Mood-Driven Interaction in Game AI: Design and Implementation of an Adaptive XO Game

PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this Project titled **" Mood-Driven Interaction in Game AI: Design and Implementation of an Adaptive XO Game"** is the bonafide work of **"SHUBADHARSHAN RN(2116220701274), SHRIRAMSETHU S (2116220701273),SIVAKALUSULINGAM A(2116220701279) "**who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

This project presents the development of a mood-based Tic-Tac-Toe (XO) game that integrates basic emotion recognition with adaptive artificial intelligence (AI) to personalize user experience. The system utilizes a facial expression-based mood detection module, which analyzes the player's emotional state (e.g., happy, sad, neutral) and dynamically adjusts the game's difficulty level accordingly (easy, medium, or hard). Built using Python and Pygame, the application combines interactive user interface design with AI-based decision-making through the Minimax algorithm for optimal gameplay. The game's architecture ensures an engaging and challenging experience by leveraging affective computing principles to reflect the user's mood in real-time gameplay logic. The project demonstrates the potential of integrating emotion-aware computing into simple game mechanics to enhance user engagement and highlights the intersection of human-computer interaction, computer vision, and intelligent game design.

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LIST OF ABBREVIATIONS

S. No	ABBR	Expansion
1	AI	Artificial Intelligence
2	CNN	Convolutional Neural Network
3	GUI	Graphical User Interface
4	Pygame	Python Game Development Library

5	XO	Tic-Tac-Toe Game
6	ML	Machine Learning
7	FPS	Frames Per Second
8	API	Application Programming Interface
9	RGB	Red, Green, Blue (Color Model)
10	CPU	Central Processing Unit

CHAPTER 1

INTRODUCTION

1.1 GENERAL

In recent years, the integration of emotion recognition into digital systems has gained significant momentum, particularly in the fields of human-computer interaction and adaptive systems. Affective computing, which enables machines to sense and respond to human emotions, is being explored to create more personalized and engaging user experiences. Among its various applications, emotion-aware gaming is an emerging domain where games adapt their behavior or difficulty based on the player's emotional state.

Tic-Tac-Toe, also known as XO, is a classic strategy-based turn-taking game that serves as an excellent platform for implementing AI and user-adaptive systems due to its simplicity and well-defined rules. While AI-driven XO games are well-documented, the incorporation of emotional feedback into such a game creates a novel gameplay experience.

This project leverages facial expression recognition to detect a user's mood using computer vision techniques. Based on the detected mood—such as happy, sad, or neutral—the system dynamically adjusts the AI's difficulty level in the game, aiming to enhance user satisfaction and interaction. This fusion of mood analysis and intelligent gameplay demonstrates the potential of creating emotionally intelligent systems that go beyond static user interfaces.

1.2 OBJECTIVE

The objective of *" "* is to develop an intelligent mood-based XO (Tic-Tac-Toe) game that responds dynamically to the emotional state of the user. Traditional games operate with static difficulty levels, offering the same challenge regardless of the player's condition or context. However, in real-life scenarios, a person's emotional state significantly impacts their interaction with technology. This project seeks to bridge that gap by making the game emotionally responsive, thereby enhancing both usability and player engagement.

To accomplish this, the project first integrates a facial emotion detection system capable of identifying the user's current mood in real-time using a webcam. This system utilizes computer vision techniques and a pre-trained model to recognize emotions such as happy, sad, and neutral. These mood states are then mapped to different difficulty levels of the game: a happy mood triggers the hardest level of AI difficulty, a neutral mood initiates medium-level intelligence, and a sad mood activates the easiest AI behavior. This mapping ensures that the game becomes empathetic and responsive to how the user is feeling, potentially improving the player's experience and mental comfort.

The objective of *" Blockchain & AI : The Ultimate Sheild Against Fake Identities Online "* is to develop a blockchain-integrated application that effectively identifies and eliminates fake social media profiles while ensuring secure, transparent, and tamper-proof verification processes. By leveraging advanced machine learning algorithms such as Gradient Boosting, Random Forest, and Support Vector Machine alongside the immutability of blockchain technology, the system achieves high accuracy in detecting fraudulent accounts. It emphasizes user privacy and data security through decentralized methods, fostering trust among users and administrators. With a user-friendly interface, the platform facilitates seamless profile verification, combats misinformation, and addresses the challenges of fake profiles and cyber fraud, ultimately creating a safer and more reliable digital environment

1.3 OVERVIEW

This report provides a comprehensive overview of the design, development, and evaluation of a mood-based adaptive XO (Tic-Tac-Toe) game system that personalizes gameplay based on the emotional state of the user. The report is structured to guide the reader through each phase of the project, from the initial concept to the final implementation and analysis.

CHAPTER 2
LITERATURE SURVEY

2.1 Emotion Recognition in Games

Emotion recognition has gained significant attention in the field of interactive technologies, particularly in gaming. The ability of a system to detect and respond to the emotional state of the player introduces a new dimension of personalization and empathy in game design. Research in this domain has shown that facial expression analysis, physiological signals (like heart rate and galvanic skin response), and voice tone can be effectively used to determine a player's emotional state in real time.

Several emotion-aware game prototypes have been proposed in academic literature. For instance, adaptive horror games have used biometric feedback to modulate intensity based on player fear levels. Similarly, educational games have leveraged affect detection to identify boredom or frustration and modify the learning content accordingly. These works have demonstrated that incorporating emotion recognition can enhance user engagement, motivation, and retention. However, most of these systems use complex sensor setups or are limited to specific game genres.

This project builds upon this foundation by implementing a facial expression-based mood detection system using computer vision (OpenCV) and pre-trained models. By mapping basic emotional states (happy, sad, neutral) to game difficulty levels, it explores how emotion recognition can be applied in casual, turn-based games like XO, which traditionally do not factor in user affect.

