NFL Injury Prediction

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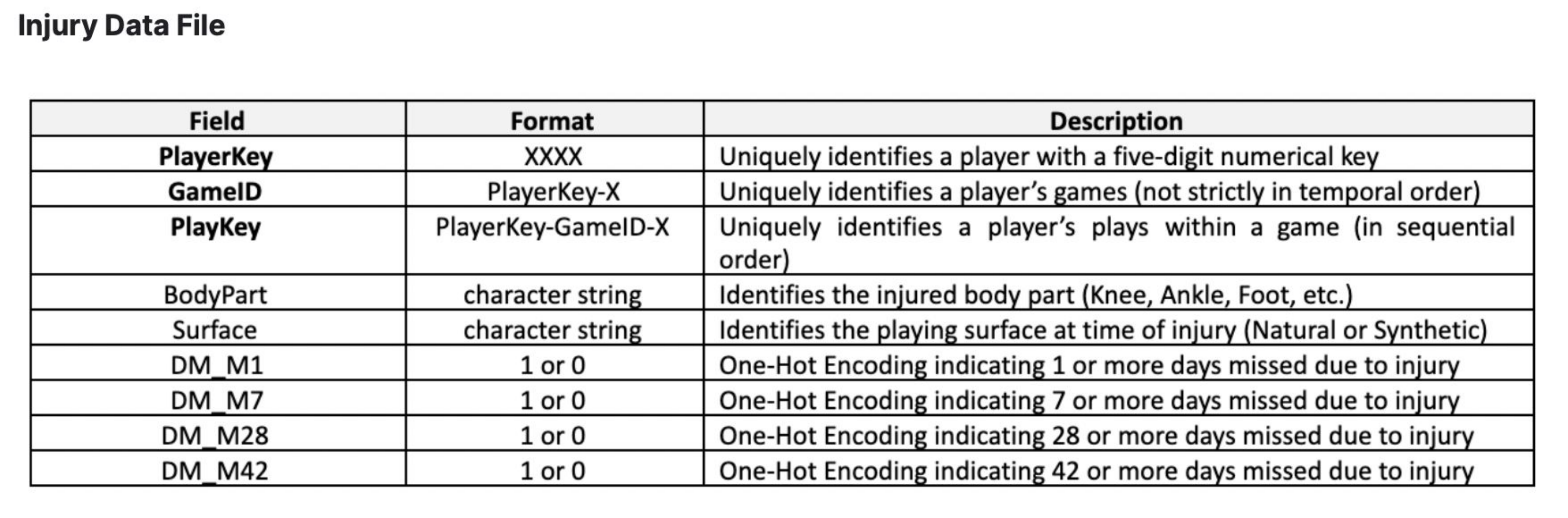
DATASCI 207 Final Project

Objective

Build a classification model that can help predict injuries to NFL players based on a suite of factors present during a typical NFL game

