Post-ASR Correction in Hindi: Comparing Language Models and Large Language Models in Low-Resource Scenarios

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Abstract

Automatic Speech Recognition (ASR) systems for low-resource languages like Hindi often produce erroneous transcripts due to limited annotated data and linguistic complexity. Post-ASR correction using language models (LMs) and large language models (LLMs) offers a promising approach to improve transcription quality. In this work, we compare fine-tuned LMs (mT5, ByT5), fine-tuned LLMs (Nanda 10B), and instruction-tuned LLMs (GPT-4o-mini, LLaMA variants) for post-ASR correction in Hindi. Our findings reveal that smaller, fine-tuned models consistently outperform larger LLMs in both fine-tuning and in-context learning (ICL) settings. We observe a U-shaped inverse scaling trend under zero-shot ICL, where mid-sized LLMs degrade performance before marginal recovery at extreme scales, yet still fall short of fine-tuned models. ByT5 is more effective for character-level corrections such as transliteration and word segmentation, while mT5 handles broader semantic inconsistencies. We also identify performance drops in out-of-domain settings and propose mitigation strategies to preserve domain fidelity. In particular, we observe similar trends in Marathi and Telugu, indicating the broader applicability of our findings across low-resource Indian languages.

1 Introduction

Automatic Speech Recognition (ASR) systems enable seamless human-computer interaction (Zierau et al., 2023), especially in linguistically diverse countries such as India. ASR technology is increasingly adopted across domains such as agriculture, education, e-commerce, and governance, helping to bridge digital accessibility gaps (Javed et al., 2022; Bhogale et al., 2023b). However, building robust ASR systems for Hindi, the most widely spoken Indian language, remains a significant challenge due to its low-resource nature, limited availability of high-quality annotated speech data (Adiga et al., 2021), and complex linguistic characteristics including regional variations, code-mixing, and orthographic diversity (Kachru, 2006).

To address these challenges, post-ASR correction has emerged as an effective strategy. It involves using language models (LMs) trained in large text-only corpora, which are more widely available than speech-text pairs, to refine noisy ASR outputs in low-resource languages like Hindi (Kumar et al., 2022). This task can be framed as a high-overlap text-editing problem (Malmi et al., 2022), where the goal is to minimally modify an ASR hypothesis to align it more closely with the correct transcript, handling phonetic, grammatical and semantic errors[1].

Recent advances in pre-trained language models, including both smaller encoder-decoder models (e.g., T5 (Raffel et al., 2020)) and large language models (LLMs) (e.g., GPT (Brown et al., 2020), LLaMA (Touvron et al., 2023)), have made it possible to correct such errors using either fine-tuning or zero-shot / few-shot in-context learning (ICL). Although LLMs are expected to generalize better due to their larger parameter counts and exposure to massive training corpora, it remains unclear whether they actually outperform smaller, task-specific models in domain-sensitive post-ASR correction, particularly in low-resource and morphologically rich languages.

This leads to two key research questions:

1. **How does model performance scale with size** in the context of Hindi ASR post-correction?
2. **How do in-context learning (ICL) approaches using LLMs compare with fine-tuned smaller models**, particularly in handling source-specific ASR errors?

To answer these questions, we perform a systematic comparison of fine-tuned language models (mT5, ByT5) and LLMs (GPT-4o-mini, LLaMA

[1]For more details, please refer to Appendix B

variants) in both fine-tuned and ICL configurations. Our study benchmarks these models with the Lahaja Hindi ASR dataset (Javed et al., 2024a) using ASR hypotheses generated by open-source models such as IndicWav2vec (Javed et al., 2022) and IndicConformer (Javed et al., 2024a).

We find that smaller fine-tuned models (mT5, ByT5) consistently outperform much larger LLMs across both in-domain and out-of-domain scenarios. Surprisingly, we observe a U-shaped inverse scaling trend in zero-shot ICL settings, where mid-sized LLaMA models (3B-10B) degrade performance compared to both smaller and extremely large models, yet even the largest models fail to match the performance of fine-tuned mT5. This highlights the importance of source-specific inductive biases in modeling ASR errors over general-purpose linguistic knowledge.

We further show that ByT5 is especially effective in correcting character-level errors, such as transliteration mistakes, numeric misrecognitions, and compound word splits, while mT5 better handles broader semantic inconsistencies and domain-level shifts. Preliminary experiments on Marathi and Telugu ASR outputs also reveal similar trends, indicating that our findings may generalize to other low-resource Indian languages[2].

