

An Othello game board with a green grid and black and white pieces. The board is tilted, and the pieces are arranged in a game state. The word "Othello" is visible on the bottom left corner of the board.

Othello CNN

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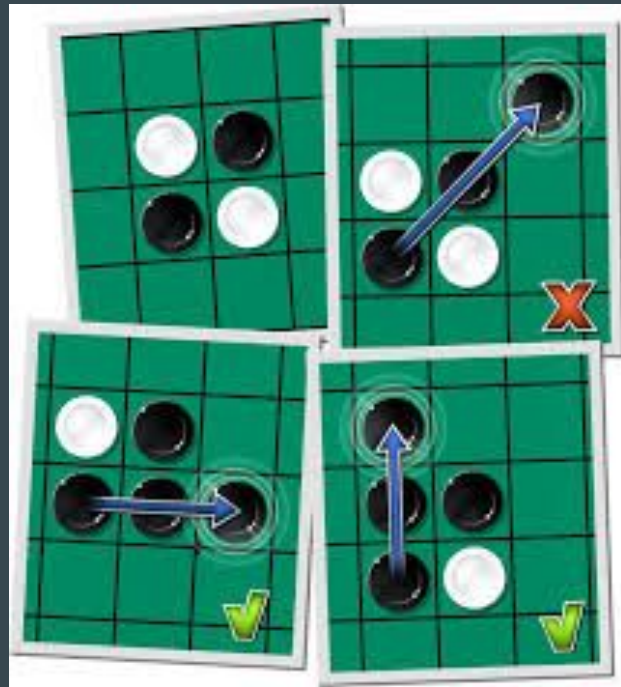
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Brief Background

The goal of the project was to develop a Convolutional Neural Network for the game Othello. The planned approaches included:

- Supervised Learning
- Reinforcement Learning
- Performance Benchmarking/Testing

Only performance benchmarking/testing was completed against a minimax algorithm bot. Supervised learning and reinforcement learning were not fully explored.

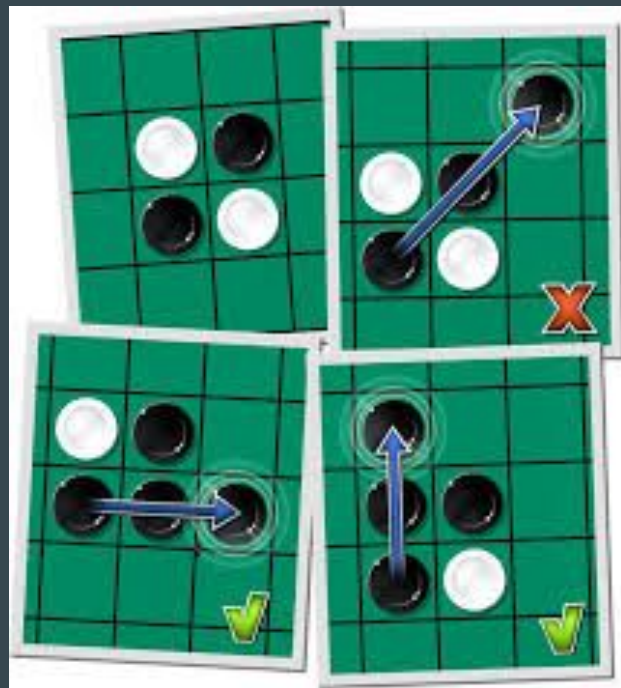


Brief Background

The project was done using three main steps:

- Data Cleaning/Preprocessing
- Training and Tuning
- Performance Benchmarking/Testing

The dataset we used was from the eOthello database, a csv file containing >25,000 games from the 100 best Othello players on the website.



Data Cleaning/Preprocessing: Data Cleaning

In the CSV file, specific rows were removed if they were missing a winner or a game string.

