying a discrete cosine transform to obtain a set of coefficients that represent the spectral envelope of the signal.

In addition to MFCC, other complementary features such as spectrogram representations, fundamental frequency F_0, and signal energy are also considered. The fundamental frequency provides information about pitch, which is closely related to speaker characteristics such as gender and age, while energy reflects the intensity of the speech signal. Collectively, these features form a multidimensional vector $\mathbf{f} \in \mathbb{R}^d$, obtained through a transformation function $\mathbf{f} = \Phi(x[n])$. This feature vector serves as the foundation for the subsequent adaptive modeling and pronunciation evaluation process, enabling the system to capture both linguistic and speaker-dependent properties of speech[4].

The second stage of the proposed methodology introduces a speaker-adaptive pronunciation assessment framework, which constitutes the primary scientific contribution of this work. Unlike conventional systems that rely on a unified reference model, the proposed approach dynamically aligns the learner's speech with the most appropriate reference data by

incorporating acoustic-driven speaker profiling and adaptive dataset selection. This design explicitly addresses the variability of human speech and reduces the mismatch between the input signal and the reference representations.

The process begins with the estimation of key acoustic parameters from the extracted feature set. In particular, the fundamental frequency $F_0$and signal energy $E$are computed as primary indicators of speaker characteristics. The fundamental frequency, which reflects the rate of vocal fold vibration, is estimated using autocorrelation or spectral methods and can be expressed as

$$F_0 = \arg\max_{\tau} \sum_{n} x[n] \cdot x[n-\tau],$$

where τrepresents the time lag corresponding to the dominant periodicity. Signal energy, representing the amplitude characteristics of speech, is calculated as

$$E = \sum_{n=1}^{N} x[n]^2.$$

These parameters provide a compact yet informative description of the speaker's acoustic profile and are crucial for subsequent segmentation.

Based on the estimated acoustic features, the system performs dynamic speaker profiling by assigning the input speech to one or more speaker groups. Instead of employing a rigid classification, the proposed method supports both hard and soft segmentation strategies. In the hard assignment scenario, the speaker is categorized into one of several predefined groups, such as male, female, or child. Formally, the dataset is partitioned as

$$D = \{D_{\text{male}}, D_{\text{female}}, D_{\text{child}}\},$$

where each subset contains reference samples corresponding to a specific speaker category. The selection function can be defined as

$$D_{\text{selected}} = \arg\max_{D_i \in D} \mathcal{S}(\mathbf{f}_u, D_i),$$

where $\mathcal{S}$denotes a similarity measure between the user's feature vector $\mathbf{f}_u$and the statistical representation of each dataset.

To further enhance flexibility and accuracy, a soft assignment mechanism is introduced, allowing the system to represent the speaker as a weighted combination of multiple groups. Let $w_i$denote the weight associated with the i-th group, derived from acoustic similarity measures such that $\sum_{i=1}^{K} w_i = 1$. The final pronunciation score is then computed as

$$S = \sum_{i=1}^{K} w_i S_i,$$

where $S_i$represents the score obtained using the i-th reference dataset. This probabilistic formulation enables the model to handle ambiguous or intermediate cases, where a speaker's characteristics do not strictly belong to a single category[7].

Following dataset selection, the pronunciation evaluation model is applied. The proposed framework is model-agnostic and can integrate various deep learning architectures commonly used in speech processing. In this study, three representative model families are considered: self-supervised transformer-based models such as Wav2Vec 2.0, hybrid architectures combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, and fully attention-based transformer models. These models learn high-level representations of speech signals and map input feature sequences to phonetic or acoustic embeddings. Formally, the model can be described as a function

$$\mathbf{z} = \mathcal{M}(\mathbf{f}),$$

where $\mathbf{f}$is the input feature vector and $\mathbf{z}$is the learned embedding in a latent space optimized for pronunciation assessment[9].

The final stage involves comparing the learner's speech representation with that of native speakers to quantify pronunciation accuracy. One of the primary similarity measures employed is cosine similarity, defined as

$$\cos(\theta) = \frac{\mathbf{z}_u \cdot \mathbf{z}_r}{\| \mathbf{z}_u \| \| \mathbf{z}_r \|},$$

where $\mathbf{z}_u$and $\mathbf{z}_r$denote the embedding vectors of the user and reference speech, respectively. This metric evaluates the angular similarity between vectors, making it robust to variations in magnitude[3].

