ISyE 6740 - Spring 2024
Final Report

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Project Title: Predicting NCAA Quarterback Success in the National Football League

GitHub Repository: `https://github.com/jmayanja33/quarterback-evaluation-models/tree/master`

Contents

1 Problem Statement

The National Football League is a multi-billion dollar enterprise, with millions of fans all over the world. Every Sunday from September to January, these fans watch their teams, some cheering on a Super Bowl contender, and others suffering through a losing season. For many in the latter, looking forward to the annual NFL draft in April is much more exciting than the current games, as their team will likely have a high pick, and the chance to select a franchise changing player. Oftentimes, the players selected at the top of the draft are quarterbacks, as they are the leader of a team's offense.

Finding a quarterback that can become a franchise changing player has actually proven to be a very challenging task. Since 1970, over 500 quarterbacks have been selected, and the probability that one becomes a First Team All-Pro selection is just 4.6%. This probability rises to 9.4% for quarterbacks in the first round, and 11.9% for quarterbacks drafted in the Top 5 (*Fox Sports*).

Since quarterback is such an important position, when given the opportunity, drafting a high end quarterback is vital for a team's long term success. The current evaluation methods in place for draft eligible quarterbacks are not incredibly strong, and have missed on multiple quarterbacks every year. These systems are mostly visual, with teams sending scouts to watch each player, and then potentially interviewing the player if interested.

This project aims to enhance the current quarterback evaluation methods through the use of machine learning. Machine learning has the ability to reveal hidden patterns and trends in data, and a strong model would be able to reveal which quarterbacks are NFL ready, and which simply exposed weak points in the college game that disappear in the NFL. Five models will be created, one to predict the quarterback's tier in the NFL, one to predict the number of first team all pro selections for the quarterback, one to predict the number of years as a starter, one to predict the number of Pro Bowl selections, and one to predict their weighted career approximate value.

The quarterback tier is the variable of main concern, as it is a summary of the other four dependent variables, and theoretically less volatile. Even though many factors go in to creating a successful quarterback, success in this project is determined by how well NCAA football statistics for each of these quarterbacks can predict what tier of NFL quarterback they will become (from elite to failure). Secondary success will be defined by how well the four subsequent models provide supplemental explanation for the tier prediction.

2 Data

2.1 Data Sources

The majority of the data for this project came from the *Sports Reference* family of websites. *Pro Football Reference* has a listing of every selection from each NFL draft on their website. Since technology and strategy have changed as the game of Football has developed, only the players drafted between the years 2000-2024 were used in this project. The NCAA statistics for these players were found on *Sports Reference*'s NCAA football database, *SRCFB*, and their combine data was found on the *NFL Combine Results* website.

2.2 Data Collection

Unfortunately, none of this data currently compiled in an easily accessible format, such as csv or json. The easiest way to collect it was to scrape it from each of the websites listed above, using the Beautiful Soup and Pandas Python libraries.

From each NFL draft between 2000-2004, the statistics in the *NFL Statistics* column of Table 1 were scraped from the *Pro Football Reference* website for each quarterback drafted (these statistics were from the player's entire NFL career).

NFL Statistics	NCAA Statistics	Combine Measurements
Age at Draft	College	Height
Final Year in the NFL	Conference	Weight
First Team All-Pro Selections	Years Played	-
Pro Bowl Selections	Games Played	-
Number of Years as a Starter	Completions	-
Weighted Career Approximate Value[1]	Passes Attempted	-
Games Played	Passing Yards	-
Completions	Passing Touchdowns	-
Passes Attempted	Interceptions	-
Passing Yards	Passer Rating	-
Passing Touchdowns	Rushing Attempts	-
Interceptions	Rushing Yards	-
Rushing Attempts	Rushing Touchdowns	-
Rushing Yards	Wins	-
Rushing Touchdowns	Losses	-
-	Highest AP Poll Ranking	-
-	Conference Wins	-
-	Conference Losses	-

Table 1: Features Scraped

For each of these quarterbacks, their corresponding NCAA football statistics were scraped from *SRCFB*. *SRCFB* only holds data for FBS quarterbacks, so data for any FCS quarterbacks drafted was unable to be collected. The statistics in the *NCAA Statistics* column of Table 1 were collected from each drafted quarterback's NCAA career.

This data served as all of the football statistics used in the project. Two csv files were created from these datasets, one to hold all of the NFL statistics for each player, and one to hold the NCAA statistics. Any player that had missing NFL or NCAA statistics was dropped, as only 304 quarterbacks were drafted during this time span, which was not enough to reliably impute missing data. This left 275 quarterbacks with complete data to be used for model training and testing.

