

# FATIGUE MONITORING & INJURY PREVENTION IN ELITE SWIMMERS

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Foundations of Machine Learning 24/25



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# PROJECT OVERVIEW

# THE PROBLEM

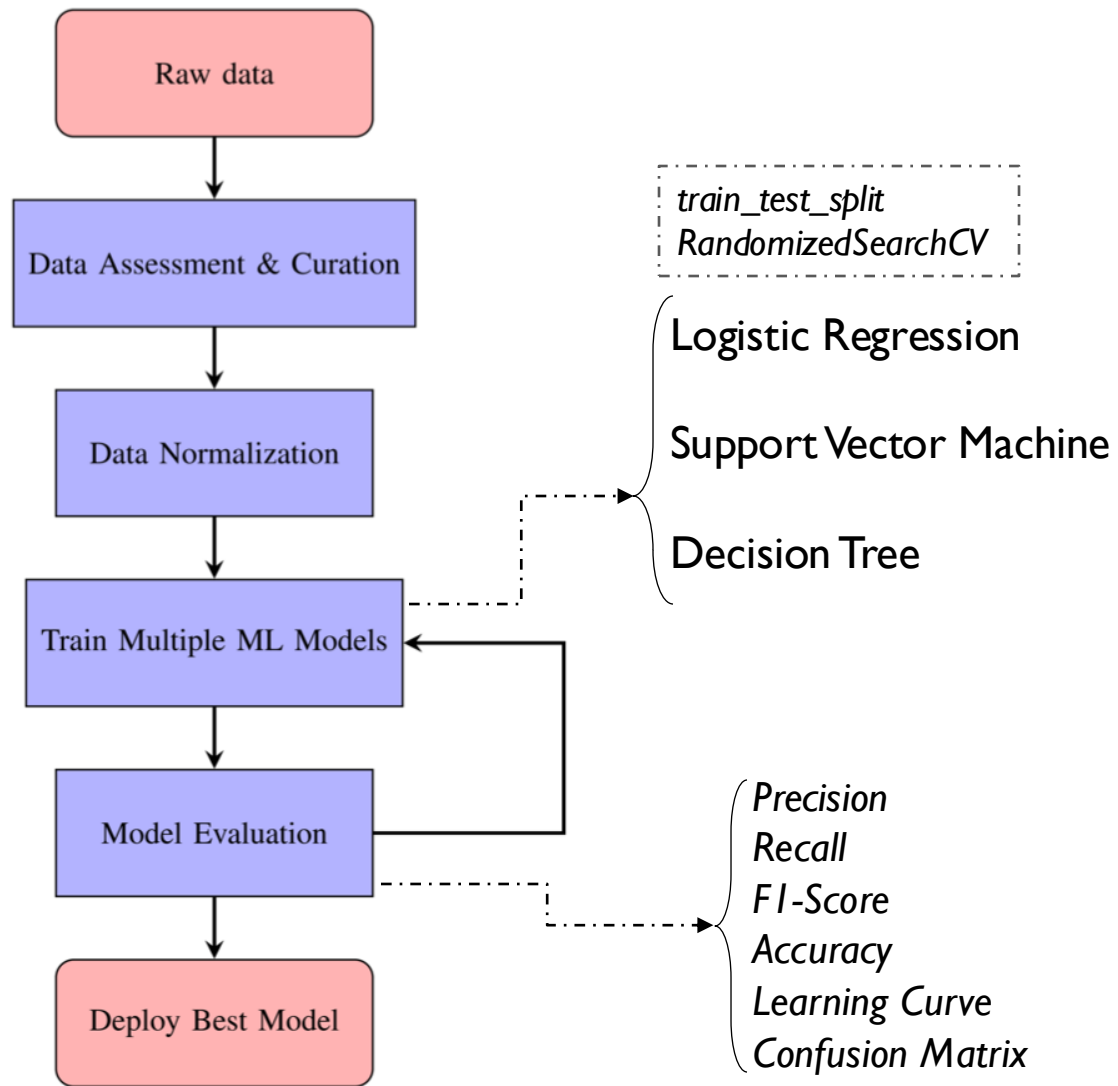
- Improving performance of elite athletes is the ultimate goal of any sports coach.
- Balance between workload and rest is crucial.
- Too high effort, may lead to injury, too low and some gains may be left on the table.





## STATE OF THE ART

- Fatigue and injury prediction using ML models, such as Logistic Regression, Random Forest, Support Vector Machine, among others, across different sports contexts.
- Feature engineering and selection is among the most debated topics.
- Overfitting problems.