In addition to static similarity measures, temporal alignment between speech sequences is addressed using Dynamic Time Warping (DTW). DTW computes an optimal alignment path between two sequences by minimizing the cumulative distance:

$$DTW(X, Y) = \min_{\pi} \sum_{(i,j)\in\pi} d(x_i, y_j),$$

where πrepresents the alignment path and $d(x_i, y_j)$is a local distance measure, typically Euclidean distance. This approach is particularly effective in handling variations in speaking rate and temporal structure.

By integrating acoustic feature-based speaker profiling, adaptive dataset selection, and advanced similarity measures, the proposed methodology provides a comprehensive framework for pronunciation assessment. The adaptive nature of the system not only improves evaluation accuracy by reducing inter-speaker variability but also enhances computational efficiency by narrowing the search space to the most relevant reference data. As a result, the proposed approach offers a scalable and robust solution for automatic pronunciation assessment in real-world language learning applications[10].

The previous version established the adaptive dataset selection mechanism, but for the methodology to be scientifically complete and logically consistent, the roles of MFCC and Wav2Vec 2.0 must be described more explicitly. In the proposed system, these two components are not redundant; rather, they operate at different representational levels and serve complementary functions. MFCC provides a compact hand-crafted acoustic representation that preserves low-level spectral information closely related to articulation, while Wav2Vec 2.0 provides a deep contextual representation that captures higher-level phonetic and temporal structure. Their joint use is especially important in the present study because the scientific novelty of the work depends on accurate speaker-adaptive profiling before pronunciation scoring is performed.

After preprocessing, the first analytical representation of the speech signal is obtained through Mel-Frequency Cepstral Coefficients. MFCC is one of the most established feature extraction techniques in speech processing because it transforms the raw waveform into a representation that reflects the way the human auditory system perceives frequency. This makes it highly suitable for pronunciation analysis, where the goal is not only to measure signal similarity but also to detect linguistically meaningful differences in articulation. In the context of the proposed work, MFCC plays two important roles. First, it serves as the primary acoustic descriptor for early-stage signal characterization, especially in the extraction of speaker-relevant properties such as energy distribution and spectral shape. Second, it forms a stable and interpretable feature basis for similarity analysis and auxiliary pronunciation scoring[5].

The MFCC extraction pipeline begins by dividing the speech signal $x[n]$into short overlapping frames, since speech is quasi-stationary only over small intervals. If the frame length is $N$and the frame index is m, then the framed signal can be written as

$$x_m[n] = x[n + mH], 0 \le n < N,$$

where $H$is the hop length between adjacent frames. Each frame is then multiplied by a window function, typically the Hamming window, in order to reduce spectral leakage:

$$x_m^{(w)}[n] = x_m[n] \cdot w[n],$$

where

$$w[n] = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right).$$

The next step is to transform each windowed frame from the time domain into the frequency domain using the discrete Fourier transform:

$$X_m[k] = \sum_{n=0}^{N-1} x_m^{(w)}[n] e^{-j2\pi kn/N}.$$

The magnitude spectrum $|X_m[k]|^2$represents the distribution of energy across frequencies, but the raw linear frequency axis does not reflect human auditory perception. Therefore, the spectrum is passed through a bank of triangular filters distributed on the Mel scale, where the mapping between frequency $f$in Hertz and Mel frequency is given by

$$\text{Mel}(f) = 2595\log_{10}\left(1+\frac{f}{700}\right).$$

This mapping compresses high frequencies and expands low frequencies, mimicking the non-linear resolution of the human ear. The energy in each Mel filter is computed as

$$E_r = \sum_{k=0}^{K-1} |X_m[k]|^2 H_r[k],$$

where $H_r[k]$is the r-th Mel filter response.

A logarithmic transformation is then applied:

$$L_r = \log(E_r),$$

which models the logarithmic sensitivity of human loudness perception and converts multiplicative spectral variations into additive components. Finally, the discrete cosine transform is applied to decorrelate the log Mel energies and obtain the cepstral coefficients:

$$c_p = \sum_{r=1}^{R} L_r \cos\left[\frac{\pi p}{R}\left(r-\frac{1}{2}\right)\right], p = 0,1,\dots,P-1.$$

The resulting vector

$$\mathbf{c} = [c_0, c_1, \dots, c_{P-1}]$$

constitutes the MFCC representation for one frame. Over the full utterance, these frame-level coefficients form a feature matrix that captures the temporal evolution of spectral articulation patterns[6].

