DAB-01 Capstone Presentation

GOAL 2030

TAKING SINGAPORE TO THE WORLD CUP

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TODAY'S AGENDA

HOW MANY COACHES HAVE OUR NATIONAL TEAM HAD SINCE 2012?

A: 3

B: 5

C: 6

D: 8

HOW MANY COACHES HAVE OUR NATIONAL TEAM HAD SINCE 2012?

C: 6

Ogura is the third consecutive Japanese coach to take charge of the Lions.

Lions coach Nishigaya fired after less than 2 years in charge; performances 'below expectation', says FAS

Football: S'pore national coach Tatsuma Yoshida quits top job after Suzuki Cup

"We failed badly. We don't have many youngsters coming through to replace the likes of (Noh) Alam Shah, Indra (Sahdan) or (Khairul) Amri - who has been playing forever now.

Singapore footballers trounced 7-0 by Malaysia in heaviest SEA Games loss in decades

We're five years behind our rivals: Fandi

Lions taught lesson by South Korea in 7-0 mauling

Lions goalkeeper Izwan Mahbud praised for one-man show in Japan draw

Throwback Tuesday:The time Alam Shah plundered seven goals against Laos

Singapore lifted the AFF Suzuki Cup for a record fourth time with a 3-2 aggregate win over Thailand, who could only muster a 1-0 second leg victory in Bangkok on Saturday despite dominating the game.

Radojko Avramovic (2003 to 2012)

Unheralded when he arrived in Singapore, Raddy Avramovic departed as one of the best head coaches the Lions have ever had. Quiet, soft-spoken but with a steely glare and temperament, the no-nonsense Serbian built a mentally-strong, tough-to-beat quality among the Lions, as they enjoyed their finest period in international football, winning three AFF Championships during Avramovic's reign (2004, 2007 and 2012). His brand of football might not be beautiful, but it sure was remarkably effective.

Rating: 5 out of 5

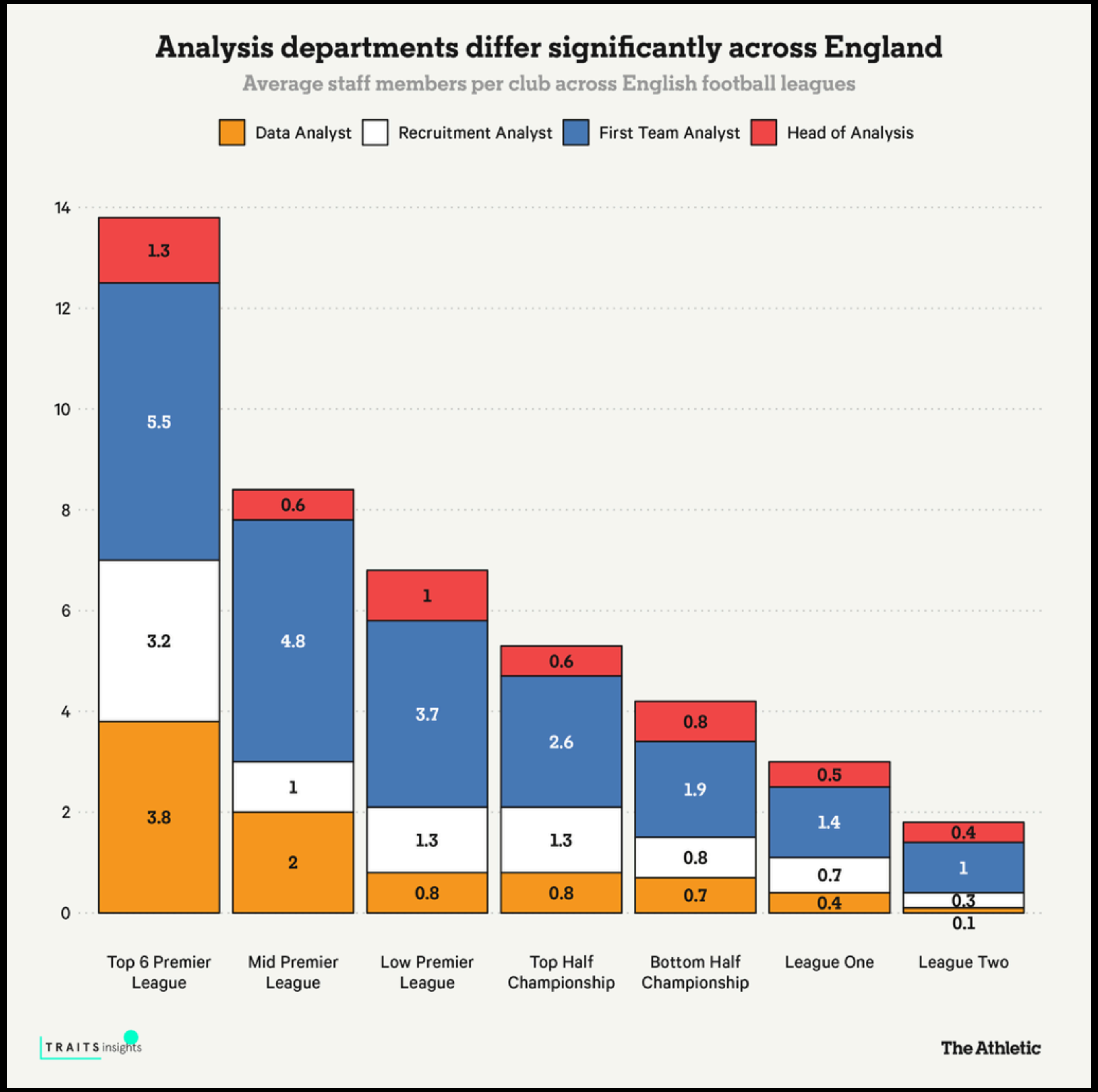
BACKGROUND

Liverpool are widely considered to be world-leaders when it comes to data analytics. Since the club's takeover by the Fenway Sports Group in 2010, the club has adopted an emphasis on statistics that has long been part of sport in the USA but is relatively new to England.

Brighton's owner/chairman Tony Bloom ensures club staff use data provided by his company Starlizard, which has helped turn lesser-known players into Premier League stars, including Kaoru Mitoma, Moises Caicedo, Alexis Mac Allister and Julio Enciso.

Similarly, his Brentford counterpart, Matthew Benham, is the founder of statistical research company Smartodds — primarily designed for professional gamblers but crucial in helping Thomas Frank's side find value in the player recruitment market.

