RESPIN-S1.0: A read speech corpus of 10000+ hours in dialects of nine Indian Languages

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NeurIPS 2025, Datasets & Benchmarks Track



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Motivation: Dialectal Gap in Indian ASR

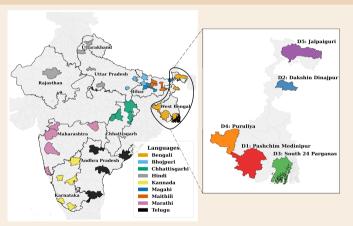
- Indian speech tech often trained on standard/urban varieties → poor performance for rural, low-literacy speakers.
- Public-service domains (agriculture, banking/finance) are especially affected.
- **Objective:** release a large, dialect-rich, ethically collected read-speech corpus to support ASR and dialect identification (DID) research.

Why RESPIN-S1.0?

- Source-level dialect representation.
- Domain-grounded text.
- Reproducible splits for benchmarks.

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Geographic and Dialectal Coverage



- Covers 9 major Indian languages and 38+ district-linked dialects.
- Dialect regions explicitly mapped to Census 2011 administrative districts, enabling reproducible and geographically grounded analysis.
- Facilitates comparison across
 Indo-Aryan and Dravidian
 linguistic families within a unified corpus.

RESPIN-S1.0: Summary

- Languages: 9 (bn, bh, ch, hi, kn, mg, mt, mr, te)
- **Dialects:** 38+ district-linked varieties
- **Speech:** 10,416 h Clean + 2,288 h Semi-noisy + 1,617 h Noisy = **14,322** h
- **Speakers:** ~18k from 1,500+ pincodes
- **Domains:** Agriculture & Banking/Finance
- **Text:** 209k+ native-authored sentences
- Ethics: IISc approval, mobile-app consent, fair compensation

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Text Corpus Design

- \sim 2.1L native-authored prompts across the two target domains.
- 3–5 dialects per language; domain balance enforced at authoring time.
- \sim 3.6% sentences filtered during validation for mismatch/anomalies.
- Limited translation (6–17%) only where dialectal gaps existed; Bengali is fully native-authored.
- Also released: dialect-specific phonetic lexicons aligned with validated text (see paper/appendix for details).

Lexicon and Text Statistics by Language

Lang	Chars	Lexicon Phones	LexWds	#Dials	#Sents	Text Corpus TotalWds	Vocab	AvgLen
bh	71	54	14.1k	3	23.916	250.542	14,000	3.75
bn	64	50	18.6k	5	21,959	213,648	18,631	4.73
ch	68	50	13.2k	4	21,281	317,907	13,184	3.36
hi	72	55	16.6k	5	21,782	255,543	16,460	3.94
kn	66	50	50.8k	5	25,178	235,511	50,622	6.51
mg	72	54	21.7k	4	23,281	253,834	21,600	3.87
mr	68	51	35.7k	4	25,012	220,768	35,464	5.47
mt	72	55	19.3k	4	25,803	286,950	19,197	3.87
te	63	48	39.2k	4	21,772	191,238	39,015	6.42

Number of dialects (#D), sentences (#S), total words (TotW), vocabulary size (Vocab), and average sentence length (AvgL).

Observations

- Dravidian languages (kn, te) → highest lexical diversity and longer sentences.
- Indo-Aryan languages (bh, ch, mg)
 → more compact vocabularies.

Audio Statistics and Quality Slab Distribution

	ise Durati	on (n)	Aggregate Audio Statistics				
Clean	Semi	Noisy	Total(h)	#Utts	#Spkrs	AvgDur(s)	
1116.96	105.87	76.57	1299.4	982,394	1,532	4.76	
1213.24	189.96	6.73	1409.9	986,295	1,964	5.15	
1295.97	198.27	90.12	1585.0	966,754	1,777	5.90	
944.59	362.79	390.86	1698.6	1,231,540	2,525	4.97	
1344.10	250.10	226.23	1671.0	990,756	2,009	6.07	
1279.48	112.39	72.74	1529.5	1,077,792	2,239	5.11	
1379.44	335.21	199.94	1814.6	1,353,012	2,391	4.83	
723.06	510.24	405.29	1638.6	1,048,311	2,076	5.63	
1303.98	222.53	148.99	1675.5	1,114,563	2,064	5.41	
10,416	2,288	1,617	14,322	9,751,417	18,577	-	
	1116.96 1213.24 1295.97 944.59 1344.10 1279.48 1379.44 723.06 1303.98	1116.96 105.87 1213.24 189.96 1295.97 198.27 944.59 362.79 1344.10 250.10 1279.48 112.39 1379.44 335.21 723.06 510.24 1303.98 222.53	1116.96 105.87 76.57 1213.24 189.96 6.73 1295.97 198.27 90.12 944.59 362.79 390.86 1344.10 250.10 226.23 1279.48 112.39 72.74 1379.44 335.21 199.94 723.06 510.24 405.29 1303.98 222.53 148.99	1116.96 105.87 76.57 1299.4 1213.24 189.96 6.73 1409.9 1295.97 198.27 90.12 1585.0 944.59 362.79 390.86 1698.6 1344.10 226.23 1671.0 1279.48 112.39 72.74 1529.5 1379.44 335.21 199.94 1814.6 723.06 510.24 405.29 1638.6 1303.98 222.53 148.99 1675.5	1116.96 105.87 76.57 1299.4 982,394 1213.24 189.96 6.73 1409.9 986,295 1295.97 198.27 90.12 1585.0 966,754 944.59 362.79 390.86 1698.6 1,231,540 1344.10 250.10 226.23 1671.0 990,756 1279.48 312.39 72.74 1529.5 1,077,792 1379.44 335.21 199.94 1814.6 1,353,012 723.06 510.24 405.29 1638.6 1,048,311 1303.98 222.53 148.99 1675.5 1,114,563	1116.96 105.87 76.57 1299.4 982,394 1,532 1213.24 189.96 6.73 1409.9 986,295 1,964 1295.97 198.27 90.12 1585.0 966,754 1,777 944.59 362.79 390.86 1698.6 1,231,540 2,525 1344.10 250.10 226.23 1671.0 990,756 2,009 1279.48 112.39 72.74 1529.5 1,077,792 2,239 1379.44 335.21 199.94 1814.6 1,353,012 2,391 723.06 510.24 405.29 1638.6 1,048,311 2,076 1303.98 222.53 148.99 1675.5 1,114,563 2,064	

