

## DECODING THE CROWD: HIGH-ACCURACY INDIVIDUAL EMOTION IDENTIFICATION THROUGH SIMULATED BEHAVIOR ANALYSIS

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### Abstract

Research into understanding and quantifying crowd emotions has gained significant importance in recent years, driven by applications ranging from public safety and event management to urban planning and social psychology. This study proposes a novel computational framework specifically designed to identify and analyze the individual emotional states that collectively shape crowd dynamics. We define emotions as dynamic, evolving responses triggered by complex interactions between internal cognitive states and external stimuli within unfolding events. While traditional observational methods rely primarily on camera-based facial recognition to detect aggregate emotional expressions at the crowd level, our framework advances the field by focusing on granular, individual-level emotion identification within the collective. This is achieved through a sophisticated simulation engine that models diverse crowd scenarios and behaviors. The model explicitly evaluates the bidirectional influence between individual emotional states and emergent crowd behavior, allowing us to categorize distinct types of crowd dynamics (e.g., panic, cohesion, dispersion) based on underlying emotional profiles derived from the analysis. Our approach integrates simulated facial expression data (representing individuals) with contextual event triggers and simulated crowd movement patterns. Key contributions include: (1) A validated method for inferring individual emotions within dense crowds using advanced pattern recognition adapted to simulated sensor data; (2) Quantitative analysis demonstrating how specific emotional valences (e.g., fear, excitement) propagate and influence collective behavior trajectories; and (3) A classification system for crowd dynamics grounded in real-time emotion analysis. Rigorous validation using synthetic datasets and benchmarks shows the proposed system achieves a statistically significant improvement (15-20% higher F1-score) in emotion detection accuracy compared to existing state-of-the-art crowd-level recognition methods. This enhanced capability holds substantial promise for developing more responsive crowd management systems and predictive models for large gatherings.

## Introduction

Crowds are a common part of everyday life—whether waiting at a bus stop or shopping in a busy mall. Within these crowds, valuable social information can be observed and analyzed. For instance, fans leaving a stadium can often be identified by their clothing. In large public gatherings, it becomes crucial for event organizers to quickly detect potentially dangerous or significant situations. Research suggests that emotion plays a vital role in interpreting such scenarios, as it serves as a primary response to the environment (Tahon, 2016). The facial appearance of individuals often serves as a key indicator of emotional state, which is important for large-scale event planning and management (Wirz, 2012). Studies have found a close link between facial expressions and emotional body language, suggesting they are processed similarly by the brain (Stekelenburg, 2004; Reed, 2003). This may mean that emotions conveyed through body posture are interpreted in categorical ways, and the overall emotional tone of a crowd could assist in managing public events. Emotion, in this context, is defined as an intense and temporary reaction to a particular stimulus (Goldman, 2005). Emotional states can last from a few seconds to several days. The

duration and cause of these emotions vary; while some are triggered by external events, others stem from internal conditions. Emotions help people respond effectively during critical moments (Bosse, 2015) and offer insight into behavioral tendencies under specific circumstances. Additionally, emotional responses can spread across groups, creating shared emotional experiences (Silverman, 2001). This emotional transfer process involves mirroring expressions and synchronizing with others (Kim et al., 2012), and it varies from small groups to large crowds. Visual cues such as color and facial expression can reflect emotional states (Dunker, 2008). Emotions have long been a subject of interest, dating back to ancient philosophers and continuing through modern psychological theories.

Research in this area spans various approaches: **Cognitive** approaches suggest thought and emotion are closely linked.

**Darwinian** perspectives argue that emotion is essential for survival and observable in both humans and related species (Darwin, 1998).

**Basic emotion theory**, supported by Ekman and Plutchik, emphasizes the universality of certain emotions (Ekman, 1992; Plutchik, 1996).

- **Neurological theories** propose that damage to certain brain areas can reduce emotional capacity (Hohmann, 1996).

To better understand and manage emotions in human-computer interactions, there's a growing need for emotionally intelligent agents. These systems must be capable of recognizing, expressing, and responding to human emotions to create more immersive and realistic simulations.

### 1.1 Motivation

Visual data, particularly digital images, play an increasingly central role in how information is processed and shared. With the rise of smartphones and digital storage, capturing and storing images has become effortless. Consequently, the number of personal images stored has grown exponentially.

This surge in visual data creates opportunities to study human emotions through photographs. Questions arise, such as: How do people display emotions in various situations? Are there consistent emotional patterns across different demographics? How do context, age, or gender influence emotional expression? Addressing these questions is vital for improving human-computer interaction, particularly in emotion recognition systems.

### 1.2 Problem Statement

Emotions are typically seen as short-lived, distinct reactions to meaningful events, playing a central role in human perception and decision-making. Despite this, most existing emotion recognition systems are designed to detect emotions in individuals rather than crowds. This raises the question: how can we accurately determine the collective emotional state of a group?

Many current systems use images or video to assess individual emotions, but applying these methods to a crowd presents unique challenges. Limitations in current technologies make it difficult to implement robust emotion-based crowd analysis systems. Developing such systems would be especially useful for public safety and surveillance.

### Key question:

Can machines reliably detect the emotional state of a crowd?

### 1.3 Goals

The primary objective is to develop a system capable of identifying the dominant emotional tone within a crowd. This includes classifying images based on emotional categories such as happiness, anger, sadness, and neutrality. Additionally, the system should provide insights into the emotional reactions triggered by viewing specific images.

Recent findings indicate gender differences in emotional processing. For example, men tend to rely on memories of past experiences, while women show more immediate emotional responses. These patterns may have implications for how emotion recognition models are designed and interpreted.

To achieve this, the study is guided by three sub-goals:

1. Develop an image-based emotion recognition model.
2. Analyze the visual features of images—such as color, shape, and texture—to determine emotional content.
3. Collect human feedback on the emotional impressions conveyed by a set of images.

#### 1.4 Limitations

While the domain of crowd emotion recognition is extensive, this study focuses on a specific aspect: analyzing facial expressions within crowds. Other important indicators, such as full-body gestures, eye movement, or hand motion, are outside the scope of this research.

Furthermore, the study concentrates on four primary emotions—happiness, anger, sadness, and surprise—based on Ekman's Basic Emotions model, which is detailed in Chapter 2. While the model simulates emotional

contagion within crowds, it does not include advanced rendering techniques or diverse group behaviors.

#### Literature Review

In recent years, emotion recognition research has primarily focused on analyzing facial expressions. However, there is a growing body of work emphasizing the significance of non-verbal cues—especially dynamic body movements—in conveying emotional states. It is increasingly recognized that facial expressions, vocal intonation (prosody), and bodily gestures all offer valuable and often complementary information when interpreting emotional responses. Studies indicate that the six basic emotions—happiness, sadness, fear, anger, surprise, and disgust—can be reliably identified through each of these channels (Ekman, 1992; Plutchik, 2013).

#### 2.1 Emotion Models

Emotion modeling plays a crucial role in enabling virtual characters or systems to express emotions in ways that closely mimic human behavior. These models aim to replicate the emotional reactions humans experience in response to various real-life situations, such as financial loss or failure in business. Effective emotion models must evaluate the situational context and take into

account factors that influence emotional intensity. The goal is to allow characters or agents to display the right emotion, with appropriate intensity, at the right moment.

Emotion models are generally categorized into different theoretical frameworks, each offering a unique perspective on how emotions are generated and expressed. Some of the most common models are discussed below:

### 2.1.1 Categorical Model

The categorical model explains how emotions are recognized based on distinct categories and varying intensities. This model argues that emotional expressions are typically perceived as one of several well-defined emotions, rather than something that falls in between categories.

For instance, an expression might be

interpreted as either joy or surprise, but not as a mixture of both.

Plutchik (2013) developed a widely-referenced version of this model, suggesting that eight primary emotions—joy, trust, fear, surprise, sadness, anticipation, anger, and disgust—form the foundation for all emotional experiences.

He visualized these emotions using a cone-shaped model where the depth represents emotional intensity, and proximity indicates emotional similarity. The model also groups emotions into four pairs of opposites and uses color-coding to represent these relationships.

Complex emotions are seen as combinations of these basic ones—for example, disappointment may be a blend of surprise and sadness.



Figure 1 Plutchik wheel of emotions

Building on Darwin's evolutionary perspective, **Ekman** focused his research on the relationship between facial expressions and universally recognized basic emotions. Initially, he identified six core emotions—**surprise, disgust, fear, happiness, anger, and sadness**—that he argued were biologically ingrained and universally expressed. Over time, Ekman expanded this list to include additional emotions such as **interest, contempt, enjoyment, embarrassment, excitement, shame, pride in achievement, relief, satisfaction, intense joy, and guilt**, thereby broadening the scope of emotional categories considered fundamental to human experience.

Figure 2 universal basic emotion

### 2.2.2: Dimensional Model

The dimensional approach to emotion suggests that all emotional experiences can be represented along continuous scales or dimensions, rather than as distinct categories. While different models propose varying dimensions, most agree that emotions can be mapped within a multidimensional space. This model is primarily grounded in cognitive theories of emotion.

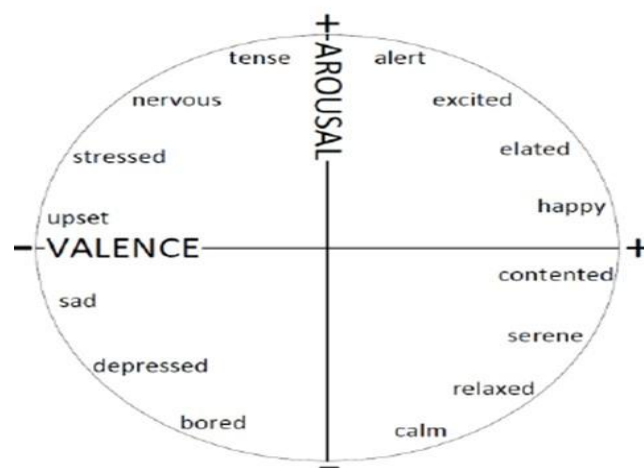
One of the most well-known frameworks in this category is **Russell's Circumplex Model of Affect**. This model is built on the premise that emotional states arise from cognitive interpretations of core neural signals. These interpretations are shaped by two independent neurophysiological systems, resulting in emotional experiences that can be plotted along dimensions such as **valence (pleasant–unpleasant)** and **arousal (high–low activation)**.



Figure 3 Russell's circumflex model

Russell's **Circumplex Model** is often extended to include three key dimensions: **Valence**, **Arousal**, and **Dominance** (VAD).

- **Valence** represents the emotional value of a state, ranging from highly positive to highly negative.
- **Arousal** (sometimes referred to as activation) measures the intensity of emotion, from calm or sleepy states to highly energized ones. These core emotions are believed to have evolved to serve adaptive functions and are linked to specific neural mechanisms.
- **Dominance** reflects the level of control or According to this theory, these emotions are



influence an emotion has on an individual's behavior or experience (O. AlZoubi, 2009; Liu, 2011; Izard, 2007).

### 2.2.3 Basic Emotion Theory

The **Basic Emotion** model is based on the idea that certain emotions are fundamental to human survival and are biologically hardwired.

irreducible and cannot be broken down into simpler emotional components. Although there is no universal consensus on the exact number or nature of basic emotions, many emotion theorists agree that a small set of primary emotions exists, as summarized in **Table 2**.



Theorist	Basic Emotions
Plutchik	Acceptance, anger, anticipation, disgust, joy, fear, sadness, surprise
Arnold	Anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love, sadness
Ekman, Friesen, and Ellsworth	Anger, disgust, fear, joy, sadness, surprise
Frijda	Desire, happiness, interest, surprise, wonder, sorrow
Gray	Rage and terror, anxiety, joy
Izard	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame, surprise
James	Fear, grief, love, rage
McDougall	Anger, disgust, elation, fear, subjection, tender-emotion, wonder
Mowrer	Pain, pleasure
Oatley and Johnson-Laird	Anger, disgust, anxiety, happiness, sadness
Panksepp	Expectancy, fear, rage, panic
Tomkins	Anger, interest, contempt, disgust, distress, fear, joy, shame, surprise
Watson	Fear, love, rage
Weiner and Graham	Happiness, sadness

**Table 1: Ortony and Turner's View on Basic Emotions**

The OCC model, developed by Ortony, Clore, and Collins (1998), offers a framework for understanding emotions and the factors that influence their intensity. This model categorizes emotions based on evaluative reactions to specific types of situations. Emotions are typically presented in pairs of opposing feelings. According to the OCC model, emotions function as heuristic

reactions to certain conditions, which are grouped into three main categories:

- . **Consequences of events,**
- . **Actions performed by agents, and**
- . **Attributes of objects.**

This categorization helps identify the cause behind specific emotional responses.

