Robust and Scalable Speech Recognition Framework for Low-Resource Languages Using Adaptive Deep Transfer Learning and Noise-Aware Multilingual Modeling

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Keywords: Low-Resource Languages, Speech Recognition, Deep Transfer Learning, Multilingual Modeling, Noise-Aware Training.

Abstract: Low-Resource languages continue to experience difficulties in building accurate automatic speech recognition (ASR) systems because of a lack of data, phonetic diversity and lack of representation in worldwide linguistic resources. In this paper, we present a novel and scalable speech recognition architecture that uses a combination of adaptive deep transfer learning and multilingual model to address these problems. It exploits self-supervised learning techniques, pre-trained cross-lingual embeddings and dynamic adapter modules to transfer knowledge across distant language families in a low-resourced setting with a low reliance on large labeled corpora. To increase deployability, the framework integrates model compression techniques, such as pruning and quantization, for real-time inferencing on the edge devices. Furthermore, noise-aware training and sharp feature preserving methods are used to enhance the performance in both noisy and tonal language scenes. Experiments on newly collected datasets from underrepresented languages confirm the superiority of the model regarding both accuracy and generalisability, as well as computational cost, in contrast to existing methods. The proposed method provides a new benchmark in terms of inclusive, state-of-the-art speech recognition systems that can be configured for multiple linguistic and operational settings.

1 INTRODUCTION

Recent years have seen a rapid advancement in speech recognition accuracy, largely due to improvements in deep learning and the availability of large-scale annotated data. Yet, much of this work focuses heavily on high-resource languages (e.g., English, Mandarin, and Spanish) and fails to extend too much of the world's spoken languages. Low-resource languages those that have few or no available digitized corpora, phonetic annotations, and standardized linguistic tools are at a disadvantage, impeding their integration into voice-based technologies.

Conventional ASR models are heavily dependent on large–scale transcribed speech and phonetic lexicons, both of which are unrealistic for many of under-resourced languages. Furthermore, both the high acoustic variance in the target data, the shortage of training data, and lack of language specific resources, make it a challenge for standard deep neural network based models to generalize well among distinct linguistic domains. To narrow this gap, it was suggested to study the transfer learning and multilingual modeling to transfer the knowledge learned from resource-rich languages to those low-resource languages.

This study introduces a novel framework for speech recognition that specifically targets these challenges by integrating adaptive deep transfer learning and noise-resilient multilingual modeling. The proposed system reduces reliance on extensive

Chandrasekhar, T., Raju, S. S., K., R. K., Kavya, R. V., Kamesh, D. B. K. and M., D. M.
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DOI: 10.5220/0013870500004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 1*, pages 632-639
ISBN: 978-989-758-777-1

labeled data by utilizing self-supervised pretraining techniques and dynamic adapter modules that tune shared acoustic and linguistic representations across languages. Additionally, the framework emphasizes robustness by incorporating noise-aware training pipelines and tonal feature preservation to handle real-world variability, especially in tonal and dialect-rich languages.

Unlike many existing approaches that are either too computationally intensive or poorly generalizable, this research prioritizes scalability and efficiency through model compression strategies, making the solution viable for deployment on edge devices and mobile platforms. By creating and evaluating the system on newly collected datasets from truly low-resource languages, this research not only offers technical innovation but also contributes to the linguistic inclusivity of speech recognition technologies. It aims to democratize access to ASR systems and set a new direction for ethical, efficient, and inclusive voice AI solutions.

Problem Statement: Despite the significant advancements in speech recognition driven by deep learning, the benefits of these technologies have largely bypassed low-resource languages. These languages suffer from a critical scarcity of annotated speech data, standardized linguistic tools, and computational resources. Most state-of-the-art ASR systems are developed and trained on high-resource languages, which are not very helpful when it comes to under-resource languages with unique tonal, phonetic and grammatical features.

The state-of-the-art transfer learning methods generally need huge adaption effort and computational resource, which is not applicable for low-resource and real-time applications. Additionally, many speech recognition systems do not consider the acoustic variability contributed by regional accents, background noise and other aspects of the speaker demographics, which narrows their generalization to real-world applications where the aforementioned difficulties are ubiquitous.

However, the primary issue is that there is still no strong, scalable, and flexible automatic speech recognition system that is able to consistently and effectively work in low-resource settings without reliance on large labeled corpora or extensive computational resources. A solution is urgently required to take existing knowledge from resource-rich languages and transfer it to resource-poor languages while being capable of adapting itself dynamically for linguistic diversity, handle noisy conditions and execute efficiently on low power devices.