354387	-1	d3c3c4c5f6e3c6f 4b5a6f2f3b4a5a3 b3a2b6d6f1c2a4a 7d2f5e2d1e6g5e1 c1b1g3g6e7f7f8h 5h4h3h6g4h2c7g2 d7e8d8b2b7...
353677		c4e3f5e6d3c5d6c 6f3c3b4b3d2f4f6 c2b5a5a4a3e2d1e 7g5g4h4d7c7b6g3 f2g6h3h2d8f7h5h 6g2h1g1f8e8c8b7 f1g7h8e1g8...
359712	1	f5f6e6d6e7f4g5d 7c6e8c5c4c8d8f8 g4d3f7c3c7e3g3g 8e2h3h5h4h2g6f3 d2b4b3b6f2c2d1f 1e1c1b8a3b5g7a4 g1a5a6b1a1...



354387	-1	d3c3c4c5f6e3c6f 4b5a6f2f3b4a5a3 b3a2b6d6f1c2a4a 7d2f5e2d1e6g5e1 c1b1g3g6e7f7f8h 5h4h3h6g4h2c7g2 d7e8d8b2b7...
359712	1	f5f6e6d6e7f4g5d 7c6e8c5c4c8d8f8 g4d3f7c3c7e3g3g 8e2h3h5h4h2g6f3 d2b4b3b6f2c2d1f 1e1c1b8a3b5g7a4 g1a5a6b1a1...

Data Cleaning/Preprocessing: Game Objects

CNNs interpret visual data like patterns in images, so the game strings were converted to board instances. These instances included 8x8 matrices containing 0s, 1s, and -1s, referring to empty spaces, black pieces, and white pieces in that order.

