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Research Article

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Emotio-Intelligent: A New Adaptive Approach for Intelligent Evacuation in Crisis Situations

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Abstract

Addressing the critical challenge of evacuation, especially in crisis situations where uncontrollable emotions can significantly impact decision-making, is of paramount importance. In this article, the Emotional Intelligent Model is presented, a new approach that seamlessly integrates dynamic emotion recognition with an adapted intelligent evacuation strategy for crisis scenarios. Our methodology harnesses a combination of convolutional neural networks (CNN) for dynamic emotion sensing and long-term memory recurrent neural networks (LSTM) to provide decision support during evacuation. This paper provides an in-depth exploration of our system's architecture, encompassing the dynamic emotion recognition and personality profiling methods, as well as the adaptive evacuation strategy.

During the experimental and validation phases, the MESA simulation platform was used. The results achieved confirm the effectiveness of the integrated emotional approach, which contributes to safer and smarter evacuation procedures in crisis situations.

Keywords: Facial Emotion Recognition (FER), Artificial Intelligence, Evacuation, Disaster, Deep Learning, Neural Networks, LSTM.

1. Introduction

Among the main challenges of securing human lives, rapid and well-organized evacuation of people to safe places remains crucial. However, this process can be disrupted by situational factors, particularly in emergency situations, such as panic and desperation, which can obstruct evacuation efforts or render them ineffective. It is therefore essential to consider the emotional factors to ensure the success of evacuations, particularly in crisis situations. Emotional intelligence represents a change in crisis management methods, aimed at improving evacuation procedures by recognising emotions and providing decision support. In this context, an approach called "Emotio-Intelligent" is being introduced.

This approach seamlessly integrates dynamic sentiment recognition with an intelligent evacuation strategy that adapts to crisis scenarios such as floods and accidents inside large factories. Our methodology uses a combination of convolutional neural networks (CNN) for dynamic emotion sensing and recurrent neural networks for long-term memory (LSTM) to provide decision support during evacuation.

The MESA simulation platform was used. The results supported the effectiveness of the integrated emotional approach, which contributed to safer and smarter evacuation procedures in crisis situations.

Existing studies overlook the emotional state of people affected by emergency rescue operations, which underlines the importance of this paper. This study aims to understand how rescue decisions are made considering the emotional state of those involved in a rescue operation. The aim of this article is twofold. First, the central role of emotion recognition in the field of crisis management will be highlighted, elucidating how emotions can shape individual and group behavior during evacuation procedures. Next, a comprehensive review of the intelligent affective approach, which is a synthesis of cutting-edge techniques that combines the power of convolutional neural networks (CNNs) for emotion detection and recurrent neural networks for long-term memory (LSTMs), will be presented [1.2]. For decision support during evacuations.

In the following sections, complex modeling of emotions and personality traits will be addressed, inspired by the OCC (Ortony, Clore, and Collins) and OCEAN (Five-Factor Model) models, respectively. In addition, the architecture of the intelligent emotional system will be described in depth, which includes four fully integrated and interconnected modules: face detection, feature extraction, emotion classification, and emotional evacuation decision making [3.4].

Preliminary results from training and evaluation of the LSTM model will be presented, highlighting the potential impact of the proposed approach in intelligent evacuation during crisis scenarios. This research is expected to have a critical role in improving population safety in emergency situations and will call for widespread adoption of the emotionally intelligent approach to strategic planning and skilful implementation of situation-specific evacuation procedures [5.6]. Our main contribution to this endeavor is the integration of Emotio-Intelligence with emerging technologies, a concerted effort to address the challenges inherent in securing evacuations in crisis situations. In the following sections, we will provide a concise overview of the theoretical underpinnings of the proposed approach, present the emotional intelligent model, and discuss the findings of the experimental study and model validation.

2. Related Work

In recent years, there has been a growing interest in integrating emotion assessment into decision support systems for crisis scenarios [7]. This involves using facial expressions to aid decision-making in emergency context.

Numerous studies have explored this area, employing traditional machine learning techniques like fuzzy logic in conjunction with machine learning (ML), as well as current approaches such as deep learning, convolutional neural networks (CNNs), transfer learning, and Bayesian Networks for emotion detection.

In this context, Sirine Lasfar and Dalel Kanzari introduce an S-S-LSTM method to identify dominant sentiments within influential social communities in crisis periods [8]. Chamola et al. in used “Machine learning” for predicting disasters and assisting in disaster management tasks, such as determining crowdevacuation routes, analyzing social media posts, and handling post-disaster situations. As well, the authors in used “Bayesian Networks” for explain how people make rational decisions using noisy and vague sensory feedback. Ibtissem Daoudi and al [9-12]. used “Data Mining” to Explain Improving Learner Assessment and Evaluation in Serious Crisis Management Games [13].

The authors in used “Big Data” To explain human behaviors in evacuation crowd dynamics: from modeling to “big data” toward crisis management. In this work, a newly renamed balanced FER2013 dataset is presented [14]. A balanced CNN-LSTM is designed and trained [15]. A new deep neural network architecture for recognizing the face sign expression, using the pretrained MobileNetv2 model images weights and the modified balanced version of the FER2013 dataset is designed and implemented [16].

