

Classification of the Chess Endgame problem using Logistic Regression, Decision Trees, and Neural Networks

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Abstract

In this study we worked on the classification of the Chess Endgame problem using different algorithms like logistic regression, decision trees and neural networks. Our experiments indicates that the Neural Networks provides the best accuracy (85%) then the decision trees (79%). We did these experiments using Microsoft Azure Machine Learning as a case-study on using Visual Programming in classification. Our experiments demonstrates that this tool is powerful and save a lot of time, also it could be improved with more features that increase the usability and reduce the learning curve. We also developed an application for dataset visualization using a new programming language called Ring, our experiments demonstrates that this language have simple design like Python while integrates RAD tools like Visual Basic which is good for GUI development in the open-source world.

Introduction

In a puzzle game like a Chess, the game could have the next three stages [1-3].

1. Chess Opening
2. Chess Middlegame
3. Chess Endgame

The Chess Endgame is a state where we have a few numbers of pieces left on the board [4-5]. There are many studies that uses different algorithms to predict the result of the Chess endgame [6-8]. In this study we will apply a group of algorithms on the chess endgame problem (King Rook vs King) and test the accuracy of the multiclass classifiers [9-10].

The remainder of this paper is organized as follows. Section 2. Describe the related works. Section 3. Illustrates the problem definition. Section 4. Demonstrates using Microsoft Azure Machine Learning to implement the different models. while Section 5. Demonstrates using the Ring programming language to build the Chess Endgame Application which provides Data Set Visualization and a use interface for game result prediction. Finally, we present the future work and the conclusion in Section 6.

Related Work

The UCI Machine Learning Repository contains the King-Rook vs King data set [11]. In 1994, The Data Set authors (Bain et all) report classification results with an accuracy of 16% over the entire data set [12-13]. Their study is done using inductive logic programming [14-16]. In 2006, Lassabe et al. studied using Inductive logic programming (ILP) and Genetic Programming (GP) to create computer programs that play the chess end game, but their study does not present the classification results [17].

In 2012, Wayne Iba (Westmont College), used genetic algorithms and report accuracy between 20% and 30% using 1000 samples of the Data Set in the training stage [18]. Instead of using Inductive logic programming or Genetic Programming, the Machine Learning field contains a lot of algorithms and methods that we can try to use like Logistic Regression [19-20], Modern decision trees algorithms like Decision Jungle [21-22], Decision Forest [23-25].

Also, we can use the Artificial Neural Networks [26-32].

The next table presents the results in the previous studies

Index	Author	Algorithm	Accuracy	Year	Ref.
1	Wayne Iba	Genetic Algorithms	30%	2012	18
2	Lassabe	IPL & GP	Not Available	2006	17
3	Bain et all	Inductive Logic Programming	16%	1994	15

Table 1.

Visual programming languages (VPLs) are tools that can be used to create computer programs and software without writing textual code directly. In VPLs programming are done using more than one dimension, and a mix of text, shapes and icons could be used. Also some visual programming languages add the time dimension to programming [33-34].

There are VPLs in many domains and Microsoft Azure Machine Learning tool uses Visual Programming to reduce the learning curve and increase the productivity of producing machine learning models that could be intenerated to many applications [35-37]. We can use Microsoft Azure Machine learning to try many algorithms quickly and get results in short time. Also we can use a modern textual programming language like the Ring programming language to develop the application. Ring is a new language influenced with many programming language. It's dynamic and simple like Python but, comes with Rapid Application Development tools like Visual Basic [38]. The language is designed for developing the second generation of the Programming Without Coding Technology software [39-41]. PWCT is a popular visual programming language which is used in many applications and systems including the development of the Supernova language and the Critical Nodes application for the LASCNN algorithm [42-43]. Ring is influenced by many programming languages including Lua, Python, Ruby, C, C#, Basic, QML, xBase, and Supernova. [44]

The Chess Game

In the Chess Game each player goal is delivering a checkmate by trapping the opponent's king. "The possible number of chess games is so huge that no one will invest the effort to calculate the exact number.", Jonathan Schaeffer (University of Alberta). The chess board contains eight files (a,b,c,d,e,f,g,h) and eight ranks (1,2,3,4,5,6,7,8). The position of each piece on the board could be determined using the file and the rank. A common chess endgame situation is having (King-Rook) vs (King).

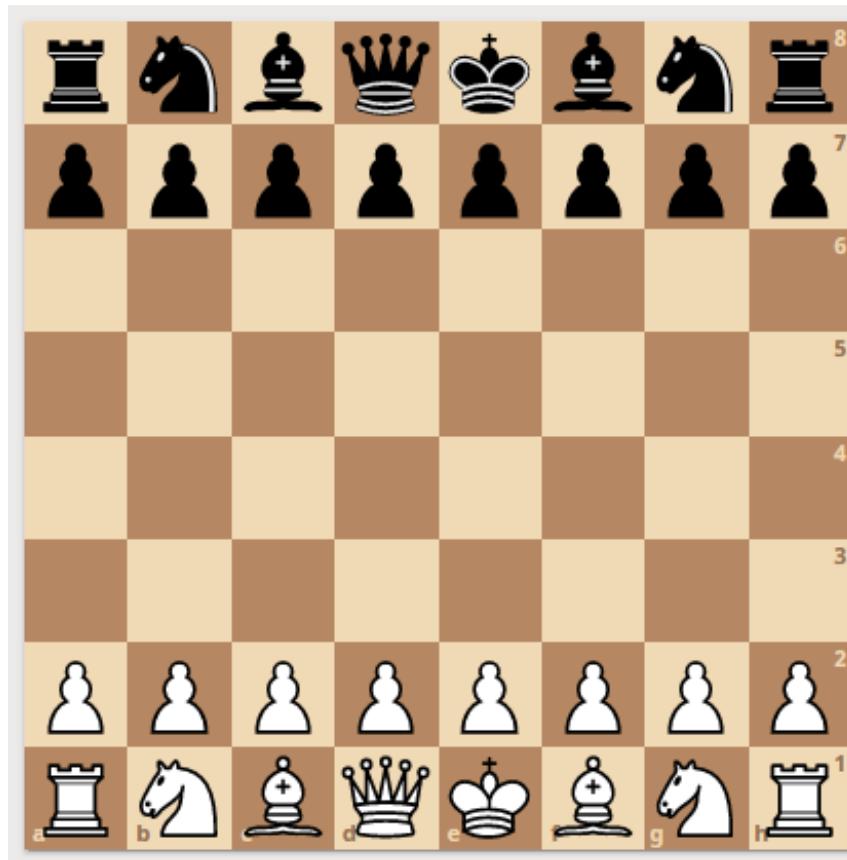


Fig. 1

Chess (King-Rook vs King) Data Set

The data set contains 28056 instances, the date donated is 1994-06-01 and the number of attributes is six.

Attribute Information:

- 1. White King file (column)
- 2. White King rank (row)
- 3. White Rook file
- 4. White Rook rank
- 5. Black King file
- 6. Black King rank
- 7. optimal depth-of-win for White in 0 to 16 moves, otherwise drawn {draw, zero, one, two, ..., sixteen}.

