

Speech AI Suite - Complete Project Overview

⌚ Project Summary

Speech AI Suite is a professional, production-ready multi-task speech analysis platform that performs four critical audio classification tasks using state-of-the-art self-supervised learning models. This project combines cutting-edge deep learning with practical web application design, achieving 79.14% accuracy on emotion recognition and serving as a comprehensive reference for speech representation learning.

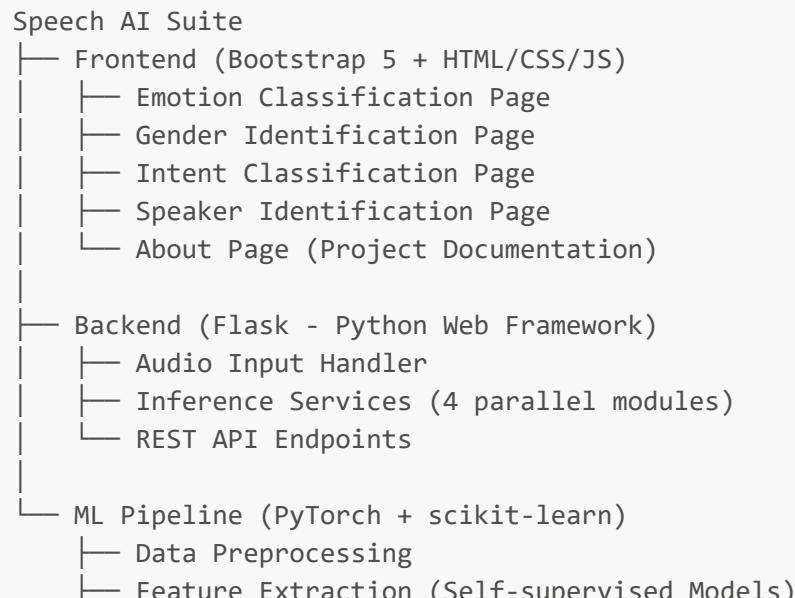
Research Paper Foundation:

- "From Raw Speech to Fixed Representations: A Comprehensive Evaluation of Speech Embedding Techniques" (IEEE/ACM 2024)
-

📊 Four Core Tasks

Task	Model	Classifier	Accuracy	Dataset	Classes
Emotion Classification	HuBERT-large	SVM	79.14%	CREMA-D	6 (Neutral, Happy, Sad, Angry, Fear, Disgust)
Gender Identification	WavLM-base-plus	Logistic Regression	—	Mixed	2 (Male, Female)
Intent Classification	WavLM-base-plus	SVM	—	SLURP	20 (Voice Commands)
Speaker Identification	XLSR-53	Logistic Regression	—	Mixed	Variable (Speaker IDs)

🏗 System Architecture



```
└── Model Training & Evaluation  
    └── Inference Modules
```

🔗 Complete Data Processing Pipeline

Stage 1: Data Preprocessing

Input: Raw audio files (WAV, MP3, FLAC, OGG, M4A, WebM) **Process:**

1. Audio loading and normalization
2. Resampling to 16kHz (standard for speech models)
3. Duration filtering (remove too short/long samples)
4. Label mapping and standardization
5. Data split: Train (70%), Validation (15%), Test (15%)

Output: Preprocessed dataset metadata (CSV format)

Stage 2: Feature Extraction

Input: Preprocessed audio files **Process:**

1. Load pre-trained self-supervised model (HuBERT, WavLM, or XLSR-53)
2. Extract final hidden layer representations
3. Apply pooling strategy (mean, std, or concatenation)
4. Normalize embeddings using StandardScaler

Mathematical Operation:

```
embedding = Model(audio) → hidden_states[last_layer]  
pooled_embedding = Pool(hidden_states)  
normalized_embedding = StandardScaler.transform(pooled_embedding)
```

Output: Fixed-dimensional embeddings (1024-2048 dimensions)

Stage 3: Dimensionality Reduction

Input: High-dimensional embeddings **Process:**

1. Apply PCA to reduce to 200 components
2. Fit scaler on training data
3. Transform validation/test data

Mathematical Operation:

```
X_reduced = PCA(n_components=200).fit_transform(X_embeddings)
```

