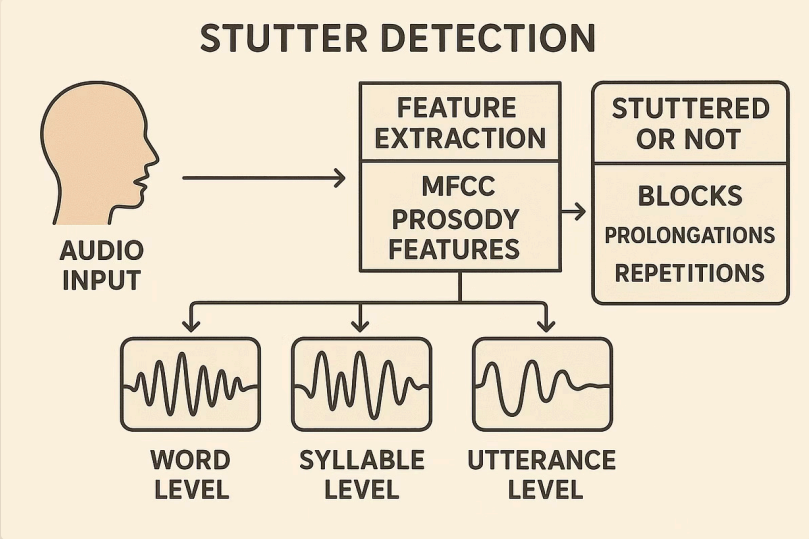
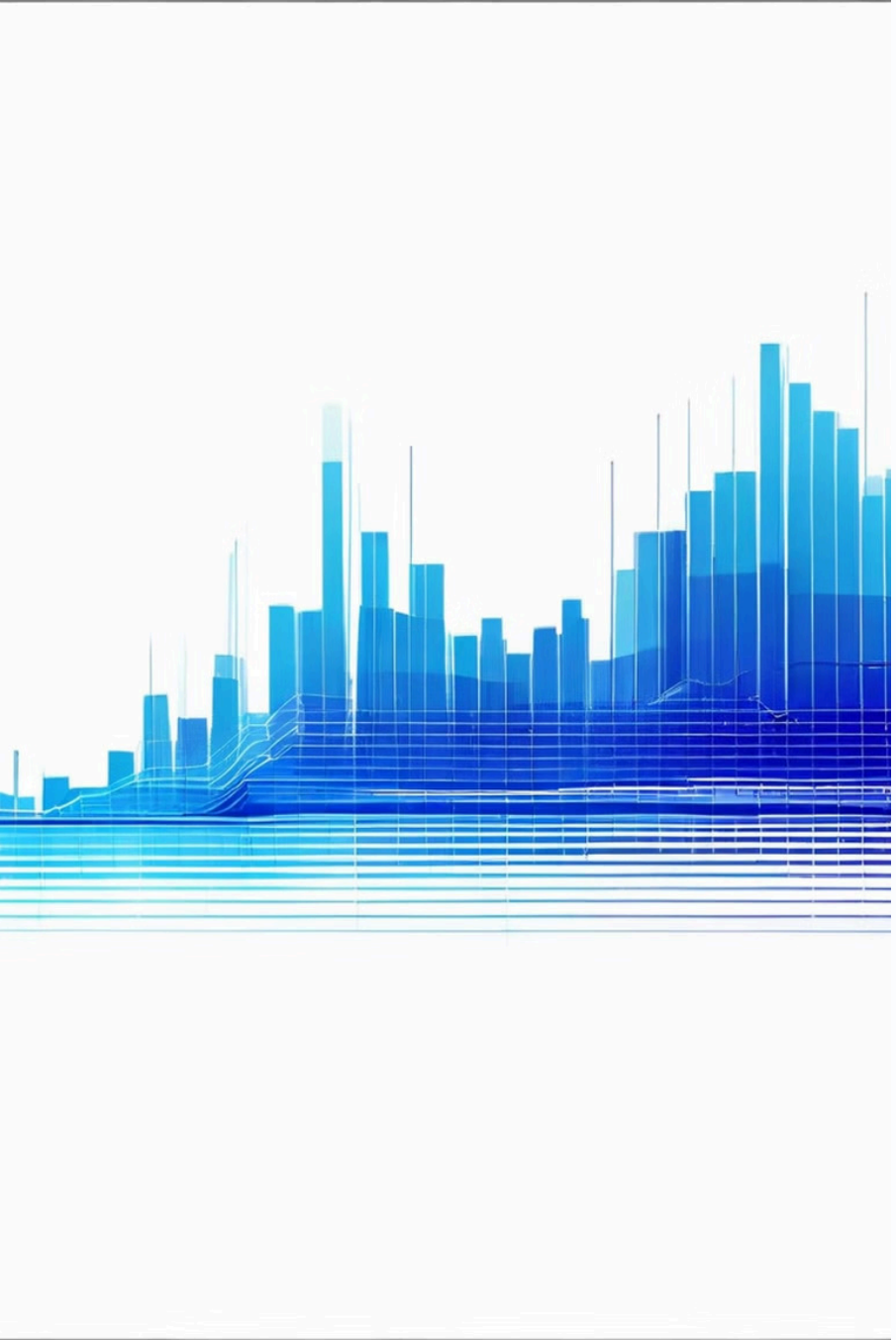


Stutter Detection using MFCC and Prosody Features at Word , Syllable and Utterence levels

Team Members:

T. Sri Vishnuvarun (2022102031)

Vedansh Agrawal (2021112010)



Dataset Overview: SEP-28k

Dataset Source

Released by Apple as part of the ml-stuttering-events-dataset project

Dataset Size

28,177 audio clips from podcasts, each 3 seconds long (16kHz sampling rate)

Binary Classification Task

Identifying stuttered vs. non-stuttered speech

Quality Control Labels (Labels we have removed)

Unsure

PoorAudioQuality

DifficultToUnderstand

NaturalPause

Music

NoSpeech

Preprocessing Overview

Download Statistics

- Total episodes attempted: 385
- Successfully downloaded: 263 (68.3%)
- Failed downloads: 122 (31.7%)

Source-specific success rates:

- High success (95-100%): HeStutters, HVSA, StutterTalk, WomenWhoStutter
- Low success (0%): StrongVoices, StutteringIsCool

Dataset Creation Process

- Filtered out clips with any quality issues
- Ensured consistent length (48,000 samples = 3 seconds)
- Created binary labels based on stutter presence

Final dataset composition:

- Total valid clips: 9,751
- Stuttered clips: 6,322 (64.8%)
- Non-stuttered clips: 3,429 (35.2%)

Feature Extraction Process and Model Building

MFCC Features Extraction for Stutter Detection

- **Definition**: Mel-Frequency Cepstral Coefficients represent the short-term power spectrum of sound
- **Importance**: Capture the vocal tract characteristics that are crucial for detecting speech abnormalities
- **Advantage**: MFCCs mimic human auditory perception by using mel scale (logarithmic perception of pitch)
- **Application**: Particularly effective for detecting stutter patterns due to their sensitivity to rapid spectral changes.

MFCC Features Extraction Process

- **Pre-emphasis**: Apply filter (coef=0.97) to amplify higher frequencies
- **Framing**: Segment audio into 25ms windows with 10ms hop length
- **Mel Filterbank**: Apply 13 filters on mel scale to mimic human hearing
- **DCT Transformation**: Convert to cepstral domain to separate vocal tract information
- **Normalization**: Scale coefficients for consistent feature ranges across recordings

Features Derived from MFCCs

- **Delta Coefficients**: Capture velocity (first derivative) of spectral change
- **Delta-Delta**: Measure acceleration (second derivative) of spectral trajectories
- **Temporal Fluctuation**: Standard deviation of frame-to-frame differences
- **Local Variability**: Measure of rapid changes in 50ms windows (stuttering indicator)
- **Transition Rate**: Rate of spectral transitions (repetition indicator)
- **MFCC Stability**: Overall stability of spectral envelope (fluency indicator)

Feature Vector Composition

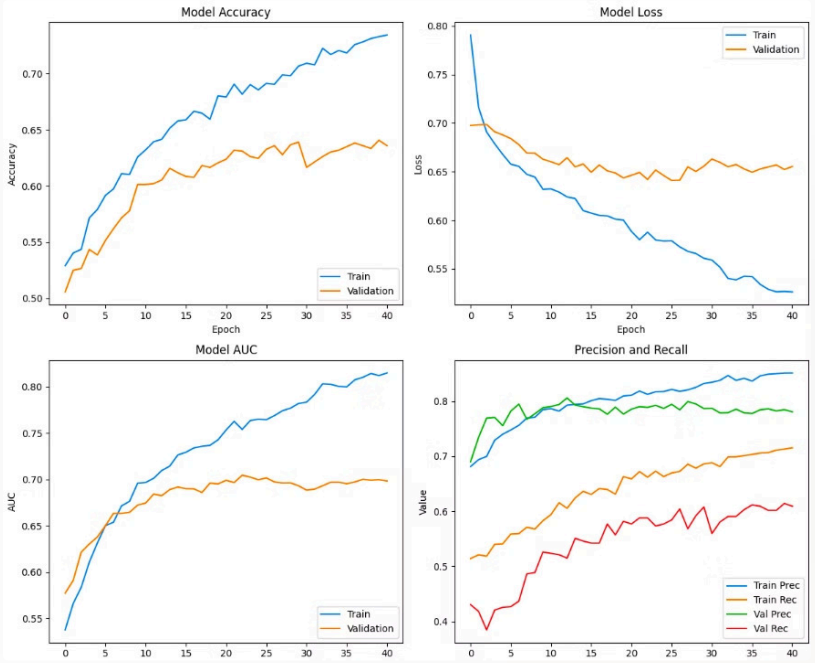
- **Basic MFCC Statistics**: Mean and standard deviation of 13 coefficients
- **Temporal Dynamics**: Delta and Delta-Delta mean values
- **Variability Metrics**: Temporal fluctuation and local variability patterns
- **Transition Features**: Overall transition rate and stability measures
- **Total Features**: 80 features per audio clip (extracted with optimized parameters)