White King file	White King rank	White Rook file	White Rook rank	Black King file	Black King rank	Result
a	1	b	3	c	2	draw
a	1	c	1	c	2	draw
a	1	c	1	d	1	draw
a	1	c	1	d	2	draw
a	1	c	2	c	1	draw
a	1	c	2	c	3	draw
a	1	c	2	d	1	draw
a	1	c	2	d	2	draw
a	1	c	2	d	3	draw
a	1	c	3	c	2	draw
a	1	c	3	d	2	draw
a	1	c	3	d	3	draw
a	1	c	3	d	4	draw
b	1	g	3	e	5	sixteen
b	1	g	3	f	5	sixteen
b	1	g	3	g	5	sixteen
b	1	g	6	e	4	sixteen
b	1	g	6	e	5	sixteen
b	1	g	6	e	6	sixteen
b	1	g	6	f	4	sixteen
b	1	g	6	g	4	sixteen
b	1	g	7	e	5	sixteen
b	1	g	7	e	6	sixteen
b	1	g	7	e	7	sixteen
b	1	g	7	f	5	sixteen
b	1	g	7	g	5	sixteen

Fig. 2

The King can move one square in any direction (horizontally, vertically, or diagonally) while the Rook can move any number of squares in vertical or horizontal direction. According to the Data Set the player who will play the next move will control the Black King. In the next game the optimal result is (Draw) because the Black King can move from (C2) to (B3) and take the Rook which means (King vs. King) which is a draw.

Piece	File	Rank
White King	a	1
White Rook	b	3
Black King	c	2

Table. 2

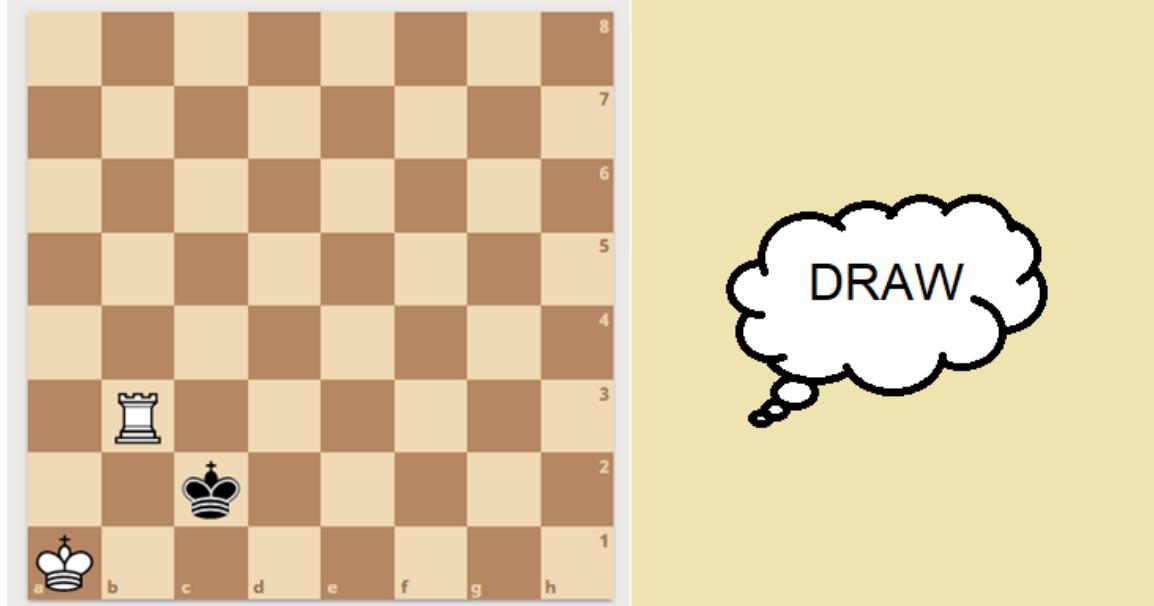


Fig. 3

In the next game, the White will win in one move

Piece	File	Rank
White King	c	1
White Rook	c	3
Black King	a	2

Table. 3

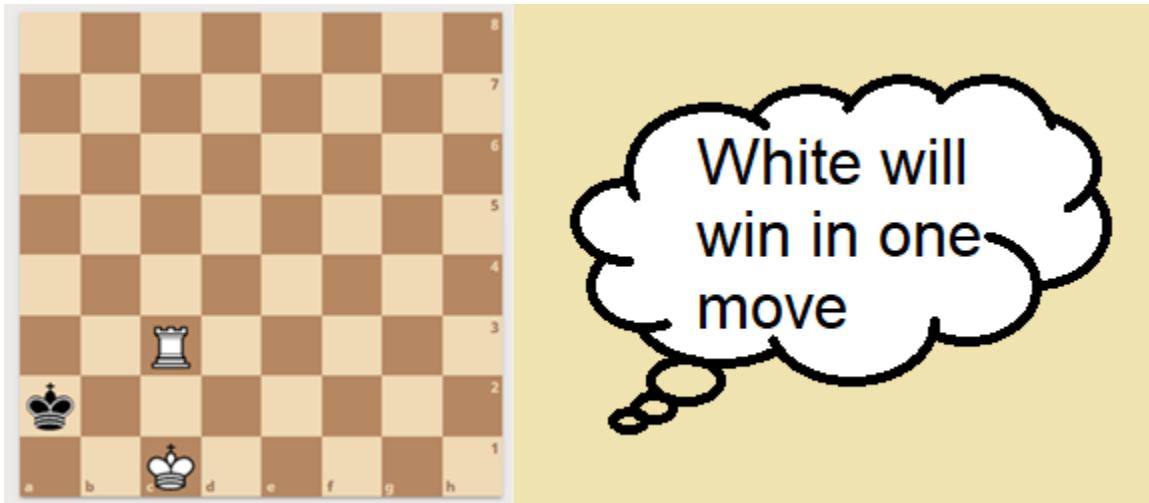


Fig. 4

The Black king must play, He can't move to A3, B3 because of the White Rook, and can't move to B1,B2 because of the White King. He can move only to A1

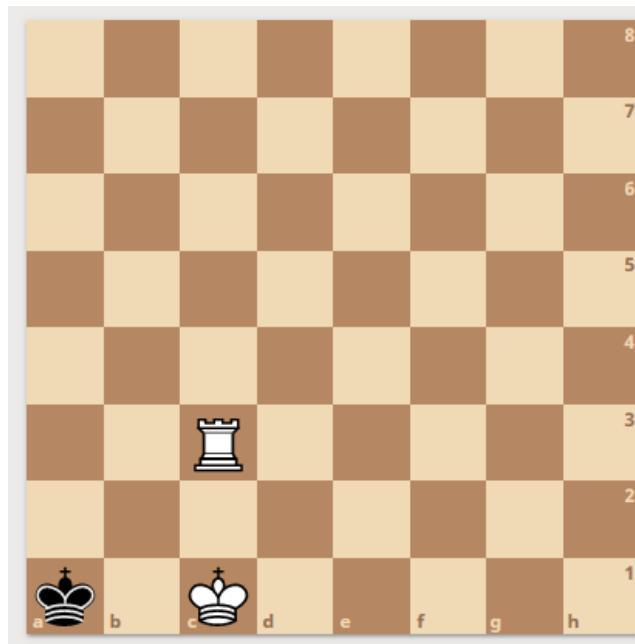


Fig. 5

In this situation, the White Rook moves from C3 to A3 and the white player wins the game (Checkmate for the Black King)

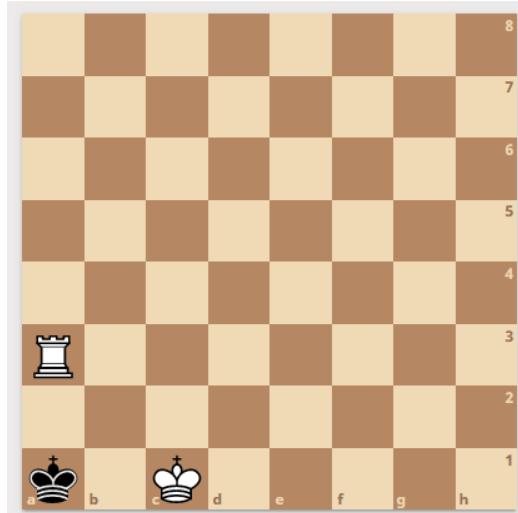


Fig. 6

Algorithms and development tools

This study uses the next algorithms for classification.

