SPEECH UNDERSTANDING

Emotion Detection in Speech
A Comparative Study of State-of-the-Art Approaches

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Introduction

Task Definition. Emotion detection in speech aims to classify spoken audio into predefined emotional categories such as happy, sad, angry, calm, surprised, etc. This task is essential in human-computer interaction, healthcare, customer service, and security applications.

Real-World Importance

- Virtual Assistants: Enhances user experience by adapting responses based on emotional state.
- Healthcare: Supports mental health diagnosis and emotional well-being monitoring.
- Customer Service: Detects customer sentiment for improved interactions.
- Security & Surveillance: Identifies stress or aggression in security applications.

State-of-the-Art Models for Emotion Detection

Traditional Machine Learning Approaches

- Support Vector Machines (SVM), Random Forest, and k-NN models trained on hand-crafted features such as MFCCs, spectral, and prosodic features.
- Strengths: Computationally efficient and interpretable.
- Limitations: Requires extensive feature engineering and lacks robustness for real-world applications.

Deep Learning-Based Approaches

- CNN-Based Models
  - Model Example: CNN+LSTM Hybrid
  - Method: Uses spectrograms as input to convolutional layers followed by LSTMs for temporal feature extraction.
  - Strengths: Captures both spatial and temporal dependencies.
  - Limitations: Requires large amounts of labeled data.
- Recurrent Neural Networks (RNNs) & Transformers
  - Model Example: BiLSTM, GRUs, Wav2Vec2.0
  - Method: Processes raw audio features or MFCCs using LSTMs or transformers for sequential learning.
  - Strengths: Handles sequential dependencies efficiently.
  - Limitations: Prone to overfitting and computationally expensive.
- Self-Supervised Learning (SSL) Approaches
  - Model Example: Wav2Vec2.0 (Meta), HuBERT, Whisper
  - Method: Learns representations from raw audio without labeled data and fine-tunes on emotion datasets.
  - Strengths: Requires less labeled data, generalizes better.
  - Limitations: Large-scale models demand high computational resources.

Comparative Analysis of SOTA Models

Model	**Feature Extraction**	**Strengths**	**Limitations**
SVM	MFCCs, Spectral	Simple, interpretable	Needs manual features
CNN+LSTM	Spectrograms	Captures spatial & temporal info	High data requirement

BiLSTM	MFCCs, Raw Audio	Sequential modeling	Overfitting risk
Wav2Vec2.0	Raw Waveforms	Generalization, less labeling needed	Computationally expensive
HuBERT	Self-supervised	High accuracy, unsupervised learning	Needs fine-tuning
Whisper	Large-Scale Transformer	Robust multilingual support	Large model size

