



## A PRIVACY-PRESERVING FEDERATED MULTIMODAL EMOTIONAL INTELLIGENCE FRAMEWORK FOR ADAPTIVE HUMAN-ROBOT COLLABORATION IN INDUSTRY 5.0

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### Abstract

The fast development of Industry 5.0 highlights the need for human-centric automation that requires the cooperation of intelligent robots with humans based on their emotional, cognitive, and behavioral states. The conventional approaches to Human-Robot Collaboration (HRC) include perception and decision making related to tasks but not the ability of robots to perceive dynamic human states. The contribution of this paper is developing the Federated Multimodal Emotional Intelligence Framework (FMEI) that is required for adaptive HRC based on privacy-preserving federated learning and multimodal affective computing.

In particular, the framework involves multimodal fusion to process heterogeneous emotional cues including facial expression, speech signal, physiological, and behavioral modalities. The distributed federated learning algorithm allows training the models in collaboration between robots and edge devices without sending private human data to central servers. The developed model will recognize

emotions, predict human states, and generate adaptive robot actions.

The goal of the framework is increasing the safety, trust, efficiency, and personalization of collaboration in industrial environment. Experimental evaluation may involve multimodal emotion datasets and simulated industrial robotic applications. Some performance criteria to measure may include accuracy, F1-score, latency, communication efficiency, and privacy preservation.

**Keywords:** Federated Learning, Multimodal AI, Emotional Intelligence, Human-Robot Collaboration, Affective Computing, Industry 5.0, Deep Learning, Privacy-Preserving AI.

### 1. Introduction

The fusion of AI and robots has revolutionized industrial settings from automated systems to collaborative ecosystems where humans and robots collaborate with each other. As opposed to traditional industrial robots, collaborative robots demand contextuality, flexibility, and human consciousness.

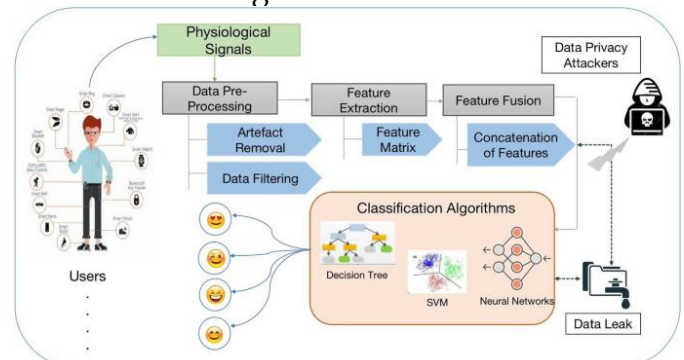
Emotions of humans play an important role in affecting decisions, efficiency, communication, and safety of collaborative tasks. Thus, robot systems equipped with emotional intelligence that have the ability to analyze human emotional states can enhance their interactions and reliability.

Current emotional aware robotic systems primarily rely on centralized machine learning systems which involve the need for large-scale personal data gathering. It raises issues of privacy, security, and scalability. Federated Learning (FL) offers another way of training AI models where multiple devices collaborate while keeping data private locally. This study aims at proposing federated multimodal emotional intelligence framework for robots to recognize human emotions and behave accordingly in industrial collaboration.

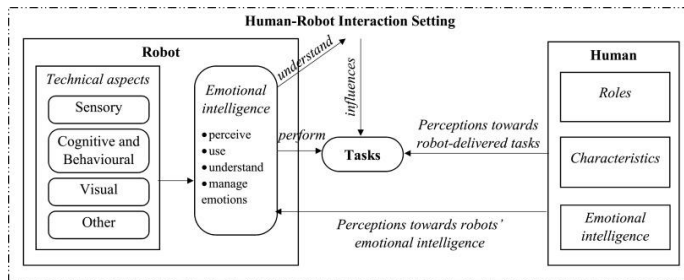
- Lack of personalization for individual workers
- The inability to be adaptable in uncertain industrial environment
- The recent scientific research stresses the significance of the multimodal data on physiological, audio and facial information for creating a human-aware robots.

