

Comparative Analysis of Hate Classification in Audio: A Study of Waveform vs. Spectrogram-based Approaches



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Problem definition

- **Objective:** Compare hate speech classification using raw waveforms and spectrogram-based approaches in audio data.
- Hypothesis: Spectrogram-based models will outperform raw waveform models.
- Data Source: Text-to-speech synthesized audio from social media comments.

Key Related Works

- •Traditional ML: Logistic Regression, Random Forest, SVM for audio hate speech detection.
- •wav2vec2: Meta's model for learning speech representations.
- •AST: MIT's attention-based model for audio classification.
- •Coqui-TTS: Open-source Text-to-Speech generator.

Method

- Models:
 - Wav2vec2: Fine-tuned on raw audio waveforms.
 - AST: Fine-tuned on spectrograms treated as images.
 - **DistilBERT:** Fine-tuned on text data for comparison.
- Preprocessing: Text extraction, hate speech score assignment, text-to-speech synthesis using Coqui-TTS.
- Training Configurations: Varied learning rates, batch sizes, and gradient accumulation steps due to hardware constraints

Parameter	wav2vec2	AST	DistilBERT	Parameter
Learning Rate	4E-5	3E-5	8E-5	Learning Rate
Batch Size	32	16	32	Batch Size
Gradient Accumulation Steps (GAS)	4	2	4	Gradient Accumulation Steps (GAS)

Dataset(s)

•Source: UC Berkeley D-Lab "Measuring Hate Speech".

•Details: 39,565 samples, balanced for hate and non-hate speech, synthesized for audio.

Validation

- Models Used: wav2vec2 (raw waveforms), AST (spectrograms), DistilBERT (text).
- Key Metrics:
 - -Validation Set

Model	Loss	Accuracy	Recall	Precision	F1 Score
Wav2vec2	0.656	0.622	0.785	0.599	0.680
AST	0.631	0.649	0.837	0.614	0.708
DistilBER T	0.998	0.774	0.812	0.753	0.781

-Test Set

Model	Loss	Accuracy	Recall	Precision	F1 Score
Wav2vec2	0.660	0.619	0.782	0.594	0.676
AST	0.644	0.632	0.819	0.600	0.693
DistilBERT	1.064	0.754	0.793	0.741	0.766

Limitations

- •Synthetic Data: May not fully capture nuances of real human speech.
- •Computational Constraints: Affected model performance due to reduced batch sizes and steps.

Conclusion

- Findings: Audio classification is effective for hate speech detection.
- Performance: AST slightly better than wav2vec2; both close to DistilBERT.
- Implications: Potential for further research with larger, diverse, human speech datasets.

References

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[3] V. Sanh, L. Debut, J. Chaumond, and T. Wolf, "DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter," CoRR, vol. abs/1910.01108, 2019.