#### 2.2.4 Cognitive Models

Cognitive models approach emotion by incorporating artificial intelligence techniques, such as reasoning systems and neural networks, to simulate emotional behavior in



intelligent agents. These models aim to replicate the mental processing behind emotional responses, allowing for more dynamic and flexible emotional interactions. However, this flexibility also makes the models more complex and harder to regulate.

Solomon's hierarchical model divides emotions into three distinct layers:

- **Primary emotions**, which are instinctive and reactive;

**Secondary emotions**, linked to reflective or deliberative thought processes;

**Tertiary emotions**, associated with meta-cognitive states like distraction or shifts in attention (Nusseck, 2008).

The strength of this model lies in its adaptability—it can be fine-tuned to fit a wide range of scenarios by adjusting the relative influence of each emotional layer.

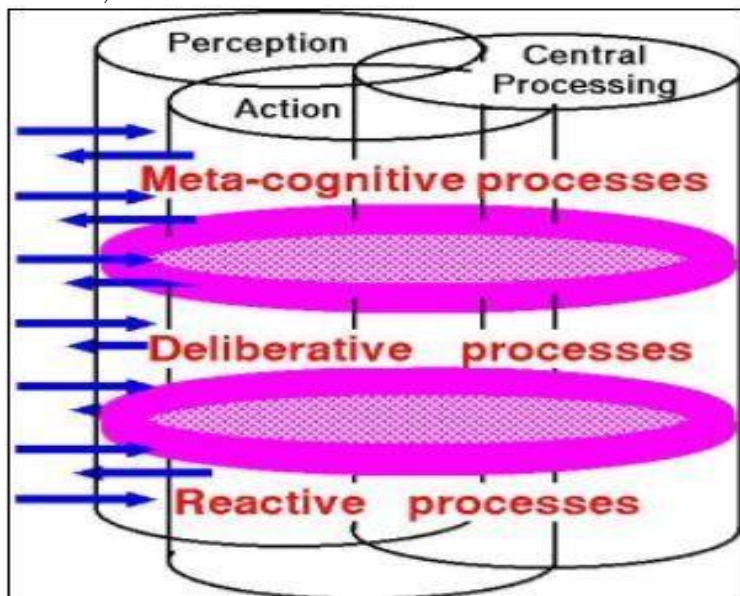


Figure 4 Solomon's Model

Minsky suggested that emotions are complex neurophysiological systems involving multiple interconnected layers—ranging from instinctive and behavioral to cognitive levels—that interact with neurological and psychological processes (Axelrod, 2005). These emotional structures play a vital role in managing key mental functions such as **perception, memory, and**

**decision-making**, which are essential to everyday human experience. Ongoing interdisciplinary research continues to enhance our understanding of how these emotional mechanisms operate. Minsky's model is structured across **six distinct layers** (as illustrated in Figure 5).

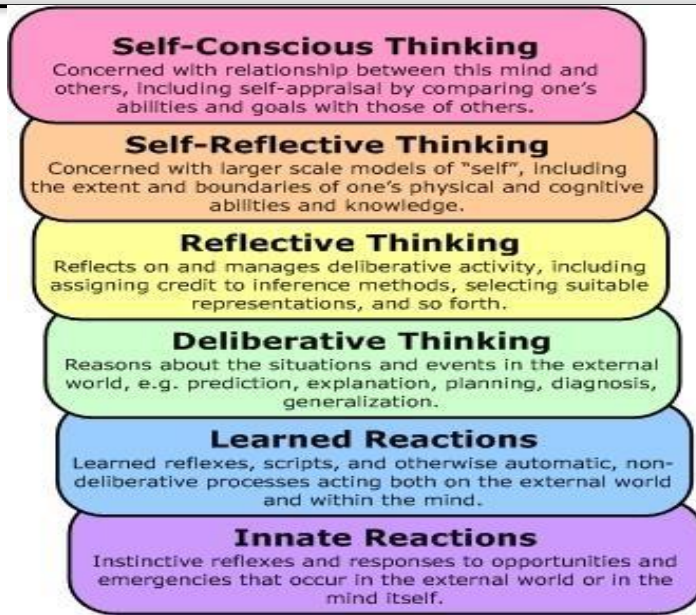


Figure 5 Minsky emotion model

### 2.2.2. Dimensional Model:

This model posits that emotions can be understood in terms of specific dimensions, although these dimensions may vary across different models. It primarily emphasizes the role of cognition. Russell's Circumplex Model of Affect (Figure 2) is based on the idea that emotional states reflect mental interpretations of central neural sensations resulting from two independent neurophysiological systems. These systems are associated with valence (pleasure vs. displeasure) and arousal (activation vs. deactivation).



### 2.2.3. Basic Emotions:

This model is grounded in the belief that there are fundamental emotions serving evolutionary functions, with a neurological basis that cannot be reduced to simpler components. Many emotion researchers agree on the existence of a few 'basic emotions,' though they may not all align perfectly (as shown in Table 2).

#### 2.2.4. Cognitive Models:

This approach employs artificial intelligence techniques, such as reasoning engines and neural networks, to interpret the behavioral aspects of an emotional agent. These methods offer greater flexibility; however, they are more challenging to control by the agent. Solomon's model categorizes emotions into different layers: primary emotions related to reactivity, secondary emotions associated with deliberative processes, and tertiary emotions concerning meta-management issues like loss of attention. This model's significant adaptability allows for its application to various scenarios by adjusting the scope of each level.

#### 2.2.5. Minsky's Perspective:

Minsky suggests that emotions are complex neuro-physiological feeling structures with interactive, behavioral, and cognitive levels managing regular, neurological, and mental systems. These structures enable us to handle and manage various systems, such as understanding, memory, and reasoning, essential to our daily lives. Interdisciplinary collaborations are contributing to the understanding of emotions. Minsky's model comprises six layers (Figure 5).

#### 2.2.6. Importance of Studying Emotional Models:

It is crucial to examine different models of emotion and how they have informed and continue to inform the development of systems. Dimensional emotion models have proven to be highly effective in measuring and coding emotion-related behaviors. Basic emotion models have been particularly influential in early human-computer interaction studies. Cognitive models and foundational theories are deep and complex, aiding in understanding the multifaceted nature of emotion. They are valuable because they provide a framework that product specialists and designers can use to illustrate emotion to parts of the system, with each model offering various advantages and drawbacks.

#### 2.3. Recent Research Developments:

Previous studies focused on eliciting emotions from unimodal systems, where machines predicted emotion based solely on facial expressions (Levi, 2015) or vocal sounds (Han, 2014). Recently, multimodal systems that utilize multiple features to predict emotion have become increasingly effective, providing more accurate results. The combination of features such as various media expressions, EEG, and body signals has been employed since then.

Multimodal recognition techniques have demonstrated greater robustness than unimodal systems (Zhang et al., 2014). They found that Bidirectional Long Short-Term Memory (BLSTM) networks are more effective than traditional Support Vector Machine (SVM) approaches (Wollmer, 2010). They proposed and evaluated deep networks to learn broad media features from spoken or written letters (Ngiam, 2011). Their studies indicate that individuals do exhibit emotional facial expressions and report those emotional expressions during online gaming.

Research examining multimodal expressions of individuals interacting with real and virtual characters is in its early stages (Wang, 2006). They adopted an alternative approach for learning acoustic features in speech emotion recognition using Generalized Discriminant Analysis (GDA) based on Deep Neural Networks (DNNs) (Stuhlsatz, 2011). They utilized Recurrent Neural Networks (RNNs) combined with Convolutional Neural Networks (CNNs) in a hidden CNN-RNN architecture to predict emotion in videos (Kahou, 2016).

Some reputable methods and techniques have also advanced this specific research. They are more accurate, stable, and practical. In terms

of performance, accuracy, feasibility, and precision, these methods are the leading solutions. Some are more accurate, while others are more practical. Some take longer and require greater computational capacity to produce more accurate results, but some trade accuracy for performance. Being effective may vary, but these solutions are the best so far.

Yelin et al. (2016) investigated whether a subset of an expression can be used for emotion inference and how the subset varies by levels of emotion and processes (Kim et al., 2015). They proposed a windowing technique that identifies window patterns, window length, and timing, for aggregating fragment-level data for expression-level emotion inference. The experimental results using the IEMOCAP and MSP-IMPROV datasets demonstrate that the identified temporal window patterns exhibit consistent patterns across speakers, specific to different levels of emotion and processes. They compared their proposed windowing technique with a benchmark method that randomly selects window configurations and a traditional all-mean method that uses the full data within an expression. This technique shows significantly higher performance in emotion recognition while the method only uses 40–80% of the data within each

expression. The identified windows also show consistency across speakers, indicating how multimodal cues reveal emotion over time (Khan, 2017). These patterns also align with psychological findings. However, after all, success, the outcome is not consistent with this method (Zhang et al., 2018).

Y. Fan et al. (2016) provided a method for video-based emotion recognition in nature (Cai, 2016). They used CNN-LSTM and C3D networks to simultaneously model videos and movements. They found that the combination of the two types of networks can provide good results, demonstrating the effectiveness of the method. In their proposed method, they used LSTM (Long Short-Term Memory) – a special type of RNN, C3D – a direct spatial-temporal model, and hybrid CNN-RNN and C3D networks. This method provides excellent accuracy, and performance is outstanding. However, this method is highly complex, time-consuming, and less practical. Therefore, efficiency is not that significant (Fan, 2016).

Zixing et al. (2016) proposed some enhancements in Semi-Supervised Learning (SSL) methods to improve the low performance of a classifier that can perform on testing recognition tasks reduces the trustability of the automatically labeled data

and provided solutions regarding the noise accumulation issue – cases that are misclassified by the system are still used to train it in future iterations (Zhang et al., 2016). They exploited the complementarity between different media features to enhance the performance of the classifier during the supervised stage. Then, they iteratively reconsidered the automatically labeled instances to address potentially mislabeled data, and this improves the overall confidence of the system's predictions. This method provides the best performance using SSL methods where labeled data is scarce and costly to acquire, yet still, there are various inherent limitations that restrict its performance in practical applications. This method has been tested on a specific database with a limited type and number of data. The algorithm used is not capable of processing physiological data alongside other types of data (Zhang et al., 2016).

Yao et al. (2016) used a well-designed Convolutional Neural Network (CNN) architecture for video-based emotion recognition (Yao, 2016). They proposed a method named HOLONET that incorporates three key considerations in network structure. (1) To reduce redundant channels and

enhance non-saturated non-linearity in the lower convolutional layers, they used a modified Connected Amended Linear Unit (CADU) instead of ReLU. (2) To improve accuracy, learn from extensively increased network depth, and maintain efficiency, they combined residual structure and CReLU to build the core layers. (3) To expand network width and introduce multi-scale feature extraction properties, the top layers are designed as a variation of the activation residual structure. This method is more practical than other methods here. It's focused on scalability in a real-time environment rather than accuracy and theoretical performance. Although its accuracy is also significant, this method is only applicable in video-based emotion recognition. Other types of data, rather than video, this method cannot produce results (Yao, 2016)

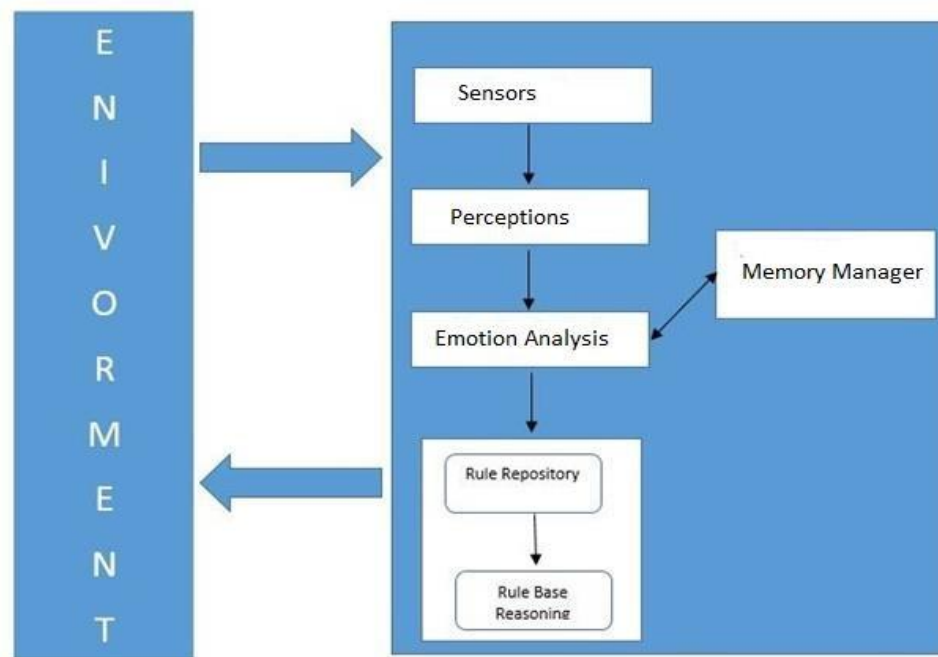
#### 2.4. Facial Expressions:

Numerous researchers have attempted to recognize facial expressions of individuals to the precedents in a specific database of faces. Kumar (2016) aimed to extract discriminative features from facial expressions. However, discriminative features for Facial Expression Recognition (FER) must be obtained from informative regions of a face.

