Proposal for the Tic-Tac-Toe Image Recognition and Gameplay with Minimax AI

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1 Introduction

1.1 Overview

Tic-Tac-Toe is a popular classic two-player game[1] where the main objective is to place three identical marks in a row, column, or diagonal. In this project, we will focus on image recognition to identify this gameplay on a physical board or paper; basically automating the process of playing Tic-Tac-Toe using computer vision techniques and artificial intelligence. Specifically, we propose to design a system that:

- Classifies the game state from an image of the board.
- Predicts the next best move for the computer (playing as O), using the Minimax algorithm for decision-making.
- Visualizes the game in a clear, user-friendly way, highlighting the next predicted move.

This system will have applications in creating interactive Tic-Tac-Toe game agents, assisting in AI-powered gameplay analysis, or serving as a baseline for more advanced computer vision-based AI systems.

1.2 Problem Statement

The challenge of this project is twofold:

1. Image Classification: Developing an effective method to interpret the state of the Tic-Tac-Toe game board from images, classifying each cell as either X, O, or blank.
2. Optimal Move Prediction: Using an intelligent decision-making algorithm (Minimax) to predict the best move for the computer (playing as O), considering the current board configuration.

While the first task requires robust image processing and deep learning techniques, the second task involves implementing game-theory algorithms like Minimax to provide an optimal strategy for the computer.

1.3 Objectives

The main objectives of this project are as follows:

- Design a deep learning model to accurately classify symbols (X, O, blank) in a Tic-Tac-Toe grid from input images.
- Implement the Minimax algorithm to evaluate and predict the optimal next move for the computer (O).
- Develop a visualization system that displays the current game state and predicted move, aiding users in understanding the AI's decision-making process.

1.4 Project Scope and Limitations

Scope

This project focuses on analyzing Tic-Tac-Toe boards from images, classifying X, O, and empty cells using a CNN-based model, and predicting the next move with Minimax. The game state is visualized, with the predicted move clearly highlighted.

- Image Input: The input will be an image of a Tic-Tac-Toe board containing the current game state.
- Classification: The system will identify X, O, and empty cells with a CNN-based model.
- Game Theory: The computer will use Minimax to predict the next best move for O.
- Visualization: The board state, along with the predicted move, will be visualized clearly for the user.

Limitations

The system may struggle with complex backgrounds and low-quality images. The accuracy and precision of the classification depends on the quality of training data, and the solution is meant for popular 3x3 boards. Performance may degrade with larger grids or lower resolution images, affecting real-time predictions.

- Complexity of Backgrounds: The system might struggle with cluttered backgrounds or low-quality images.
- Accuracy: The accuracy of the image classification model is highly dependent on the quality of the training data.
- Board State Representation: For larger or more complex grids (e.g., 4x4 or 5x5), the current solution may need adjustments or recalibration.
- Real-time Performance: For real-time prediction, the system may face delays, especially on high-resolution images or complex board states.

2 Literature Review

2.1 Related Works

The Tic-Tac-Toe game is widely used for AI concepts and research due to the complete information it provides and the finite number of possible game states, making it an excellent model for implementing decision-making algorithms like Minimax. Eppes [8] identified games as the ideal platform and environment for learning more about artificial intelligence, suggesting that simple games like Tic-Tac-Toe are perfect for testing strategies and algorithms in controlled settings. The Minimax algorithm optimizes a player's decision-making by minimizing potential losses in worst-case scenarios [7]. For Tic-Tac-Toe, this involves evaluating all possible game states to determine the best possible move for the AI. With the use of the concept of combination game theory in Tic Tac Toe, Roopali and Deva [9] mini-max algorithm estimate a step ahead. Ideally, players analyze all possible outcomes to ensure a good win rate. Given that Tic-Tac-Toe is a simple 3x3 game, the resulting state-space tree is relatively small. Anurag, Pratul, and Kalyanmoy [10] implements Genetic Algorithms for the identification of multiple no-loss strategies in Tic Tac Toe, and this gives more insight into the exploration of the strategies'. Anurag, Pratul, and Kalyanmoy [10] also maximize the use of MATLAB matrix analysis to evaluate solutions and develop new strategies. The integration of image recognition in gaming has transformed user interactions. [6, 8] work explored how computer vision can help to enhance mobile gaming using known features such as AR, gesture recognition, and object detection and how image recognition bridges the gap between physical and digital gaming environments, a concept that is central to the Tic-Tac-Toe AI.