The final two data points scraped were height (in inches) and weight (in pounds) for each quarterback. These were scraped from the *NFL Combine Results*, and added as features to both the NFL quarterback dataset and the NCAA quarterback dataset.

3 Methodology

3.1 Exploratory Data Analysis

3.1.1 Clustering

In order to classify quarterbacks into tiers, the tiers must first be defined. The most logical way to do this was through a mix of machine learning and human review. Two clustering methods, K-Means clustering and HDBSCAN, were used to cluster the quarterbacks into initial tiers, based on their NFL career statistics. External factors such as injuries skewed some of the results, so manual review was performed after clustering to move some quarterbacks to the most appropriate tier. Note that clustering was only performed on quarterbacks drafted between 2000-2022, as these quarterbacks have had enough time to prove where their NFL rank. The quarterbacks drafted in the 2023 and 2024 draft classes were as an extra test set at the end of the project.

Four clustering runs were performed in total, two for each algorithm. One with the data as is, and one with the data normalized. Initial results yielded much better performance from the K-Means models, as the HDBSCAN models identify a noise cluster. While many quarterbacks do not make it in the NFL, they are not considered noise, and need at least one centralized cluster dedicated to them. For this reason, the K-Means algorithm was selected as the algorithm to cluster the quarterbacks into tiers.

View the two elbow plots in Figure 1. From these plots, it is visible that the non-normalized data split best into 5 clusters, and the normalized data split best into 6 clusters. Observe the plots in Figure 2, which plot 2-dimensional representations of each of the clusters (these were created using PCA dimensionality reduction). While the clusters for the non-normalized data have a more spherical shape, upon review, it was clear that the clusters generated with the normalized data created better ties, as it grouped players together based more on their playing styles. The initial assumption for this is that the data normalization canceled out any difference in numerical statistics over the course of 25 years, and yielded data that represented more of a player's tendencies on the field. For this reason, the normalized K-Means clusters were selected. View the tier associated with each cluster in Table 2, and the 14 changes made to these clusters in Table 3. View descriptions of each of the tiers below:

1. **Starting Quarterbacks**: Solid, well rounded players that can consistently win games.

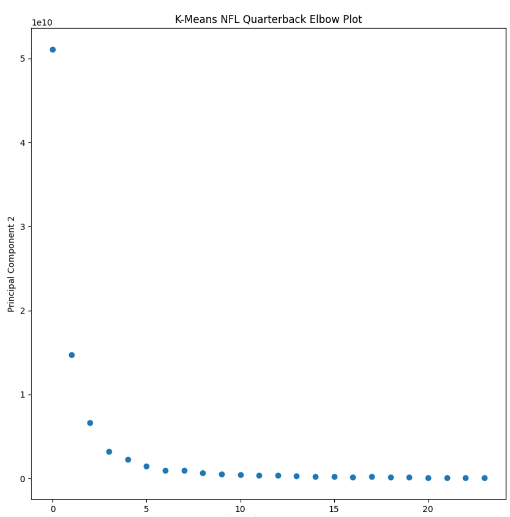
2. **Practice Squad Members**: Depth players that could be a solid emergency option for a few games.

3. **Backup Quarterbacks**: Players that can win games for longer stretches in a single season, but not long term.

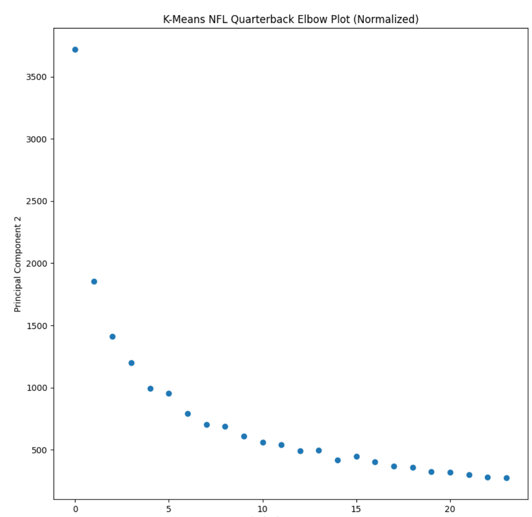
4. **High End Mobile Quarterbacks**: Elite players that often attack defenses with their high end rushing abilities. These players also have very solid passing abilities.

