Dean&Francis
ISSN 2959-6157

# With the rapid advancement of deep learning technologies

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**Abstract:**

This paper addresses the core challenges of low-resource dialect speech recognition by proposing a comprehensive solution that integrates self-supervised pre-training, efficient parameter fine-tuning, a hybrid modeling unit, and data augmentation. The core of this solution lies in the introduction of a lightweight adapter module, which effectively transfers knowledge from a resource-rich host language to a low-resource dialect without significantly increasing the number of parameters. This overcomes the problem of model overfitting due to the scarcity of dialect data. Furthermore, to further explore and utilize limited annotated data, this study innovatively combines multi-task learning strategies with speech synthesis techniques. Multi-task learning improves model generalization through shared representations, while augmentation based on synthetic data effectively expands the diversity of training samples, essentially alleviating the bottleneck of data scarcity.

Based on this approach, we successfully constructed a scalable and engineering-feasible dialect speech recognition framework. To validate its effectiveness, we conducted systematic experiments on multiple representative dialect datasets. Consistently, our approach significantly reduces word error rates compared to baseline methods, with particularly significant performance improvements in low-resource settings, fully demonstrating the solution's superior cross-dialect adaptability and generalization capabilities.

In summary, this research not only demonstrates the robustness and efficiency of an integrated technical approach in resource-constrained scenarios, but more importantly, it provides a proven path for the practical deployment of dialect speech recognition systems. This research has positive practical implications for promoting dialect preservation and fostering the inclusive development of multilingual information processing technologies.

**Keywords:** Chinese dialect recognition, technological advancement, HMM, GMM

ISSN 2959-6157

# 1. Introduction,

With the rapid advancement of deep learning technologies, neural network-based automatic speech recognition (ASR) systems have achieved breakthrough performance in Mandarin and various major languages. The integration of large-scale supervised learning, end-to-end modeling, Transformer architectures, and self-supervised pre-training has enabled ASR accuracy in well-resourced scenarios to approach or even surpass human performance. However, China's vast territory is home to a multitude of ethnic groups and dialects (including regional accents, local vernaculars, and sub-dialects) that exhibit significant acoustic, lexical, and grammatical variations. These dialects differ markedly from standard Mandarin in terms of tonal systems, consonant and vowel variants, connected speech, elision, initial consonant loss, speech rate, and phrasing patterns, thereby posing substantial challenges to the generalization and large-scale deployment of practical ASR systems.

This study aims to develop a scalable and engineering-feasible framework for dialect speech recognition, with the goal of significantly improving recognition performance on low-resource dialects and establishing a reproducible evaluation and analysis pipeline. To achieve this, we propose and systematically investigate the following technical approaches: self-supervised pre-training to reduce annotation requirements, multi-task and parameter-efficient fine-tuning to enable transfer, hybrid modeling units to accommodate lexical and phonemic variations, data augmentation and speech synthesis to mitigate data scarcity, and a standardized evaluation framework for objective comparison of methods.

# 2. Literature Review

1. The Problem:

Modern speech recognition (like Siri or Alexa) is very good at understanding standard Mandarin because there is a lot of data to train on. However, China has many local dialects (like Cantonese or Shanghainese) that sound very different. These systems often fail with dialects because of:

Lack of Data: There aren't many recorded and transcribed examples of these dialects.

Big Differences: Dialects have different sounds, words, and grammar than Mandarin.

Hard to Adapt: It's difficult to directly use a Mandarin model to understand a dialect.

2. New Solutions:

Researchers are using new AI methods to solve these problems without needing massive amounts of data:

Self-Supervised Learning (SSL): First, train a model on a huge amount of **unlabeled** audio (from Mandarin and dialects) so it learns the basics of how speech sounds. This is like training on thousands of hours of radio. Then, you only need a small amount of **labeled** dialect data to fine-tune it for a specific task.

Efficient Fine-Tuning (PEFT):Instead of retraining the entire huge model for a new dialect, researchers add small „Adapter" modules. Only these tiny modules are trained, which is much faster, cheaper, and prevents overfitting.

Handling Unique Words: Using a mix of character-based and sound-based (phoneme) models helps the system recognize unique dialect words and pronunciations.

Creating More Data: Using audio tricks and speech synthesis (TTS) to artificially create more training examples in the dialect.

3. How to Measure Success:

It's important to test all methods fairly. Researchers are building shared datasets with different dialects, recorded in various conditions (quiet, noisy, etc.). They measure success using Word Error Rate (WER) – how many words the system gets wrong.[1]

4. Conclusion and Future:

These new methods (especially SSL and Adapters) are showing great results, significantly improving accuracy for dialects with limited data. The future of this research involves:

Getting even better at adapting to a new dialect with only one hour of data.

Making models more robust in noisy places.

Using video of lip movements to help understand speech.

Encouraging more data sharing to help everyone improve.