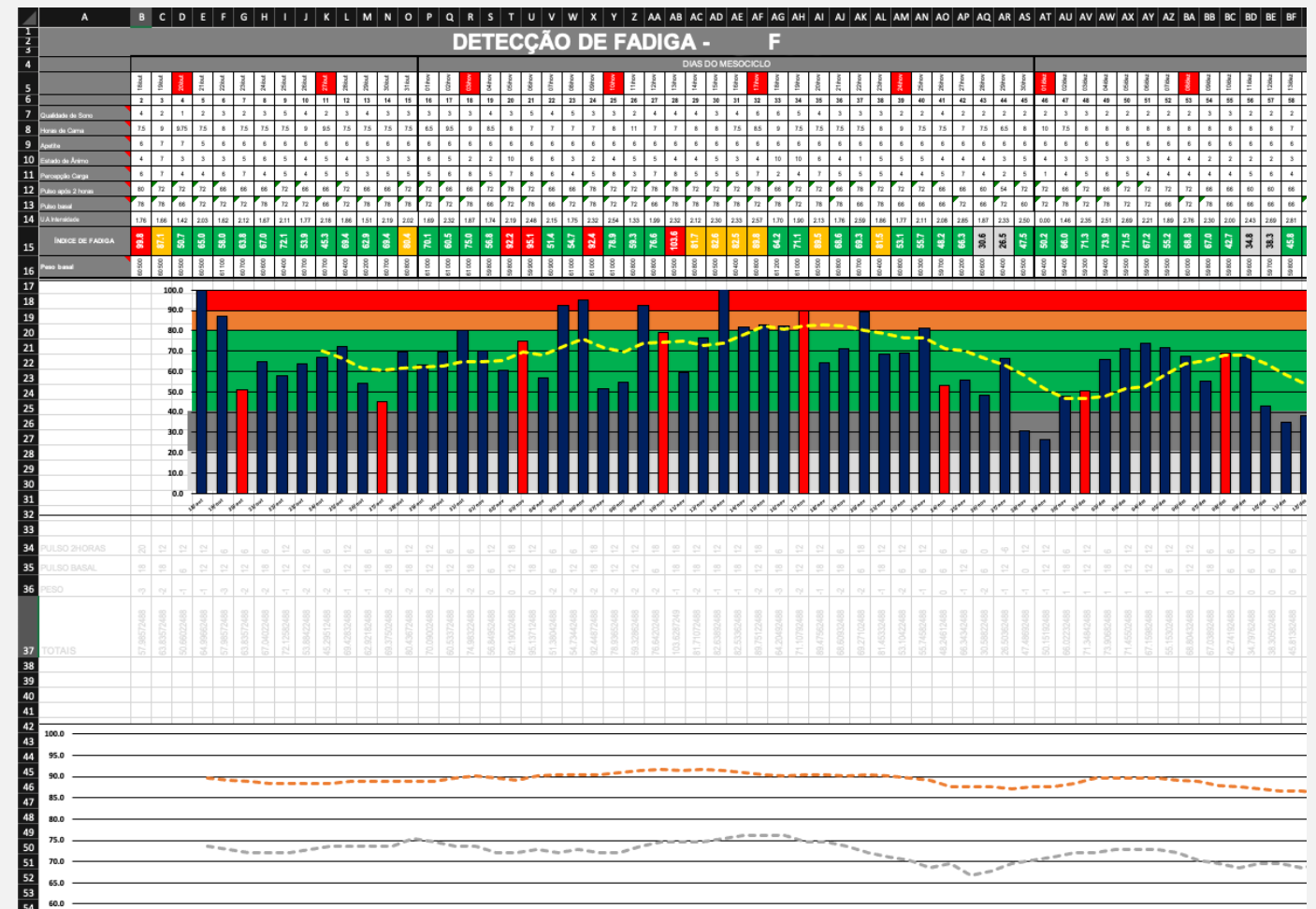


## METHODOLOGY

# DATA ANALYSIS

# RAW DATA

- Swimming club CAPGE
- Season 2019/2020
- 7 athletes
- 11 different metrics
- Around 200 obs. per athlete



# STRUCTURED DATA

	Date	Appetite	StSpirit	pEffort	ual	FatigInd	DeltaWt (%)	DeltaHrtwo	Name	Sex_F	SleepInd
0	2019-10-18	6.0	4.0	6.0	1.76	99.809325	NaN	2.0	F_f	1	-3.50
1	2019-10-19	7.0	7.0	7.0	1.66	87.095325	0.000000	-6.0	F_f	1	-7.00
2	2019-10-20	7.0	3.0	4.0	1.42	50.660225	0.000000	6.0	F_f	1	-8.75
3	2019-10-21	5.0	3.0	4.0	2.03	64.996625	0.000000	0.0	F_f	1	-5.50
4	2019-10-22	6.0	3.0	6.0	1.62	57.985725	0.009917	-6.0	F_f	1	-5.00
...	...	...	...	...	...	...	...	...	...	...	...
1267	2020-05-12	6.0	5.0	6.0	2.00	115.433793	0.000000	12.0	I_f	1	-5.00
1268	2020-05-13	6.0	5.0	5.0	2.00	53.098793	0.000000	6.0	I_f	1	-6.50
1269	2020-05-14	6.0	5.0	5.0	2.00	53.423793	0.000000	6.0	I_f	1	-6.00
1270	2020-05-15	6.0	5.0	6.0	2.00	80.333793	0.000000	6.0	I_f	1	-5.00
1271	2020-05-16	6.0	5.0	5.0	2.00	65.123793	0.000000	0.0	I_f	1	-6.00