Key Insights

- **14.3k h** validated across 9 languages and 18k+ speakers.
- Clean slab (>10k h): benchmark-quality subset for ASR and DID.
- Semi/Noisy slabs: support robustness, domain-shift, and fairness studies.
- Short avg. durations (4–6 s): suitable for fine-grained alignment and acoustic modeling.

Validation Process and Slab Assignment

Multi-stage Validation Pipeline

- **Automatic Scoring:** Forced alignment and semi-automated models compute alignment confidence scores for every utterance.
- Manual Verification: ~5% of utterances per dialect manually inspected to calibrate and refine thresholds.
- Slab Assignment: Recordings categorized into Clean, Semi-noisy, and Noisy based on scoring outcomes, verified through multi-stage manual validation.

Design Rationale

- Ensures a high-quality benchmark core while preserving naturally occurring variability.
- Facilitates reproducible evaluation across clean and challenging conditions.
- Provides a transparent and scalable quality-control pipeline for future RESPIN releases.

Corpus Design, Validation, and Ethical Safeguards

Dialectal and Data Integrity

- All stages—text creation, speaker recruitment, and validation—conducted *per dialect* to preserve linguistic authenticity.
- \sim 1500 domain-specific subtopics (e.g., soil health, crop insurance, UPI, KYC) curated for balanced domain coverage.
- Dialect-aware reviewer workflow ensured consistent text-audio-dialect alignment across composing, recording, and validation stages.

Ethical and Demographic Safeguards

- Speaker enrollment via the Bolo mobile app with WhatsApp-based verification and informed consent.
- Participant demographics (age, gender, region) verified for internal consistency before release.
- Ethics approval obtained from IISc; contributors received fair compensation in compliance with research standards.

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Benchmarking Setup

Models evaluated

- TDNN-HMM [2]
- E-Branchformer [3]
- Whisper (Tiny/Base/Small) [4]
- IndicWav2Vec, SPRING-Wav2Vec2, SPRING-Data2Vec-AQC

Protocol

- All trained/fine-tuned only on RESPIN standardized train splits.
- Evaluated per language using common dev/test.

Benchmarking on RESPIN-S1.0

Model	Avg. CER (%)	Avg. WER (%)				
Pretrained (non-RESPIN fine-tuning)						
SeamlessMÅT-v2-Large	22.23	51.81				
IndicW2V	17.09	49.25				
SPRING-W2V2	13.29	39.58				
SPRING-Data2Vec-AQC	12.88	38.83				
Traditional (RESPIN scratch)						
TDNN-HMM	4.99	17.28				
E-Branchformer	4.52	16.63				
Fine-tuned on RESPIN						
Whisper-Tiny	10.66	32.44				
Whisper-Base	7.31	25.36				
Whisper-Small	5.69	20.08				
IndicW2V	4.60	19.84				
SPRING-W2V2	3.71	15.92				
SPRING-Data2Vec-AQC	3.58	15.40				

Averages over 9 RESPIN languages.

Key empirical findings

- Best overall: SPRING-Data2Vec-AQC (RESPIN fine-tuned) achieves the lowest average error: 3.58% CER, 15.40% WER.
- Effect of RESPIN fine-tuning: Whisper and SSL models substantially improve over their non-RESPIN counterparts → dialectal adaptation is essential.
- Pretrained (non-RESPIN) models underperform on dialect-rich speech (WER ~39–52%), showing domain mismatch.
- Traditional RESPIN-scratch models (TDNN-HMM, E-Branchformer) remain competitive baselines (WER 16–17%) for lower-capacity settings.
- Overall: RESPIN-S1.0 enables a clear ranking of ASR systems under Indian dialectal variation.

Applications, Impact, and Limitations

Applications

- MADASR 2023/2025 and other dialect-aware ASR challenges.
- ASR, DID, LID, robustness, fairness evaluations.

Impact

- $lue{}$ Focus on agriculture & finance ightarrow directly useful for rural public-service speech systems.
- Reproducible, open splits meet NeurIPS D&B expectations.

Limitations

- Read speech only; spontaneous/conversational planned.
- Domains limited to two verticals; future: healthcare, education, governance.
- Smartphone-based collection may miss non-digital users.

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Conclusion and Future Directions

Conclusion

- RESPIN-S1.0: 9 languages, 38+ dialects, 14k+ hours, dialect-preserving pipeline.
- Ships with text, phonetic lexicons, metadata, and benchmark-ready splits.

Future work

- Extend to spontaneous / conversational speech.
- Add more public-service domains.
- Release companion benchmark recipes for SSL and large ASR models.

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- Their contributions were instrumental in developing the large-scale, dialect-rich **RESPIN-S1.0** corpus.

Thank You!

Questions or Suggestions?



Code Repository

github.com/labspire/respin_baselines

OpenReview Link

openreview.net/forum?id=qL8M2dOY4L

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