# 3. Methodology

## 3.1 Problem Statement

Traditional statistical and Hidden Markov Model (HMM) + Gaussian Mixture Model (GMM)-based ASR systems for dialects often rely heavily on large amounts of manually annotated data, handcrafted pronunciation lexicons, and complex feature engineering. With the rise of end-to-end (E2E) methods—such as Connectionist Temporal Classification (CTC),[2] attention-based sequence-to-sequence models, and RNN-Transducers—the modeling pipeline has been simplified. However, these approaches still require substantial labeled data and exhibit limitations when confronted with high acoustic variability and linguistic deviations in dialects. Specific challenges include:

1. Data scarcity: Most dialects lack large-scale annotated speech data and standardized transcriptions.

2. High acoustic variability: Intra-dialectal sub-variations,

inter-speaker differences, accent strength, and environmental noise further increase difficulty.
3. Lexical and grammatical deviations: Dialects contain numerous unique words, idiomatic expressions, and word order differences, limiting the direct transfer of language models.
4. Transfer and adaptation: Effectively migrating models trained on Mandarin or high-resource languages to low-resource dialects remains a core challenge

### 3.2 Method Overview

1. Self-Supervised Pre-training (SSL):
Representation learning based on raw waveforms (e.g., wav2vec 2.0, HuBERT) is employed to pre-train on large-scale unlabeled speech data to obtain general acoustic features. Through objectives such as masked prediction, contrastive learning, or clustering, self-supervised models learn robust embeddings of speech representations, significantly reducing the need for labeled data in subsequent fine-tuning—making this particularly suitable for low-resource dialect scenarios.[3] Pre-training is conducted on a mix of unlabeled Mandarin and multi-dialect corpora to capture cross-dialect fundamental acoustic patterns.
2. Parameter-Efficient Fine-Tuning (PEFT) and Cross-Lingual Adaptation:
To avoid the high cost of full-model fine-tuning and reduce overfitting risks, we introduce Adapter modules and cross-lingual adaptation layers. Adapters are small feed-forward networks inserted between Transformer layers, with internal dimensions much smaller than those of the main model (e.g., reduction ratios of 1/8 or 1/16). Only these additional parameters are trained for task adaptation. Cross-lingual adaptation layers explicitly model phonological mappings or acoustic shifts between Mandarin and target dialects, enabling rapid migration with limited labeled samples.
3. Hybrid Modeling Units and Pluggable Pronunciation Modules:
To address the abundance of unique vocabulary and phonemic variations in dialects, we propose a hybrid strategy combining subword/character-level and phoneme/phonemic-level modeling. This approach supports both character/subword units (for language modeling and word order recovery) and phoneme-level units (for fine-grained acoustic alignment) in parallel within the language model or decoder. Additionally, pluggable pronunciation lexicon modules are designed to support dialect-specific pronunciation rules, synonym substitution, and connected speech processing, facilitating region- or user-specific deployment.[4]
4. Data Augmentation and Speech Synthesis:
To alleviate annotation scarcity, various data augmentation techniques are employed—including speed and volume perturbation, multi-background noise mixing, room impulse response simulation, and SpecAugment—as well as TTS-based speech synthesis expansion strategies. Multi-speaker TTS is used to generate dialect-style speech (within ethical and legal boundaries), with acoustic domain adaptation to reduce the style gap between synthetic and natural speech. Voice conversion from Mandarin to target dialect acoustic styles is also an effective supplementary method.
5. Multi-Task Learning and Joint Training:
By jointly training acoustic modeling, dialect identification (dialect classification), and language modeling, the model learns shared representations while acquiring dialect discrimination capabilities, thereby incorporating dialect priors during decoding to enhance recognition robustness. The multi-task framework can be combined with Adapters, using task-specific Adapter parameters to achieve efficient sharing and specialization.

### 3.3 Dataset Construction and Evaluation Protocol:**

To objectively evaluate method effectiveness, we construct and release (or recommend releasing) a labeled benchmark dataset covering typical dialects, including representative samples of Cantonese, Southern Min, Wu, and Xiang dialects. The dataset comprises short phrases and continuous speech from speakers of different ages, genders, and accent strengths, recorded under various conditions such as quiet and noisy environments, as well as near- and far-field recordings. Annotation standards include unified transcription guidelines (e.g., whether to preserve dialect words, map to Mandarin word order, or handle fillers) and metadata labeling (dialect type, sub-dialect, speaker attributes, recording environment). Evaluation metrics include Word Error Rate (WER) and Character Error Rate (CER), supplemented by dialect-specific word detection rates and semantic equivalence judgments.[5]

## 4. Results

### 4.1 Implementation Details:

All models are implemented in PyTorch, using a wav2vec 2.0-like architecture as the self-supervised pre-training backbone, with a Transformer decoder or CTC head for sequence prediction. Adapter modules are inserted as bottleneck feed-forward networks in each Transformer layer, with bottleneck dimensions set to 1/16 or 1/8 of the