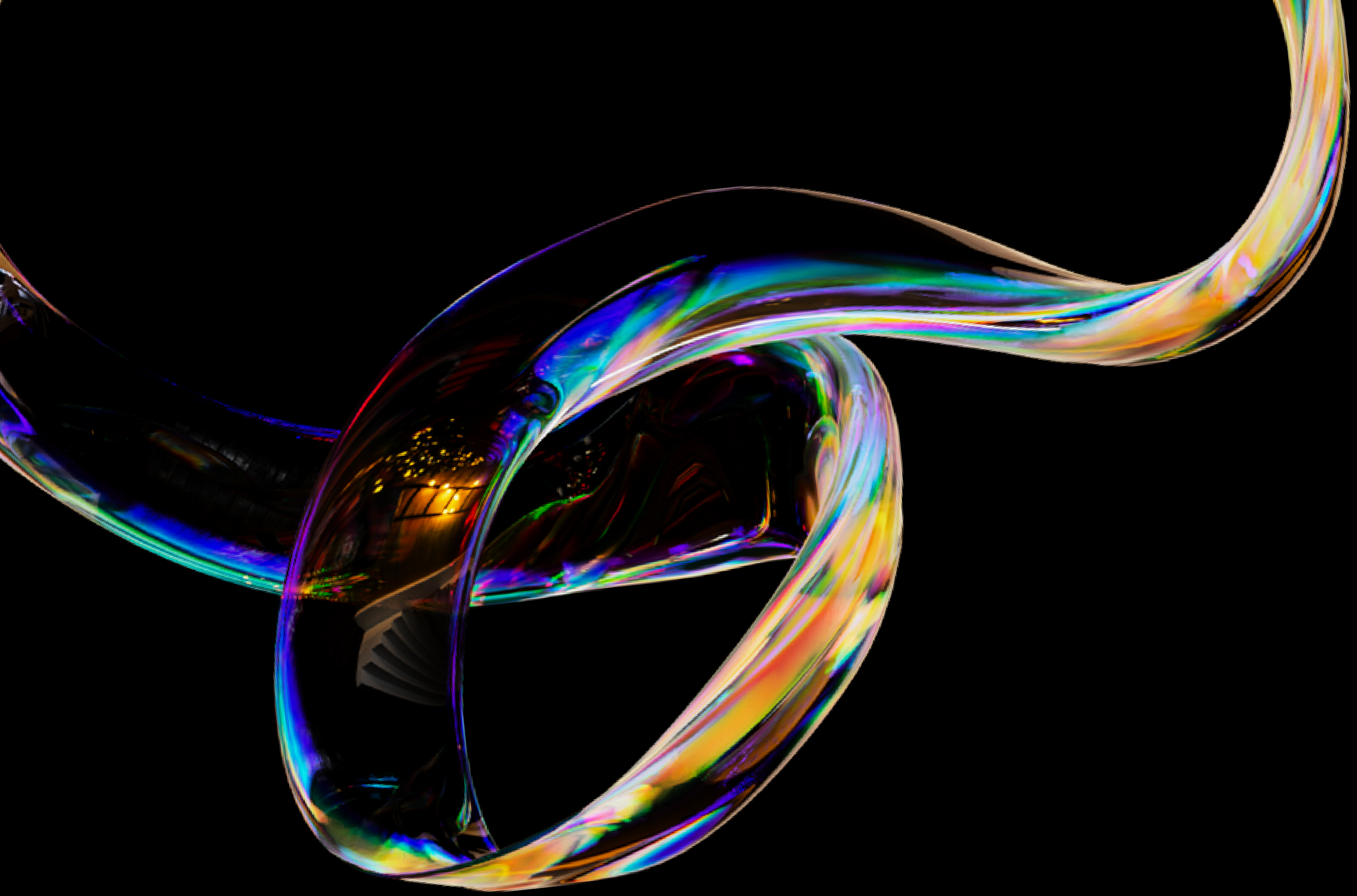
BACKGROUND



[New York Times]

BACKGROUND

- Data-wise, there are resources such as Opta player stats, that are pretty comprehensive for the big leagues.
- Other sites include FBref, WhoScored, FootyStats, and SofaScore.
- But only SofaScore has data on Singapore matches.
- As such, Singapore football is already not on the same playing field when it comes to data in football.



PROBLEM STATEMENT

Keeping Up with Trends

In the greater footballing world, data has become an indispensable tool for improving team performance, scouting and making strategic decisions.
Our country could do with using data in guiding our footballing decisions.

Lack of Data-Driven Tools

Current selection processes in Singapore rely heavily on subjective judgments, leading to potential biases and overlooked talents. On a whole, this is hindering the team's performance at the national level.

Limited Data Availablity

As mentioned earlier, the absence of comprehensive and accessible data for Singapore, in turn hinders the development of data-driven selection tools.

OUR PRODUCT

Live Data Scraping

The app will first scrape the data from the SofaScore website, obtain key player information and player statistics.

The app will also pre-process this data in advance of the next two features.

Player Role Predictor

The app will be capable of predicting a player's ability in 11 key roles on a football team, recommending whether they are suitable for that role.

Squad Generator

Based on the players' scores on each role, the app will be able to recommend a full squad for the national team.

The size of the squad and number of players for each role can be customised to suit all competitions' needs.

MODELLING RESULTS
AVERAGE ACROSS THE 11 ROLES

train_accuracy	test_accuracy	train_f1	test_f1	TT
0.9910	0.9289	0.9910	0.9275	0.0362

RESULTS

target	train_accuracy	test_accuracy	train_f1	test_f1	TT
Class_Traditional Keeper	0.978022	1.000000	0.978664	1.000000	0.016
Class_Sweeper Keeper	1.000000	1.000000	1.000000	1.000000	0.025
Class_Ball Playing Defender	1.000000	0.956522	1.000000	0.960339	0.102
Class_No Nonsense Defender	1.000000	0.956522	1.000000	0.954694	0.023
Class_Full Back	1.000000	0.956522	1.000000	0.952704	0.036
Class_All Action Midfielder	1.000000	0.869565	1.000000	0.875049	0.024
Class_Midfield Playmaker	1.000000	1.000000	1.000000	1.000000	0.021
Class_Traditional Winger	1.000000	1.000000	1.000000	1.000000	0.031
Class_Inverted Winger	1.000000	0.869565	1.000000	0.870062	0.024
Class_Goal Poacher	0.923077	0.869565	0.922790	0.864803	0.026
Class_Target Man	1.000000	0.739130	1.000000	0.725064	0.070

DEMO

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IMPACT

PROGRESS AND FUTURE WORK

Aug 2024

Phase 1a: We achieved the prediction functionality, allowing us to find out the best players in each role.