3 Proposed Method

3.1 Data Collection and Preprocessing

The first step involves gathering labeled images of Tic-Tac-Toe boards. These images will be preprocessed using standardised methods[2-5]. These includes techniques to:

- Convert images to grayscale to reduce complexity.
- Resize images to a consistent dimension (e.g., 32x32 pixels).
- Normalize the pixel values for better model training.

3.2 Convolutional Neural Network (CNN) for Symbol Classification

A CNN model will be trained to classify the state of each individual cell in the Tic-Tac-Toe grid:

- The model architecture will consist of convolutional layers to extract features[11] and fully connected layers for classification.

- The output of the model will be a classification of the symbol in each grid cell (X, O, or blank).

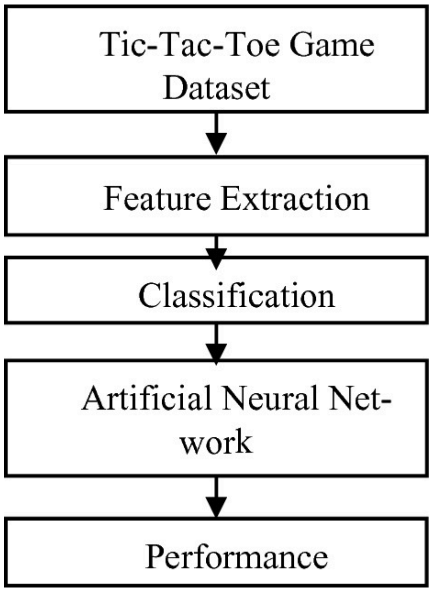

Fig. 1. Architecture of the CNN model for classifying the state of individual cells in a Tic-Tac-Toe grid. The model uses convolutional layers for feature extraction and fully connected layers for classification into three categories: X, O, or blank.

3.3 **Minimax Algorithm for Move Prediction**

The Minimax algorithm will be implemented to predict the next best move for the computer. The algorithm works by evaluating all possible moves, recursively simulating the game until a terminal state (win, lose, or tie) is reached. The evaluation function assigns a score to each move, with the goal being to maximize the computer's chances of winning and minimize the opponent's chances:

- Maximizing: The computer (playing O) aims to maximize its score.
- Minimizing: The opponent (playing X) simply aims to minimize the computer's score.

3.4 **Visualization Technique**

In this project, the visualization of the Tic-Tac-Toe game state and the predicted move will be done using inbuilt Python library and functions. The Matplotlib library is a great tool for creating static, animated, and interactive plots in Python. Once the board state is classified and the next move is predicted, the system will visualize the game state. A grid will be displayed, with X and O positions. The predicted move will be highlighted to show the next move the AI will make.

4 Evaluation and Metrics

The performance of the system will be evaluated based on:

- Classification Accuracy: The percentage of correctly classified cells (X, O, or blank) in the game board.
- Minimax Performance: The effectiveness of the Minimax algorithm in predicting the optimal next move.
- Visualization Quality: The clarity and correctness of the visual output, including the prediction of the next move.

Evaluation will be conducted on a test set of Tic-Tac-Toe images, with accuracy scores and visual assessments of the predictions.

5 Expected Outcome

The expected outcome is a fully functional system capable of:

- Classifying the game state of a Tic-Tac-Toe board from an image.
- Predicting the next optimal move for the computer using the Minimax algorithm.
- Visualizing the game state and highlighting the predicted move for the user.

6 Conclusion

This project will provide a solid foundation for building AI agents that can play Tic-Tac-Toe using both computer vision and game theory. The proposed implementation is to create a system that recognizes (X, O, and blank) on a Tic Tac Toe game board and make predictions of the optimal moves using image processing and minimax algorithms. The outcome is evaluated by a human playing against the AI suggestions, based on an actual time setting. The Tic Tac Toe AI was adopted for a 3x 3 version of Tic Tac Toe and the AI has more optimized performance that's dependent on Analysis of Minimax Algorithm. The Minimax algorithm, rooted in the game theory, enables the system to predict and make optimal moves for the AI player (O), thereby enhancing a competitive gameplay against human opponents. Even with noisy environments and misclassification of the game inputs, through rigorous training, testing, and validation the AI will be more reliable to play against human players.

7 GitHub Repository

This project will be in the following GitHub repository, including the dataset, codes, proposal and report.

https://github.com/Malachi216/TicTacBot

8 Bibliography

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