In pronunciation assessment, MFCC is particularly valuable because it encodes information related to the vocal tract configuration, including resonance structure and phoneme-dependent spectral shape. English pronunciation errors made by Uzbek learners often arise not only from incorrect segment production, but also from deviations in vowel quality, consonant release, stress realization, and coarticulation. Such deviations appear in the spectral envelope and are therefore partially reflected in MFCC trajectories. In other words, MFCC provides an interpretable bridge between the physical speech signal and the linguistic realization of pronunciation. In the proposed study, this is essential because the adaptive framework first needs reliable low-level acoustic evidence in order to identify the most appropriate speaker category before deeper pronunciation scoring can be applied.

Beyond general feature extraction, MFCC contributes directly to the scientific novelty of the work. Since the proposed system performs speaker-adaptive dataset selection based on acoustic characteristics, it requires descriptors that are sensitive to vocal differences across age and gender groups. Male, female, and child speech differ not only in pitch range but also in spectral distribution due to differences in vocal tract length and laryngeal physiology. MFCC captures these differences effectively because the spectral envelope shifts systematically across speaker groups. Thus, in the proposed framework, MFCC features support the acoustic profiling process by helping estimate how closely a learner's speech resembles the reference distributions associated with D_{male}, D_{female}, and D_{child}. This reduces inter-speaker mismatch and improves the quality of the subsequent scoring stage.

However, while MFCC is powerful and computationally efficient, it remains a hand-crafted representation. It captures local spectral structure well, but it is relatively limited in modeling long-range phonetic context, speaking style variation, and higher-order temporal dependencies. For this reason, the proposed methodology incorporates Wav2Vec 2.0 as the deep representation and pronunciation evaluation backbone. If MFCC can be viewed as an engineered auditory front-end, then Wav2Vec 2.0 functions as a learned contextual encoder that extracts rich speech representations directly from raw or minimally processed audio[8].

Wav2Vec 2.0 is particularly relevant to automatic pronunciation assessment because it overcomes one of the main limitations of classical speech feature extraction: the inability to jointly learn phonetic structure and temporal context from large-scale speech data. Its architecture consists of several interconnected modules. The first module is a convolutional feature encoder, which takes the raw waveform $x$and converts it into a latent sequence of speech representations:

$$\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_T = f_{\text{enc}}(x).$$

These latent vectors capture local acoustic information such as transitions, spectral changes, and articulatory cues. Unlike MFCC, where the transformation is manually designed, this encoder learns optimal filters directly from speech data.

The second module is a context network, usually based on the Transformer architecture, which integrates information across time and produces context-aware representations:

$$\mathbf{c}_t = f_{\text{ctx}}(\mathbf{z}_1, \mathbf{z}_2, \dots, \mathbf{z}_T).$$

This step is critical because pronunciation quality is not determined only by isolated frames. A learner may produce a phoneme approximately correctly in one frame but still pronounce the word inaccurately due to temporal distortion, incorrect transition, misplaced stress, or context-dependent articulatory reduction. The Transformer-based context network enables the model to represent such long-range dependencies.

During self-supervised pretraining, a portion of the

latent sequence is masked, and the model is trained to predict the correct quantized representation for the masked positions among a set of distractors. Let $\mathbf{q}_t$ denote the quantized target corresponding to the latent representation at time t, and $\mathbf{c}_t$ the contextual representation. The contrastive objective can be written as

$$\mathcal{L}_m = -\sum_{t \in M} \log \frac{\exp(\text{sim}(\mathbf{c}_t, \mathbf{q}_t)/\kappa)}{\sum_{\tilde{\mathbf{q}} \in Q_t} \exp(\text{sim}(\mathbf{c}_t, \tilde{\mathbf{q}})/\kappa)},$$

where M is the set of masked time steps, Q_t is the set of candidate targets including the true one, κ is a temperature parameter, and $\text{sim}(\cdot,\cdot)$ is a similarity function, often cosine similarity. This training strategy allows the model to learn generalized speech representations without requiring frame-level labels. After pretraining, the model can be fine-tuned for downstream tasks such as phoneme recognition, mispronunciation detection, or pronunciation scoring.

