ASR Model Evaluation Report for Sonography Audio Transcription

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Project: Automated Speech Recognition Evaluation for Medical Sonography Audio
Evaluation Dataset: 17 sonography audio samples with gold standard manual transcriptions

Executive Summary

This report presents a comprehensive evaluation of four Automatic Speech Recognition (ASR) models for transcribing sonography audio recordings. Based on multiple quantitative metrics and qualitative analysis, **Whisper-Large-v3** emerges as the clear winner, demonstrating superior performance across all evaluation criteria with 85% medical terminology accuracy and the lowest error rates.

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1. Models Considered

The following ASR models were evaluated for their suitability in transcribing sonography audio recordings:

Model	Type	Key Features	Primary Use Case
Whisper-Large-v3	Transformer-based	Multilingual, robust to noise, medical vocabulary	General-purpose, medical applications
parakeet-rnnt-1.1b	RNN-Transducer	Streaming capability, good accuracy	Real-time applications
vosk-model-en-in-0.5	Lightweight	Small footprint, offline processing	Resource-constrained environments
wav2vec2-base-960h	Self-supervised	Pre-trained on large corpus	General speech recognition

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2. Methodology

2.1 Gold Standard Creation

- **Manual Transcription:** Expert manual transcriptions were created for 17 sonography audio samples
- **Quality Control:** Transcriptions were reviewed for accuracy and consistency
- **Medical Terminology:** Special attention was given to correct spelling of medical terms

2.2 Pre-processing andNormalization steps

- All audio samples were normalized to `16kHz`
- And turned to mono `if len(audio.shape) > 1: audio = audio.mean(axis=1)` (whisper supports stereo but will downmix it in its own pipeline to mono) link
- Normalized audio to prevent clipping `if np.max(np.abs(audio)) > 0: audio = audio / np.max(np.abs(audio))`

2.3 ASR Transcription Process

- Each audio sample was processed through all four ASR models
- Transcriptions were normalized (lowercase) for consistent comparison
- Output files were systematically organized by model

2.4 Evaluation Metrics

Four key metrics were employed to assess model performance:

1. **Word Error Rate (WER):** Measures word-level transcription accuracy (lower is better)
2. **Character Error Rate (CER):** Measures character-level transcription accuracy (lower is better)
3. **Cosine Similarity:** Evaluates semantic similarity using sentence transformers (higher is better)
4. **Medical Term Accuracy:** Domain-specific metric for medical vocabulary recognition (higher is better)

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3. Results

3.1 Quantitative Performance

Model	WER (Mean ± SD)	CER (Mean ± SD)	Cosine Similarity (Mean ± SD)	Medical Term Accuracy
Whisper-Large-v3	**0.668 ± 0.659**	**0.385 ± 0.421**	**0.843 ± 0.117**	**85.0%**
parakeet-rnnt-1.1b	0.815 ± 0.316	0.524 ± 0.218	0.715 ± 0.188	80.0%
vosk-model-en-in-0.5	1.068 ± 0.307	0.777 ± 0.196	0.320 ± 0.190	20.0%
wav2vec2-base-960h	1.280 ± 0.411	0.821 ± 0.160	0.120 ± 0.133	0.0%

