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VOCALSENSE

iMPLEMENTATION OF RESEARCH PAPER LSTM based Emotion Detection

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Introduction

SPEECH EMOTION RECOGNITION (SER)

- AUTOMATICALLY IDENTIFIES SPEAKER'S EMOTIONAL STATE FROM AUDIO
- CRITICAL FOR CUSTOMER ANALYTICS, MENTAL HEALTH, HUMAN-COMPUTER INTERACTION

CHALLENGES:

- SPEAKER VARIABILITY
- LIMITED DATASETS
- TEMPORAL DEPENDENCIES IN SPEECH

OUR SOLUTION:

- DUAL-LAYER LSTM ARCHITECTURE BASED ON YANG ET AL.
- DATASET EXPANSION: REVDAS (1,440) → MIXED DATASETS (11,680 FILES)
- ACHIEVED 83.26% ACCURACY WITH <100MS INFERENCE TIME

Literature Survey - Traditional vs Deep Learning

TRADITIONAL APPROACHES:

- **HAND-CRAFTED FEATURES (MFCCS, PITCH, ENERGY)**
- **CLASSICAL ML: SVMS, GMMS, HMMS**
- **LIMITATIONS: EXTENSIVE FEATURE ENGINEERING, POOR TEMPORAL MODELING**

DEEP LEARNING ERA:

- **CNNS FOR SPATIAL PATTERNS FROM SPECTROGRAMS**
- **RNNS/LSTMS FOR TEMPORAL CONTEXT**
- **HYBRID CNN-LSTM: STATE-OF-THE-ART ON BENCHMARKS**

DUAL-LAYER LSTM (YANG ET AL.):

- **HIERARCHICAL STRUCTURE: LAYER 1 (SHORT-TERM) + LAYER 2 (LONG-TERM PATTERNS)**
- **IMPROVED ACCURACY WHILE MAINTAINING LOW LATENCY (<100 MS)**

Methodology - Preprocessing & Features

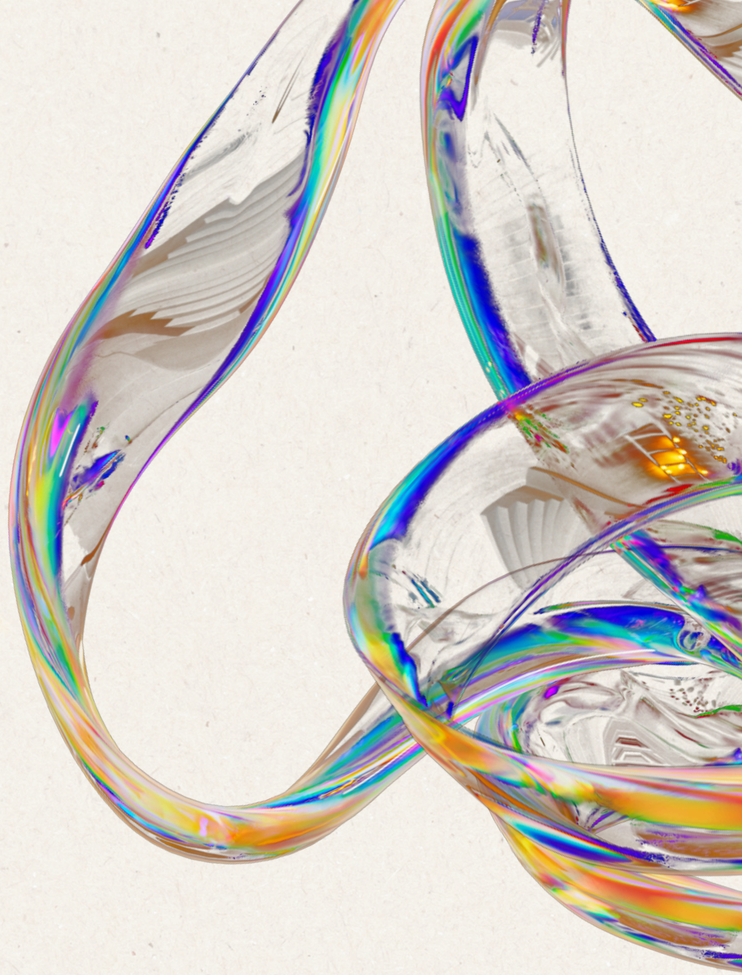
PREPROCESSING:

- **RESAMPLING: 22,050 HZ**
- **MONO CONVERSION**
- **FIXED DURATION: 3.0 SECONDS (TRUNCATION/ZERO-PADDING)**

FEATURE EXTRACTION:

- **MFCCS (40) + DELTA MFCCS → TIMBRE**
- **CHROMA & TONNETZ → HARMONIC CONTENT**
- **MEL-SPECTROGRAMS → FREQUENCY-TIME REPRESENTATION**
- **SPECTRAL CONTRAST → TEXTURE**

NORMALIZATION: STANDARDSCALER FOR STABLE CONVERGENCE



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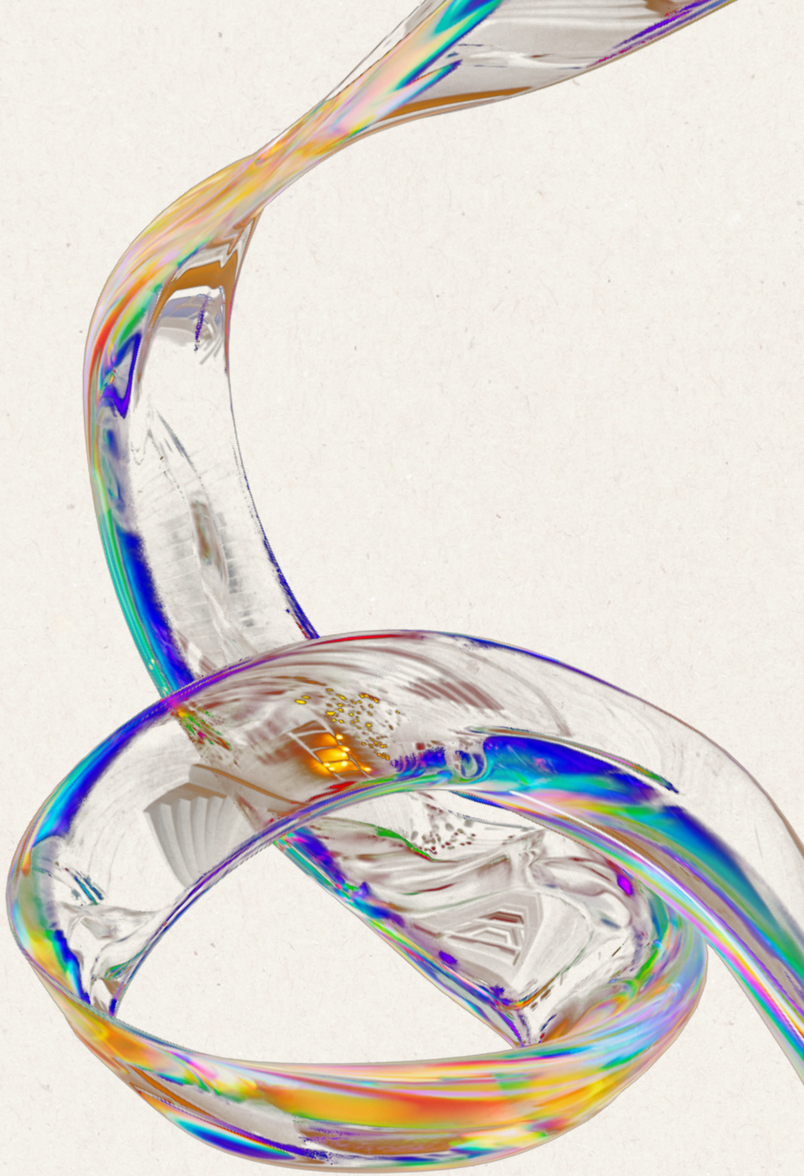


Methodology - Model Architecture

INPUT FEATURES (T, D)

↓

LSTM LAYER 1: 256 UNITS (RETURN_SEQUENCES=TRUE)

↓

BATCH NORMALIZATION + DROPOUT (0.4)

↓

LSTM LAYER 2: 128 UNITS (RETURN_SEQUENCES=FALSE)