### 3. Proposed Framework

Architecture of Federated Multimodal Emotional Intelligence



**Fig 2. Federated Multimodal Emotional Intelligence**



**Fig.1 - Human - Robotic Systems**

### 2. Reasons for the Research

Limitations of the current HRC include:

- The inability to recognize emotions in real-time
- The reliance on unimodal approaches to sensing
- The issues related to the privacy of collecting human behavior information

### Layer 1: Multimodal Data Gathering

Sensors capture:

- Facial expressions (camera-based vision)
- Speech and voice information
- Multimodal physiological information:
  - ✓ Heart rate
  - ✓ EEG
  - ✓ ECG
  - ✓ Skin reaction
  - ✓ Human activities

**Layer 2: Local Emotional Features Learning**

Deep learning architectures will obtain emotional features by:

- CNN/Vision Transformer for face
- Transformer architecture for speech emotion recognition
- LSTM/Deep Neural Network for physiological data

**Layer 3: Federated Learning Module**

Robots and edge devices work together to train a global model for emotional intelligence.

**Flow of actions:**

Worker → Local AI Model → Model Update Encryption → Federated Server → Global Model → Robots

**Benefits:**

- Privacy-preserving
- Communication-cost reduction
- Personalized learning
- Distributed intelligence

**Level 4: Emotional Decision-Making and Robot Adaptation**

Depending on user states observed:

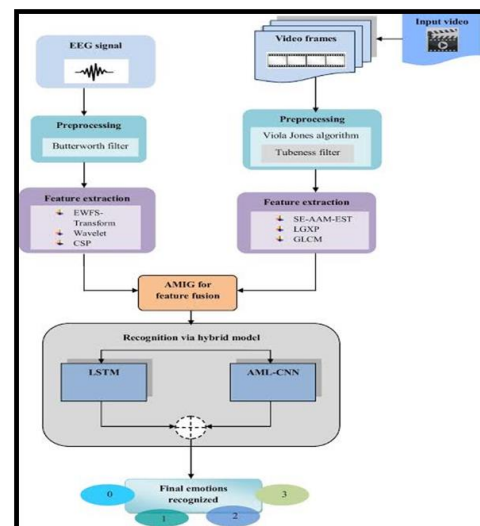
User state	-	Robot Adaptation
Stressed	-	Low speed/assistance
Tired	-	Break/suggest changes to task
Confused	-	Provide guidance
Overconfident	-	Autonomy

**4. Proposed Algorithm**

**Algorithm for Federated Multimodal Emotional Intelligence (FMEI)**

**Inputs:** Facial expressions, speech, physiology, behavior

- Step 1:** Acquire multimodal emotional signals from users.
- Step 2:** Apply deep learning algorithms for extraction of features.
- Step 3:** Fusion of multimodal features.
- Step 4:** Develop emotional intelligence models locally.
- Step 5:** Encrypt and share model parameters by federated aggregation.
- Step 6:** Develop global adaptive emotional intelligence model.
- Step 7:** Adjust robot behavior according to emotional states.



**Fig 3: Multimodal Emotion Recognition Model**

### 5. Mathematical Model

Mathematical model for federated optimization:

$$\min_w \sum_{k=1}^K \frac{n_k}{n} L_k(w)$$

where:

- $w$  = global model parameters
- $K$  = number of participating robots
- $L_k$  = local loss function
- $n_k$  = local dataset size

### Multimodal Fusion Model:

$$F = \alpha V + \beta A + \gamma P$$

Where:

- $V$  = visual feature
- $A$  = audio feature
- $P$  = physiological feature
- $\alpha, \beta, \gamma$  = fusion weight

### 6. Experimental Setup

Possible data sets:

- FER2013 – Facial emotion recognition
- RAVDESS – Speech emotion recognition
- DEAP – Physiological emotion recognition
- MultiPhysio-HRC – Multimodal industrial human-robot collaboration data set

### Performance Metrics

Criteria	Evaluation
Emotion Precision	Classification precision
F1 Score	Model accuracy
Latency	Real-time performance
Communication Overhead	Federated efficiency
Privacy Degree	Data privacy
Adaptability	Robot response accuracy

### 7. Anticipated Contributions

The proposed research makes the following contributions:

1. A privacy preserving federated model for emotional intelligence.
2. Multimodal fusion technique for human emotion recognition.
3. Adaptive robot behavior according to human emotions.
4. Scalable AI system for Industry 5.0 cooperation.
5. Greater trust and safety in human-robot interaction.

### 8. Applications

- Smart manufacturing
- Collaborative robots assembly lines
- Healthcare robots
- Automated industrial assistants
- Intelligent warehouses
- Human-centric factories



## 9. Conclusion

This paper introduces an approach towards Federated Multimodal Emotional Intelligence framework for adaptive Human-Robot Collaboration. The combination of federated learning, multimodal affective computing, and intelligent robot control facilitates emotional adaptation to a privacy-aware and personalized robotic collaboration. The framework is applicable to the concept of Industry 5.0, where robots and humans collaborate through trust, intelligence, and understanding.

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