Output: 200-dimensional vectors

Stage 4: Model Training

Input: Reduced embeddings + labels **Process (varies by task):**

- **SVM:** Multi-class SVM with RBF kernel, hyperparameter tuning via GridSearchCV
- **Logistic Regression:** L2 regularization, balanced class weights
- **Cross-validation:** 5-fold CV for robust performance estimation

Output: Serialized model + scaler + label encoder (.pk1 files)

Stage 5: Inference

Input: New audio file (user upload/recording) **Process:**

1. Load audio with audio processing library
2. Extract embedding using same model as training
3. Scale embedding using training scaler
4. Predict using trained classifier
5. Get probability scores using `predict_proba()`

Output: Predicted label + confidence scores (probabilities)

.Deep Learning Models Used

1. HuBERT-large (Emotion Classification)

- **Full Name:** Hidden-Unit BERT for Self-supervised Speech Representation
- **Publisher:** Meta AI (Facebook)
- **Architecture:** Transformer-based with 24 layers, 1024 hidden dimensions
- **Output Dimension:** 1024-dimensional embeddings
- **Pre-training:** Masked prediction on 960 hours of Libri-Light unlabeled data
- **Why Used:** Best performance for emotion classification in our experiments

2. WavLM-base-plus (Gender & Intent)

- **Full Name:** Large-Scale Self-Supervised Pre-Training for Full Stack Speech Processing
- **Publisher:** Microsoft Research
- **Architecture:** 12 transformer layers, 768 hidden dimensions
- **Output Dimension:** 768-dimensional embeddings
- **Pre-training:** 10,000 hours of speech with masked prediction
- **Why Used:** Efficient, fast inference while maintaining good accuracy

3. XLSR-53 (Speaker Identification)

- **Full Name:** Wav2Vec 2.0 XLSR (Cross-Lingual Speech Representations)
- **Publisher:** Meta AI
- **Architecture:** 12 transformer layers, 1024 hidden dimensions
- **Output Dimension:** 1024-dimensional embeddings

- **Pre-training:** 56,000 hours of multilingual speech
- **Why Used:** Robust speaker identification across languages and accents

Mathematical Framework

Feature Extraction Formula

```
E = PoolingStrategy(HiddenStates[-1])
```

Where:

- E = Output embedding (fixed-dimension vector)
- HiddenStates[-1] = Last transformer layer output (sequence of vectors)
- PoolingStrategy ∈ {mean, max, std, concatenation}

Mean Pooling: $E = \text{mean}(\text{HiddenStates}[-1])$

Std Pooling: $E = \text{std}(\text{HiddenStates}[-1])$

Concatenation: $E = \text{concatenate}(\text{mean}, \text{std}) \rightarrow 2x \text{ dimensions}$

Classification Formula

For SVM:

```
y_pred = sign( $\sum \alpha_i * K(x, x_i) + b$ )
```

Where:

- K = RBF kernel: $K(x, x') = \exp(-\gamma ||x - x'||^2)$
- γ (gamma) = $1/n_{\text{features}}$
- C (regularization) = 1.0

For Logistic Regression:

```
P(y=class_i) = exp(w_i · x + b_i) /  $\sum \exp(w_j \cdot x + b_j)$ 
```

Where:

- w_i = weights for class i
- b_i = bias for class i
- x = input embedding (scaled)

Cross-Validation Strategy

For each of k=5 folds:

1. Split data into train (80%) and validation (20%)
2. Train classifier on train fold
3. Evaluate on validation fold

4. Record metrics

```
Final_Accuracy = mean(fold_accuracies)
```

Data Formats & Datasets

Input Audio Formats Supported

- **WAV:** Uncompressed PCM, 16-bit
- **MP3:** Compressed, variable bitrate
- **FLAC:** Lossless compression
- **OGG/Opus:** Open-source compression
- **M4A:** Apple audio format
- **WebM:** Browser-native recording format

Datasets Used

CREMA-D (Emotion Classification)

- **Size:** ~7,500 utterances
- **Duration:** ~47 hours total
- **Speakers:** 91 unique speakers
- **Emotions:** 6 (Neutral, Happy, Sad, Angry, Fear, Disgust)
- **Language:** English
- **Recording:** Studio quality, multiple takes per emotion
- **Format:** WAV files at 16kHz