DNN Model Architecture for Stutter Detection using mfcc features

- **Input Layer**: Dense layer with 128 neurons (**input shape = 80 features**)
- **Hidden Layers**: 64→32 neurons with ReLU activation
- **Regularization**: BatchNormalization + Dropout (0.4, 0.4, 0.3) to prevent overfitting
- **Output Layer**: Single neuron with sigmoid activation (binary classification)
- **Total Parameters**: 21,633 (84.50 KB) for efficient deployment

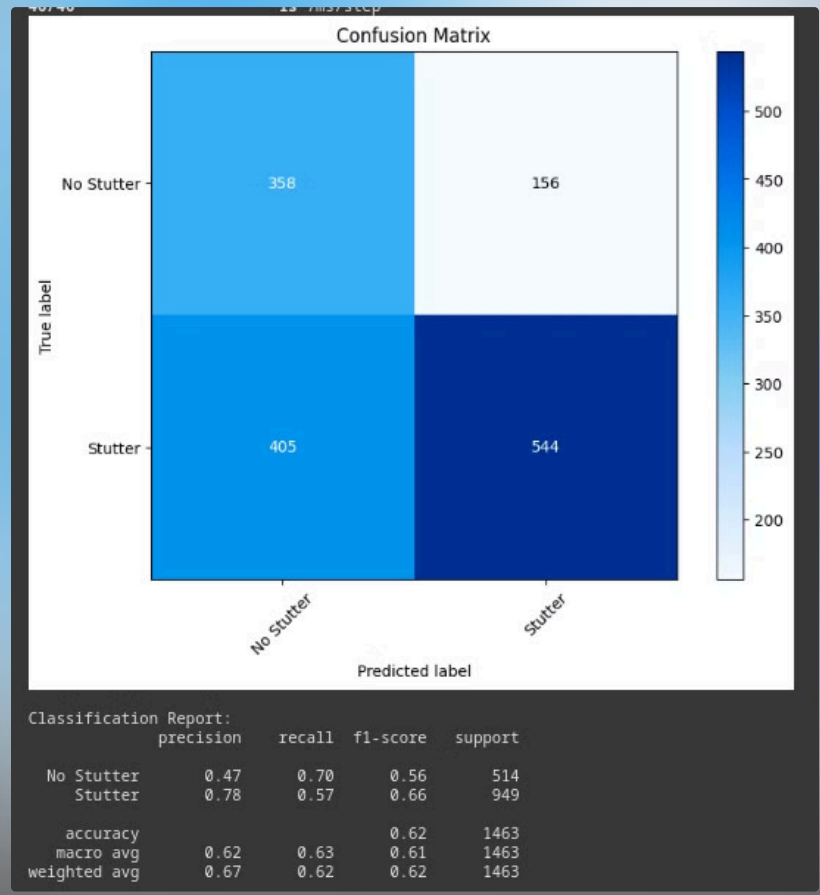
Training Process

- **Dataset Split**: 70% training, 15% validation, 15% testing
- **Class Balancing**: Weighted loss function for imbalanced stutter/non-stutter samples
- **Optimization**: Adam optimizer with binary cross-entropy loss
- **Early Stopping**: Patience=15 epochs with best weights restoration
- **Learning Rate Schedule**: ReduceLROnPlateau with factor=0.5, patience=5



Model Performance

- **Accuracy**: 61.65% on test set
- **AUC**: 0.6783 (reasonable discrimination ability)
- **Precision**: 0.7771 (high reliability of positive predictions)
- **Recall**: 0.5732 (moderate detection of actual stutters)
- **F1-Score**: 0.66 for stutter class vs 0.56 for non-stutter class



Classification Report:

	precision	recall	f1-score	support
No Stutter	0.47	0.70	0.56	514
Stutter	0.78	0.57	0.66	949
accuracy			0.62	1463
macro avg	0.62	0.63	0.61	1463
weighted avg	0.67	0.62	0.62	1463

Prosody Features (Utterance Level)

- We have extracted persody features at utterance level (full 3-second clips)

Feature extraction process

- **Pre-processing**: Pre-emphasis filtering (coef=0.97) to enhance higher frequencies
- **Pitch Analysis**: Using pYIN algorithm for robust pitch tracking (F0 extraction)
- **Energy Analysis**: Root Mean Square (RMS) analysis of amplitude envelope
- **Temporal Analysis**: Zero-crossing rate and speech rate calculation
- **Voice Quality**: Jitter, shimmer, and HNR measurements for voice stability

Prosody features that we have extracted

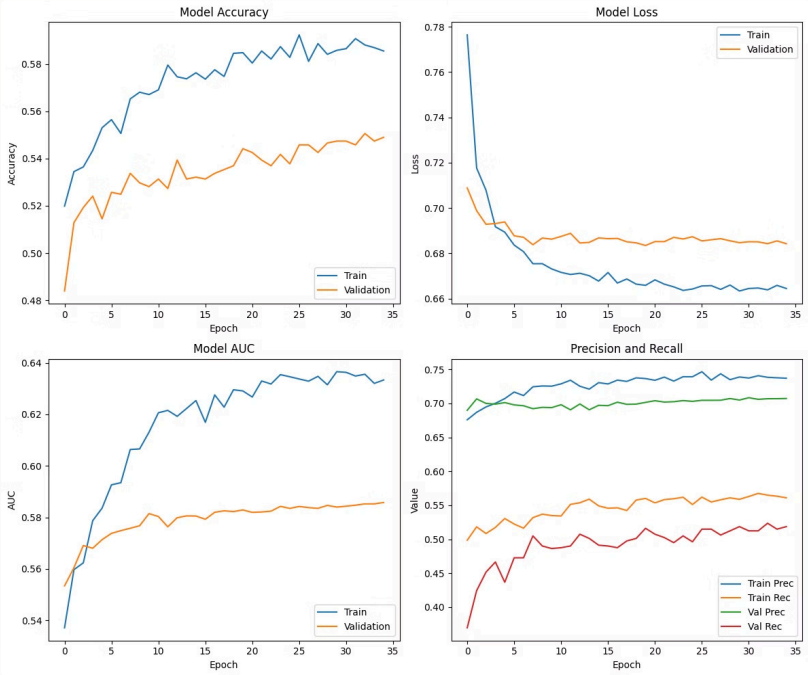
- **Pitch Features**:
  - F0_mean: Average pitch height
  - F0_std: Pitch variability
  - F0_range: Span between minimum and maximum pitch
- **Energy Features**:
  - RMS_mean: Overall loudness
  - RMS_std: Loudness variability
- **Temporal Features**:
  - ZCR: Rate of sign-changes in waveform (consonant detection)
  - Speech_rate: Density of onsets per second

Voice Quality Features

- **Jitter**: Cycle-to-cycle pitch variation (>0.015 indicates stutter)
  - Formula: Average absolute difference between consecutive F0 periods
- **Shimmer**: Cycle-to-cycle amplitude variation (>0.035 indicates stutter)
  - Formula: Average absolute difference between consecutive amplitude peaks
- **HNR Estimate**: Harmonics-to-Noise Ratio (lower values indicate roughness)
  - Normal speech >18dB, stuttered speech often <12dB

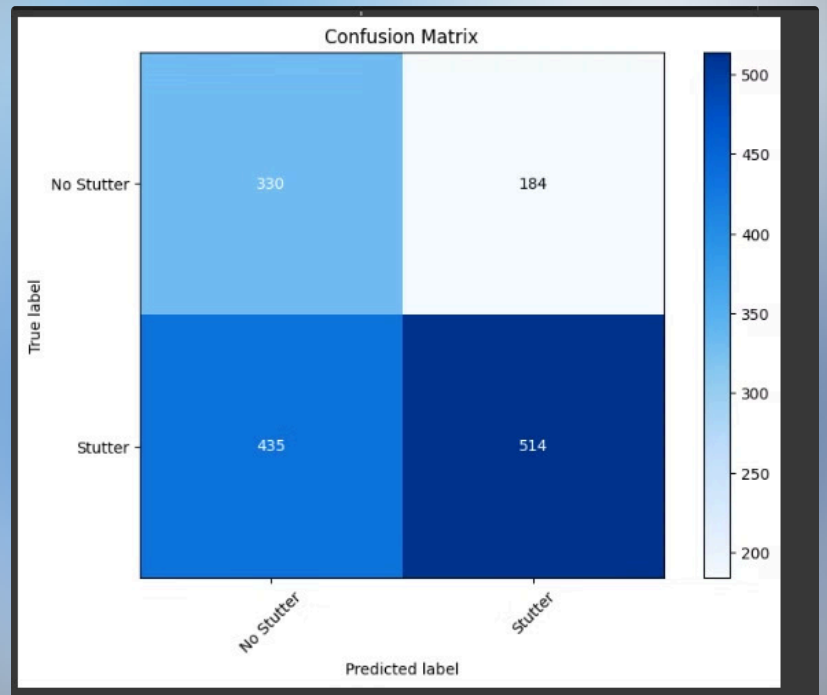
Model Architecture for Stutter Detection using prosody features

- **Input Layer**: 64 neurons receiving 13 prosodic features
- **Hidden Layers**: 32→16 neurons with ReLU activation
- **Regularization**: BatchNormalization + Dropout (0.3, 0.3, 0.2)
- **Output Layer**: Single neuron with sigmoid activation
- **Optimization**: Adam optimizer with binary cross-entropy loss
- **Training Strategy**: Early stopping (patience=15) and LR reduction



Model Performance

- **Accuracy**: 57.69% on test set
- **AUC**: 0.6322 (moderate discrimination ability)
- **Precision**: 0.7364 (74% of predicted stutters are correct)
- **Recall**: 0.5416 (54% of actual stutters detected)
- **Class-specific Performance**:
  - Stutter class: F1-score = 0.62
  - No Stutter class: F1-score = 0.52



Classification Report:

	precision	recall	f1-score	support
No Stutter	0.43	0.64	0.52	514
Stutter	0.74	0.54	0.62	949
accuracy			0.58	1463
macro avg	0.58	0.59	0.57	1463
weighted avg	0.63	0.58	0.59	1463

