Orange Data Hoops Challenge

"The Data-Alley Oops"



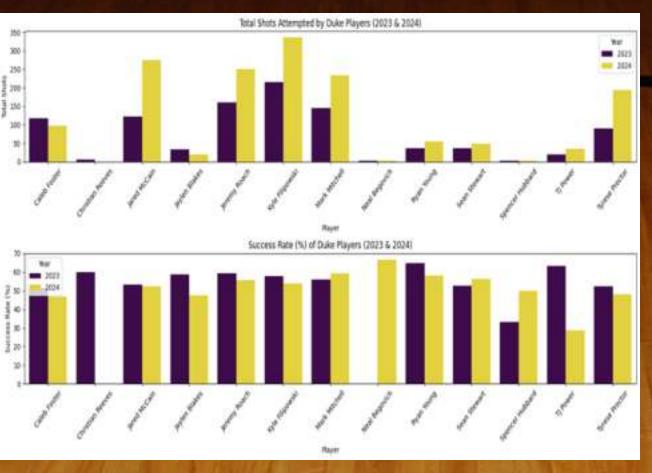
Goal: Understanding Player Performance and predicting the winning Shot.

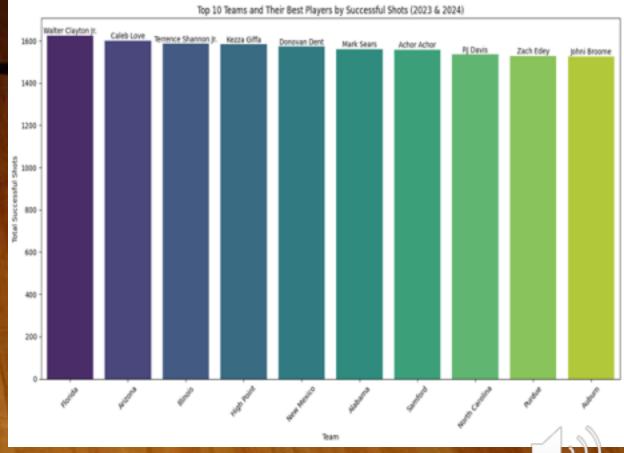
Challenges:

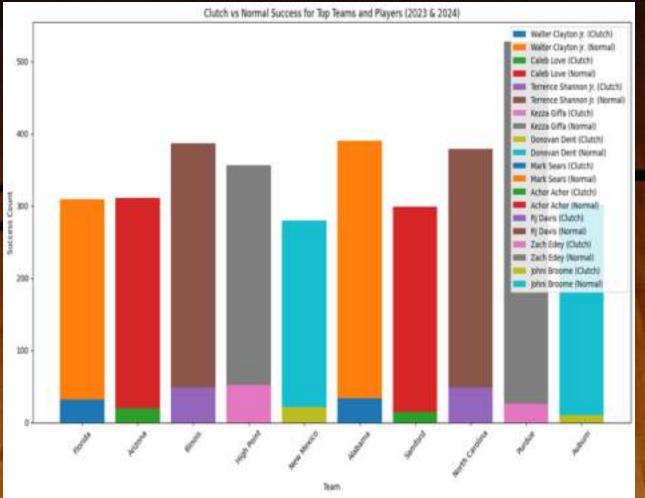
- Data Inefficiency: Initial data lacked accuracy for predictions, so we
 engineered new features focused on clutch and efficiency metrics.
- Missing Values: The dataset had numerous nulls, requiring careful imputation to ensure model reliability.
- Time Constraints: Limited time meant prioritizing key features and adjustments to quickly boost accuracy.