SLURP (Intent Classification)

- **Size:** ~63,000 utterances
- **Task:** Spoken Language Understanding
- **Intents:** 20+ voice command categories
- **Domains:** Smart home, entertainment, productivity
- **Language:** English
- **Format:** Audio files at 16kHz

Technology Stack

Backend Framework

- **Flask:** Lightweight Python web framework
- **Werkzeug:** WSGI utilities for request handling
- **Python 3.10+:** Runtime environment

Deep Learning Libraries

- **PyTorch:** Tensor operations, model inference

- **Transformers (HuggingFace)**: Pre-trained models loading
- **torchaudio**: Audio processing and resampling
- **librosa**: Audio feature computation
- **soundfile**: Audio file I/O

Machine Learning & Data Science

- **scikit-learn**: SVM, Logistic Regression, PCA, StandardScaler
- **numpy**: Numerical computations
- **pandas**: Data manipulation (CSV handling)
- **scipy**: Scientific computing utilities

Frontend

- **Bootstrap 5**: Responsive UI framework
- **HTML5**: Semantic markup
- **CSS3**: Styling with gradients and animations
- **JavaScript (Vanilla)**: Audio recording/playback, form handling
- **Bootstrap Icons**: SVG icon library

Development & Deployment

- **Git**: Version control
- **Git LFS**: Large file storage (for .pkl models)
- **GitHub**: Repository hosting
- **Virtual Environment**: Python dependency isolation

🚀 Project Development Workflow

1. Data Preparation Phase

```
Raw Audio Files (CREMA-D, SLURP)
  ↓
  1_data_preprocessing.py
  ↓
Normalized CSV Metadata
```

2. Feature Extraction Phase

```
Audio Files + Preprocessing Metadata
  ↓
  2_wavlm_feature_extraction.py
  ↓
NumPy Arrays (.npz files)
Embedding Dimensions: 1024 or 768
```

3. Model Training Phase

```
Extracted Embeddings + Labels  
↓  
3_train_classifiers.py  
↓  
Trained Models (.pkl files)  
- SVM/LogReg classifier  
- StandardScaler  
- LabelEncoder
```

4. Evaluation Phase

```
Trained Models + Test Set  
↓  
4_evaluation_metrics.py  
↓  
Metrics (Accuracy, F1, Precision, Recall)  
Confusion Matrices
```

5. Deployment Phase

```
Trained Models (.pkl)  
↓  
Backend Flask Server  
↓  
REST API Endpoints  
↓  
Web UI (HTML/CSS/JS)
```