This paper makes the following key contributions:

1. **Empirical identification of an inverse scaling trend** in Hindi post-ASR correction, where mid-sized LLMs underperform compared to both smaller LMs and larger LLMs under zero-shot ICL.
2. **Systematic benchmarking of fine-tuned LMs and instruction-tuned LLMs**, demonstrating that fine-tuned small models (mT5, ByT5) significantly outperform larger LLMs such as the GPT-4o mini and LLaMA variants in both ICL and fine-tuning settings.
3. **Granular error-type analysis**, showing ByT5's strength in fine-grained character-level corrections, and mT5's robustness in semantic error correction and domain generalization.
4. **Proposal and evaluation of mitigation strategies** for domain shift in ASR correction, including domain-replicative training and in-domain/out-of-domain data mixing.
5. **Cross-lingual validation**, showing that a similar model behavior is observed for Marathi and Telugu, suggesting generalizability across Indic languages.

[2]Code and Model:
https://anonymous.4open.science/r/PostCorrection-B2B7/

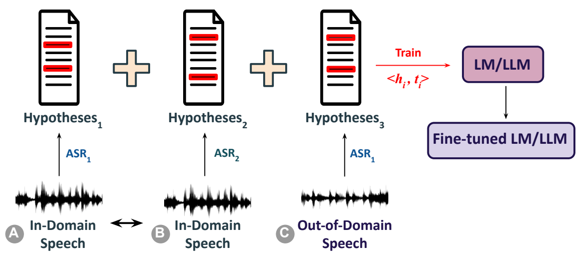

Figure 1: Overview of the data preparation process illustrating how in-domain and out-of-domain speech are used for fine-tuning LM and LLM models.

2 Methodology

We frame post-ASR correction as a text-editing task, where the goal is to transform a noisy ASR hypothesis into a corrected transcript using language models (LMs) or large language models (LLMs). This section outlines our dataset formulation, training setup, and the strategy used to handle domain variation in low-resource settings.

Let $D^{id}_{train} = \{(a_i, t_i) \mid 1 \leq i \leq n\}$ denote an in-domain speech-text dataset (share similar speaker distributions, topics, vocabulary, and contextual characteristics with the target evaluation set), where a_i is a speech utterance and t_i is the corresponding ground truth transcript. This dataset is used to train an ASR model A^{id}_1. To create training data for post-ASR correction, we decode the speech with A^{id}_1, generating a 1-best hypothesis h_i for each a_i, resulting in a dataset $H^{id}_{train} = \{(h_i, t_i) \mid 1 \leq i \leq n\}$. Here, h_i serves as the noisy input and t_i as the reference transcript.

Moreover, due to the limited availability of in-domain speech-text data, we also consider out-of-domain datasets to augment training. Let D^{ood}_{train} be a dataset with different characteristics (differ in speaker distribution, style, topic), used to train another ASR model A^{ood}_2. The resulting hypotheses form $H^{id}_{train} = \{(a_i, h_j, t_i) \mid 1 \leq i, j \leq n\}$ and $H^{ood}_{train} = \{(h_k, t_k) \mid 1 \leq k \leq m\}$ as shown in Figure 1.

We fine-tune both the LMs and LLMs in $H^{id}_{train} = \{(h_i, t_i) \cup (h_j, t_i) \mid 1 \leq i, j \leq n\}$ and H^{ood}_{train}, enabling them to learn typical ASR error patterns and their corrections. At inference time, ASR hypotheses from a held-out set D^{id}_{test} are corrected using these models. In addition, we also use the ASR hypotheses H^{id}_{train} for the evaluation of the ICL.

