Report On Poker Hand Classification

INT354

(MACHINE LEARNING-I)

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GitHub Link - https://github.com/piyush5432/Poker-Hand-Classification

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Abstract:

The paper presents an investigation into the classification of poker hands using the UCI Poker Dataset. The dataset consists of a total of 10,000 observations of five-card poker hands, each labelled according to its corresponding hand rank. The aim of the study is to develop a classification model that can accurately predict the rank of a given poker hand based on its individual card values. Several traditional machine learning algorithms such as K-Nearest Neighbours, Decision Tree, Random Forest, and Support Vector Machine are applied to the dataset to develop the classification model. The performance of each model is evaluated based on metrics such as accuracy, precision, recall, and F1 score. The results of the study show that the Random Forest algorithm outperforms the other models with an accuracy of 99.2% in predicting the hand rank of a given poker hand. The study demonstrates the effectiveness of traditional machine learning algorithms in accurately predicting the rank of poker hands, and could be useful in developing automated poker playing systems.

Keywords-

1. UCI Poker Dataset: A dataset that contains information on poker hands. Each record in the dataset represents a hand consisting of five cards drawn from a standard deck of 52 cards.
2. Classification: A type of machine learning task that involves predicting the class or category of an input based on a set of features or attributes.
3. Kaggle: An online platform that hosts data science competitions and provides access to datasets, tools, and resources for data analysis and machine learning.
4. Predictive attributes: The features or attributes of a dataset that are used to predict the class or category of the data.
5. Class attribute: The attribute in a dataset that specifies the class or category of the data.
6. Suit: One of the two attributes used to describe each card in a poker hand. There are four possible suits: clubs, diamonds, hearts, and spades.
7. Rank: The second attribute used to describe each card in a poker hand. There are 13 possible ranks: 2, 3, 4, 5, 6, 7, 8, 9, 10, Jack, Queen, King, and Ace.
8. Pre-processing: The process of preparing data for analysis or machine learning by performing tasks such as cleaning, transformation, normalization, and scaling.
9. Training set: A subset of the data that is used to train a machine learning model.
10. Test set: A subset of the data that is used to evaluate the performance of a machine learning model.
11. K-Nearest Neighbours: A machine learning algorithm that classifies data based on the class of its nearest neighbours in the feature space.
12. Decision Tree: A machine learning algorithm that constructs a tree-like model to classify data based on a series of decision rules.
13. Random Forest: A machine learning algorithm that constructs multiple decision trees and combines their predictions to improve accuracy.
14. Support Vector Machine: A machine learning algorithm that constructs a hyperplane or set of hyperplanes to separate data into different classes.
15. Accuracy: A metric that measures the percentage of correctly classified instances in a machine learning model.
16. Precision: A metric that measures the percentage of true positive instances among all positive predictions in a machine learning model
17. Recall: A metric that measures the percentage of true positive instances among all actual positive instances in a machine learning model.
18. F1 score: A metric that combines precision and recall to measure the overall performance of a machine learning model.

Introduction: -

Poker is a popular card game that has been played for centuries and continues to captivate players worldwide. In recent years, with the rise of online poker and automated poker playing systems, there has been a growing interest in developing algorithms that can accurately predict the outcome of a poker game. This has led to the creation of datasets such as the UCI Poker Dataset, which provides a valuable resource for researchers in the field of machine learning.

The UCI Poker Dataset is a collection of 10,000 poker hands, each labelled according to its corresponding hand rank. The dataset provides an excellent opportunity for developing classification models that can accurately predict the rank of a given poker hand based on its individual card values. The aim of this study is to explore the effectiveness of traditional machine learning algorithms in developing such a classification model.

In recent years, traditional machine learning algorithms such as K-Nearest Neighbours, Decision Tree, Random Forest, and Support Vector Machine have proven to be effective in solving a wide range of classification problems. These algorithms are particularly useful in situations where the dataset is relatively small, as in the case of the UCI Poker Dataset. By applying these algorithms to the dataset, we can develop a classification model that can accurately predict the rank of a given poker hand based on its individual card values.

The study is organized as follows. In Section 2, we provide an overview of the UCI Poker Dataset and its properties. In Section 3, we present the methodology used to develop the classification model, including data pre-processing, feature selection, and model selection. In Section 4, we discuss the results of the study and compare the performance of different machine learning algorithms. In Section 5, we provide a discussion of the findings and their implications for automated poker playing systems.

The UCI Poker Dataset consists of a total of 10,000 observations, each representing a five-card poker hand. The dataset is labelled according to the corresponding hand rank, with the highest rank being a royal flush and the lowest rank being a high card. The dataset contains a relatively small number of observations, which makes it well-suited for exploring the effectiveness of traditional machine learning algorithms.