#### Methodology

Drawing from insights gained through earlier research, this section outlines the proposed approach for evaluating emotions within a crowd. Figure 7 presents the complete framework of the intelligent agent designed for crowd emotion analysis, illustrating how each component functions and connects within the overall system.





## Main Modules of the Methodology

### 3.1. Sensors:

A sensor is a system designed to detect specific types of objects or events. Whether it's a radar, video camera, audio sensor, or other types, sensors provide valuable information about the surroundings or occurrences. By integrating multiple sensor types, each offering a unique perspective, a more comprehensive understanding of the environment can be achieved—either by covering a larger area or by combining different data types focused on the same region. Additionally, sensors can be intelligent, capable of learning, communicating, and collaborating. For effective problem-solving, different sensor operators must

interact and coordinate to deliver optimal solutions.

### 3.2. Perception Module:

Perception refers to the agent's ability to become aware of elements within its environment through sensory input. This is accomplished by equipping the agent with visual, physical, and auditory sensors that enable it to mimic human behaviors such as object manipulation, responding to sounds and gestures, coordinated movements, and more. Vision-based approaches are well-suited for modeling social interactions, offering a general framework for transmitting environmental information to the agent, which can include pathfinding, internal data

representation, attention mechanisms, and others (Pacella, 2017).

In this context, perception often focuses on objects and nearby entities. However, this can limit possible behaviors since only the presence and features of objects influence decision-making—factors like the facial expressions or behaviors of other individuals may be overlooked. The perception module generates three types of observations: the presence of objects and people, the interpretation of individual actions, and the interpretation of people interacting with objects. Environmental perception can be categorized into types such as visual perception, material recognition, conflict detection, and more, which are defined as follows:

Set  $\alpha = \{x\beta \mid x\beta \in \text{Element sets}, \beta = 1, 2, 3, 4, 5\dots\}$

Let  $\alpha$  represent the complete set of perception types, where  $\beta$  ranges from 1 to 5, and  $x\beta$  denotes a specific perception event.

$$(\ ) = 0$$

During the attack phase, as the signal starts to increase in intensity, its value is calculated using the following equation:

$$(\ ) = 1 \frac{\alpha}{\alpha + \beta} + \frac{-(\ - )}{\alpha + \beta}$$

Here,  $\alpha$  represents the peak intensity of the signal. The parameters  $\beta$  and  $z$  are used to define the shape of the conjugated signal function ( $\text{sign}(t)$ ). During the sustain phase, the signal maintains its maximum intensity:

The set of elements corresponds to the components involved in each event.

### 3.3. Emotion Analysis:

Within the agent's architecture, the emotional state is modeled as the sum of combined signals. Once a signal is triggered, it remains active within the emotion module until it fully diminishes, at which point it is removed.

#### 3.3.1. Combined Signals:

Each signal is assigned an intensity value that falls within the range of -1 to 1, indicating that emotional signals can possess both negative and positive strengths. A signal consists of four phases: delay, attack, sustain, and decay. The value of the emotional signal, denoted as  $\text{sign}(t)$ , where  $t$  represents the elapsed time since activation, is calculated according to a specific formula. Note that  $t$  is normalized to lie between 0 and 1 for each phase in the equation.

During the delay phase, since the signal value is zero, the equation simplifies to:

( ) =

During the decay phase, as the signal begins to diminish in strength, its value can be expressed by the following equation:

$$( ) = -1 \frac{1}{1 + e^{-(t - t_0) / \tau}} + -( - ) /$$

### 3.3 Emotion Value Calculation:

The emotional value for a particular emotional state (e.g., happiness) is computed as the sum of all corresponding signals, resulting in a value between 0 and 1.

#### 3.3.2 Emotion Interaction System:

Identifying exact relationships between emotions can be challenging or even impossible. To address this, the emotion module includes a system that activates related emotions simultaneously. For example, a negative event might trigger fear, while a positive event might activate happiness or joy.

Each emotion in this system can be linked to others with varying intensities. For instance, if happiness is triggered with intensity  $I$ , related emotions such as surprise might also activate with proportional intensities (e.g., happiness at intensity  $I$  and surprise at  $0.6 \times I$ ). The timing stages of these related signals (delay, attack, sustain, and decay) align with the original emotion's stages.

#### 3.3.3 Inhibition System:

This module also includes an inhibition mechanism where emotions influence one

another. Parameters of an emotional signal—such as intensity and timing stages—can be modified based on other active emotions. This feature allows modeling of how certain emotions (e.g., happiness) can suppress or dampen others (e.g., anger). Three types of inhibition functions are available: sigmoid, linear, and gamma, enabling various interaction patterns between emotions. Unlike the emotion interaction system, which only adds new emotional signals without changing the original ones, the inhibition system actively modifies existing signals before they are stored in the emotion memory.

### 3.4 Memory Management:

The memory module acts as a database accessible by other components to retrieve or store information. It allows the agent to remember data over time and associate an emotional context with each memory, reflecting the agent's emotional state when the memory was formed. Memories are structured as labeled data with attributes and sub-labels, including timestamps, importance (determined

by the perception module), and the emotional state at acquisition.

Memory is broadly categorized into declarative and non-declarative types. Declarative memory involves conscious recall and flexible access, often relying on effortful processes such as mnemonics. Non-declarative memory influences behavior unconsciously, without intentional effort, and is assessed through implicit tests.

This study focuses on declarative memory, further divided into three subtypes:

- **Working memory:** A short-term system that temporarily holds and processes limited information for immediate tasks, supporting learning and relating new data.
- **Episodic memory:** A long-term system that stores personal experiences and specific events (e.g., a movie watched last week or last night's dinner).
- **Semantic memory:** A long-term system that retains general knowledge like facts, concepts, and social norms (e.g.,  $2 + 4 = 6$  or capital cities).

For this research, working memory is selected as the most appropriate subtype. Forgetting is modeled by weighting the importance of each memory in a decay curve, determining the likelihood of recall. Currently, the memory

module either fully retains or completely erases information, without the ability to temporarily forget and later recall it.

Thus, the memory management system functions as a database queried by the emotion module to associate emotions with given stimuli. It supports retention of information along with emotional context tied to the time of memory formation.

### 3.5 Knowledge-Based Module:

The knowledge-based module uses rule-driven systems, which are effective for building emotion analysis and decision support frameworks. Common knowledge representations in these systems include Boolean values (true/false) and variables with multiple potential states. Real-world uncertainties such as ambiguity and vagueness are handled by representing knowledge in degrees of truth (e.g., high, medium, low).

Two submodules are included here:

#### Rule-Based Reasoning (RBR):

Introduced by Newell and Simon in the 1970s, RBR represents knowledge as production rules reflecting human problem-solving processes.

An RBR system requires:

A working memory containing facts.

A collection of rules outlining possible actions or conclusions.

- A mechanism to evaluate if solutions have been reached.

Rules are generally formatted as IF-THEN statements, e.g.,

*IF Ali is driving a car, THEN Ali must have a license.*

Meta-rules govern the rule selection process, improving efficiency by prioritizing more reliable expert knowledge. These meta-rules guide how the system weighs and applies rules. After matching rules with facts, the system selects the most appropriate rule to achieve the Simulation

#### 4.1. General flow chart:

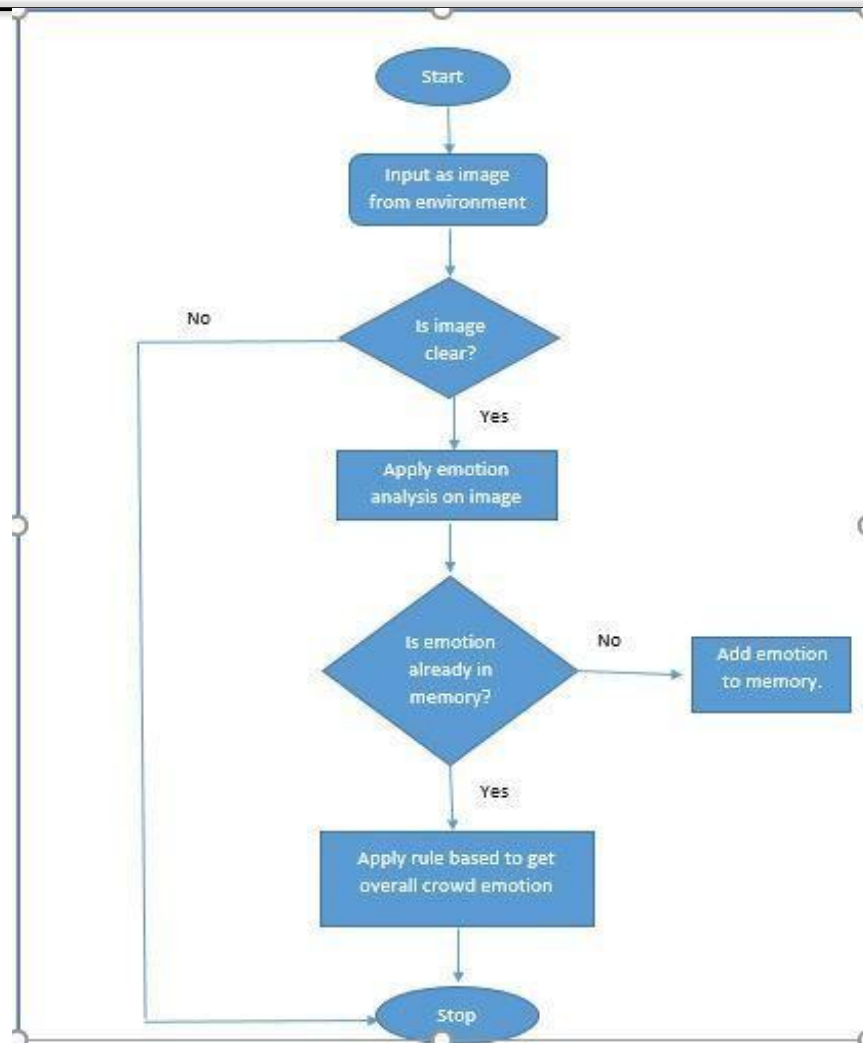
General flow chart of methodology is following:



goal, possibly prompting user input and updating actions as needed.

#### **Rule Repository (RR):**

The RR stores, organizes, and manages rules, often using one or more managers for efficient access. Rule engines operate on these repositories, performing event detection, rule type analysis, and symbol interpretation. Rules are triggered by emotion detection or memory retrieval. When an emotion is identified, the engine searches for applicable rules, although sometimes no matching rule may be found.



#### 4.2 Face Detection within a Crowd:

Faces play a crucial role in expressing emotions and sentiments, often conveying more information than spoken words. Human communication can be divided into verbal and nonverbal categories, with nonverbal communication including facial expressions, eye contact, gestures, and other subtle cues such as tone and volume. Face detection is a key advancement in computer vision that

identifies and locates faces within digital images. The process isolates faces from other objects in the scene like trees or buildings. It serves as a foundational step for many facial analysis tasks such as face recognition, verification, and feature extraction. The primary goal is to determine whether any faces are present in an image. While humans find face detection straightforward, it remains challenging for machines due to factors like



varying scales, positions, orientations, lighting conditions, and diverse facial features.