3. Theoretical Foundations

Emotional modeling plays an essential role in the development of our Emotio-Intelligent approach, and at the heart of our strategy is the renowned OCC model by Ortony, Clore and Collins. Recent research in this field, such as studies published in leading journals , underline the importance of this model, which provides a comprehensive framework for understanding the dynamics of emotional responses [17-19].

The OCC model has been shown to be both simple and resilient in categorising emotions according to their underlying meaning. In the present study, particular attention was paid to identifying and examining key emotions in emergency scenarios, in particular fear, anger, sadness, and complacency. These emotions have distinct characteristics and elicit specific reactions, which have been sought to be characterized and interpreted in order to improve decision-making processes during evacuation scenarios.

Drawing on recent research findings, our Emotio-Intelligent approach strives to better understand human behavior by recognizing emotions in constrained situations such as crisis evacuation. In this approach, the significant influence of individual personality traits is also taken into account in the decision-making process in crisis situations. In this regard, the OCEAN model, also known as the Five-Factor Model (FFM), has been incorporated to characterize personality. This widely accepted model divides personality into five broad dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism.

Personality traits have a considerable influence on how individuals react to highly stressful situations such as evacuations. For example, an extraverted person may be more inclined to ask for help and cooperate with others during an evacuation, while a more neurotic person may experience heightened anxiety and negative emotions. By integrating these personality dimensions into our Emotio-Intelligent framework, this work aims to better understand individuals' behavior and adapt evacuation strategies to their psychological tendencies.

LSTM neural networks for emotion detection

Within the scope of the present Emotio-Intelligent research project, long-term memory neural networks (LSTMs) are emerging as key components for emotion recognition and analysis. LSTMs represent a specialized iteration of recurrent neural networks (RNNs),particularly adept at capturing and retaining information over long sequences of data, a capability precisely suited to the nuanced and evolving emotional states encountered in crisis scenarios [20,21].

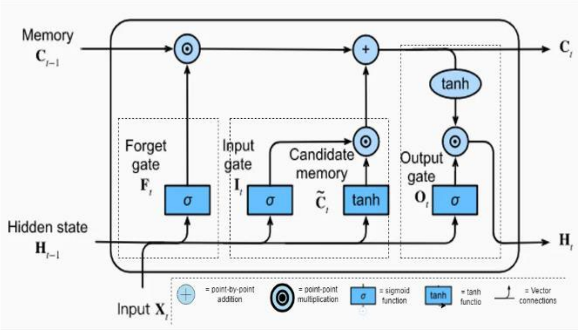

Figure 1: Global LSTM Architecture [22] Mathematically, the LSTM Structure can be Formulated as follows:

-Forget Gate:

$$F_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f) \quad (1)$$

-Input Gate:

$$I_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i) \quad (2)$$

Output Gate:

$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o) \quad (3)$$

Where $\boldsymbol{W_{xi}}$, $\boldsymbol{W_{xf}}$, $\boldsymbol{W_{xo}}$, $\boldsymbol{W_{hi}}$, $\boldsymbol{W_{hf}}$, $\boldsymbol{W_{ho}}$ are weight parameters and $\boldsymbol{b_i}$, $\boldsymbol{b_f}$, $\boldsymbol{b_o}$ are bias parameters .

Input Node: $\tilde{C}$

$$\tilde{C}_t = \tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c) \quad (4)$$

where $\boldsymbol{W_{xc}}$ and $\boldsymbol{W_{hc}}$ are weight parameters and $\boldsymbol{b_c}$ is a bias parameter.

-Memory Cell Internal State:

$$\boldsymbol{C_t} = F_t \odot \tilde{C}_{t-1} + I_t \odot \tilde{C}_t \quad (5)$$

Hidden State:

$$\boldsymbol{H_t} = O_t \odot \tanh(C_t) \quad [22] \quad (6)$$

This ensures that the values of **H** are always in the interval [-1, 1].

Using LSTMs allows us to learn from sequential data, such as image sequences that capture individuals' facial expressions over time. This dynamic approach enables us to understand the fluid nature of emotions, identifying critical moments when individuals may switch to emotions such as fear, anger or other important emotional states during evacuations. This temporal awareness aligns perfectly with the core principles of our Emotio-Intelligent project, where the rise and fall of emotions play a central role in driving emotional decision-making during evacuations.

The integration of emotion and personality modeling with LSTM neural networks is the foundation of the Emotio-Intelligent approach. This interaction provides valuable perspective on the development of smarter, emotion-driven evacuation strategies suited to individual needs in crisis situations.

4. Proposed Approach

The Emotio-Intelligent approach proposes a multidisciplinary strategy for improving crisis management, with a particular focus on evacuations. It is based on three fundamental elements, each of which be crucial in improving the overall effectiveness of our system. These fundamental elements are emotion modelling, personality modelling and the architecture of the evacuation support system.