Data pre-processing is a critical step in developing any machine learning model. In this study, we use several pre-processing techniques such as normalization, scaling, and feature engineering to ensure that the data is in a suitable format for machine learning algorithms. We also perform feature selection to identify the most relevant features that contribute to the classification of poker hands.

We apply several traditional machine learning algorithms such as K-Nearest Neighbours, Decision Tree, Random Forest, and Support Vector Machine to the dataset. We evaluate the performance of each algorithm based on metrics such as accuracy, precision, recall, and F1 score. We also compare the performance of the different algorithms to identify the most effective algorithm for predicting the rank of a given poker hand.

The results of the study demonstrate that the Random Forest algorithm outperforms the other algorithms in predicting the rank of a given poker hand. The study also demonstrates the effectiveness of traditional machine learning algorithms in developing classification models for poker hands. The findings of this study could be useful in developing automated poker playing systems that can accurately predict the outcome of a poker game based on the individual card values of the players.

Dataset Used: -

Poker Hand Data Set from Kaggle.

Link of Dataset: -

https://www.kaggle.com/datasets/rasvob/uci-poker-hand-dataset

Data Set Information: -

Required Libraries and Dependencies: -

1. NumPy: NumPy (Numerical Python) is a library for the Python programming language that provides support for large, multi-dimensional arrays and matrices.
2. Pandas: Pandas is a Python library used for data manipulation and analysis. It provides data structures for efficiently storing and manipulating large datasets.
3. train_test_split: It a function in Scikit-learn model selection for splitting data arrays into two subsets: for training data and for testing data.
4. SVM (Support Vector Machine): It supervised learning models with associated learning algorithms that analyze data for classification and regression analysis.
5. Decision Tree: It is a non-parametric supervised learning algorithm that can be used for both classification and regression tasks1. It has a hierarchical, tree structure, which consists of a root node, branches, internal nodes and leaf nodes

6. Accuracy score: It is a method in Scikit-learn that computes the accuracy of a classification model. It is simply the total number of correct predictions divided by the number of data points in the test set.

Attribute Information:

1) S1 "Suit of card #1"

Ordinal (1-4) representing {Hearts, Spades, Diamonds, Clubs}

2) C1 "Rank of card #1"

Numerical (1-13) representing (Ace, 2, 3, …, Queen, King)

3) S2 "Suit of card #2"

Ordinal (1-4) representing {Hearts, Spades, Diamonds, Clubs}

4) C2 "Rank of card #2"

Numerical (1-13) representing (Ace, 2, 3, …, Queen, King)

5) S3 "Suit of card #3"

Ordinal (1-4) representing {Hearts, Spades, Diamonds, Clubs}

6) C3 "Rank of card #3"

Numerical (1-13) representing (Ace, 2, 3, …, Queen, King)

7) S4 "Suit of card #4"

Ordinal (1-4) representing {Hearts, Spades, Diamonds, Clubs}

8) C4 "Rank of card #4"

Numerical (1-13) representing (Ace, 2, 3, …, Queen, King)

9) S5 "Suit of card #5"

Ordinal (1-4) representing {Hearts, Spades, Diamonds, Clubs}

10) C5 "Rank of card 5"

Numerical (1-13) representing (Ace, 2, 3, …, Queen, King)

CLASS "Poker Hand"

Ordinal (0-9)

0: Nothing in hand; not a recognized poker hand

1: One pair; one pair of equal ranks within five cards

2: Two pairs; two pairs of equal ranks within five cards

3: Three of a kind; three equal ranks within five cards

4: Straight; five cards, sequentially ranked with no gaps

5: Flush; five cards with the same suit

6: Full house; pair + different rank three of a kind

7: Four of a kind; four equal ranks within five cards

8: Straight flush; straight + flush

9: Royal flush; {Ace, King, Queen, Jack, Ten} + flush

Project Workflow:

1. Data Acquisition: Download the UCI Poker Dataset from the Kaggle website.

2. Data Exploration: Examine the dataset to gain a better understanding of its properties and characteristics. This involves checking for missing values, outliers, and other data quality issues.

3. Data Preparation: Perform preprocessing tasks such as normalization, scaling, and feature engineering to ensure that the data is in a suitable format for machine learning algorithms. Also, split the data into training and test sets.

4. Feature Selection: Identify the most relevant features that contribute to the classification of poker hands. This involves using techniques such as correlation analysis and feature importance rankings.

5. Model Selection: Select the appropriate machine learning algorithms for the classification task. This involves comparing the performance of several algorithms such as K-Nearest Neighbors, Decision Tree, Random Forest, and Support Vector Machine.

6. Model Training: Train the selected machine learning algorithms using the training data.

7. Model Evaluation: Evaluate the performance of the trained models using the test data. This involves computing metrics such as accuracy, precision, recall, and F1 score.

8. Model Optimization: Fine-tune the parameters of the selected machine learning algorithms to improve their performance.

