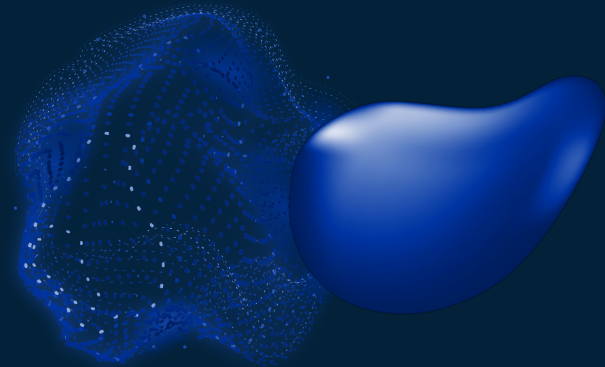


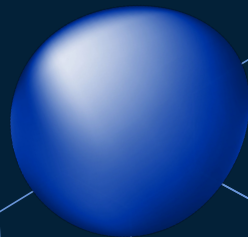
# Poker Dataset Training

By Prince, Lakshya, LV

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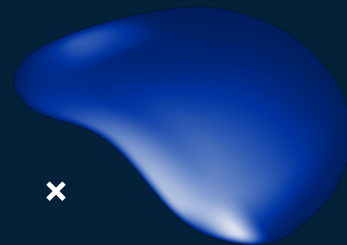
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# 01

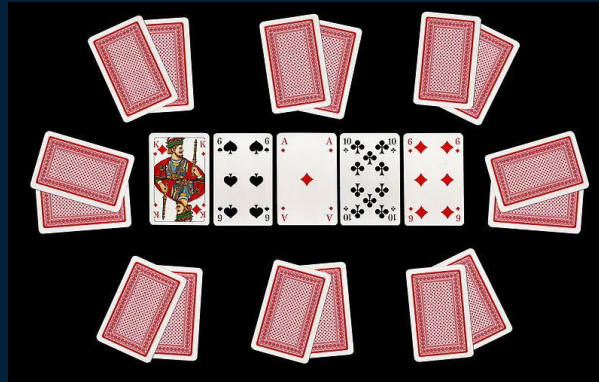
# Introduction

Poker Dataset

# What is Poker ?

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- 2 Cards one after another distributed to each player.
- 5 Cards on the table dealt by Dealer (person distributing the cards)
- Best 5 cards are picked for rankings that determines the win.
- 10 types of Patterns



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# Target Variables (0-9)



1. Royal Flush



6. Straight



2. Straight Flush



7. Three of a Kind



3. Four of a Kind



8. Two Pairs



4. Full House



9. One Pair



5. Flush



10. High Card

0.000154%

The royal flush is a case of the straight flush. It can be formed 4 ways (one for each suit), giving it a probability of 0.000154% and odds of 649,739 : 1.

# DataSet Structure & Features.

	S1	C1	S2	C2	S3	C3	S4	C4	S5	C5	CLASS
0	1	10	1	11	1	13	1	12	1	1	9
1	2	11	2	13	2	10	2	12	2	1	9
2	3	12	3	11	3	13	3	10	3	1	9
3	4	10	4	11	4	1	4	13	4	12	9
4	4	1	4	13	4	12	4	11	4	10	9

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)
11. CLASS "Poker Hand" Ordinal (0-9)