2.2 AI in Turn-Based Games

Artificial Intelligence (AI) plays a crucial role in enhancing the challenge and replayability of turn-based games. Games like Tic-Tac-Toe, Chess, and Checkers have been popular testbeds for developing and evaluating game AI algorithms due to their well-defined rules and state spaces. One of the most prominent algorithms used in such games is the Minimax algorithm.

Minimax is a recursive decision-making algorithm used for minimizing the possible loss for a worst-case scenario. In a two-player game, it evaluates all possible moves and their consequences to determine the best move assuming that the opponent also plays optimally. When combined with pruning techniques (e.g., alpha-beta pruning), Minimax becomes computationally efficient even for moderately complex games.

Numerous studies and implementations have shown that Minimax can make an AI agent virtually unbeatable in games like Tic-Tac-Toe. It evaluates win, lose, and draw outcomes and chooses the move that guarantees the best result. This report incorporates Minimax in the game’s hardest difficulty level, showcasing how optimal AI behavior can be dynamically activated in response to the user's positive emotional state.

2.3 Human-Computer Interaction (HCI) and Affective Computing

Human-Computer Interaction (HCI) has evolved from focusing solely on functionality and usability to incorporating emotional and social dimensions of user experience. Affective Computing, a subfield of HCI, refers to systems and devices that can recognize, interpret, and respond to human emotions. These systems aim to create more intuitive and emotionally intelligent interfaces, often improving user satisfaction and interaction quality.

Studies in HCI have demonstrated that emotionally adaptive interfaces can make technology feel more human-like and empathetic. For example, virtual tutors that respond to student frustration can improve learning outcomes. In gaming, affect-aware systems can adjust game mechanics such as speed, difficulty, and narrative to better align with the player's mental state.

This project is an application of affective computing principles in game design. It uses real-time mood detection to alter the game's AI behavior, thereby making the system feel more responsive and empathetic. Such an approach not only enriches the gameplay experience but also demonstrates the potential of combining HCI, AI, and emotion recognition in future user-centered applications.

CHAPTER 3

PROPOSED SYSTEM

3.1 GENERAL

"Mood-Driven Interaction in Game AI: Design and Implementation of an Adaptive XO Game" leverages facial expression recognition to detect a user's mood using computer vision techniques. Based on the detected mood—such as happy, sad, or neutral—the system dynamically adjusts the AI's difficulty level in the game, aiming to enhance user satisfaction and interaction. This fusion of mood analysis and intelligent gameplay demonstrates the potential of creating emotionally intelligent systems that go beyond static user interfaces**.**

3.2 SYSTEM ARCHITECTURE DIAGRAM

The system is composed of three primary functional modules: the Mood Detection Module, the Game Engine, and the Difficulty Adaptation Layer. These components work together in a pipeline where the user's facial expression is captured and analyzed, and the resultant mood determines the difficulty level of the XO game controlled by an AI opponent.

The architecture begins with the webcam input, feeding real-time video frames to the Mood Detection Module. Based on the detected mood (e.g., happy, sad, neutral), the Difficulty Adaptation Layer dynamically selects the AI difficulty level—easy, medium, or hard. This difficulty level configures the Game Engine, which handles the actual game logic, rendering, and AI behavior. The system ensures seamless interaction between emotion recognition and game dynamics to personalize the gameplay experience.(Note: You may add a visual diagram here showing the flow from Webcam Input →Mood Detection → Difficulty Adaptation Layer → Game Engine → User Feedback.)