4.1 Emotions Modeling

The proposed approach emphasises the importance of factoring emotions into crisis scenarios. It uses the OCC model (Ortony, Clore and Collins) to provide a comprehensive understanding of the emotional process of individuals in crisis situations. Critical emotions for evacuation, such as fear, subjective anger, sadness, and complacency, were identified by linking them to specific responses to emergency situations. Through this modeling, the proposed system can detect, understand and respond to individuals' emotions in real time during the evacuation process.

4.2 Personality Modeling

In addition to modeling emotions, individuals' personalities are integrated into the emotional model. To do this, the OCEAN model is used (Five-Factor Model - FFM), which identifies five major personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. These traits profoundly influence individuals' behaviors in crisis situations, especially during evacuations. By taking into account each individual's personality, our system is able to propose evacuation strategies tailored to their preferences and specific emotional reactions.

4.3 Evacuation system architecture

To validate and test the proposed approach: "Emotion-Intelligent" a simulation platform was developed using the MESA framework. This platform provides the possibility of creating a realistic and personal virtual environment where the behavior of individuals can be monitored during simulated evacuation situations.

The Mesa platform provides advanced features for modeling autonomous agents, such as emotional characters and eviction experts. Through this platform, the influence of emotions and personality on the evacuation process can be deeply investigated, as well as the effectiveness of the proposed emotional intelligent approach in a safer and more personalized evacuation process.

The proposed Emotio-Intelligent approach integrates emotional and personality modeling, based on LSTM neural networks, the OCC model, and the OCEAN model to design an improved emotion-driven evacuation system. The Mesa simulation platform provides a suitable framework for assessing and refining our approach, allowing the development of advanced solutions to improve the safety and efficiency of evacuations during crises. [22,23].

4.4 Architecture of Emotio-Intelligent

Most existing emotion recognition solutions follow a common architectural pattern, consisting of three main modules that function independently. These three key modules are as follows:

1- Face detection Module.
2- Feature extraction Module.
3- Classification Module.

These three modules interact to create a comprehensive system for emotion recognition.
In the proposed approach, a fourth additional module designed for decision support is integrated:

• **Face Detection:** This module is designed to recognize and locate faces in input images or video streams. It plays an essential role in ensuring that only relevant regions containing faces are further processed.

• **Decision Support :** This module analyses recognized emotions and offers guidance and recommendations for appropriate actions in evacuation scenarios. It factors in aspects like emotion intensity, crowd dynamics, and safety protocols to facilitate wellinformed decisions.

• **Feature Extraction:** The feature extraction module concentrates on extracting significant facial attributes from the identified facial regions. These attributes may encompass geometric measurements, textural information, or facial landmarks that encapsulate distinct characteristics related to various emotions.

• **Classification:** Employing machine learning algorithms such as CNN or LSTM, the classification module categorizes the extracted features and predicts the corresponding emotion. It undergoes training on a labelled dataset of emotions to grasp the patterns and relationships between the features and emotional states.

The system's overall capabilities. It transcends simple emotion recognition and provides valuable information and support in critical moments, safeguarding the well-being of people in emergency situations. These modules are shown in detail in Figures 2 and 3

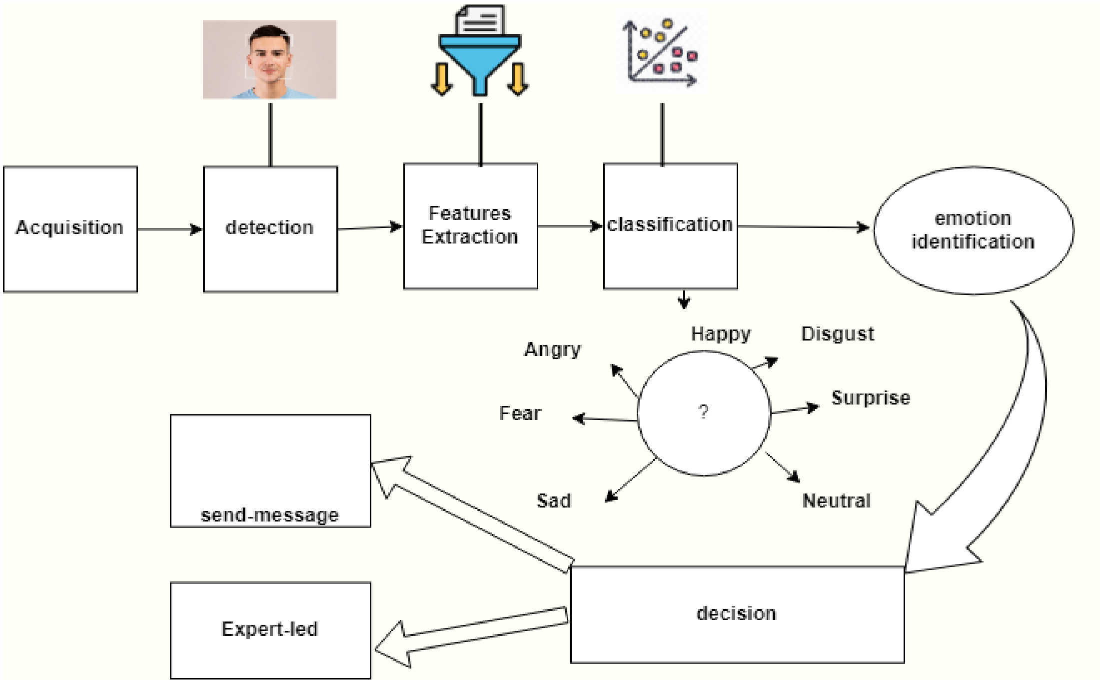

Figure 2: Overall Architecture of Our Emotion Recognition System and Decision Support In Case Of Evacuation.

