Comparing Feed-Forward and Convolutional Neural Networks by Training Poker AIs

Delkhaz Ibrahimi
Department of Computer Science
Middle Tennessee State University
Murrfreesboro, Tennessee USA
dai2i@mtmail.mtsu.edu

Loraina Lampley
Department of Computer Science
Middle Tennessee State University
Murrfreesboro, Tennessee USA
lnl2v@mtmail.mtsu.edu

Brandon Lowery
Department of Computer Science
Middle Tennessee State University
Murrfreesboro, Tennessee USA
bdl3k@mtmail.mtsu.edu

Jeremy Watts
Department of Computer Science
Middle Tennessee State University
Murrfreesboro, Tennessee USA
jnw5c@mtmail.mtsu.edu

***Abstract*—Computer gaming has brought about a need for computerized players that can perform with relative success against human players. The difficultly of this task is proportionate to the game that the AI needs to learn. Poker game AI need to be able to make intelligent decisions to decide whether to bet on a hand. Before the successful poker AI can play against professional players, the AI needs to be trained to classify its hand. Neural networks can be used for this training with varying success depending on the neural network used. Feed-forward neural networks and convolutional neural networks are both used primarily for classification. Feed-forward neural networks have shown the capacity to perform this task with relative accuracy. This experiment tests whether a convolutional neural network would also be able to perform poker hand classification at a similar or higher capacity. When undergoing training with the same data, the accuracy was measured to determine the comparative success and demonstrate which can perform the task better. The experimental results showed that the feed-forward neural network had a 98% accuracy and the convolutional neural network had a 98% accuracy at hand classification. This implies that a poker AI that could compete professionally would be potentially as successful using a feed-forward network as a convolutional neural network for the classification layer. The next considered step is to test these neural networks in a game of poker with human players using the classification of the neural network to make the game decisions.**

***Index Terms*—feed-forward, convolutional, neural network, poker, AI, classification**

I. Introduction

Gaming is a common way to test an individuals aptitude to complete a specified challenge. In competitive gaming, the individuals ability is often measured against a set precedent or another human player. Competitive games have evolved to now include computer games with computerized players that an individual can compete against. This creates the problem of how to create a good computerized player that would be able to actively respond to the game conditions as it progresses throughout the various stages of the game. A solution to this problem would be to find a technique that could develop a computerized artificial intelligence, AI, that could identify the circumstances of the game and then react based on those observations. One technique that can be used for the development of the AI, is the implementation of a neural network to train the AI in the game procedure. A computer player that was trained by the neural network would then be able to compete in the game with some capacity to respond to the game environment. The level of training necessary would be relative to the complexity of the game.

Poker is an example of a competitive game that is often generated with computerized players. The game itself has many variations of differing complexity. The poker variant 5-Card Stud has 2,598,960 different hand combinations in a standard 52 card deck. This is from only one draw of a 5-card hand, but a draw phase would lead to an even larger pool of possibilities. These different hands are then classified into categories based on the value of the cards. The categories of hands, ranks and odds of each hand are detailed in **Table** I. With this many possible hands, it is easy to see how difficult it could be to train an AI to categorize all the possible hands. The difficulty continues as poker not only has an ample collection of hands, but also adds an element of betting, raising, or folding based on the likelihood of one player having the better hand. This decision can be assisted by knowing the rank of the current hand and the odds of the opponent having a hand that has a higher rank. Computerized players must be able to identify the hand and then use a categorical approach and significant training to determine how likely it is to have a better hand then the other player. A poker AI that uses only a categorical approach would choose to bet, raising or fold armed with nothing else other than its ability to classify a hand. Then it would determine how likely it is to be in the lead based on prior knowledge of the statistics of that hand. A professional poker AI would need to use extra steps to adapt to the individual game, but classification remains the basis for poker playing.

This investigation is meant to compare a feed-forward neural network and a convolutional neural network to train an AI to classify poker hands. The competence of the neural networks is measured by the accuracy that the model shows for classification. A feed-forward and a convolutional neural network are created using the same training and testing data. These neural networks are then tested against each other to determine the viability of these different neural networks to classify poker hands. Feed-forward neural networks have previously been used for poker hand classification. The feed-forward neural network provides a decent classifier, but it remains to be seen if it is the best available for the task. Furthering the attempt to create the best classification neural network, a convolutional neural network will be trained using the same data as a feed-forward network to determine if a convolutional neural network can serve as another practical classifier.