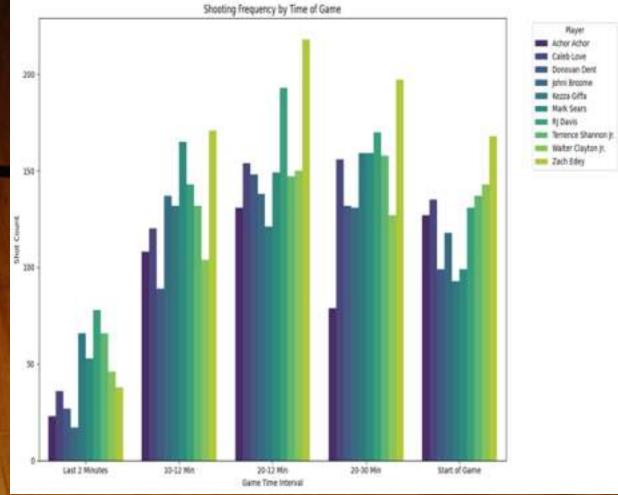
Exploratory Data Analysis (EDA)

Identified key features impacting game outcomes like scoring trends and clutch performance under pressure.





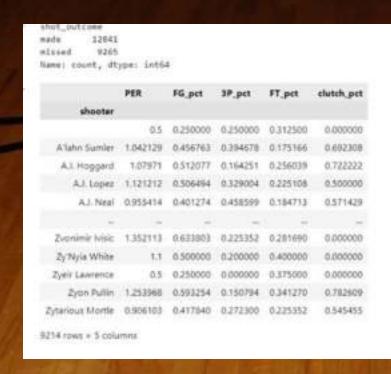


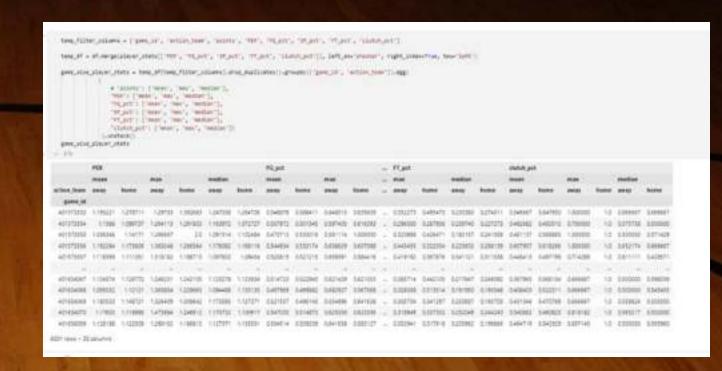




Feature Engineering

Engineered new features such as rest days,
 PER(Player Efficiency Rate), Field goal (FG), three-point (3P) percentages and player clutch stats.





```
games_and_dates = df[['game_id', 'date', 'home', 'many']].drop_duplicates()
games_and_dates["date"] = pd.to_datetime(games_and_dates["date"])
# combine the home and away teams into a single column, but two rows per game
games_and_dates = pd.melt(games_and_dates, id_vars=['game_id', 'date'], value_vars=['home_away', value_name='team')
games_and_dates.drop(columns=['home_away'], implace=True)
games_and_dates.sort_values(by=['team', 'date'], implace=True)
games_and_dates['rest_days'] = games_and_dates.groupby('team')['date'].diff().dt.days -
games_and_dates
```

rest_days	team	date	game_id	
NaN	ANTELOPE	2023-12-30	401600143	11465
NaN	AR-Fort Smith	2023-12-10	401592097	11872
NaN	AR-Pine Bluff	2023-11-06	401594537	6377
2.0	AR-Pine Bluff	2023-11-09	401604754	377
1.0	AR-Pine Bluff	2023-11-11	401611838	378
	-	1	-	-
2.0	Youngstown St	2024-02-17	401587744	7428
5.0	Youngstown St	2024-02-23	401587749	10008
1.0	Youngstown St.	2024-02-25	401587754	8734
2.0	Youngstown St	2024-02-28	401587756	1903
7.0	Youngstown St	2024-03-07	401625696	5980