5. **Hall of Fame Quarterbacks**: Elite players that a franchise will contend with every season for a decade or longer

6. **High End Pocket Passers**: Elite players that attack defenses with their high end passing abilities from the pocket, and their Football IQ. These players are not quite as mobile as the mobile quarterbacks in Tier 4.

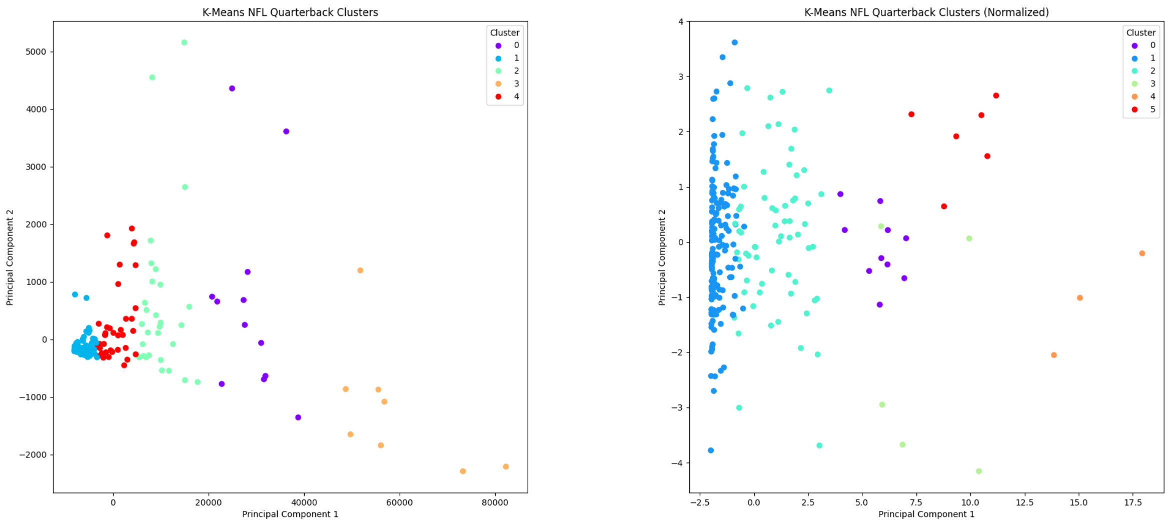


(a) K-Means Elbow Plot for Non-Normalized NFL Statistics



(b) K-Means Elbow Plot for Normalized NFL Statistics

Figure 1: Elbow Plots for K-Means Clustering



(a) K-Means Clusters Non-Normalized NFL Statistics

(b) K-Means Clusters for Normalized NFL Statistics

Figure 2: K-Means Clusters

Cluster Label	Quarterback Tier
0	Starting Quarterbacks
1	Practice Squad Members
2	Backup Quarterbacks
3	High End Mobile Quarterbacks
4	Hall of Fame Quarterbacks
5	High End Pocket Passers

Table 2: Cluster Labels to NFL QB Tier

Player	Old Tier	New Tier
Joe Burrow	Backup Quarterback	High End Pocket Passer
Joshua Dobbs	Practice Squad Member	Backup Quarterback
Patrick Mahomes	Starting Quarterback	High End Mobile Quarterback
Robert Griffin III	Backup Quarterback	High End Mobile Quarterback
Justin Herbert	Backup Quarterback	Starting Quarterback
Jalen Hurts	Backup Quarterback	High End Mobile Quarterback
Andrew Luck	Starting Quarterback	High End Pocket Passer
Baker Mayfield	Backup Quarterback	Starting Quarterback
Dak Prescott	Starting Quarterback	High End Mobile Quarterback
Brock Purdy	Backup Quarterback	Starting Quarterback
Mason Rudolph	Practice Squad Member	Backup Quarterback
Matt Schaub	Backup Quarterback	Starting Quarterback
Tua Tagovailoa	Backup Quarterback	Starting Quarterback
Deshaun Watson	Backup Quarterback	High End Mobile Quarterback

Table 3: Clustering Manual Edits

3.1.2 Scaling and Dimensionality Reduction

Assigning tiers to each quarterback was the final step in the data collection, as that completed all data points for all independent and dependent variables. Before model building was able to begin, relationships between the independent features must be explored first. If multicollinearity is present between any features, then prediction results could be skewed or the model could be overfit, as certain features could be dependant on each other. View the *Raw VIF* column from Table 4(a), which displays the Variance Inflation Factor (VIF) for each independent variable, normalized.