359712	1	f5f6e6d6e7f4g5d 7c6e8c5c4c8d8f8 g4d3f7c3c7e3g3g 8e2h3h5h4h2g6f3 d2b4b3b6f2c2d1f 1e1c1b8a3b5g7a4 g1a5a6b1a1...
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```
[0, 0, 0, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 0, 0, 0],  
[0, 0, 0, -1, 1, 0, 0, 0],  
[0, 0, 0, 1, 1, 1, 0, 0],  
[0, 0, 0, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 0, 0, 0],  
[0, 0, 0, 0, 0, 0, 0, 0]
```

Data Cleaning/Preprocessing: Pruning

To better optimize the training data, the original 25000 games were reduced to 10500. Of this, 5000 were white wins, 5000 are were wins, and 500 were ties. The board instances of these games were then converted into a PyTorch Tensor.

25000 Games

483716	1	f5f6e6f4g6f7g5e 7d6c7d7h4h5c4h3 c8c5g4f8e8g3g8f 3c6c3c2d8h7h6h2 e3g7h8d2h1e2g2f 2d3g1f1e1d1c1b6 b5a5a6a7b7...
482856	1	f5f4e3d6f3g5f6g 3g4e7h6g6h4d3f2 f1e6h5h3f7d7d8f 8e8c8c7g8g2b7g7 e2h2h1g1h8d1h7b 8a8d2c1b1b6c2c6 c5c4b4a7a6...
482854	1	f5f4e3f6d3c5d6c 7d7c4e6f2f3c6c3 d8f1e2d2c2g5g6e 7d1g4e1c1h3h4f8 f7e8h6g3b1h5h2g 7b3b5a6a4h7b2b4 a3a5a7a1b6...



5000 white wins - 5000 black wins
- 500 ties -

1	f5f6e6f4g6f7g5e 7d6c7d7h4h5c4h3 c8c5g4f8e8g3g8f 3c6c3c2d8h7h6h2 e3g7h8d2h1e2g2f 2d3g1f1e1d1c1b6 b5a5a6a7b7...
1	f5f4e3d6f3g5f6g 3g4e7h6g6h4d3f2 f1e6h5h3f7d7d8f 8e8c8c7g8g2b7g7 e2h2h1g1h8d1h7b 8a8d2c1b1b6c2c6 c5c4b4a7a6...

Data Cleaning/Preprocessing: Final Training Dataset

Finally, the data was ready to be used. To train the CNN directly, the data had to be processed into a PyTorch Dataset. To do so, the subsequent steps were followed:

1. OthelloDataset was created to iterate through each game and its sequence of board instances
2. A second channel was added to the PyTorch Dataset to keep track of player moves associated with each board state
3. A move index was calculated for each individual tensor; this data was appended to the OthelloDataset
4. A PyTorch dataloader was created using the dataset with a batch size of 32 randomized games

Training and Tuning: Model Setup

The Othello model was initialized and works by taking in a board instance, extracting spatial patterns via four specified convolutional layers, and by using these four connected layers to output 64 move probabilities (per board move). We initially used 3 layers, but added a 4th one due to high loss.

Fully connected layers (FC1 & FC2) process flattened convolutional features using PyTorch's `nn.Linear`. The optimizer (PyTorch Adam) updates weights with a learning rate of 0.001 to balance precision and stability. These layers perform matrix operations to transform the input board instances.

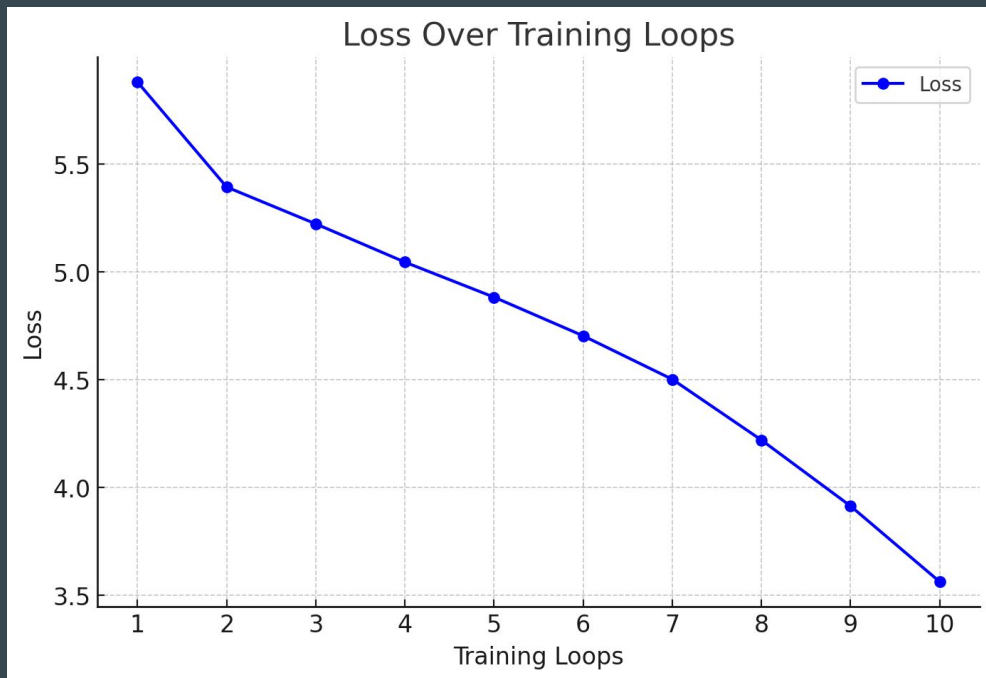
Training and Tuning: Training Loops