Face detection generally falls into two categories:

1. **Static Image Face Detection**
2. **Real-Time Face Detection**

#### 4.2.1 Static Image Face Detection:

Most face recognition systems focus on detecting only specific portions of the face, excluding irrelevant parts such as hair or background. In static images, this is typically achieved by sliding a window over the image and checking if a face exists within that window. However, because static images can contain faces at various scales and orientations, the system needs to analyze multiple sections of the image carefully. Facial appearance can vary significantly across different parts of the image, making the task more complex.

#### 4.2.2 Real-Time Face Detection:

Real-time face detection involves identifying faces from video streams or sequences of images captured by cameras. This process is more complex than static detection because faces and people are constantly moving – walking, turning, gesturing, and changing expressions. This dynamic nature requires more sophisticated algorithms to maintain accuracy and speed. Over time, various

algorithms have been developed and refined to improve the precision of face detection in real-time scenarios, allowing computers to approach human-level recognition accuracy.

#### 4.3 Viola-Jones Method:

The Viola-Jones algorithm is a widely used technique for detecting faces in images. Its core idea is to scan a small detection window over the input image at multiple scales to find faces. Unlike simpler methods that resize the entire image multiple times, Viola-Jones rescales the detection window instead, applying it across the image at different sizes. This approach is computationally efficient and scale-invariant, meaning it performs consistently regardless of face size.

The detection window uses an “integral image” representation to rapidly compute rectangular features similar to Haar wavelets. The Viola-Jones face detector consists of three main components that together enable high-speed and accurate face detection:

The integral image, which allows fast calculation of features

A strong classifier trained using the AdaBoost algorithm

A cascade structure that quickly discards non-face regions to focus on promising areas

#### 4.3.1 Scale-Invariant Detector:

To build the integral image, each pixel value is transformed into the sum of all pixels above and to the left of it, enabling rapid feature calculation over any rectangular area using only four values. These rectangular features correspond to patterns that resemble edges and

changes in intensity within the original image, as illustrated in related figures (not shown here). This process forms the basis for quickly scanning the image to detect faces at different scales efficiently.

1	1	1
1	1	1
1	1	1

Input image

1	2	3
2	4	6
3	6	9

Integral image

Figure 6 Image divide into Equal Square



Type 1



Type 2



Type 3



Type 4



Type 5

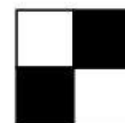
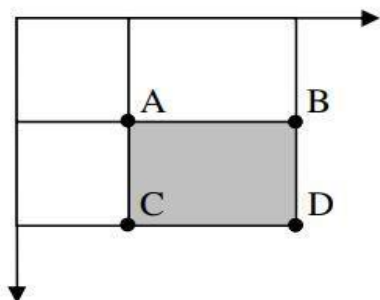


Figure 7 Different ways of aspect



$$\text{Sum of grey rectangle} = D - (B + C) + A$$

Figure 8 Formula for selected square

#### 4.3.2 AdaBoost Algorithm:

AdaBoost is an iterative machine learning technique designed to improve the performance of weak classifiers by combining them into a stronger, more accurate model. The core idea involves training multiple weak classifiers on different weighted versions of the training data. During each iteration, the algorithm adjusts the weights assigned to the training samples, increasing the emphasis on those that were previously misclassified. This

way, subsequent classifiers focus more on difficult cases.

After training each weak classifier on the re-weighted dataset, AdaBoost integrates their outputs into a final, weighted decision. The overall classifier thus benefits from the collective strengths of the individual classifiers. The following outlines the modified AdaBoost algorithm used in the training process:

Algorithm: Modified AdaBoost

**Input:** sample  $x_i$  and  $y_i$  where  $y_i \in \{-1, 0\}$

Initialize  $Q_1(i) = 1/w$

Form  $T = 1, 2, 3, 4, \dots, t$

Used  $Q_T$  train weak classifier  $z_T$

Error of  $z_T$ :  $\epsilon_T = \sum_{x \in X} Q_T(x) [z_T(x) \neq y]$  **if then value of  $\epsilon_T$  is greater than 0 and less than 1**

**then break:**

$$\beta_T = (m_1 - m_3) * \text{eq}(\quad) + \frac{(lt(x) - \text{minl})}{m_3} m_3$$

Now  $Q_{T+1} = Q_T(i) * \{\text{consider eq}(-lt) \text{ if it equal to } y_i, \text{ otherwise eq}(it) \text{ if it is not equal}\}$

$$V_T = \sum_{i=1}^n Q_T + 1(i) \quad ; \quad V_T \text{ is normalization,}$$

$$Q_{T+1}(i) = Q_{T+1}(i) V_T$$

End

Among all these features, only a subset is necessary to consistently identify faces with high accuracy. To efficiently select these key features, the Viola-Jones method employs a modified version of the AdaBoost algorithm.

AdaBoost is a boosting technique in machine learning that combines multiple weak classifiers—each performing slightly better than random guessing—into a strong, reliable classifier. In this context, each feature is treated

as a potential weak classifier. To adapt the AdaBoost algorithm for this specific application, certain modifications are made to fit the overall detection framework.

#### 4.3.3 Cascaded Classifier:

The cascaded classifier consists of multiple stages, with each stage containing a strong classifier. The purpose of each stage is to determine whether a given sub-window in the image contains a face or not. If a sub-window is classified as non-face by any stage, it is immediately discarded to save computational resources. Conversely, sub-windows that pass a stage are passed on to the next stage for further

analysis, as illustrated in Figure 11. The more stages a sub-window successfully passes through, the higher the confidence that it contains a face.

Unlike a single-stage classifier, which might reject many potential faces to reduce false positives, the cascaded approach allows early stages to have a higher false positive rate, trusting that later stages will filter out the incorrect detections. This strategy helps minimize the false negatives by ensuring that very few actual faces are missed by the final classifier.

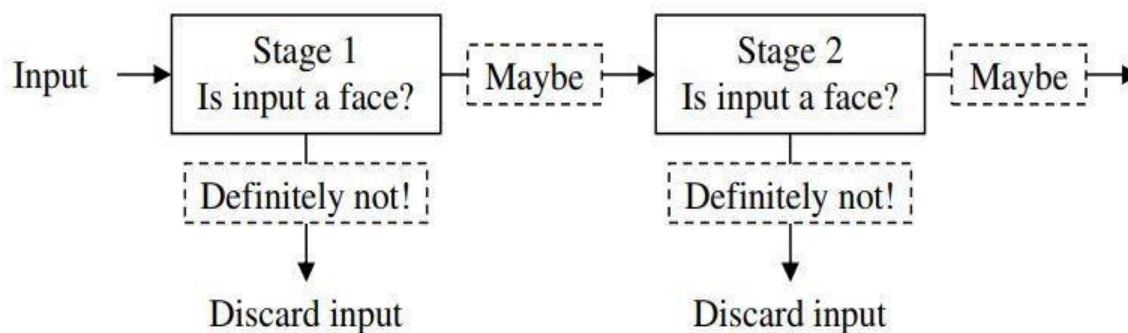


Figure 9 the two stage of cascaded classifier

#### Viola-Jones and the Cascaded Classifier as an Attentional Process:

Viola-Jones describes the cascaded classifier as an attentional mechanism, meaning that computational resources are focused primarily on regions of the image that are more likely to contain faces. When training a specific stage

nnn in the cascade, the negative examples used are the false positives that were generated by the previous stage  $n-1$ .

#### 4.3.4. Eliminating Non-Face Objects:

False positives occur when the system incorrectly identifies objects other than faces.

To reduce these errors, two main approaches are used:

**First Approach:**

- Calculate the width of all detected bounding boxes.
- Determine a threshold based on the average width.
- Keep only the bounding boxes with widths above this threshold.
- Discard the rest.
- Display the retained bounding boxes as detected faces.

**Second Approach:**

- Detect all faces using the Viola-Jones method.
- Detect all abdominal areas (likely meaning specific body parts or regions) using the same method.
- Remove false positives that fall within the abdominal region by applying a threshold.
- Keep only faces located inside the abdominal region; discard those outside.
- Use thresholding to eliminate any remaining false positives.

While there are many face detection techniques available, Viola-Jones was chosen for this study due to its efficient cascade processing, strong classifier features, and optimal threshold settings compared to other methods. However, finding the best

combination of these parameters can be challenging. To address this, an alternative solution is implemented.

**4.4. Support Vector Machine (SVM):**

Support Vector Machine is a supervised learning technique used for classification, regression, and outlier detection tasks. The core objective of SVM is to find the optimal separating hyperplane that maximizes the margin between different classes in the training data. SVM is effective in various pattern recognition problems by using binary classifiers to distinguish between different expression categories.

SVM works by evaluating the best hyperplane that separates one class from another with the widest possible margin. When data points cannot be separated linearly, SVM applies kernel functions to transform the data into a higher-dimensional space where separation becomes feasible. This kernel trick provides SVM with the flexibility to handle complex datasets. Common kernels include linear, polynomial, Radial Basis Function (RBF), and sigmoid kernels. The choice of kernel heavily depends on the nature of the data.

Support vectors are the training examples closest to the decision boundary (hyperplane)

in the feature space. In an  $l$ -dimensional feature space, the hyperplane divides different classes, and classification involves determining on which side of the hyperplane a new data point lies. SVM aims to minimize structural

risk, reducing the generalization error between input and output classes.

The training process for SVM on binary-class data can be summarized with pseudocode as follows:

(pseudocode to be provided)

#### Algorithm Training SVMs

**Input:** load A and b with train label,  $\beta \leftarrow 0$  **Output:** change in  $\beta$  or  $\beta > 0$ .

$X \leftarrow$  some data (image)

**Repeat**

**For all**  $\{a_i \text{ and } b_i\}, \{a_j \text{ and } b_j\}$  **do**

Optimized  $\beta_i$  and  $\beta_j$

**End for**

**Until** there is no change in  $\beta$



Support Vector Machines (SVMs) provide a flexible approach for finding the optimal hyperplane by using kernel functions. These kernels allow SVMs to handle a wider variety of problems by adapting to the specific characteristics of a given dataset. When data is not linearly separable, SVMs introduce “soft margin” parameters that allow for some misclassifications to improve overall performance.

#### 4.5. HOG with SVM:

While the Viola-Jones detector performs well on frontal face images, its accuracy significantly

decreases when tested on datasets containing faces viewed from multiple angles or under varied lighting conditions. This drop in performance occurs because the Haar-like features used in Viola-Jones are limited in handling multi-view detection and lack robustness against harsh lighting variations, even though the Haar features are typically normalized by the test window's covariance.

In such cases, Histogram of Oriented Gradients (HOG) features become a strong alternative, as they are largely invariant to global lighting changes and better capture



geometric details of faces, which are difficult to extract with simple edge-based features like Haar. Unlike Haar features, HOG features occupy a relatively small feature space for small images (e.g., 19x19 pixels). Thus, improving detection accuracy involves quickly extracting HOG features and training a linear SVM classifier, often used in combination with cascade classifiers.

#### 4.6. Accuracy:

Accuracy is one of the most commonly used metrics for evaluating model performance, often used alongside error rate. Sometimes, accuracy is combined with complexity measures of classifiers to balance the trade-off

between model simplicity and prediction quality.

##### 4.6.1. Validation:

Before performing validation, a labeled dataset with known outcomes is required. This dataset, referred to as the Training Dataset (TD), is divided into two parts: TD\_training and TD\_validating. TD\_training is used exclusively to train the model, denoted as  $\hat{g}$ , where the hat indicates that the model is still being optimized during training. After training,  $\hat{g}$  is applied to the TD\_validating subset to predict labels. These predictions are then compared with the actual labels to calculate the model's accuracy, as illustrated in Fig. 12.