Training Dataset	Dataset Size	IndicWav2Vec ASR Hyp.	IndicWav2Vec ByT5	IndicWav2Vec mT5	IndicWav2Vec LLaMA	IndicConformer ASR Hyp.	IndicConformer ByT5	IndicConformer mT5	IndicConformer LLaMA
D1: In-Domain Speech with ASR model	63500	28.60	**24.17**	32.92	76.72	18.02	18.22	**17.50**	76.04
D2: + In-Domain Speech with Diff. ASR model	127306	28.60	**26.62**	29.09	**27.8**	18.02	18.07	**16.75**	23.24
D3: + Out-of-Domain Speech with ASR model	1021472	28.60	**25.14**	**23.74**	**26.03**	18.02	**17.52**	**16.31**	21.49

Table 1: WER Comparison for Various fintuned LMs (ByT5-small, mT5-base) and LLM (LLaMA)

3 Experiment and Results

Training Dataset	Dataset Size	IndicWav2Vec ByT5	IndicWav2Vec mT5	IndicConformer ByT5	IndicConformer mT5
D1: IndicVoice [IC]	63500	**24.17**	32.92	18.22	**17.50**
IndicVoice [W2V]	63500	**26.00**	**26.67**	18.37	**16.81**
Shrutilipi [IC]	127306	31.37	29.67	24.18	22.19
Kathbath + Shrutilipi [IC]	127306	30.45	27.76	23.34	19.48
Shrutilipi [W2V]	127306	30.10	29.96	25.04	22.55
Kathbath + Shrutilipi [W2V]	127306	28.84	29.05	22.30	20.75
D2: IndicVoice [IC+W2V]	127306	**26.62**	29.09	18.07	**16.75**
D3: **D2** + other ASR dataset [IC]	1021472	**25.14**	**23.74**	**17.52**	**16.31**
D2 + other ASR dataset [W2V]	1021472	**23.66**	**22.97**	**17.55**	**16.45**
D2 + other ASR dataset [IC + W2V]	1021472	**23.36**	**23.00**	**17.46**	**16.17**

Table 2: Performance comparison of ByT5-small (ByT5) and mT5-base (mT5) models on the Lahaja test dataset trained with different training datasets. The WER of the IndicWav2Vec (W2V) model is 28.6, while the IndicConformer (IC) model is 18.02 .

Datasets: We evaluate post-ASR correction models using the Lahaja dataset (Javed et al., 2024a), which comprises 12.5 hours of Hindi speech from 132 speakers across 83 districts. It includes read, extempore, and conversational speech, making it suitable for evaluating domain-specific correction performance. For fine-tuning, we use the IndicVoice corpus (Javed et al., 2024b) (65 hours, 287 speakers), selected for its domain and vocabulary overlap with Lahaja. To assess generalization, we include two out-of-domain datasets: Kathbath (Javed et al., 2023) (read speech) and Shrutilipi (Bhogale et al., 2023a) (conversational radio broadcasts), offering diverse linguistic and stylistic characteristics.

Baseline: We generate ASR hypotheses using two open-source Hindi ASR models. **IndicWav2Vec**(Javed et al., 2022), based on the wav2vec 2.0 architecture. **IndicConformer**(Javed et al., 2024a), based on the conformer architecture. As detailed in Appendix D, preliminary comparisons showed these models consistently outperform other Hindi ASRs in both WER and CER in the Lahaja dataset. These hypotheses serve as the input for post-ASR correction models.

Model Configurations: We compare the following LMs and LLMs:

ByT5 (Xue et al., 2022): A tokenizer-free, byte-level T5 variant, effective for character-level corrections.

mT5 (Xue, 2020): A multilingual T5 variant using SentencePiece tokenization, trained on Common Crawl data including Hindi.

LLaMA-3-Nanda-10B-Chat (Choudhury et al., 2025): A 10B bilingual LLM adapted from LLaMA-3-7B with continued pretraining on 65B Hindi tokens.

GPT-4o mini (OpenAI, 2024): A closed-weight instruction-tuned model, evaluated in zero- and few-shot in-context learning (ICL) settings.

ByT5 and mT5 are fine-tuned on the 1-best ASR hypotheses paired with reference transcripts. GPT-4o-mini is evaluated using a few-shot prompt[3], with examples drawn from IndicVoice through random sampling and sentence embedding similarity (Joshi et al., 2023) to ensure contextual relevance. We also carried out a pilot experiment with n = 5 hypotheses for ByT5 in D1, observing a WER of 45, indicating that while multi-hypothesis inputs may provide additional signal, the improvements are limited without targeted modeling.