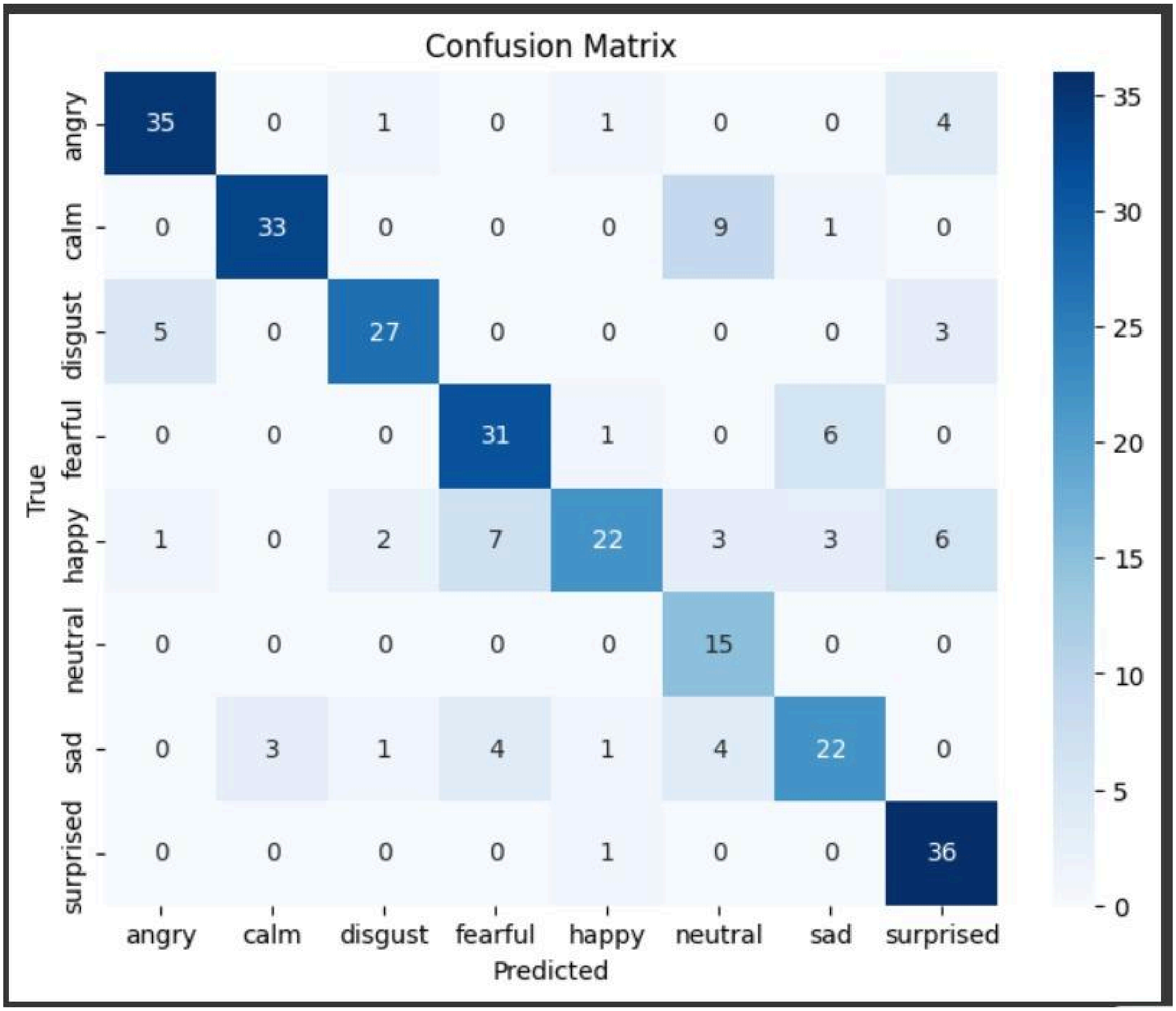
Evaluation Metrics & Results

Metrics Used

- Accuracy: Measures the percentage of correctly classified samples.
- Precision, Recall, and F1-score: Evaluates per-class performance, balancing false positives/negatives.
- Confusion Matrix: Visualizes model misclassifications.

Observations from Results

- Overall Accuracy: 76.7% using Wav2Vec2.0-based classification.
- Best Classified Emotions: Angry (85% Precision, 85% Recall) and Surprised (73% Precision, 97% Recall).
- Poorly Classified Emotions: Neutral (48% Precision, 100% Recall) and Happy (85% Precision, 50% Recall) indicate high false negatives.
- Misclassification Trends: Some emotions (e.g., happy & neutral) are often confused due to acoustic similarities.



	angry	calm	disgust	fearful	happy	neutral	sad	surprised
angry	35	0	1	0	1	0	0	4
calm	0	33	0	0	0	9	1	0
disgust	5	0	27	0	0	0	0	3
fearful	0	0	0	31	1	0	6	0
happy	1	0	2	7	22	3	3	6
neutral	0	0	0	0	0	15	0	0
sad	0	3	1	4	1	4	22	0
surprised	0	0	0	0	1	0	0	36

Open Problems and Future Directions

Open Challenges

- Data Scarcity: Emotional datasets are limited and imbalanced.
- Ambiguity in Emotions: Overlapping emotions (e.g., happy vs. neutral) cause misclassifications.
- Domain Adaptation: Models trained on one dataset often fail in real-world scenarios.
- Multilingual & Noisy Environments: Current models struggle with diverse accents and background noise.

Opportunities & Future Work

- Self-Supervised Learning (SSL): More models like Wav2Vec2.0 to reduce reliance on labeled data.
- Cross-Language Emotion Models: Develop robust multilingual speech emotion recognition.
- Explainability & Interpretability: Improve model transparency to understand misclassification trends.
- Multimodal Emotion Detection: Combining facial expressions & speech for enhanced accuracy.

Conclusion

- The SVM-based model achieved 76.7% accuracy, showing competitive results.
- Deep learning models like Wav2Vec2.0 and HuBERT outperform traditional methods but require large datasets and high computational resources.
- Future research should focus on self-supervised learning, multimodal approaches, and multilingual emotion recognition to enhance robustness.

Final Recommendation

For practical use cases, Wav2Vec2.0 or HuBERT-based models are preferred due to their robustness, while SVM remains a lightweight alternative for low-resource scenarios.