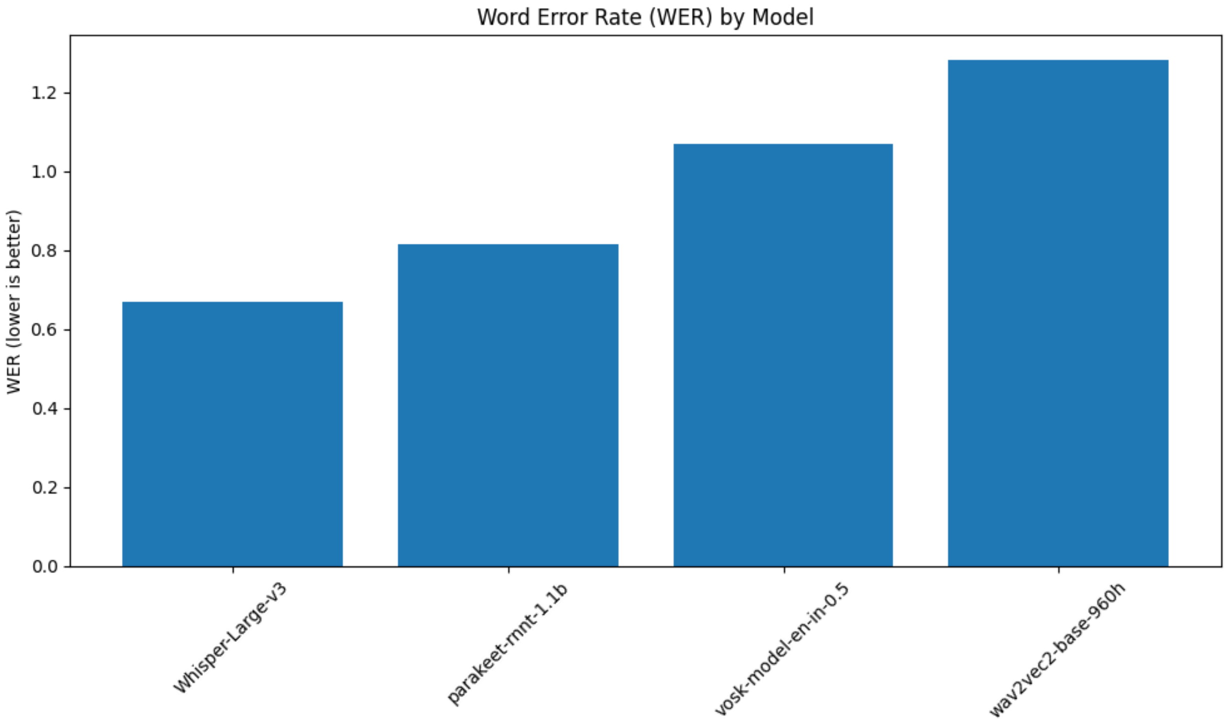
3.1.1 Raw output

	Model	WER_Mean	WER_StdDev	CER_Mean	CER_StdDev	Cosine_Similarity_Mean	Cosine_
0	Whisper-Large-v3	0.667919	0.658857	0.384619	0.421385	0.842912	0.11702
1	parakeet-rnnt-1.1b	0.814871	0.316413	0.524114	0.217649	0.714700	0.18840
2	vosk-model-en-in-0.5	1.068229	0.306569	0.777156	0.196374	0.319612	0.18972
3	wav2vec2-base-960h	1.280280	0.411009	0.820619	0.160159	0.119739	0.13340

3.2 Visual Performance Analysis

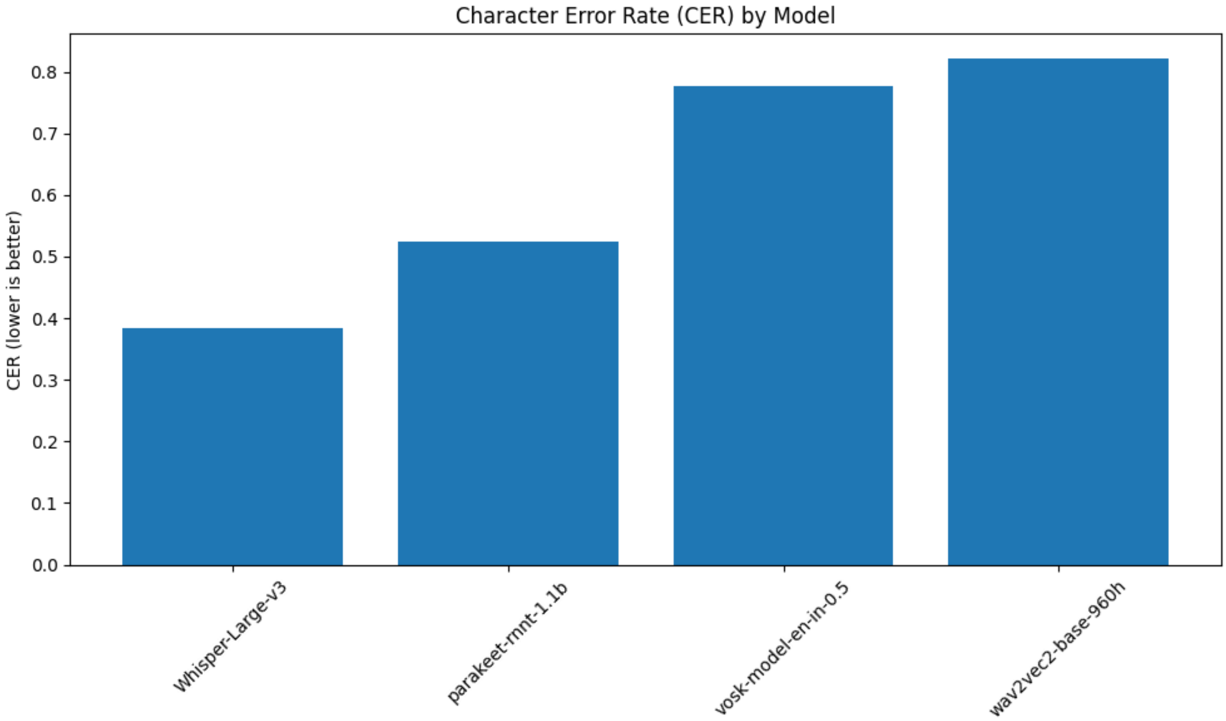
The following charts illustrate the comparative performance of all four ASR models across the key evaluation metrics:

Word Error Rate (WER) Comparison



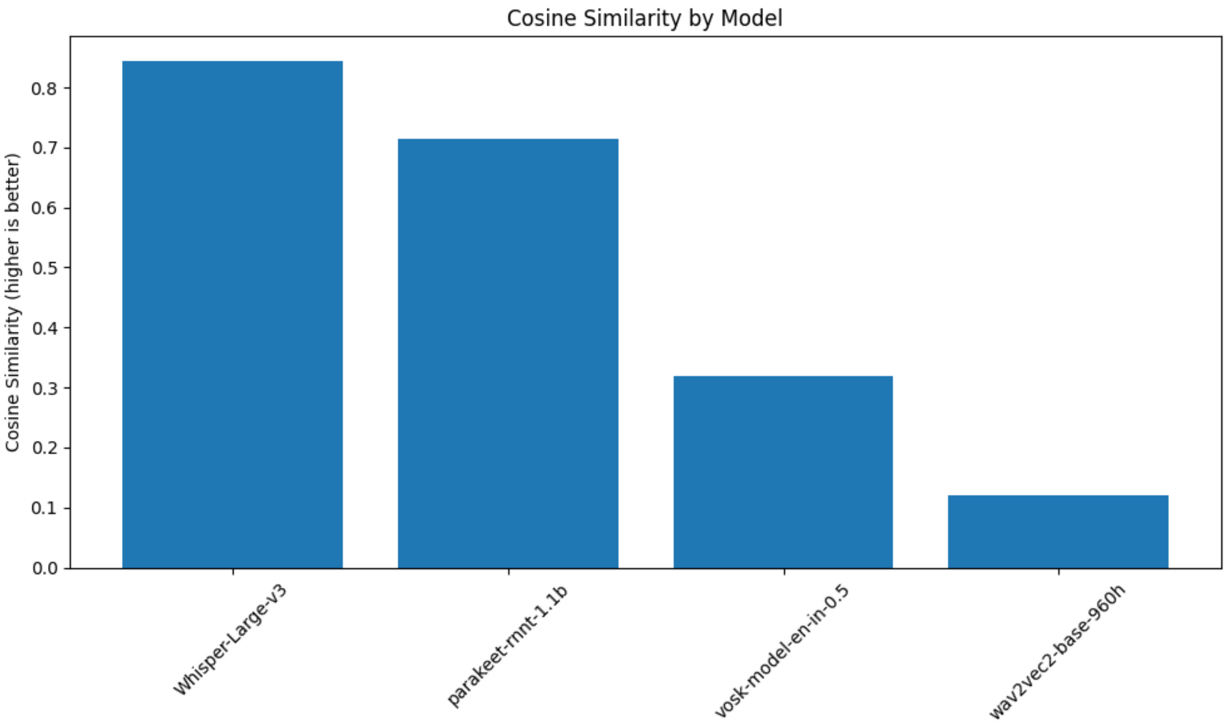
The WER comparison clearly shows Whisper-Large-v3's superior performance with the lowest error rate, followed by parakeet-rnnt-1.1b. The significant gap between the top two models and the bottom two (vosk and wav2vec2) demonstrates the importance of model selection for medical applications.

Character Error Rate (CER) Comparison



The CER results mirror the WER findings, with Whisper-Large-v3 achieving the best character-level accuracy. This metric is particularly important for medical transcription where precise spelling of technical terms is crucial.