3.1 Results of Fine-tuned LMs and LLMs

Table 1 and Table 2 present the WER of fine-tuned models across three training configurations: D1 (in-domain speech with a single ASR), D2 (in-domain speech using a different ASR model), and D3 (in-domain plus out-of-domain speech). We observe a consistent performance improvement from D1 to D3 for ByT5 and mT5, across outputs from both IndicWav2Vec and IndicConformer. Notably, D3 yields the lowest WER for both models (e.g., mT5 achieves 16.31 on IndicConformer in D3 vs. 17.50 in D1), suggesting that incorporating diverse ASR hypotheses from out-of-domain sources can enrich the model's exposure to varied error patterns [4]. This leads to better generalization while preserving domain fidelity. These findings underscore the ef-

[3]For prompt, see Appendix I

[4]Similar trends were observed across Indic languages (Appendix F).

fectiveness of multi-ASR, multi-domain training as a practical strategy to improve post-ASR correction in low-resource settings.

3.2 Results of ICL

Experiment	Shots	IndicWav2Vec	IndicConformer
-	0-Shot	28.60 → 31.77	18.02 → 25.14
SE Similarity	1-Shot	28.60 → 29.22	18.02 → 22.88
	3-Shot	28.60 → 28.18	18.02 → 22.04
	5-Shot	**28.60 → 27.14**	18.02 → 20.89

Table 3: WER Comparison for Various Shot Settings using GPT-4o mini (ICL)

In Table 3, we evaluate the ICL capability of a LLM, GPT-4o mini. We assess post-ASR correction in both zero-shot, 1-shot and few-shot settings. Our findings demonstrate the adaptability of few-shot learning, leveraging sentence embeddings (SE) to improve ASR correction. However, in the case of IndicConformer, this approach resulted in an increase in the WER of the ASR hypothesis.

Smaller fine-tuned models such as **mT5** and **ByT5** consistently outperform larger LLMs like GPT-4o-mini and LLaMA-3. This suggests that task-specific inductive bias and domain adaptation are more effective than sheer model scale for post-ASR correction in low-resource settings[5].

4 Ablation Study

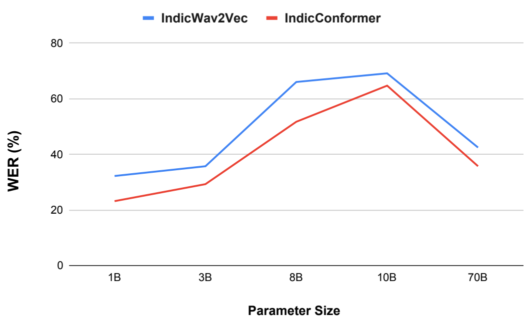

Figure 2: Inverse scaling phenomenon in Hindi post-ASR correction across varying LLaMA model sizes.

We evaluated the impact of model size on Hindi post-ASR correction under a zero-shot ICL setup, relying solely on the pre-trained knowledge of each model without additional fine-tuning. As shown in Figure 2, increasing the number of parameters (3.1 1B → 3.2 3B → 3.1 8B → Nanda-10B-Chat 10B → 3.3 70B) reveals an n-shaped trend in the word error rate (WER): performance improves initially, then worsens and may slightly recover at higher scales. This inverse scaling behavior indicates that larger models do not necessarily guarantee better correction accuracy.

[5]For additional analysis, see Appendix E.

Training Dataset	Ratio	Dataset Size	IndicWav2Vec		IndicConformer	
			ByT5	mT5	ByT5	mT5
D2 + *OAD* [IC]	3:7	381415	22.44	25.89	17.19	**16.03**
D2 + *OAD* [W2V]	3:7	381415	**22.26**	25.81	17.65	16.51
D2 + *OAD* [IC]	2:8	571962	22.32	26.51	17.74	**16.02**
D2 + *OAD* [W2V]	2:8	571962	22.29	26.68	17.58	16.62

Table 4: Evaluation of post-ASR correction on Lahaja dataset mixing the in-domain and out-of-domain dataset in fixed ratio. (**D2** = IndicVoice [IC+W2V] and *OAD* = other ASR dataset)

We observe residual degradation at higher out-of-domain proportions, highlighting the limitations of fixed-ratio scheduling alone. Table 4 shows that a 3:7 sampling ratio in-domain to out-of-domain per batch yields the best post-ASR correction performance, suggesting that batch composition is key to retaining in-domain error patterns. This points to the need to incorporate techniques such as domain-aware regularization fine-tuning to improve domain fidelity in low-resource settings.