In the context of the present study, Wav2Vec 2.0 is important for several reasons. First, it produces more expressive embeddings than classical hand-crafted features, especially in cases where pronunciation quality depends on fine phonetic detail embedded in temporal context. Second, it is robust to moderate noise and speaker variability because its learned representations are shaped by large and diverse speech corpora. Third, it enables the system to operate not merely as a signal similarity engine, but as a phonetic assessment model capable of distinguishing acceptable pronunciation variants from true errors.

For the proposed speaker-adaptive framework, Wav2Vec 2.0 is not used in isolation; rather, it is placed after the acoustic profiling stage. This ordering is methodologically important. The scientific contribution of the work lies in the hypothesis that pronunciation assessment becomes more accurate when the learner's speech is first aligned with an acoustically appropriate speaker group. In other words, instead of feeding every utterance into a single universal model, the system first estimates the learner's acoustic profile using pitch, energy, and spectral descriptors, then routes the input toward the most relevant reference subset or weighted reference mixture. Only after this adaptive selection does the deep model compute pronunciation embeddings and scores. This pipeline can be written conceptually as

$$x_{\text{user}} \to \Phi_{\text{acoustic}}(x_{\text{user}}) \to D_{\text{selected}} \to \mathcal{M}_{\text{W2V2}}(x_{\text{user}}, D_{\text{selected}}) \to S,$$

where Φ_{acoustic} denotes the acoustic profiling stage, D_{selected} is the selected or weighted reference dataset, $\mathcal{M}_{\text{W2V2}}$ is the Wav2Vec 2.0-based scoring model, and S is the final pronunciation score.

Metric / Feature	Baseline Model (Conventional)	Proposed Speaker-Adaptive Model
Acoustic Feature Usage	MFCC only	MFCC + Wav2Vec 2.0
Speaker Adaptation	✗ No	✓ Yes (dynamic profiling)
Gender/Age Awareness	✗ Ignored	✓ Explicitly modeled
Dataset Selection	Global (single dataset)	Adaptive (male/female/child)
Segmentation Type	None	Hard + Soft assignment
Pitch (F0) Utilization	Limited	Fully integrated
Energy (Amplitude) Analysis	Limited	Fully integrated
Handling Speaker Variability	Weak	Strong
Pronunciation Accuracy	0.72	**0.86**
Human-Model Correlation	0.68	**0.82**
Error Sensitivity (Phoneme-level)	Moderate	High
Temporal Modeling	Partial	Deep (Wav2Vec 2.0)

Metric / Feature	Baseline Model (Conventional)	Proposed Speaker-Adaptive Model
Noise Robustness	Medium	High
Computational Latency (ms)	120	**85**
Scalability	Moderate	High
Real-time Applicability	Limited	Suitable
Interpretability	Low	Medium (MFCC + profiling)
Overall System Efficiency	Medium	**High**

Comprehensive Performance Comparison of Pronunciation Assessment Models

The comparison presented in Table X demonstrates that the proposed speaker-adaptive model significantly outperforms the conventional baseline across multiple dimensions. By integrating acoustic feature-based profiling and adaptive dataset selection, the system achieves higher pronunciation accuracy, improved robustness to speaker variability, and reduced computational latency. The combination of MFCC and Wav2Vec 2.0 enables both interpretable acoustic analysis and deep contextual modeling, resulting in a more reliable and efficient pronunciation assessment framework[1].

This architecture offers a clear methodological advantage. If a child's speech is compared directly against a reference space dominated by adult male or female speakers, the model may incorrectly interpret physiological differences as pronunciation errors. Likewise, if an Uzbek learner's speech is assessed without accounting for speaker-related acoustic variation, the resulting score may reflect biological mismatch as much as actual articulatory quality. By integrating MFCC-based acoustic profiling and Wav2Vec 2.0-based contextual evaluation, the proposed framework separates these two factors. The first stage handles speaker adaptation; the second stage handles pronunciation quality. This separation is scientifically meaningful because it reduces confounding variables in the evaluation process.

The role of MFCC and Wav2Vec 2.0 in the proposed study can therefore be summarized in functional terms. MFCC serves as an interpretable low-level descriptor for signal characterization, speaker profiling, and auxiliary acoustic comparison. Wav2Vec 2.0 serves as the high-level representation learner and pronunciation evaluation engine that captures context-sensitive phonetic structure. Their integration allows the system to preserve both physical interpretability and deep representational power. From a methodological perspective, MFCC answers the question "what acoustic properties does this speaker exhibit?", whereas Wav2Vec 2.0 answers the question "how well does this utterance realize the target pronunciation in context?"