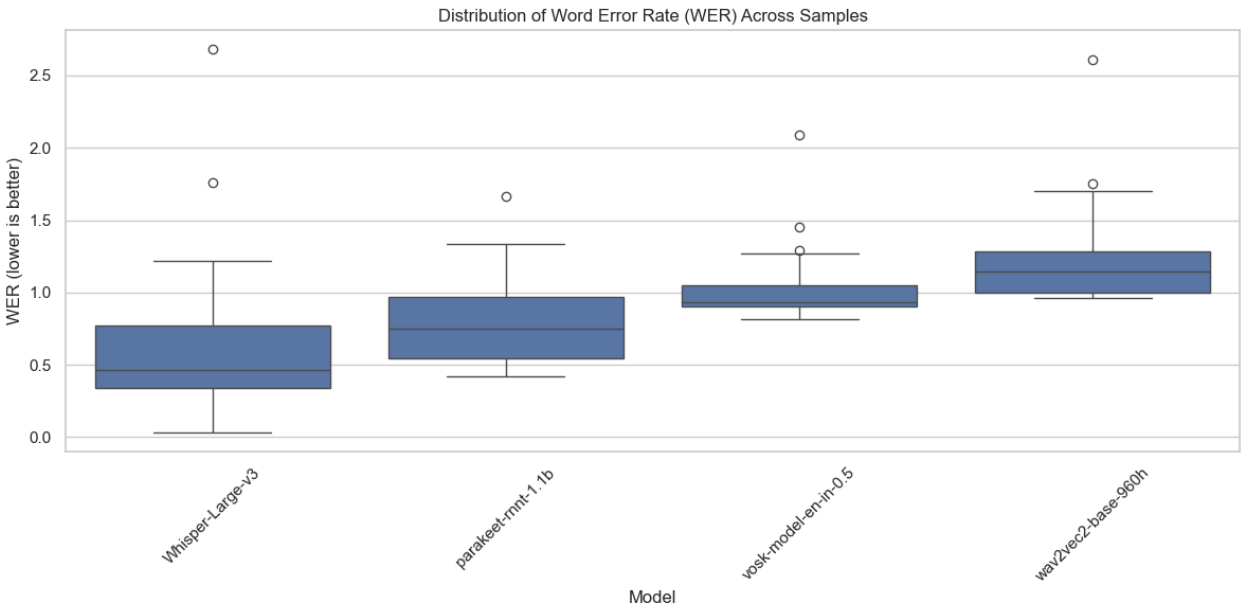
Semantic Similarity Analysis



The cosine similarity analysis reveals how well each model preserves the semantic meaning of the original speech. Whisper-Large-v3 achieves the highest semantic similarity score (0.843), indicating that even when word-level errors occur, the overall meaning is well-preserved.