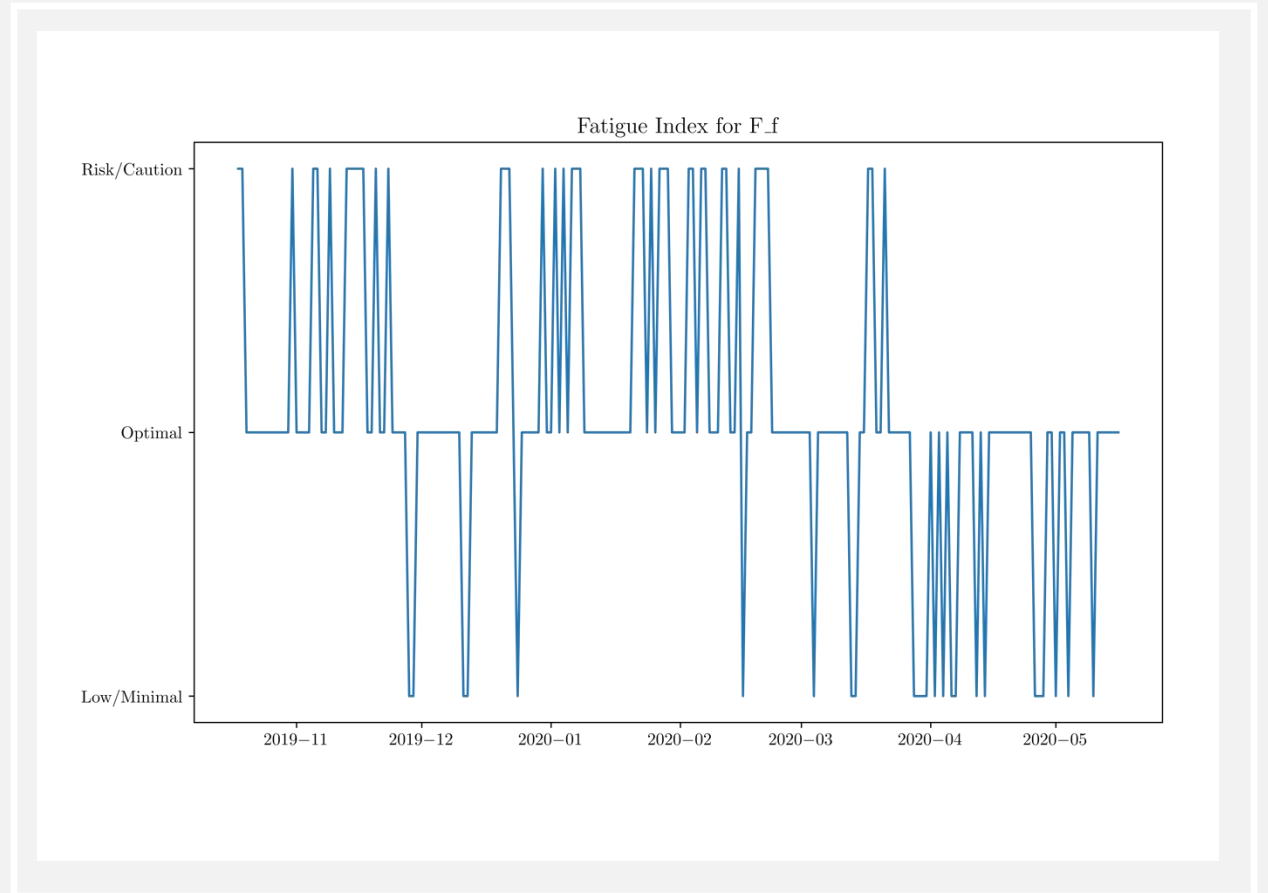
1272 rows x 11 columns

# FEATURE ENGINEERING

- The figure, illustrating the periodicity of training loads, highlights the dynamic nature of fatigue.
- Using EWMA helps to manage this complexity.

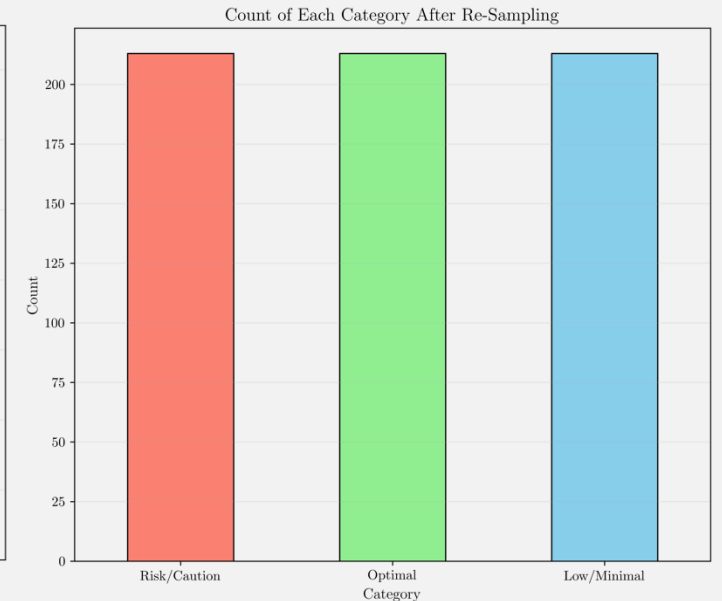
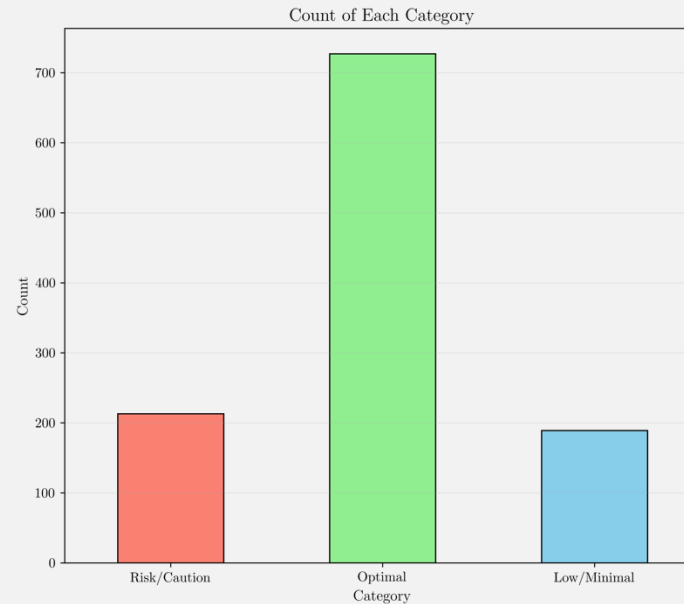
$$\text{EWMA}_{\text{today}} = \text{Feature}_{\text{today}} \cdot \lambda_a + (1 - \lambda_a) \cdot \text{EWMA}_{\text{yesterday}}$$

$$\lambda_a = \frac{2}{N + 1}$$



# OVERCOMING DATA CHALLENGES

Range	Initial Classes	Final Classes
$\geq 90$	Risk	Risk/Caution
$\geq 80$	Caution	
$\geq 40$	Optimal	Optimal
$< 40$	Low/Minimal	Low/Minimal