- Multiclass Decision Forest
- Multiclass Decision Jungle
- Multiclass Logistic Regression
- Multiclass Neural Network

The next tools are used for development.

- Microsoft Azure Machine Learning
- The Ring programming language

Steps

- Prepare and Analysis the Data Set
- Normalize the Data.
- Split the Data (Training Data & Test Data)
- Select the Model (Algorithm)
- Training
- Testing (Calculate the Accuracy)
- Compare the Results Between the different Algorithms.

Using Azure Machine Learning

The screenshot shows the Microsoft Azure Machine Learning Studio (classic) interface. On the left, there's a sidebar with icons for Projects, Experiments, Web Services, and Datasets. The Datasets section is selected, showing a list titled 'datasets'. Under 'MY DATASETS', there is one entry: 'chess.csv'. The details for this dataset are shown in a table:

NAME	SUBMITTED BY	DESCRIPTION	DATA TYPE	CREATED	SIZE	PROJECT
chess.csv	msfclipper	Chess	GenericCSV	3/6/2021 3:03:12 PM	546.83 KB	test1

At the bottom of the screen, there are buttons for NEW, DOWNLOAD, DELETE, GENERATE DATA ACCESS CODE, and ADD TO PROJECT.

Fig. 7

Logistic Regression

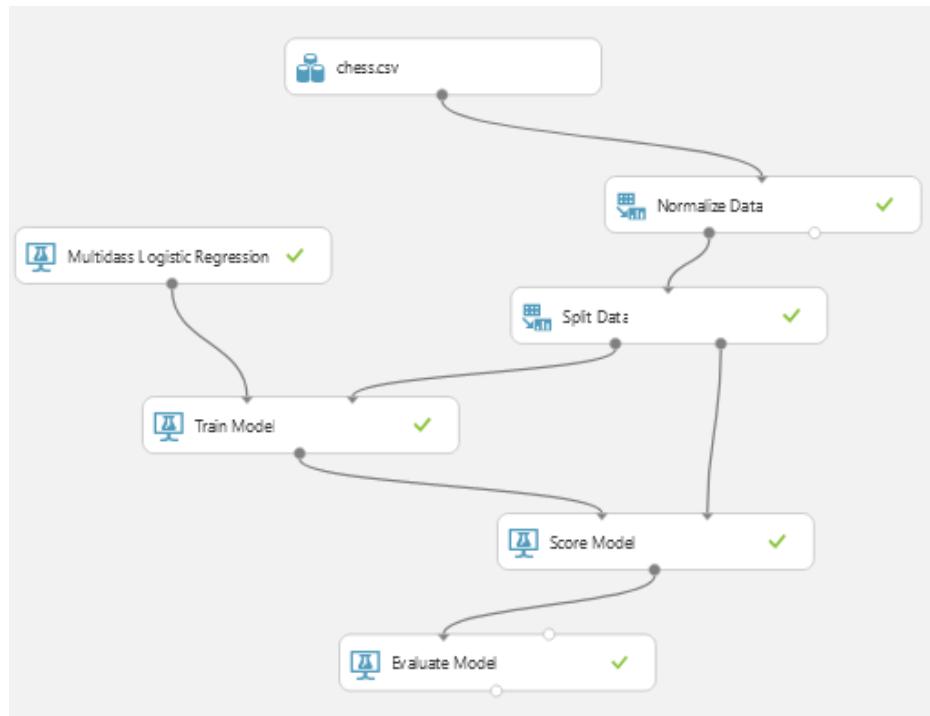


Fig. 8

◀ Metrics

Overall accuracy	0.321255
Average accuracy	0.924584
Micro-averaged precision	0.321255
Macro-averaged precision	NaN
Micro-averaged recall	0.321255
Macro-averaged recall	0.282853

Fig. 9

Multiclass Decision Jungle

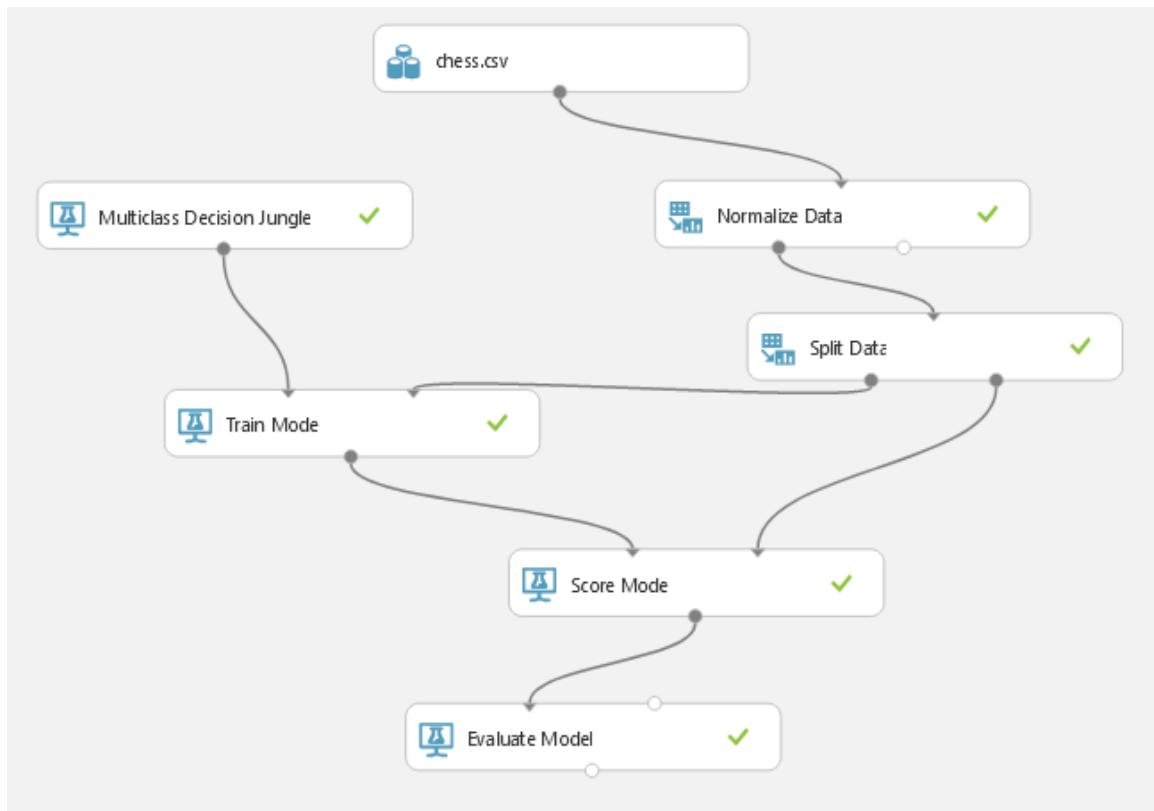


Fig. 10

◀ Metrics

Overall accuracy	0.496376
Average accuracy	0.944042
Micro-averaged precision	0.496376
Macro-averaged precision	NaN
Micro-averaged recall	0.496376
Macro-averaged recall	0.455527