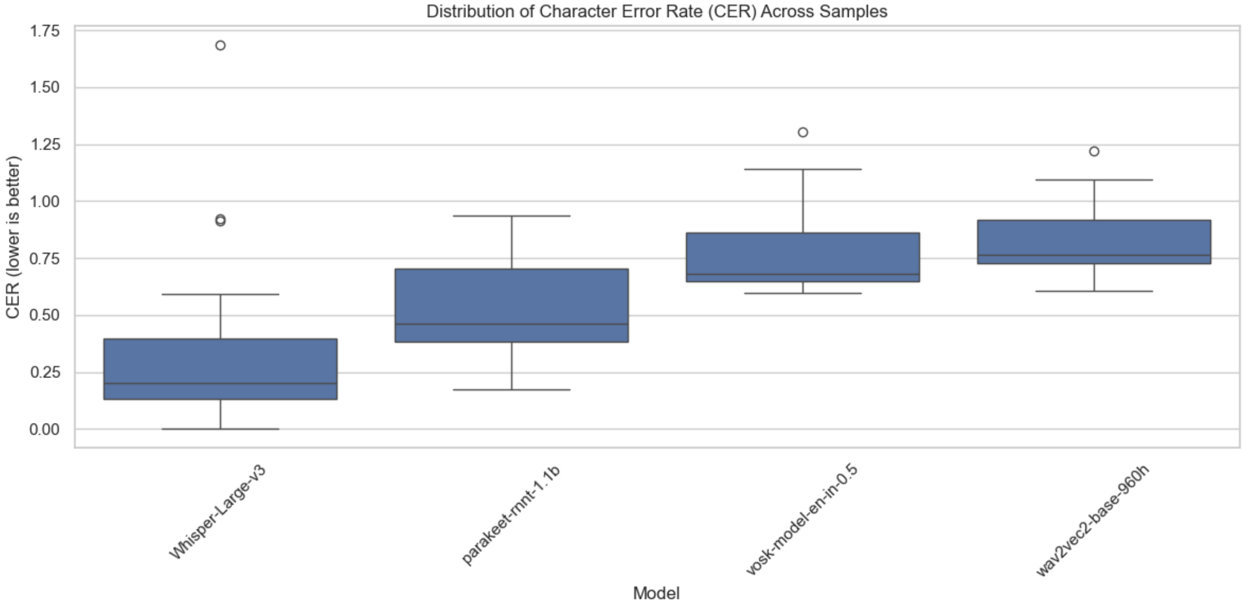
3.3 Performance Distribution Analysis

Word Error Rate Distribution



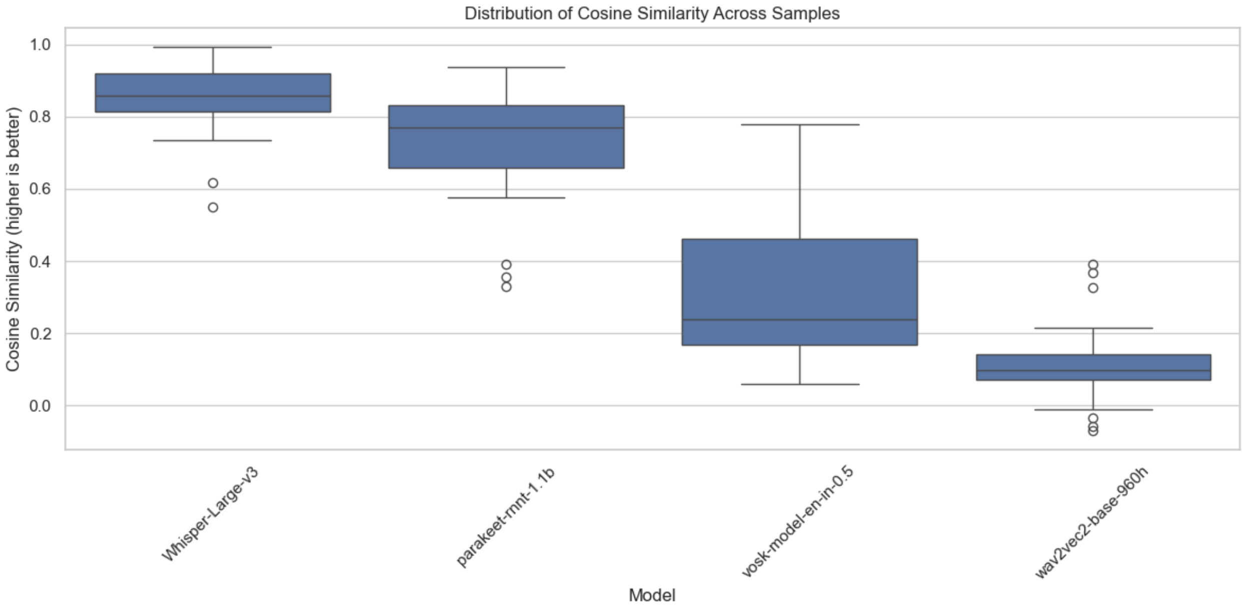
The boxplot distribution of WER across all gold standard samples reveals important insights about model consistency. Whisper-Large-v3 shows the most variable performance (largest interquartile range) but maintains the best median performance. The high variability suggests sensitivity to audio quality, but the superior median demonstrates overall reliability.