# DataSet Overview



**Instances**

1025010

**Features**

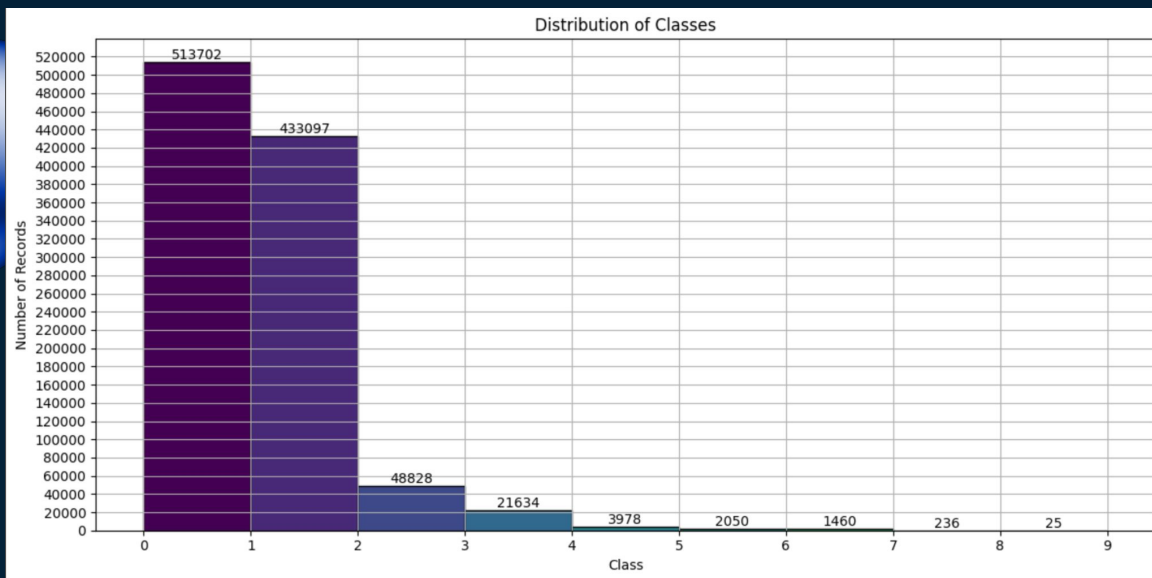
10  
Categorical, Integer

**Dataset**

Multivariate

**Split**

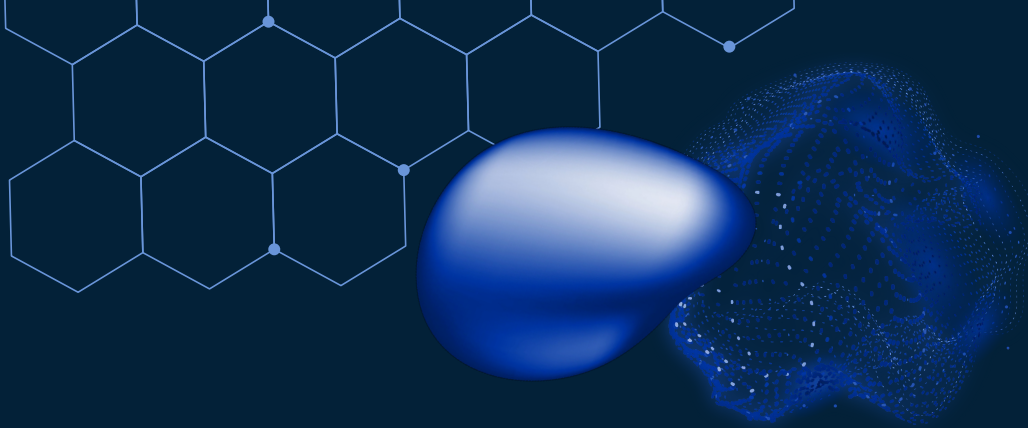
70% Training  
30% Testing



Training dataset shape: (717507, 10)  
Testing dataset shape: (307503, 10)