Phase 1b: Roles expanded from 8 to 11, app functions include filtering and recommendations.

Sep 2024 (Present)

Phase 2a: We achieved the squad generation functionality, with customisation of numbers for different tournaments.

Phase 2b: Live scaping of player stats, processing integrated into the app.

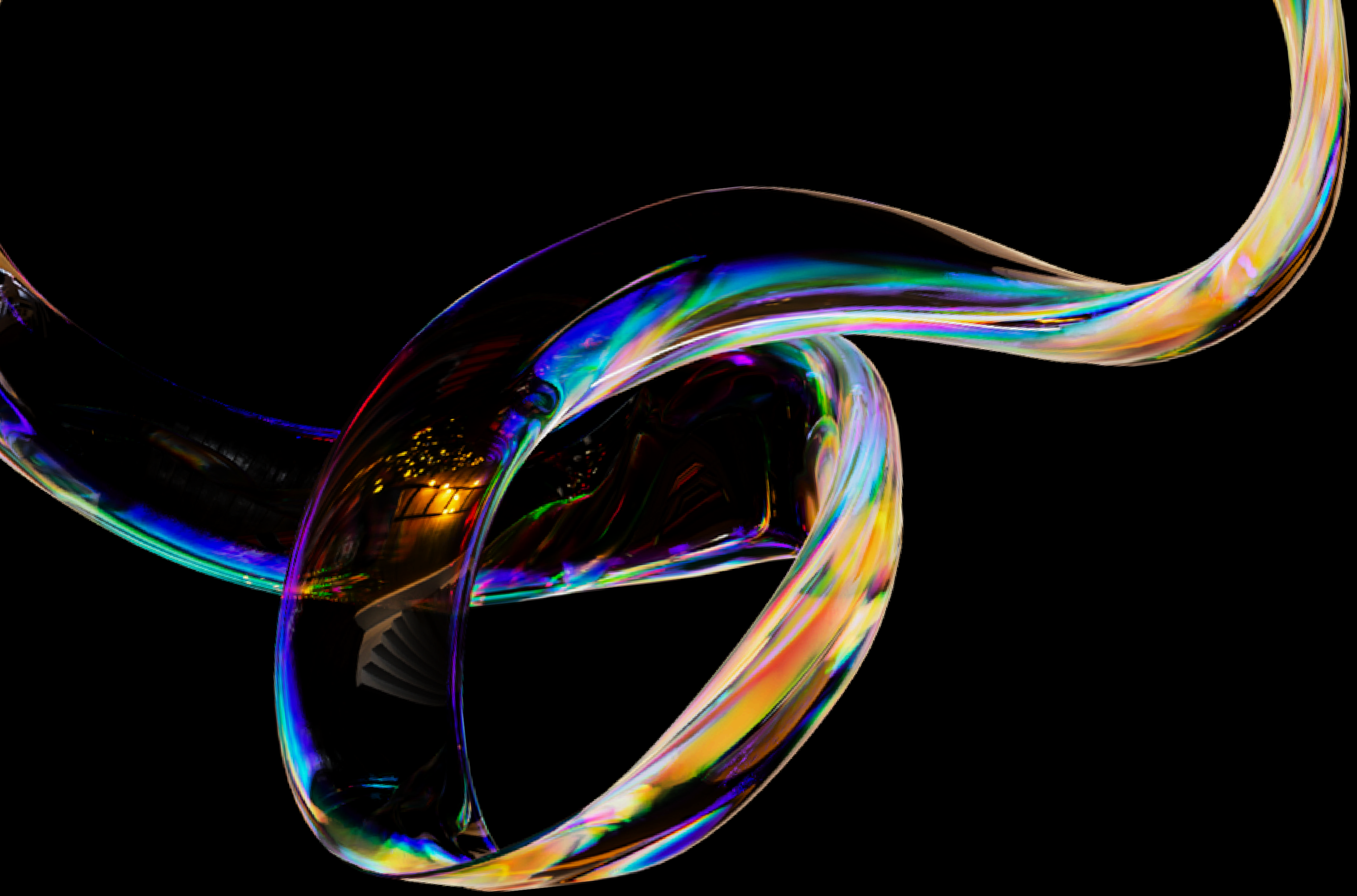
Q4 2024

Phase 2c: Expansion of database to include foreign based Singapore players. Potential of working with overseas clubs to achieve this.

Recommendation of potential foreign players to be naturalised.

Q1 2025

Phase 3: Allowing for other team data to be input into the system, so that squad generation can take into account their strengths and weakness, and deliver the best squad to face the opponent.



PROBLEM STATEMENT

Not Up to Date with Global Trends

In the greater footballing world, data has become an indispensable tool for improving team performance, scouting and making strategic decisions.
Our country could do with using data in guiding our footballing decisions.

Lack of Data-Driven Tools

Current selection processes rely heavily on subjective judgments, leading to potential biases and overlooked talents. On a whole, this is hindering the team's performance at the national level.

Limited Data Availablity

The absence of comprehensive and accessible data hinders the development of data-driven selection tools.

SOLUTIONS TO THE PROBLEMS

Limited Data Availablity

While we can’t increase the data collected, what we can do to turn it into a tool, is by scraping the data off the website and turning it into usable data for analyses.

Lack of Data-Driven Tools

Our app is hence the first locally created tool aimed at turning player data into predictors of player ability in roles, as well as generating the best squad based on ability.

Not Up to Date with Global Trends

By making use of data through this tool, this will allow our national team to catch up with other countries who have made use of data tools to be a step ahead in choosing their national teams.

EXISTING TOOLS VS GOAL 2030

	Existing Tools (e.g., Wystat, Inscout)	Current Local Scene	GOAL 2030
Pricing	Fee-Paying	Free, because it doesn't exist	Free
Features	• Must have advanced knowledge to use • Video based • Many features (too many)	• Subjective judgement • Biases towards certain players • Overlooked players	• Data pulled into the app • Streamlined comparison into player roles • Squad Generation
Usage Limits	• Limited by subscription	• Unusable	• No Limits
Upcoming Features	Not publicly announced	No additional services included	Further features in development (players from foreign leagues, opposition analysis)

BENEFITS

Football Association of Singapore (FAS)

Their coaches get more help in choosing the best squad for the National Team, rather than recommendations from club coaches, allowing them to focus on other things.