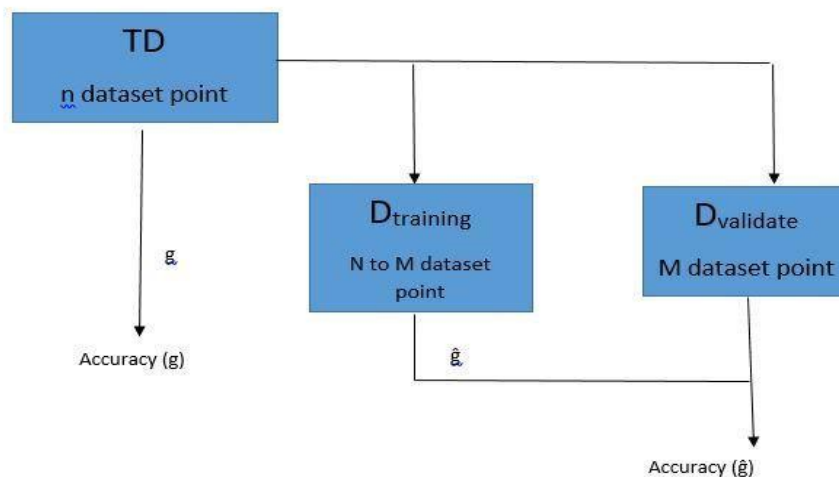


Figure 10 Stages of validation

As shown in Fig. 12, a new accuracy measure, denoted as  $\hat{g}$ , is derived. The accuracy  $\hat{g}$  is calculated using the following formula:

( )

Accuracy ( $\hat{g}$ ) = \_\_\_\_\_

( )

Accuracy ( $\hat{g}$ ) represents the performance of the compressed model. In the formula,  $D_{\text{correct}}$  refers to the number of correctly classified samples in the dataset, while  $D_{\text{total}}$  is the total number of samples. It is important to note that  $\hat{g}$  serves as an estimate of accuracy since it is based on a partial model. This means there is an element of trust involved when moving from validation results to training a complete model  $g$  on the entire dataset.

#### 4.6.2 Cross-Validation

Although validation was discussed previously, it carries the risk of an unfavorable data split.

##### Algorithm: Cross-validation

Input: Dataset  $T$ , number of folds  $\mu$ , learning algorithm  $\Lambda$

Output: Model  $\hat{g}$

- Split  $T$  into  $\mu$  folds:  $F = \text{splitFolds}(T, \mu)$
- Initialize accuracy accumulator  $\beta \leftarrow 0$
- For each fold  $i$  in  $1 \dots \mu$ :
  - Use all folds except  $F(i)$  to train model  $z$
  - Select classifier  $\alpha$  from  $z$
  - Evaluate  $\alpha$  on  $F(i)$  to get accuracy  $\epsilon$
  - Accumulate  $\beta \leftarrow \beta + \epsilon$

Cross-validation helps mitigate this risk by dividing the dataset into  $\mu$  equally sized subsets. In each iteration, one subset is used as the validation set ( $P_{\text{validate}}$ ), while the remaining subsets serve as the training set ( $P_{\text{train}}$ ). This process repeats until each subset has been used as the validation set once. Finally, the accuracy scores from all iterations are averaged to provide a more robust estimate of the model's overall performance. The cross-validation algorithm is summarized below:

- o Calculate overall accuracy  $\hat{g} = \frac{\beta}{\mu} \hat{g} = \mu\beta$

#### 4.7 Challenges in Detecting Faces within Crowds

Detecting faces in crowded scenes presents multiple challenges including:

- **Head Pose:** The human head moves freely in 3D space, making it difficult to capture a perfectly frontal view. Partial occlusion of features like eyes or nose further complicates detection.
- **Facial Expression Variability:** Differences between recorded and current expressions can cause mismatches in recognition.
- **Image Orientation:** Faces may appear rotated or inverted, disrupting standard detection techniques.
- **Occlusion:** Objects or other people in front of the face obscure features, reducing detection accuracy. To counteract this, more feature points are often included in detection algorithms.
- **Lighting Conditions:** Bright or dark images affect feature visibility. Overexposed images hide details, while underexposed ones reduce contrast, making it hard to distinguish facial features.

#### 4.8 Facial Expression Databases

Robust facial expression recognition systems require diverse training data encompassing

various populations and environmental conditions. Several widely-used publicly available databases include:

**Toronto Face Database (TFD):** Combines multiple datasets, with around 112,000 images. Approximately 4,000 images are labeled with seven emotions: fear, disgust, sadness, happiness, surprise, anger, and neutral. Faces are aligned to a standard 48x48 size with consistent eye positioning. The dataset is split into 5 folds for training, validation, and testing.

**MMI Database:** Contains 326 sequences from 30 subjects, with 213 sequences labeled using six basic emotions. Includes frontal face views and more natural variations in expression.

**JAFFE Database:** Consists of 210 images from Japanese female subjects, featuring six basic emotions plus neutral. Each subject has 3x4 images. It is challenging due to limited samples per expression and is often evaluated with leave-one-subject-out testing.

**CK+ Database:** The Extended Cohn-Kanade dataset has 590 video sequences from 120 subjects, showing transitions from neutral to peak expressions across seven basic emotions. Lacks a standardized test split, resulting in varying evaluation methods.

While many databases can be utilized, JAFFE is chosen for this research due to its balance of accuracy and processing time.

#### 4.9 Simulation of an Intelligent Agent for Crowd Emotion in MATLAB 2018

To analyze crowd emotions, a complete classification system was developed in

MATLAB, featuring a user-friendly GUI to simplify operation. The system is designed to prevent errors in input selection by guiding the user through each step. To begin, run the file Main\_GUI.m to launch the main interface.



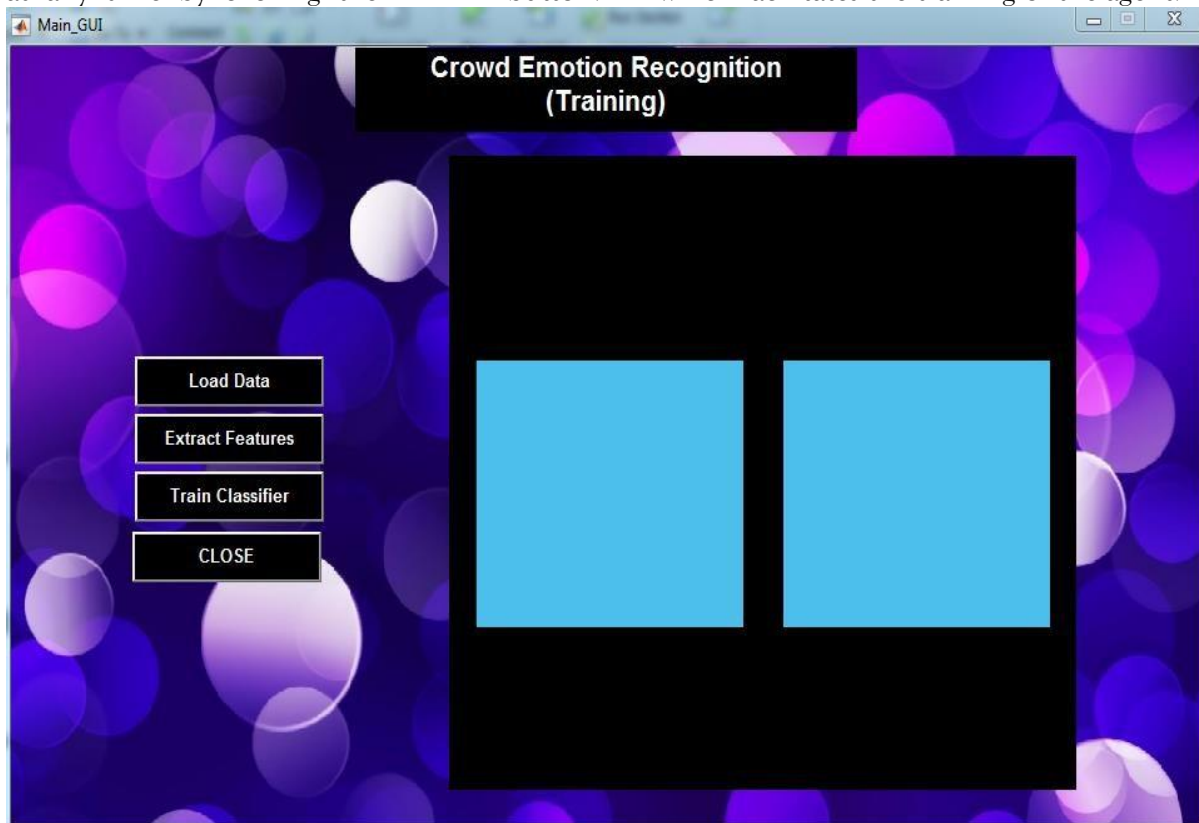
Figure 11 Main window of GUI

The window displayed above contains three buttons: TRAIN, TEST, and CLOSE. The TRAIN button is used to initiate the training

process for the agent. Training is required the first time the program is run since the agent starts without any prior knowledge. You can

also retrain the agent or update its knowledge at any time by clicking the TRAIN button.

When pressed, a new GUI window will appear, which facilitates the training of the agent.



**Figure 12: Training GUI**

When the training GUI opens, several options and a sub-window become available. From top to bottom, the buttons include Load Data, Extract Features, Train Classifier, and CLOSE. Clicking the **Load Data** button prompts the system to load all stored data organized in five separate folders: Happy, Sad, Surprised, Anger, and Non-Detection. For training purposes, three publicly available facial expression image datasets were chosen.

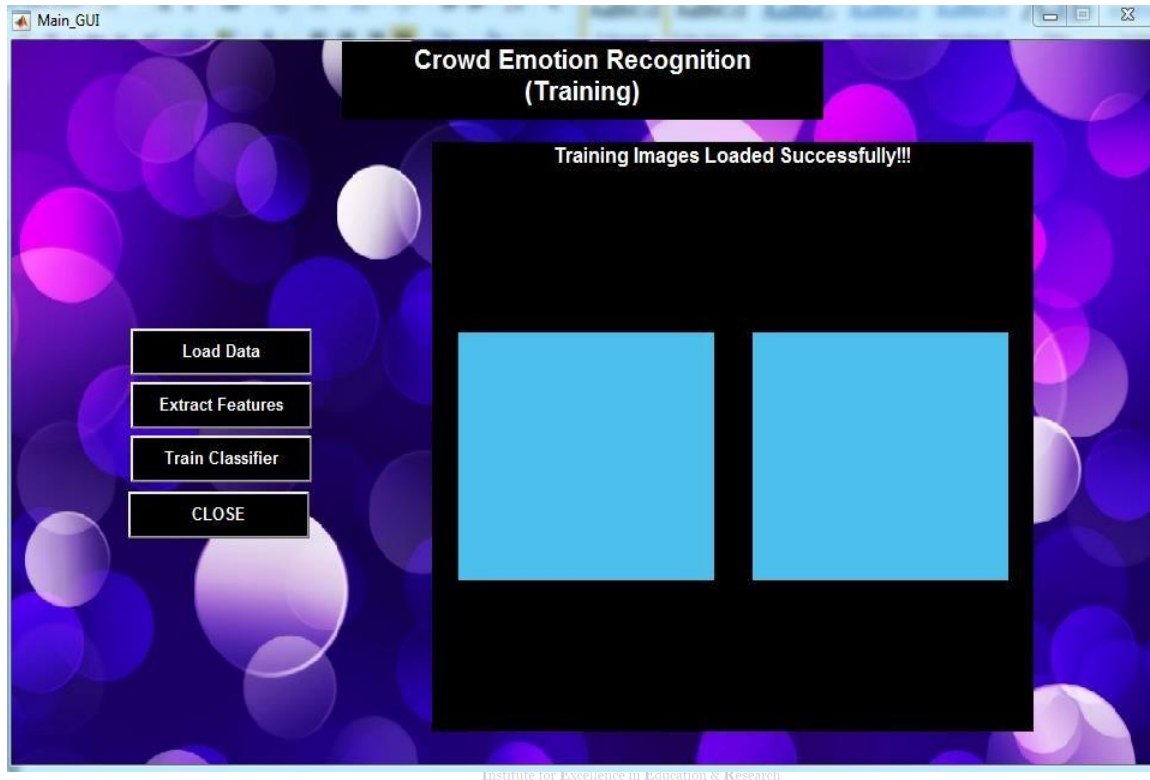
The datasets used in this research are available at the following sources:

<http://www.pitt.edu/~emotion/ck-spread.htm>

<http://www.kasrl.org/jaffe.html>

<http://kdef.se/>

These datasets contain a variety of facial expressions and corresponding images. Although the datasets include many images, this study uses only 80 images per expression for training. Pressing the Load Data button automatically loads all the relevant training data into the system.