# 0

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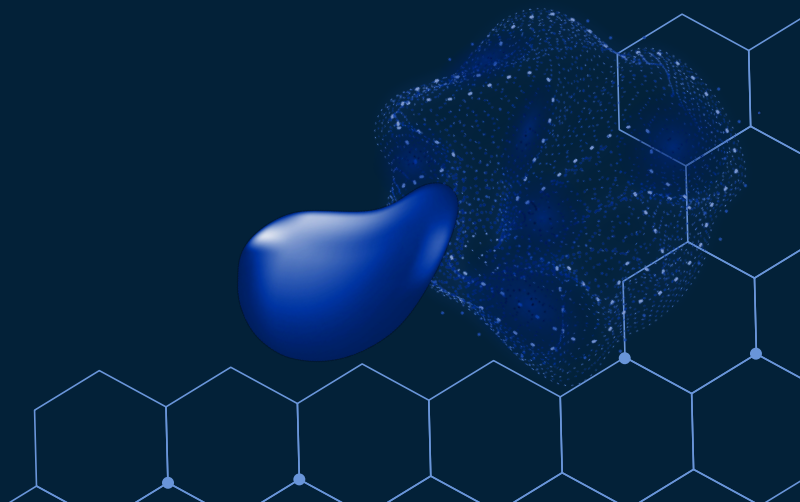
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# 2 Models

Poker Dataset



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# Decision Tree

- Performance: Accuracy of 63%
- Characteristics: Decision trees are a type of model that makes decisions based on a set of binary rules. They're quite interpretable but can be prone to overfitting if not pruned correctly.
- Analysis: Given that poker hand classification is quite a complex problem with potential non-linear relationships, a simple decision tree might not capture all the complexities. However, decision trees can serve as a good baseline and are very fast to train.

```
print("Number of nodes in the decision tree:", clf.tree_.node_count)
print("Depth of the tree:", clf.get_depth())
```

```
Number of nodes in the decision tree: 441143
Depth of the tree: 40
```

```
print("Accuracy for descision Tree is", accuracy(cm2))
Testing_error = 1 - accuracy(cm2)
print("Testing Error is:", Testing_error)
```

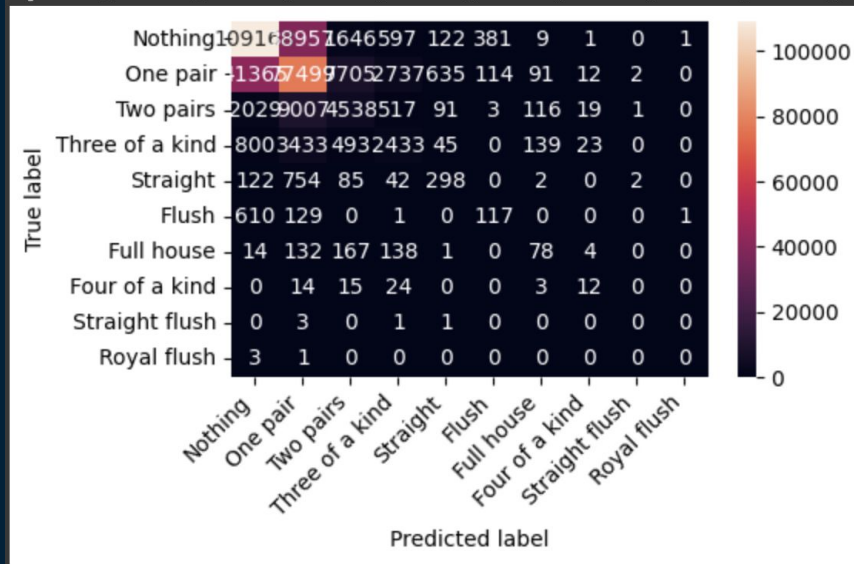
```
Accuracy for descision Tree is 0.6393466080005723
Testing Error is: 0.3606533919994277
```



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Confusion matrix:

```
[[109168 38957 1646 597 122 381 9 1 0 1]
 [ 41365 77499 7705 2737 635 114 91 12 2 0]
 [  2029  9007 4538 517 91 3 116 19 1 0]
 [   800  3433 493 2433 45 0 139 23 0 0]
 [   122   754 85 42 298 0 2 0 2 0]
 [   610  129 0 1 0 117 0 0 0 1]
 [    14   132 167 138 1 0 78 4 0 0]
 [     0    14 15 24 0 0 3 12 0 0]
 [     0     3 0 1 1 0 0 0 0 0]
 [     3     1 0 0 0 0 0 0 0 0]]
```