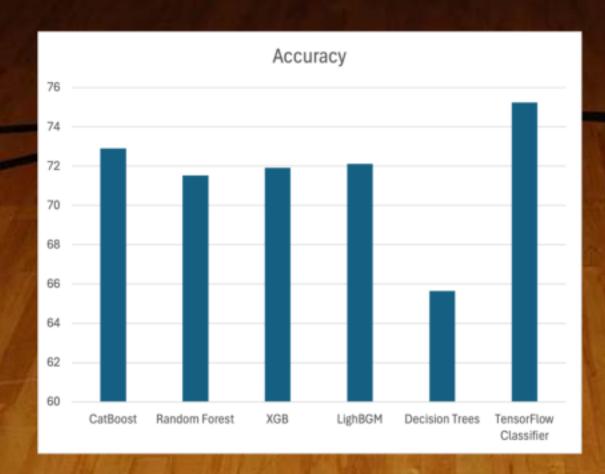
```
# Merge the dataframes
      home wins = game wins.merge(home games[["game id", "home"]].drop duplicates(), one game id', howe left')
      # Calculate total games played by each team at bone
      total_home_games * home_wins.groupby('home')['game_id'].count()
      # Calculate total wins by each team at home
      home_wins = home_wins.groupby('home')['winner'].sum()
      # Calculate win percentage
      home_win_percentage = (home_wins / total_home_games) * 100
      home win percentage
11) J 0.1s
   hone
   AR-Pine Bluff
                    61.538462
                    57,142857
   Abilene Chrstn
   Air Force
                    25,000000
   Akron
                     78,947368
                    83,333333
   Alabama
                      444
   Wright St
                    52.941176
   Wyowing
                    58,823529
   Xavier
                    57,894737
   Yale
                     81,818182
                    50.000000
   Youngstown St
   Length: 364, dtype: float64
```

Modelling

 Method-1: The first iteration of the model does not incorporate game situations or dynamic variables such as scores or in-game events. It is designed to make predictions based solely on pregame factors and static team/player metrics.

 Method-2: The enhanced model includes all relevant details, integrating dynamic game situations such as current scores, time remaining, and possession data. This allows for more contextual and accurate predictions based on real-time game scenarios.

Method -1: Used 6 different models for prediction and chose the one with the best accuracy.





```
# Predict on the testing data
   y_pred = catboost_classifier.predict(X_test)
   # Evaluate the model
   print(f'Accuracy: (accuracy_score(y_test, y_pred))')
   print('Classification Report:')
   print(classification_report(y_test, y_pred))
   print('Confusion Matrix:')
   print(confusion_matrix(y_test, y_pred))
Accuracy: 0.7289628180039139
Classification Report:
                           recall f1-score
             precision
                                             support
                             0.55
                                       0.60
                                                  372
         0.0
                  0.65
         1.0
                  0.76
                             0.83
                                       0.80
                                                  650
                                       0.73
                                                1022
    accuracy
                                      0.79
                                                1022
   macro avg
                  0.71
                             0.69
weighted avg
                  0.72
                             0.73
                                      0.72
                                                1022
Confusion Matrix:
[[204 168]
[109 541]]
```

```
Accuracy: 0.7152641878669276
RandomForest Classification Report:
                           recall f1-score
              precision
                                              support
        0.0
                   0.64
                             0.50
                                       0.56
                                                  372
        1.0
                   0.75
                             0.84
                                       0.79
                                                  650
                                       0.72
                                                 1022
    accuracy
                             0.67
                                       0.68
                                                 1022
                   0.69
  macro avg
weighted avg
                   0.71
                             0.72
                                       0.71
                                                 1022
Confusion Matrix:
[[187 185]
 [106 544]]
```

	precision		recall	f1-score	support
	0.0	0.63	0.56	0.59	372
	1.0	0.76	0.81	0.79	650
accu	racy			0.72	1022
macro	avg	0.70	0.69	0.69	1022
weighted	avg	0.71	0.72	0.72	1022