Table 4: VIF

(a) VIF Values

Feature	Raw VIF	Standardized VIF
College	4.6412	1.1052
Conference	3.9708	1.1740
Years	649.7806	26.7586
Games Played	123.9167	6.5880
Completions	477.3483	63.0659
Passes Attempted	654.5410	80.8027
Passing Yards	369.9306	43.7905
Passing Touchdowns	69.6274	10.2509
Interceptions	24.4683	4.0843
Passer Rating	35.1166	1.6039
Rushing Attempts	41.8878	11.3301
Rushing Yards	15.6676	10.9844
Rushing Touchdowns	17.7542	7.8213
Wins	409.3188	36.9693
Losses	229.0746	40.1820
Highest Rank	1.8870	1.6202
Conference Wins	33.0633	4.7590
Conference Losses	22.9731	5.6062
Points For	252.35087	15.3083
Points Against	150.0669	12.1879
Height	1439.9804	2.0568
Weight	743.5569	1.8834
Draft Age	484.3802	1.4184

(b) VIF After Scaling and PCA

Principal Component	VIF
PC1	1
PC2	1
PC3	1
PC4	1
PC5	1
PC6	1
PC7	1
PC8	1
PC9	1
PC10	1

VIF Values closer to 0 indicate less correlation between features. From Table 4(a), it is clear that there is correlation between many of the raw features. Standardizing a dataset often reduces correlation between variables. View the *Standardized VIF* column from Table 4, which calculates the VIF for the same data after standardization to a normal distribution.

It is clear that standardization helped removed some multicollinearity, but there is still a large amount remaining as shown by many high VIF values. To eliminate the the multicollinearity, the data will be transformed into 10 dimensions using Principal Component Analysis (PCA). View the results in Table 4(b), with all VIF values equal to 1. 10 dimensions was decided upon as that kept enough complexity of the original data while eliminating correlation between all features.

3.1.3 Data Split

Once normalized, standardized, and PCA reduced, the data was split for model training. Since the full dataset was rather small (275 data points), only a training and test set could be created. The data was split randomly into these sets, with 85 percent of the data (212 data points) going to the training set, and the remaining 15 (38 data points) going to the test set. Once again, a final test set of 25 data points was created from the 25 quarterbacks drafted in the last two years (2023, and 2024), which served as the real world data for the models to give initial predictions on.

3.2 Model Training

As stated earlier, five models were created, one for each of the following dependent variables:

1. Quarterback Tier
2. First Team All Pro Selections
3. Number of Years as a Starter
4. Pro Bowl Selections
5. Weighted Career Approximate Value

The main focus was on the Quarterback Tier model, as this essentially is a summary of the other four variables, and there are many more subjective factors which influence the other four. If their models were strong, these secondary variables would be used to help explain the Quarterback Tier prediction.

The following five model types were tested. Each model was be evaluated with a grid-search and 5 fold cross validation for each dependent variable, and the best model was be kept for each. The metrics used to evaluate model performance were accuracy for Quarterback Tier, and Root Mean Squared Error for all others.

Model Types:

1. Artificial Neural Network
2. K-Nearest Neighbors
3. Random Forest
4. Support Vector Machines
5. XGBoost

3.2.1 Artificial Neural Network

Artificial Neural Networks were chosen as a model candidate as neural networks excel at finding hidden and complex patterns within datasets. Due to the compressed nature of this project, cross validation was not able to be used for the the neural networks as it was too computationally expensive. These models were created using Tensorflow and the hyperparameters used are listed in Table 5(a). View the accuracy metrics for each dependent variable in Table 5(b)

Table 5: Artificial Neural Network Hyperparameters

(a) ANN Hyperparameters

Hyperparameter	Value(s)
Hidden Layers	2
Neurons per Hidden Layer	8
Hidden Layer Activation Function	ReLU
Loss Function (Regression)	Mean Squared Error
Loss Function (Classification)	Sparse Categorical Crossentropy
Optimizer	Adam

(b) ANN Accuracy Metrics

Dependent Variable	Accuracy	RMSE
Quarterback Tier	0.7105	-
First Team All Pro Selections	-	0.1828
Number of Years as a Starter	-	3.1245
Pro Bowl Selections	-	1.4752
Weighted Career Approximate Value	-	32.8968

3.2.2 K-Nearest Neighbors

K-Nearest Neighbors was chosen as a model candidate as each data point in this dataset represents a quarterback, and this algorithm makes predictions based on the closet (or most similar) data points to a certain point (or in this case, the most similar quarterbacks). These models were created using SciKit-Learn, with the Number of Neighbors, Distance Metric, and Weights being the hyperparameters tuned using 5-fold cross validation. See the hyperparameter values tested in Table 6(a), and the optimal values found listed in Table 6(b).