Face Detection Module: This module identifies and locates faces in images or videos, constituting the essential first step in emotion recognition.

Feature Extraction Module: This module extracts relevant features from the detected faces, such as facial expressions, muscle movements, or other visual cues, to provide actionable data for emotional analysis.

Classification Module: This module classifies the extracted features to identify and categorize emotions, enabling the system to recognize and understand individuals' emotional states.

Emotion identification: refers to the process of recognizing and categorizing human emotions based on various cues, such as facial expressions, vocal tone, body language, or physiological responses. This involves the ability to accurately discern and label emotions like happiness, sadness, anger, fear, and others.

Decision module: is a critical component where the system makes choices and takes action based on the emotional state of the agent. The system's decision-making process is influenced by the agent's emotional state, and it follows a specific set of rules to determine the appropriate course of action.

For instance, if the system detects that the agent is experiencing fear, it may opt to guide the agent with the assistance of an expert. This expert guidance could involve providing personalized instructions, reassurance, or support tailored to alleviate the agent's fear and ensure their safety during the evacuation.

On the other hand, if the system determines that the agent's emotional state does not indicate fear, it may choose a different approach. In this case, it might send a message to the agent, which contains information about the shortest and safest evacuation path. This decision is made with the goal of facilitating a swift and secure evacuation process, taking into account the agent's emotional state as a factor in the decision-making process.

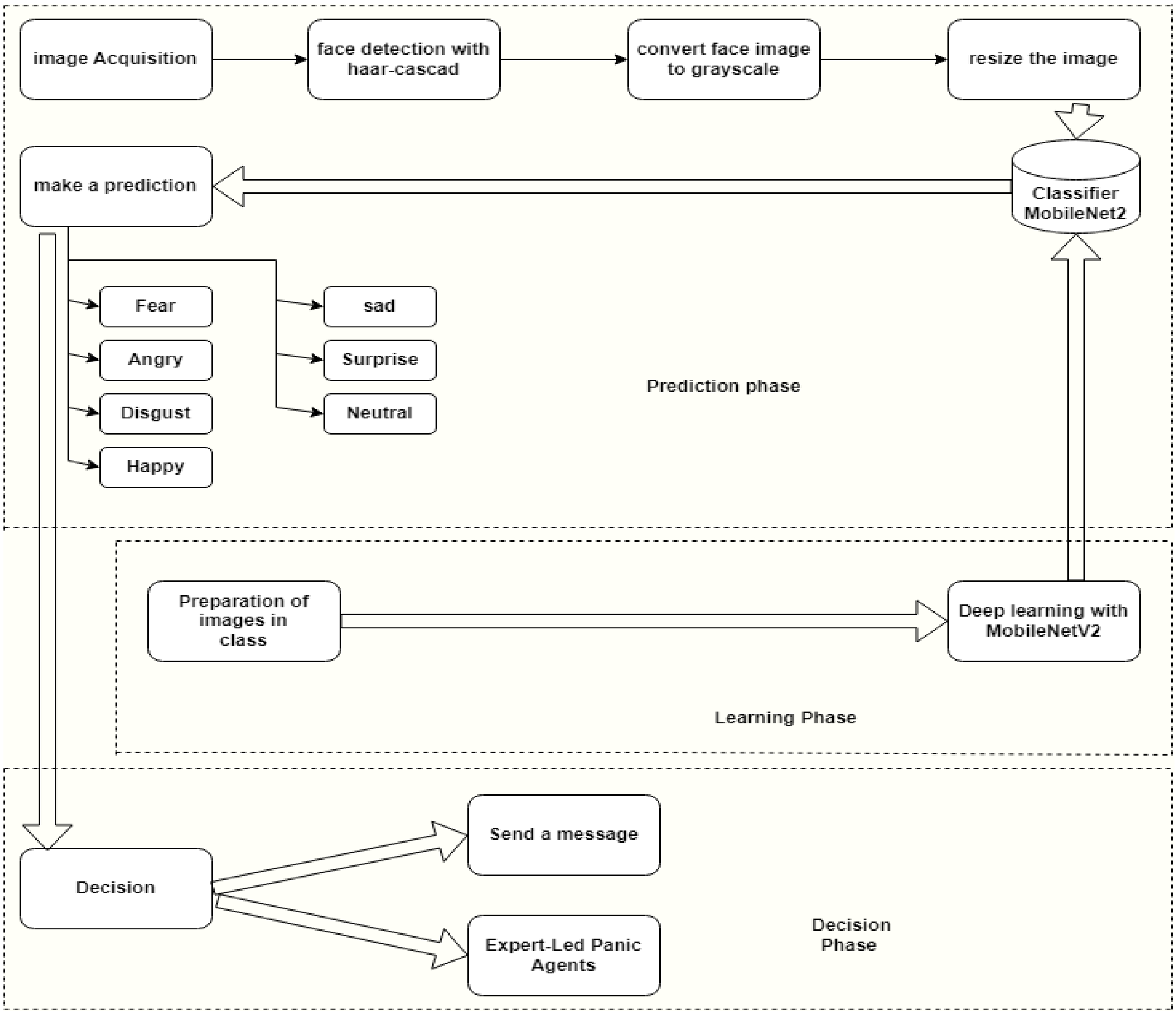

Figure 3: Overall Diagram of Our Emotion Recognition System and Decision Support In Case Of Evacuation.