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Decision Tree Model

# Problems with Decision Tree

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- Adaptability Issues: Difficulty in adapting decision tree models to different poker environments. Poker strategies can vary widely, requiring continual updates to the model. While working on the model it also vary as their would be changing strategy on poker players and there are various different game format as well.
- Data Quality Issues: Importance of high-quality data for training decision tree models. potential data quality issues: bias, class imbalance which is where distribution of data between classes is highly skewed. So Class 1-5 have most data and rest have very less leading to imbalance.

# GaussianNB

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- Performance: Accuracy of 50%
- Characteristics: Naive Bayes classifiers assume that the features are independent given the class labels. This assumption is rarely true in real life and especially not in a game like poker where the combination of cards greatly influences the hand's strength.
- Analysis: The assumption of feature independence could be the reason for the lower accuracy since poker hands are inherently about the relationship between cards.

×

```
gnb = GaussianNB()

# Training the classifier
gnb.fit(X_train_scaled, Y_train)

# Making predictions
Y_pred = gnb.predict(X_test_scaled)

# Calculating the accuracy of the model
accuracy = accuracy_score(Y_test, Y_pred)

print(f"Model accuracy: {accuracy * 100:.2f}%")

Model accuracy: 50.12%
```

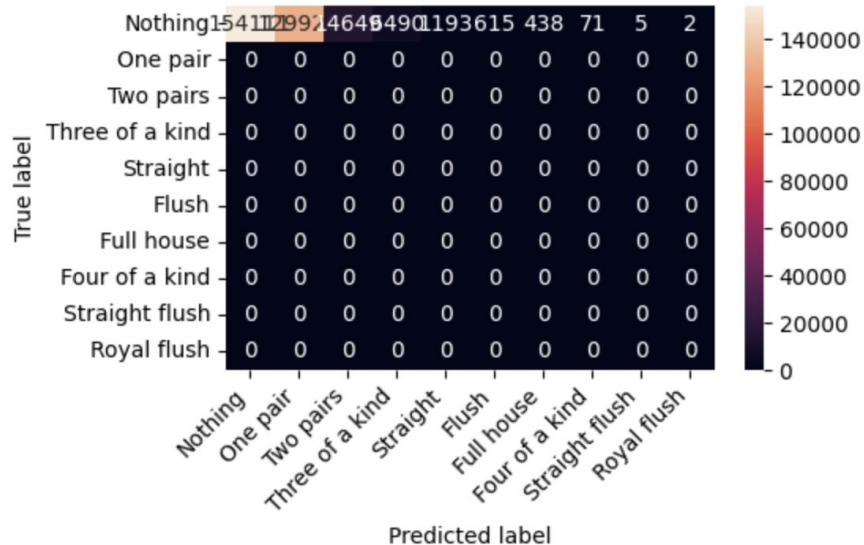
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Confusion matrix:

```
[[154111 129929 14649 6490 1193 615 438 71 5 2]
 [ 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 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 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 0 0 0 0 0 0 0 0 0]]
```



GaussianNB

×

# Artificial Neural Network

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- Performance: Accuracy of 99.46% (ReLU Activation Function).
- Characteristics: ANNs are powerful models that can capture complex and non-linear relationships between features. They can be computationally intensive and require a lot of data to perform well.
- Analysis: The high accuracy suggests that the ANN was able to model the interactions between the cards very effectively. The network likely learned the complex patterns and dependencies between features that are critical for predicting poker hands.