Previously Overlooked Players

Players who consistently have been overlooked for the national team, but have proven through their stats that they are capable.

Budding Footballers

Young footballers, with the knowledge that success in a sport is not a lottery, will be more willing to take it more seriously.

Singaporeans

With better squad selection, hopefully comes better performances, and something to root for. Winning the ASEAN Championships again, or making it to the Asian Cup?

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THANK YOU

Questions?

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APPENDIX

BEST MODELS

Role	1st Model	2nd Model	3rd Model
Class_Traditional Keeper	KNeighborsClassifier	DecisionTreeClassifier	RidgeClassifier
Class_Sweeper Keeper	LogisticRegression	ExtraTreesClassifier	GaussianNB
Class_Ball Playing Defender	ExtraTreesClassifier	RidgeClassifier	LinearDiscriminantAnalysis
Class_No Nonsense Defender	LogisticRegression	ExtraTreesClassifier	LGBMClassifier
Class_Full Back	LogisticRegression	RidgeClassifier	ExtraTreesClassifier
Class_All Action Midfielder	LogisticRegression	KNeighborsClassifier	RidgeClassifier
Class_Midfield Playmaker	LogisticRegression	ExtraTreesClassifier	XGBClassifier
Class_Traditional Winger	LogisticRegression	RidgeClassifier	LinearDiscriminantAnalysis
Class_Inverted Winger	LogisticRegression	RidgeClassifier	LinearDiscriminantAnalysis
Class_Goal Poacher	KNeighborsClassifier	ExtraTreesClassifier	LogisticRegression
Class_Target Man	RandomForestClassifier	XGBClassifier	ExtraTreesClassifier

TRADITIONAL KEEPER

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
K Neighbors Classifier	0.978022	1.000000	0.978664	1.000000	0.034
Decision Tree Classifier	1.000000	1.000000	1.000000	1.000000	0.016
Ridge Classifier	0.978022	1.000000	0.978664	1.000000	0.015
Random Forest Classifier	1.000000	1.000000	1.000000	1.000000	0.096
Linear Discriminant Analysis	0.978022	1.000000	0.978664	1.000000	0.015
Ada Boost Classifier	1.000000	1.000000	1.000000	1.000000	0.058
Gradient Boosting Classifier	1.000000	1.000000	1.000000	1.000000	0.080
Extra Trees Classifier	1.000000	1.000000	1.000000	1.000000	0.083
Extreme Gradient Boosting	1.000000	1.000000	1.000000	1.000000	0.025
Logistic Regression	1.000000	1.000000	1.000000	1.000000	0.030
Naive Bayes	0.857143	0.913043	0.874459	0.925362	0.019
SVM - Linear Kernel	1.000000	1.000000	1.000000	1.000000	0.020
Light Gradient Boosting Machine	1.000000	0.956522	1.000000	0.949781	0.039
Dummy Classifier	0.857143	0.913043	0.791209	0.871542	0.018

SWEEPER KEEPER

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Logistic Regression	1.000000	1.000000	1.000000	1.000000	1.373
Extra Trees Classifier	1.000000	0.913043	1.000000	0.900725	0.110
Naive Bayes	0.934066	0.913043	0.930769	0.900725	0.014
Random Forest Classifier	1.000000	0.913043	1.000000	0.900725	0.098
K Neighbors Classifier	0.989011	0.956522	0.988935	0.953974	0.025
Ridge Classifier	0.945055	0.913043	0.943825	0.900725	0.018
Linear Discriminant Analysis	0.945055	0.913043	0.943825	0.900725	0.020
Extreme Gradient Boosting	1.000000	0.913043	1.000000	0.900725	0.250
SVM - Linear Kernel	0.956044	0.869565	0.956044	0.861921	0.013
Light Gradient Boosting Machine	1.000000	0.913043	1.000000	0.900725	0.037
Ada Boost Classifier	1.000000	0.913043	1.000000	0.900725	0.054
Gradient Boosting Classifier	1.000000	0.869565	1.000000	0.861921	0.045
Decision Tree Classifier	1.000000	0.869565	1.000000	0.861921	0.015
Dummy Classifier	0.736264	0.826087	0.624426	0.747412	0.012

BALL-PLAYING DEFENDER

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Extra Trees Classifier	1.000000	0.956522	1.000000	0.960339	0.065
Ridge Classifier	0.978022	0.956522	0.977656	0.960339	0.018
Linear Discriminant Analysis	0.978022	0.956522	0.977656	0.960339	0.017
K Neighbors Classifier	0.956044	0.956522	0.954465	0.960339	0.025
Random Forest Classifier	1.000000	0.956522	1.000000	0.960339	0.104
Light Gradient Boosting Machine	1.000000	0.956522	1.000000	0.960339	0.051
Logistic Regression	1.000000	0.956522	1.000000	0.960339	0.020
Naive Bayes	0.956044	0.956522	0.956676	0.960339	0.024
Ada Boost Classifier	1.000000	0.956522	1.000000	0.960339	0.061
Extreme Gradient Boosting	1.000000	0.956522	1.000000	0.960339	0.030
SVM - Linear Kernel	1.000000	0.956522	1.000000	0.960339	0.018
Decision Tree Classifier	1.000000	0.956522	1.000000	0.960339	0.020
Gradient Boosting Classifier	1.000000	0.956522	1.000000	0.960339	0.054
Dummy Classifier	0.758242	0.913043	0.653984	0.871542	0.016

NO-NONSENSE DEFENDER

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Logistic Regression	1.000000	0.956522	1.000000	0.954694	0.030
Extra Trees Classifier	1.000000	0.826087	1.000000	0.808924	0.079
Light Gradient Boosting Machine	1.000000	0.826087	1.000000	0.808924	0.036
Ada Boost Classifier	1.000000	0.869565	1.000000	0.846632	0.066
Extreme Gradient Boosting	1.000000	0.869565	1.000000	0.846632	0.021
K Neighbors Classifier	0.901099	0.782609	0.897531	0.773469	0.028
Ridge Classifier	0.956044	0.869565	0.955672	0.864081	0.017
Linear Discriminant Analysis	0.956044	0.869565	0.955672	0.864081	0.013
Random Forest Classifier	1.000000	0.826087	1.000000	0.808924	0.122
Naive Bayes	0.912088	0.782609	0.912717	0.773469	0.014
Gradient Boosting Classifier	1.000000	0.869565	1.000000	0.846632	0.052
SVM - Linear Kernel	0.890110	0.826087	0.883770	0.808924	0.015
Decision Tree Classifier	1.000000	0.652174	1.000000	0.680124	0.015
Dummy Classifier	0.659341	0.782609	0.523979	0.687169	0.017