The training loop runs for 10 epochs on our game dataset. Train 1 took 30 minutes (8.6MB), while Train 2 with the extra layer took 2 hours (10MB). The loss function, found in `model.py`, applies weighted cross-entropy based on player color and game outcome. Loss is back-propagated, and weights are updated after each batch.

The loss and training statistics are printed after each epoch to help track model performance.

Training and Tuning: Train 1 Output

The results were saved as a PyTorch state dictionary to store all the data and parameters.
Below are the results of the second main train.



Train 1 Output (3 conv layers):

Data set up

Model set up

Epoch [1/10], Loss: 5.8806

Epoch [2/10], Loss: 5.3936

Epoch [3/10], Loss: 5.2227

Epoch [4/10], Loss: 5.0452

Epoch [5/10], Loss: 4.8826

Epoch [6/10], Loss: 4.7033

Epoch [7/10], Loss: 4.5016

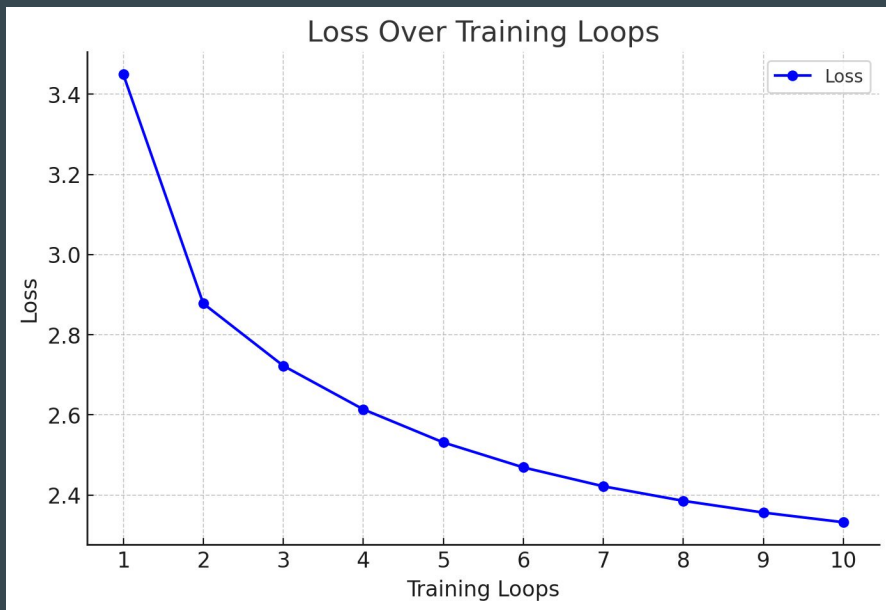
Epoch [8/10], Loss: 4.2197

Epoch [9/10], Loss: 3.9136

Epoch [10/10], Loss: 3.5624

Training and Tuning: Train 2 Output

The results were saved as a PyTorch state dictionary to store all the data and parameters.
Below are the results of the second main train.



Train 2 Output (4 conv layers):

Data set up

Model set up

Epoch [1/10], Loss: 3.4500

Epoch [2/10], Loss: 2.8779

Epoch [3/10], Loss: 2.7225

Epoch [4/10], Loss: 2.6138

Epoch [5/10], Loss: 2.5312

Epoch [6/10], Loss: 2.4689

Epoch [7/10], Loss: 2.4217

Epoch [8/10], Loss: 2.3854

Epoch [9/10], Loss: 2.3561

Epoch [10/10], Loss: 2.3320

Performance Benchmarking/Training

For the performance testing of our CNN, we let it play against a minimax algorithm for Othello since it is a commonly used algorithm for Othello due to its efficiency.

We set the depth of the minimax algorithm to 8, to balance between the playing strength and computation time. In the 20 games played, our CNN bot tied every game as white, and lost every game as black.

Game	Starting Color (CNN)	Winner	Score
1	Black	MM	30-34
2	Black	MM	30-34
3	Black	MM	30-34
4	Black	MM	30-34
5	Black	MM	30-34
6	Black	MM	30-34
7	Black	MM	30-34
8	Black	MM	30-34
9	Black	MM	30-34
10	Black	MM	30-34
11	White	Tie	32-32
12	White	Tie	32-32
13	White	Tie	32-32
14	White	Tie	32-32
15	White	Tie	32-32
16	White	Tie	32-32
17	White	Tie	32-32
18	White	Tie	32-32
19	White	Tie	32-32
20	White	Tie	32-32

Conclusion

We developed an Othello bot CNN based on a set of expert games and achieved a significant loss reduction through two trains, with our addition of another convolutional layer. While the model demonstrated efficient move prediction, its performance against a minimax Othello bot at ply 8 revealed limitations that we hope to address in the future.

We'd like to improve our bot further by implementing reinforcement learning on our current CNN. This training would play itself, using a Q-score to measure performance. We would also like to train our Othello bot against other online bots, since they likely use advanced heuristic models for their AI.