The general scheme of the system for emotion recognition and decision support in an evacuation situation consists of three key phases:

Prediction Phase: In this initial phase, the system predicts and assesses the emotional state of the agent. This is achieved through the analysis of various emotional cues, such as facial expressions, vocal tone, or physiological responses. If the agent's emotion is identified as fear, the system proceeds to the next phase where an expert will provide guidance and support to the panicked agent. However, if the agent's emotion does not indicate fear, the system prepares for the decision-making phase.

Learning Phase: This phase involves the accumulation of knowledge and data about the evacuation scenario and the emotional responses of agents. The system learns from past experiences and refines its ability to recognize emotions accurately. This learning phase is essential for the system to continuously improve its emotional recognition capabilities.

Decision-Making Phase: In the final phase, the system makes decisions based on the agent's emotional state. If the agent is identified as experiencing fear during an evacuation, the system engages an expert who guides and assists the panicked agent. On the other hand, if the agent's emotion does not signify fear, the system initiates a different action by sending a message to the agent. This message typically contains information about the shortest and safest evacuation path, with the aim of ensuring a secure and efficient evacuation process while considering the emotional state of the agent.

These three phases work together to create a comprehensive system that recognizes and responds to the emotions of individuals during evacuation, ensuring that appropriate support and guidance are provided to enhance safety and effectiveness.

5. Simulation and Implementation

To validate and test the proposed emotional intelligent approach, a simulation platform was developed using the Mesa framework [24]. This platform allows the creation of a realistic and personal virtual environment, where the behavior of individuals can be monitored during simulated evacuation situations.

The Mesa platform provides advanced features for modeling independent agents, such as emotional personas and eviction experts. Thanks to this platform, the extent to which emotions and personality influence the evacuation process can be studied in depth, as well as the effectiveness of the proposed emotional-intelligent approach for a safer and more adaptive evacuation process.

The Mesa simulation platform provides an appropriate framework for evaluating and optimising the approach, enabling us to develop advanced solutions for improving the safety and efficiency of evacuations in crisis situations [25].

5.1 Data Preparation

The proposed methodology was trained and tested using the open-source FER2013 dataset, which is created for an ongoing project by Pierre-Luc Carrier and Aaron Courville from university of Montreal, then shared publicly for a Kaggle competition, shortly before ICML 2013[19]. The dataset consists of 35.887 labelled 48x48 grayscale human facial expressions. These are afraid (11.42%), angry (11.13%), disgusted (1.21%), happy (20.1%), neutral (13.84%), sad (13.46%) and surprised (8.84%). To train and test the performance of the proposed classification model, 80% of the group was selected for training and the rest for testing. Figure 4 shows some sample images from the FER2013 dataset.

Figure 4: Sample Images from the FER2013 Dataset.

5.2 CNN-LSTM Fusion

To capture the temporal dynamics of facial expressions, the capabilities of convolutional neural networks (CNNs) and long-term memory neural networks (LSTMs) have been leveraged. Our approach uses convolutional neural networks to extract salient features from facial images, while long-term memory neural networks systematically analyze these features to track the evolution of emotions as the crisis scenario unfolds. This combined framework enables our model to accurately identify critical emotions such as fear, anger and sadness, while deftly capturing emotional transitions in the evolving crisis context.

5.3 LSTM Model Training And Evaluation

The proposed LSTM-based model underwent rigorous training on a custom training dataset, using a backpropagation technique to optimize the network weights. The categorical entropy loss function was used as a measure of quantification the disparity between model predictions and actual emotional states derived from facial images.

After training, the model was subjected to evaluation using a test dataset, which yielded exceptional accuracy in emotion recognition, confirming the effectiveness of the proposed CNN-LSTM approach in emotion modeling.

5.4 Evacuation Simulation with Emotio-Intelligent

The proposed intelligent emotional model has been seamlessly integrated into a simulation platform developed using the Mesa framework [26]. This platform facilitates the creation of realistic evacuation scenarios and the real-time monitoring of individual behaviors.During simulations, emotionally aware agents equipped with our Emotio-Intelligent model demonstrated greater decision-making acuity during evacuations. By taking into account the emotional attributes and personality of each individual, our system skilfully proposed tailormade evacuation strategies, resulting in safer and more rational evacuations, characterized by reduced delays and increased overall safety.In summary, the implementation of our EmotioIntelligent approach has yielded promising results in terms of emotion .