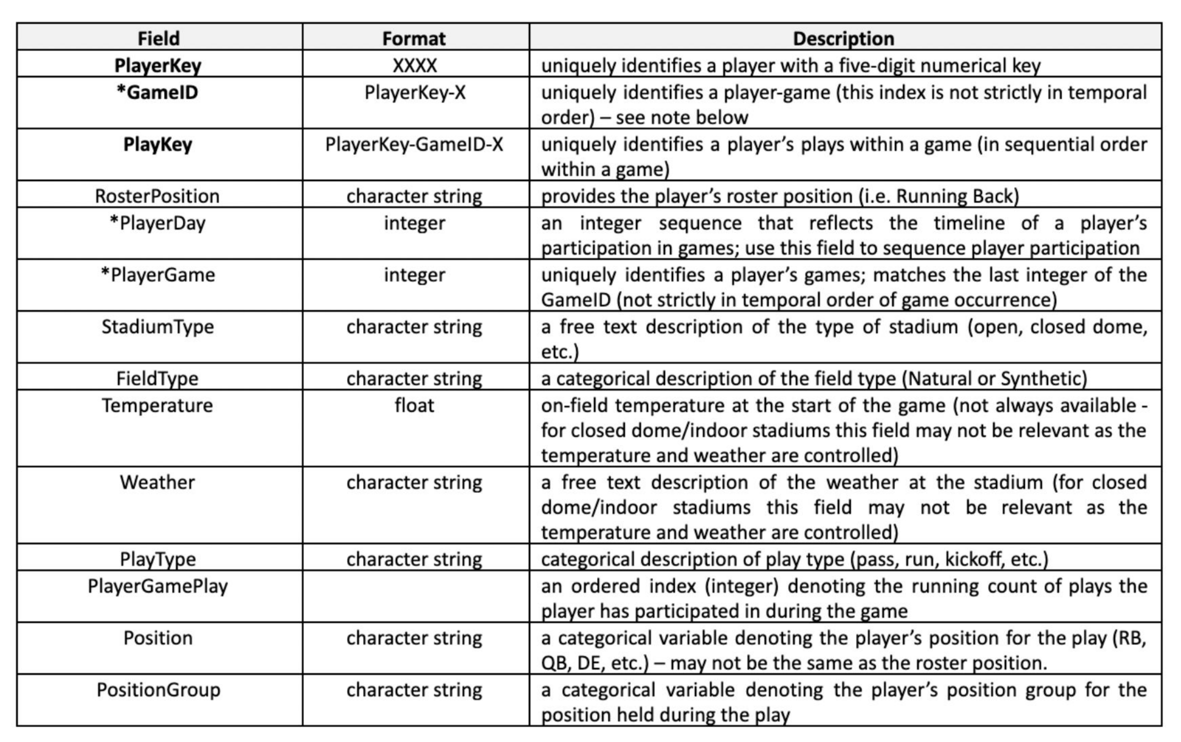
Injury Data



Injury Data File

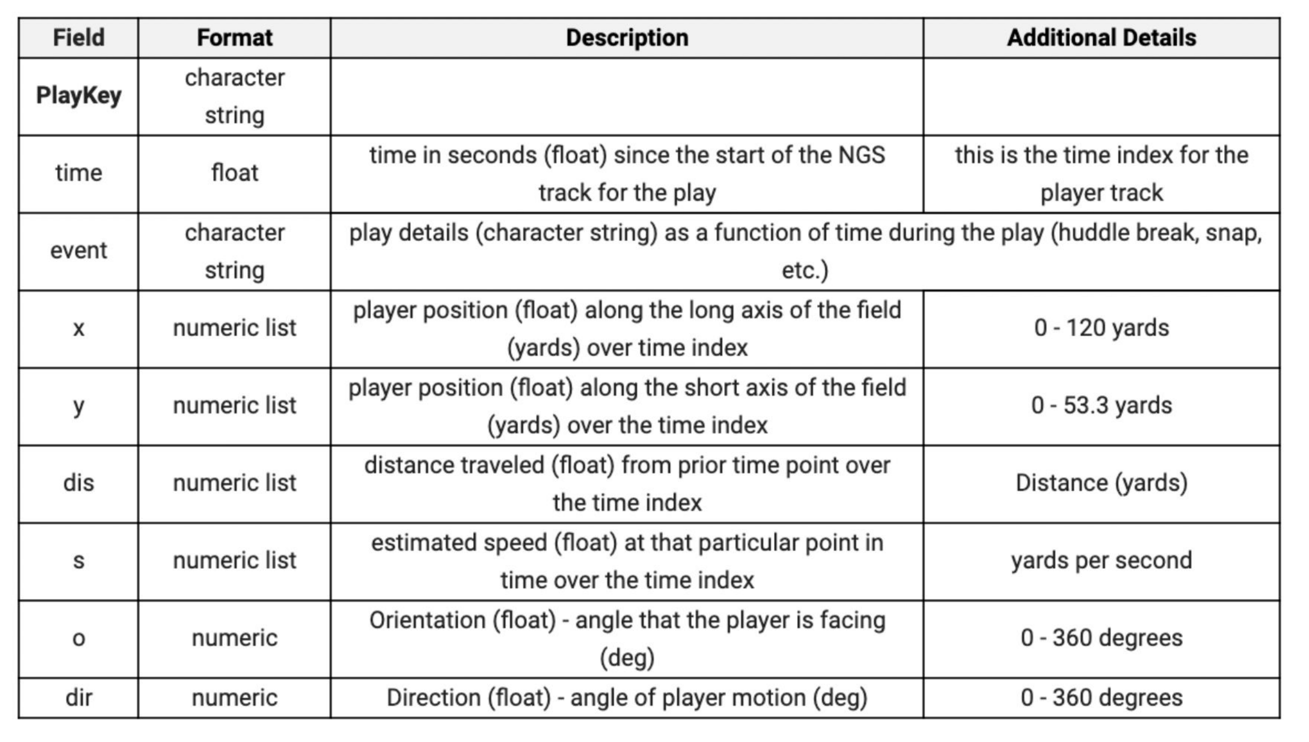
Field	Format	Description
PlayerKey	XXXX	Uniquely identifies a player with a five-digit numerical key
GameID	PlayerKey-X	Uniquely identifies a player's games (not strictly in temporal order)
PlayKey	PlayerKey-GameID-X	Uniquely identifies a player's plays within a game (in sequential order)
BodyPart	character string	Identifies the injured body part (Knee, Ankle, Foot, etc.)
Surface	character string	Identifies the playing surface at time of injury (Natural or Synthetic)
DM_M1	1 or 0	One-Hot Encoding indicating 1 or more days missed due to injury
DM_M7	1 or 0	One-Hot Encoding indicating 7 or more days missed due to injury
DM_M28	1 or 0	One-Hot Encoding indicating 28 or more days missed due to injury
DM_M42	1 or 0	One-Hot Encoding indicating 42 or more days missed due to injury

Play Level Data



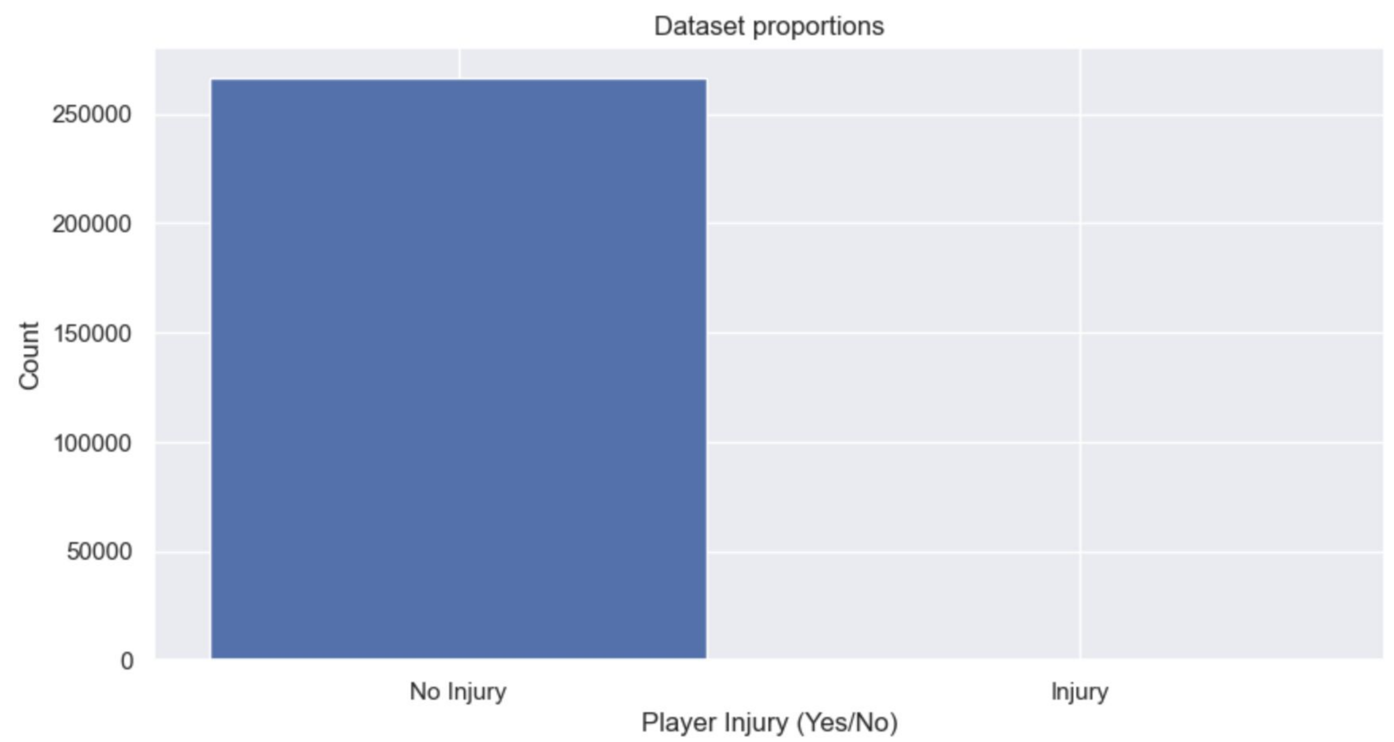
Field	Format	Description
PlayerKey	XXXX	uniquely identifies a player with a five-digit numerical key
***GameID**	PlayerKey-X	uniquely identifies a player-game (this index is not strictly in temporal order) – see note below
PlayKey	PlayerKey-GameID-X	uniquely identifies a player's plays within a game (in sequential order within a game)
RosterPosition	character string	provides the player's roster position (i.e. Running Back)
*PlayerDay	integer	an integer sequence that reflects the timeline of a player's participation in games; use this field to sequence player participation
*PlayerGame	integer	uniquely identifies a player's games; matches the last integer of the GameID (not strictly in temporal order of game occurrence)
StadiumType	character string	a free text description of the type of stadium (open, closed dome, etc.)
FieldType	character string	a categorical description of the field type (Natural or Synthetic)
Temperature	float	on-field temperature at the start of the game (not always available - for closed dome/indoor stadiums this field may not be relevant as the temperature and weather are controlled)
Weather	character string	a free text description of the weather at the stadium (for closed dome/indoor stadiums this field may not be relevant as the temperature and weather are controlled)
PlayType	character string	categorical description of play type (pass, run, kickoff, etc.)
PlayerGamePlay		an ordered index (integer) denoting the running count of plays the player has participated in during the game
Position	character string	a categorical variable denoting the player's position for the play (RB, QB, DE, etc.) – may not be the same as the roster position.
PositionGroup	character string	a categorical variable denoting the player's position group for the position held during the play