TABLE I
POKER HAND TYPES

Rank	Hand Name	Odds
10	***Royal Flush***	***0.00000154***
9	***Straight Flush***	***0.00001385***
8	***Four of a Kind***	***0.00024010***
7	***Full House***	***0.00144058***
6	***Flush***	***0.00196540***
5	***Straight***	***0.00392465***
4	***Three of a Kind***	***0.02112845***
3	***Two Pair***	***0.04753902***
2	***Pair***	***0.42256903***
1	***Nothing***	***0.50117739***

[a]Probabillities based on Five Card Stud. [1].

II. BACKGROUND

There have been many advancements in training a computer AI to play games competitively against expert human players. Some of the games include common strategy board games, classic arcade games, and card games. A recent development in computer AI gaming is the attempt to make an AI that could play professional poker. The difficulty in training an AI to play poker verses other games, is that the previous games allow the players to have all the information. Poker, however, relies on the players inability to know the hand of the other players. This is necessary for betting, raising, folding, and bluffing on a professional level. The lack of information changes the way the AI must learn how to play.

Poker AI are limited and unable to diagnose a pattern of the other player by known human signs. An expert poker AI needs to learn to adjust its strategy during the game to account for the unknown factor available in poker. The goal is to adjust the AI strategy with every round. DeepStack is the first algorithm capable of beating a professional poker player during heads-up-no-limit Texas holdem poker. This would serve as the ultimate test for an AI as the game highly relies on the players ability to understand and diagnose a pattern of the other players. This algorithm continuously resolves the games strategy during the game as the AI learns how to play against the opponent. DeepStack uses Deep Counterfactual Value Networks, that include a feedforward neural network. This presents the chance for many new advancements in artificial intelligence when applied to other decisions that are made with imperfect information. [2].

Before a poker AI can ever be trained for tournament play, the neural network would need to be able to classify poker hands and determine the odds for that hand. Even the most advanced AI would suffer if it was not able to determine what was in its hand. This indicates that a decision for the classification neural network would be instrumental in the beginning stages of creating a professional AI. There have been many classification neural networks that have been tested for this purpose. Computer Scientist Suraiya Jabin, created a feed-forward neural network that insured a 94% accuracy when classifying a poker hand. [3]. In this article, it is shown how the feed-forward neural network was constructed and alternate ideas for future advancement.

III. METHODS

The first step was to create two separate neural networks after importing keras. [4]. The same data was used for the training to determine which neural network would have the best accuracy at classifying poker hands. A feed-forward neural network is a multilayer neural network that passes information through the layers. The information is fed-forward through the input layer, then the hidden layer(s), and lastly to the final layer that produces the output of the neural network. Feed-forward neural networks are primarily used for classification. A convolutional neural network is a specialized kind of neural network for processing data by finding the relationships of subsamples of that data. A convolutional neural network consists of convolution layer(s), pooling layer(s), and the fully connected layers. Convolutional neural networks are primarily used for image classification. [5].

These networks will be used to classify poker hands with data provided by Robert Cattral and Franz Oppacher from the Computer Science department at Carleton University featured at the UCI Machine Learning Library. [6]. This dataset has the information on the classification of the different poker hands and odds, as well as training and testing data that can be loaded into the neural networks. These datasets were encoded to both neural networks providing each with the same data. This was done with the help of the Guide to Encoding Categorical Values in Python. [7].

The architecture of neural networks is important to understand how the neural network was able to train and learn. The architecture of the feed-forward network was a model that consisted of four Dense layers. Compiled with the Adam optimizer with default values, the model provided 536, 074 parameters. The architecture of the convolutional neural network model consisted of two convolution layers, a max pooling layer, flatten layer, dense layer, dropout layer, and a final dense layer. Compiled with the Adam optimizer with default values, the model provided 660, 764 parameters. Training on each was done on the specific model with a batch size of 100 and 25 epochs. The accuracy and loss were plotted and can be seen in the provided figures: Feed-forward neural network

Fig. 1 and convolutional neural network Fig. 2. The completed neural networks with the plotted accuracy showed the neural networks ability to classify the poker hands.

IV. Results

The accuracy and loss plots give the implication that convolutional neural networks are also suited to the task of classifying poker hands. Feed-forward neural networks showed a steady improvement as the accuracy continued to increase and the loss continued to decrease. Fig. 1. This means that the feed-forward neural network was able to learn gradually with the data provided for training. The final loss dropped to 0.08 and the accuracy rose to 0.98. This concludes that the neural network would be able to correctly classify the hand roughly 98% of the time. The convolutional neural network also showed consistent improvements, but with faster rate between around 6 epochs and 12 epochs reaching to almost 90% accuracy. The accuracy and loss improved more slowly to the end of the test. This would imply that the neural network was able to classify the poker hands faster with less epochs. The final loss dropped to 0.05 and the accuracy rose to 0.979. This concludes that the convolutional neural network would also be able to correctly classify the hand roughly 98% of the time.

