Poster Showcase
#IAEM25

# AI for Supporting Dispatchers' Mental Health: Proof-of-Concept for Stress Detection Based on Emotional State

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## Introduction and Background

Dispatchers face critical mental health challenges, yet research and support strategies remain underdeveloped.

**Mental Health Risks**
Significant impacts: PTSD, anxiety, depression, etc. [36, 41]
Research gap: dispatchers overlooked compared to police/firefighters [13]

**Sources of Stress**
Operational: high-pressure calls, trauma exposure, limited training [47]
Structural: inadequate support, lack of debriefs, poor staffing, restrictive policies [47]

**Shifting Toward Solutions**
Paradigm shift needed: stronger peer support and interventions [39], shift from surveys [41] and interviews [17, 30]
Innovative approaches: AI offers potential [16, 54] but remains underexplored, with risks and biases to consider

## Project Overview

Developed by a team of researchers and public safety practitioners (DPSS, University of Michigan), this project presents a vision for leveraging AI to detect stress of telecommunicators and provides practical, industry-informed insights on bias and considerations surrounding real-world implementation

**Objective:** Develop an AI-driven approach using natural language processing (NLP) and speech emotion recognition (SER) to detect stress in dispatcher-like communications, laying the groundwork for future applications with real calls.
**Innovation**: Deliver a first proof-of-concept model for stress detection, moving toward context-aware cognitive support in dispatcher operations.
**Significance**: Address a critical gap in dispatcher mental health research, often overlooked, while aligning solutions and recommendations with real-world practice.
**Impact**: Position AI as a discreet, proactive tool to help leadership support dispatcher well-being and resilience.

## Methodology

The high-level overview of our methodology entails the steps of:

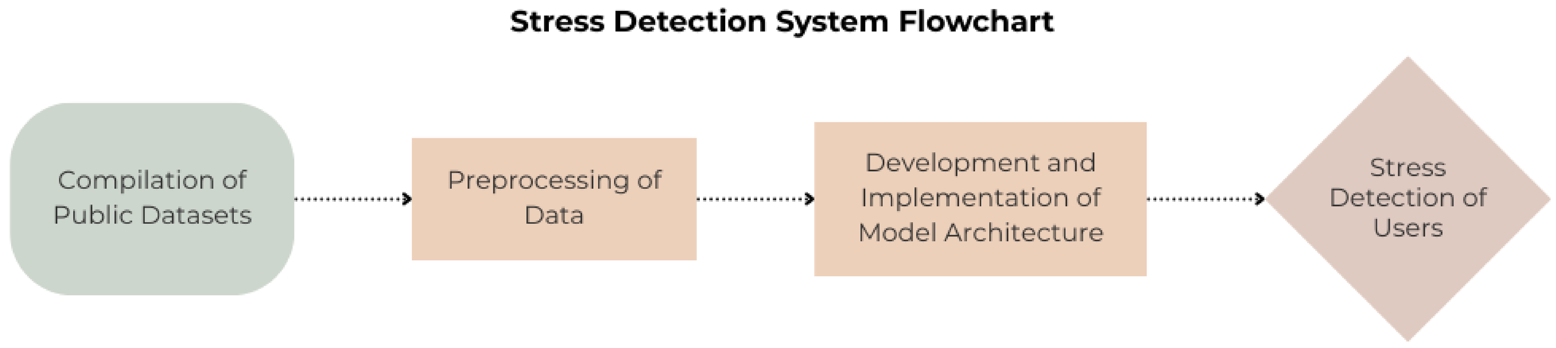


Figure 1. Overview of stress detection system.

## Methodology (cont.)

**1. Public Dataset Compilation (Proxy Data).**

**Data Sources:** Six publicly available emotional speech databases (English & Spanish) were combined to create a pilot dataset for AI-assisted stress detection in dispatchers. English Datasets (4):CREMA-D [10], RAVDESS [26], SAVEE [18], TESS [40]. Spanish Datasets (2):ESCORPUS-PE [37], MESD [14].

**Dataset Strengths:** High-quality, pre-labeled audio by trained actors, diverse speakers, broad emotional coverage.

**Final Dataset:** 17,800 WAV files across 8 emotion categories (Angry, Disgusted, Fearful, Sad, Neutral, Calm, Surprised, Happy).