Word-Level Features

Boundary Detection

- **Energy-Based Segmentation Method**:
  - Calculate RMS energy contour (hop length = 512)
  - Apply adaptive threshold: mean(energy) + 0.5 × std(energy)
  - Identify silent regions (energy < threshold)
  - Filter for minimum silence duration (≥ 150ms)
  - Convert to speech segments between silences
  - Keep only segments > 100ms

Word-Level Analysis

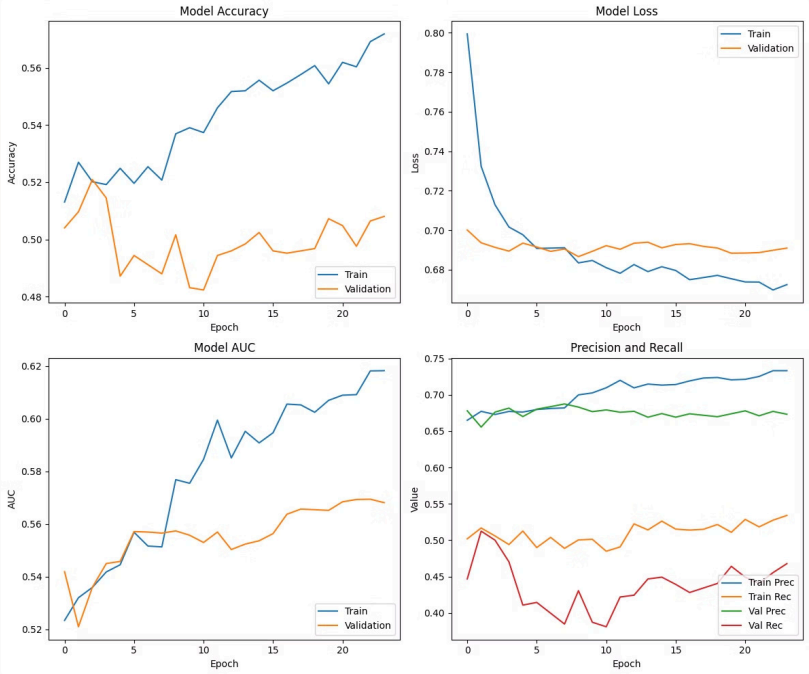
- **Acoustic Features**:
  - MFCC coefficients (mean, std)
  - Delta & Delta-Delta MFCCs
  - Transition rate & MFCC stability
  - Temporal fluctuation & local variability
- **Prosodic Features**:
  - F0 (pitch) statistics
  - Jitter & Shimmer (voice stability)
  - Harmonics-to-Noise Ratio
  - Zero-crossing rate

Model Architecture

- **Input Layer**:
  - Dense (128 neurons, ReLU)
  - BatchNormalization + Dropout (0.4)
- **Hidden Layers**:
  - Dense (64) → BatchNorm → Dropout (0.4)
  - Dense (32) → BatchNorm → Dropout (0.3)
  - Dense (16) → BatchNorm → Dropout (0.2)
- **Output Layer**:
  - Dense (1, sigmoid activation)
  - Binary classification (stutter/no-stutter)

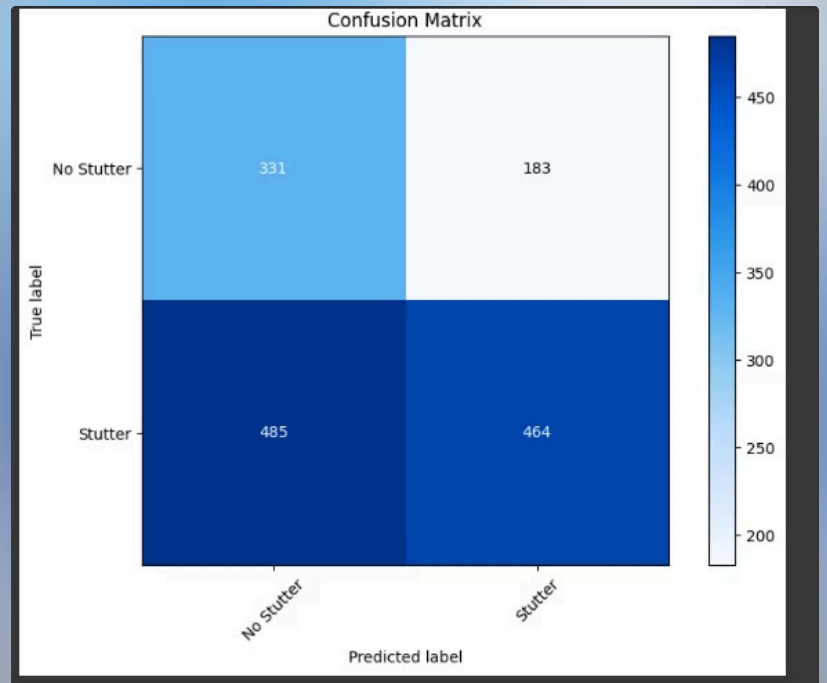
Training Process

- **Optimization**:
  - Adam optimizer with binary cross-entropy loss
  - Class weights for imbalanced dataset
  - Batch size: 32
- **Training Strategy**:
  - Early stopping (patience=15)
  - Learning rate reduction (factor=0.5)
  - 70/15/15 train-validation-test split



Model Performance

- **Classification Metrics**:
  - Accuracy: 54.34%
  - AUC: 0.6073
  - Precision: 0.7172 (good positive prediction reliability)
  - Recall: 0.4889 (moderate stutter detection rate)
- **Class Performance**:
  - Stutter class: P=0.72, R=0.49, F1=0.58
  - No Stutter class: P=0.41, R=0.64, F1=0.50



Classification Report:

	precision	recall	f1-score	support
No Stutter	0.41	0.64	0.50	514
Stutter	0.72	0.49	0.58	949
accuracy			0.54	1463
macro avg	0.56	0.57	0.54	1463
weighted avg	0.61	0.54	0.55	1463

Syllable-Level Features

Syllable Segmentation Approach

- **Group Delay Function (GDF)**: A signal processing technique for accurate syllable boundary detection.
- **Multi-band Processing**: Analyzes three sub-band signals to improve detection accuracy
- **Advantages**: More precise than energy-based methods for detecting stutter patterns

Syllable Boundary Detection Process

- **Step 1**: Create three filtered versions of the speech signal
  - Original signal (full spectrum)
  - Low-pass filtered signal (removes fricatives)
  - Band-pass filtered signal (attenuates semivowels)
- **Step 2**: Compute energy contours for each sub-band
- **Step 3**: Apply Group Delay Function transformation
- **Step 4**: Detect peaks in GDF (syllable boundaries)
- **Step 5**: Combine evidence from all sub-bands

Model Architecture

Input Layer:

64 neurons receiving syllable features

Hidden Layers:

32 neurons with ReLU + BatchNorm + Dropout (0.3)

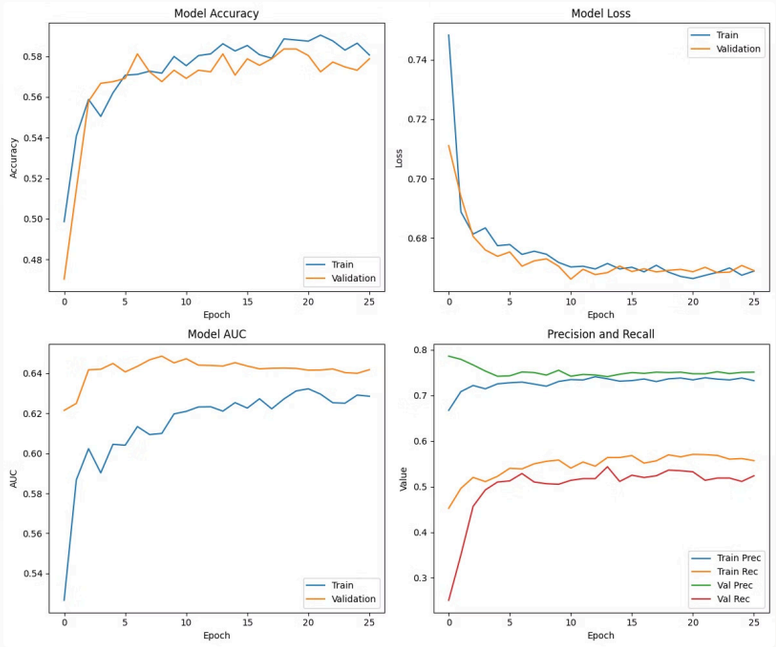
16 neurons with ReLU + BatchNorm + Dropout (0.2)

Output Layer:

Single neuron with sigmoid activation

Total Parameters: 4,417 (17.25 KB)

Trainable Parameters: 4,193 (16.38 KB)

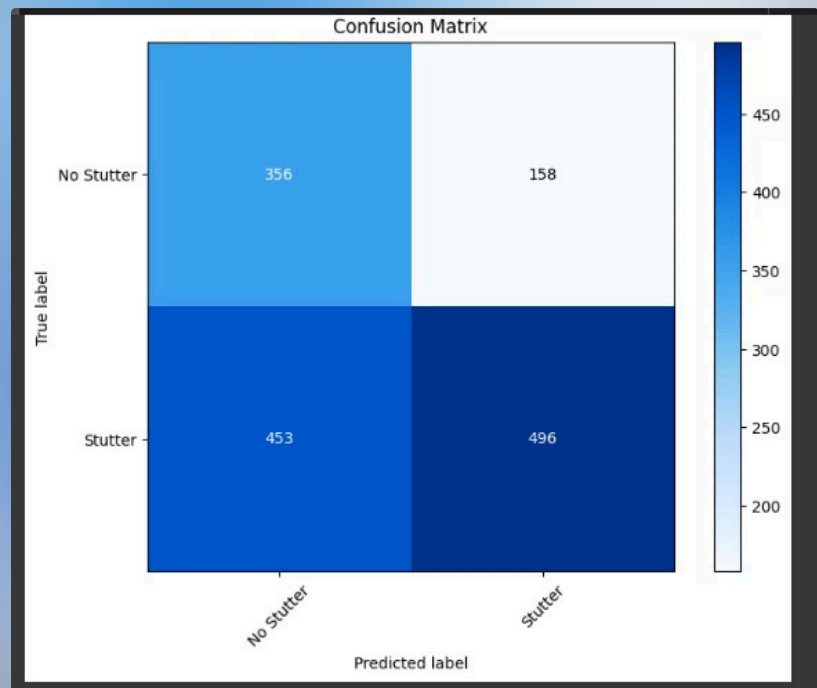


Training Process

- **Dataset Split**: 70% training, 15% validation, 15% testing
- **Optimization**: Adam optimizer with binary cross-entropy loss
- **Learning Rate**: Adaptive reduction (0.001 → 0.0005 → 0.00025)
- **Early Stopping**: Patience=15 with best weights restoration