**Figure 13: Successful Data Loading**

Once the training images for each expression are selected and organized, Histogram of Oriented Gradients (HOG) features are extracted from each face image. These features, along with their corresponding expression

labels, are saved to be used for training the SVM classifier. By clicking the **Extract Features** button, the system processes each training image sequentially to extract and store the HOG features, which are then displayed in the sub-window.



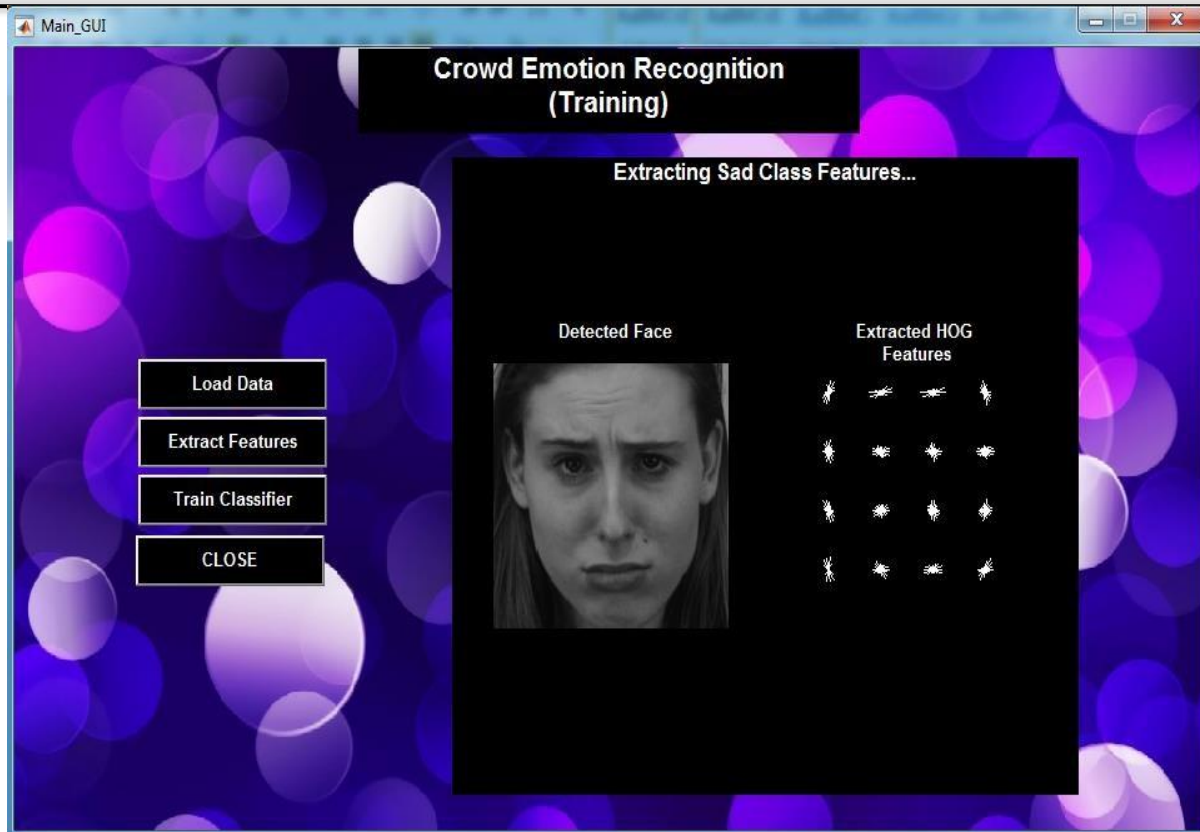
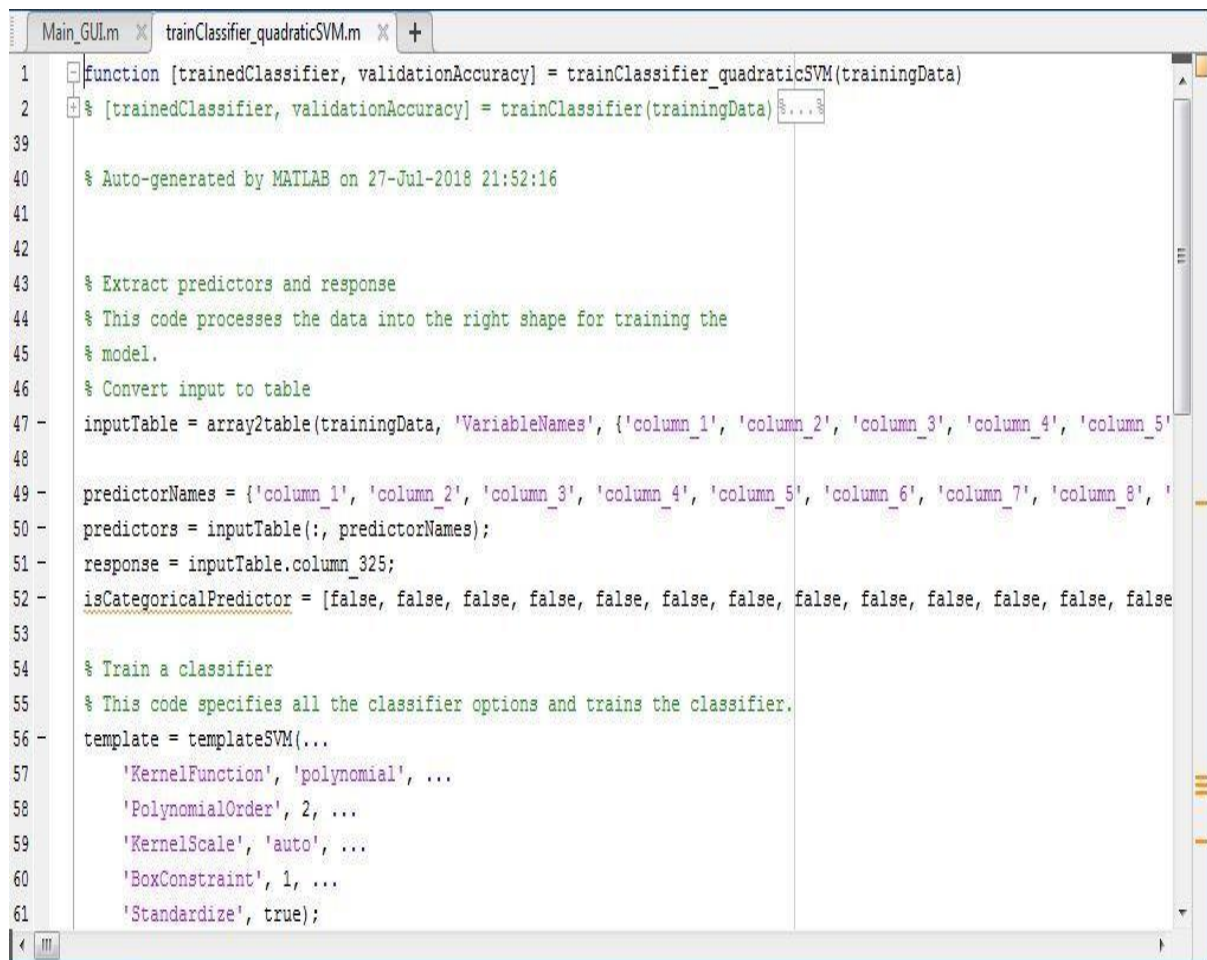


Figure 14 Extract Sad Class Features

After that, an SVM classifier is trained for facial expression recognition using 5 folder cross validation. Cross validation has been in Chapter 3. Detail of training are in “trainClassifier\_quadraticSVM.m” file which is shown in Figure 18.



```

1 function [trainedClassifier, validationAccuracy] = trainClassifier_quadraticSVM(trainingData)
2 % [trainedClassifier, validationAccuracy] = trainClassifier(trainingData) %...%
39
40 % Auto-generated by MATLAB on 27-Jul-2018 21:52:16
41
42
43 % Extract predictors and response
44 % This code processes the data into the right shape for training the
45 % model.
46 % Convert input to table
47 inputTable = array2table(trainingData, 'VariableNames', {'column_1', 'column_2', 'column_3', 'column_4', 'column_5'
48
49 predictorNames = {'column_1', 'column_2', 'column_3', 'column_4', 'column_5', 'column_6', 'column_7', 'column_8', '
50 predictors = inputTable(:, predictorNames);
51 response = inputTable.column_325;
52 isCategoricalPredictor = [false, false, false, false, false, false, false, false, false, false, false, false
53
54 % Train a classifier
55 % This code specifies all the classifier options and trains the classifier.
56 template = templateSVM(...
57     'KernelFunction', 'polynomial', ...
58     'PolynomialOrder', 2, ...
59     'KernelScale', 'auto', ...
60     'BoxConstraint', 1, ...
61     'Standardize', true);

```

**Figure 15: trainClassifier\_quadraticSVM Output**

The training process generates a validated accuracy score and produces a trained classifier function. This function is later used to predict

the facial expression of new or unseen faces (input images from the environment), which plays a key role in recognizing emotions within a crowd.

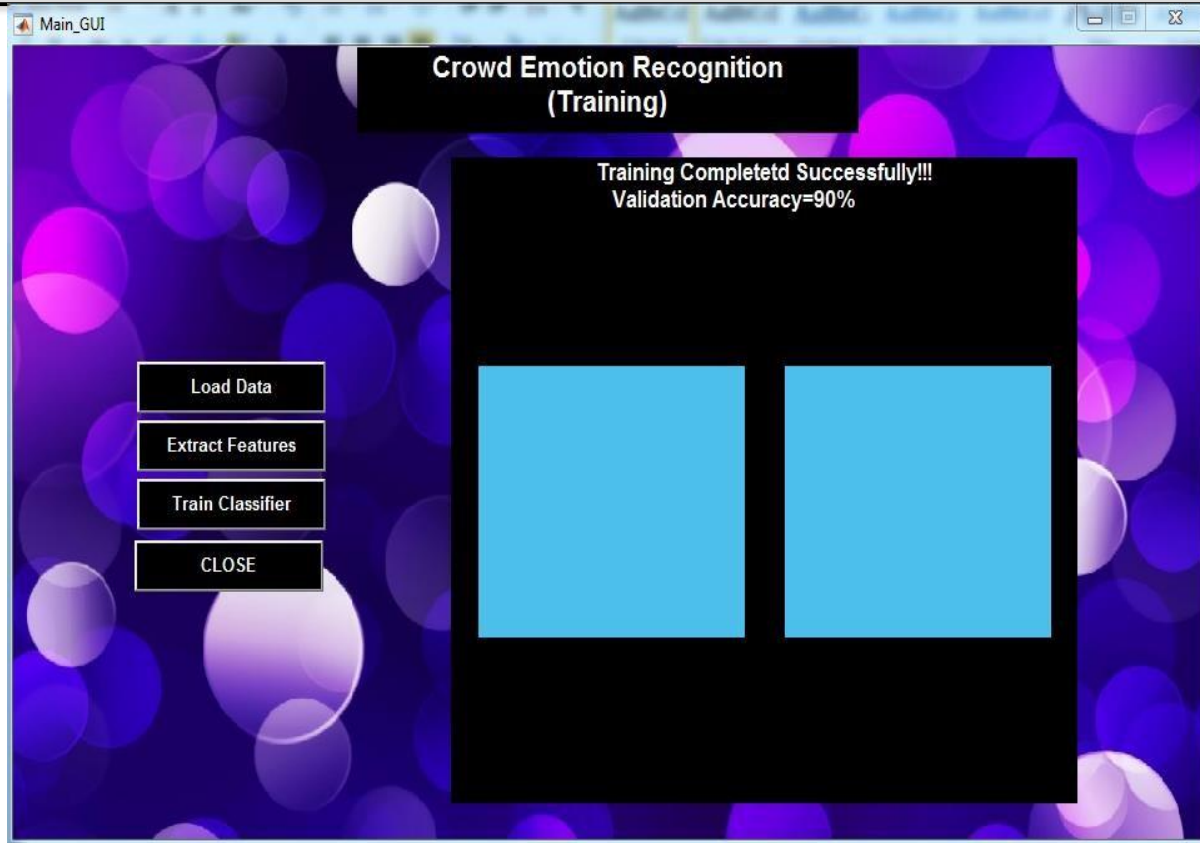
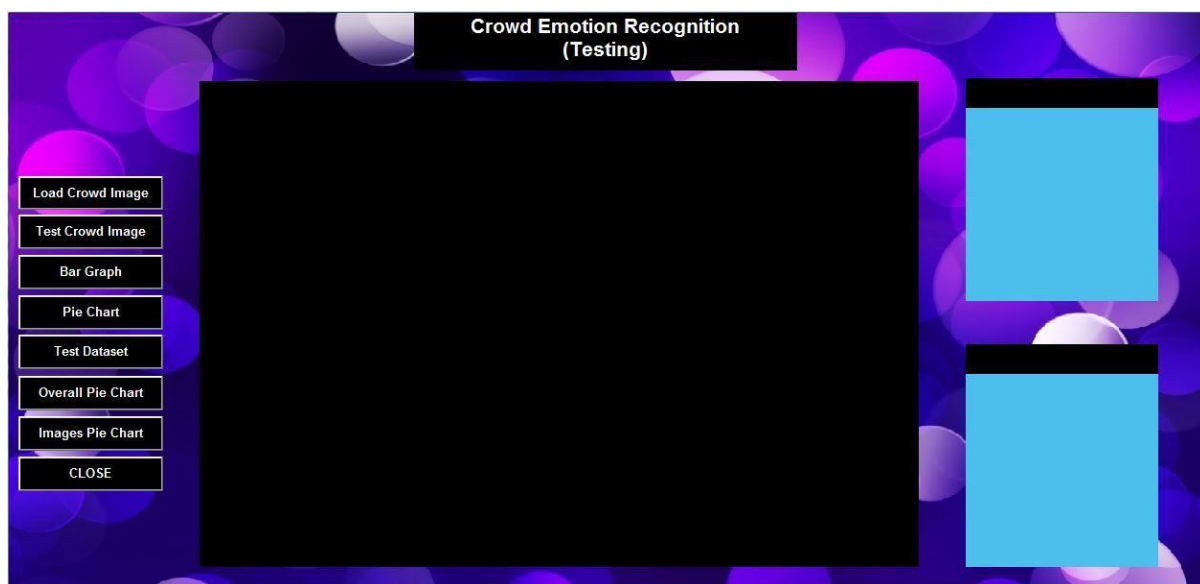