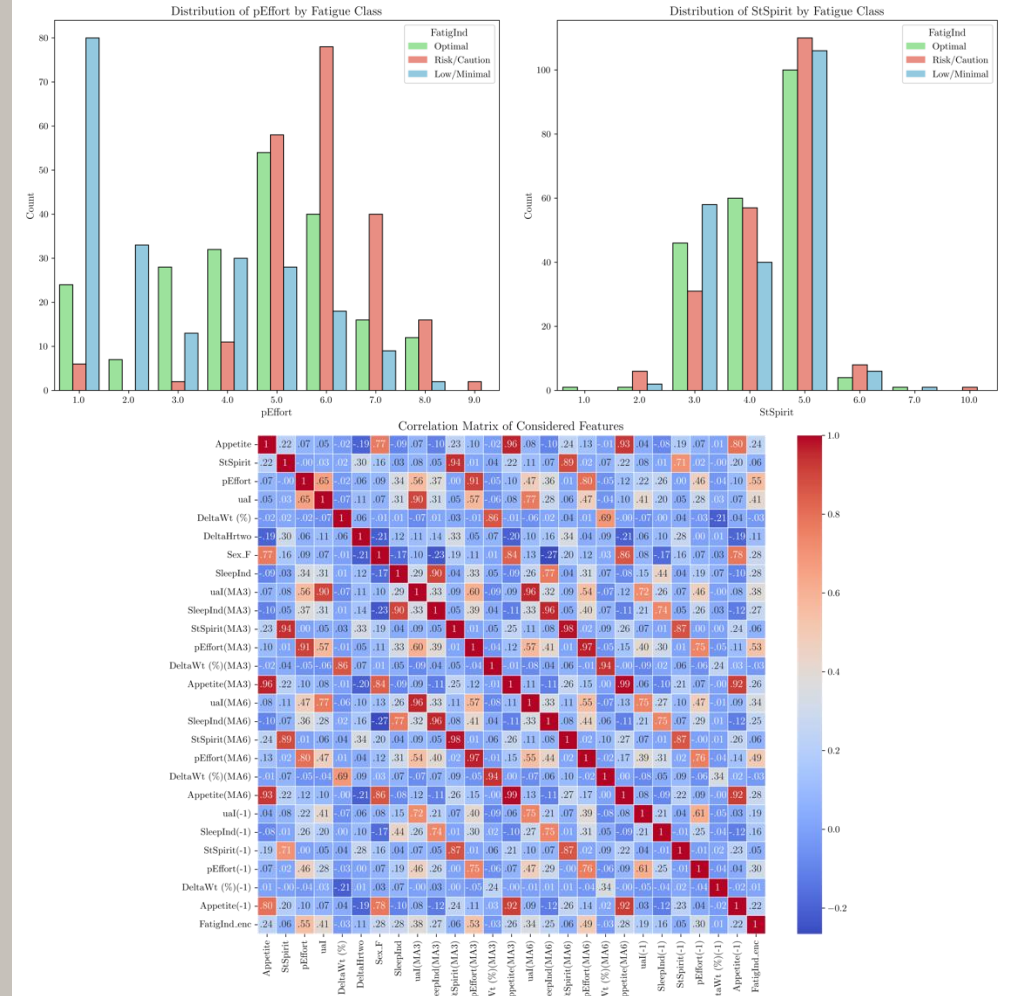


~~SMOTE and random undersampling~~

Random oversampling and undersampling

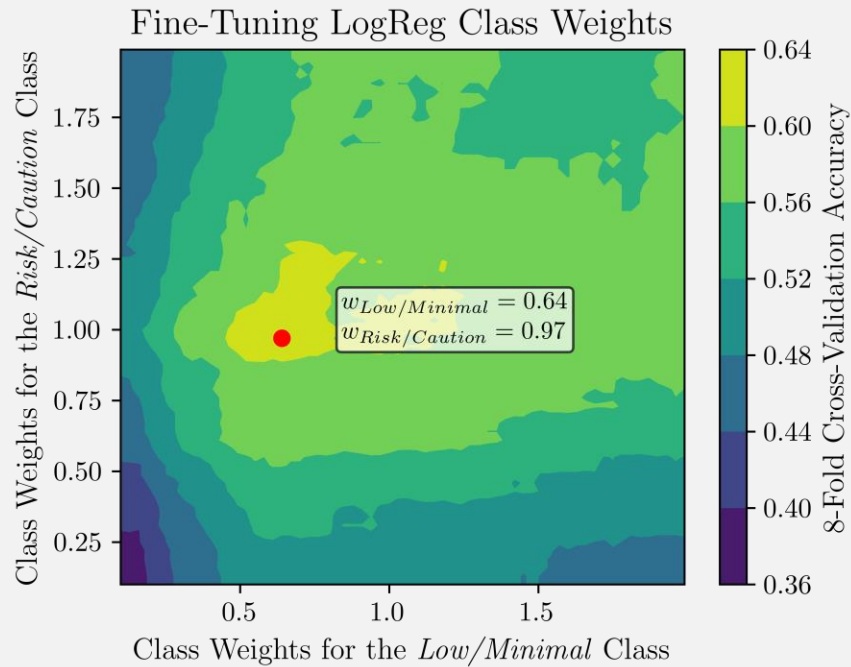
# FEATURE SELECTION

Feature	Description
<i>Sex_F</i>	Athlete's gender.
<i>pEffort</i>	Perceived effort from the workout.
<i>ual</i>	Intensity from each workout.
<i>SleepInd</i>	Index based on quality of sleep and time in bed.
<i>Appetite(MA6)</i>	Appetite measure, averaged with EWMA(6).
<i>pEffort(MA6)</i>	<i>pEffort</i> averaged with EWMA(6).
<i>ual(MA6)</i>	<i>ual</i> averaged with EWMA(6).
<i>SleepInd(MA6)</i>	<i>SleepInd</i> averaged with EWMA(6).