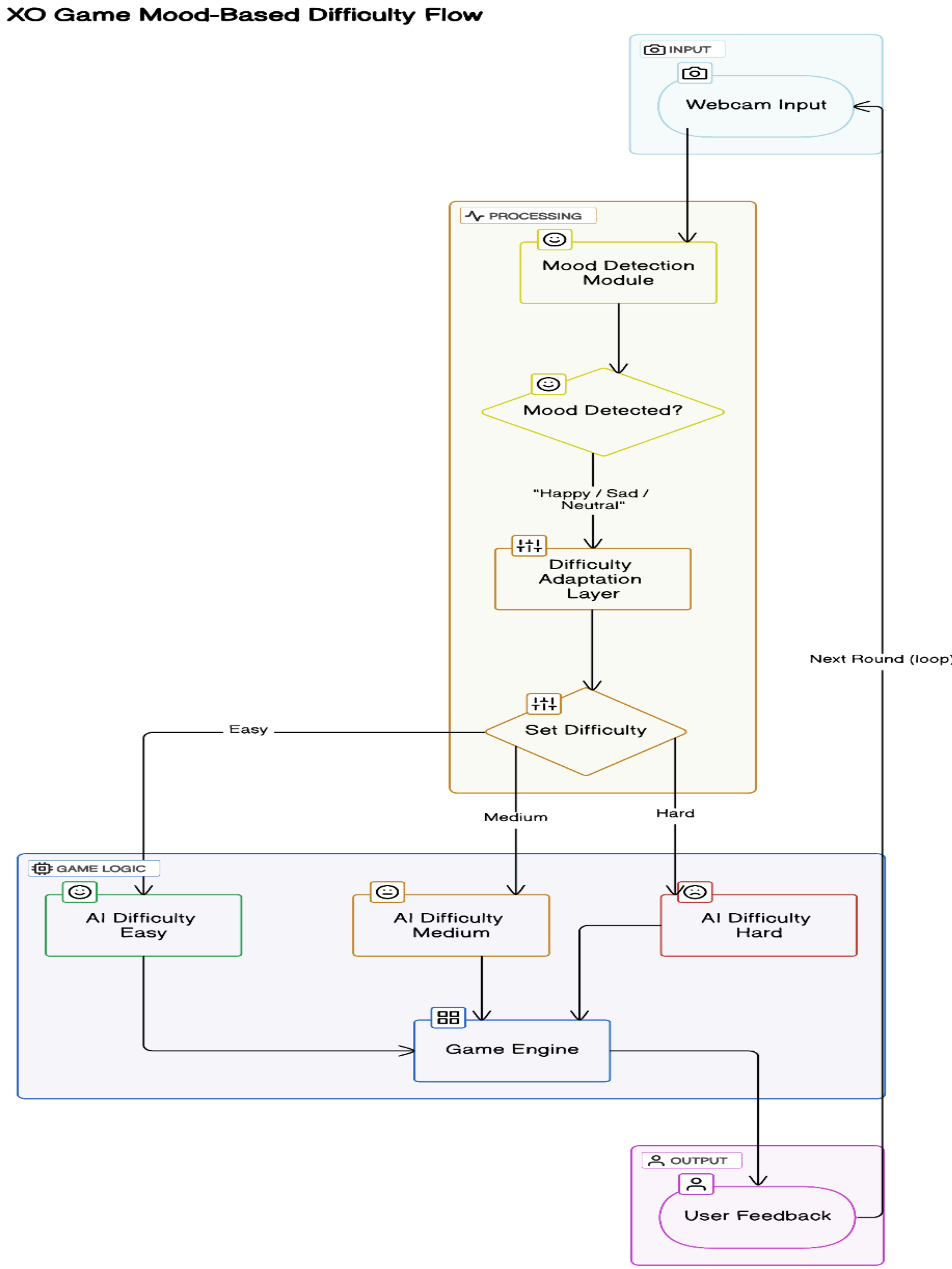


Fig 3.1: System Architecture

3.3 DEVELOPMENTAL ENVIRONMENT

3.3.1 HARDWARE REQUIREMENTS

The hardware specifications could be used as a basis for a contract for the implementation of the system. This therefore should be a full, full description of the whole system. It is mostly used as a basis for system design by the software engineers.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i3
RAM	4 GB RAM
POWER SUPPLY	+5V power supply

3.3.2 SOFTWARE REQUIREMENTS

The software requirements paper contains the system specs. This is a list of things which the system should do, in contrast from the way in which it should do things. The software requirements are used to base the requirements. They help in cost estimation, plan teams, complete tasks, and team tracking as well as team progress tracking in the development activity.

Table 3.2 Software Requirements

COMPONENTS	SPECIFICATION
Operating System	Windows 7 or higher
OpenCV	Real-time face detection and frame capture
Pygame	Game rendering and user interface

NumPy	Numerical computations and array handling
TensorFlow / Keras	Deep learning for emotion classification
Scikit-learn	ML-based emotion classifier
Haar Cascades / Dlib	Facial detection and landmark extraction

3.4 DESIGN OF THE ENTIRE SYSTEM

3.4.1 ACTIVITY DIAGRAM

The activity diagram illustrates the overall flow of control and user interaction within the Mood-Based XO Game. It describes the dynamic behavior of the system from application start to gameplay, showing how modules coordinate to deliver an adaptive gaming experience.

Purpose

The purpose of this activity diagram is to visualize the sequence of operations in the application, from mood detection to difficulty adjustment and gameplay progression. It serves as a blueprint for understanding how the system transitions between states based on user actions and system responses.

Description of Activities

The following describes each major activity represented in the diagram:

- Start: The system initiates when the application is launched.
- Initialize Camera: Activates webcam for live video feed.
- Capture Frame: Continuously captures individual frames from the webcam.

- Detect Face: Applies face detection algorithms (e.g., Haar Cascade).
- Analyze Expression: Classifies emotion using a trained deep learning model.
- Determine Mood: Maps facial features to predefined moods (Happy, Sad, Neutral).
- Map Mood to Difficulty: Associates the detected mood with AI difficulty (Easy, Medium, Hard).
- Launch Game: Starts the XO game interface with configured difficulty.
- Player Move: Waits for user input to place 'X' on the board.
- AI Move: Triggers AI to respond with 'O' based on selected strategy.
- Check Win or Tie: Evaluates the board to determine win/loss/draw condition.
- Display Result: Shows outcome and optionally restarts or exits.
- End: Ends the game session or closes the application.