Table 6: K-Nearest Neighbors Hyperparameters

(a) KNN Hyperparameters Tested

Hyperparameter	Value(s)
Number of Neighbors	1, 3, 5, 7, 9, 11, 13, 15, 17, 19
Distance Metric	Manhattan, Euclidean
Weights	Uniform, Distance

(b) KNN Hyperparameters Selected

Dependent Variable	Number of Neighbors	Distance Metric	Weights	Accuracy	RMSE
Quarterback Tier	9	Manhattan	Uniform	0.6316	-
First Team All Pro Selections	19	Euclidean	Uniform	-	0.0931
Number of Years as a Starter	19	Euclidean	Uniform	-	2.8904
Pro Bowl Selections	19	Euclidean	Uniform	-	1.3363
Weighted Career Approximate Value	19	Euclidean	Uniform	-	30.0526

3.2.3 Random Forest

Random Forest was selected as a model candidate, as it is a bagging algorithm, meaning that it takes the opinions of predictions on multiple subsets of the data to make a final decision. In an industry like the NFL, where many different scenarios can play out based on roster moves and injuries, this algorithm could account for many of these cases, helping the variance accounted for by the final models.

The Random Forest models were created using SciKit-Learn. Number of Estimators and Max Tree Depth were the hyperparameters tuned using 5-fold cross validation. See the hyperparameter values tested in Table 7(a), and the optimal values found listed in Table 7(b).

Table 7: Random Forest Hyperparameters

(a) Random Forest Hyperparameters Tested

Hyperparameter	Value(s)
Number of Estimators	100, 200, 300, 400, 500
Max Tree Depth	1, 2, 3, 4, 5, 6, 7, 8, 9, 10

(b) Random Forest Hyperparameters Selected

Dependent Variable	Number of Estimators	Max Tree Depth	Accuracy	RMSE
Quarterback Tier	300	4	0.6579	-
First Team All Pro Selections	200	1	-	0.0932
Number of Years as a Starter	100	1	-	3.027
Pro Bowl Selections	100	1	-	1.454
Weighted Career Approximate Value	100	1	-	31.758

3.2.4 Support Vector Machines (SVM)

The SVM algorithm was selected as a candidate as if there were hard classifier boundries between the different quarterback tiers, the algorithm would do very well making predictions within those boundaries. Like the neural networks, cross-validation was unable to be used for SVM due to it's computational expense in a short period of time. These models were created using Scikit-Learn and custom values for the hyperparameters C, the Kernel, and gamma (γ) are listed in Table 8(a). View the accuracy metrics for each dependent variable in Table 8(b).

Table 8: Support Vector Machines Hyperparameters

(a) SVM Hyperparameters

Hyperparameter	Value(s)
C	0.1
Kernel	RBF
Gamma (γ)	auto

(b) SVM Accuracy Metrics

Dependent Variable	Accuracy	RMSE
Quarterback Tier	0.6579	-
First Team All Pro Selections	-	0.0935
Number of Years as a Starter	-	3.2049
Pro Bowl Selections	-	1.4671
Weighted Career Approximate Value	-	34.5434

3.2.5 XGBoost

Similar to the Random Forest algorithm, the XGBoost algorithm was selected as a candidate as it is also an ensemble method, so it could also theortically capture more of the variance in this data. Instead of bagging however, XGBoost is a boosting algorithm, meaning that it takes a series of weak learners in sequential order, and boosts each one's predictions based on the errors of the previous ones.

The XGBoost models were created using the XGBoost python library. The Learning Rate, Number of Estimators, and Max Tree Depth were the hyperparameters tuned using 5-fold cross validation. See the hyperparameter values tested in Table 9(a), and the optimal values found listed in Table 9(b).

Table 9: XGBoost Hyperparameters

(a) XGBoost Hyperparameters Tested

Hyperparameter	Value(s)
Number of Estimators	100, 200, 300, 400, 500
Max Tree Depth	1, 2, 3, 4, 5, 6, 7, 8, 9, 10

(b) XGBoost Hyperparameters Selected

Dependent Variable	Learning Rate	Num. of Estimators	Max Depth	Accuracy	RMSE
Quarterback Tier	0.01	200	3	0.6842	-
First Team All Pro Selections	0.01	100	3	-	0.1123
Number of Years as a Starter	0.01	100	3	-	2.7631
Pro Bowl Selections	0.01	100	3	-	1.4479
Weighted Career Approximate Value	0.01	100	3	-	32.0447

4 Results and Discussion

4.1 Model Selection

Observe Table 10, which displays the the models selected for each dependent variable. The models selected had the highest accuracy, or lowest RMSE, for each dependent variable. Note that while XGBoost had the lowest RMSE for Number of Years as a starter by a slight margin, it seemed overfit to the training data as it did not yield great predictions on the live test dataset of young quarterbacks, so KNN was selected.