**2. Preprocessing.**
Tasks: Audio cleaning, feature extraction, and normalization.

**3. Model Architecture.**

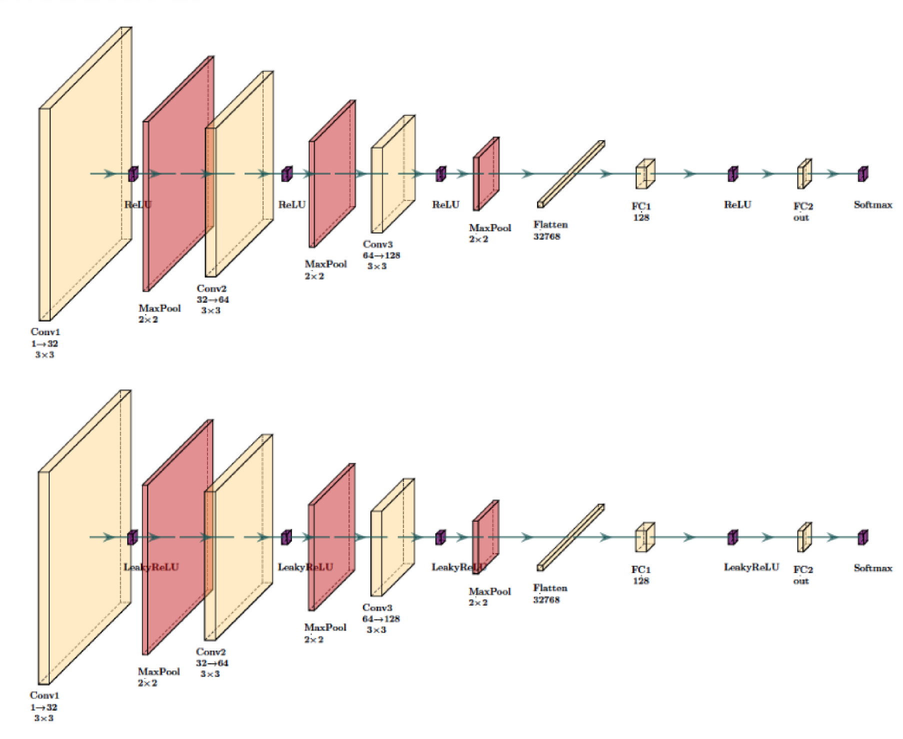

Figure 2. Architecture of the EmotionCNN model used for the five classifiers (Broad, Positive, Negative, Sad vs. Neutral, Happy vs. Angry). This version uses ReLU or LeakyReLU activations after each convolutional and dense layer to improve gradient flow for subtle emotional cues. The model processes128×128 Mel Spectrograms through three convolutional layers with ReLU or LeakyReLU activation, followed by max-pooling, a fully connected layer, and an output layer. Softmax is applied during inference for prediction confidence.

**4. Stress Detection.**

System Workflow

**Listen** → Monitors dispatcher speech in short chunks; stops if silent (1.5 sec) or spacebar pressed; resets automatically for continuous monitoring.

**Process** → Audio is processed through five classifiers; best-performing model used for stress detection.

**Detect** → Sliding window (last 10 results) checks for stress-related emotions; privacy protected by discarding non-stress outputs.

**Alert** →3+ stress predictions in a row OR 6+ per call → message prompts dispatcher to use stress-reduction strategies. 6+ predictions → supervisor discreetly notified for intervention.

**Log** → Records start/end times of stress periods in stress_periods_log.txt; audio deleted after processing (only timestamps + emotion labels saved).

## Results/Findings and Next Steps

**Best Classifier:** The Sad vs. Neutral classifier performed strongest and is recommended as the first step for detecting emotional states in dispatcher mental health initiatives.
**Two-Step Pipeline (for real-time use):** Step 1: Run the Sad vs. Neutral classifier. Step 2: Use one multi-class model (e.g., Positive or Broad, which handle neutral emotions well) depending on call center needs.
**Why:** This pipeline reduces system overload while maintaining reliable real-time stress detection.

### Bias Mitigation

Following the Wells–Du Bois protocol [32], the findings are presented as guided recommendations for responsible future deployment.

1. Bad Data – Inadequate Data: *Report sample sizes and model performance by subpopulation.*
2. Bad Data – Tendentious Data: *Disclose subjectivity in actor-produced recordings and labels.*
3. Algorithmic Bias – Harms of Identity Proxy: *Check for proxies (e.g., language) before deployment.*
4. Algorithmic Bias – Harms of Subpopulation Difference: *Use augmentation/normalization to balance representation.*
5. Algorithmic Bias – Harms of Misfit Models: *Apply robust validation; prioritize interpretable models.*
6. Human Intent - Do No Harm: *Document architectures; share process and findings, not sensitive data.*
7. Human Intent - Harms of Ignorance: *Delete audio after processing; retain only timestamps/logs.*

### Considerations for Real-World Use

1. **Incorporate call type variability:** Account for differences in dispatcher emotions across call types (e.g., violent incidents vs. calls involving children or erratic information) to improve model adaptability.
2. **Leverage complementary datasets:** Combine center-specific data with publicly available actor datasets to expand volume, capture masking behaviors, and consider dispatcher experience levels in analysis.
3. **Personalize models:** Build individual baselines for each dispatcher; involve dispatchers in early training (e.g., post-shift annotations) to distinguish genuine stress from communication style.
4. **Establish governance protocols:** Ensure secure, access-controlled handling of individualized reports to protect dispatcher privacy, reduce stigma, and build trust in deployment.

## Conclusion

*This scalable, low-cost AI model can help address dispatcher burnout, reported by ~85% of over 100,000 U.S. dispatchers [33, 55]. By giving supervisors insight into workforce stress and morale, it can support retention, strengthen the dispatcher workforce, and enhance emergency response capacity - ultimately saving more lives.*

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References:

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