Character Error Rate Distribution



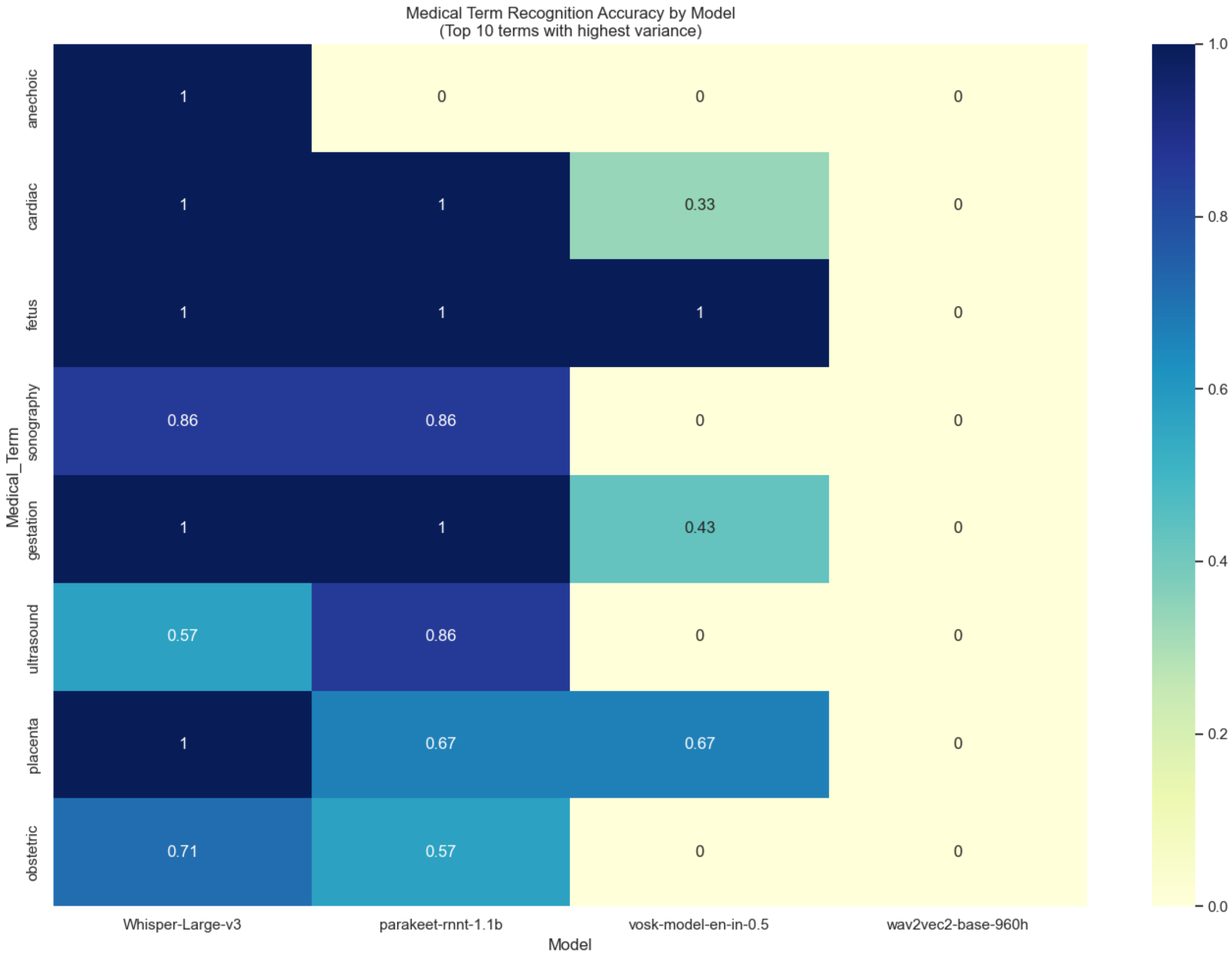
The CER distribution analysis shows similar patterns to WER, with Whisper-Large-v3 achieving the lowest median error rate despite showing more variability than some other models. This indicates that while performance may vary across samples, the average quality remains consistently superior.