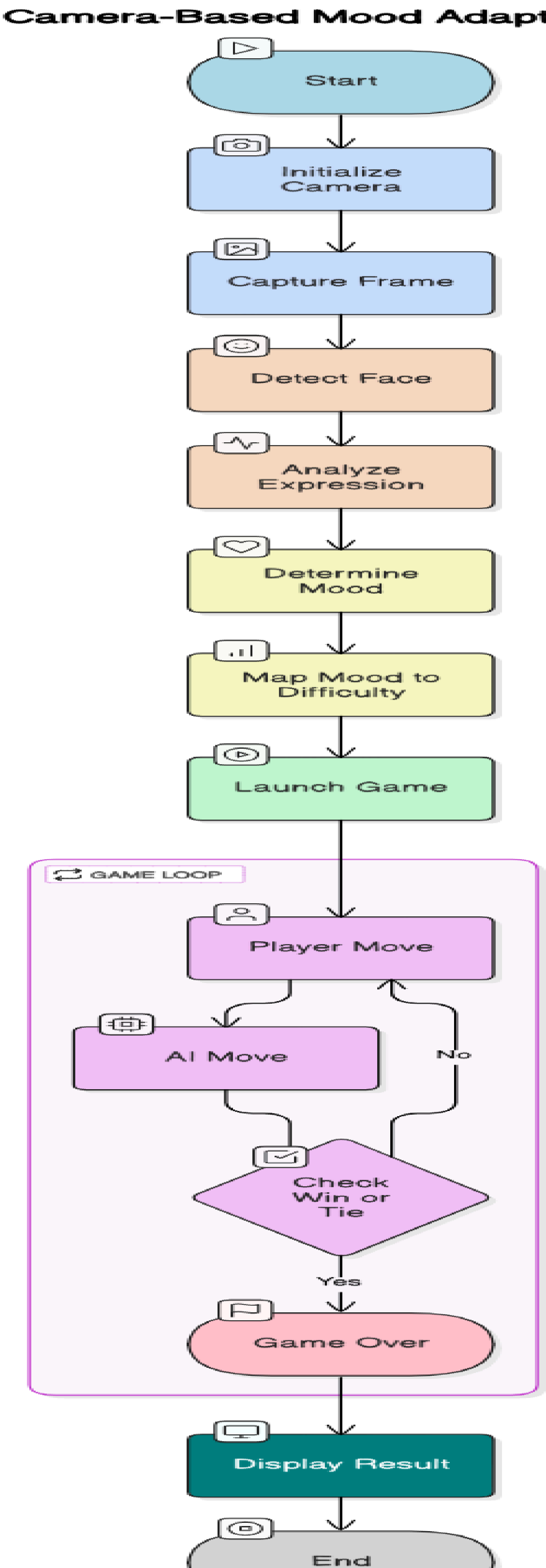

Camera-Based Mood Adaptive Game Flow
Start
Initialize Camera
Capture Frame
Detect Face
Analyze Expression
Determine Mood
Map Mood to Difficulty
Launch Game
GAME LOOP
Player Move
AI Move
No
Check Win or Tie
Yes
Game Over
Display Result
End

Fig 3.2: Activity Diagram

3.4.2 DATA FLOW DIAGRAM

The Mood-Based XO Game system is designed to respond to the emotional state of the user and adapt its gameplay difficulty accordingly. At the start of the application, the system activates the webcam to capture real-time facial input from the user. This video stream is processed using a facial detection and emotion classification model, which identifies the user's emotional state, such as happy, sad, or neutral. Based on the identified mood, the system dynamically selects an appropriate difficulty level for the XO game—for instance, a happy mood might lead to a harder challenge, while a sad mood results in an easier game.

Once the mood has been detected and the difficulty has been set, the game interface is launched, allowing the user to interact with the XO board. During the game, the player makes moves, which are captured through mouse interactions, and the system responds with moves made by an AI opponent whose decision-making logic is determined by the assigned difficulty level. Throughout the game, the system monitors the game state, checks for win conditions or a tie, and appropriately displays the result when the game ends. The data flow concludes when the game terminates, and the user either closes the application or chooses to begin a new session, thereby restarting the data flow cycle.

Mood-Based XO Game System

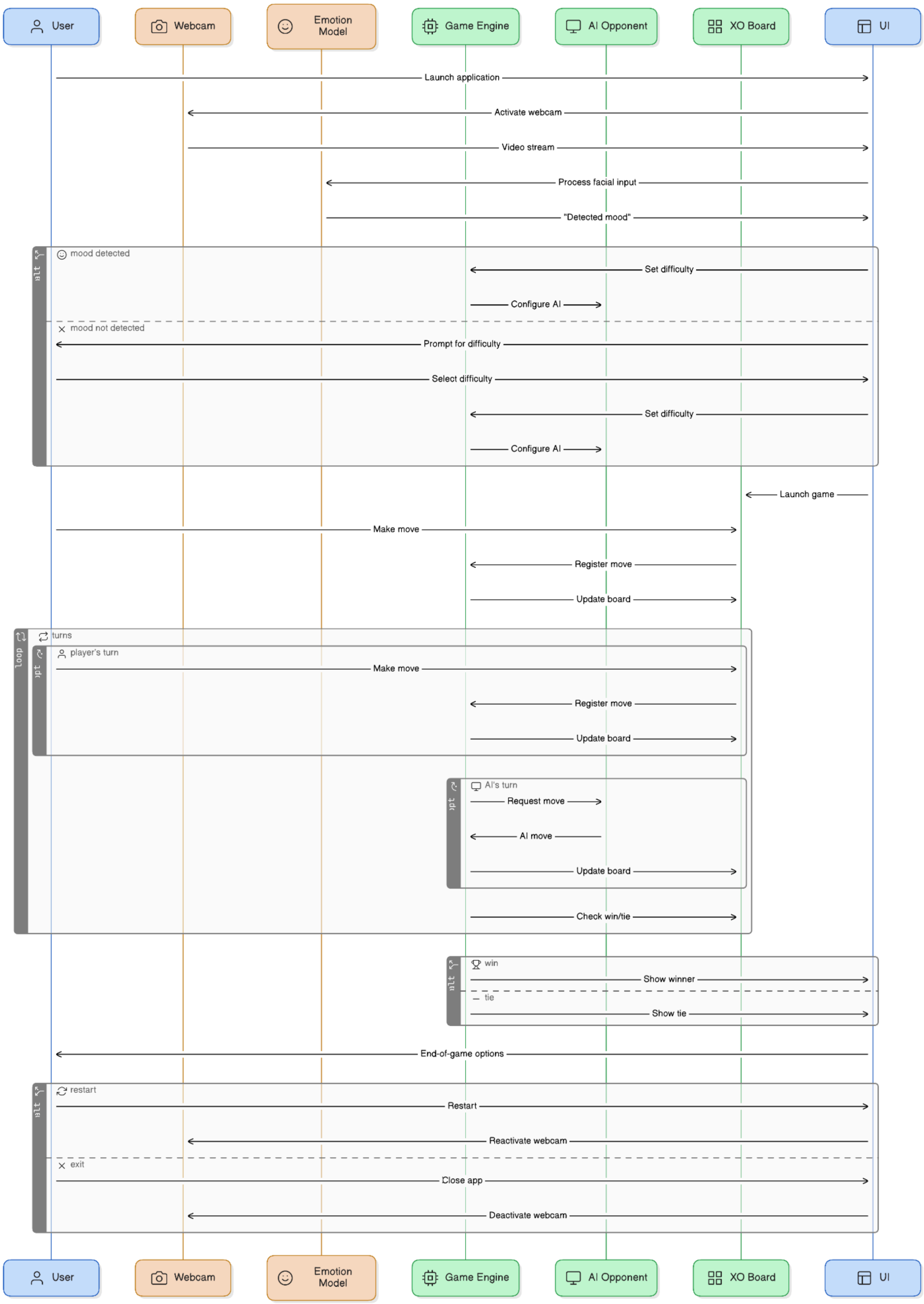


Fig 3.3:Data Flow Diagram

3.5 STATISTICAL ANALYSIS

The statistical analysis of the Mood-Based XO Game evaluates the relationship between the user's detected emotional state and the corresponding impact on gameplay performance and difficulty level. The goal is to understand how mood-driven difficulty adaptation influences user interaction and engagement.