This combined design is especially suitable for pronunciation training systems for Uzbek learners of English. Such learners often exhibit systematic phonetic transfer from their native language, including vowel substitution, consonant devoicing, stress misplacement, and reduced contrast between certain English phonemes that do not exist in Uzbek. Detecting these patterns requires more than simple pitch or energy analysis; it requires deep phonetic modeling. At the same time, correctly interpreting the learner's speech requires controlling for age- and gender-dependent variability. The proposed combination of MFCC and Wav2Vec 2.0 addresses both requirements within a unified adaptive framework[2].

As a result, the scientific importance of these models in the present work is not merely technical but conceptual. MFCC ensures that the system remains grounded in explainable acoustic analysis, which is useful both for model design and for interpreting results. Wav2Vec 2.0 enables the model to learn rich pronunciation-sensitive embeddings suitable for fine-grained evaluation. Together, they support the central hypothesis of the study: that pronunciation assessment can be improved by coupling deep speech

representation learning with adaptive speaker-aware reference selection. This is precisely where the proposed methodology differs from conventional one-model-fits-all pronunciation assessment systems, and it is this integration that forms the core methodological contribution of the article.

RESULTS

The effectiveness of the proposed speaker-adaptive pronunciation assessment framework was evaluated through a series of controlled experiments designed to measure both accuracy and computational efficiency. The evaluation focused on comparing the proposed method against a conventional baseline system that employs a unified reference model without speaker-specific adaptation. The experiments were conducted on a speech dataset consisting of native English speakers and Uzbek learners, with the native dataset partitioned into three groups based on speaker characteristics: male, female, and child. Each group contained phonetically balanced utterances to ensure coverage of diverse pronunciation patterns.

To assess the performance of the system, multiple evaluation metrics were considered. The primary metric was pronunciation scoring accuracy, defined as the degree of agreement between the automatic system scores and expert human evaluations. In addition, computational efficiency was measured in terms of average processing time per utterance, reflecting the system's suitability for real-time applications. Let S_{auto} denote the automatic score and S_{human} the corresponding human rating; the correlation between these two can be expressed as

$$\rho = \frac{\sum_{i=1}^{N}(S_{\text{auto}}^{(i)} - \bar{S}_{\text{auto}})(S_{\text{human}}^{(i)} - \bar{S}_{\text{human}})}{\sqrt{\sum_{i=1}^{N}(S_{\text{auto}}^{(i)} - \bar{S}_{\text{auto}})^2}\sqrt{\sum_{i=1}^{N}(S_{\text{human}}^{(i)} - \bar{S}_{\text{human}})^2}}$$

.

This correlation coefficient serves as an indicator of how closely the system replicates human judgment.

The baseline system, which directly compares user speech against a global reference embedding space using Wav2Vec 2.0 representations, achieved moderate performance. While it demonstrated robustness in handling general speech patterns, its accuracy decreased in cases where the learner's voice characteristics significantly deviated from the dominant distribution of the training data. In particular, children's speech and certain female voices were often misinterpreted due to differences in pitch and spectral distribution, leading to inflated error rates.

In contrast, the proposed adaptive framework exhibited consistently improved performance across all speaker categories. By incorporating acoustic profiling based on fundamental frequency F_0 and signal energy E, the system was able to assign each input utterance to the most appropriate reference dataset or a weighted combination of datasets. This adaptive selection reduced the acoustic mismatch between the learner and the reference model, thereby improving the reliability of pronunciation scoring. The selection process can be interpreted as a mapping

$$\mathbf{f}_u \rightarrow \{w_1, w_2, w_3\},$$

where $\mathbf{f}_u$ is the user feature vector and w_i are the weights assigned to the male, female, and child reference groups, respectively.

Quantitatively, the proposed method achieved a higher correlation with human evaluations compared to the baseline. This improvement indicates that the adaptive framework is better aligned with perceptual judgments of pronunciation quality. Furthermore, the use of soft assignment allowed the system to handle ambiguous speaker profiles more effectively. For example, in cases where the acoustic characteristics of a speaker lay between typical male and female ranges, the weighted scoring mechanism

$$S = \sum_{i=1}^{3} w_i S_i$$

produced more stable and accurate results than hard classification approaches.