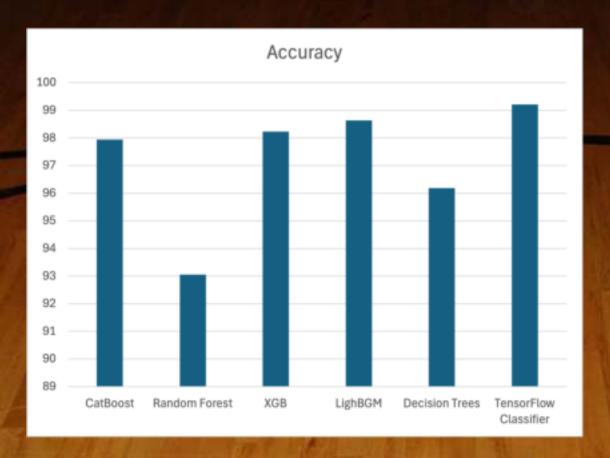
[125 525]]

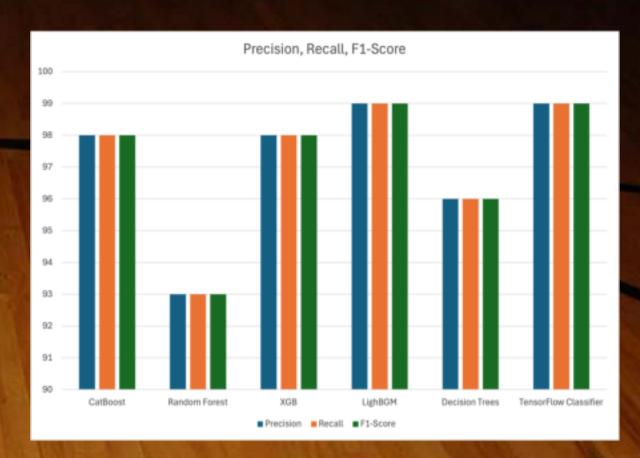
lightbgm	Clas	sification R	eport:		
		precision	recall	f1-score	support
	0.0	0.64	0.55	0.59	372
	1.0	0.76	0.82	0.79	650
accur	acy			0.72	1022
macro	avg	0.70	0.68	0.69	1022
veighted	avg	0.71	0.72	0.72	1022

Accuracy	: 0.6	565557729941	291		
Decision	Tree	Classificati	on Report	:	
		precision	recall	f1-score	support
	0.0	0.53	0.53	0.53	372
	1.0	0.73	0.73	0.73	650
accu	racy			0.66	1022
macro	avg	0.63	0.63	0.63	1022
weighted	avg	0.66	0.66	0.66	1022
Confusion	n Mat	rix:			
[[199 17]	3]				
[178 47	2]]				

ensorflow C	lassification	10.00			
	precision	recall	f1-score	support	
0.0	0.69	0.57	0.63	372	
1.0	0.78	0.86	0.81	650	
accuracy			0.75	1022	
macro avg	0.74	0.71	0.72	1022	
weighted avg	0.75	0.75	0.75	1022	
Confusion Ma	trix:				
[213 159]					
[94 556]]					

Method -2: Used the same 6 models for prediction and chose the one with the best accuracy.





```
# Fit the model on the training data
   catboost_classifier.fit(X_train, y_train)
   # Predict on the testing data
   y_pred = catboost_classifier.predict(X_test)
   # Evaluate the model
   print(f'Accuracy: {accuracy_score(y_test, y_pred)}')
   print('Classification Report:')
   print(classification_report(y_test, y_pred))
   print('Confusion Matrix:')
   print(confusion matrix(y test, y pred))
Accuracy: 0.9794520547945206
Classification Report:
                          recall f1-score support
             precision
                            8.97
                                      0.97
        0.0
                  8.98
                                                 372
                  0.98
                            0.99
                                      8.98
                                                 658
        1.0
```

0.98

0.98

accuracy

Confusion Matrix:

macro avg

weighted avg

[[359 13]

[8 642]]