5.5 Plate Form : MESA

Mesa is an open-source agent-based modeling (ABM) framework written in Python [27]. It provides a platform for creating simulations that involve multiple agents interacting in a complex system [28,29].

In this analysis, leveraging the Mesa platform was chosen as the basis for the proposed emotional intelligence approach. By leveraging MESA's capabilities, a dynamic simulation environment can be created where emotional agents interact and make decisions based on their emotional states. This allows studying the influence of emotions on crisis situations and evaluating the effectiveness of proposed evacuation and decision-making strategies.

In the following sections, the details of how Mesa is integrated into the implementation will be delved into and the specific features and functionality it offers to support the proposed emotional intelligence approach will be discussed.

6. Results and Discussion

Now some possible scenarios from the completed simulation will be presented and analyzed:

- Scenario 1: In case of several agents who do not know the safest path.
- Scenario 2: In case of several agents knowing the safest path.
- Scenario 3: During evacuation, a large number of agents experience a shift in their emotional state towards fear.
- Scenario 4: During the evacuation, the emotional state of a number of Agents shifts towards a feeling of joy or happiness.

1- Scenario 1: In Case of Several Agents Who Do Not Know the Safest Path

In case of high danger, the level of fear increases and distress begins to appear "Distress" while the agent begins to lose the level of self-satisfaction. The dominant character in this case is fear, so the situation will be more complicated, which prevents the agent from trying again to find the emergency exit. Figure 5 illustrates the simulation of this scenario.

Figure 5 also shows the fluctuation of the emotional state from one person to another during the evacuation process. For example, the number of terrified people ranges between 40 and 50 people, as shown in the figure. Here the role of the proposed approach is highlighted, which is to determine the emotional state of people, which will help in making the appropriate rescue decision.

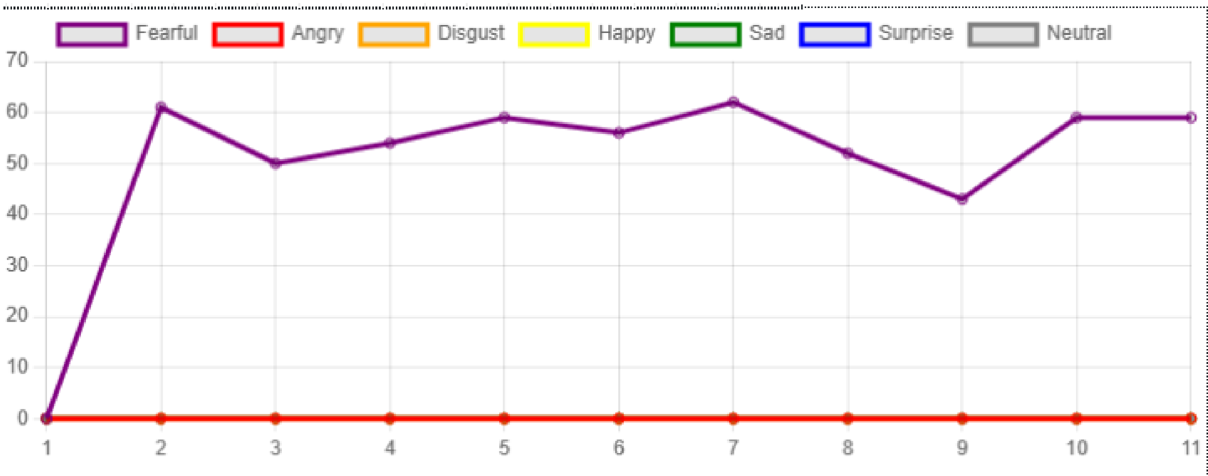

Figure 5: Scenario 1

In this scenario, several experts are relied upon to guide frightened agents.
Figure 6 explains more the result of this scenario.