5 Conclusion

In this work, we explore the effectiveness of LMs and LLMs for post-ASR correction in Hindi, highlighting the surprising result that smaller, fine-tuned models such as mT5 and ByT5 consistently outperform much larger LLMs like GPT-4o-mini and LLaMA variants. Our findings reveal a U-shaped inverse scaling trend, observed under zero-shot in-context learning, where increasing model size initially degrades performance before marginal improvements at extreme scales, yet still falls short of the smaller models. ByT5 excels at fine-grained character-level corrections, while mT5 is more effective at capturing broader semantic inconsistencies. We also identify significant performance degradation in high out-of-domain settings and propose mitigation strategies to preserve domain-specific fidelity in post-ASR correction. Preliminary experiments on Marathi and Telugu also reflect similar patterns, indicating that our findings may generalize across other low-resource Indian languages. These results underscore the importance of source-specific inductive biases and demonstrate that lightweight, fine-tuned models are often better suited than general-purpose LLMs for improving ASR quality in such contexts.

Limitations

As part of future work, we would like to work on the following limitations of our work:

- Although the study focuses mainly on Hindi, this language-specific scope may constrain the generalizability of the findings to other low-resource Indian languages with distinct linguistic characteristics. Although preliminary evaluations are conducted in Marathi and Telugu, they lack detailed analysis. In addition, the absence of linguistic experts for these languages limits the depth of error categorization and interpretation.

- ICL results are limited to GPT-4o mini and evaluated under only a few-shot and SE-based prompting. The comparison of GPT-4o is missing due to limited funds.

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A Appendix

In the Appendix, we provide:

1. Section B: Illustrative Example of Hindi ASR Errors
2. Section C: Related Works
3. Section D: Model Comparison
4. Section E: Additional Analysis
    (a) Section E.1: LM/LLM comparison
    (b) Section E.2: Effect of domain-specific regularization
5. Section F: Additional Languages
6. Section G: Compound Word Error Detection Algorithm
7. Section H: Compute Infrastructure
8. Section I: Prompts

B Illustrative Example of Hindi ASR Errors

Compound words, such as (/rathayātrā/), which refers to an annual Hindu chariot festival, erroneously the word can split into (/ratha yātrā/) (ratha means chariot, yātrā means travel, journey), thus altering their meaning. Word segmentation errors are also common, particularly with derivational and infectional word groups (Karthika et al., 2025),

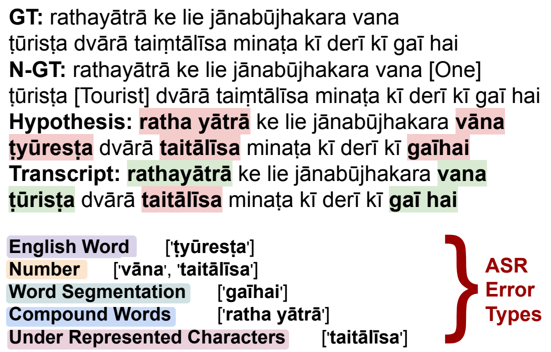

Figure 3: Example of ASR hypothesis errors in Hindi, categorized by error types: English word transliteration (*ṭyūresṭa*), number transcription (*vāna*, *taitālīsa*), word segmentation (*gaīhai*), compound word splitting (*ratha yātrā*), and underrepresented character errors (*taitālīsa*).

where phrases like (/kē liē/) or (/gaī hai/) can become incorrectly merged. Misrecognition of numbers further complicates Hindi ASR. For instance, the English numbers, such as "one" (expected as (/ vana /)), are often phonetically transcribed as (/ vāna /), and native Hindi numbers, like (/taitālīsa/) (taitālīsa means forty three), can be distorted due to inadequate training data. Code-mixed content, such as(/ rathayātrā kē liē jānabūjhakara vana ṭūrisṭa dvārā taitālīsa minaṭa kī dērī kī gaī hai /)[6], further complicates ASR tasks, as systems struggle to manage transitions between Hindi and English seamlessly. Lastly, phonetic and orthographic variability arising from regional accents, dialects, and optional diacritics or conjunct consonants leads to systematic recognition errors as shown in Figure 3.