Fig. 11

Multiclass Decision Forest

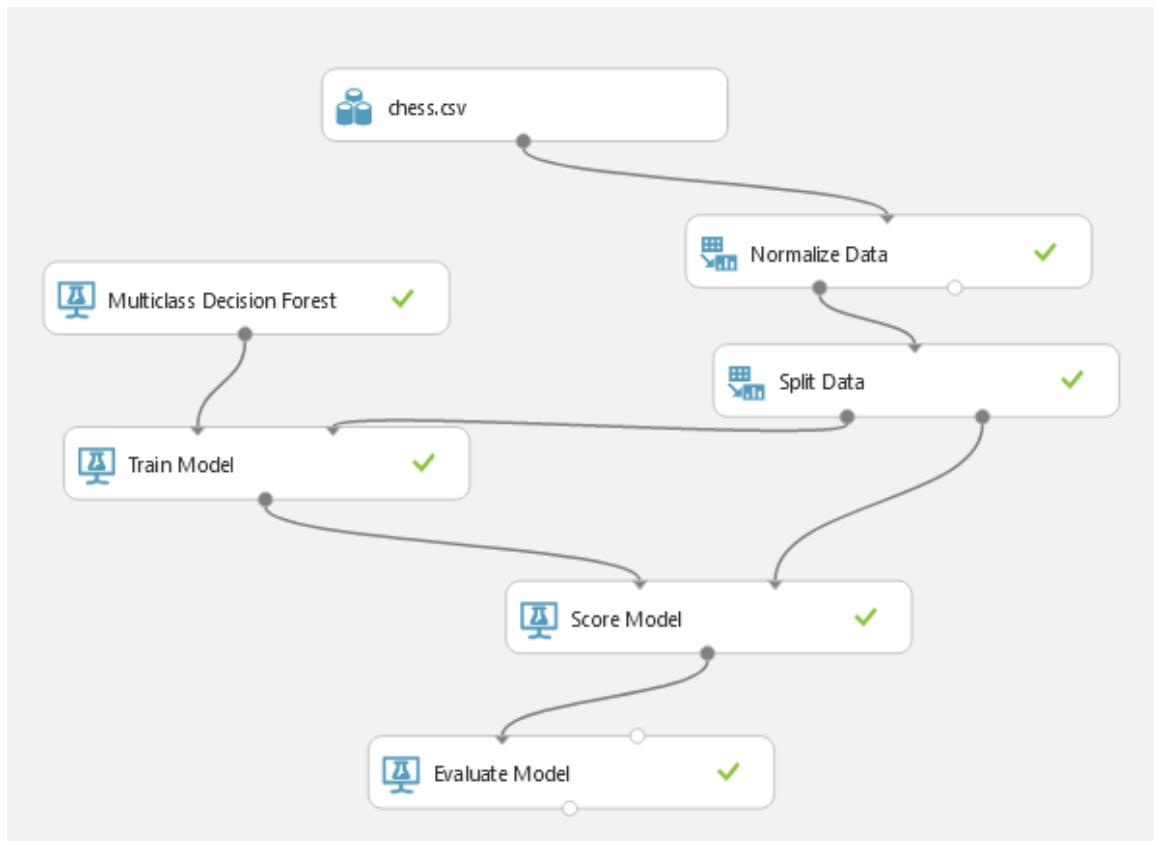


Fig. 12

◀ Metrics

Overall accuracy	0.793038
Average accuracy	0.977004
Micro-averaged precision	0.793038
Macro-averaged precision	0.798891
Micro-averaged recall	0.793038
Macro-averaged recall	0.792915

Fig. 13

Neural Network

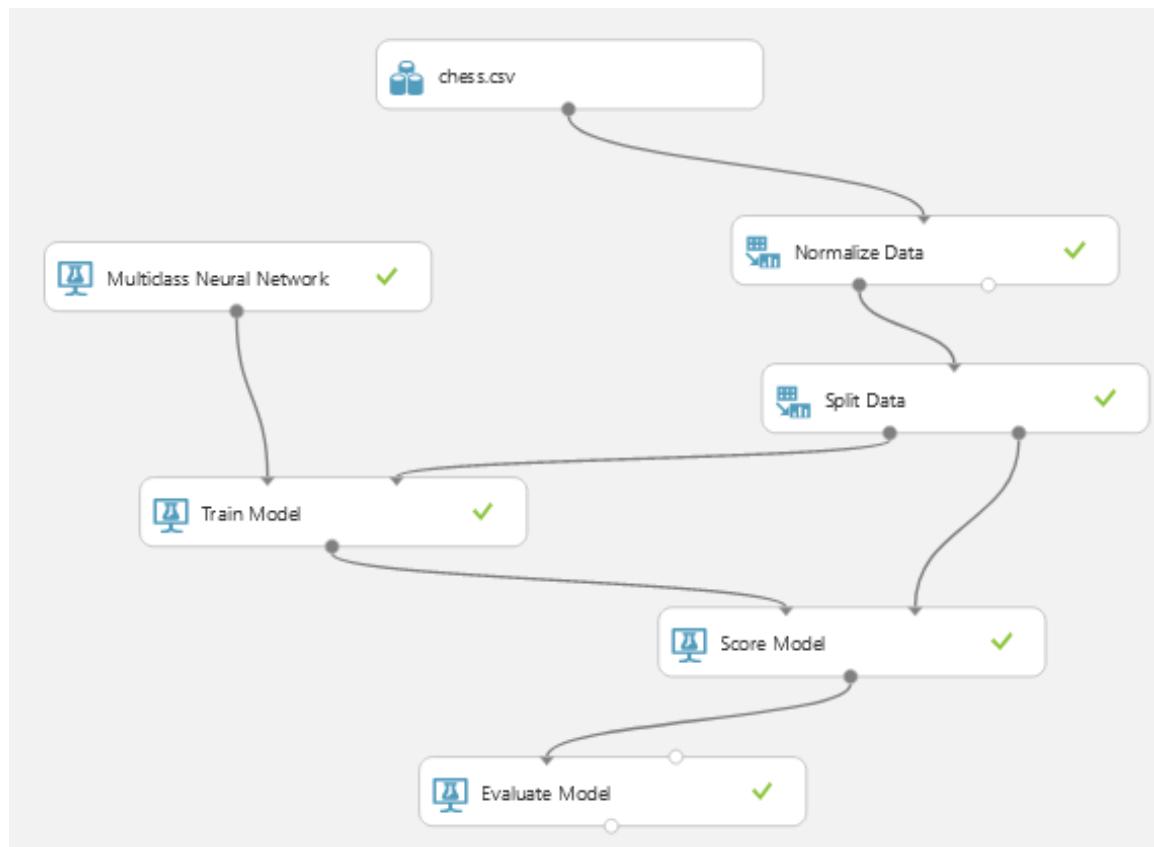


Fig. 14

◀ Metrics

Overall accuracy	0.622668
Average accuracy	0.958074
Micro-averaged precision	0.622668
Macro-averaged precision	0.631862
Micro-averaged recall	0.622668
Macro-averaged recall	0.565878

Fig. 15

Early Results

Algorithm	Overall Accuracy	Average Accuracy
Multiclass Decision Jungle	0.496376	0.944042
Multiclass Decision Forest	0.793038	0.977004
Logistic Regression	0.321255	0.924584
Neural Network	0.622668	0.958074

Fig. 16



Fig. 17

Changing the Neural Network Parameters

The Azure Machine Learning tool provide some parameters that we can set for our neural network, like the number of nodes, training time and the number of iterations. We tried many variations of these parameters and checked the change in the accuracy.