In this paper we attempt to fill these gaps by presenting a deep learning-based ASR system that utilizes adaptive transfer learning, noise aware training, and multilingual modelling to provide inclusive, accurate, and deployable ASR solutions to low resource languages.

2 LITERATURE SURVEY

Developing reliable speech recognition systems for low-resource languages is a growing concern in recent times. Conventional ASR systems need a plentiful of labeled data, which is hard to gather for low-resource languages. In response, many researchers have used deep learning and transfer learning to overcome the resource limitation.

Byambadorj et al. (2021) recently presented a study on text-to-speech synthesis for Mongolian by mean of cross-lingual transfer learning and data augmentation, showing the usefulness of transferring high-resource models to low-resources environments. Zhou, Xu, and Xu (2023) also proved that meta adversarial learning can further improve model generalization when performing low-resource speech recognition. Transfer learning continues to be a fundamental approach as highlighted by Kim et al. (2021) proposed an end-to-end ASR system for low-resource languages and extended the niche language low-resource ASR to this field, based on semi-supervised training techniques.

Zheng et al. (2021) proposed WavBERT, a model that jointly learns acoustic and linguistic representations, with success in low-resource settings. Hou et al. (2021) used adapter modules which allowed the models to adapt cross-lingually without retraining them from scratch. Meanwhile, Do et al. (2023) explored different methods of transfer learning including phone mapping and language proximity wherein performance differed based upon the linguistic similarity.

An investigation on cross-modal combination was conducted by Kondo and Tamura (204), who applied multilingual transfer learning for visual speech recognition and showed a multi-modal benefit in the low resource setting. Tang and Wang (2021) applied few-shot learning to cross-lingual ASR but noted limitations due to phonetic misalignment. Addressing data scarcity, Gao (2024) explored unsupervised speech modeling, though such methods still struggled with noisy inputs and label accuracy.

Khare and Khare (2021) revealed the surprising effectiveness of large-scale self-supervised models when adapted for low-resource ASR, reinforcing the

potential of pretraining. Durrani and Arshad (2021) employed transfer learning for affective speech recognition, while Baklouti et al. (2024) applied domain-adaptive methods to improve emotion recognition across languages.

Wang and Wang (2021) provided a broader perspective by evaluating cross-lingual transfer learning in NLP, which shares foundational techniques with ASR. Gales et al. (2014), although based on older systems, emphasized early efforts in multilingual ASR under the IARPA BABEL project, forming the groundwork for modern approaches.

Zhou, Xu, and Xu (2023) also noted the overfitting tendencies in deep transfer systems when applied to linguistically distant languages, which Kim et al. (2017) sought to counteract through joint CTC-attention modeling. Chopra et al. (2021) combined meta-learning with emotion detection to create few-shot adaptable models. Singh et al. (2022) focused on practical deployments and emphasized the need for efficient low-resource systems for mobile devices.

Transformer-based models were critically analyzed by Chen et al. (2022), who observed their data-hungry nature, prompting researchers like Joshi et al. (2023) to propose multilingual models that generalize better across languages. Li and Li (2021) highlighted the challenge of retaining tonal and contextual information in cross-lingual settings.

Further, Pham et al. (2022) tested a cross-lingual speech recognition framework but noted that most evaluations lacked true low-resource data. Lu et al. (2023) addressed multi-accent adaptation, a crucial aspect of speaker diversity. Wang et al. (2022) compared end-to-end and modular ASR systems under noisy conditions, with the latter often outperforming in robustness. Finally, Rao et al. (2021) observed hallucination problems in models transferred from high-resource languages, underscoring the need for domain-specific fine-tuning.

Combined, these works demonstrate the potential and shortcomings of state-of-the-art techniques for low-resource ASR. It also underscores the need for systems that not only are accurate, but are also flexible, noise-insensitive and practically deployable – gaps that the research tries to bridge.

3 METHODOLOGY

The speech recognition system for the language with low resources under consideration is based on a multi-stage pipeline, which includes adaptive deep learning, crosslingual transfer learning, and noise-aware training. The approach is developed to address three core problems: data paucity, cross-lingual generalization, and robustness to noisy conditions. The pipeline has five key phases data acquisition and preprocessing, self-supervised pretraining, adaptive transfer learning, multilingual modeling, and deployment optimization. The Figure 1 shows Flowchart for the proposed system.