Player Tracking Data

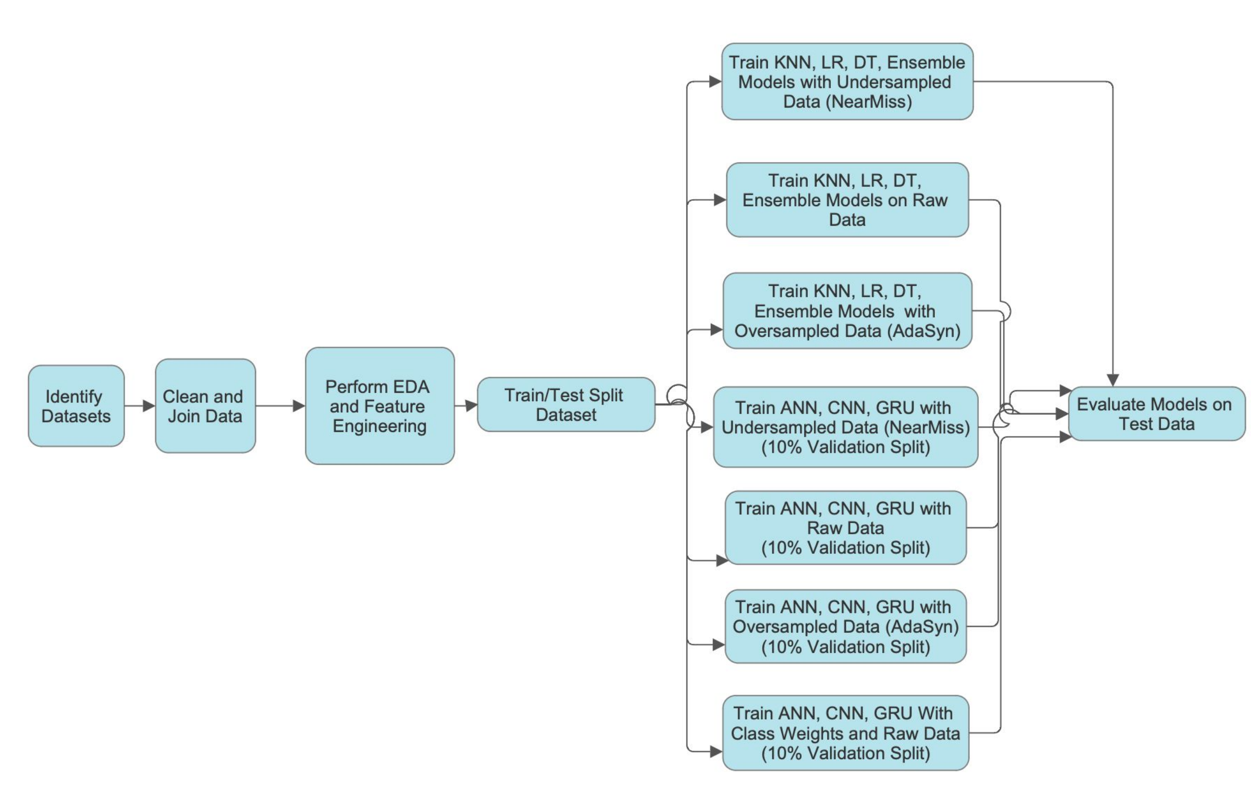


Field	Format	Description	Additional Details
PlayKey	character string		
time	float	time in seconds (float) since the start of the NGS track for the play	this is the time index for the player track
event	character string	play details (character string) as a function of time during the play (huddle break, snap, etc.)	
x	numeric list	player position (float) along the long axis of the field (yards) over time index	0 - 120 yards
y	numeric list	player position (float) along the short axis of the field (yards) over the time index	0 - 53.3 yards
dis	numeric list	distance traveled (float) from prior time point over the time index	Distance (yards)
s	numeric list	estimated speed (float) at that particular point in time over the time index	yards per second
o	numeric	Orientation (float) - angle that the player is facing (deg)	0 - 360 degrees
dir	numeric	Direction (float) - angle of player motion (deg)	0 - 360 degrees