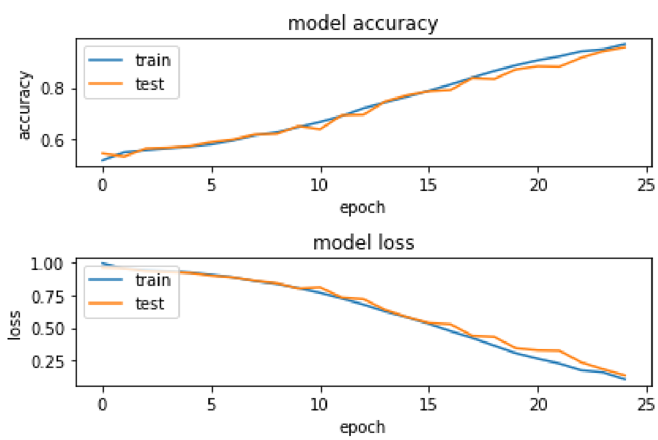

Fig. 1. Accuracy and loss for feed-forward neural network shows consistant improvement during training and testing.

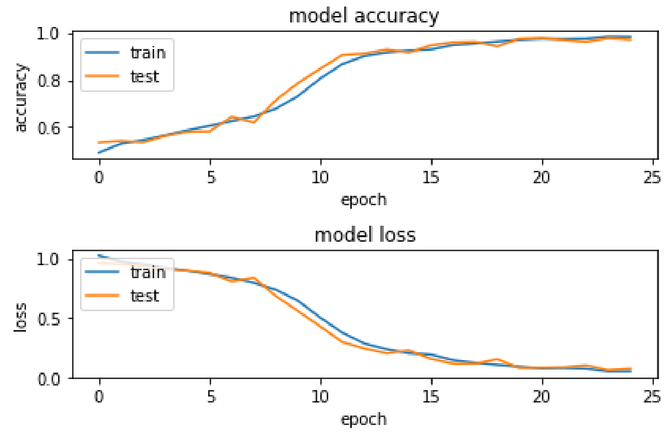

Fig. 2. Accuracy and loss for convolutional neural network shows a faster improvement before steadying towards the end of training and testing.

.

V. Discussion

The result of the investigation showed that a convolutional neural network was similarly competent at classifying poker hands as feed-forward neural networks. The experimental neural networks show high accuracy for both neural networks when using the same data. When considering game play against a human player, it becomes clear that the accuracy of classifying the poker hands would affect the neural networks ability to win. Convolutional neural networks appear to be another viable neural network for classification in poker. This holds the possibility of training both neural networks with different models to maximize the classification ability. The data provided a good training and testing set to be used for future models. With the modification of the architecture, it will be possible to make a neural network that has an even greater capacity to make more informed decisions. Developing a neural network that is very successful at classifying poker hands, will form the first step of creating further professional poker AI that can compete in tournament style poker.

The next step in furthering this investigation, could be uploading the neural networks into a poker game as the game AI. This would give a good opportunity to further test the convolutional neural network classification. The game would provide a method to check on the performance of the neural networks against another opponent. The ratio of the neural networks to win will be directly related to the ability to classify the poker hands. Since this would provide a categorical approach, the AI would only be successful at making informed decisions if it could calculate the odds. If the neural network was not able to classify the poker hands accurately for the games, the neural network would play only slightly better than a random function to decide on what cards to draw. The neural network would have a chance to win, but the overall win ratio would be low. A successful neural network would have a larger win ratio, since the classification was accurate. The final output would display the hands of the players as well as who won, so that the neural network could be monitored. This provides for an interesting future development to further test a convolutional neural network in classification of poker hands.

References

[1] M. Shackleford. (2018, March) Poker probabillities - wizard of odds. [Online]. Available: https://wizardofodds.com/games/poker/

[2] M. Moravcík, M. Schmid, N. Burch, V. Lisý, D. Morrill, N. Bard, T. Davis, K. Waugh, M. Johanson, and M. H. Bowling, "Deepstack: Expert-level artificial intelligence in no-limit poker," *CoRR*, vol. abs/1701.01724, 2017. [Online]. Available: http://arxiv.org/abs/1701.01724

[3] S. Jabin, "Poker hand classification," pp. 269–273, 04 2016.

[4] F. Chollet *et al.*, "Keras," https://keras.io, 2015.

[5] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, http://www.deeplearningbook.org.
[6] D. Dheeru and E. Karra Taniskidou, "UCI machine learning repository," 2017. [Online]. Available: http://archive.ics.uci.edu/ml
[7] C. Moffitt, "Guide to encoding categorical values in python." [Online]. Available: http://pbpython.com/categorical-encoding.html