Model Performance

- **Accuracy**: 58.24% on test set
- **AUC**: 0.6531 (moderate discrimination ability)
- **Precision**: 0.7584 (76% of predicted stutters are correct)
- **Recall**: 0.5227 (52% of actual stutters detected)
- **Class-specific Performance**:
  - Stutter class: P=0.76, R=0.52, F1=0.62
  - No Stutter class: P=0.44, R=0.69, F1=0.54



Classification Report:

	precision	recall	f1-score	support
No Stutter	0.44	0.69	0.54	514
Stutter	0.76	0.52	0.62	949
accuracy			0.58	1463
macro avg	0.60	0.61	0.58	1463
weighted avg	0.65	0.58	0.59	1463

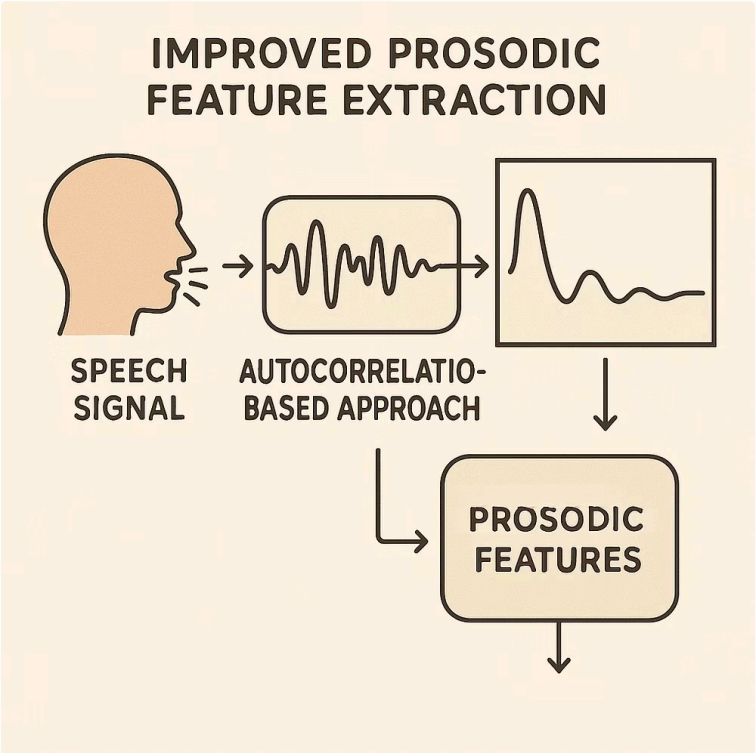
Model Performance Comparison

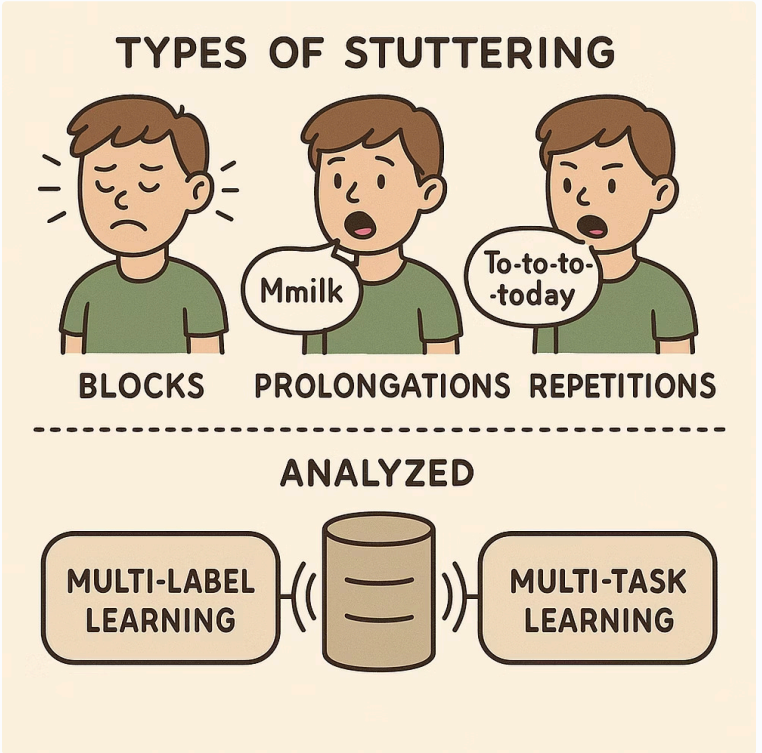
Metric/Feature	MFCC Model	Prosodic Model	Word-Level Model	Syllable-Level Model
Performance Metrics				
Accuracy	61.65%	57.69%	54.34%	58.24%
AUC	0.6783	0.6322	0.6073	0.65331
Precision	0.7771	0.7364	0.7172	0.7584
Recall	0.5732	0.5416	0.4889	0.5227
F1 (Stutter)	0.66	0.62	0.58	0.62
F1 (No Stutter)	0.56	0.52	0.50	0.54
Model Architecture				
Hidden Layers	128-64-32	64-32-16	128-64-32-16	64-32-16
Model Size	84.50 KB	51.62 KB	97.12 KB	17.25 KB

Key Observations:

- Syllable-level model achieves highest accuracy with fewest parameters
- Prosodic features offer best balance of performance and interpretability
- Word-level model struggles with recall despite complex architecture
- All models show precision-recall trade-off, favoring precision

Feedback from Mid evaluation





Improved Prosodic Feature Extraction

- We have refined prosody feature extraction using an autocorrelation-based approach to reduce reliance on built-in functions.

Multi-label Classification

- We have expanded stutter detection to classify specific stutter types like blocks, prolongations, and repetitions using specialized multi-label and multi-task learning models.

Improved Prosodic Feature Extraction

Signal Processing Approach for Prosodic Feature Extraction

Main Concept:

- We avoid library black-boxes and instead use fundamental signal processing techniques for all prosodic features.
- **Autocorrelation** is the core technique for pitch (F0) estimation, leveraging the periodic nature of voiced speech.

Autocorrelation for Pitch:

- The autocorrelation function measures the similarity of a signal with a delayed version of itself.
- For a periodic (voiced) frame, the autocorrelation peaks at lags corresponding to the pitch period.
- By searching for the strongest peak within a plausible pitch period range, we estimate the fundamental frequency (F0).

Pipeline Steps:

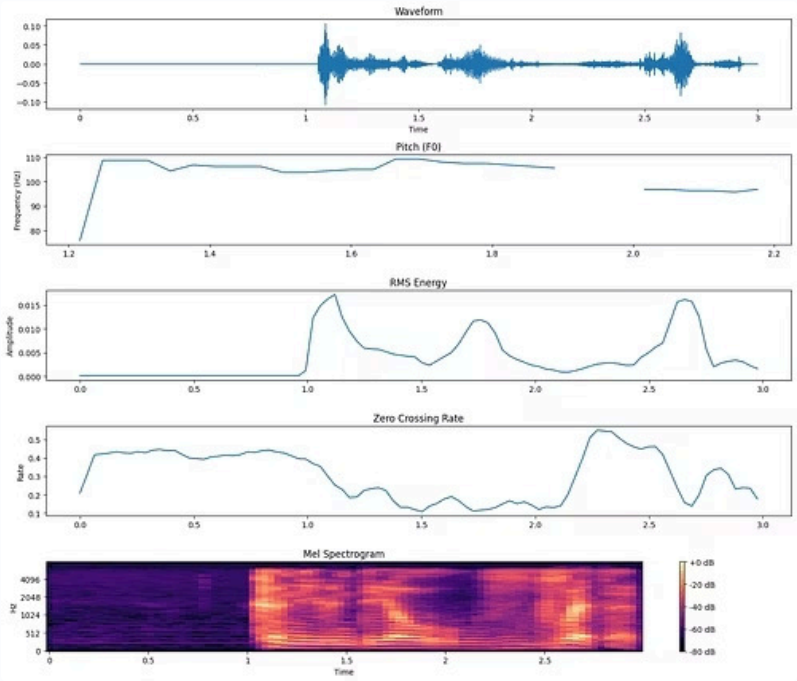
1. **Pre-emphasis:**
    - Boosts high-frequency content for better analysis.
2. **Framing & Windowing:**
    - The signal is divided into overlapping frames (e.g., 25 ms, 10 ms hop) and each frame is windowed (Hamming).
3. **Per-frame Feature Extraction:**
    - Each feature is computed directly from the time-domain signal or its basic transforms.

Improved Prosodic Feature Extraction

How Each Prosodic Feature is Computed

- **Pitch (F0):**
  - For each frame, compute autocorrelation.
  - Find the maximum peak within the expected lag range (corresponding to human pitch).
  - If the peak is strong[1], F0 = sampling rate / lag of peak; else, mark as unvoiced.
- **RMS Energy:**
  - For each frame, compute the root mean square (RMS):
    $\text{RMS} = \sqrt{\frac{1}{N}\sum x[n]^2}$
  - Captures loudness/amplitude envelope.
- **Zero Crossing Rate (ZCR):**
  - For each frame, count the number of times the signal crosses zero.
  - Indicates voicing and presence of fricatives.
- **Speech Rate:**
  - Count the number of prominent peaks in the RMS envelope.
  - Peaks correspond to syllabic or word onsets; rate = peaks per second.
- **Jitter:**
  - Compute pitch periods from valid F0 frames.
  - Jitter = mean absolute difference between consecutive periods, normalized by mean period.
- **Shimmer:**
  - Compute RMS for each frame.
  - Shimmer = mean absolute difference between consecutive RMS values, normalized by mean RMS.
- **HNR (Harmonics-to-Noise Ratio):**
  - Compute autocorrelation of the whole signal.
  - Compare main peak (periodic energy) to side-lobes (noise);
    HNR = $10 \log_{10}(\text{max side-lobe}/(\text{main peak} - \text{max side-lobe}))$

Result Visualization – Prosodic Features for a Test Clip



Waveform: The raw audio signal displayed over time.