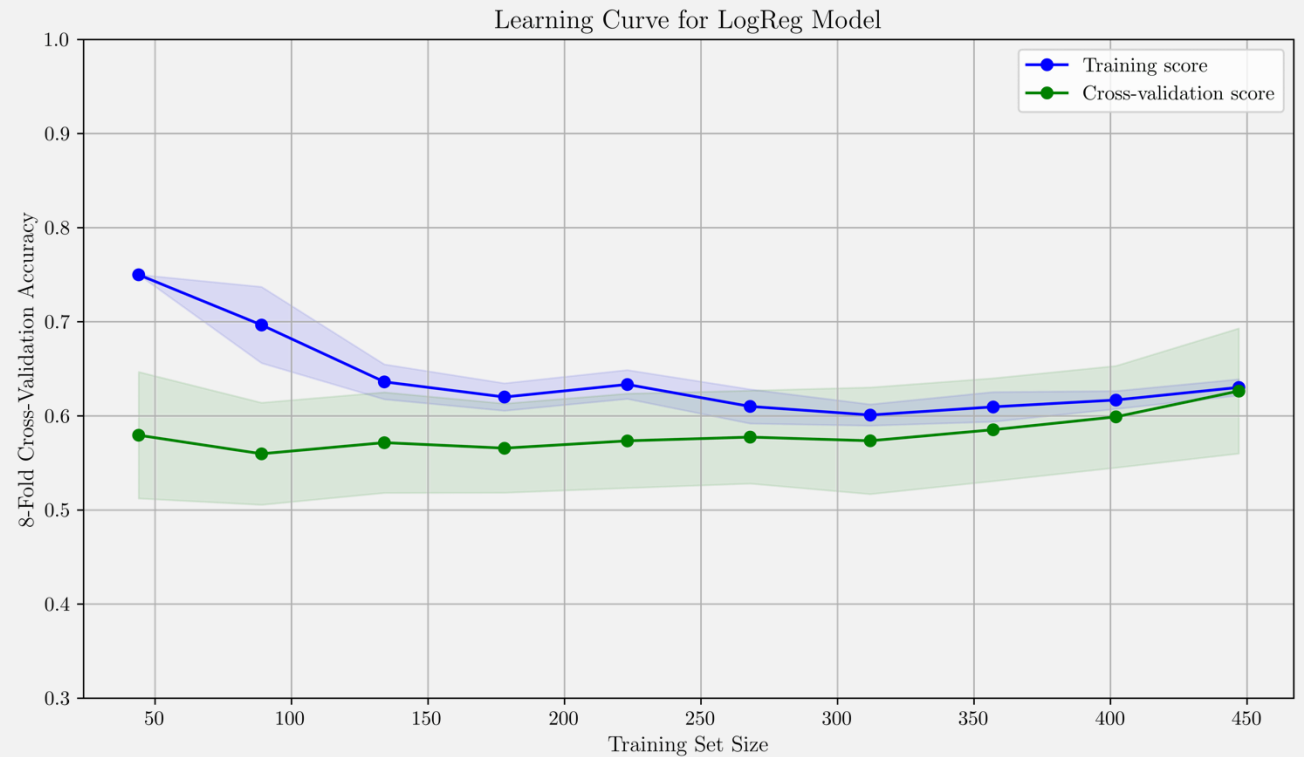


# MACHINE LEARNING MODELS

# LOGISTIC REGRESSION

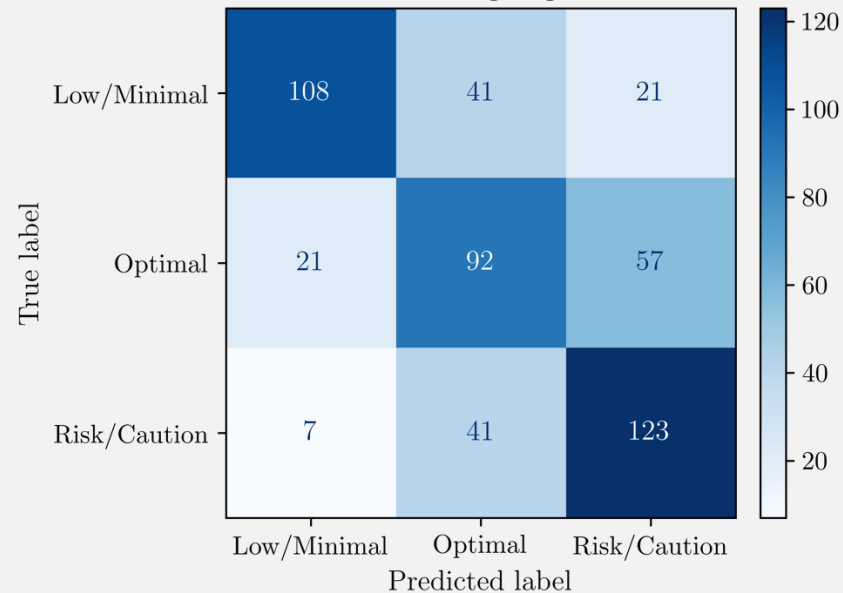


Hyperparameter	Possible Values	Best Value
$C$	[0.01, 300]	2.13
Regularization	{ $L1$ , $L2$ , none}	$L1$

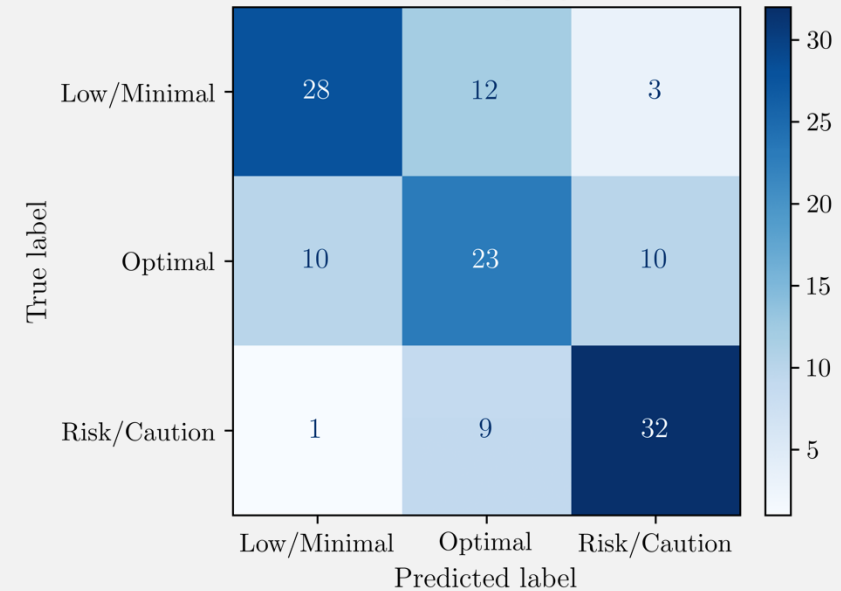


# LOGREG RESULTS

Confusion Matrix for LogReg Model - Train Set



Confusion Matrix for LogReg Model - Test Set



Classification Report: Train Set

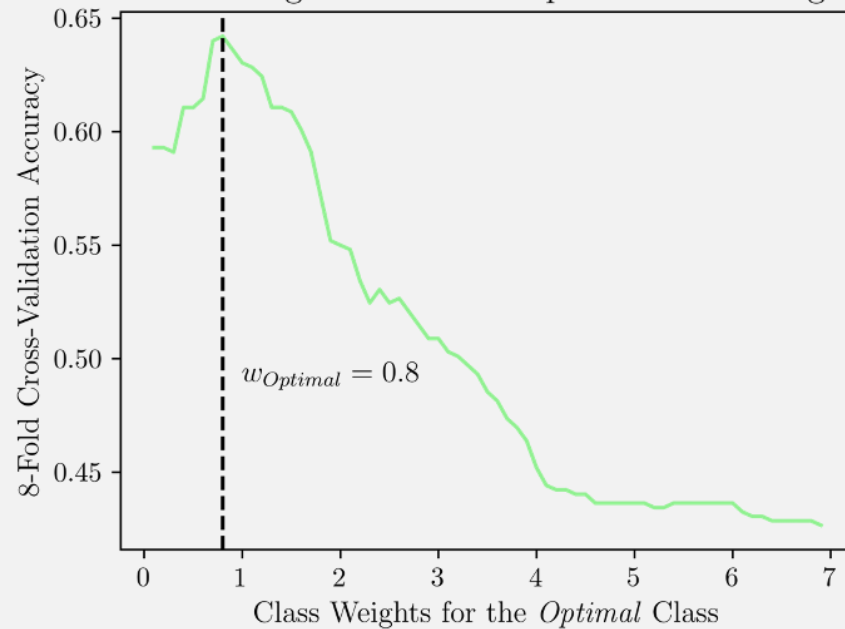
Class	Precision	Recall	F1-Score	Support
Low/Minimal	0.79	0.64	0.71	170
Optimal	0.53	0.54	0.53	170
Risk/Caution	0.61	0.72	0.66	171
<b>Accuracy</b>			0.63	511
<b>Macro avg</b>	0.64	0.63	0.63	511
<b>Weighted avg</b>	0.64	0.63	0.63	511