Imbalanced Data

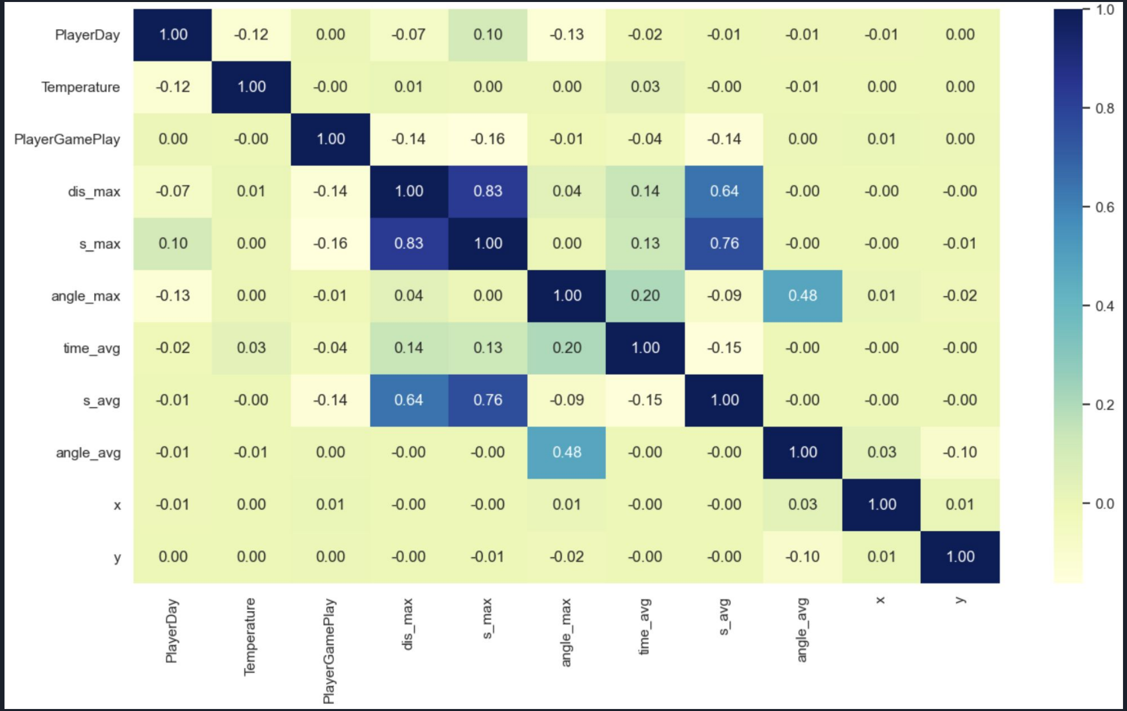


Approach and Methodology


Identify Datasets
Clean and Join Data
Perform EDA and Feature Engineering
Train/Test Split Dataset
Train KNN, LR, DT, Ensemble Models with Undersampled Data (NearMiss)
Train KNN, LR, DT, Ensemble Models on Raw Data
Train KNN, LR, DT, Ensemble Models with Oversampled Data (AdaSyn)
Train ANN, CNN, GRU with Undersampled Data (NearMiss) (10% Validation Split)
Train ANN, CNN, GRU with Raw Data (10% Validation Split)
Train ANN, CNN, GRU with Oversampled Data (AdaSyn) (10% Validation Split)
Train ANN, CNN, GRU With Class Weights and Raw Data (10% Validation Split)
Evaluate Models on Test Data

Feature Engineering

- Fill missing values
- Compute average and max speed, distance, etc
- Drop highly correlated features
- Merge three datasets together to create input for models



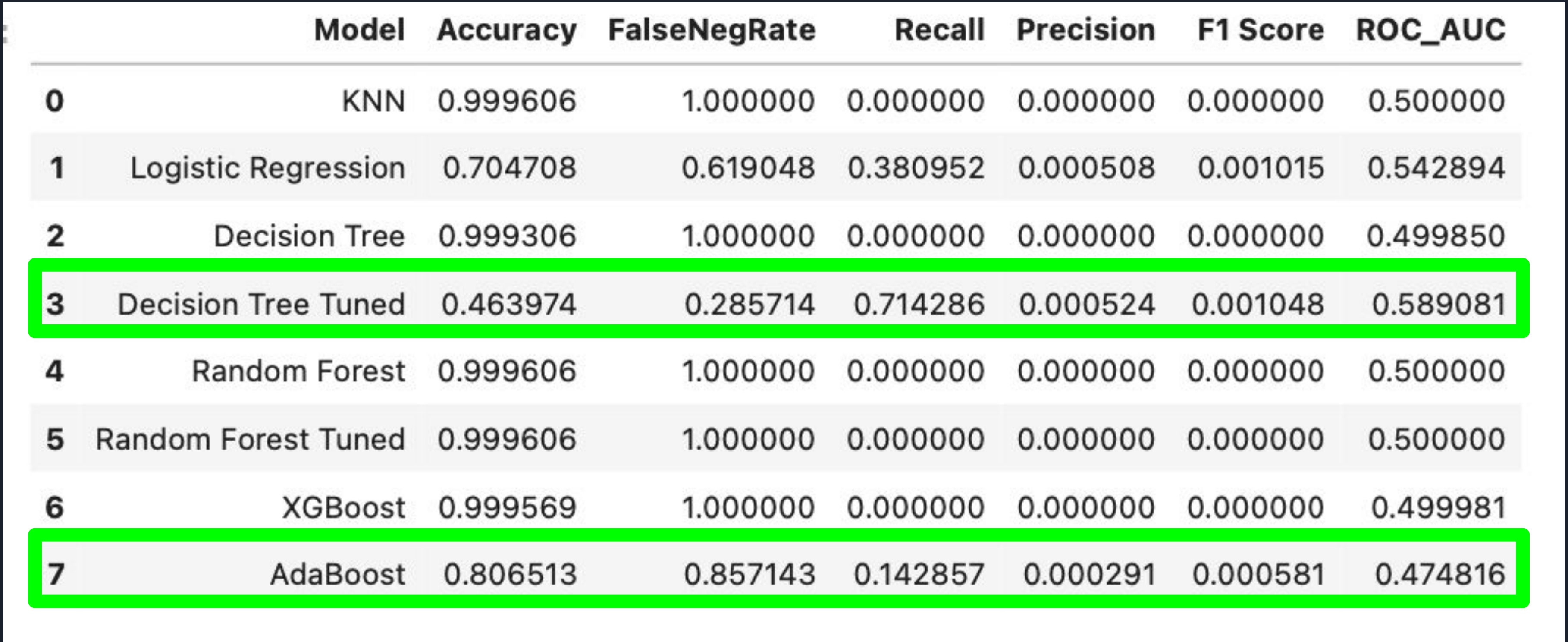
	PlayerDay	Temperature	PlayerGamePlay	dis_max	s_max	angle_max	time_avg	s_avg	angle_avg	x	y
PlayerDay	1.00	-0.12	0.00	-0.07	0.10	-0.13	-0.02	-0.01	-0.01	-0.01	0.00
Temperature	-0.12	1.00	-0.00	0.01	0.00	0.00	0.03	-0.00	-0.01	0.00	0.00
PlayerGamePlay	0.00	-0.00	1.00	-0.14	-0.16	-0.01	-0.04	-0.14	0.00	0.01	0.00
dis_max	-0.07	0.01	-0.14	1.00	0.83	0.04	0.14	0.64	-0.00	-0.00	-0.00
s_max	0.10	0.00	-0.16	0.83	1.00	0.00	0.13	0.76	-0.00	-0.00	-0.01
angle_max	-0.13	0.00	-0.01	0.04	0.00	1.00	0.20	-0.09	0.48	0.01	-0.02
time_avg	-0.02	0.03	-0.04	0.14	0.13	0.20	1.00	-0.15	-0.00	-0.00	-0.00
s_avg	-0.01	-0.00	-0.14	0.64	0.76	-0.09	-0.15	1.00	-0.00	-0.00	-0.00
angle_avg	-0.01	-0.01	0.00	-0.00	-0.00	0.48	-0.00	-0.00	1.00	0.03	-0.10
x	-0.01	0.00	0.01	-0.00	-0.00	0.01	-0.00	-0.00	0.03	1.00	0.01
y	0.00	0.00	0.00	-0.00	-0.01	-0.02	-0.00	-0.00	-0.10	0.01	1.00