Pitch (F0): Frame-by-frame pitch contour estimated using autocorrelation.

RMS Energy: Amplitude envelope highlighting syllabic and word onsets.

Zero Crossing Rate: Indicates voicing and fricative activity in each frame.

Mel Spectrogram: Frequency content over time, provided as a reference.

- **Interpretation:**
  - Sudden drops or irregularities in pitch and energy often indicate stuttering events.
  - Regions with high Zero Crossing Rate usually correspond to unvoiced or turbulent sounds.
  - Our custom pipeline enables detailed, interpretable analysis of these features, fully addressing feedback and improving the reliability of the stutter detection system.

Multi Label Classification using DNN

Stutter Categories

Prolongation

Elongated sounds (e.g., "mmmmmy name")

Block

Speech stoppage/struggle with sounds

Sound Repetition

Repeating phonemes (e.g., "m-m-my")

Word Repetition

Repeating entire words (e.g., "I-I-I want")

Interjection

Filler words (e.g., "um", "uh")

No Stutter

The audio clip is clean and contains no stutter

Differences Compared to Binary Classification

- Changed the DNN architecture to have 6 neurons in the last layer keeping the activation function the same which is sigmoid
- Changed the labels for each data point, instead of one label which is 1 or 0 for yes stutter or no stutter, we now have 6 labels which represent the above 6 classes presence or not.
- There is heavy class imbalance in each of the 6 classes where '0' is present in almost 80% of the audio clips. To fix this, each class required weights which we manually computed and then manually applied in our loss function to ensure that the model does not predict 0 most of the time as that would lead to higher accuracy.
- Instead of one confusion matrix, we now have 6 different matrices, one for each class. Each matrix gives a proper representation of how well the model does for each individual class.

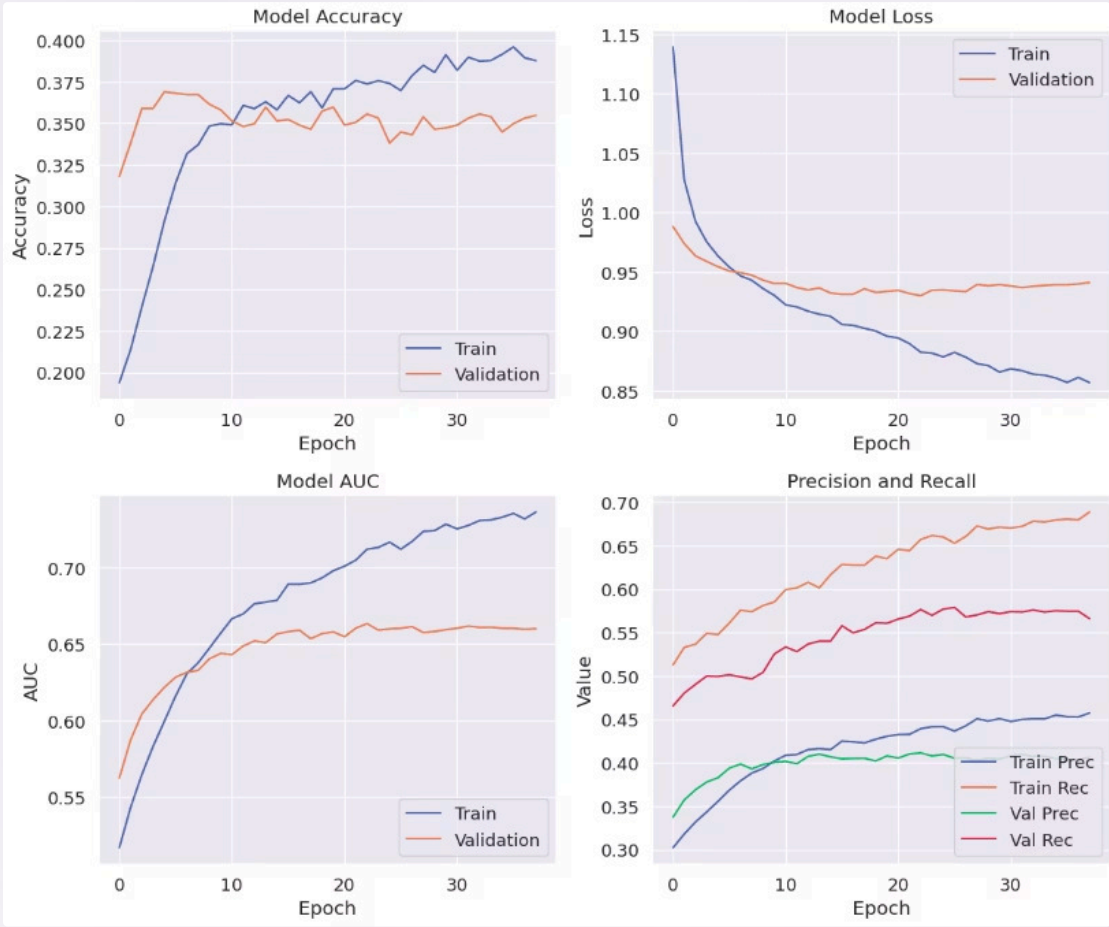
Model Performance for each Feature

DNN Model Architecture for Stutter Detection using mfcc features

- **Input Layer**: Dense layer with 128 neurons (**input shape = 80 features**)
- **Hidden Layers**: 64→32 neurons with ReLU activation
- **Regularization**: BatchNormalization + Dropout (0.4, 0.4, 0.3) to prevent overfitting
- **Output Layer**: Six neurons with sigmoid activation (binary classification)
- **Total Parameters**: 21,633 (84.50 KB) for efficient deployment

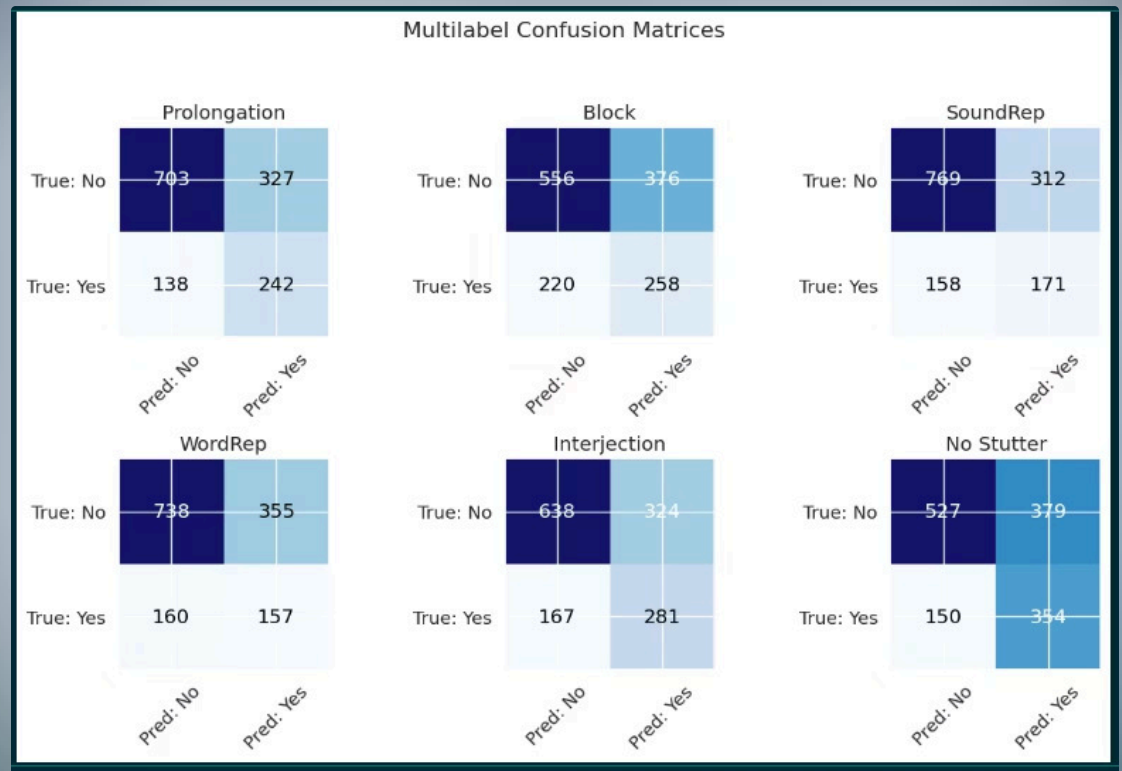
Training Process

- **Dataset Split**: 70% training, 15% validation, 15% testing
- **Class Balancing**: Weighted loss function for imbalanced stutter/non-stutter samples
- **Optimization**: Adam optimizer with binary cross-entropy loss
- **Early Stopping**: Patience=15 epochs with best weights restoration
- **Learning Rate Schedule**: ReduceLROnPlateau with factor=0.5, patience=5



Model Performance

- **Accuracy**: 35.11% on test set
- **AUC**: 0.6709 (reasonable discrimination ability)
- **Precision**: 0.4137 (high reliability of positive predictions)
- **Recall**: 0.5957 (moderate detection of actual stutters)