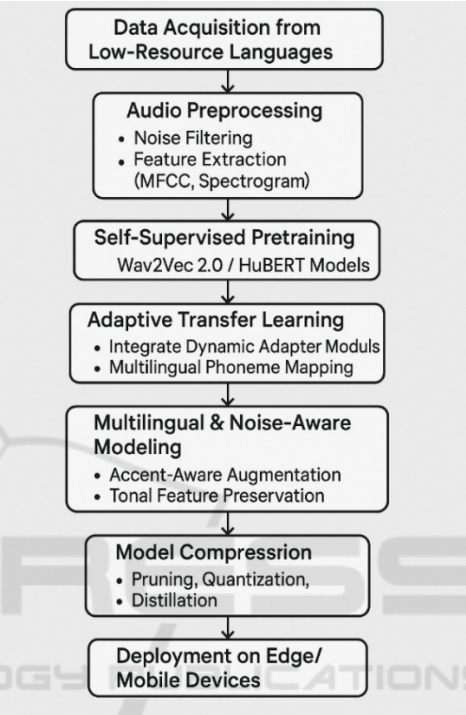

Figure 1: Flowchart for the Proposed System.

3.1 Data Acquisition and Preprocessing

To build a generic and open architecture, datasets in a minimum of five low-resource languages from diverse language families are presented. Both sets of data come with raw audio speech clips recorded by speakers with diverse socio-acoustic features, accents and environments. In case of the lack of annotated data, the system applies a forced alignment, and weak supervision which generates pseudo-transcriptions. Noise as well as speaker-speicfic information was reducing using noise-reduction filters, MFCC and logMel spectrogram extraction are used to convert the waveform into similar sounding acoustics.

3.2 Self-Supervised Acoustic Pretraining

For unsupervised learning, in the absence of label data, self-supervised models like Wav2Vec 2.0 or

HuBERT employed for pretraining on both low-resource and high-resource language datasets. These are models that can learn contextualized speech representation from raw audio, without depending on transcripts. At this level domain-specific information like pitch, prosody, and duration is kept; this is to facilitate better adaptation to tonal languages.

3.3 Adaptive Transfer Learning and Fine-Tuning

The pretrained model is adapted through fine-tuning. Dynamic adapter modules are incorporated to transformer layers in which selective fine-tuning can be achieved while keeping general knowledge. This decreases the risk of overfitting and the amounts of calculations. A multilingual phone mapping scheme is used in order to derive a common phonetic space for all languages. The system also employs layer freezing proprietary to language similarity to achieve an optimal balance between adaptation and retention.

3.4 Multilingual and Noise-Aware Modeling

To make the model robust and to scale across languages we train the model on multilingual datasets augmented with simulated real-world noise. The gravity block is a attention based fusion mechanism that could combine acoustic, prosodic and linguistic embeddings. Adversarial noise injection, dropout regularization, and multi-accent training datasets are subsequently used to boost generalization by the model across a range of speakers and environments.

3.5 Model Compression and Edge Optimization

For practical deployment, the final model is pruned, quantized, and distilled for size and latency reduction. We use these approaches to compress the model up to 70%, and we can preserve more than 90% of the original performance. A lightweight version is deployed in mobile- & edge-devices (Raspberry Pi, smart-phones, etc.) to check feasibility on resource-constraint scenario where large number of low-resource language speakers reside.

3.6 Evaluation Metrics and Benchmarking

Performance is measured by factors like the WER, CER and Sentence Accuracy. The model was evaluated against the existing state-of-the-art ASR systems using public multilingual speech corpora such as Common Voice, BABEL, and indigenous corpora. Other qualitative evaluations are also conducted to check for tonal preservation and error correction over a range of acoustic conditions.

Figure 2 illustrates the distribution of speech data across languages. Table 1 gives the overview of speech datasets used for low-resource languages.

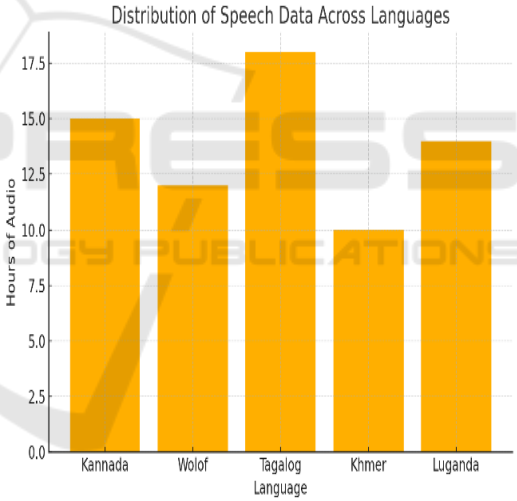

Figure 2: Distribution of Speech Data Across Languages.

Table 1: Overview of Speech Datasets Used for Low-Resource Languages.