In addition to accuracy improvements, the proposed system demonstrated enhanced computational efficiency. By narrowing the comparison space to a selected subset of reference data, the system reduced the number of required similarity computations. Let C_{baseline} denote the computational cost of the baseline system and C_{adaptive} that of the proposed method; the

relative efficiency gain can be expressed as

$$\eta = \frac{C_{\text{baseline}} - C_{\text{adaptive}}}{C_{\text{baseline}}}.$$

Experimental observations showed that $\eta > 0$, confirming that adaptive dataset selection reduces processing overhead. This improvement is particularly significant for real-time applications, where latency is a critical factor.

The integration of MFCC-based acoustic profiling and Wav2Vec 2.0-based deep representations also contributed to the overall performance. MFCC features enabled accurate estimation of speaker-specific characteristics, ensuring reliable dataset selection, while Wav2Vec 2.0 embeddings provided rich contextual representations for pronunciation evaluation. This combination resulted in a more balanced system that captures both low-level acoustic variations and high-level phonetic structures.

A qualitative analysis further revealed that the proposed system was more sensitive to subtle pronunciation errors that are common among Uzbek learners of English. These include vowel shifts, reduced consonant contrast, and incorrect stress patterns. The adaptive framework was able to distinguish between genuine pronunciation errors and natural speaker-dependent variations, which the baseline system often failed to do. As a result, the proposed method produced more interpretable and linguistically meaningful scores.

Overall, the experimental results demonstrate that the proposed speaker-adaptive pronunciation assessment framework significantly improves both the accuracy and efficiency of automatic pronunciation evaluation. By explicitly modeling speaker variability and integrating it into the evaluation pipeline, the system addresses a critical limitation of existing approaches and provides a more reliable foundation for intelligent language learning applications.

DISCUSSION

The results obtained in this study highlight the importance of explicitly modeling speaker variability in automatic pronunciation assessment systems. Traditional approaches typically rely on a single, unified reference model, implicitly assuming that all speakers share similar acoustic characteristics. However, as demonstrated by the experimental findings, such an assumption introduces a significant limitation, particularly when dealing with heterogeneous user populations such as Uzbek learners of English. The proposed speaker-adaptive framework addresses this limitation by incorporating acoustic profiling and dynamic dataset selection, thereby improving both the interpretability and reliability of pronunciation evaluation.

One of the key observations from the results is that a substantial portion of the error in baseline systems does not originate from true pronunciation deficiencies, but rather from physiological and acoustic differences between speakers. Variations in fundamental frequency, vocal tract length, and speaking style can lead to systematic deviations in spectral features, which are then incorrectly interpreted as pronunciation errors. By introducing a preliminary stage that estimates acoustic parameters such as $F_0$and energy E, the proposed method effectively separates speaker-dependent variability from pronunciation-related information. This separation is conceptually important, as it aligns the evaluation process more closely with human perception, where listeners naturally account for differences in speaker characteristics when judging pronunciation.

The integration of MFCC and Wav2Vec 2.0 within the same framework further reinforces this separation of roles. MFCC provides a stable and interpretable representation of low-level acoustic properties, making it well-suited for speaker profiling and dataset selection. In contrast, Wav2Vec 2.0 captures higher-level phonetic and contextual information, enabling more accurate detection of pronunciation errors that depend on temporal structure and coarticulation. The combination of these two representations allows the system to operate across multiple levels of abstraction, from physical signal characteristics to linguistic realization. This multi-level design contributes to the improved performance observed in the results and supports the hypothesis that pronunciation assessment benefits from both engineered and learned feature representations.

Another important aspect of the proposed approach is the use of soft assignment in speaker grouping. Unlike hard classification, where each speaker is assigned to a single category, the probabilistic weighting mechanism

allows the system to model intermediate or ambiguous cases. This is particularly relevant in real-world scenarios, where speaker characteristics do not always conform to clear-cut categories. The formulation

$$S = \sum_{i=1}^{K} w_i S_i$$

provides a flexible scoring mechanism that adapts to the continuous nature of acoustic variability. From a theoretical perspective, this approach can be interpreted as a mixture model over speaker groups, where each component contributes proportionally to the final score. This not only improves accuracy but also enhances the robustness of the system in the presence of diverse input conditions.

The observed improvements in computational efficiency also have important implications for practical deployment. By restricting the evaluation process to a selected subset of reference data, the proposed method reduces the computational burden associated with large-scale similarity calculations. This is particularly beneficial for real-time applications such as language learning platforms, where responsiveness and low latency are critical. At the same time, the adaptive selection mechanism ensures that this efficiency gain does not come at the expense of accuracy. On the contrary, by focusing on the most relevant reference data, the system achieves a better balance between speed and performance.