0.98

0.98

0.98

0.98

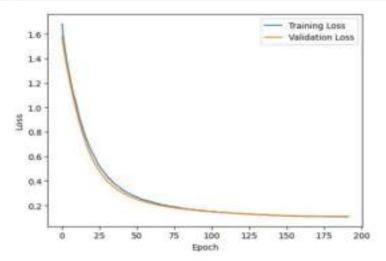
0.98

1022

1822

1022

```
Accuracy: 0.9921722111502935
Tensorflow Classification Report:
             precision
                         recall f1-score support
                                               372
                           1.00
                                    0.99
                                               658
                                    0.99
                                              1822
   accuracy:
                                    0.99
                                              1922
   macro avg.
                 9.99
                           0.00
                           0.99
                                    0.99
                                              1022
weighted avg
                 0.99
Confusion Matrix:
[[366 6]
[ 2 648]]
```





	precision		pre		recall	f1-score	support
e	0.0	0.99	0.97	0.98	372		
1	0	0.98	0.99	0.99	650		
accura	icy			0.99	1022		
macro a	vg	0.99	0.98	0.99	1022		
weighted a	ivg	0.99	0.99	0.99	1022		
Confusion	Matrix:						
[[362 10]	Ĺ						
[4 646]	1						

Accuracy: 0.961839530332681 DecisionTree Classification Report: recall f1-score support precision 0.0 0.94 0.95 0.95 372 1.0 0.97 0.97 0.97 650 0.96 1022 accuracy 0.96 macro avg 0.96 0.96 1022 weighted avg 0.96 0.96 0.96 1022 Confusion Matrix: [[354 18] [21 629]]

	precision	recall	f1-score	support
0.0	0.95	0.85	0.90	372
1.0	0.92	0.98	0.95	650
accuracy			0.93	1022
macro avg	0.94	0.91	0.92	1022
weighted avg	0.93	0.93	0.93	1022
Confusion Mat	rix:			
[[317 55]				
[16 634]]				

		precision recall		f1-score	support
6	0.0	0.98	0.97	0.98	372
1	1.0	0.98	0.99	0.99	650
accura	асу			0.98	1022
macro a	avg	0.98	0.98	0.98	1022
weighted a	avg	0.98	0.98	0.98	1022
Confusion	Mat	rix:			
weighted a	Mat		0.98	0.98	102

Interactive Interface

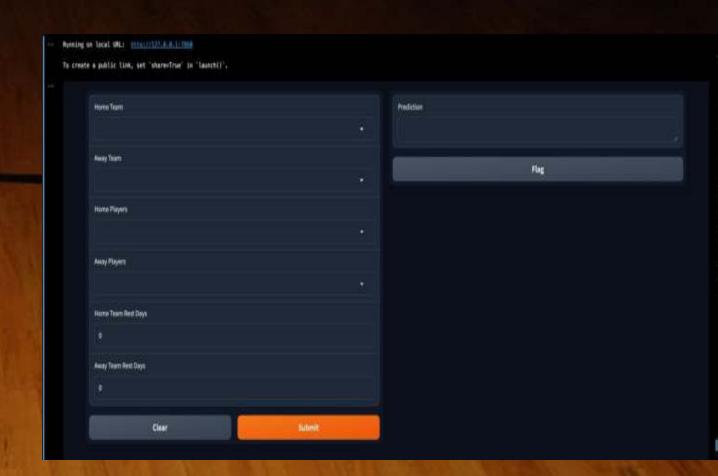
• Used "Gradio UI Design" to create a user-friendly interface that simplifies input and output for the user.