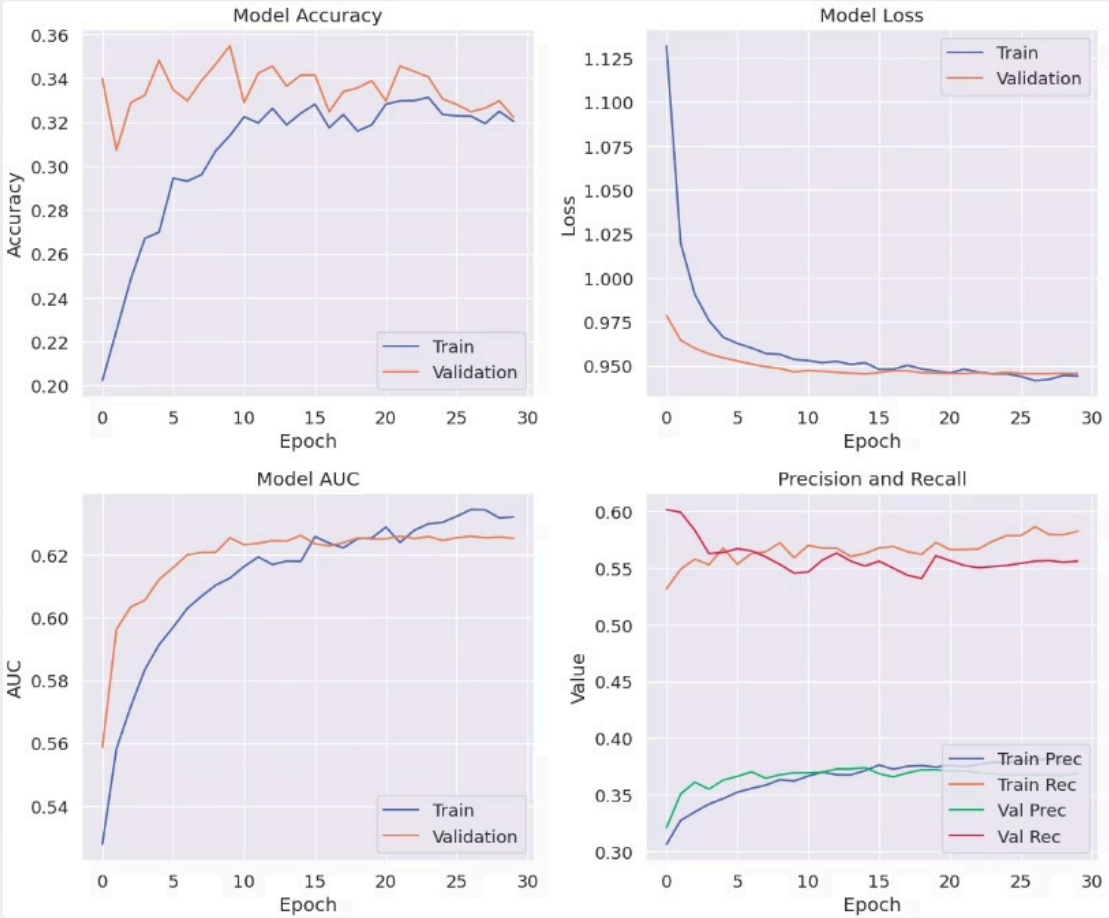


Classification Report:

	precision	recall	f1-score	support
Prolongation	0.43	0.64	0.51	380
Block	0.41	0.54	0.46	478
SoundRep	0.35	0.52	0.42	329
WordRep	0.31	0.50	0.38	317
Interjection	0.46	0.63	0.53	448
No Stutter	0.48	0.70	0.57	504
micro avg	0.41	0.60	0.49	2456
macro avg	0.41	0.59	0.48	2456
weighted avg	0.42	0.60	0.49	2456
samples avg	0.44	0.61	0.49	2456

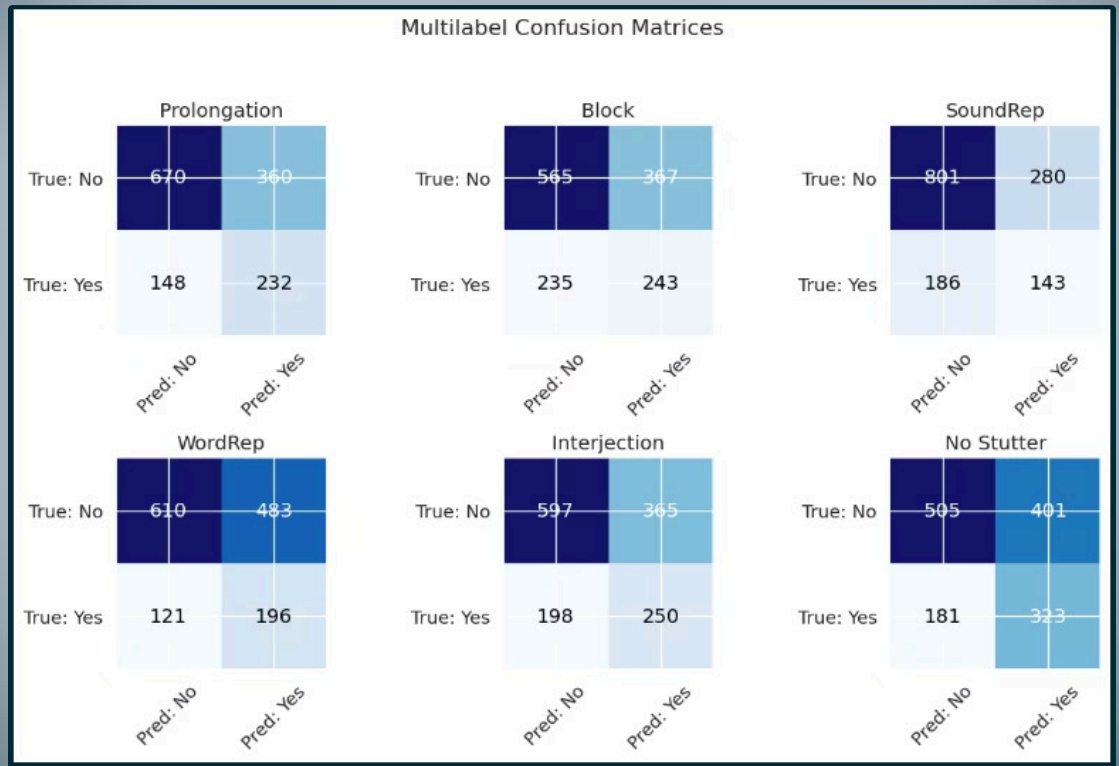
Model Architecture for Stutter Detection using Prosody features

- **Input Layer**: 64 neurons receiving 13 prosodic features
- **Hidden Layers**: 32→16 neurons with ReLU activation
- **Regularization**: BatchNormalization + Dropout (0.3, 0.3, 0.2)
- **Output Layer**: Six neurons with sigmoid activation
- **Optimization**: Adam optimizer with binary cross-entropy loss
- **Training Strategy**: Early stopping (patience=15) and LR reduction



Model Performance

- **Accuracy**: 34.82% on test set
- **AUC**: 0.6291 (reasonable discrimination ability)
- **Precision**: 0.3807 (high reliability of positive predictions)
- **Recall**: 0.5647 (moderate detection of actual stutters)



Classification Report:

	precision	recall	f1-score	support
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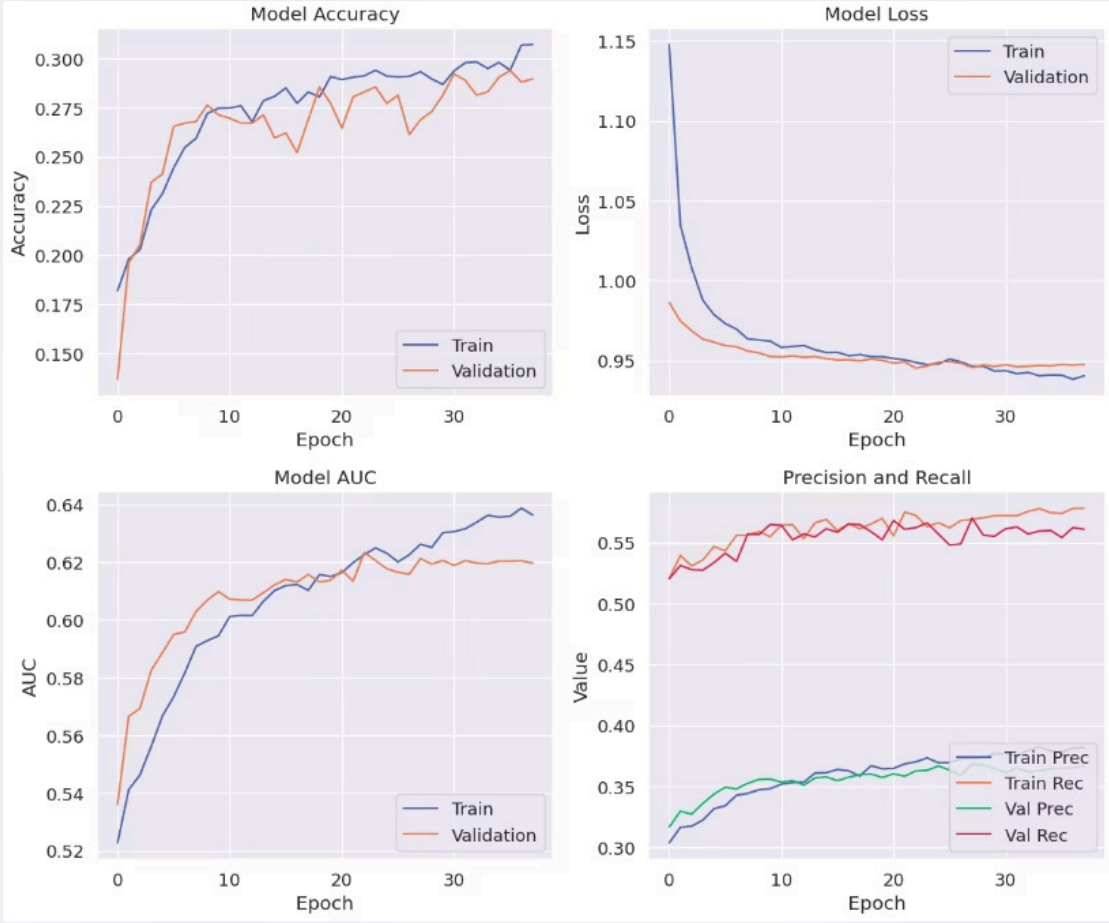
Block	0.40	0.51	0.45	478
SoundRep	0.34	0.43	0.38	329
WordRep	0.29	0.62	0.39	317
Interjection	0.41	0.56	0.47	448
No Stutter	0.45	0.64	0.53	504
micro avg	0.38	0.56	0.45	2456
macro avg	0.38	0.56	0.45	2456
weighted avg	0.39	0.56	0.46	2456
samples avg	0.39	0.59	0.45	2456