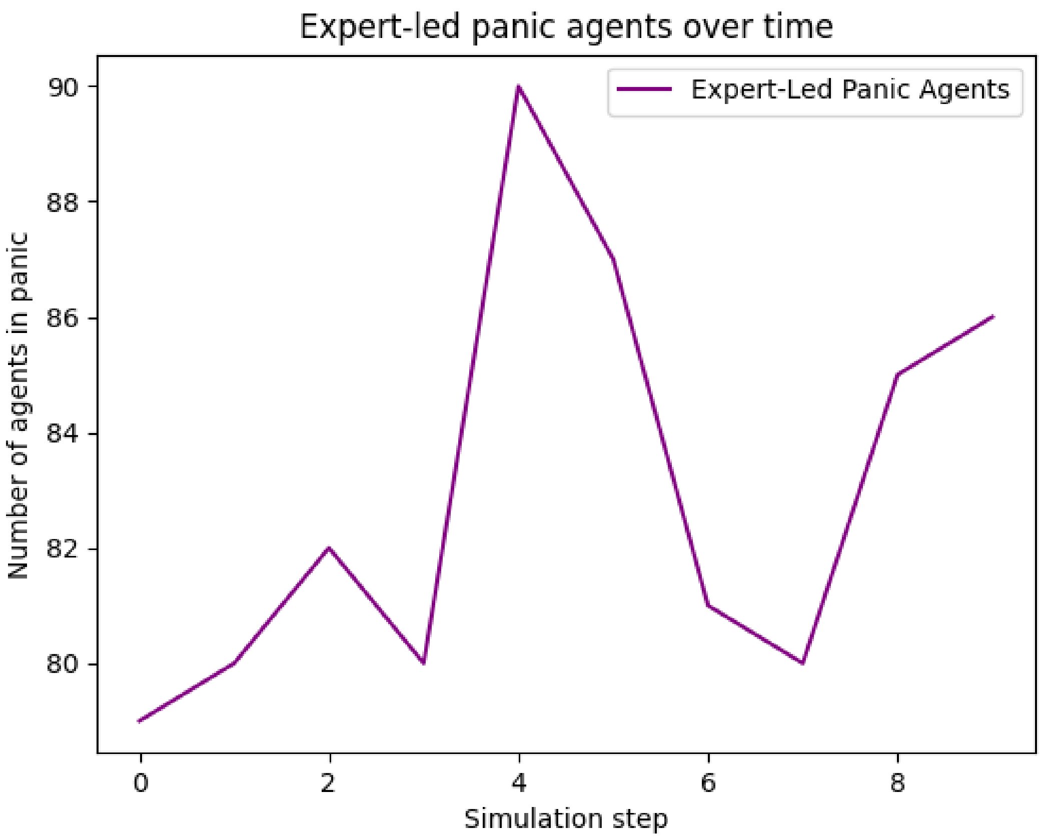

Figure 6: Expert-Led Panic Agents

Figure 6 also shows that at the beginning of the evacuation process, the number of people feeling panic increased. The number approached 90 people feeling panic, then it began to decrease as a result of the intervention of experts to guide them during the evacuation process.

2- Scenario 2: If There Are Multiple Agents Who Know The Safest Path

In this case, the dominant emotion is trust (happy customers) because the agent knows the safest route and will follow the path indicated by the proposed evacuation system Emoti-Intelligent.

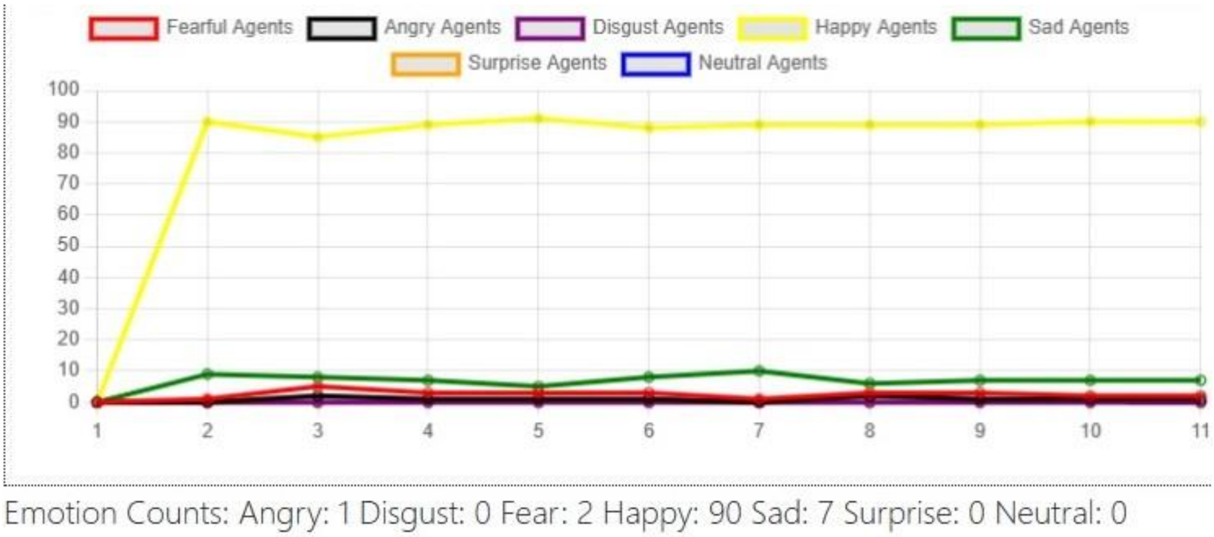

Figure 7: Scenario 2

3- Scenario 3: During the evacuation process, a large number of agents in some cases experience a shift in their emotional state towards fear: this necessitates the involvement of a greater number of experts and is one of the goals of the proposed "Emotio-Intelligent" evacuation system to maintain the safety of people. Figure 8 shows a simulation of this scenario.