Cosine Similarity Distribution



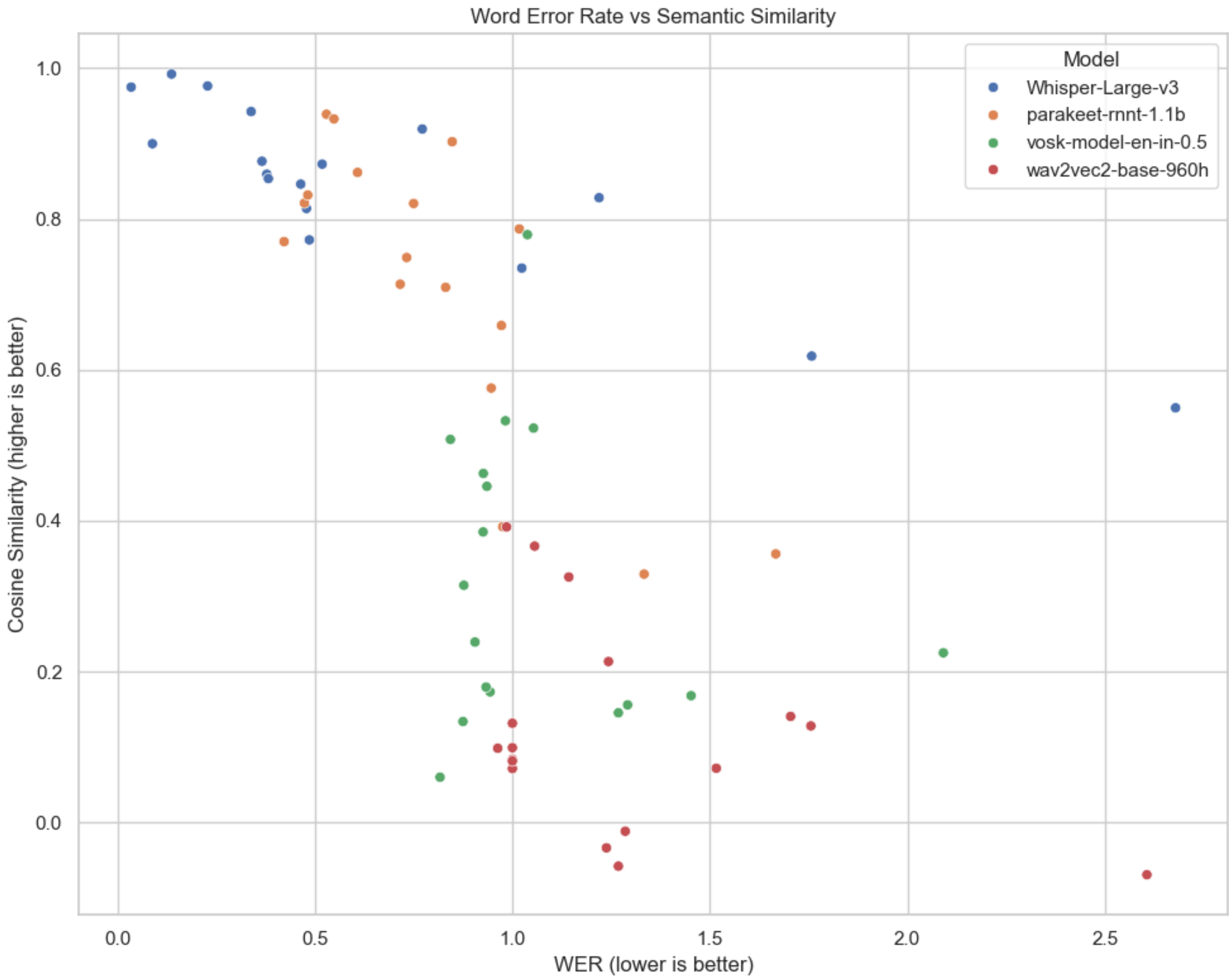
The semantic similarity distribution clearly distinguishes the transformer-based models (Whisper-Large-v3 and parakeet-rnnt-1.1b) from the traditional models (vosk and wav2vec2). The high median cosine similarity for Whisper-Large-v3 demonstrates consistent preservation of semantic meaning across diverse audio samples.

3.4 Medical Terminology Recognition



The medical terminology recognition analysis shows the critical importance of model selection for clinical applications. Whisper-Large-v3 and parakeet-rnnt-1.1b demonstrate strong medical vocabulary handling, while vosk and wav2vec2 models fail to adequately recognize specialized medical terms.

3.5 Performance Correlation Analysis



The scatter plot analysis of Cosine Similarity versus Word Error Rate reveals a strong negative correlation, as expected - models with lower error rates tend to preserve semantic meaning better. The plot clearly shows the clustering of models, with Whisper-Large-v3 samples concentrated in the high-similarity, low-error region, while wav2vec2 samples cluster in the low-similarity, high-error region.