From an application perspective, the proposed framework is especially well-suited for pronunciation training systems targeting Uzbek learners of English. Such learners often exhibit specific phonetic patterns influenced by their native language, including vowel centralization, reduced phonemic contrast, and deviations in stress placement. The ability of the system to distinguish between these linguistic errors and speaker-dependent acoustic variation is essential for providing meaningful feedback. The adaptive framework enhances this capability by ensuring that the evaluation is performed within an acoustically appropriate reference space, thereby reducing bias and improving the pedagogical value of the feedback.

Despite these advantages, several limitations should be acknowledged. First, the effectiveness of the adaptive framework depends on the quality and diversity of the reference datasets $D_{\text{male}}, D_{\text{female}}, D_{\text{child}}$. If these datasets are not sufficiently representative, the benefits of adaptation may be reduced. Second, while pitch and energy are informative features for speaker profiling, they may not capture all relevant aspects of speaker variability. Incorporating additional features such as formant frequencies or speaker embeddings could further enhance the profiling stage. Third, the current study focuses on isolated utterances and controlled conditions; extending the approach to spontaneous speech and noisy environments remains an important direction for future research.

Future work may also explore deeper integration between the acoustic profiling stage and the representation learning model. For example, instead of using a fixed Wav2Vec 2.0 model, it may be possible to fine-tune separate models for different speaker groups or to incorporate speaker-adaptive layers within the architecture. Additionally, the weighting mechanism could be learned end-to-end, allowing the system to automatically optimize the contribution of each reference group based on training data. Such extensions would further strengthen the adaptive nature of the framework and potentially lead to additional performance gains.

In summary, the findings of this study demonstrate that incorporating speaker-aware adaptation into pronunciation assessment systems leads to measurable improvements in both accuracy and efficiency. By combining acoustic feature-based profiling, adaptive dataset selection, and deep representation learning, the proposed approach provides a more nuanced and effective solution to the problem of automatic pronunciation evaluation. The results not only validate the proposed methodology but also suggest a broader paradigm shift toward adaptive and personalized speech assessment systems in language learning technologies.

CONCLUSION

This study presented a speaker-adaptive approach to automatic pronunciation assessment, addressing a fundamental limitation of conventional systems that rely on a single, generalized reference model. By recognizing that human speech varies significantly across speakers due to physiological and acoustic factors such as age, gender, pitch, and energy, the proposed framework introduces a methodology that

adapts the evaluation process to the individual characteristics of each user. This adaptation allows the system to distinguish more effectively between genuine pronunciation errors and natural speaker-dependent variations.

The proposed methodology integrates multiple stages of speech processing into a coherent pipeline, starting from signal acquisition and preprocessing, followed by feature extraction and acoustic profiling, and culminating in adaptive model-based evaluation. The use of MFCC features enables reliable extraction of low-level acoustic properties, which are essential for identifying speaker characteristics, while the incorporation of Wav2Vec 2.0 provides powerful deep representations capable of capturing complex phonetic and contextual information. Together, these components ensure that the system operates at both the acoustic and linguistic levels, resulting in a more accurate and robust pronunciation assessment process.

A key contribution of this work is the introduction of dynamic dataset selection based on acoustic profiling, combined with a flexible scoring mechanism that can account for mixed or ambiguous speaker characteristics. This approach reduces the mismatch between the learner's speech and the reference data, leading to improved alignment with human perceptual judgments. In addition to enhancing accuracy, the proposed framework also improves computational efficiency by narrowing the evaluation space to the most relevant subset of reference data, making it suitable for real-time language learning applications.

The results of the study demonstrate that incorporating speaker adaptation into pronunciation assessment systems leads to significant improvements in performance. The system not only achieves higher agreement with human evaluations but also provides more consistent and interpretable scoring across diverse speaker groups. This is particularly important in the context of English language learning for Uzbek speakers, where pronunciation errors are often influenced by both linguistic transfer and speaker-specific acoustic properties.

Overall, the proposed approach offers a meaningful advancement in the field of automatic pronunciation assessment by combining signal processing techniques, adaptive modeling strategies, and deep learning-based representations within a unified framework. It highlights the importance of personalization and adaptability in speech-based systems and provides a foundation for future research aimed at developing more intelligent and user-centered language learning technologies.

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