↓

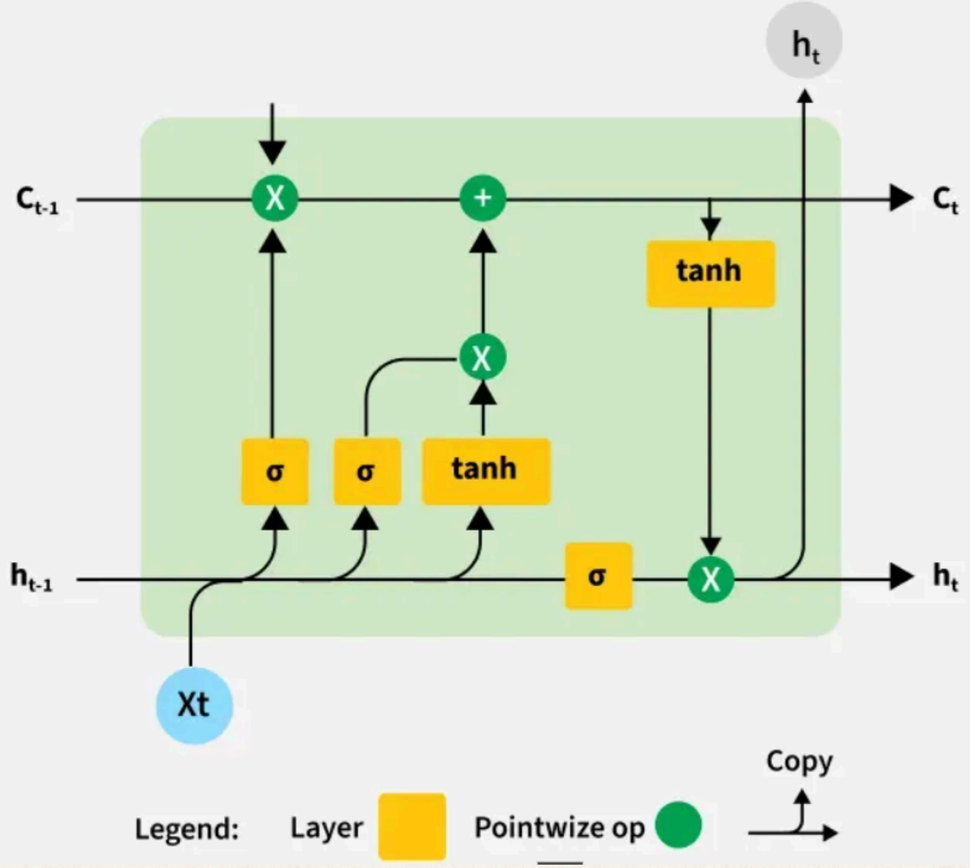
BATCH NORMALIZATION + DROPOUT (0.5)

↓

DENSE LAYER: 256 UNITS (RELU)

↓

OUTPUT: 8 CLASSES (SOFTMAX)



Results - Training Dynamics & Inference

TRAINING CONVERGENCE:

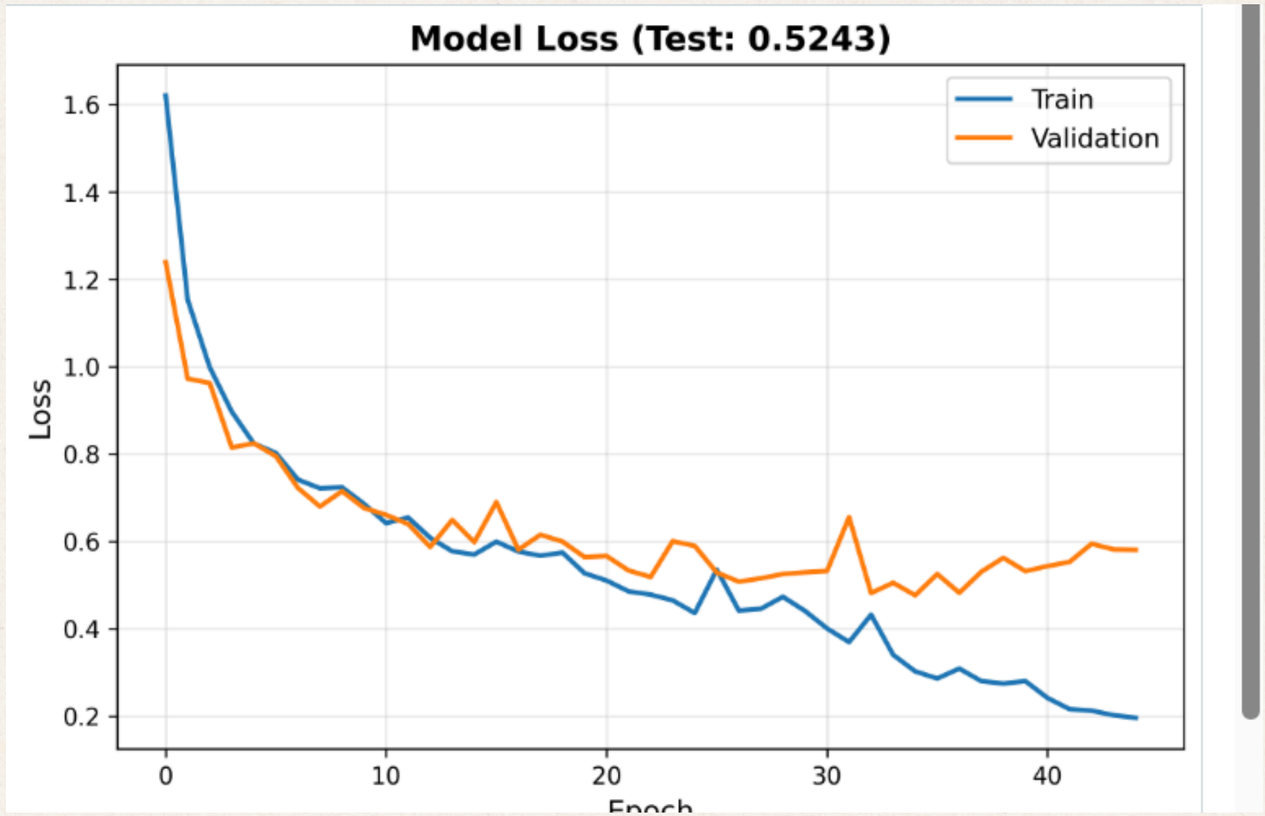
- STABLE TRAINING AND VALIDATION CURVES
- NO SIGNIFICANT OVERFITTING
- REDUCELRONPLATEAU ENABLED FINE-TUNING

INFERENCE PERFORMANCE:

- LATENCY: <100 MS PER 3-SECOND AUDIO CLIP
- HARDWARE: STANDARD CPU (NO GPU REQUIRED)
- SUITABILITY: REAL-TIME APPLICATIONS

DEPLOYMENT:

- STREAMLIT WEB INTERFACE
- FEATURES: AUDIO UPLOAD, PREDICTION, VISUALIZATION (WAVEFORM, MEL-SPECTROGRAM)



Results - Error Analysis

CONFUSION MATRIX INSIGHTS:

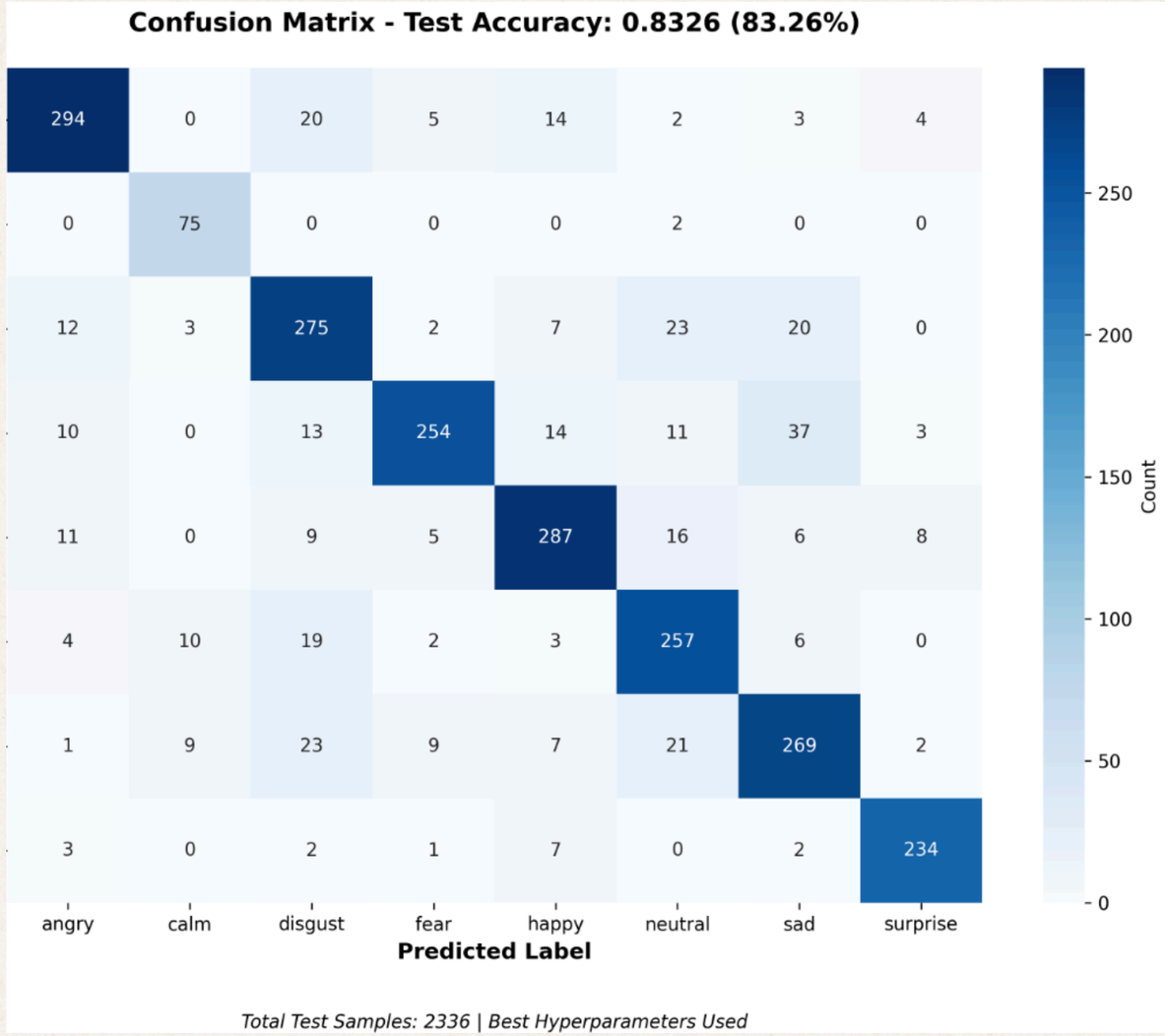
HIGH PERFORMANCE EMOTIONS (>85% ACCURACY):

- ✓ ANGRY, FEARFUL, DISGUST, CALM
- DISTINCTIVE ACOUSTIC CHARACTERISTICS

CHALLENGING EMOTIONS (CONFUSION AREAS):