FULL-BACK

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Logistic Regression	1.000000	0.956522	1.000000	0.952704	0.034
Ridge Classifier	0.967033	0.913043	0.966441	0.913043	0.019
Extra Trees Classifier	1.000000	0.913043	1.000000	0.913043	0.108
Linear Discriminant Analysis	0.967033	0.913043	0.966441	0.913043	0.013
K Neighbors Classifier	0.901099	0.913043	0.899323	0.913043	0.022
Random Forest Classifier	1.000000	0.913043	1.000000	0.913043	0.091
Ada Boost Classifier	1.000000	0.956522	1.000000	0.952704	0.058
Naive Bayes	0.912088	0.869565	0.912088	0.877210	0.016
Extreme Gradient Boosting	1.000000	0.913043	1.000000	0.913043	0.029
Light Gradient Boosting Machine	1.000000	0.956522	1.000000	0.952704	0.031
Decision Tree Classifier	1.000000	0.913043	1.000000	0.913043	0.029
Gradient Boosting Classifier	1.000000	0.956522	1.000000	0.952704	0.057
SVM - Linear Kernel	0.934066	0.869565	0.935276	0.877210	0.016
Dummy Classifier	0.703297	0.869565	0.580787	0.808898	0.012

ALL-ACTION MIDFIELDER

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Logistic Regression	1.000000	0.869565	1.000000	0.875049	0.033
K Neighbors Classifier	0.934066	0.869565	0.932758	0.875049	0.023
Ridge Classifier	0.945055	0.869565	0.944268	0.875049	0.017
Gradient Boosting Classifier	1.000000	0.913043	1.000000	0.913043	0.054
Linear Discriminant Analysis	0.956044	0.869565	0.955641	0.875049	0.013
Naive Bayes	0.923077	0.826087	0.923390	0.826087	0.014
Decision Tree Classifier	1.000000	0.782609	1.000000	0.802936	0.015
Extreme Gradient Boosting	1.000000	0.869565	1.000000	0.861921	0.024
Random Forest Classifier	1.000000	0.869565	1.000000	0.861921	0.105
Light Gradient Boosting Machine	1.000000	0.869565	1.000000	0.861921	0.045
Ada Boost Classifier	1.000000	0.913043	1.000000	0.913043	0.045
Extra Trees Classifier	1.000000	0.869565	1.000000	0.861921	0.077
SVM - Linear Kernel	0.868132	0.869565	0.857553	0.861921	0.020
Dummy Classifier	0.670330	0.826087	0.538028	0.747412	0.013

MIDFIELD PLAYMAKER

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Logistic Regression	1.000000	1.000000	1.000000	1.000000	0.026
Extra Trees Classifier	1.000000	0.956522	1.000000	0.949781	0.085
Extreme Gradient Boosting	0.989011	0.956522	0.989131	0.949781	0.029
Light Gradient Boosting Machine	1.000000	0.956522	1.000000	0.949781	0.034
Ada Boost Classifier	1.000000	0.956522	1.000000	0.949781	0.054
Naive Bayes	0.945055	1.000000	0.946714	1.000000	0.022
Linear Discriminant Analysis	0.989011	1.000000	0.988881	1.000000	0.015
K Neighbors Classifier	0.934066	0.956522	0.930538	0.949781	0.025
Random Forest Classifier	1.000000	0.956522	1.000000	0.949781	0.085
SVM - Linear Kernel	0.945055	1.000000	0.947616	1.000000	0.016
Ridge Classifier	0.989011	1.000000	0.988881	1.000000	0.015
Gradient Boosting Classifier	1.000000	0.956522	1.000000	0.949781	0.056
Decision Tree Classifier	1.000000	0.956522	1.000000	0.949781	0.016
Dummy Classifier	0.813187	0.913043	0.729404	0.871542	0.012

TRADITIONAL WINGER

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Logistic Regression	1.000000	1.000000	1.000000	1.000000	0.039
Ridge Classifier	0.967033	1.000000	0.966920	1.000000	0.013
Linear Discriminant Analysis	0.967033	1.000000	0.966920	1.000000	0.014
Extreme Gradient Boosting	1.000000	0.956522	1.000000	0.956356	0.036
Ada Boost Classifier	1.000000	0.956522	1.000000	0.956356	0.047
Gradient Boosting Classifier	1.000000	0.913043	1.000000	0.913043	0.057
Naive Bayes	0.835165	0.913043	0.838123	0.912040	0.017
Random Forest Classifier	1.000000	0.956522	1.000000	0.956522	0.096
Extra Trees Classifier	1.000000	0.913043	1.000000	0.912714	0.112
Decision Tree Classifier	1.000000	0.869565	1.000000	0.869068	0.016
SVM - Linear Kernel	0.923077	0.913043	0.923728	0.912040	0.018
Light Gradient Boosting Machine	1.000000	0.956522	1.000000	0.956356	0.053
K Neighbors Classifier	0.879121	1.000000	0.878708	1.000000	0.029
Dummy Classifier	0.637363	0.478261	0.496202	0.309463	0.014