Success/Failure Criteria

- General Rule: >70% Model Recall
- Secondary Metrics
  - Accuracy
  - F1 Score
  - Precision
  - ROC_AUC Score

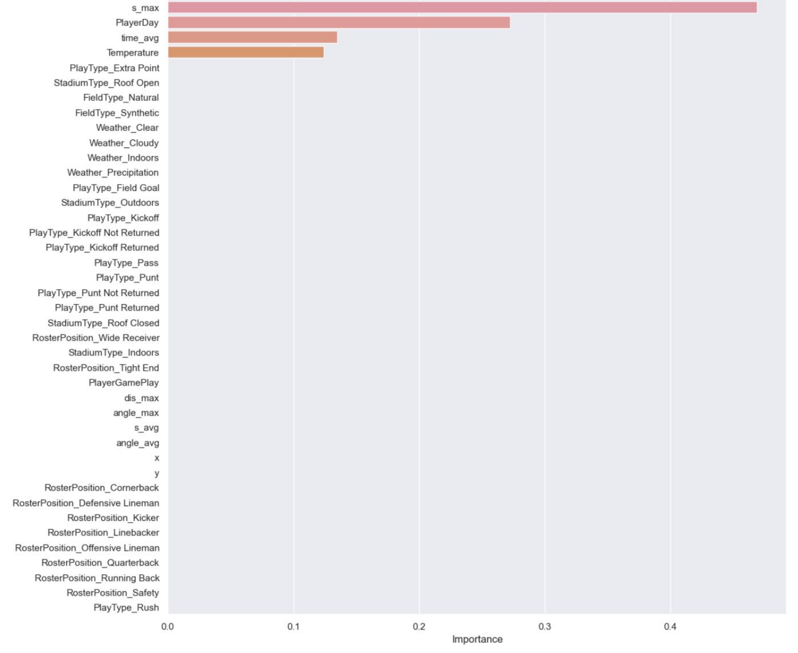
Model Results (Non-Neural Networks)

Models Using Raw Data (With Class Weights)

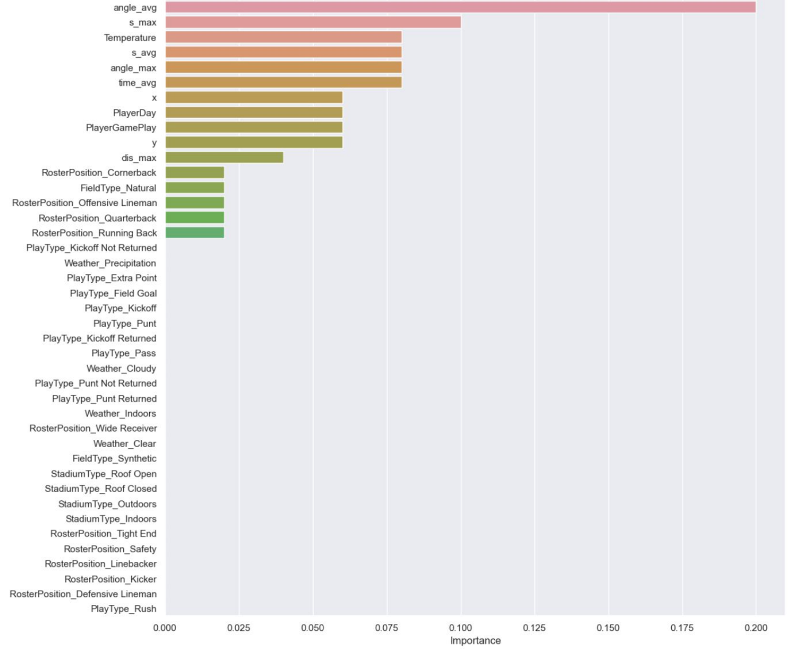


	Model	Accuracy	FalseNegRate	Recall	Precision	F1 Score	ROC_AUC
0	KNN	0.999606	1.000000	0.000000	0.000000	0.000000	0.500000
1	Logistic Regression	0.704708	0.619048	0.380952	0.000508	0.001015	0.542894
2	Decision Tree	0.999306	1.000000	0.000000	0.000000	0.000000	0.499850
3	Decision Tree Tuned	0.463974	0.285714	0.714286	0.000524	0.001048	0.589081
4	Random Forest	0.999606	1.000000	0.000000	0.000000	0.000000	0.500000
5	Random Forest Tuned	0.999606	1.000000	0.000000	0.000000	0.000000	0.500000
6	XGBoost	0.999569	1.000000	0.000000	0.000000	0.000000	0.499981
7	AdaBoost	0.806513	0.857143	0.142857	0.000291	0.000581	0.474816