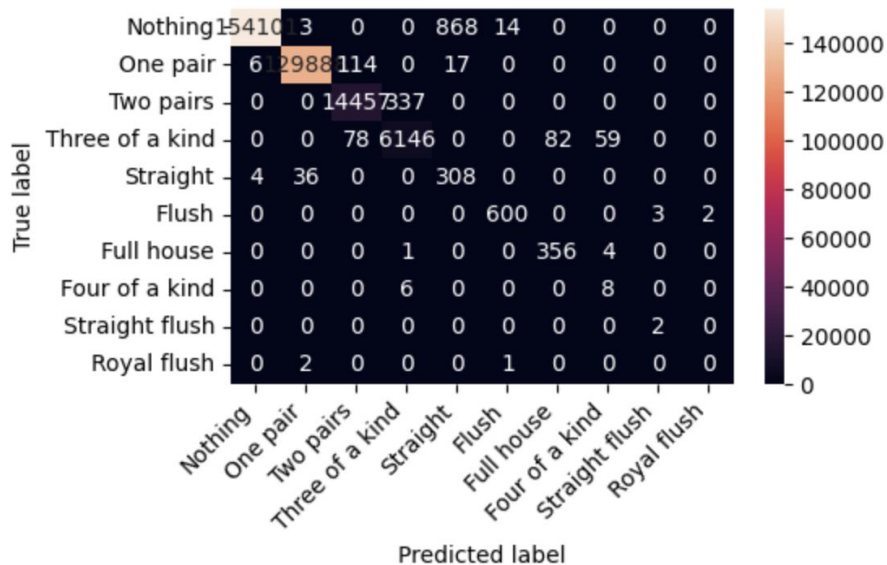
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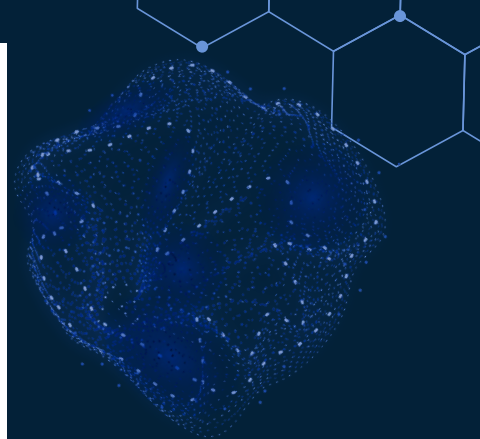
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Confusion matrix:

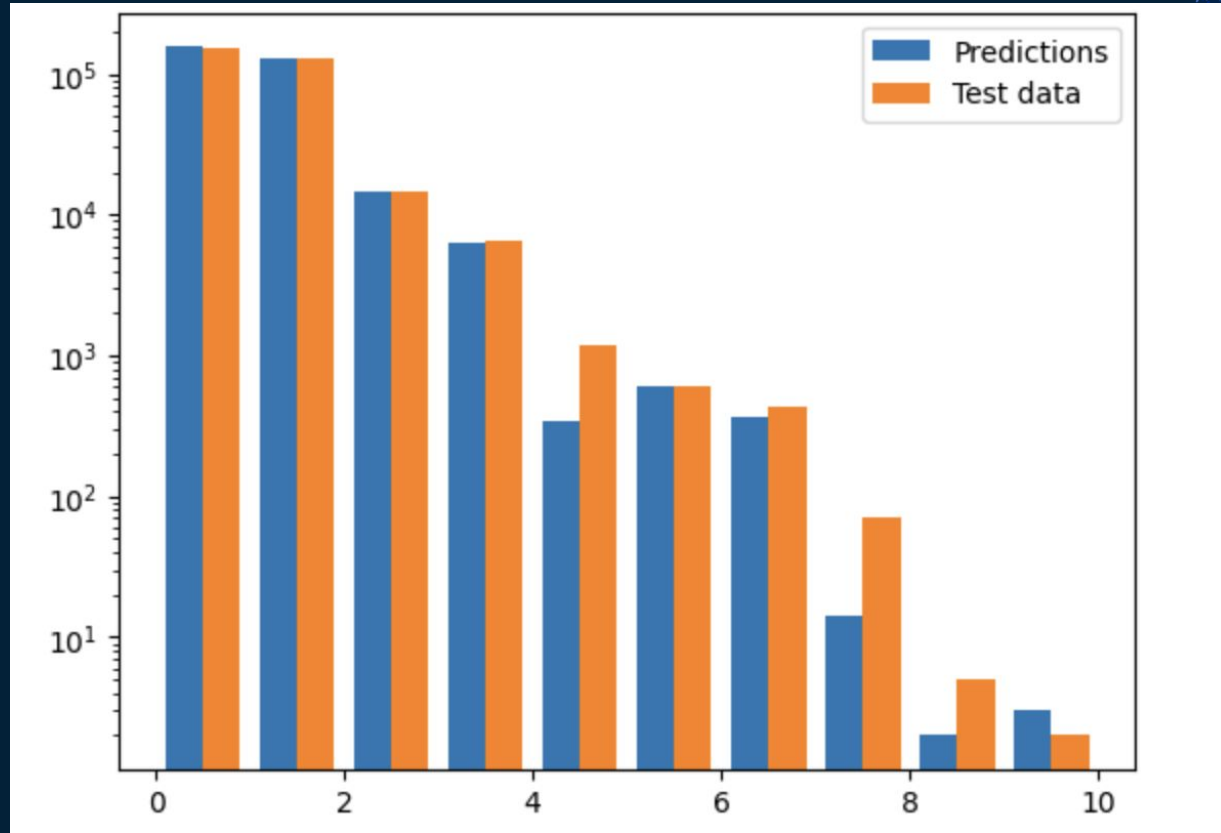
```
[[154101      3      0      0 868 14      0      0      0      0]
 [      6 129888 114      0 17      0      0      0      0      0]
 [      0      0 14457 337      0      0      0      0      0      0]
 [      0      0 78 6146      0      0      82 59      0      0]
 [      4 36      0      0 308      0      0      0      0      0]
 [      0      0      0      0      0 600      0      0      3      2]
 [      0      0      0      1      0      0 356      4      0      0]
 [      0      0      0      6      0      0      0      8      0      0]
 [      0      0      0      0      0      0      0      0      2      0]
 [      0      2      0      0      0      1      0      0      0      0]]
```



ANN Model



x



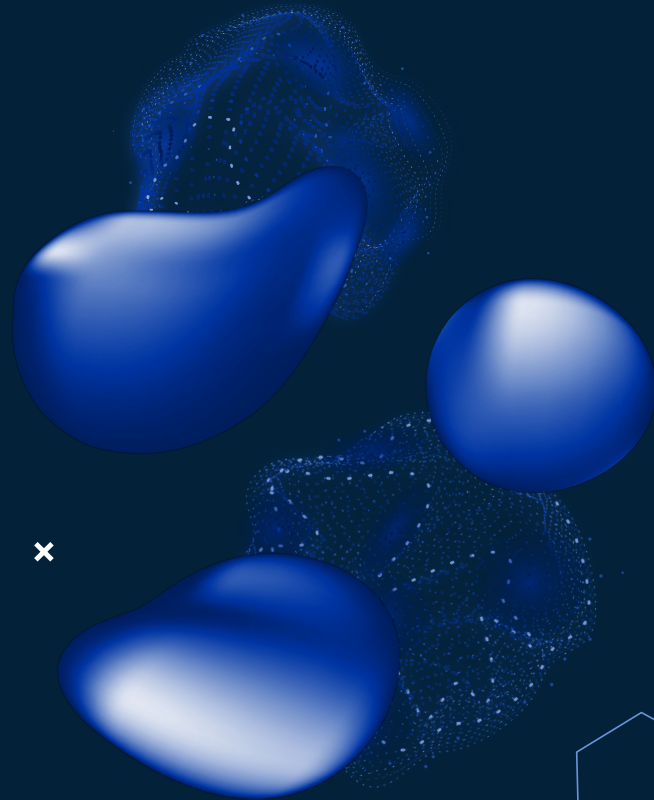
ANN Model Accuracy between classes.



x

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# What did we Learned ? (Conclusion)



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A white line-art pattern of a hexagonal grid, resembling a honeycomb or molecular structure, located in the bottom right corner of the slide.