No. of Nodes	Learning rate	No. of iterations	Overall Accuracy	Average Accuracy
100	0.1	100	0.62	0.95
100	0.1	1000	0.66	0.96
100	0.1	10000	0.64	0.96
1000	0.1	100	0.66	0.96
1000	0.1	1000	0.71	0.96
1000	0.1	10000	0.71	0.96
10000	0.1	100	0.65	0.96
10000	0.1	1000	0.72	0.96
10000	0.1	10000	0.72	0.96
100	0.01	100	0.60	0.95
100	0.01	1000	0.67	0.96
100	0.01	10000	0.69	0.96
1000	0.01	100	0.60	0.95
1000	0.01	1000	0.71	0.96
1000	0.01	10000	0.72	0.96
10000	0.01	100	0.55	0.95
10000	0.01	1000	0.71	0.96
10000	0.01	10000	0.73	0.97
100	0.001	100	0.33	0.92
100	0.001	1000	0.60	0.95
100	0.001	10000	0.68	0.96
1000	0.001	100	0.28	0.92
1000	0.001	1000	0.58	0.95
1000	0.001	10000	0.73	0.97
10000	0.001	100	0.18	0.90
10000	0.001	1000	0.54	0.94
10000	0.001	10000	0.72	0.96

Table. 4

From these experiments, we can reach 73% accuracy using 1000 nodes, 0.001 learning rate and 10000 iterations. The next screen shot from Microsoft Azure Machine Learning demonstrates the selection of the Multiclass neural network from many other networks that we tried to test.

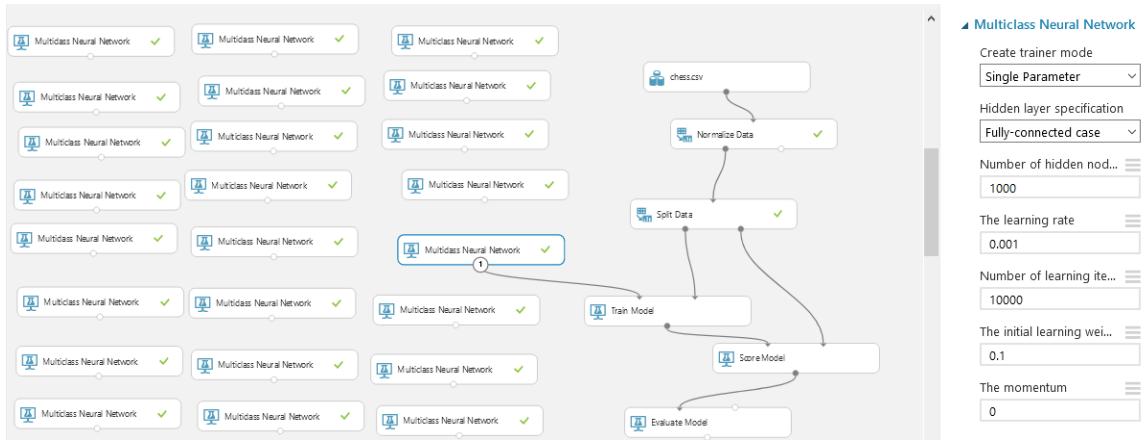


Fig. 18

Neural Networks with many layers

The Azure Machine Learning tool support defining neural networks with many layers through a simple scripting language called Net#. We used this language to define custom neural networks to increase the accuracy.

Net# Script	No. of nodes	Learning Rate	No. of iterations	Overall Accuracy	Average Accuracy
input Data auto; hidden H [200] from Data all; output Out [18] sigmoid from H all;	200	0.1	100	0.65	0.96
input Data auto; hidden H [200] from Data all; hidden H2 [200] from H all; output Out [18] sigmoid from H2 all;	400	0.1	100	0.72	0.96
input Data auto; hidden H [200] from Data all; hidden H2 [200] from H all; hidden H3 [200] from H2 all; output Out [18] sigmoid from H3 all;	600	0.1	100	0.77	0.97
input Data auto; hidden H [200] from Data all; hidden H2 [200] from H all; hidden H3 [200] from H2 all; hidden H4 [200] from H3 all;	800	0.1	100	0.76	0.97

output Out [18] sigmoid from H4 all;					
input Data auto; hidden H [1000] from Data all; hidden H2 [1000] from H all; hidden H3 [1000] from H2 all; output Out [18] sigmoid from H3 all;	3000	0.1	100	0.85	0.98
input Data auto; hidden H [3000] from Data all; hidden H2 [3000] from H all; hidden H3 [3000] from H2 all; output Out [18] sigmoid from H3 all;	9000	0.1	100	0.85	0.98
input Data auto; hidden H [200] from Data all; hidden H2 [200] from H all; hidden H3 [200] from H2 all; output Out [18] sigmoid from H3 all;	600	0.01	100	0.66	0.96
input Data auto; hidden H [1000] from Data all; hidden H2 [1000] from H all; hidden H3 [1000] from H2 all; output Out [18] sigmoid from H3 all;	3000	0.01	100	0.62	0.95
input Data auto; hidden H [200] from Data all; hidden H2 [200] from H all; hidden H3 [200] from H2 all; output Out [18] sigmoid from H3 all;	600	0.1	1000	0.83	0.98
input Data auto; hidden H [200] from Data all; hidden H2 [200] from H all; hidden H3 [200] from H2 all; output Out [18] sigmoid from H3 all;	600	0.1	2000	0.83	0.98

Table. 5

We got the highest accuracy using 3000 nodes distributed on three hidden layers where each layer contains 1000 nodes. The activation function is Sigmod and the learning rate is 0.1 while the number of learning iterations is 100. The next screen shot demonstrates the selection of this neural network. The Net# script is written in the properties panel on the right side of the screen.

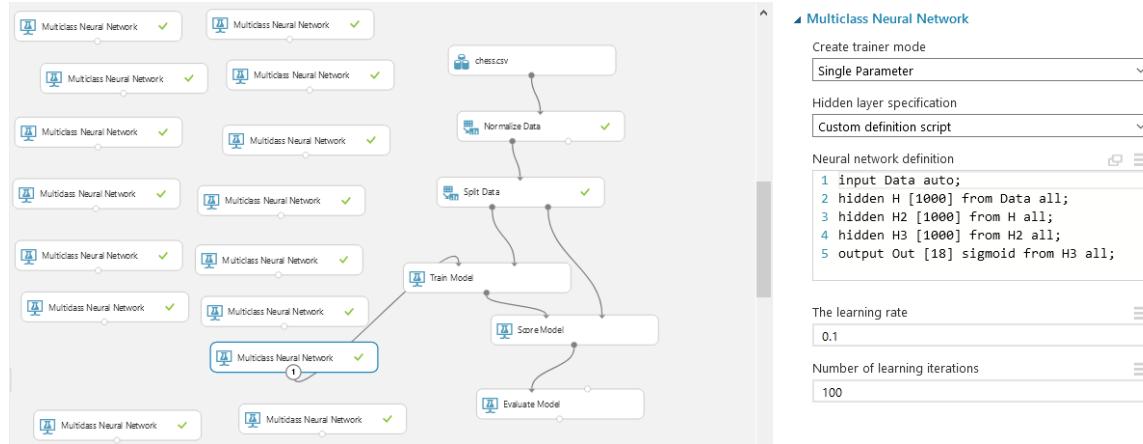


Fig. 19

The Final Results

The next table presents each model, the overall accuracy, and the average accuracy.