C Related Works

LLMs have been integrated into ASR systems through various approaches. ASR error correction uses LLM to re-score the N-best lists of potential transcriptions, refining the predictions (Ma et al., 2023; Radhakrishnan et al., 2023). Speech ICL fine-tunes LLMs with speech inputs, enabling them to handle diverse tasks (Kumar et al., 2024), while deep LLM fusion (Fathullah et al., 2024) employs LLMs as decoders in ASR architectures, integrating language modelling capabilities through mechanisms like gated cross-attention. However, both ICL speech (Pan et al., 2023) and deep LLM fusion (Fathullah et al., 2024) are computationally intensive, requiring significant resources and large labelled speech datasets, which are scarce for low-resource languages such as Hindi. Similarly, LLM re-scoring of N-best lists often underperforms compared to using a single 1-best hypothesis (Li et al., 2024), which is sufficient to address common errors such as word segmentation, underrepresented characters, and compound word handling.

D Model Comparison

Model	WER (%)	CER (%)
IndicWav2vec (Javed et al., 2022)	28.605	10.54
IndicWhisper (Bhogale et al., 2023b)	32.17	19.86
IndicConformer (Javed et al., 2024a)	18.015	6.458
Seamless M4T (Barrault et al., 2023)	52.63	29.89
data2vec_aqc (Lodagala et al., 2023)	29.63	10.6
SALSA (Mittal et al., 2024)	74.43	54.54

Table 5: Performance Comparison of Open-Source Hindi ASR Models on Hindi Lahaja dataset

Table 5 presents a comparative evaluation of open-source Hindi ASR models on the Hindi Lahaja dataset in terms of Word Error Rate (WER) and Character Error Rate (CER). Among the evaluated systems, IndicConformer (Javed et al., 2024a) achieves the best performance with a WER of 18.015% and a CER of 6.458%, significantly outperforming other models. IndicWav2Vec (Javed et al., 2022) also demonstrates strong performance with a WER of 28.605% and CER of 10.54%, while IndicWhisper and Seamless M4T show higher error rates, reflecting their limitations in capturing the linguistic nuances of Hindi. Notably, SALSA (Mittal et al., 2024) performs the worst, with a WER of 74.43% and CER of 54.54%, suggesting it is less suitable for Hindi ASR. These results reinforce the effectiveness of IndicConformer as a robust baseline for downstream post-ASR correction tasks in Hindi.

Moreover, Table 1 demonstrates how the use of larger and diverse training datasets improves model. Specifically, IndicWav2Vec and IndicConformer, combined with LM like ByT5 and mT5, exhibit marked improvements in the Lahaja test set, underscoring the effectiveness of leveraging diverse error patterns for ASR post correction training. Although fine-tuned LLaMA decline the ASR hypothesis quality.

E Additional Analysis

Table 6 and Table 7 show that ByT5 consistently corrects more character-centric errors, code-mixed tokens, compound-word splits, word-segmentation mistakes, numeric misrecognitions, and underrepresented graphemes, than mT5. This stems from

[6]means "For the chariot procession, a tourist intentionally caused a delay of forty-three minutes."

Experiments	IW → CW	CW → IW	No Change
Word Segmentation	224	216	498
Compound Words	75	74	215
English Words	637	283	3180
English Number	7	17	131
Hindi Number	36	24	94
Underrepresented Character	2254	1129	3296

Table 6: Analysis of errors in Lahaja Dataset by mT5=16.17 model train on Lahaja dataset. IW = Incorrect Word and CW = Correct Word

Experiments	IW → CW	CW → IW	No Change
Word Segmentation	241	253	722
Compound Words	84	97	206
English Words	730	456	3087
English Number	19	22	119
Hindi Number	33	28	97
Underrepresented Character	2287	1798	3263

Table 7: Analysis of errors in Lahaja Dataset by ByT5=17.46 model train on Lahaja dataset. IW = Incorrect Word and CW = Correct Word

ByT5's byte-level tokenization, which provides finer granularity for detecting single-character perturbations. In contrast, mT5's sub-word vocabulary affords stronger semantic coverage but makes it less sensitive to very fine-grained character variations.

Table 8: Latency (in seconds) of different models for post-ASR correction.

ByT5-small	ByT5-base	mT5-small	mT5-base	LLaMA	GPT-4o mini
2.29	2.79	**0.97**	**1.84**	10.17	2.03

In Table 8, we summarize the latency of different LMs/LLMs, indicating that *mt5-small* performed the fastest post-ASR correction. It also points to the fact smaller models like mT5 not only achieve significant performance gains but also are faster than larger LLMs. Hence, we incorporate mT5 for post-ASR correction is advantageous for both performance wise and latency, enabling robust ASR correction in low-resource settings.