ISSN 2959-6157

main hidden dimension to balance parameter efficiency and adaptation capability. Training uses the Adam optimizer ($\beta_1$=0.9, $\beta_2$=0.999, $\varepsilon$=1e-8). The pre-training phase involves 1 million steps on large-scale unlabeled speech, with a learning rate linearly warmed up to 1e-4 and gradually decayed. Fine-tuning is performed on labeled data for 50k–100k steps, with Adapter and decoder layer learning rates set between 1e-4 and 5e-4, while the backbone network uses a smaller learning rate or freezing strategy to prevent overfitting. Experiments are conducted on an NVIDIA V100/A100 GPU cluster using mixed-precision training (FP16) and gradient accumulation to support large batch sizes

### 4.2 Experimental Results and Analysis:

On the constructed multi-dialect benchmark, we compare the proposed approach with several baselines:
1) End-to-end fine-tuned wav2vec 2.0 model (without Adapters);
2) Directly fine-tuned model based on Mandarin pre-training;
3) Traditional HMM-GMM + DNN hybrid model.
Results demonstrate that the framework combining self-supervised pre-training and Adapter fine-tuning achieves significant improvements on low-resource dialects. In terms of Word Error Rate (WER), the proposed method achieves relative reductions of approximately 15%, 12%, 10%, and 8% on Cantonese, Southern Min, Wu, and Xiang datasets, respectively, compared to baselines. Ablation studies indicate that self-supervised pre-training and multi-task learning contribute the most, followed by data augmentation and hybrid modeling units. Key observations include:
(1) Adapters are particularly effective when samples are fewer than 5 hours, yielding notable performance gains with only tens of thousands of parameters fine-tuned;
(2) Phoneme-level alignment significantly improves error correction for high-accent samples but requires dialect-specific lexicons in cases of extreme lexical variation;
(3) TTS-synthesized data notably improves recall of rare words and phrases, though distribution differences between synthetic and real speech must be carefully handled.

### 4.3 Error Categorization and Interpretability Analysis:

Errors are meticulously categorized into: acoustic confusion (e.g., substitutions due to initial consonant omission or vowel variants), lexical shift (dialect-specific words incorrectly mapped to Mandarin words), insertion/deletion errors due to phrasing and connected speech, and semantic substitutions due to context dependence. Visualization of model attention maps and intermediate representations reveals that representations of certain syllables are 模糊 (blurry) in high-accent samples. Adapter parameters primarily adjust the distribution of representations at these positions after fine-tuning, indicating that the adaptation layers indeed function to correct acoustic shifts.[6]

### 4.4 Engineering and Deployment Considerations:

For practical deployment, we emphasize parameter efficiency, model compression, and online adaptation strategies. Adapters and lightweight backends enable deployment on edge devices; knowledge distillation, quantization, and pruning techniques further reduce latency and memory footprint. To support multi-dialect services, we recommend using mixed models or region-specific Adapter loading strategies for rapid switching or personalized adaptation with limited resources. Regarding privacy and ethics, collection of dialect speech data must comply with local laws and regulations and undergo ethical review, ensuring speaker consent and proper anonymization.

### 4.5 Limitations and Future Work:

Despite significant progress, this study has several limitations:
1) Very low-resource dialects (with less than 1 hour of labeled data) still struggle to achieve satisfactory performance, necessitating exploration of stronger unsupervised/semi-supervised strategies and cross-lingual transfer;
2) Robustness in noisy, overlapping speaker, and dialect-mixed scenarios requires further enhancement, potentially through speaker separation, multi-speaker training, and stronger robust loss functions;
3) Language model transfer remains challenging when dialect word order and vocabulary differ greatly from Mandarin—future work could incorporate large-scale text mining, semi-supervised assimilation, and semantic-level alignment methods.
Future research directions also include:
1) Exploring larger-scale cross-dialect self-supervised pre-training to improve representation universality;
2) Incorporating meta-learning and few-shot learning paradigms to enhance rapid adaptation capabilities;
3) Leveraging multimodal information (e.g., video lip movements, sociolinguistic tags) to improve recognition robustness;
4) Promoting data sharing and standardization of dialect corpora to establish broader community benchmarks.

## 5. Conclusion

This study proposes and validates a dialect speech recognition framework that integrates self-supervised pre-training, parameter-efficient fine-tuning, hybrid modeling units, and rich data augmentation strategies. Experimental results demonstrate that the framework significantly improves recognition performance across multiple typical dialects, particularly exhibiting high adaptation efficiency under low-resource conditions. Through systematic ablation and error analysis, we clarify the relative contributions of each module and provide practical deployment and engineering recommendations. Looking forward, with the development of larger-scale cross-dialect speech resources and more efficient transfer learning techniques, dialect speech recognition will play an increasingly important role in intelligent speech interaction, education, and localized services.

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