Model Architecture for Word level MFCC+ Prosodic Features

- **Input Layer**:
  - Dense (128 neurons, ReLU)
  - BatchNormalization + Dropout (0.4)
- **Hidden Layers**:
  - Dense (64) → BatchNorm → Dropout (0.4)
  - Dense (32) → BatchNorm → Dropout (0.3)
  - Dense (16) → BatchNorm → Dropout (0.2)
- **Output Layer**:
  - Dense (6, sigmoid activation)
  - MultiLabel Classification

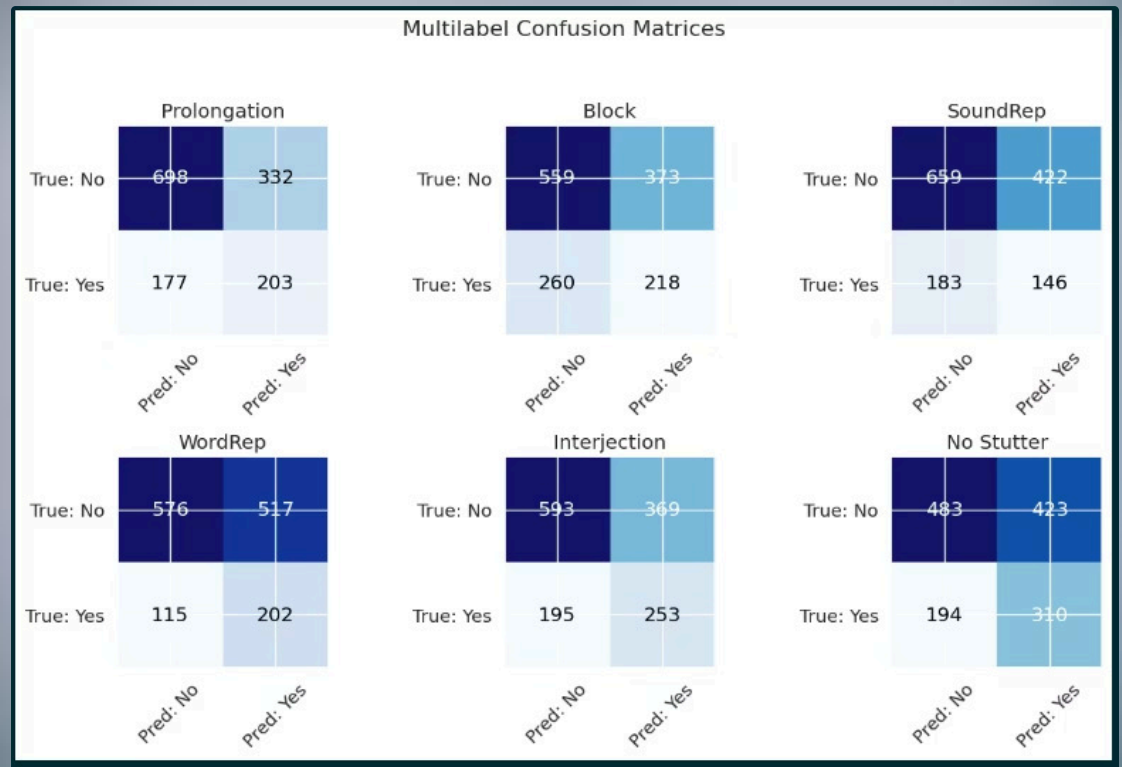
Training Process

- **Optimization**:
  - Adam optimizer with binary cross-entropy loss
  - Class weights for imbalanced dataset
  - Batch size: 32
- **Training Strategy**:
  - Early stopping (patience=15)
  - Learning rate reduction (factor=0.5)
  - 70/15/15 train-validation-test split



Model Performance

- **Classification Metrics**:
  - Accuracy: 27.02%
  - AUC: 0.5985
  - Precision: 0.3535 (good positive prediction reliability)
  - Recall: 0.5423 (moderate stutter detection rate)

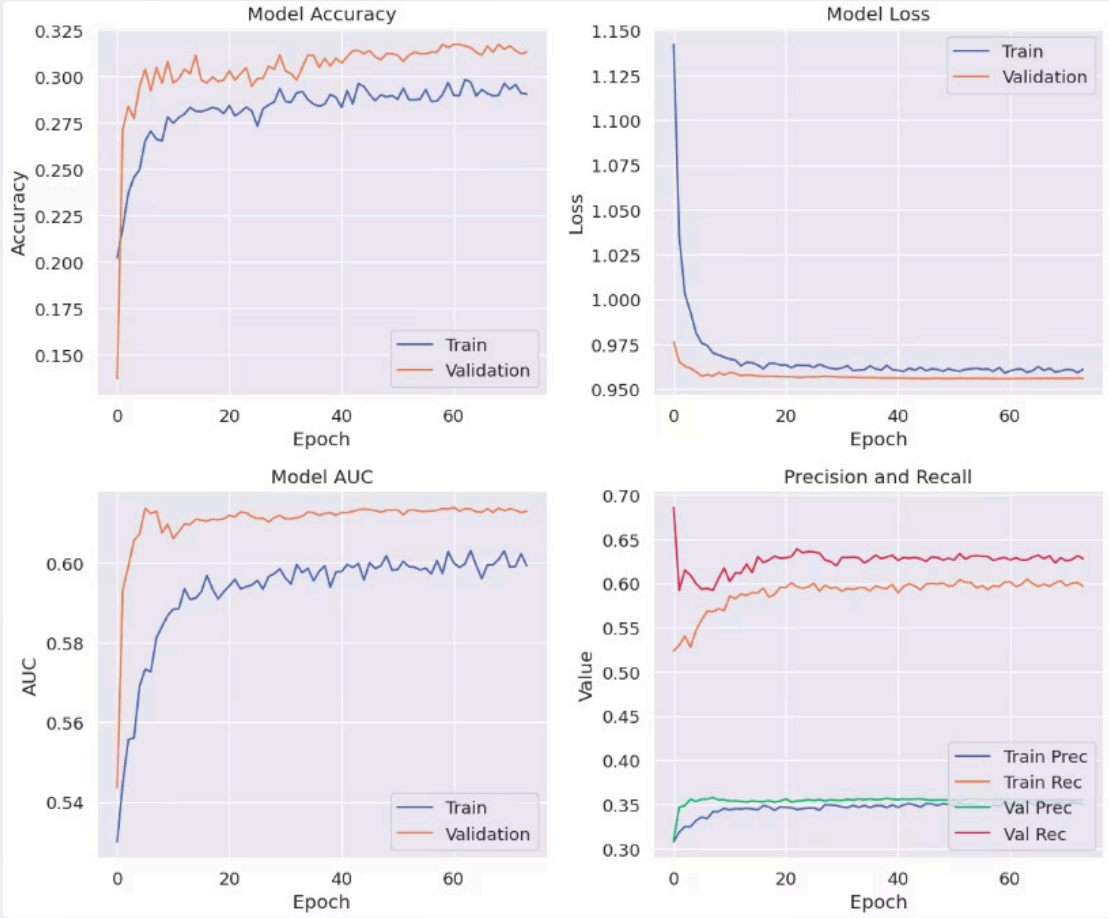


Classification Report:

	precision	recall	f1-score	support
Prolongation	0.38	0.53	0.44	380
Block	0.37	0.46	0.41	478
SoundRep	0.26	0.44	0.33	329
WordRep	0.28	0.64	0.39	317
Interjection	0.41	0.56	0.47	448
No Stutter	0.42	0.62	0.50	504
micro avg	0.35	0.54	0.43	2456
macro avg	0.35	0.54	0.42	2456
weighted avg	0.36	0.54	0.43	2456
samples avg	0.36	0.56	0.42	2456

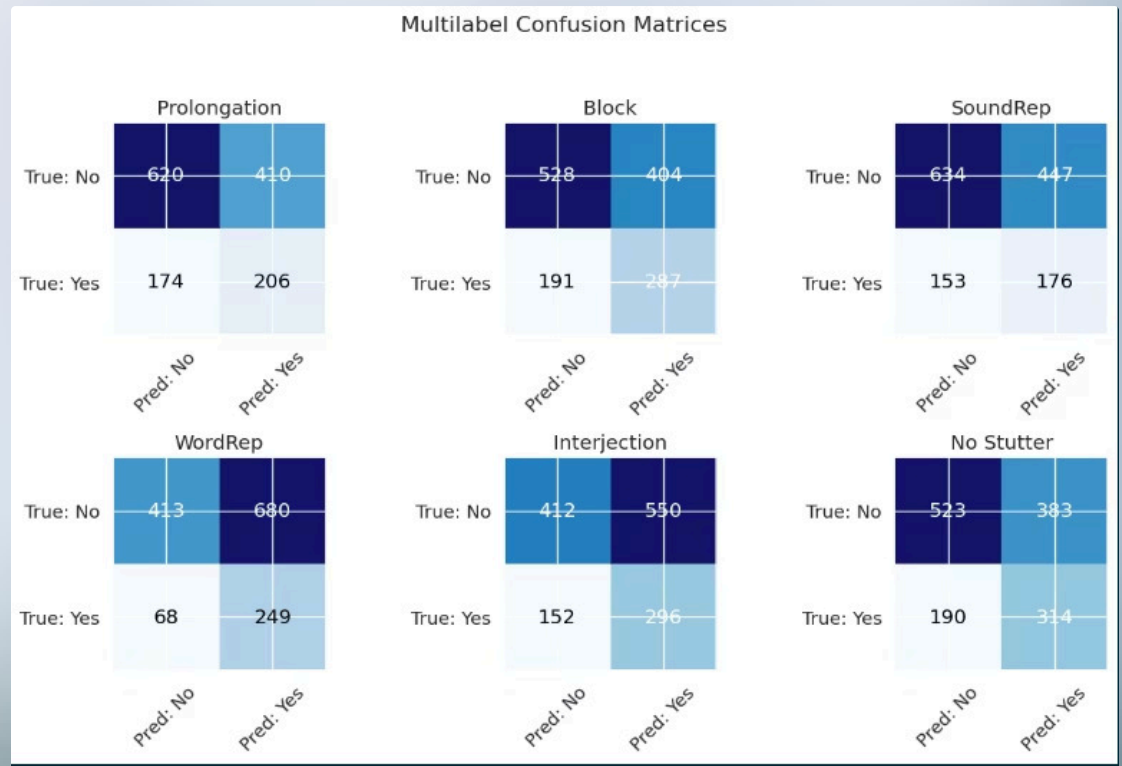
Training Process For Syllable Level MFCC+Prosodic Features