E.1 LM/LLM comparison

We have experimented with LMs (mT5 and ByT5) and LLMs (LLaMA-3-Nanda-10B-Chat) under comparable condition in terms of Hindi token used for pre-training them in absolute terms, relative terms to their size, and relative to overall presence of Hindi within the rest of the languages present to pre-train the model. We find that our observation still holds. Given that many experiments have shown that the fine-tuned model substantially updates their weights and hence the performance improvement is substantial, we empirically observe that finetuning has substantially improved the performance.

Experiment	Shots	IndicWav2Vec	IndicConformer
-	0-Shot	28.60 → 31.77	18.02 → 25.14
Random	1-Shot	28.60 → 30.95	18.02 → 24.51
	3-Shot	28.60 → 29.84	18.02 → 22.13
	5-Shot	28.60 → 29.27	18.02 → 22.19
SE Similarity	1-Shot	28.60 → 29.22	18.02 → 22.88
	3-Shot	28.60 → 28.18	18.02 → 22.04
	5-Shot	**28.60 → 27.14**	18.02 → 20.89

Table 9: WER Comparison for Various Shot Settings using GPT-4o mini (ICL)

E.2 Effect of domain-specific regularization

While fixed-ratio training helps mitigate domain forgetting by ensuring consistent exposure to limited in-domain data, an open research question remains: Can incorporating regularization techniques alongside fixed-ratio training further enhance model retention of in-domain knowledge during post-ASR correction? As shown in Table 10, fine-tuning the ByT5 and mT5 variants with a controlled ratio from the in-domain to the out-of-domain results in noticeable gains in correction performance across both IndicWav2Vec and IndicConformer outputs. However, despite these improvements, subtle performance degradation is still observed in some configurations with higher proportions out-of-domain. This suggests that additional mechanisms, such as domain-aware regularization, rehearsal-based constraints, or importance-weighted loss, could potentially reinforce in-domain retention even further. Investigating such methods in conjunction with fixed-ratio scheduling presents a promising direction for improving robustness and domain fidelity in low-resource post-ASR correction.

F Additional Languages

Our approach was tailored to Hindi, focusing on lexical and multiword interventions involving both lexical and morphemic-level knowledge. However, we have conducted evaluations for Marathi and Telugu as well. Table 11 shows the performance of various post-correction models on Marathi and Telugu subsets of the IndicTTS dataset. We compare ASR hypotheses against corrected outputs from ByT5 and mT5 models of both small and base sizes. The mT5-base model achieves a lower WER across both languages. We use the IndicTTS dataset for this evaluation as it closely resembles the Lahaja

Training Dataset	Ratio	Dataset Size	byt5-small		byt5-base		mt5-small		mt5-base	
			W2V	IC	W2V	IC	W2V	IC	W2V	IC
IndicVoice [IC+W2V] + other ASR dataset [IC]	3:7	381415	0.2620	0.1778	0.2244	0.1719	0.2817	0.1689	0.2589	**0.1603**
IndicVoice [IC+W2V] + other ASR dataset [W2V]	3:7	381415	0.2300	0.1760	**0.2226**	0.1765	0.2600	0.1713	0.2581	0.1651
IndicVoice [IC+W2V] + other ASR dataset [IC]	2:8	571962	0.2358	0.1729	0.2232	0.1774	0.2735	0.1688	0.2651	**0.1602**
IndicVoice [IC+W2V] + other ASR dataset [W2V]	2:8	571962	0.2310	0.1787	0.2229	0.1758	0.2591	0.1758	0.2668	0.1662
IndicVoice [IC+W2V] + other ASR dataset [IC]	1:9	993155	0.2442	0.1774	0.2443	0.1774	0.2512	0.1710	0.2588	**0.1614**
IndicVoice [IC+W2V] + other ASR dataset [W2V]	1:9	993155	0.2333	0.1829	0.2234	0.1762	0.2388	0.1712	0.2549	0.1638

Table 10: Evaluation of post-ASR correction on Lahaja dataset mixing the in-domain and out-of-domain dataset in fixed ratio

Language	Hypothesis	ByT5 small	ByT5 base	mT5 small	mT5 base
Marathi	25.556	26.324	26.018	25.761	**25.122**
Telugu	23.284	24.51	24.725	**22.68**	**22.05**

Table 11: Evaluation of post-ASR correction on Marathi and Telugu IndicTTS datasets.

dataset in linguistic characteristics and is in-domain with the IndicVoice dataset, ensuring consistent domain relevance for low-resource ASR evaluation.