The models are listed descending from the highest accuracy to the lowest one.

Model	Overall Accuracy	Average Accuracy
Neural Networks	0.85	0.98
Decision Forest	0.79	0.97
Decision Jungle	0.49	0.94
Logistic Regression	0.32	0.92

Table. 6

We get the highest accuracy using the Neural Networks model (85%) then the Decision forest model (79%). With respect to the Training time, the Neural Networks consumes larger time (13 hours) while the other models consume (2-3 mins). Based on these results, we encourage using Neural Networks for this type of problems when we care on the best accuracy if the training time is not a problem. In case someone wants to develop something on the fly, like doing a live demonstration without earlier preparation, or doing some quick tests, we recommend using a Decision Forest model for a short training time, and still provide good accuracy. Then switch to Neural Networks if the work is going to be more serious and will be used in production.

Web Services

We used the Microsoft Azure Machine Learning to provide a web service for each trained model (Logistic Regression, Decision Jungle, Decision Forest & Neural Networks)

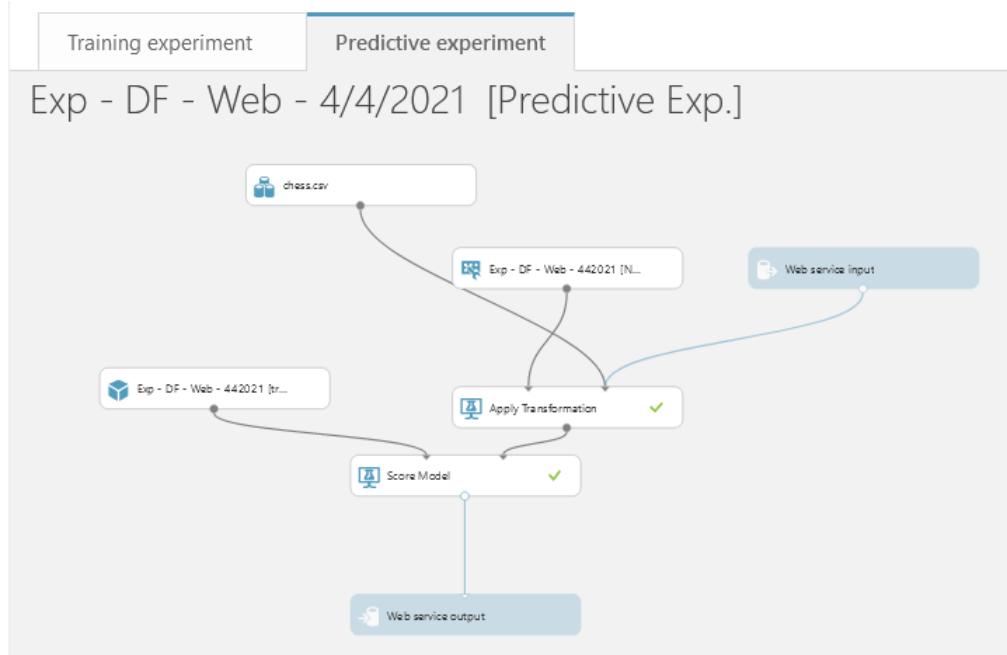


Fig. 20

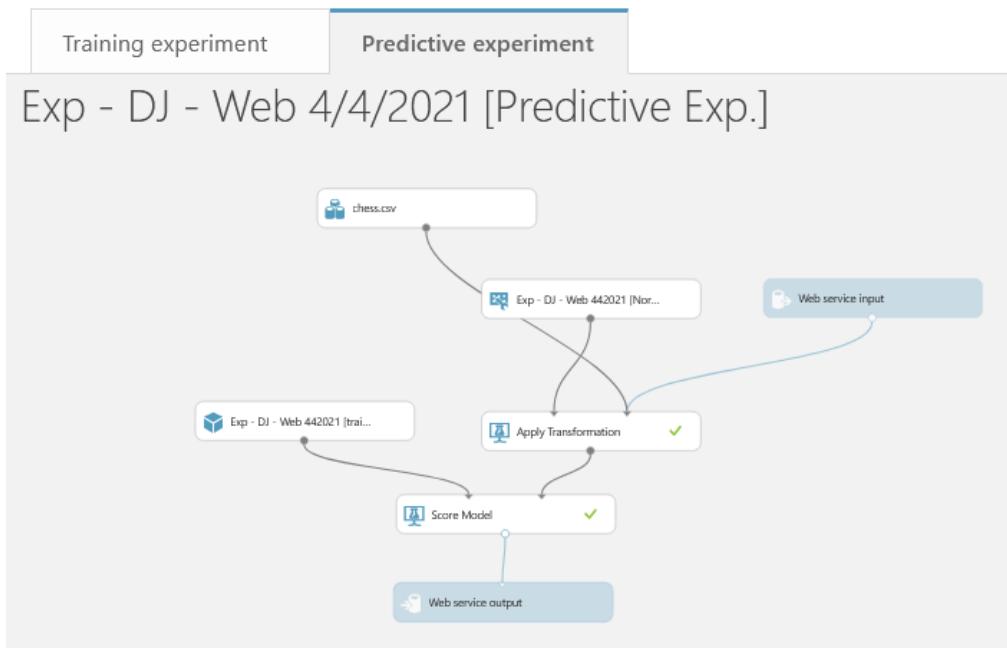


Fig. 21

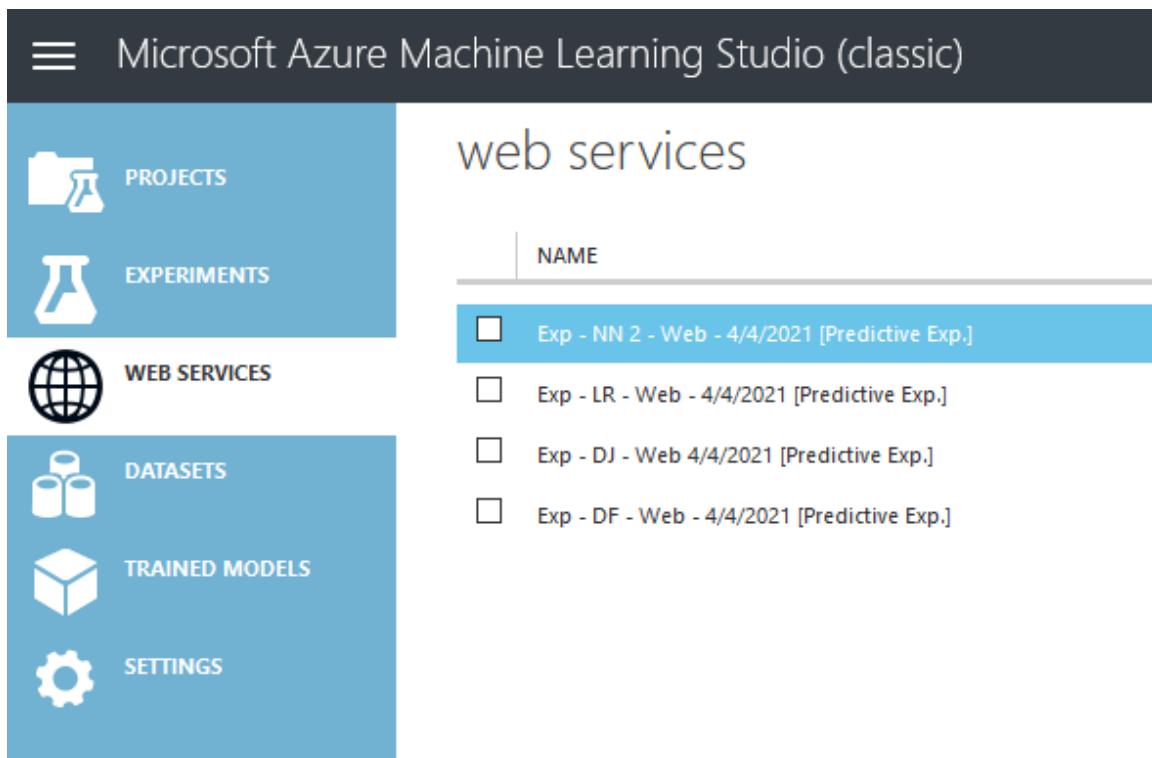


Fig. 22

We can use these web services from the Web Interface provided by Microsoft Azure Machine Learning, or we can consume it using any programming language that support calling web services.