Also note that all RMSE values for Weighted Career Approximate Value were greater than 30. In the terms of Weighted Career Approximate Value, this is a very large average gap between predicted and actual values. As a result, none of these models were deemed reliable enough for use, so this variable, and all of its models, were dropped from the project.

Dependent Variable	Model Selected	Accuracy	RMSE	R-Squared	Adj. R-Squared
Quarterback Tier	ANN	0.7105	-	-0.1737	-0.6084
First Team All Pro Selections	KNN	-	0.0931	0	-0.3704
Number of Years as a Starter	Random Forest	-	3.0273	0.0287	-0.3310
Pro Bowl Selections	KNN	-	1.3363	0.1244	-0.1999

Table 10: Selected Models

4.2 Predictions on Live Data

View Table 11 which displays the predictions of each dependent variable for each quarterback drafted in the years 2023 and 2024 using the models defined in Table 10. Since Quarterback Tier was calculated using a softmax function, Table 12 displays the probability of each quarterback developing into that tier during their career. Finally, Table 13 shows the three most similar NCAA quarterbacks (from 2000 - 2022) to each of these quarerbacks, with the similarity being calculated using cosine similarity.

Finally, note that predictions for all variables besides Quarterback Tier were rounded to one decimal place for some extra insights into each models' thoughts.

Player	1st Team All-Pro	Pro Bowls	Years Starting	Tier
Bryce Young	0	0.3	1.9	Practice Squad
C.J. Stroud	0.4	1.4	2.3	Backup Quarterback
Anthony Richardson	0.2	2.1	1	Practice Squad
Will Levis	0	0	1.4	Practice Squad
Hendon Hooker	0	0.3	1.4	Practice Squad
Jake Haener	0	0.5	2.1	Practice Squad
Stetson Bennett	0	0.4	1.8	Practice Squad
Aidan O'Connell	0	0.1	1.8	Practice Squad
Clayton Tune	0	0.1	1.8	Practice Squad
Dorian Thompson-Robinson	0.1	1.3	1.9	Practice Squad
Sean Clifford	0	0.4	2.3	Practice Squad
Jaren Hall	0	0.3	2.0	Practice Squad
Tanner McKee	0.2	0.5	2.3	Practice Squad
Max Duggan	0.1	1.5	2.1	Practice Squad
Caleb Williams	0	0.5	2.8	Practice Squad
Jayden Daniels	0	0.8	1.9	Practice Squad
Drake Maye	0.2	1.0	2.1	Practice Squad
Michael Penix Jr.	0.1	1.1	2.1	Practice Squad
J.J. McCarthy	0.2	0.9	2.3	Practice Squad
Bo Nix	0	0.5	2.4	Practice Squad
Spencer Rattler	0.1	1.2	2.3	Practice Squad
Jordan Travis	0.1	1.0	2.1	Practice Squad
Joe Milton III	0	0.1	1.8	Practice Squad
Devin Leary	0.1	0.7	1.7	Practice Squad
Michael Pratt	0.1	1.0	2.1	Practice Squad