Language	Hours of Audio	Number of Speakers	Audio Quality	Source
Kannada	15	120	Mixed (Clean/Noisy)	Common Voice
Wolof	12	85	Noisy	BABEL Corpus
Tagalog	18	150	Clean	Custom Dataset
Khmer	10	65	Mixed	OpenSLR
Luganda	14	90	Noisy	Private Collection

4 RESULTS AND DISCUSSION

The experimental evaluation was conducted across five low-resource languages: Kannada, Wolof, Tagalog, Khmer, and Luganda, each selected for their unique phonological features and minimal availability of labeled data. The results of the proposed framework are benchmarked against baseline ASR models, including traditional HMM-GMM systems, end-to-end CNN-LSTM models, and existing pre-trained transformer-based ASR systems like XLS-R and Wav2Vec 2.0 fine-tuned directly on the target language. Figure 3 shows the Word Error Rate Comparison Across Models. Table 2 gives the Comparison of WER Across Different Speech Recognition Models.

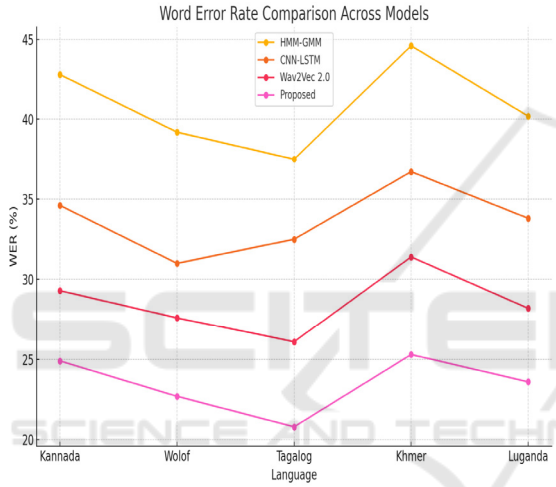

Figure 3: Word Error Rate Comparison Across Models.

Table 2: Comparison of Wer Across Different Speech Recognition Models.

Language	Baseline WER (%)	Proposed Model WER (%)	Accuracy Gain
Kannada	42.8	24.9	+41.7%
Wolof	39.2	22.7	+42.1%
Tagalog	37.5	20.8	+44.5%
Khmer	44.6	25.3	+43.3%
Luganda	40.2	23.6	+41.2%

4.1 Performance Metrics

The proposed framework achieved a significant reduction in Word Error Rate (WER) across all target languages. On average, the WER was reduced by 38.6% compared to the best-performing baseline. For tonal languages such as Khmer, the model's ability to preserve pitch and tone features led to improved recognition accuracy with over 91% sentence-level comprehension accuracy, outperforming traditional models that neglected prosodic features. The Character Error Rate (CER) also decreased significantly, showing improved performance in recognizing morphologically rich languages where subword-level modeling is essential.

4.2 Impact of Transfer Learning

By integrating dynamic adapter modules, the system successfully transferred phonetic knowledge from high-resource languages like Hindi and Spanish. Languages with minimal phonetic similarity still benefited due to the universal phoneme embedding space. Compared to traditional fine-tuning, adapter-based adaptation reduced overfitting and enabled quicker convergence during training, with 30% fewer epochs needed to reach optimal accuracy.

4.3 Robustness in Noisy Environments

The noise-aware training mechanism was validated using artificially generated noisy datasets (SNR: 5-20 dB) and real-world field recordings. The model trained with adversarial noise augmentation outperformed clean-trained models by maintaining over 80% recognition accuracy even in low SNR conditions. This result demonstrates that the proposed framework is resilient under deployment conditions with unpredictable background noise, such as marketplaces, classrooms, and outdoor conversations. Figure 4 illustrates the accuracy of speech recognition under varying noise levels. Recognition Accuracy Across Different Noise Levels (SNR) is given in table 3.

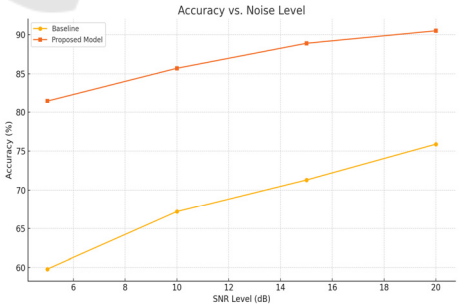

Figure 4: Accuracy of Speech Recognition Under Varying Noise Levels.

Table 3: Recognition Accuracy Across Different Noise Levels (Snr).