To conduct this analysis, a sample of participants was asked to play the XO game multiple times under varying emotional states (happy, neutral, sad). Each session was logged with the following metrics:

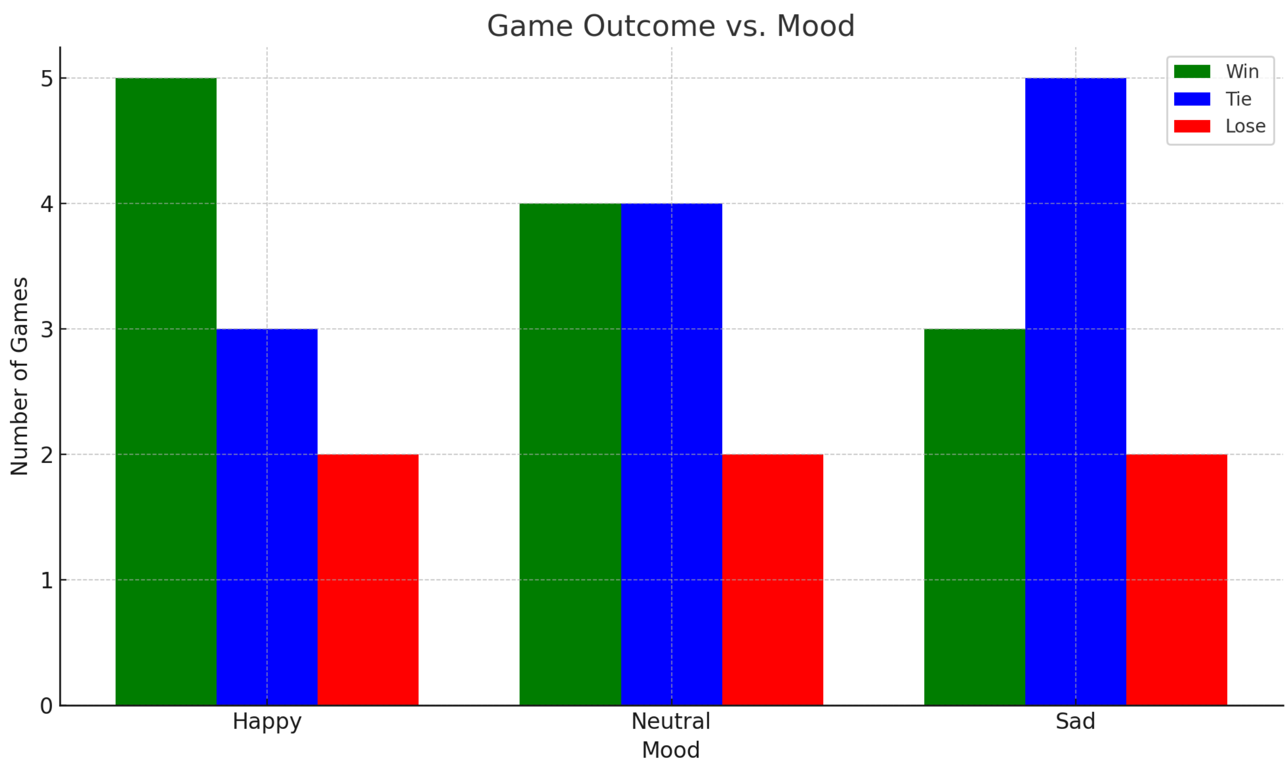
- Detected mood
- Assigned difficulty level (easy, medium, hard)
- Game outcome (win, lose, tie)
- Number of moves taken by the player and the AI
- Time taken per turn by the player