- × HAPPY ↔ SAD ↔ NEUTRAL
- SIMILAR LOW-AROUSAL ACOUSTIC PROFILES
- OVERLAPPING PITCH AND ENERGY PATTERNS

TAKEAWAY: HIGH-AROUSAL EMOTIONS ARE EASIER TO DISTINGUISH THAN LOW-AROUSAL STATES



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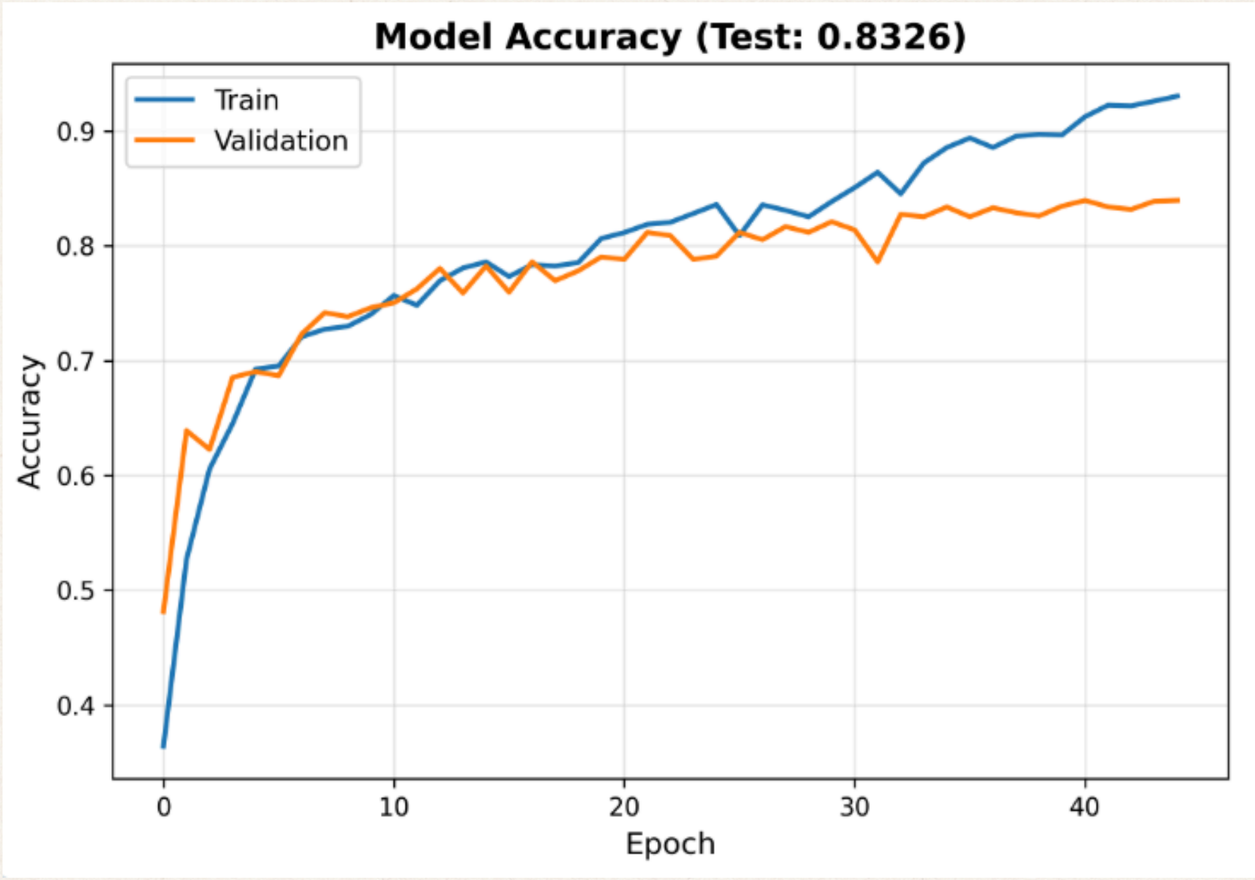

Analysis - Key Insights

1. DATASET IMPACT:
   - EXPANDING FROM 1,440 TO 11,680 FILES = +10% ACCURACY
   - DATA DIVERSITY > MODEL COMPLEXITY
2. ARCHITECTURE EFFECTIVENESS:
   - DUAL-LAYER LSTM BALANCES EFFICIENCY WITH TEMPORAL MODELING
   - HIERARCHICAL LEARNING CAPTURES BOTH LOCAL AND GLOBAL PATTERNS
3. HYPERPARAMETER OPTIMIZATION:
   - DROPOUT (0.4-0.5) CRITICAL FOR PREVENTING OVERFITTING
   - LEARNING RATE 0.001 OPTIMAL FOR CONVERGENCE
   - BATCH SIZE 128 IMPROVED GENERALIZATION
4. FEATURE ENGINEERING:
   - MULTI-FEATURE APPROACH (MFCCS, CHROMA, TONNETZ, SPECTRAL CONTRAST) ENHANCED ROBUSTNESS

Conclusions

PROJECT SUMMARY:

- IMPLEMENTED DUAL-LAYER LSTM-BASED SER SYSTEM
- EXPANDED DATASET FROM 1,440 TO 11,680 SAMPLES ACROSS 8 EMOTIONS
- ACHIEVED 83.26% TEST ACCURACY (10% IMPROVEMENT OVER BASELINE)
- DEPLOYED INTERACTIVE STREAMLIT APPLICATION WITH <100MS INFERENCE

KEY ACHIEVEMENTS: ✓ ROBUST PREPROCESSING AND MULTI-FEATURE EXTRACTION PIPELINE ✓ SYSTEMATIC HYPERPARAMETER OPTIMIZATION (500+ CONFIGURATIONS) ✓ REAL-TIME DEPLOYMENT CAPABILITY ✓ STRONG PERFORMANCE ON HIGH-AROUSAL EMOTIONS

DEMONSTRATION: DUAL-LAYER LSTMS + DIVERSE DATASETS = ROBUST SER PERFORMANCE

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