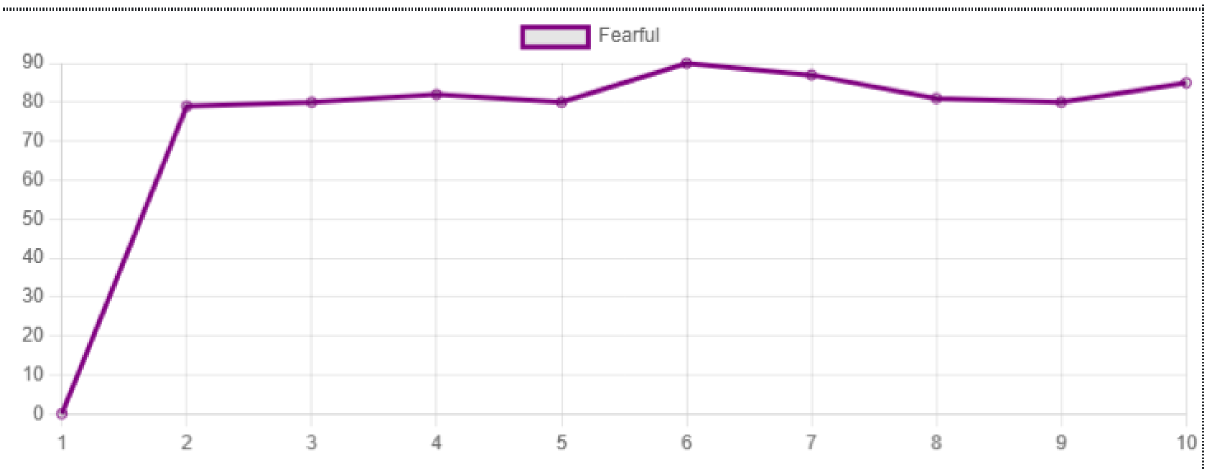

Figure 8: Scenario 3

In this particular case, a large number of experts are used to provide guidance to agents suffering from fear. In this context, the need for expert intervention steadily grows as the condition of the agents evolves.

4- Scenario 4: During the evacuation process, the emotional state of a number of agents changes towards a feeling of joy or happiness, which facilitates the evacuation process and limits the intervention of experts. Here the importance of the proposed system becomes clear, as in such a case it sends a message to every person containing the safe path. Figure 9 shows a simulation of this scenario.

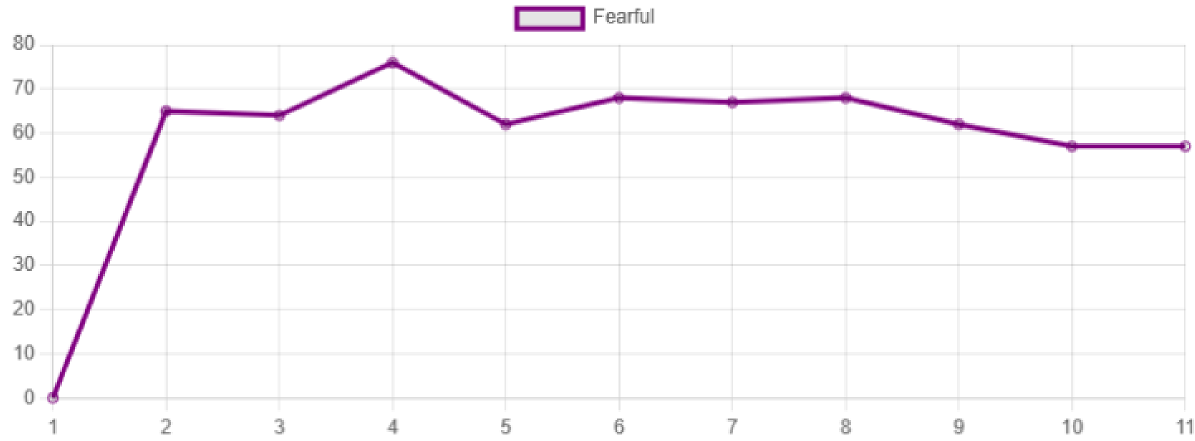

Figure 9: Scenario 4

In this situation, the need for expert intervention decreases gradually as the agent's emotional state improves, transitioning towards feelings of happiness.

7. Conclusion

In this article, a proposed emotional intelligence approach to improve crisis evacuations is presented. By combining emotion and personality modeling with LSTM neural networks, the proposed system offers a new perspective for handling evacuation scenarios in a more intelligent and empathetic way.

It has been shown that modeling emotions according to the OCC model and personality according to the OCEAN model (FFM) can allow a better understanding of the emotional reactions of individuals during a crisis situation. Using LSTM neural networks, it has been possible to capture and track individuals' emotions over time, which has proven to be essential for making informed decisions during an evacuation.

The potential impact of the proposed approach in crisis situations is significant. By providing evacuation strategies tailored to each individual's emotions and personality, risks and panic situations can be reduced, helping to prevent serious accidents and saving lives.

Therefore, the intelligent emotional approach can be adopted in designing evacuation systems. By incorporating this approach into simulations and actual evacuation scenarios, the safety of people during emergencies can be improved. This approach provides new opportunities for safer, more efficient and compassionate evacuations, helping to protect residents and save precious lives. In conclusion, this article highlights an approach that combines emotional aspects and decisionmaking in the context of crisis evacuations. Adopting an emotional intelligence approach could change the way emergency situations are managed, putting the safety of individuals at the heart of the proposed approach. This research can encourage the scientific community, practitioners, and policy makers to further explore the application of emotional intelligence in the fields of security and evacuations, thus paving the way for significant progress in crisis management.

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