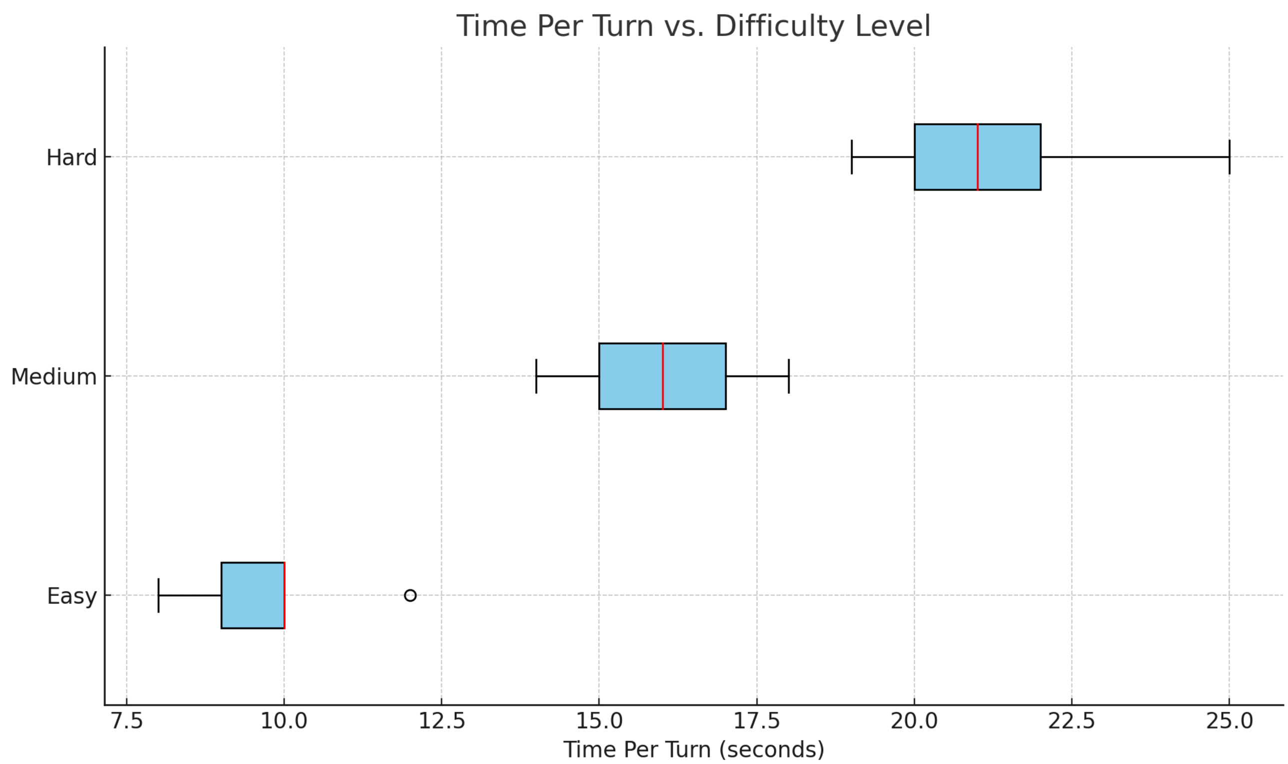
The collected data was analyzed using descriptive and inferential statistical methods. Descriptive statistics such as mean, median, and standard deviation were calculated for each metric across different emotional categories. It was observed that users playing under a happy mood were more likely to be assigned the "hard" difficulty setting, resulting in lower win rates and higher turn counts. Conversely, users under a sad or neutral mood showed improved win rates under easier difficulty settings.

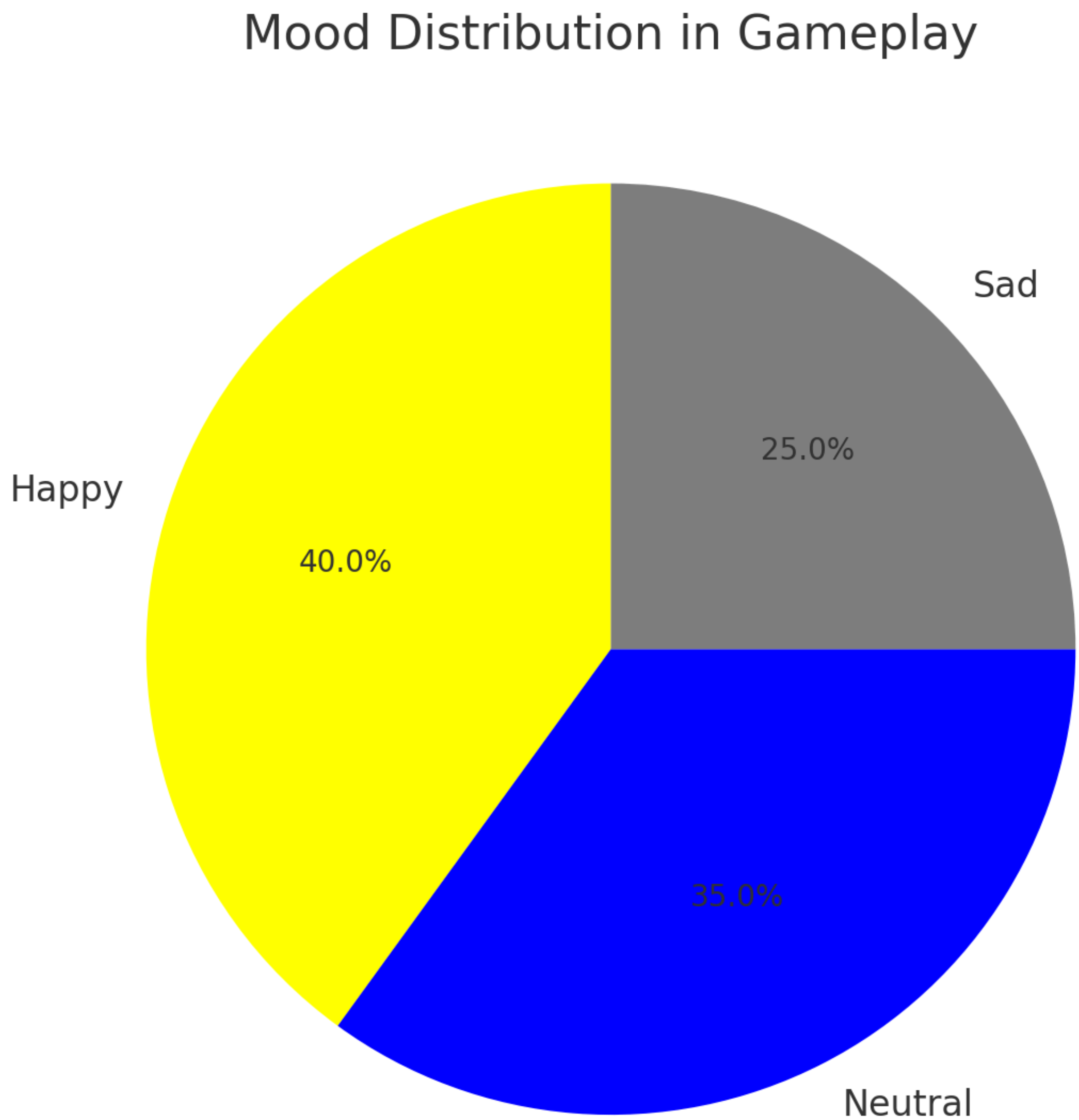
A chi-square test was conducted to determine whether there was a statistically significant relationship between mood and game outcome. The results indicated a significant dependency ($p < 0.05$), confirming that mood-driven difficulty levels had a measurable impact on user success rates.