G Compound Word Error Detection Algorithm

To systematically identify compound word errors in ASR hypotheses, we propose an algorithm that leverages a trie-based structure built from a vocabulary dictionary. As outlined in Algorithm 1, the process involves tokenizing both the ground truth (GT) and hypothesis (Hyp) utterances, generating valid substrings from GT tokens, and validating these against the constructed trie. The algorithm then checks whether the valid compound words from the ground truth appear intact in the hypothesis. If a compound word is absent or split incorrectly in the hypothesis, it is flagged as an error. This approach is particularly effective for detecting errors in morphologically rich languages like Hindi, where compound word splitting significantly alters meaning. By identifying such errors, the algorithm supports more fine-grained post-ASR correction and helps evaluate model performance on preserving lexical integrity.

H Compute Infrastructure

Compute details: For all our pre-training and fine-tuning experiments, we used two NVIDIA A100-SXM4-80GB GPUs. Each training requires 4-48 hours.

Software and Packages details: We implement all our models in PyTorch[7]

[7] https://pytorch.org/

Algorithm 1 Detecting Compound Word Errors Using a Trie

Require: Dict: Vocabulary dictionary, GT: Ground Truth utterance , Hyp: Hypothesis utterance

Ensure: $\mathrm{Er}_{\mathrm{CW}}$: List of compound word errors

Step 1: Build the Trie
Initialize an empty Trie T
for each word $\in$ Dict **do**
    Traverse T character by character
    if character does not exist in T **then**
        Create a new node
    end if
    Mark the end of word as isEndOfWord $\leftarrow$ True
end for
Step 2: Preprocess Input
Tokenize GT: $\mathrm{GT}_{\mathrm{tokens}} \leftarrow \mathrm{split(GT)}$
Tokenize Hyp: $\mathrm{Hyp}_{\mathrm{tokens}} \leftarrow \mathrm{split(Hyp)}$
Step 3: Generate Substrings
for each word $\in \mathrm{GT}_{\mathrm{tokens}}$ **do**
    Splits $\leftarrow$ splits(word)
    Store valid splits as $\mathrm{Splits}_{\mathrm{valid}}$
end for
Step 4: Validate Substrings
for each split $\in \mathrm{Splits}_{\mathrm{valid}}$ **do**
    if all substrings subsplit $\in$ split exist in T **then**
        Add split to $\mathrm{CompoundWords}_{\mathrm{valid}}$
    end if
end for
Step 5: Check for Errors
for each word $\in \mathrm{CompoundWords}_{\mathrm{valid}}$ **do**
    if word $\notin \mathrm{Hyp}_{\mathrm{tokens}}$ **then**
        Add word to $\mathrm{Er}_{\mathrm{CW}}$
    end if
end for
Step 6: Output Results
Save $\mathrm{Er}_{\mathrm{CW}}$ for further analysis

Models
mT5: mT5-small (300M parameters), mT5-base (580M parameters)
ByT5: ByT5-small (300M parameters), ByT5-base (580M parameters)
Nanda: LLaMA3-10B
GPT-4o mini: 8B parameter

I Prompt

GPT-4o mini prompt based on error-types

Example 1:
You are given an ASR hypothesis of a spoken utterance. The hypothesis may contain misrecognized words, incorrect word segments, or code-switching mistakes. Your job is to produce the best possible corrected text, relying on your own knowledge of grammar and typical usage
Please correct any errors in
1. Incorrect transliteration of English words
2. Incorrect transliteration of English numbers
3. Incorrect transcription of native Hindi numbers
4. Misrecognition of underrepresented characters
5. Splitting of compound words
6. Incorrect word segmentation

There may be more than two errors in the ASR hypothesis.
Output only the final corrected output (no extra commentary)

Hypothesis: ratha yātrā ke lie jānabūjhakara vāna ṭyūresṭa dvārā taitālīsa minaṭa kī derī kī gaī hai

Predicted Output: ratha yātrā ke lie jānabūjhakara vana ṭyūrisṭa dvārā taiṃtālīsa minaṭa kī derī kī gaī hai.