Classification Report: Test Set

Class	Precision	Recall	F1-Score	Support
Low/Minimal	0.72	0.65	0.68	43
Optimal	0.52	0.52	0.53	43
Risk/Caution	0.71	0.76	0.74	42
<b>Accuracy</b>			0.65	128
<b>Macro avg</b>	0.65	0.65	0.65	128
<b>Weighted avg</b>	0.65	0.65	0.65	128

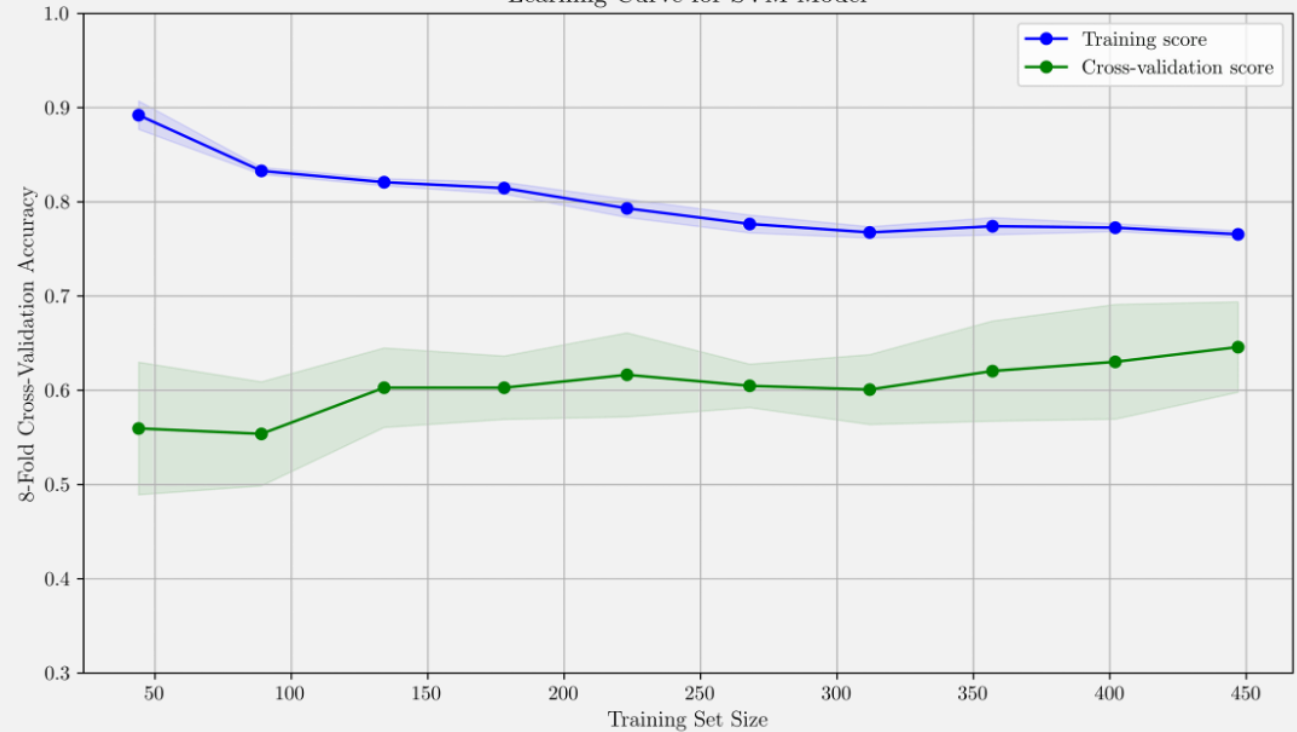
# SUPPORT VECTOR MACHINE

Fine-Tuning SVM for the Optimal Class Weight



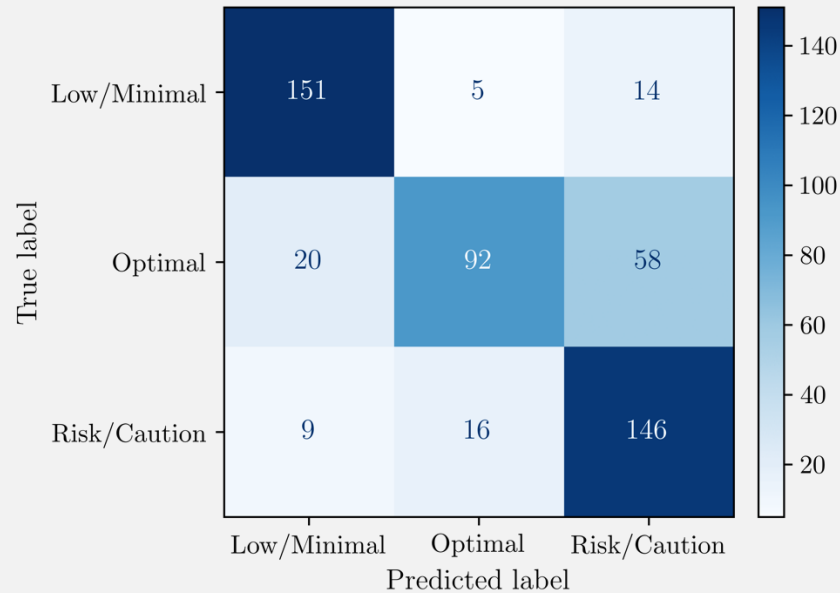
Hyperparameter	Possible Values	Best Value
$C$	[0, 100]	6.93
$\gamma$	{scale, auto, 0.1, 0.01, 0.001}	auto
Kernel	{linear, rbf, poly, sigmoid}	rbf
Degree	{1, 2, 3}	
Coef <sub>0</sub>	[-5, 5]	