Feature Importance

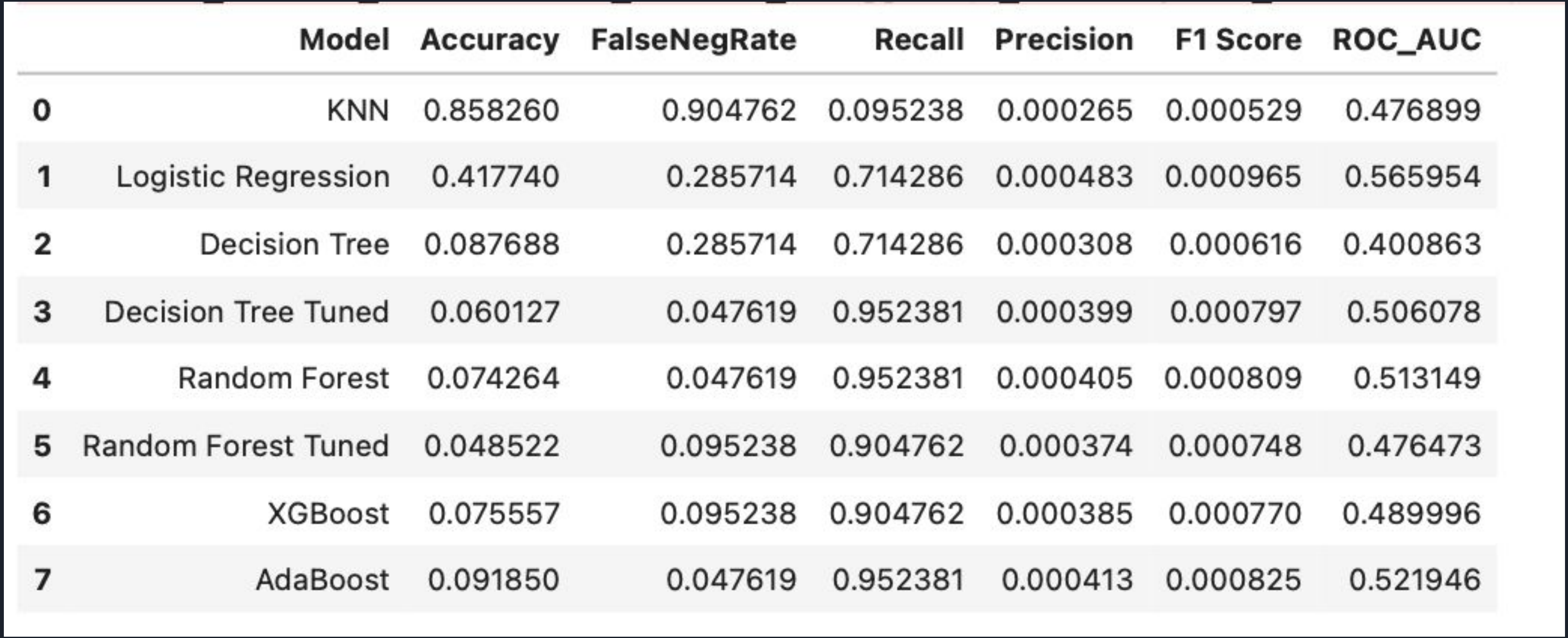


Tuned Decision Tree (Raw Data)



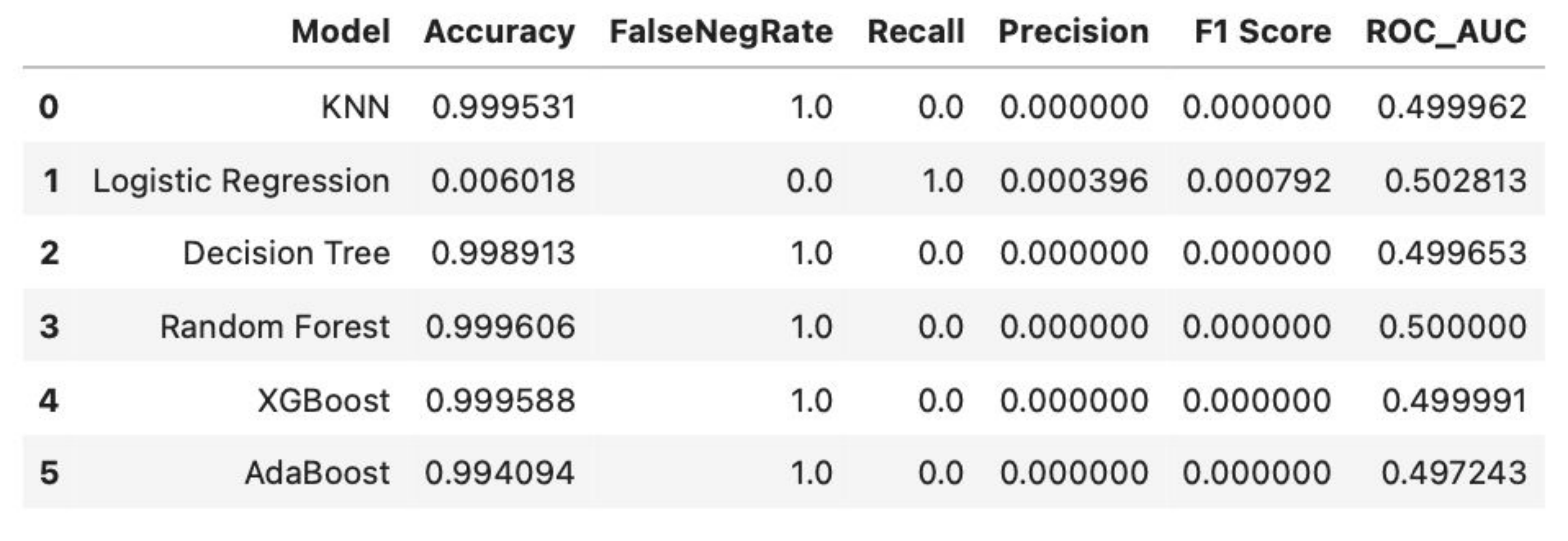
AdaBoost (Raw Data)