×

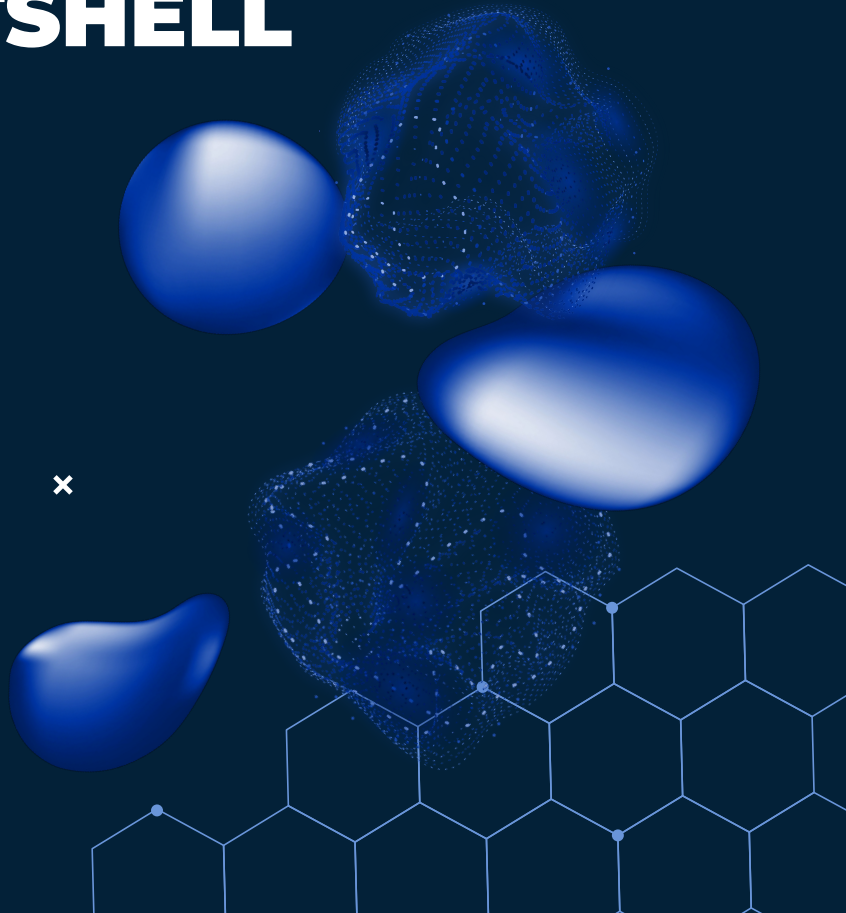
# ALL IN A NUTSHELL

First and foremost how to handle imbalanced data.

Model Effectiveness: Among the models we tested, the ANN demonstrated high performance with an accuracy of 99.46%. We understand the capability of ANNs to model complex and nonlinear relationships effectively.

Learning Insights: The differences in model performance highlight the importance of choosing the right algorithm based on the specific characteristics of the data. It also points to the necessity of considering feature interactions in predictive modeling, especially in complex scenarios like poker hand prediction.

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# Scalable ?

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## Distributed Storage

Spread data across multiple machines instead of storing on a single machine.

## Parallel Processing

Use multiple machines together to speed up analysis and model training.

## Live Accuracy

Using this model to scale to real time live accuracy indicator while poker is played.

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- Understanding Concepts to handle Imbalanced data like Cross Validation, SMOTE, ADASYN, Boosting, Bagging ... and applying them to understand them.

×



**THANKS!**

DO YOU HAVE ANY QUESTIONS?