Learning Curve for SVM Model



# SVM RESULTS

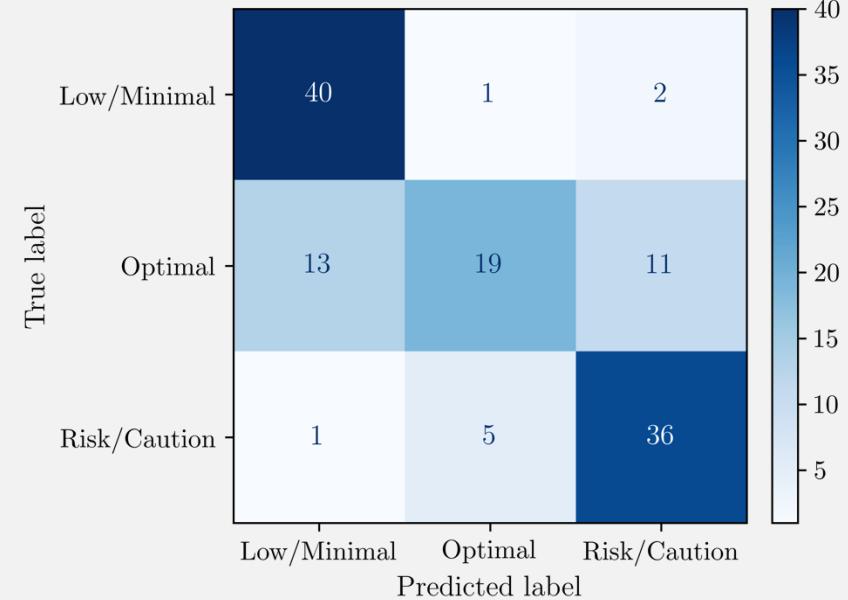
Confusion Matrix for SVM Model - Train Set



Classification Report: Train Set

Class	Precision	Recall	F1-Score	Support
Low/Minimal	0.84	0.89	0.86	170
Optimal	0.81	0.54	0.65	170
Risk/Caution	0.67	0.85	0.75	171
Accuracy			0.76	511
Macro avg	0.77	0.76	0.75	511
Weighted avg	0.77	0.76	0.75	511

Confusion Matrix for SVM Model - Test Set

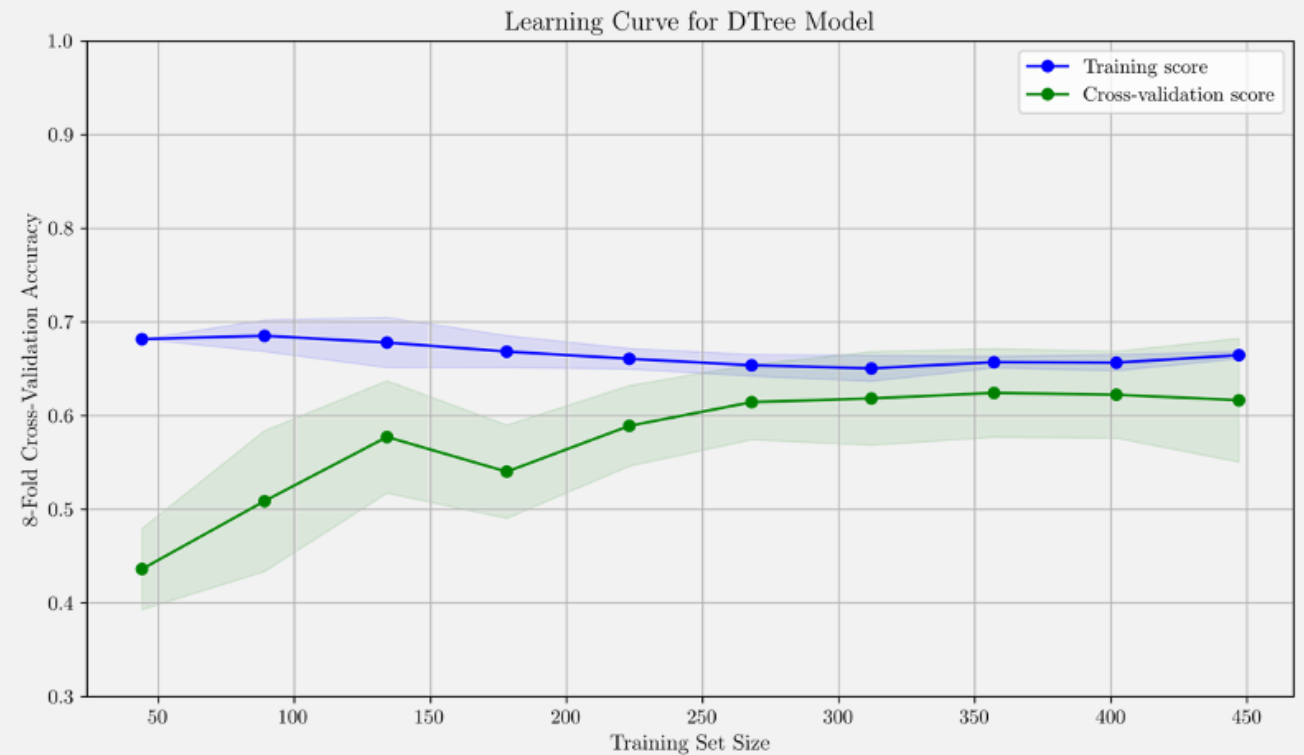
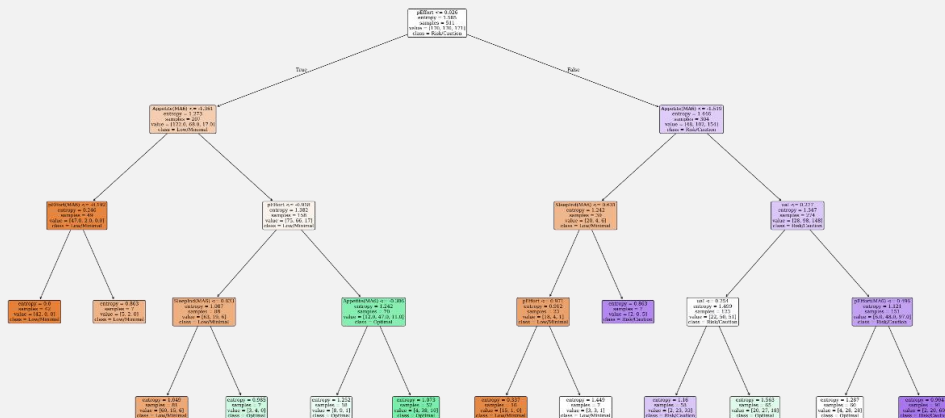