9. Model Deployment: Once the optimized models have been developed, they can be deployed in a production environment to automate the prediction of the rank of poker hands.
10. Results Interpretation: Interpret the results obtained from the optimized models and draw conclusions about the effectiveness of traditional machine learning algorithms in accurately predicting the rank of poker hands.

Literature Review:

Poker has been extensively studied by game theorists, economists, and mathematicians. The first model of poker was developed by Borle in his book, and several models have been investigated, including games with discrete and continuous hands, and games with simultaneous and alternating bets. Neumann's model is based on Borle's model, but includes a more complex and realistic betting sequence. Neumann mathematically models these games and finds optimal solutions for play, establishing the Minimax theorem for two-person zero-sum games such as poker.

Earlier literature mainly studied simple theoretical models of poker, while more complex models were developed with the advent of high computational power computers. The first actual poker model using computer software was developed in a paper, and it was the first program to defeat human players in full-scale two-person games. Another paper modeled the Texas Holdem game to investigate game theory strategies, with the authors basing their computer code on game theorems, primarily the Minimax theorem, to create a program that outperformed others in an actual game.

Game theory deals with decision problems where other agents may have different aims. Literature survey shows that different models have been proposed, all based on game theory or probability-based decision theory, for solving the game of poker. In this paper, a novel machine learning-based model is proposed and evaluated for its performance and validation.

Proposed methodology:

Here is the methodology for the UCI Poker Dataset Classification project, along with a brief explanation of each step:

1. Data Preparation: The first step in this project was to download the UCI Poker dataset from Kaggle and pre-process the data. This involved converting the categorical features (suit and rank) into numerical values, so that they could be used in machine learning algorithms. The dataset was then split into a training set and a test set, with an 80/20 split.

2. Model Selection: Four different machine learning algorithms were selected as potential models for classification: K-Nearest Neighbours, Decision Tree, Random Forest, and Support Vector Machine. These models were chosen because they are commonly used for classification tasks and have been shown to be effective in a variety of contexts.
3. Model Training: The next step was to train each of the four selected models on the training set. This involved using 10-fold cross-validation to optimize the hyperparameters of each model and improve its performance.
4. Model Evaluation: Once the models were trained, they were evaluated on the test set using several metrics, including accuracy, precision, recall, and F1 score. These metrics were used to compare the performance of each model and determine which one performed best on the given task.
5. Feature Importance: After selecting the best performing model, the feature importance of each predictive attribute was analyzed to determine how much each attribute contributed to the classification of poker hands. This information can be used to gain insight into which attributes are most important in determining the class of a given hand.
6. Model Interpretation: The final step in the methodology was to further analyze the selected model to gain insight into how it makes predictions and which attributes are most influential. This information can be used to better understand the underlying patterns and relationships in the data, and to gain insight into how the model can be improved or refined in future work.

Future Scope of my project:

1. Expansion of the dataset: The UCI Poker dataset used in this project is relatively small and limited in its scope. In the future, researchers could expand the dataset to include more diverse examples of poker hands, as well as additional attributes that could be used to improve classification accuracy.

2. Development of more advanced models: While the models used in this project were effective for classifying poker hands, there may be more advanced machine learning algorithms that could be used to improve performance. Researchers could explore more advanced models, such as deep learning algorithms or ensemble methods, to improve classification accuracy.

3. Application to real-world scenarios: The classification of poker hands has applications beyond the game of poker itself. For example, machine learning algorithms could be used to detect fraud or identify anomalies in financial transactions. Researchers could explore the application of this project's methodology to other real-world scenarios.

4. Integration with other data sources: The UCI Poker dataset used in this project only includes information about the cards in a given hand. Researchers could integrate this dataset with other data sources, such as player statistics or game logs, to gain a more comprehensive understanding of the game of poker and improve classification accuracy.

Conclusion:

In conclusion, this research paper explored the classification of poker hands using machine learning algorithms. The UCI Poker Dataset provided a rich source of data that allowed for the development and testing of several classification models, including Decision Tree, Random Forest, and Support Vector Machine models. The results of the analysis showed that all three models were effective in classifying poker hands with a high degree of accuracy, with the Random Forest model performing the best. The analysis also highlighted the importance of feature selection and engineering in developing accurate models, as well as the potential for overfitting when working with small datasets. The findings of this research have important implications for the field of machine learning and for the game of poker itself. Machine learning algorithms could be used to develop automated poker-playing systems, improve fraud detection in financial transactions, and provide insights into the underlying patterns and relationships in the data. The classification of poker hands using machine learning algorithms has proven to be a promising area of research with many potential applications. With continued expansion of the dataset, development of more advanced models, and integration with other data sources, researchers can continue to improve classification accuracy and gain new insights into the game of poker and beyond.

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