INVERTED WINGER

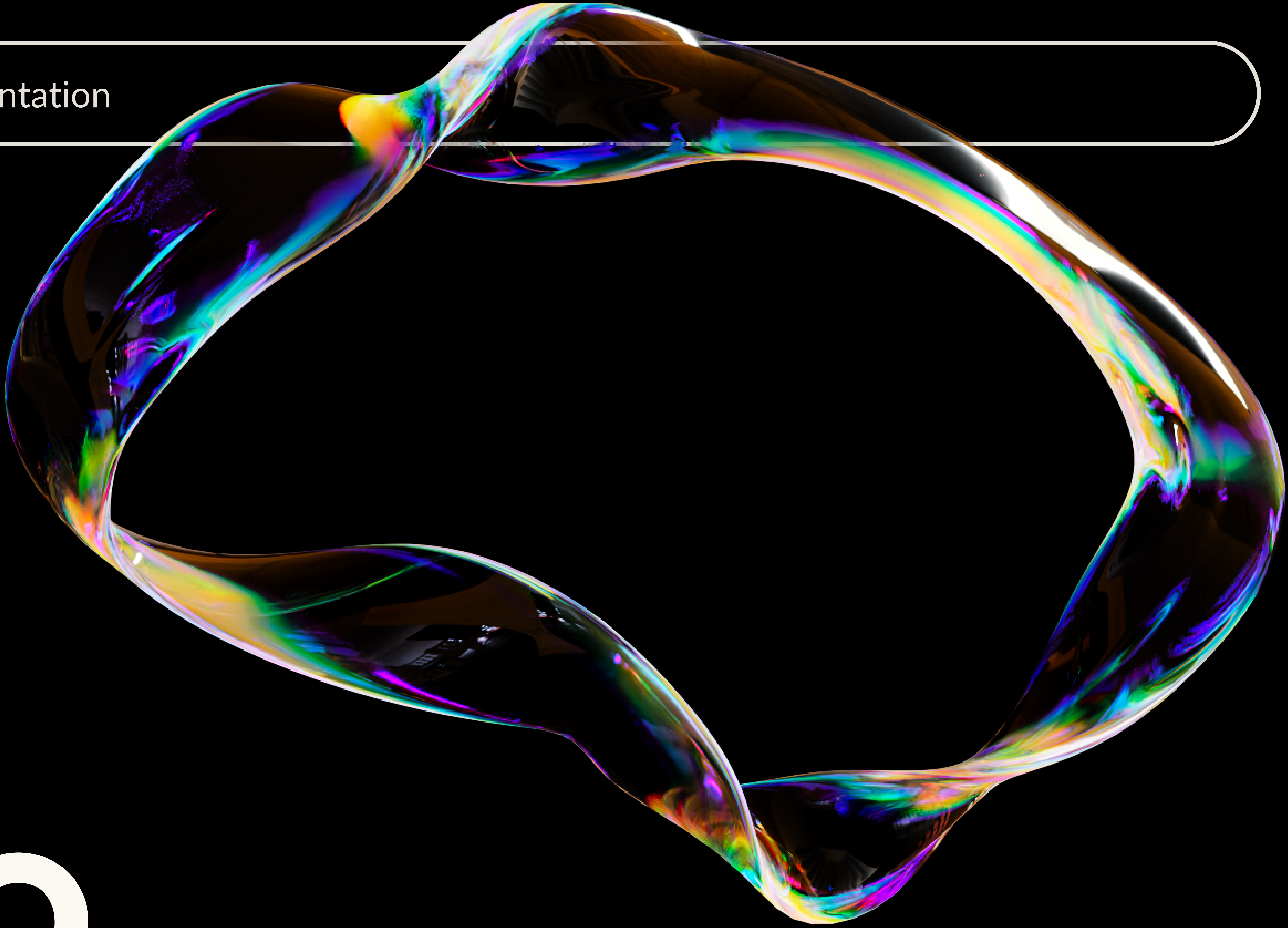
model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Logistic Regression	1.000000	0.869565	1.000000	0.870062	0.031
Ridge Classifier	0.978022	0.869565	0.978038	0.868548	0.015
Linear Discriminant Analysis	0.978022	0.869565	0.978038	0.868548	0.015
Extra Trees Classifier	1.000000	0.869565	1.000000	0.870062	0.076
Random Forest Classifier	1.000000	0.826087	1.000000	0.826087	0.089
Gradient Boosting Classifier	1.000000	0.869565	1.000000	0.869565	0.065
K Neighbors Classifier	0.934066	0.826087	0.934114	0.826087	0.030
Ada Boost Classifier	1.000000	0.913043	1.000000	0.913373	0.049
Extreme Gradient Boosting	1.000000	0.869565	1.000000	0.870062	0.028
Naive Bayes	0.879121	0.782609	0.879033	0.780914	0.016
SVM - Linear Kernel	0.824176	0.608696	0.820384	0.575035	0.019
Light Gradient Boosting Machine	1.000000	0.826087	1.000000	0.826087	0.063
Decision Tree Classifier	1.000000	0.826087	1.000000	0.826746	0.023
Dummy Classifier	0.527473	0.434783	0.364298	0.263505	0.020