Table 11: 2023-2024 Drafted Quarterbacks Career Predictions

Player	Starter	Practice Squad	Backup	Elite Mobile	Hall of Fame	Elite Pocket Passer
Bryce Young	0.1315	0.2582	0.2541	0.2061	0.0637	0.0865
C.J. Stroud	0.0520	0.2378	0.4788	0.1258	0.0714	0.0341
Anthony Richardson	0.0279	0.6658	0.2695	0.0099	0.0127	0.0143
Will Levis	0.0358	0.6990	0.1965	0.0348	0.0200	0.0139
Hendon Hooker	0.0070	0.9137	0.0665	0.0081	0.0029	0.0018
Jake Haener	0.0996	0.3001	0.2535	0.1689	0.0785	0.0993
Stetson Bennett	0.0842	0.5377	0.1853	0.1300	0.0253	0.0374
Aidan O'Connell	0.0503	0.6430	0.1126	0.0850	0.0405	0.0686
Clayton Tune	0.0935	0.4063	0.2589	0.0657	0.0883	0.0874
Dorian Thompson-Robinson	0.0662	0.6333	0.1548	0.0546	0.0425	0.0485
Sean Clifford	0.0599	0.5669	0.2464	0.0294	0.0443	0.0532
Jaren Hall	0.0032	0.6238	0.3521	0.0127	0.0071	0.0011
Tanner McKee	0.0597	0.4671	0.3259	0.0531	0.0564	0.0377
Max Duggan	0.0308	0.7279	0.1717	0.0180	0.0257	0.0259
Caleb Williams	0.0648	0.5532	0.2054	0.0337	0.0683	0.0746
Jayden Daniels	0.0196	0.8096	0.1239	0.0085	0.0184	0.0199
Drake Maye	0.0794	0.3933	0.3693	0.0447	0.0587	0.0546
Michael Penix Jr.	0.1171	0.4594	0.1482	0.1169	0.0701	0.0881
J.J. McCarthy	0.0347	0.4833	0.4477	0.0171	0.0107	0.0065
Bo Nix	0.0598	0.6278	0.1373	0.0264	0.0641	0.0845
Spencer Rattler	0.1184	0.4741	0.1315	0.1193	0.0658	0.0910
Jordan Travis	0.0002	0.9445	0.0549	0.0002	0.0001	0.0001
Joe Milton III	0.0008	0.9789	0.0187	0.0012	0.0003	0.0001
Devin Leary	0.0707	0.5046	0.2599	0.0713	0.0562	0.0373
Michael Pratt	0.0487	0.6002	0.2279	0.0273	0.0487	0.0472

Table 12: 2023-2024 Drafted Quarterbacks Tier Probabilities

Player	Comparison 1	Sim.	Comparison 2	Sim.	Comparison 3	Sim.
Bryce Young	Sam Bradford	0.9998	Brian Brohm	0.9996	Jarrett Stidham	0.9995
C.J. Stroud	Brian Brohm	0.9998	Sam Bradford	0.9997	Jake Fromm	0.9997
Anthony Richardson	Malik Willis	0.9882	Kyler Murray	0.9882	Stephen McGee	0.9880
Will Levis	Jeff Driskel	0.9998	Steve Bellisari	0.9997	Christian Ponder	0.9997
Hendon Hooker	Marques Tuiasosopo	0.9991	Drew Stanton	0.9990	Jarious Jackson	0.9985
Jake Haener	Carson Palmer	0.9998	Ryan Mallett	0.9998	Ricky Stanzi	0.9997
Stetson Bennett	Tua Tagovailoa	0.9996	Dwayne Haskins	0.9989	Joe Burrow	0.9988
Aidan O'Connell	Nick Foles	0.9998	T.J. Yates	0.9998	Josh Rosen	0.9997
Clayton Tune	Garrett Gilbert	0.9993	Kellen Clemens	0.9992	Dave Ragone	0.9991
Dorian Thompson-Robinson	Matt Corral	0.9995	Kellen Mond	0.9994	Joe Hamilton	0.9991
Sean Clifford	Tajh Boyd	0.9995	Kevin Hogan	0.9995	Zach Wilson	0.9994
Jaren Hall	Skylar Thompson	0.9994	Jeff Driskel	0.9990	Jacoby Brissett	0.9989
Tanner McKee	Tanner Lee	0.9982	Trent Edwards	0.9970	Levi Brown	0.9968
Max Duggan	Joe Hamilton	0.9998	Robert Griffin III	0.9995	Kellen Mond	0.9994
Caleb Williams	Zach Wilson	0.9998	Tajh Boyd	0.9997	Blake Bortles	0.9996
Jayden Daniels	Johnny Manziel	0.9996	Dak Prescott	0.9993	Desmond Ridder	0.9986
Drake Maye	Matt Corral	0.9995	Kellen Mond	0.9993	Chad Kelly	0.9992
Michael Penix Jr.	Garrett Grayson	0.9996	Derek Carr	0.9996	Kurt Kittner	0.9995
J.J. McCarthy	Joe Burrow	0.9996	EJ Manuel	0.9989	Tua Tagovailoa	0.9981
Bo Nix	Brock Purdy	0.9998	Colt McCoy	0.9997	Russell Wilson	0.9997
Spencer Rattler	Ryan Finley	0.9998	David Carr	0.9997	Jarrett Stidham	0.9994
Jordan Travis	Marques Tuiasosopo	0.9988	Drew Stanton	0.9987	Jarious Jackson	0.9982
Joe Milton III	Matt Flynn	0.9969	Brandon Doman	0.9959	D.J. Shockley	0.9957
Devin Leary	Cody Pickett	0.9999	Patrick Ramsey	0.9997	Matt Schaub	0.9996
Michael Pratt	David Garrard	0.9996	Kevin Hogan	0.9993	Logan Thomas	0.9992