Models Using Undersampled Data



	Model	Accuracy	FalseNegRate	Recall	Precision	F1 Score	ROC_AUC
0	KNN	0.858260	0.904762	0.095238	0.000265	0.000529	0.476899
1	Logistic Regression	0.417740	0.285714	0.714286	0.000483	0.000965	0.565954
2	Decision Tree	0.087688	0.285714	0.714286	0.000308	0.000616	0.400863
3	Decision Tree Tuned	0.060127	0.047619	0.952381	0.000399	0.000797	0.506078
4	Random Forest	0.074264	0.047619	0.952381	0.000405	0.000809	0.513149
5	Random Forest Tuned	0.048522	0.095238	0.904762	0.000374	0.000748	0.476473
6	XGBoost	0.075557	0.095238	0.904762	0.000385	0.000770	0.489996
7	AdaBoost	0.091850	0.047619	0.952381	0.000413	0.000825	0.521946

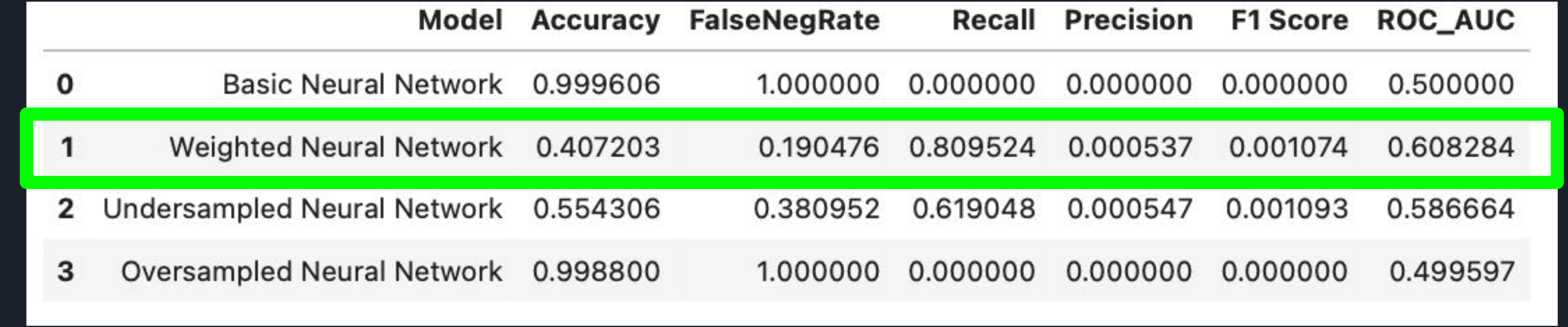
Models Using Oversampled Data



	Model	Accuracy	FalseNegRate	Recall	Precision	F1 Score	ROC_AUC
0	KNN	0.999531	1.0	0.0	0.000000	0.000000	0.499962
1	Logistic Regression	0.006018	0.0	1.0	0.000396	0.000792	0.502813
2	Decision Tree	0.998913	1.0	0.0	0.000000	0.000000	0.499653
3	Random Forest	0.999606	1.0	0.0	0.000000	0.000000	0.500000
4	XGBoost	0.999588	1.0	0.0	0.000000	0.000000	0.499991
5	AdaBoost	0.994094	1.0	0.0	0.000000	0.000000	0.497243

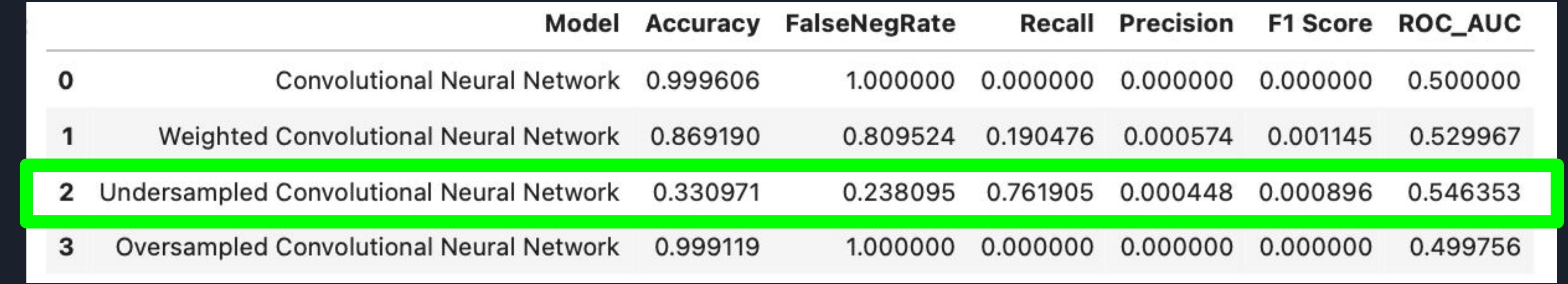
Model Results (Neural Networks)

ANN Results



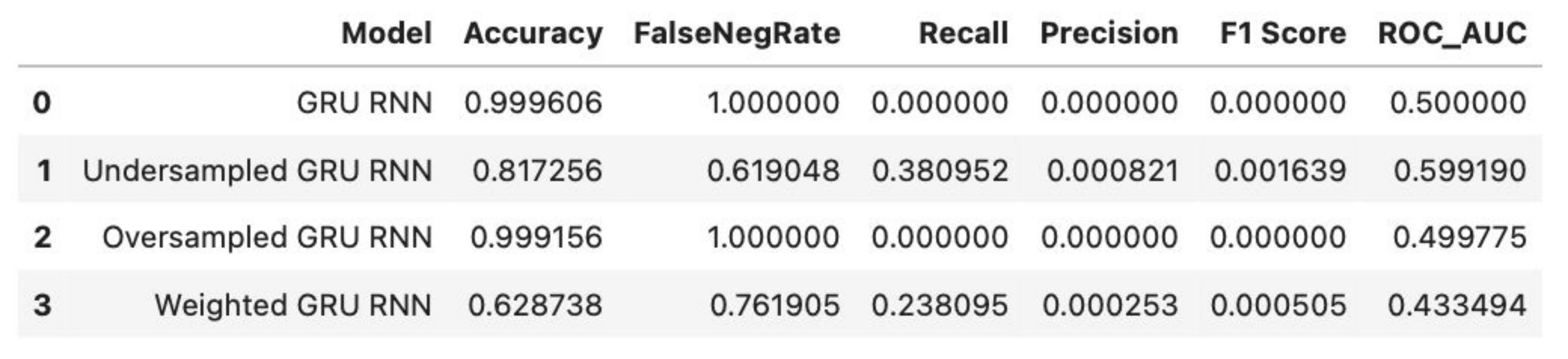
	Model	Accuracy	FalseNegRate	Recall	Precision	F1 Score	ROC_AUC
0	Basic Neural Network	0.999606	1.000000	0.000000	0.000000	0.000000	0.500000
1	Weighted Neural Network	0.407203	0.190476	0.809524	0.000537	0.001074	0.608284
2	Undersampled Neural Network	0.554306	0.380952	0.619048	0.000547	0.001093	0.586664
3	Oversampled Neural Network	0.998800	1.000000	0.000000	0.000000	0.000000	0.499597