WhiteKingFile	a
WhiteKingRank	1
WhiteRockFile	b
WhiteRockRank	3
BlackKingFile	c
BlackKingRank	2
GameResult	

WhiteKingFile	a
WhiteKingRank	-0.921857184664471
WhiteRockFile	b
WhiteRockRank	-0.662555499309983
BlackKingFile	c
BlackKingRank	-1.09049490982471
GameResult	
Scored Probabilities for Class "draw"	0.625
Scored Probabilities for Class "eight"	0

Fig. 23

Chess Endgame Data Set Application

The application comes with the next features.

- Data Set Visualization
- Data Set Statistics
- Prediction using Logistic Regression, Decision Jungle, Decision Forest, and Neural Networks

The next screen shot demonstrates the Data Set Visualization. We have 28056 samples in the data set, we can select any sample to see the chess board and pieces in the correct position according to the sample. The Visualization is fast and dynamic, once we change the selected sample, the chess board is updated automatically. In the chess board we have the Black King, White King and the White Rook. The Game Result could be Draw, Zero, One, Two,, Sixteen.

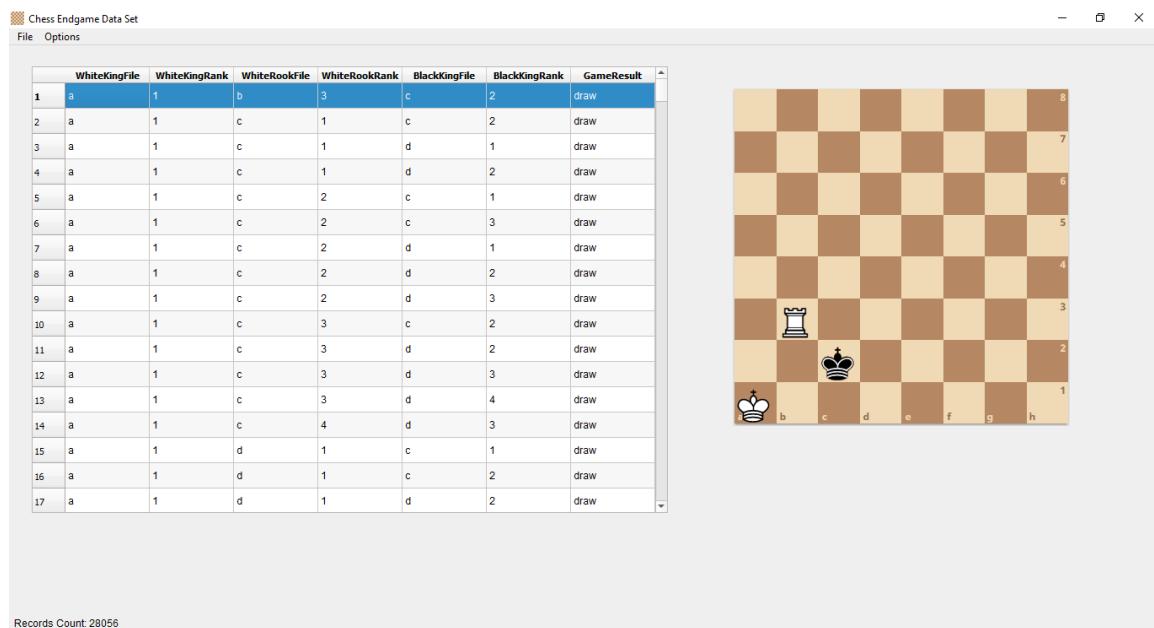


Fig. 24

The next screen shot demonstrates the Data Set statistics window. We have a Table that present the Game Result, Count and Percentage. For example, we have 2796 samples where the Game Result is a Draw which represent 9.97% of the samples.