📁 Project Structure

```
Emotion-classification/  
└── backend/  
    ├── app/  
    │   ├── app.py  
    │   ├── templates/  
    │   │   ├── base.html  
    │   │   ├── emotion.html  
    │   │   ├── gender.html  
    │   │   ├── intent.html  
    │   │   ├── speaker.html  
    │   │   └── about.html  
    │   └── index.html  
    # Flask web application  
    # Main Flask application (11 routes)  
    # HTML templates (Jinja2)  
    # Base template with navbar  
    # Emotion classification page  
    # Gender identification page  
    # Intent classification page  
    # Speaker identification page  
    # Project documentation  
    # Homepage
```

```
└── static/
    ├── css/
    │   ├── styles.css      # Main stylesheet (550+ lines)
    │   └── custom.css
    ├── js/                 # JavaScript files
    └── images/             # Logo, icons
        └── services/
            ├── emotion.py      # Inference services
            ├── gender.py       # Emotion classification (126 lines)
            ├── intent.py       # Gender identification
            ├── speaker.py      # Intent classification
            └── utils/
                └── audio.py     # Speaker identification
            config.py           # Configuration (paths, models)

        └── ml_models/
            ├── models/          # ML training & artifacts
            │   └── [More model files...]
            └── MB)               # Pre-trained models (15 .pkl files, 600+
                ├── emotion_model_svm.pkl      # SVM classifier (143.78 MB)
                ├── emotion_scaler.pkl        # StandardScaler
                ├── emotion_label_encoder.pkl # LabelEncoder
                ├── gender_classifier.pkl    # Logistic Regression
                ├── intent_classifier.pkl   # SVM classifier (16.28 MB)
                └── [More model files...]

        └── src/                # Training scripts
            ├── 1_data_preprocessing.py  # Data loading & cleaning
            ├── 2_wavlm_feature_extraction.py # Embedding extraction
            ├── 3_train_classifiers.py    # Model training
            ├── 4_evaluation_metrics.py  # Model evaluation
            └── 5_visualization_umap.py  # t-SNE/UMAP visualization

        └── data/
            ├── CREMA-D/           # Raw datasets
            ├── IEMOCAP/           # Emotion dataset
            └── processed/         # Alternative emotion dataset
                └── [More model files...]
            # CSV metadata

        └── results/             # Training results
            ├── confusion_matrix_*.csv  # Classification matrices
            ├── evaluation_results_*.json # Metrics
            └── test_predictions.csv    # Predictions on test set

        └── scripts/             # Utility scripts
            ├── train_gender_model.py
            ├── train_intent_model.py
            ├── verify_setup.py
            └── download_samples.py

    └── docs/                # Documentation
        ├── PROJECT_OVERVIEW.md      # This file (complete overview)
        ├── EMOTION_CLASSIFICATION.md # Emotion task details
        ├── GENDER_IDENTIFICATION.md # Gender task details
        ├── INTENT_CLASSIFICATION.md # Intent task details
        ├── SPEAKER_IDENTIFICATION.md # Speaker task details
        ├── ARCHITECTURE.md          # System architecture
        ├── SETUP_GUIDE.md           # Installation guide
        └── QUICKSTART.md            # Quick start guide
```

```

└── .gitattributes           # Git LFS configuration
└── requirements.txt          # Python dependencies (40+ packages)
└── README.md                 # Quick project description
└── Emotion-classification.code-workspace # VS Code workspace

```

Development Team

Name	Role	Expertise	Contribution
Sk Inthiyaz	ML Engineer & Project Lead	Architecture, Integration	Project design, backend/frontend integration, system architecture
Romith Singh	ML Engineer & Team Lead	Speaker Recognition	Speaker identification model, optimization techniques
Rohin Kumar	ML Engineer	Gender Classification	Gender identification, feature engineering
Sahasra Ganji	ML Engineer & Data Engineer	Intent Recognition	Intent classification, dataset preparation, data engineering
Rashmitha	ML Engineer & Research Engineer	Research, Bug Fixing	Bug resolution, documentation, research support

Key Concepts Explained

Self-Supervised Learning

- Models are pre-trained on **massive unlabeled speech data** (10,000-56,000 hours)
- Learn general speech representations without manual annotation
- Fine-tuning layers frozen; use embeddings as features
- Dramatically reduces annotation cost for downstream tasks

Transfer Learning

- Pre-trained models → Extract embeddings
- Embeddings fed to simple classifiers (SVM, Logistic Regression)
- Avoids training deep models from scratch
- Leverages knowledge from large-scale pre-training

Dimensionality Reduction (PCA)

- Embeddings are 768-1024 dimensional (very high)
- PCA reduces to 200 dimensions
- Removes noise while preserving variance
- Reduces memory footprint and inference time

Cross-Validation

- Protects against overfitting
 - Uses 5 folds for robust performance estimation
 - Reports mean accuracy across all folds
 - 79.14% = average across 5 folds for emotion
-

◆ Key Features

1. Real-time Audio Processing

- Record directly from browser microphone
- Upload pre-recorded files
- Support for 6+ audio formats

2. Multi-Model Support

- 4 different self-supervised models
- Mix-and-match for different tasks
- Easy to add new models

3. High Accuracy

- Emotion: 79.14% on CREMA-D
- Leverages state-of-the-art SSL models
- 5-fold cross-validation for reliability

4. Production Ready

- Proper error handling and logging
- Git LFS for large model files
- Modular architecture for maintenance
- Comprehensive documentation

5. Optimized for CPU

- No GPU requirement
- Fast inference (2-5 seconds per audio)
- Suitable for deployment on modest hardware

6. Beautiful UI

- Responsive design (works on mobile/tablet)
 - Gradient backgrounds with animations
 - Real-time audio visualization
 - Professional styling
-

🔍 Model Comparison

Why Different Models for Different Tasks?