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eway players - gr.Drupdmon(listlusique players), label-"may "layers", myltiselect-from, mas choloses-Ti
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ever_rest_days = gruthetier(lakel="husy Trans from Dogs")
satput test - or Texthood labels Freder Lor's
 ief predict winner and supitume team, away team, home players, many players, home rest days, away rest days is
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    data shot Places rest (suc') a hase rest days
    data dict["may rest may"] - may rest may
    data_dict["tume_tume_tume_ruting"] < home_text_performance[home_taxe]
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    data_dict["temm_form_roting"] = feam_performance[tons_team]
    data_dict["away_team_rating"] = team_performance[away_team]
    data_dict["home from hims wire percentage"] - home wis percentage[home_team]
    data dictificacy team new win percentage" | week win percentage laway team!
    data dict["Tome_text_wit_serientage"] = text_wit_percentage[home_text]
    data dictl'issoy team win percentage" | - team win percentage [away trans]
    data dict["form from home nours more"] = home team stores, lockfrom team, "home from home store more"]
    data distillarme from home score median" - home tope scores, bar Down tope, "home tope tope score median"
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    data_dict["many_town_swip_store_median"] = away_team_scores_loc[away_team, "away_team_many_score_median"]
    data distifuse tose core wor'l - tem scoves hellows tear, 'esse points'l
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    data_dictPoory_tom_none_mon'l = term_scores_loclaws_teas, 'even_policis'l
    data_dict["sway_team_inner_mediar"] = team_aceres_lecturey_team, 'median_points']
    data_dict["PER_man_nons"] = player_state.locInen_players, "PER"[.man()
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    data dict["TEN not many"] = player stats, loc[ever players, "PHY L.maxi")
    data dict["Filt max home"] = glayer stats.loc[home players, "Filt].max[]
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    data dict["TER median hose"] - player state.loc(tame players, 'PCB'].mediant)
    data_dict["Ni_pit_mon_non"] = player_stats_leclaver_slayers, "Ni_put'l_essel)
    data dict I've just ness home"! - glayer statu. Technon players, 'PG just'l meand!
    data_dict["Vi_jct_mm_avey"] = player_stats.loc(avey_players, 'Vi_pct').ess()
    data_dict["Ni_pct_ma_tome"] = minyer_stats.locbume_players, "Ni_pct'l_man()
    data_dict["Ni_pot_semilar_ever"] = glayer_state_leclaver_players, 'Ni_pot'l_medias()
    data dist["Wi per median home"] - player state lacibone slayers, 'Wi per 'l'addiss()
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    data dict["IP pct man hame"] = glayer state. Inclines players, "IP pct Lagget)
    data_dict["H" prt max may"] = player_state, loclaway_players, 'IP pit'l.amid's
    data_dict["3P_pct_sac_hose"] = player_stats_loc[hose_players, '3P_pct'l_sas()
    data dict[ IP per median many ] w player state. loc(ever players, IP per ] median()
    data_dict["IP per_estime_bose"] = player_stats_tachase_alayers, "IP per l_sediant)
    data dict["I" pct sees wey" - player state, loclaway players, "I" put "Lessed!
```