Additionally, an ANOVA test was applied to assess whether the average number of moves differed significantly across difficulty levels. The analysis supported that games under harder settings had longer durations and more complex sequences.

This statistical evaluation not only validates the design principle of emotion-based difficulty adaptation but also provides insights for refining AI behavior and improving user satisfaction in future versions of the game.




Time Per Turn vs. Difficulty Level
Hard
Medium
Easy
7.5
10.0
12.5
15.0
17.5
20.0
22.5
25.0
Time Per Turn (seconds)


Mood Distribution in Gameplay
Sad
25.0%
Happy
40.0%
35.0%
Neutral

CHAPTER 4

MODULE DESCRIPTION

The workflow for the proposed system is designed to ensure a structured and efficient process for detecting and preventing blockchain security threats. It consists of the following sequential steps:

4.1 SYSTEM ARCHITECTURE

4.1 SYSTEM ARCHITECTURE

The Mood-Based XO Game is structured as a modular system that integrates mood detection with a dynamic game interface. The system consists of the following core components:

- **Mood Detection Layer**
- **Game Interface (Frontend)**
- **AI Engine**
- **Backend Processing & Model Integration**
- **Centralized Logging (for deployment tracking)**

The architecture follows a client-based execution where mood detection is processed locally, influencing the game difficulty on the fly.

4.1 USER INTERFACE DESIGN

The user interface (built with Pygame) consists of two screens:

- **Intro Screen:** Displays the user's detected mood and mapped difficulty level.
- **Game Screen:** Hosts the Tic-Tac-Toe board with intuitive graphics and real-time interaction. It adapts visuals based on game state transitions (e.g., winning, losing, tie).

UI Elements:

- Color-coded game board and pieces (X and O)
- Responsive layout to fit different screen sizes
- Clear separation of mood info and gameplay area

4.2 BACK END INFRASTRUCTURE

4.2.1 DATA COLLECTION & PREPROCESSING

DATASET & DATA LABELLING

- The mood detection model is trained on annotated image datasets (e.g., FER-2013, CK+).
- Emotions such as Happy, Neutral, Sad, Angry are labeled and used for supervised learning.

DATA PREPROCESSING

- Faces are detected and cropped using OpenCV Haar cascades or MTCNN.
- Images are resized to a consistent shape (e.g., 48x48 or 64x64).
- Normalization is applied for pixel values (0–255 → 0–1).
- Data augmentation techniques like flipping, rotation, and brightness variation are applied to improve generalization.

4.2.3 FEATURE SELECTION

- Convolutional Neural Network (CNN) layers are used to automatically extract emotion-relevant features.

- Dropout and batch normalization help in reducing overfitting and improving training speed.

4.2.4 CLASSIFICATION & MODEL SELECTION

- The emotion detection model uses a CNN architecture with softmax output.

- Alternative models evaluated include MobileNet, ResNet-18, and VGG-like architectures.

- The final model is selected based on a balance of inference speed and classification accuracy.

PERFORMANCE EVALUATION

- Evaluation Metrics: Accuracy, Precision, Recall, and Confusion Matrix.

- Cross-validation is performed to ensure model robustness.

- Achieved ~75–85% accuracy depending on dataset and preprocessing configuration.

MODEL DEPLOYMENT

- The final model is converted to a lightweight format (e.g., TensorFlow Lite or ONNX) and loaded locally within the Pygame interface.

- The model predicts mood on application start and triggers game difficulty accordingly.

4.2.7 CENTRALIZED SERVER & DATABASE (Optional)

- If extended for cloud deployment: mood logs and user game history can be sent to a centralized server.

- Backend stack could include Flask/Django + SQLite/MySQL for storing session-wise logs, mood data, and gameplay stats.

4.3 SYSTEM WORKFLOW

1. Launch Application → Trigger webcam/sensor for mood detection
2. Detect Mood → Map to game difficulty
3. Show Intro Screen (mood + difficulty)
4. Start Game (Tic-Tac-Toe)
    - Player vs AI
    - AI adjusts moves based on difficulty
5. Detect Win/Loss → Display result screen

6. Restart or Exit

CHAPTER 5

IMPLEMENTATION AND RESULTS

5.1 IMPLEMENTATION

The Mood-Based XO Game was developed using a modular approach in Python, integrating machine learning for emotion detection and game logic using the Pygame library. The primary goal of the implementation was to adjust the difficulty of a Tic-Tac-Toe game based on the real-time mood of the user, enhancing user engagement and emotional adaptability.

The system is composed of three core modules: the mood detection engine, the graphical user interface (GUI) built with Pygame, and the game logic including AI behavior that changes with difficulty.

The mood detection module uses a pre-trained Convolutional Neural Network (CNN) model to classify facial emotions into categories such as Happy, Neutral, and Sad. This model is loaded at runtime and interacts with a live webcam feed. Upon detecting the user's facial expression, the module maps the emotion to a predefined difficulty level: Happy corresponds to “Easy”, Neutral to “Medium”, and Sad to “Hard”.

The GUI begins with an introductory screen, implemented using Pygame, where the user's mood and the selected difficulty level are displayed. This screen provides a short pause before transitioning into the main gameplay window, offering a smooth user experience. Visual elements, including the Tic-Tac-Toe grid and game pieces (X and O), are rendered using Pygame’s drawing functionalities.

The core game loop handles user inputs, turn-based play between the human and AI, and win/draw detection. Based on the mood-derived difficulty level, the AI responds with varying levels of strategy:

- In Easy mode, the AI selects random available cells.