Table 13: 2023-2024 Drafted Quarterbacks Most Similar Players

5 Evaluation

5.1 Metrics Discussion

Each of the four models that were kept in this project should be able to provide relatively reliable predictions. NFL rosters are very volatile, as injuries and trades occur very frequently. In addition, quarterback success is often very dependent on personality, coaching strategy, organization stability, abilities of surrounding players, and the fit of the quarterback in the team's offense. The absence of these factors in the training data is likely what contributed to low R-sqaured scores for each of these models, as these models only accounted for variance due to on-field factors.

Regardless, the Quarterback Tier model generated in this project was still able to place quarterbacks in the correct tier over 70 percent of the time. In addition, the supporting models kept provided very precise predictions that, on average, were all within 3.5 of the actual data point. While these models do not capture all of the features contributing to a quarterback's success, they still clearly do capture enough to provide a reliable image of a quarterback's most likely career path in the NFL.

5.2 Live Data Prediction Discussion

Observing the predictions made in Table 11 on the quarterbacks drafted in 2023 and 2024, it is clear that these models are not high on any as starting quarterbacks in the NFL. The models believe that each quarterback will play out the three years on their rookie contract, and then, with the exception of C.J. Stroud, be destined for the practice squad. It is reassuring to see that tier model had faith in Stroud as he won AFC rookie of the year in his first NFL season (2023). While he still has a long way to go to establish himself as a franchise quarterback, he is already much more accomplished than any of the other quarterbacks in these two draft classes.

When viewing Table 13, it is not surprising to see the model labeling most of these quarterbacks as practice squad players, as the majority of their college comparables became practice squad players in the NFL. The only exceptions to this were Stetson Bennett and J.J. McCarthy, who both had two established quarterbacks in Joe Burrow and Tua Tagovaila in their top 3 comparables. Bo Nix also had two established quarterbacks in his top 3 comparables with Brock Purdy and Russell Wilson.

Evaluating these three players in Table 12 shows that the model believes Bennett is likely the only one of these three to have a shot at an NFL career, as he was given an 18 percent chance to be a backup, and a 13 percent chance to be an elite mobile quarterback. On the other hand, McCarthy was given a 48 percent chance of being a practice squad member, and a 44 percent chance of being a backup, while Nix was given a 62 percent chance of being a practice squad player and then a 13 percent chance of being a backup.

Table 12 does yield two very interesting points from these models however. The first of these is that Bryce Young was given a 20 percent chance of being an elite mobile quarterback. Even though Young had a rough rookie season on a poor team, he still has plenty of time to revive his career, and given the right environment, the model believes he has the potential to do it. Young's chances of becoming an elite quarterback was the highest by far of both of these quarterback classes. The next closest was Jake Haener at 16 percent.

This leads into the second point, as the models have seemed to deem Haener as a wildcard prospect. His probability distribution across all six quarterback tiers is rather even, and Table 13 lists his most comparable quarterback as former Bengals franchise quarterback Carson Palmer. The models seems to believe that Haener is a true boom or bust prospect, and could thrive as an elite quarterback in the right environment.

6 Conclusion

The main model generated in this project was successfully able to classify quarterbacks into tiers based on prestige. With that being said, only three of four models to predict the supporting data for First Team All-Pro selections, Pro Bowl Selections, Number of Years as a Starter, and Weighted Career Average Value were able to be successfully generated. The likely cause of this was due to a lack of variability in the training data. The training data used only incorporated on field football statistics, when in reality quarterback success is defined by many on and off field factors. If this project was performed on a longer timeline, more data around personality, coaching, teammates, organizational stability, and team culture would be collected. This extra information would account for much more variability in a quarterback's development, and would likely boost both the accuracy and R-squared scores of each model.

However, reliable insights on a quarterback's likely NFL career path were still obtained using these models over 70 percent of the time. Of the quarterbacks in the 2023 and 2024 NFL draft classes, the models believed that, given the right environment, Bryce Young and Stetson Bennett had the best chances to become elite quarterbacks, and that wildcard prospect Jake Haener, also had a very significant chance to become an elite player. It is very important to note that scouting and due diligence are still required to confirm any predictions made by these models. The models, however, are a tool that will accelerate scouts and general managers down those correct scouting paths.

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