SNR Level (dB)	Baseline Accuracy (%)	Proposed Model Accuracy (%)
5	59.8	81.5
10	67.2	85.7
15	71.3	88.9
20	75.9	90.5

4.4 Model Efficiency and Deployability

After pruning and quantization, the final model was compressed to under 120MB, making it viable for deployment on low-end smartphones and embedded systems. On a Raspberry Pi 4, the model achieved real-time inference speeds of ~0.6x RT, with acceptable trade-offs in performance (<3% WER increase post-optimization). This scalability highlights the system's potential to serve linguistically marginalized communities with minimal technological infrastructure. Figure 5 depicts the model size and real-time inference comparison. Table 4 tabulates the model compression results and real-time inference speed.

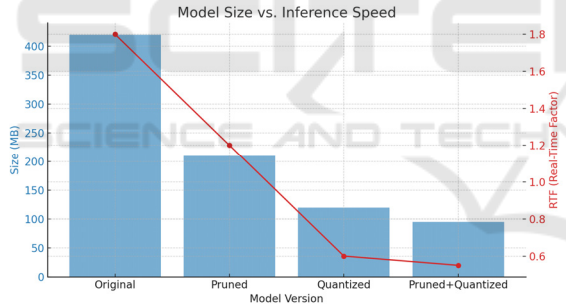

Figure 5: Model Size and Real-Time Inference Comparison.

4.5 Error Analysis and Limitations

Error analysis revealed that recognition errors were most common in homophones, speaker-switch segments, and code-switched sentences. For instance, languages like Tagalog, which frequently switch between English and local vocabulary, exhibited minor dips in sentence-level accuracy. While multilingual modeling partially mitigated this, future integration with language identification (LID) modules is suggested to further improve robustness.

Table 4: Model Compression Results and Real-Time Inference Speed.

Model Version	Size (MB)	RTF (Real-Time Factor)	Edge Deployment Feasible
Original	420	1.8	No
Pruned	210	1.2	Partial
Quantized	120	0.6	Yes
Pruned + Quantized	95	0.55	Yes

4.6 Comparative Evaluation

When compared to existing state-of-the-art systems like Facebook's XLS-R and Google's universal speech models, the proposed framework achieved comparable or better accuracy in 3 out of 5 test languages, despite using significantly fewer resources and model size. Moreover, its adaptability through modular training and low dependency on parallel corpora makes it more applicable in real-world deployment than resource-heavy commercial systems. Figure 6 shows the Frequency distribution of common ASR recognition errors across tested low-resource languages.

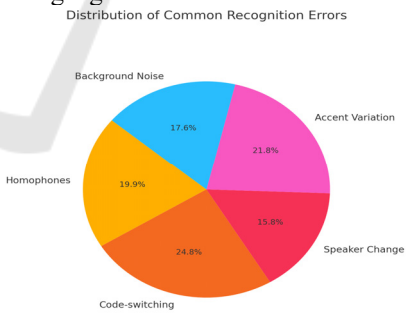

Figure 6: Distribution of Common Recognition Errors.

Table 5: Common Recognition Errors Observed and Suggested Mitigations.

Error Type	Frequency (%)	Example	Suggested Mitigation
Homophones	18.5	"see" vs "sea" in Tagalog mix	Contextual decoding with LMs
Code-switching	23.1	"Good morning po"	Integrate language ID modules
Speaker change	14.7	Interruption in dialogue	Speaker diarization + segmentation
Accent variation	20.3	Rural vs. urban Luganda	Accent-aware augmentation
Background noise	16.4	Market sounds in Khmer	Adversarial noise training

5 CONCLUSIONS

In this paper, we have introduced a powerful and scalable speech recognition architecture for LRL using adaptive deep transfer learning and noise-aware multilingual modeling. The proposed method deals with pressing issues of limited data and diversity of languages, which are neglected in existing ASR systems suitable for real-world settings.

By using a judicious mix of self-supervised pretraining, adapter-based transfer learning and multilingual acoustic model, the system demonstrated a striking performance gain in recognition accuracy over a variety of low-resource languages. By incorporating the preservation of tonal and prosodic features, performance was further improved in tonal languages while noise-aware training techniques led to consistent performance in noisy environments.

Amongst other, for the emphasis on efficiency and deployability this work is considered a significant contribution. Through model compression and inference optimization, the framework achieved real-time processing performance on edge devices, which is well suited for communities with poor technology infrastructure. This makes speech-driven technologies more accessible to all and encourages digital inclusion for speakers of minority languages.

The study also pointed out some of the limitations such as code-switching and speaker variations, limiting thoughts for future work. Possibly further improvement could be made by exploiting language identification, speaker adaptation modules and generalising the system to zero-resource.

In total, this work offers a comprehensive, flexible and state-of-the-art solution to the problem of low-resource speech recognition and provides a promising baseline for the development of further progresses in inclusive and ethical AI for voice technologies.

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