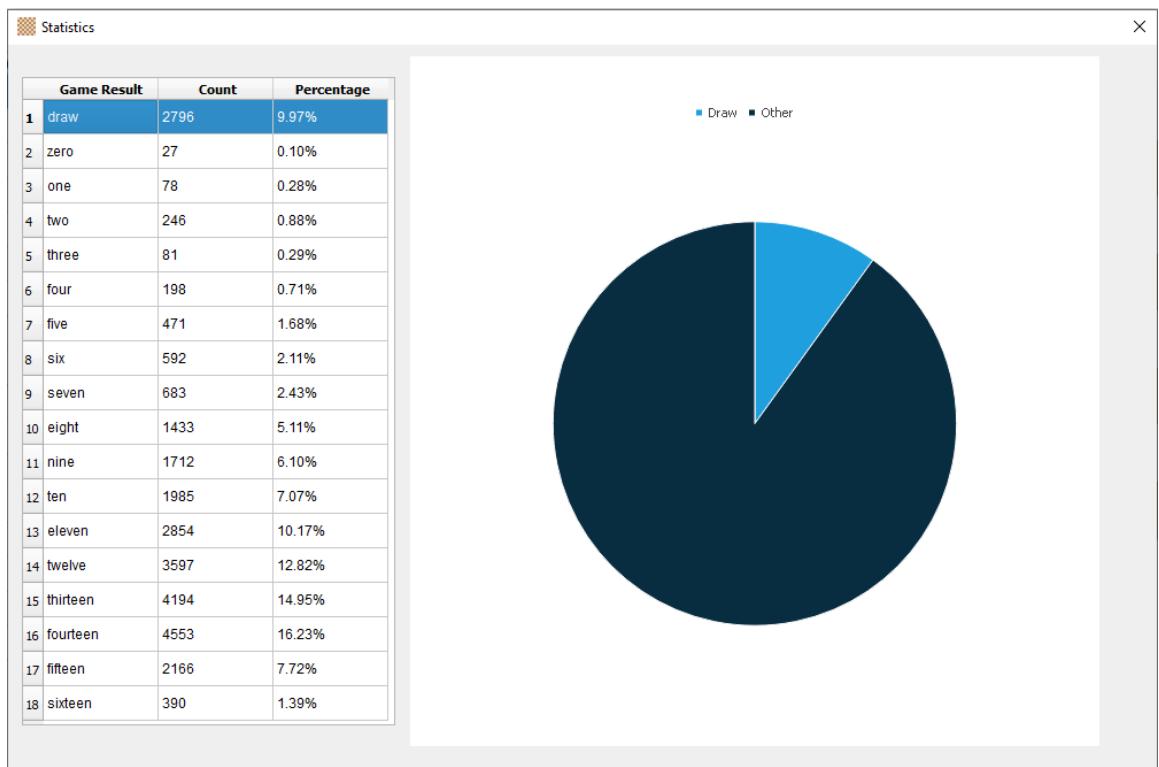


Fig. 25

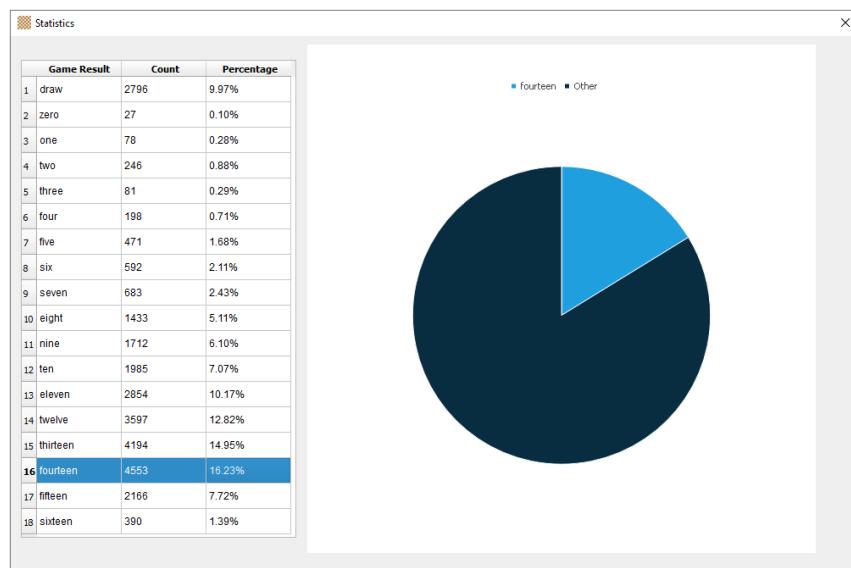


Fig. 26

The next screen shots for the Prediction window. In this window we can set the board parameters (White King file & rank, Blank King file & Rank and the White Rook file & rank). This sample could exist in the Data Set or not. Then we select the Algorithm (Multiclass Decision Forest, Multiclass Decision Jungle, Neural Network or Logistic Regression).

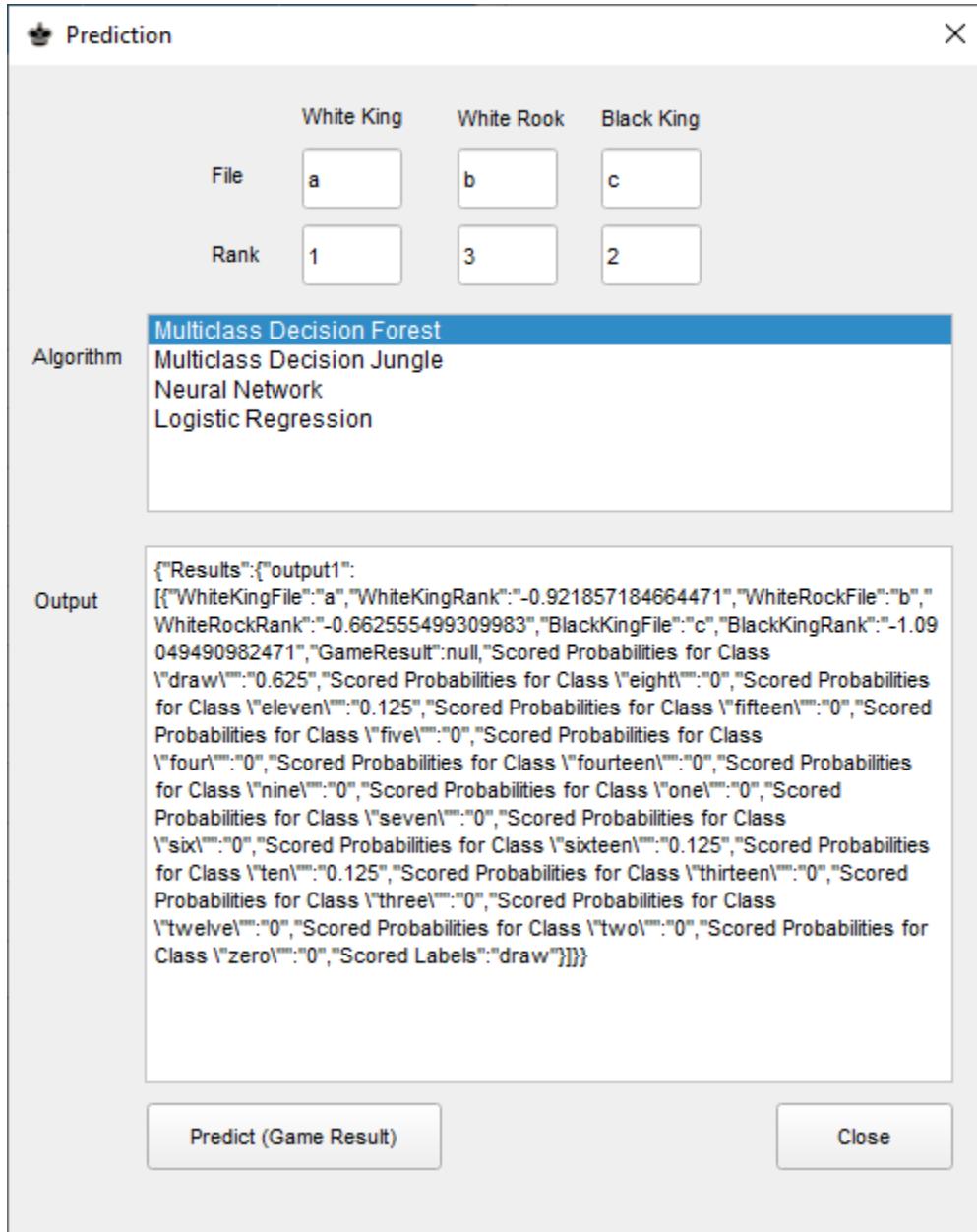


Fig. 27

Future Work

In the future we will extend our experiments, for example we will try more neural networks with different scripts that set the layers count, nodes in each layer, different connects, and different activation functions. Also, we plan to try different models like the Support Vector Machine (SVM). We plan also to try ensemble learning and use many different models together in the prediction process to get higher accuracy. An improvement that we plan to do too is developing a tool that provide a simple GUI to design the Neural Networks architecture and generate the Net# source code for the Microsoft Azure Machine Learning tool. We plan also to try the same algorithms with different Data Sets and see the change in the accuracy and analysis the results.

Conclusion

In this paper we presented a Machine Learning solution to predict the result of the Chess Endgame (King-Rook vs King) problem using different algorithms like Neural Networks, Logistic Regression, Decision Jungle and Decision Forest. We did many experiments to calculate the Accuracy of each model and determine which one provides the highest accuracy. Our results demonstrate that using Neural Networks we can reach 85% accuracy after 13 hours of training time using Microsoft Azure Machine Learning tool. We also developed an application using the Ring programming language that visualize the data set and predict the game result using different algorithms.

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