GOAL POACHER

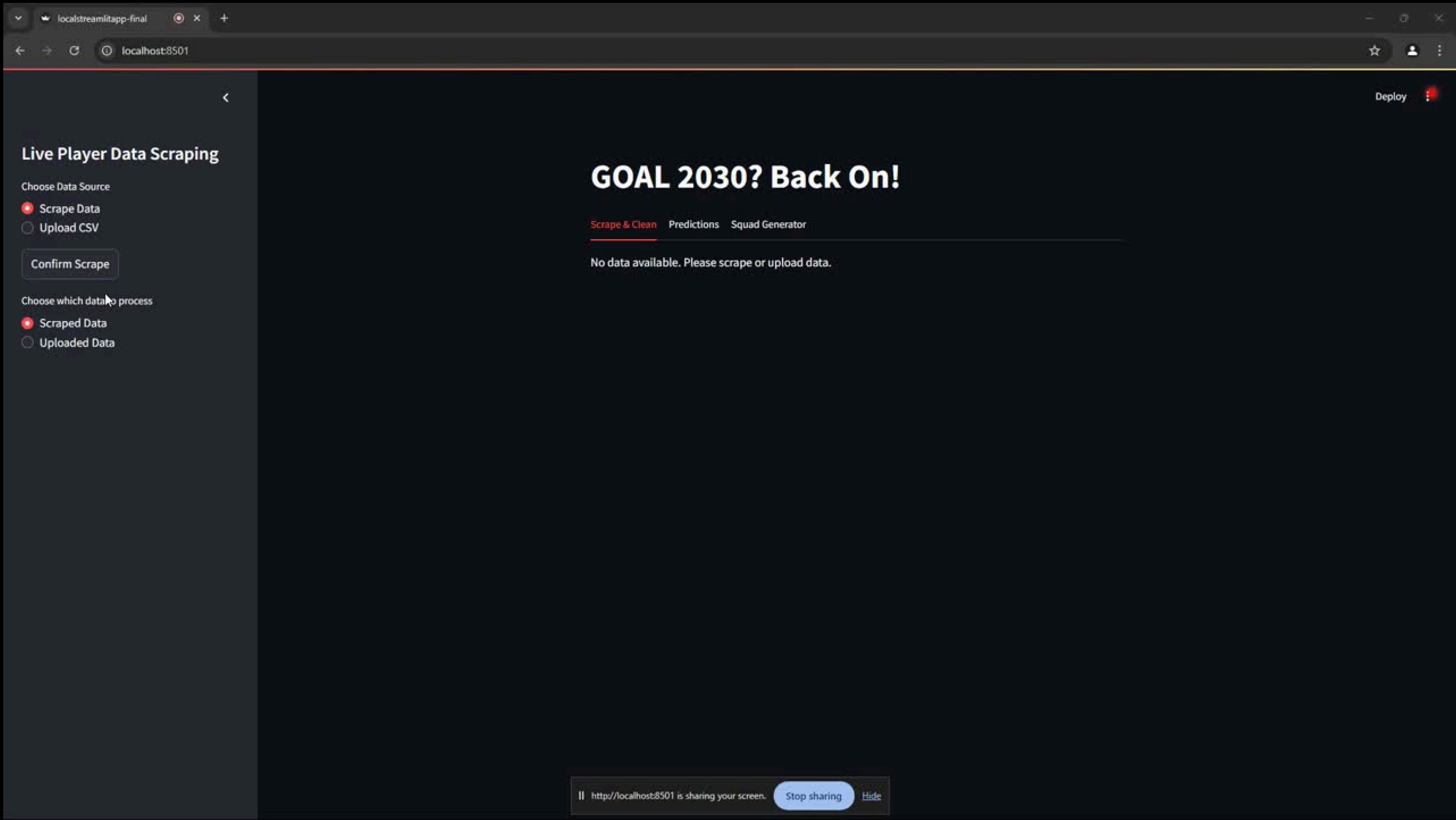
model	train_accuracy	test_accuracy	train_f1	test_f1	TT
K Neighbors Classifier	0.923077	0.869565	0.922790	0.864803	0.031
Extra Trees Classifier	1.000000	0.913043	1.000000	0.913043	0.107
Logistic Regression	1.000000	0.956522	1.000000	0.956687	0.038
Ridge Classifier	0.890110	0.869565	0.890110	0.870062	0.016
Linear Discriminant Analysis	0.890110	0.869565	0.890110	0.870062	0.019
Random Forest Classifier	1.000000	0.826087	1.000000	0.822636	0.086
SVM - Linear Kernel	0.912088	0.956522	0.910599	0.956183	0.017
Ada Boost Classifier	1.000000	0.826087	1.000000	0.826087	0.067
Extreme Gradient Boosting	1.000000	0.913043	1.000000	0.913043	0.034
Gradient Boosting Classifier	1.000000	0.913043	1.000000	0.913043	0.070
Light Gradient Boosting Machine	1.000000	0.869565	1.000000	0.868548	0.057
Naive Bayes	0.835165	0.826087	0.835728	0.822636	0.016
Decision Tree Classifier	1.000000	0.869565	1.000000	0.870062	0.019
Dummy Classifier	0.648352	0.565217	0.510037	0.408213	0.019

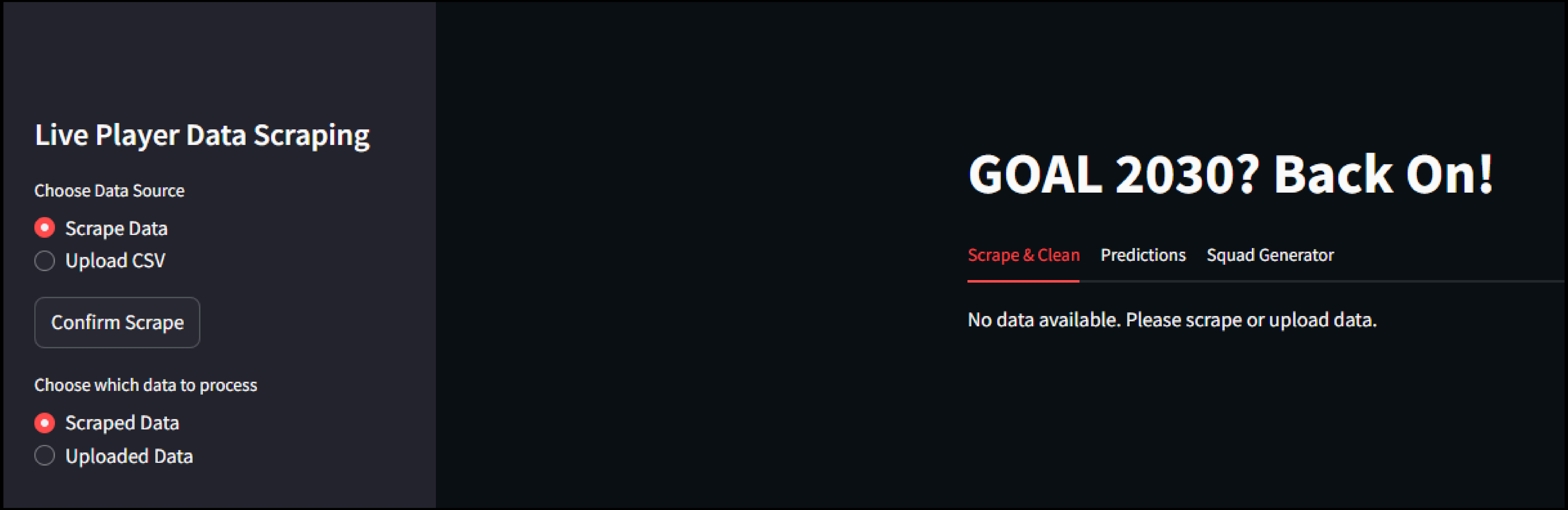
TARGET MAN

model	train_accuracy	test_accuracy	train_f1	test_f1	TT
Random Forest Classifier	1.000000	0.739130	1.000000	0.725064	0.080
Extreme Gradient Boosting	1.000000	0.869565	1.000000	0.857369	0.031
Extra Trees Classifier	1.000000	0.782609	1.000000	0.762281	0.070
K Neighbors Classifier	0.956044	0.869565	0.955833	0.857369	0.021
Ada Boost Classifier	1.000000	0.826087	1.000000	0.816709	0.052
Logistic Regression	1.000000	0.869565	1.000000	0.866525	0.022
Gradient Boosting Classifier	1.000000	0.826087	1.000000	0.826087	0.049
Light Gradient Boosting Machine	1.000000	0.782609	1.000000	0.762281	0.037
Ridge Classifier	0.934066	0.739130	0.934066	0.701449	0.015
Linear Discriminant Analysis	0.934066	0.739130	0.934066	0.701449	0.015
Decision Tree Classifier	1.000000	0.869565	1.000000	0.866525	0.019
Naive Bayes	0.879121	0.739130	0.879362	0.725064	0.015
SVM - Linear Kernel	0.868132	0.739130	0.861964	0.661899	0.020
Dummy Classifier	0.593407	0.695652	0.441986	0.570792	0.014



DEMO


localstreamlitapp-final
localhost:8501
Deploy
Live Player Data Scraping
Choose Data Source
Scrape Data
Upload CSV
Confirm Scrape
Choose which data to process
Scraped Data
Uploaded Data
GOAL 2030? Back On!
Scrape & Clean
Predictions
Squad Generator
No data available. Please scrape or upload data.
http://localhost:8501 is sharing your screen.
Stop sharing
Hide


Live Player Data Scraping
Choose Data Source
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Upload CSV
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Choose which data to process
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GOAL 2030? Back On!
Scrape & Clean
Predictions
Squad Generator
No data available. Please scrape or upload data.