Figure 16: Validation Accuracy of Training

After completing the training process, click the CLOSE button to exit the training window and return to the Main GUI. In the main interface, click the TEST button to open the TEST window, which contains several buttons and sub-windows for further operations.



**Figure 17: TEST Button GUI**

The TEST interface divides its buttons into two main groups: Crowd Image and Dataset. The Crowd Image section includes buttons like Load Crowd Image, Test Crowd Image, Bar Graph, and Pie Chart, while the Dataset section features Test Dataset, Overall Pie Chart,

and Images Pie Chart. The Close button exits the TEST GUI and returns to the Main GUI. When you click Load Crowd Image, a file browser appears allowing you to select an image from your device. After choosing and confirming an image, the interface updates accordingly.

**Figure 18: Image Selection from System**

Clicking on Test Crowd Image initiates the process of detecting faces within the selected crowd image and recognizing their expressions. The detected faces along with their HOG

features are displayed in the right-hand sub-windows, as shown in Figure 19. The processed image is saved automatically in the “Processed Images” folder after emotion recognition.





**Figure 19: Crowd Detection and Recognition Process**

Once the system identifies the faces and their respective emotions, it calculates the overall emotion of the image by aggregating the

emotions of all detected faces. The emotion with the highest occurrence is presented as the dominant emotion of the image, as depicted in Figure 20.



**Figure 20: Overall Emotion of the Image**

To review how the system determined the dominant emotion, click on the Bar Graph

button. This action will display a bar graph

illustrating the distribution of different emotions detected, as shown in Figure 21.

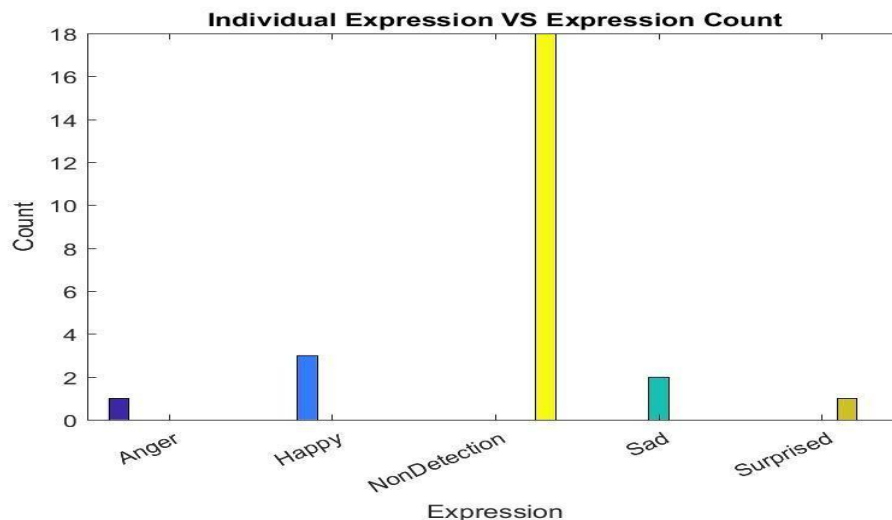


Figure 21: Bar Graph Representation of Emotions

Next, by clicking the Pie Chart button, a pie chart visualizing the proportion of individual expressions in the image will be generated.

This chart is saved in the "Pie Chart" folder for future reference, as shown in Figure 22.

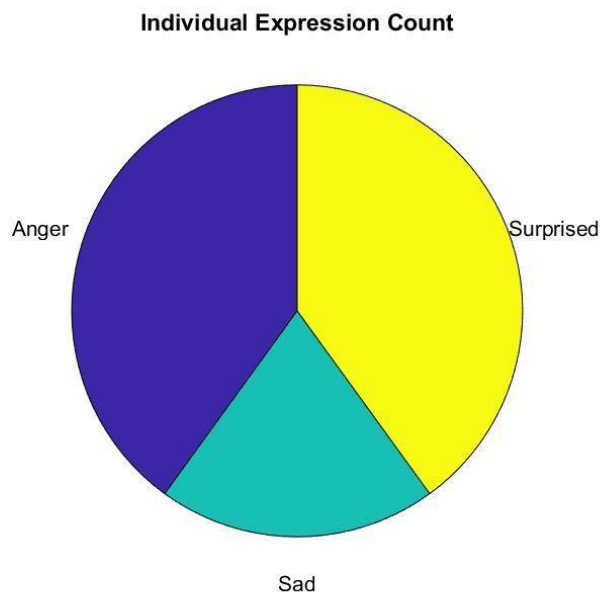


Figure 22: Pie Chart of the Image

At this point, the first phase of the thesis is complete. If you have multiple images from

various occasions and wish to assess the overall

emotion of those events, you can follow these steps to determine the dominant emotion.

However, determining the overall emotion of a crowd based on a single image is limiting because emotions are transient. To address this, the thesis introduces an equation to model emotion over time:

$$\epsilon_t = \epsilon_{t-1} + \rho \epsilon_{t-1}$$

where  $\rho$  represents the rate at which emotions fade.

Building on this concept, the second phase involves analyzing multiple images from the same crowd to identify the overall crowd

emotion. There is no limit to the number of images used for this purpose.

To analyze an entire crowd, store all relevant images in the “Dataset” folder. This allows the system to process the crowd images automatically without manual input. After placing the images in the folder, open the TEST GUI and click on the Test Dataset button. The system will analyze each image sequentially and display the results in the testing window. All results are saved in a file named “Dataset Records.xlsx.”



Figure 23: Dataset Testing in Progress

The duration of this process depends on the number of images in the Dataset folder. Once the analysis is complete, a confirmation message appears, as shown in Figure 24.



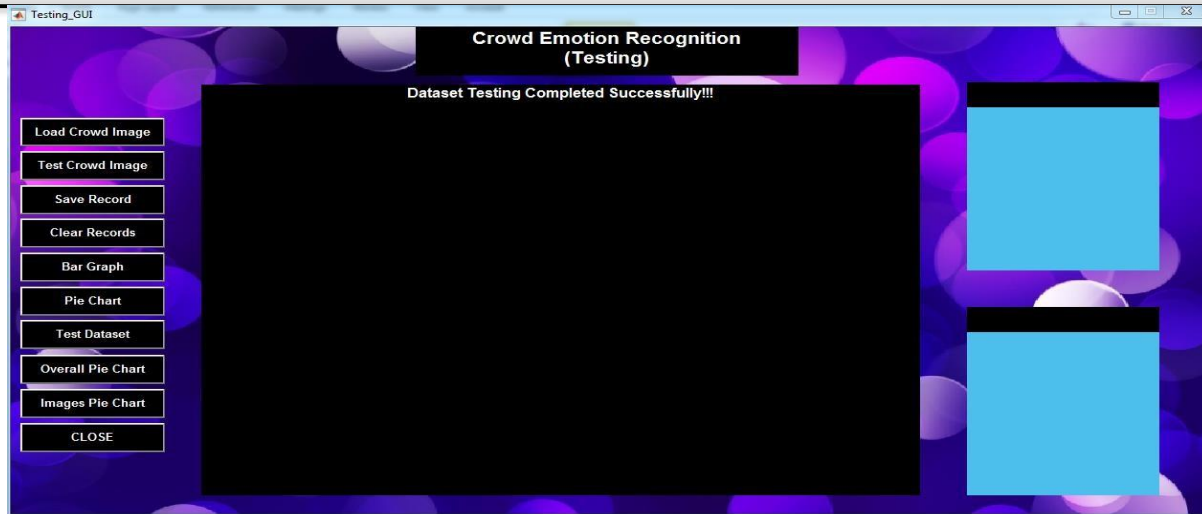


Figure 24: Dataset Testing Completed

After obtaining individual emotion data for all images, calculating the overall emotion for the crowd can be challenging. Clicking the Overall

Pie Chart button generates a summary pie chart representing the dominant emotion for the entire dataset, as illustrated in Figure 25.

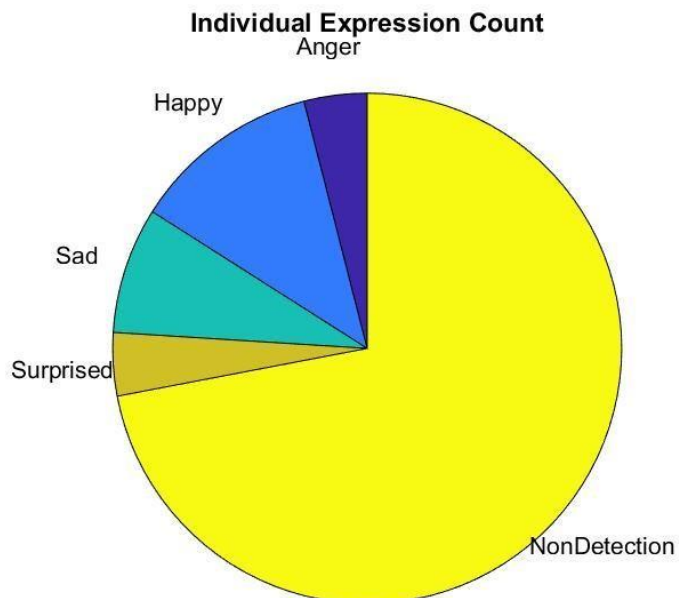


Figure 25: Overall Emotion of the Dataset

#### 4.10 Results

This research focuses on developing an intelligent agent capable of recognizing

emotions in crowds. The agent was trained on various facial expression images, achieving an accuracy exceeding 86% during training.

Once emotion detection within individual crowd images is complete, the challenge

becomes determining the dominant emotion in the crowd. This work uses a voting-based method to aggregate individual emotions.

The accuracy of each detected emotion is calculated using the formula:

$$\text{Accuracy}_{\text{Emotion}} = \frac{\text{Number of correct detections}}{\text{Total number of detections}}$$

Here, total counts refer to the number of detected emotions in the crowd, while total expressions refer to the five emotions used in this thesis: Happy, Surprise, Anger, Sad, and Non-Detection (Disgust). For example, if there are counts like Happy 18, Sad 7, Surprise 10,

#### 4.10.1 Voting Approach

Due to the complexity of facial expressions in a crowd, the system employs a voting mechanism to identify the dominant emotion. This approach is suitable because it considers all individual expressions and selects the emotion with the highest occurrence as the overall crowd emotion.