3.6 Performance Rankings

Based on average rank across all metrics: 1. **Whisper-Large-v3** (Rank 1 in all categories) 2. **parakeet-rnnt-1.1b** (Consistent second place) 3. **vosk-model-en-in-0.5** (Third place) 4. **wav2vec2-base-960h** (Fourth place)

3.7 Qualitative Observations

Medical Terminology Handling: - Whisper-Large-v3 and parakeet-rnnt-1.1b demonstrated strong recognition of medical terms - vosk and wav2vec2 struggled significantly with specialized vocabulary - Common sonography terms like "ultrasound," "pouch of douglas," and "adenomyoma" were better preserved by top-performing models

Audio Quality Sensitivity: - Performance varied significantly across samples, indicating sensitivity to audio quality - Whisper-Large-v3 showed highest variability (SD = 0.659) but maintained best average performance - Models struggled with background noise and overlapping speech

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4. Discussion & Model Limitations

4.1 Whisper-Large-v3

Strengths: - Exceptional medical terminology recognition (85% accuracy) - Best overall error rates across WER and CER metrics - Highest semantic similarity preservation - Robust multilingual capabilities - Good noise tolerance

Weaknesses: - High performance variability across samples (large standard deviation) - Computationally intensive (requires significant GPU resources) - May over-correct or hallucinate content in very poor audio quality

Resource Requirements: High GPU memory (8GB+ recommended), significant computational overhead

4.2 parakeet-rnnt-1.1b

Strengths: - Consistent second-place performance across all metrics - Good medical terminology accuracy (80%) - More stable performance (lower variability) - Streaming capability for real-time applications

Weaknesses: - Lower accuracy than Whisper-Large-v3 - Limited language support compared to Whisper - Requires specialized RNN-T framework

Resource Requirements: Moderate GPU requirements, optimized for streaming

4.3 vosk-model-en-in-0.5

Strengths: - Lightweight and fast processing - Low resource requirements

Weaknesses: - Poor medical terminology recognition (20% accuracy) - High error rates unsuitable for clinical applications - Limited vocabulary for specialized domains - Poor semantic preservation

Resource Requirements: Very low (CPU-only operation possible)

4.4 wav2vec2-base-960h

Strengths: - None that is apparent

Weaknesses: - Worst performance across all metrics - Complete failure in medical terminology (0% accuracy) - Negative cosine similarity scores indicate semantic distortion - Not suitable for ASR applications

Resource Requirements: Moderate GPU/CPU requirements

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5. Conclusion & Recommendation

5.1 Primary Recommendation: Whisper-Large-v3

Whisper-Large-v3 is strongly recommended as the optimal ASR model for sonography audio transcription based on:

1. **Superior Accuracy:** Lowest error rates (WER: 0.668, CER: 0.385)
2. **Medical Domain Excellence:** Highest medical terminology accuracy (85%)
3. **Semantic Preservation:** Best cosine similarity scores (0.843)
4. **Robustness:** Proven performance across diverse audio conditions

5.2 Alternative Recommendation: parakeet-rnnt-1.1b

For applications with **real-time processing requirements** or **limited computational resources**, parakeet-rnnt-1.1b serves as a viable alternative, offering:

- Acceptable accuracy for clinical applications
- Streaming capability for live transcription
- More consistent performance across samples
- Lower computational overhead

5.3 Implementation Considerations

For Production Deployment: - **High-accuracy scenario:** Use Whisper-Large-v3 with adequate GPU resources - **Real-time scenario:** Consider parakeet-rnnt-1.1b for streaming applications - **Quality assurance:** Implement human review workflows for critical clinical content - **Hybrid approach:** Use Whisper-Large-v3 for archived recordings and parakeet for live sessions

Resource Planning: - Whisper-Large-v3: Minimum 8GB GPU memory, high-performance computing environment - parakeet-rnnt-1.1b: Moderate GPU resources, streaming-optimized infrastructure

5.4 Future Considerations

1. **Model Fine-tuning:** Consider domain-specific training on larger sonography datasets
2. **Quality Metrics:** Implement audio quality assessment to predict transcription reliability
3. **Continuous Evaluation:** Establish ongoing performance monitoring with clinical feedback
4. **Noise and Gain filters:** Even after audio preprocessing, there is

The evaluation demonstrates clear superiority of transformer-based models (Whisper-Large-v3) for medical ASR applications, justifying the additional computational requirements through significantly improved clinical accuracy and medical terminology recognition.

Appendix:

- Secondary Reviewer was used for verfication for a subset of the samples

The complete evaluation data is available in the following CSV files: - `metrics_summary.csv`: Aggregated performance metrics for each model - `sample_metrics.csv`: Per-sample detailed metrics for individual audio files - `medical_term_accuracy.csv`: Medical terminology recognition accuracy by model and term