- **Dataset Split**: 70% training, 15% validation, 15% testing
- **Optimization**: Adam optimizer with binary cross-entropy loss
- **Learning Rate**: Adaptive reduction (0.001 → 0.0005 → 0.00025)
- **Early Stopping**: Patience=15 with best weights restoration



Model Performance

- **Classification Metrics**:
  - Accuracy: 28.44%
  - AUC: 0.5993
  - Precision: 0.3471 (good positive prediction reliability)
  - Recall: 0.6221 (moderate stutter detection rate)

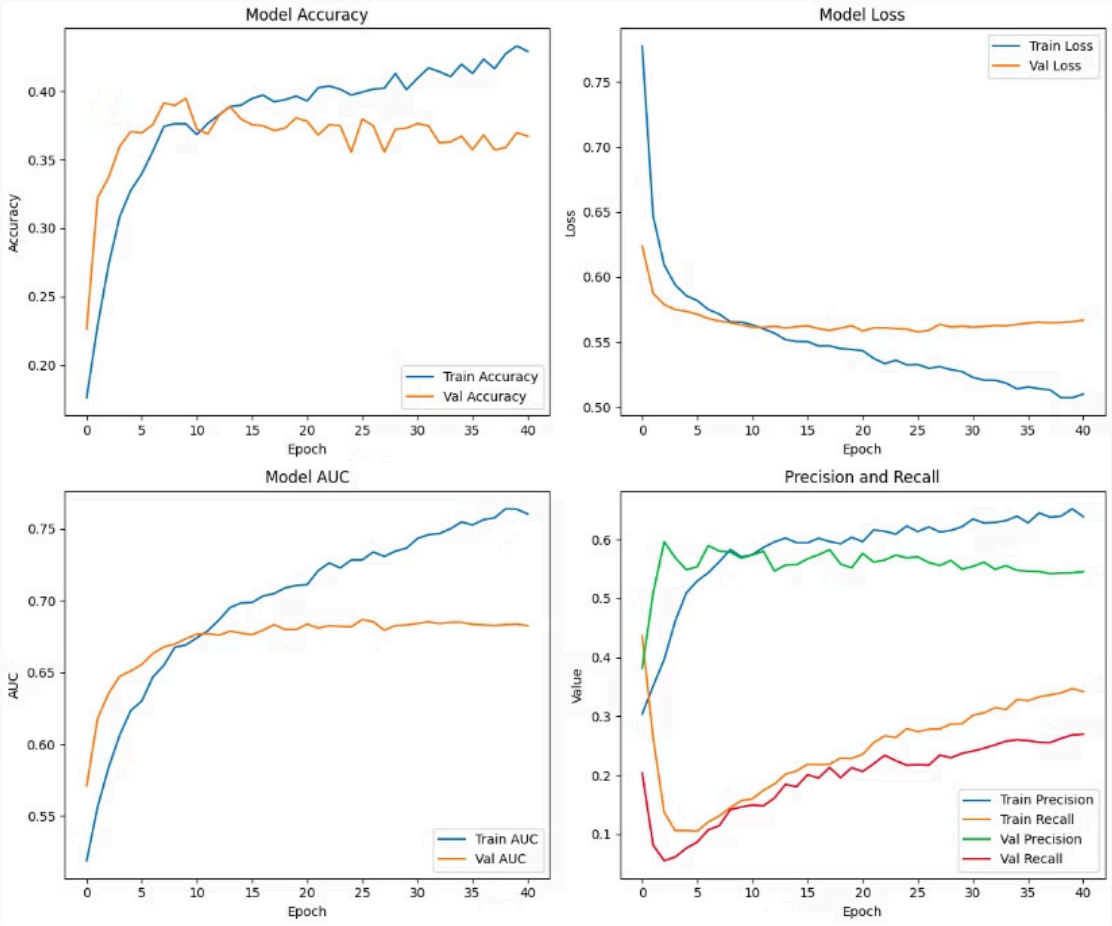


Classification Report:

	precision	recall	f1-score	support
Prolongation	0.33	0.54	0.41	380
Block	0.42	0.60	0.49	478
SoundRep	0.28	0.53	0.37	329
WordRep	0.27	0.79	0.40	317
Interjection	0.35	0.66	0.46	448
No Stutter	0.45	0.62	0.52	504
micro avg	0.35	0.62	0.45	2456
macro avg	0.35	0.62	0.44	2456
weighted avg	0.36	0.62	0.45	2456
samples avg	0.37	0.62	0.44	2456

Training Process For MFCC+ Prosodic Features

- **Dataset Split**: 70% training, 15% validation, 15% testing
- **Optimization**: Adam optimizer with binary cross-entropy loss
- **Learning Rate**: Adaptive reduction (0.001 → 0.0005 → 0.00025)
- **Early Stopping**: Patience=15 with best weights restoration



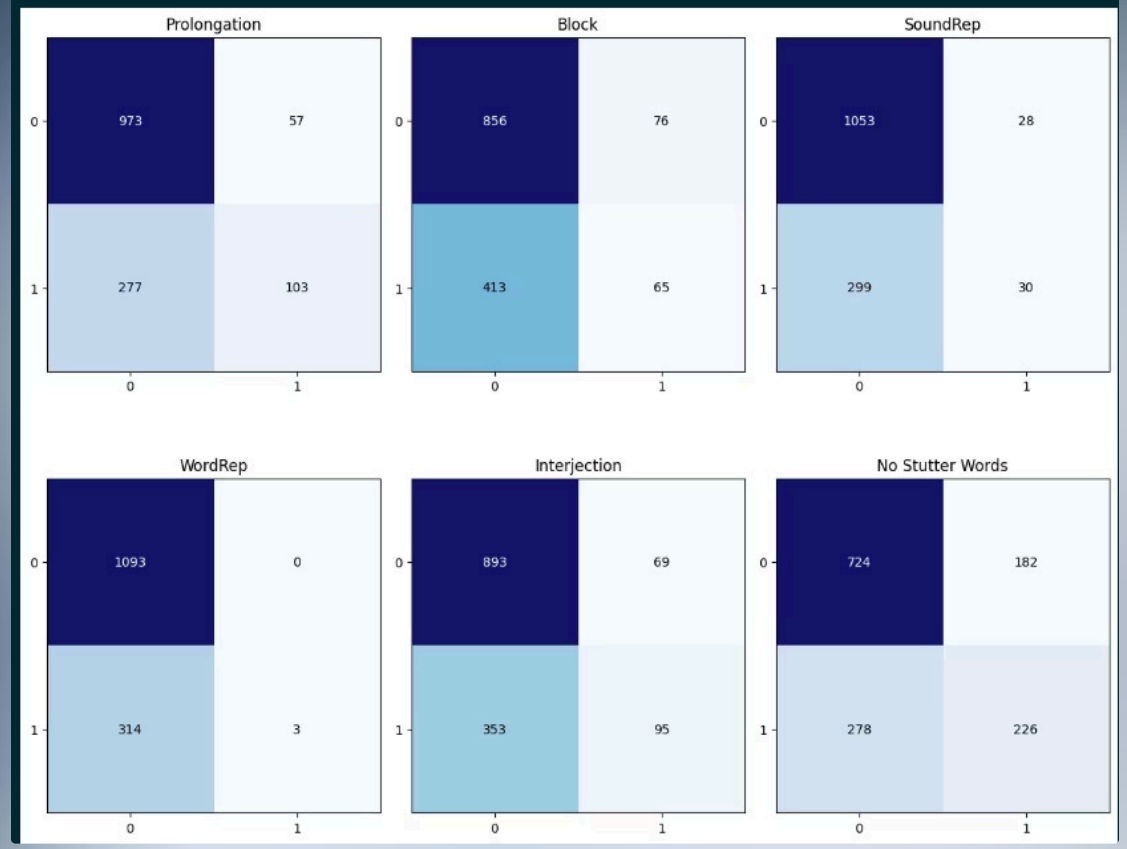
Model Performance

- **Classification Metrics**:
  - Accuracy: 37.45%
  - AUC: 0.6905
  - Precision: 0.5589 (good positive prediction reliability)
  - Recall: 0.2125 (moderate stutter detection rate)

```
Classification Report:
                    precision    recall  f1-score   support

      Prolongation       0.64      0.27      0.38       380
             Block       0.46      0.14      0.21       478
         SoundRep        0.52      0.09      0.16       329
           WordRep       1.00      0.01      0.02       317
      Interjection       0.58      0.21      0.31       448
No Stutter Words         0.55      0.45      0.50       504

         micro avg       0.56      0.21      0.31      2456
         macro avg       0.63      0.19      0.26      2456
      weighted avg       0.61      0.21      0.28      2456
       samples avg       0.30      0.26      0.27      2456
```



Model Performance Comparison

Metric/Feature	MFCC Model	Prosodic Model	Word-Level Model	Syllable-Level Model	MFCC + Prosodic Model
Performance Metrics					
Accuracy	35.11%	34.82%	27.02%	28.44%	37.45%
AUC	0.6709	0.6291	0.5985	0.5993	0.6905
Precision	0.4137	0.3807	0.3535	0.3471	0.5589
Recall	0.5957	0.5647	0.5423	0.6221	0.2125
Model Architecture					
Hidden Layers	128-64-32	64-32-16	128-64-32-16	64-32-16	128-64-32
Model Size	84.50 KB	51.62 KB	97.12 KB	17.25 KB	90.65 KB

Key Observations:

- MFCC+Utterance level model achieves highest accuracy
- Prosodic features offer best balance of performance and interpretability
- Word-level model struggles with Precision despite complex architecture
- All models show precision-recall trade-off, favoring Recall

Thank You