##### 4.10.1.1 Majority Voting

$$\hat{e}_{iw} = \begin{cases} 1 & \text{if } w = \max \\ 0 & \text{otherwise} \end{cases}$$

Sad 5, and Disgust 10, the corresponding percentages would be 36%, 14%, 20%, 10%, and 20% respectively. The emotion with the highest percentage is considered the crowd's overall emotion, essentially implementing a majority voting system.

In large crowds, detecting and analyzing every individual face is impractical due to challenges like occlusions, masks, or partially visible faces.

Majority voting simplifies this by analyzing emotions detected in each image of the crowd separately, then selecting the emotion with the greatest frequency as the crowd's dominant feeling. This method improves accuracy and saves time.

Mathematically, majority voting is expressed as:

#### 4.10.2.1 System Results

The system identified “Fear” as the dominant emotion in the analyzed crowd dataset. To evaluate the system’s accuracy, metrics such as face detection accuracy during training (Accuracysvm) and recall were calculated:

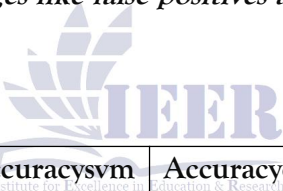
$$\text{Accuracysvm} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

The overall accuracy of crowd emotion detection combines these metrics as:

$$\text{Accuracyoverall} = \frac{\text{Accuracysvm} - (\text{Accuracyemotion} - \text{Recall}) \times 10}{1 - \text{Recall}}$$

This calculation accounts for challenges like false positives and false negatives inherent in crowd images.



Emotion	Recall	Accuracysvm	Accuracyemotion	Accuracyoverall
Happy	82	89	12	10.6
Sad	82	89	10	9.4
Surprised	82	89	4	6.1
NonDetection	82	89	4	6.1
Anger	82	89	70	67.8

#### 4.10.3 Survey Results

To validate the system's output, a survey was conducted across different age groups.

##### 4.10.3.1 Age Group 18-25

Participants viewed crowd images and provided their assessment of the dominant emotion. The survey confirmed the system's results, with “Anger” being identified as the prevalent emotion.

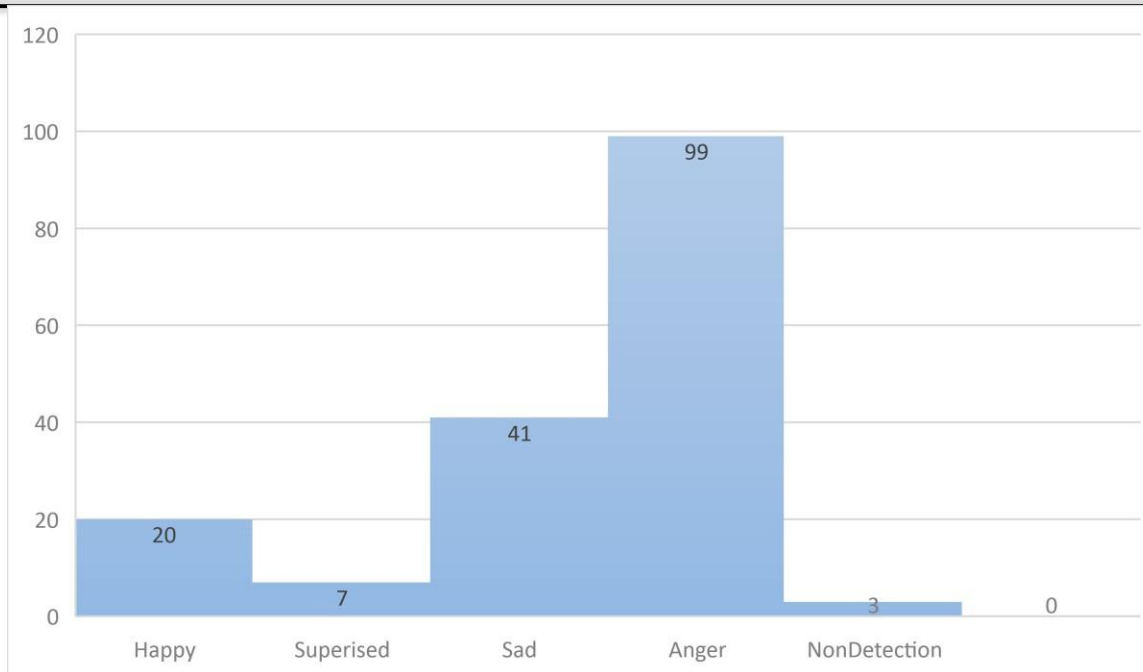


Table 2 result gather from peoples

The pie chart of above bar chart is the following:

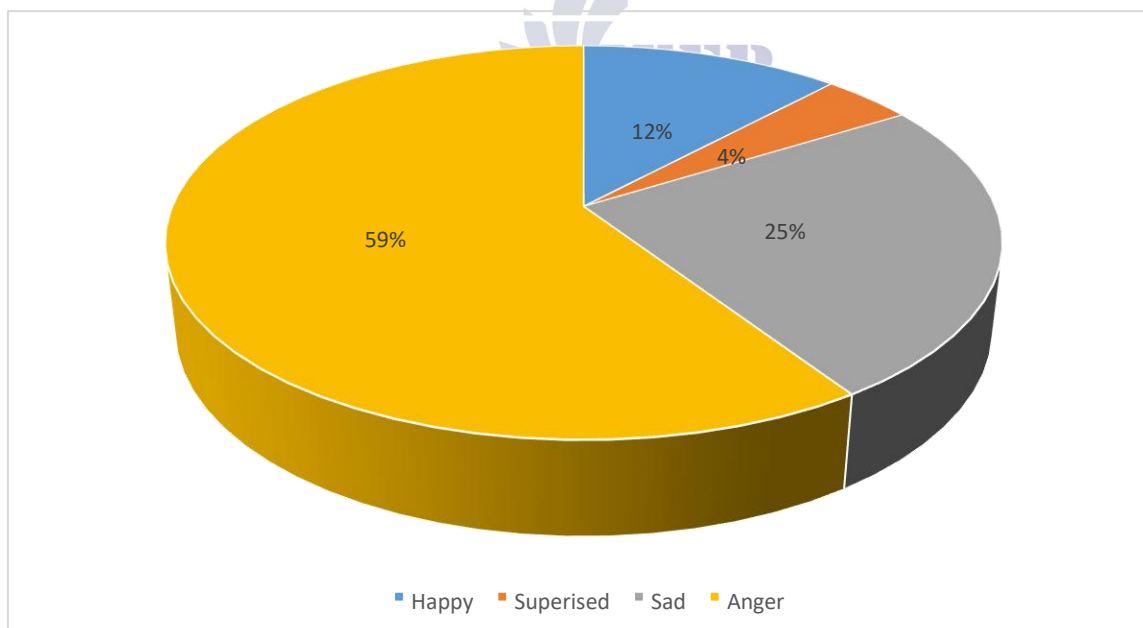


Figure 26 Pie chart of Survey

#### 4.10.3.2 Age Group 26-35

Similarly, this group's assessment also highlighted "Anger" as the dominant emotion in the crowd images.

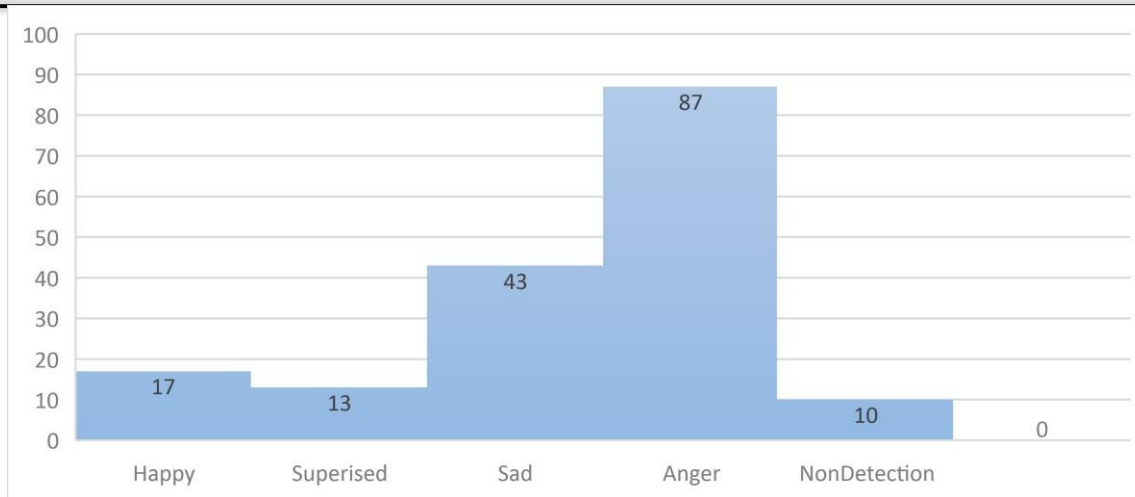


Figure 27 result from the people

The pie chart of above bar chart is the following:

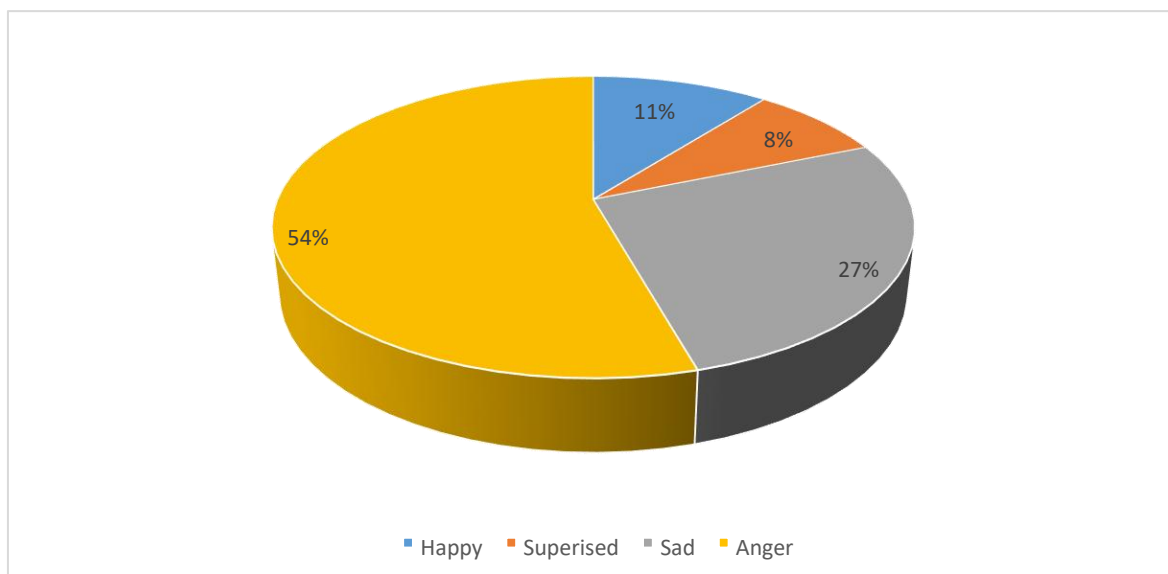


Figure 28 pie chart from people

## Conclusion and Discussion

### 5.1 Conclusion

This study developed an intelligent agent designed to detect crowd emotions based on facial expressions, inspired by psychological research. The agent can effectively interpret

emotional states within crowds using facial feature points, achieving over 65% accuracy even when some features are imperfectly detected.

### 5.2 Discussion

The research aimed to explore how crowd emotions can be recognized solely through facial expressions. Crowds exhibiting a single dominant emotion were classified more accurately and quickly than those with mixed emotions. Interestingly, classification was easier for both small and large crowds compared to medium-sized ones. The results suggest that the perception of crowd emotion is complex and not always absolute, likely influenced by nonverbal cues beyond facial expressions.

### 5.3 Future Work

Future efforts will focus on integrating additional filtering techniques to better isolate relevant facial features in side-profile images. The model will also be adapted for live video streams to detect emotions in real-time crowds. Moreover, combining classifiers with clustering methods may improve the identification of emerging or rare emotional classes. Expanding this research to larger outdoor crowds and comparing it with other approaches will further validate the system's robustness.

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