CNN Results



	Model	Accuracy	FalseNegRate	Recall	Precision	F1 Score	ROC_AUC
0	Convolutional Neural Network	0.999606	1.000000	0.000000	0.000000	0.000000	0.500000
1	Weighted Convolutional Neural Network	0.869190	0.809524	0.190476	0.000574	0.001145	0.529967
2	Undersampled Convolutional Neural Network	0.330971	0.238095	0.761905	0.000448	0.000896	0.546353
3	Oversampled Convolutional Neural Network	0.999119	1.000000	0.000000	0.000000	0.000000	0.499756

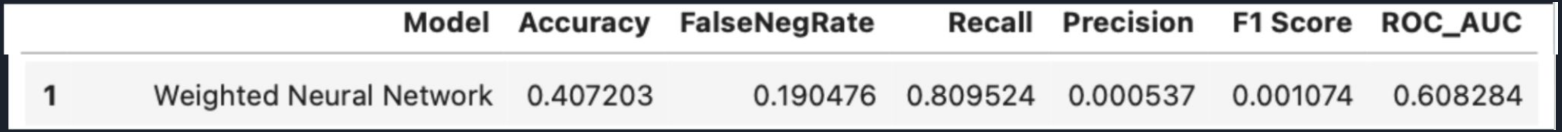
GRU Results



	Model	Accuracy	FalseNegRate	Recall	Precision	F1 Score	ROC_AUC
0	GRU RNN	0.999606	1.000000	0.000000	0.000000	0.000000	0.500000
1	Undersampled GRU RNN	0.817256	0.619048	0.380952	0.000821	0.001639	0.599190
2	Oversampled GRU RNN	0.999156	1.000000	0.000000	0.000000	0.000000	0.499775
3	Weighted GRU RNN	0.628738	0.761905	0.238095	0.000253	0.000505	0.433494

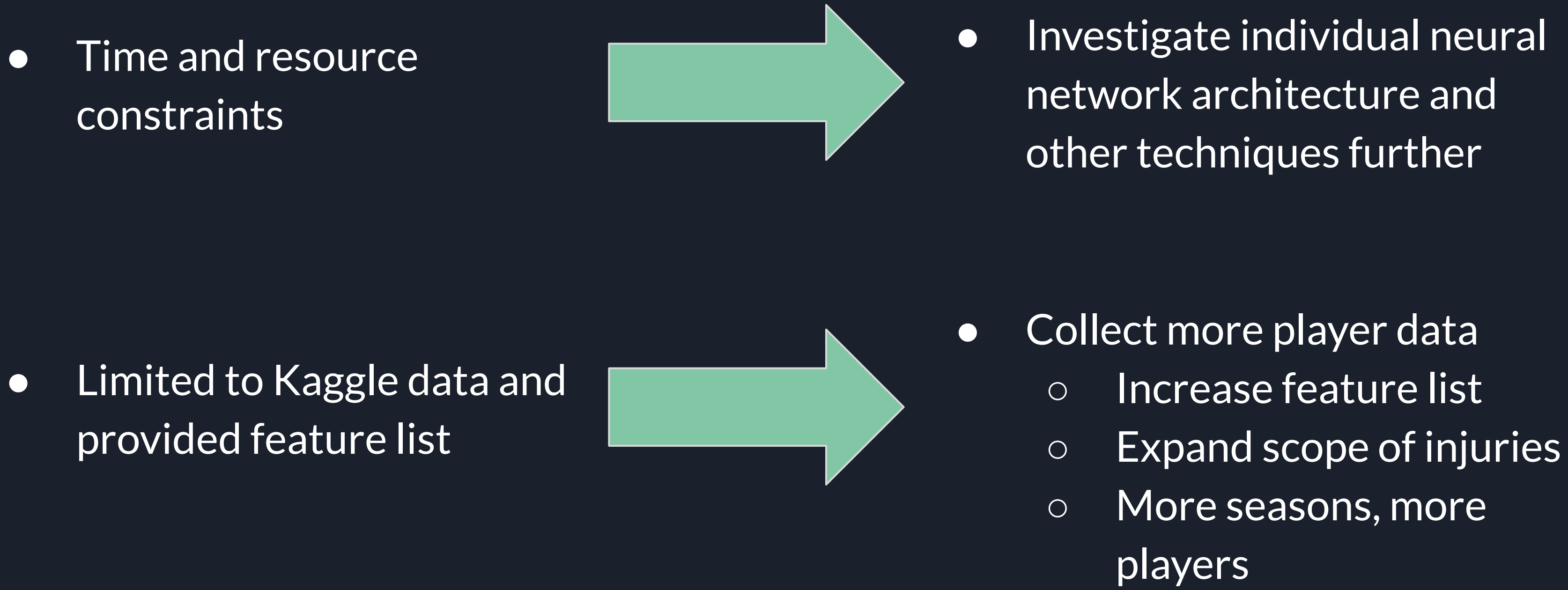
Discussion

- Weighted Neural Network gave overall best performance
    - Recall (0.80), F1(0.0011), Accuracy (0.41)
    - Was not trained with augmented data
- Heavy Imbalance in data still a big issue
    - Undersampling helped results slightly
    - Oversampling mainly just led to overfitting
- Overall Precision and F1 scores very low



	Model	Accuracy	FalseNegRate	Recall	Precision	F1 Score	ROC_AUC
1	Weighted Neural Network	0.407203	0.190476	0.809524	0.000537	0.001074	0.608284

Limitations and Future Work



- Time and resource constraints

- Investigate individual neural network architecture and other techniques further

- Limited to Kaggle data and provided feature list

- Collect more player data
  - Increase feature list
  - Expand scope of injuries
  - More seasons, more players

Thank You!