GOAL 2030? Back On!

Scrape & Clean   Predictions   Squad Generator

Loaded Player Data:

	Player Name	Total played	Started	Minutes per game	Goals	Scoring frequency	Goals per g
0	boris kopitovic	13	13	90	12	101 min	
1	kunori seia	13	13	90	10	119 min	
2	thitipat ekarunpong	1	0	10	0	None	
3	faris ramli	13	12	82	4	265 min	
4	kyoga nakamura	13	13	90	0	None	

	Player Name	NATIONALITY	HEIGHT	PREFERRED FOOT	SHIRT NUMBER	POSITION	Goals per game	Assists	Accurate per game
3	faris ramli	SIN	168 cm	Right	30	M	62.5	87.5	78.25
5	shah shahiran	SIN	173 cm	Right	8	M	25	50	94
6	taufik suparno	SIN	165 cm	Right	13	M	50	50	82.75
7	joel chew joon herng	SIN	168 cm	Right	12	M	25	25	86.5
8	yasir hanapi	SIN	170 cm	Right	18	M	37.5	62.5	92.5
9	saifullah akbar	SIN	165 cm	Right	20	M	25	25	90.25
10	caelan cheong tze jay	SIN	None	None	58	M	25	25	75.25
11	kieran tan	SIN	None	None	80	M	25	25	100
12	glenn kweh	SIN	172 cm	Left	11	D	62.5	62.5	82.75
14	jared gallagher	SIN	175 cm	Right	6	D	25	25	94.75
16	irfan najeeb	SIN	178 cm	Right	23	D	50	37.5	94
17	amirul adli bin azmi	SIN	181 cm	Right	5	D	25	25	94
18	amirul haikal hassim	SIN	162 cm	Left	17	D	25	25	77.5
19	syahrul sazali	SIN	179 cm	Right	22	D	25	25	88.75
21	syazwan buhari	SIN	172 cm	Right	24	G	25	25	94.75
22	ridhuan barudin	SIN	182 cm	Right	31	G	25	25	84.25
24	shawal anuar	SIN	164 cm	Right	7	F	100	100	84.25
26	haiqal pashia	SIN	161 cm	Right	23	F	37.5	37.5	92.5

GOAL 2030? Back On!

Scrape & Clean | Predictions | Squad Generator

Models loaded successfully.

Predictions:

Select a Position/Role:

Goal Poacher ×

Prediction Threshold:

0.50

0.00 1.00

- [x] Show Recommended
- [ ] Show Not Recommended

Goal Poacher

	Player Name	↓ Goal Poache	Recommended
1,042	shawal anuar	75.0161	Recommended
1,067	ignatius ang yu heng	67.4726	Recommended
1,094	daniel goh	63.2048	Recommended
1,026	faris ramli	63.0063	Recommended
1,058	naqiuddin eunos	61.8341	Recommended
1,044	song ui young	61.3379	Recommended
1,034	glenn kweh	59.2454	Recommended
1,036	irfan najeeb	58.7629	Recommended

GOAL 2030? Back On!

Scrape & Clean | Predictions | Squad Generator

Squad Generation

Select Total Squad Size:

23

11 35

Set the number of players per position based on the total squad size:

Total Goalkeepers:

3 − +

Total Defenders:

8 − +

Total Midfielders:

8 − +

Total Attackers:

4 − +

Set the number of players per role based on the total players chosen for that position:

Goalkeeper Roles:

Traditional Keepers

2 − +

Sweeper Keepers

1 − +

Defender Roles:

Ball-Playing Defenders

2 − +

No-Nonsense Defenders

2 − +

Full-Backs

4 − +

Midfielder Roles:

All-Action Midfielders

2 − +

Midfield Playmakers

2 − +

Traditional Wingers

2 − +

Inverted Wingers

2 − +

Attacker Roles:

Goal Poachers

2 − +

Target Men

2 − +

Generate Squad

	Player Name	Position	Role	Score
1	zharfan rohaizad	Goalkeeper	Traditional Keeper	65.17
2	zaiful nizam	Goalkeeper	Traditional Keeper	63.98
3	syazwan buhari	Goalkeeper	Sweeper Keeper	76.94
4			Defender	
5	jordan emaviwe	Defender	Ball-Playing Defender	76.24
6	ryaan sanizal	Defender	Ball-Playing Defender	74.51
7	kieran teo	Defender	No-Nonsense Defender	80.30
8	bernard pereira joshua	Defender	No-Nonsense Defender	68.74
9	fathullah rahmat	Defender	Full-Back	64.09
10	hami syahin	Defender	Full-Back	64.03
11	akram azman	Defender	Full-Back	62.95
12	jared gallagher	Defender	Full-Back	62.11
13			Midfielder	
14	madhu mohana	Midfielder	All-Action Midfielder	66.65
15	tajeli salamat	Midfielder	All-Action Midfielder	66.13
16	kan kobayashi	Midfielder	Midfield Playmaker	70.50
17	shahdan bin sulaiman	Midfielder	Midfield Playmaker	68.53
18	haiqal pashia	Midfielder	Traditional Winger	63.28
19	yasir hanapi	Midfielder	Traditional Winger	62.27
20	shawal anuar	Midfielder	Inverted Winger	77.66
21	faris ramli	Midfielder	Inverted Winger	68.24
22			Attacker	
23	ignatius ang yu heng	Attacker	Goal Poacher	67.47
24	naqiuddin eunos	Attacker	Goal Poacher	61.83
25	faizal roslan	Attacker	Target Man	65.13
26	daniel goh	Attacker	Target Man	65.04