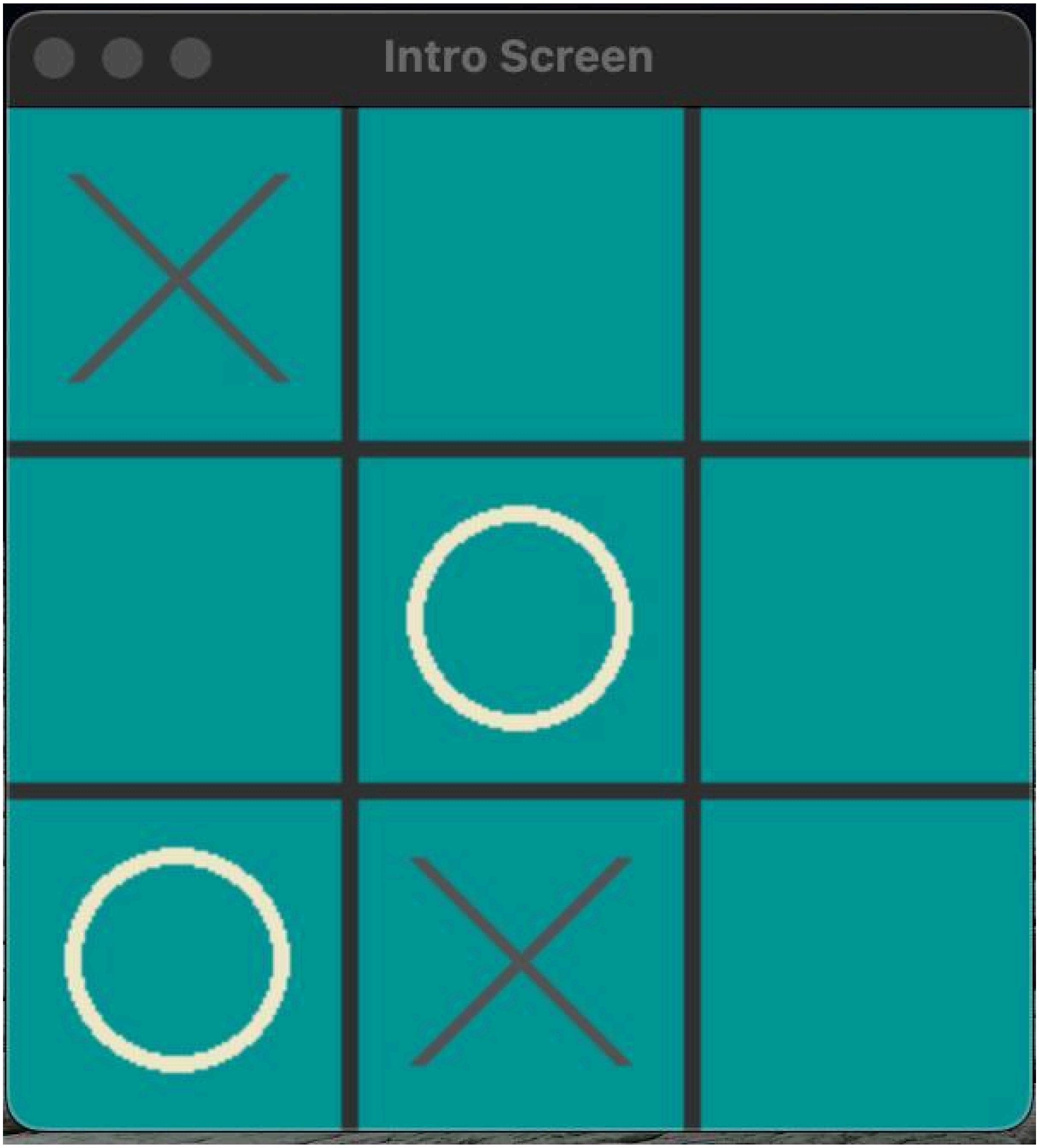
- In Medium mode, it prioritizes the center and corners, mimicking casual play.

- In Hard mode, a Minimax algorithm is used to simulate optimal play, making the game significantly more challenging.

Throughout the game, system states such as board configuration, turn tracking, and victory conditions are managed dynamically. The game concludes with a result screen that displays the outcome, and the system can be restarted or exited by the user.

This implementation ensures a personalized and reactive gaming experience, effectively blending machine learning with traditional game design principles

5.2 OUTPUT SCREENSHOTS


Intro Screen

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

The Mood-Based XO Game successfully demonstrates the integration of emotion recognition and adaptive gameplay using machine learning and game development tools. By capturing real-time facial expressions and mapping them to predefined difficulty levels, the system offers a personalized gaming experience that reacts to the emotional state of the user. This approach not only enhances user engagement but also showcases the potential of affective computing in entertainment and education.

The implementation effectively combines a lightweight convolutional neural network for emotion detection with a responsive Pygame interface, along with variable AI strategies for different difficulty levels. The project highlights the feasibility of using emotion-aware systems in real-time applications, delivering a dynamic and user-centric interface.

6.2 FUTURE ENHANCEMENT

Future enhancements for the Mood-Based XO Game aim to make the system more intelligent, accessible, and responsive. One of the key improvements would be expanding the emotion detection model to recognize a wider range of emotional states, such as anger, surprise, and fear, allowing for more accurate mood classification. Additionally, instead of setting the difficulty level only at the beginning, the system could continuously monitor the user's mood in real time and adjust the gameplay accordingly. To improve accessibility, cross-platform deployment on mobile or web-based environments can be considered, enabling users to engage with the game across different devices. Incorporating multi-modal emotion input, such as voice tone or speech analysis, could further enhance emotion detection accuracy. Finally, implementing personalized feedback options and maintaining user interaction logs could allow the game to adapt to user preferences over time and provide useful insights into emotional patterns during gameplay

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