Task	Model	Reason
Emotion	HuBERT-large	Large model needed for fine-grained emotion distinction (6 classes)
Gender	WavLM-base-plus	Simple binary classification; faster inference sufficient
Intent	WavLM-base-plus	Medium complexity (20 classes); good speed/accuracy tradeoff
Speaker	XLSR-53	Multilingual robustness; handles diverse speaker accents

🔗 Interview Confidence Points

When presenting this project in interviews, emphasize:

1. Research Foundation

- Grounded in IEEE/ACM 2024 research paper
- Evaluated 3 SOTA self-supervised models
- Published methodology

2. End-to-End Pipeline

- Data preprocessing → Feature extraction → Training → Inference
- Each stage documented with mathematical formulas
- Reproducible with provided scripts

3. Production Considerations

- Git LFS for managing large model files
- Error handling for unsupported formats
- Configurable batch processing for CPU
- Comprehensive logging and monitoring

4. Architecture Decisions

- Why each model was chosen
- Trade-offs between accuracy and speed
- Dimensionality reduction rationale
- Cross-validation strategy

5. Reproducibility

- All hyperparameters documented
- Training scripts with fixed random seeds
- Version control of all code and data

6. Scalability

- Can add new tasks (follow 4-stage pipeline)
- Modular service design
- Easy to deploy on cloud (AWS, Azure, GCP)

📋 Recommended Reading Order

1. **Start Here:** This file (PROJECT_OVERVIEW.md)
 2. **Then:** EMOTION_CLASSIFICATION.md (most developed task)
 3. **Next:** GENDER_IDENTIFICATION.md, INTENT_CLASSIFICATION.md, SPEAKER_IDENTIFICATION.md
 4. **Finally:** ARCHITECTURE.md (system design details)
-

🚀 Getting Started

Installation

```
# Clone repository
git clone https://github.com/sk-inthiyaz/Emotion-classification.git
cd Emotion-classification

# Create virtual environment
python -m venv venv
source venv/bin/activate # On Windows: venv\Scripts\activate

# Install dependencies
pip install -r requirements.txt

# Download models (via Git LFS)
git lfs pull

# Run Flask app
cd backend/app
python app.py
```

Access the Application

- **URL:** <http://localhost:5000>
 - **Emotion Classification:** <http://localhost:5000/emotion>
 - **Gender Identification:** <http://localhost:5000/gender>
 - **Intent Classification:** <http://localhost:5000/intent>
 - **Speaker Identification:** <http://localhost:5000/speaker>
 - **About/Documentation:** <http://localhost:5000/about>
-

📊 Performance Summary

Metric	Value
Emotion Accuracy	79.14% (5-fold CV on CREMA-D)
Emotion F1-Score	0.78 (macro average)
Inference Time	2-5 seconds (CPU, depending on audio length)

Metric	Value
Model Download Size	~600 MB (all .pkl files via Git LFS)
Memory Usage	~2 GB (during feature extraction)
Supported Languages	English (main), multilingual support via XLSR-53

License & Attribution

- **Research Paper:** IEEE/ACM 2024
- **Models:** HuggingFace (open-source pre-trained models)
- **Datasets:** CREMA-D, SLURP (academic use)
- **Code:** Open-source, GitHub repository

Related Links

- **HuBERT Paper:** <https://arxiv.org/abs/2106.07447>
- **WavLM Paper:** <https://arxiv.org/abs/2110.13900>
- **XLSR Paper:** <https://arxiv.org/abs/2006.13979>
- **CREMA-D Dataset:** <https://github.com/CheyneyComputerScience/CREMA-D>
- **SLURP Dataset:** <https://github.com/parietal-io/slurp>
- **HuggingFace Models:** <https://huggingface.co>

Project Completion Status

- Data preprocessing pipeline
- Feature extraction (3 models)
- Model training & evaluation
- Inference service (4 tasks)
- Web UI with Bootstrap
- Documentation & README
- Git LFS for large files
- Production-ready code

Created: December 2024 **Last Updated:** December 11, 2025 **Repository:** <https://github.com/skinthiyaz/Emotion-classification>

This documentation serves as a comprehensive reference for understanding, implementing, and extending the Speech AI Suite project.