```
# Create a Sataframe from the data
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                   # Rearrange the columns to watch the bedelts light order
                   mate at - data of Diculamed
                   # Predict the vinning fear and MY.
                   results - predict winning team and player skiesrnicathoost classifier, date of, home team, many team, home players, many players!
                   # Cornect the results to a string
                   support = ["in".joint[fffcenvit(E)] when with a probability of drawatt[]]. 273 and the MAP in (result[]]) for result in result[]]
                   return extput(#0
 0.04
           predict winner and explantage have translible, unique many translibly
                                                                      anima players limberises;
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 'Haine wins with a probability of 8.09 and the MVP is Brandon Rush'
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Manning on local UNL: http://idia.ii.iiiiiiii
To create a public tink, set 'share-True' in 'taunch()'
```

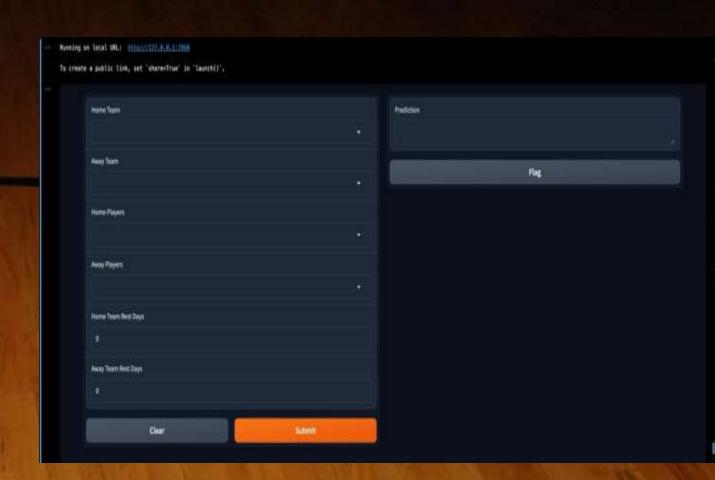
Interactive Interface

- User Inputs:
- Select home and away teams.
- Choose 7 players per team from dropdowns and also include Home & Away Rest Days for better prediction.



Interactive Interface

- Prediction Outputs:
- Winning team.
- Probability of winning.
- MVP responsible for the winning shot.



Prediction Logic

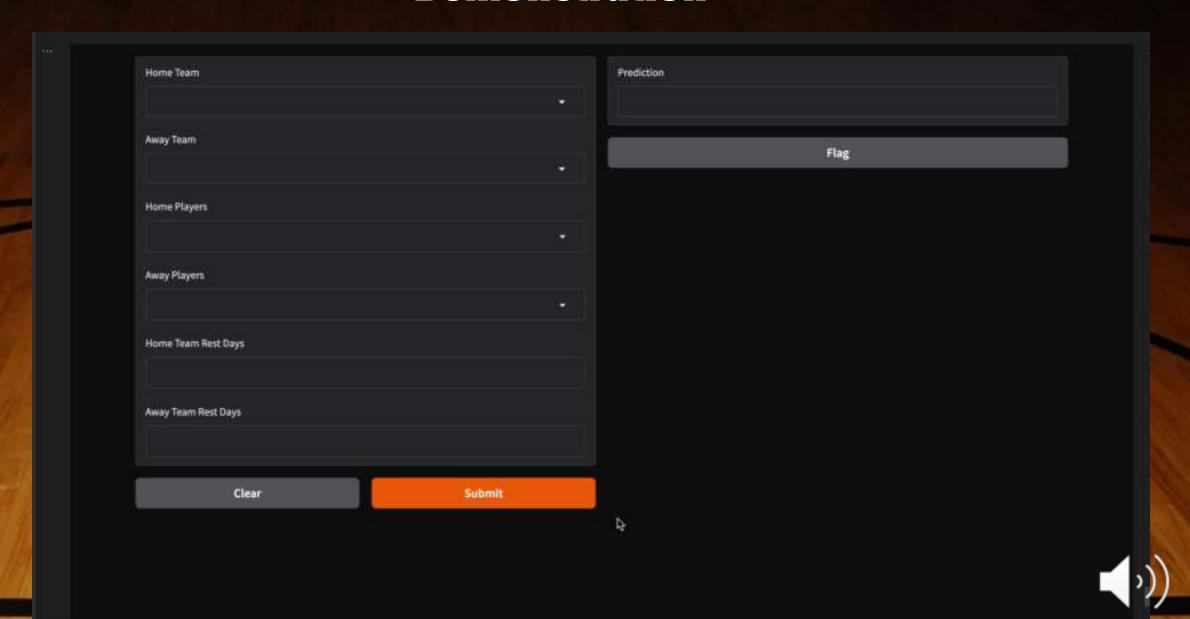
Winning Team Prediction:

 The neural network determines the likelihood of home or away victory based on input features.

Player Selection:

- Weighted scoring formula: Score = (clutch_pct × 0.4) + (PER × 0.6)
- The player with the highest score from the predicted winning team is identified as the MVP.

Demonstration



Results & Insights

Use Cases:

- For Coaches: Strategic decision-making for critical game moments.
- For Analysts: Advanced player performance analytics.
- For Fans: Enhanced engagement through predictive insights.

Future Scope

Enhancements

- Improve model accuracy by incorporating real-time data streams.
- Extend predictions to other aspects like defensive plays.
- Add deeper player-level metrics (e.g., fatigue, injury probability).

Future Scope

Conclusion

- Successfully integrated data science and sports analytics.
- Intuitive tool for predicting game-changing moments.
- Open for questions and feedback.