Classification Report: Test Set

Class	Precision	Recall	F1-Score	Support
Low/Minimal	0.74	0.93	0.82	43
Optimal	0.76	0.44	0.56	43
Risk/Caution	0.73	0.86	0.79	42
Accuracy			0.74	128
Macro avg	0.75	0.74	0.72	128
Weighted avg	0.75	0.74	0.72	128

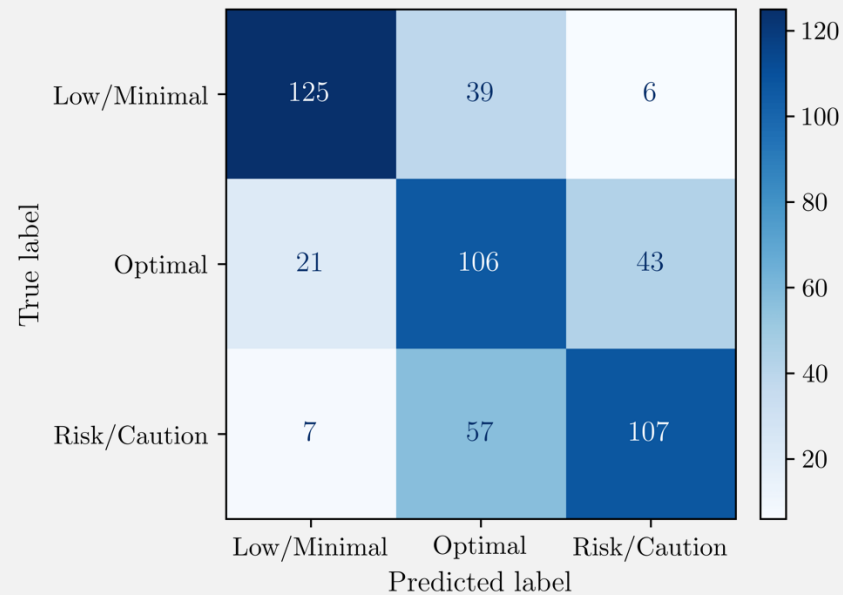
# DECISION TREE

Hyperparameter	Possible Values	Best Value
Split Criterion	{gini, entropy}	entropy
Max Depth	[2, 3, ..., 8]	4
Min Samples to Split	[5, 6, ..., 20]	11
Min Samples per Leaf	[3, 4, ..., 10]	7



# DTREE RESULTS

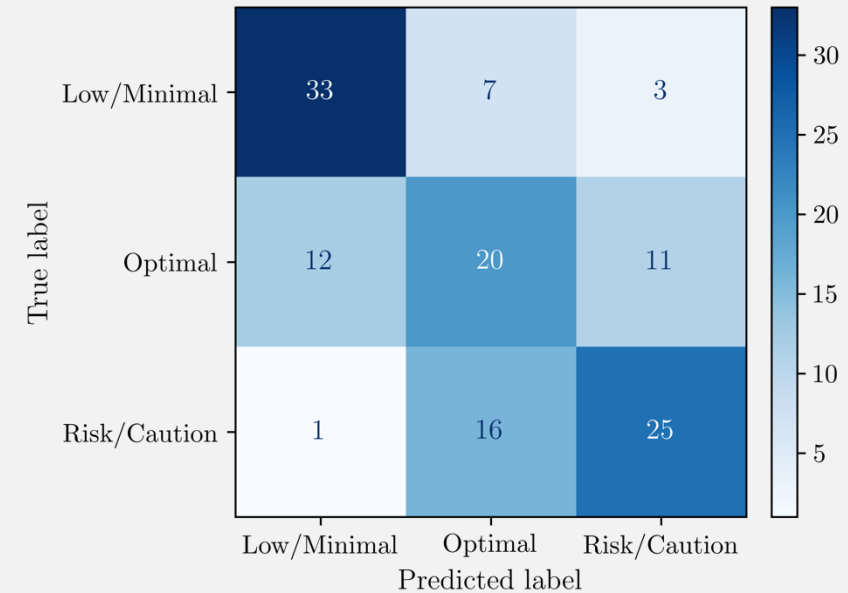
Confusion Matrix for DTree Model - Train Set



Classification Report: Train Set

Class	Precision	Recall	F1-Score	Support
Low/Minimal	0.82	0.74	0.77	170
Optimal	0.52	0.62	0.57	170
Risk/Caution	0.69	0.63	0.65	171
<b>Accuracy</b>			0.66	511
<b>Macro avg</b>	0.68	0.66	0.67	511
<b>Weighted avg</b>	0.68	0.66	0.67	511

Confusion Matrix for DTree Model - Test Set



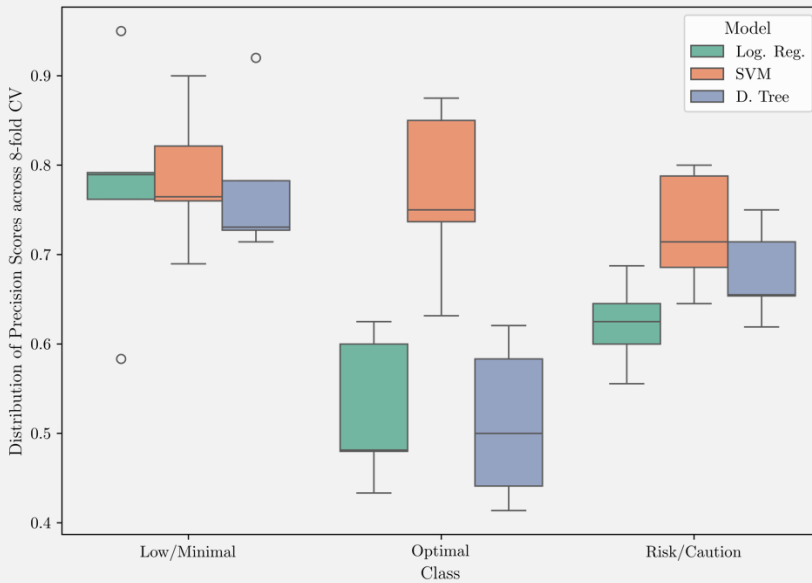
Classification Report: Test Set

Class	Precision	Recall	F1-Score	Support
Low/Minimal	0.72	0.77	0.74	43
Optimal	0.47	0.47	0.47	43
Risk/Caution	0.64	0.60	0.62	43
<b>Accuracy</b>			0.61	128
<b>Macro avg</b>	0.61	0.61	0.61	128
<b>Weighted avg</b>	0.61	0.61	0.61	128

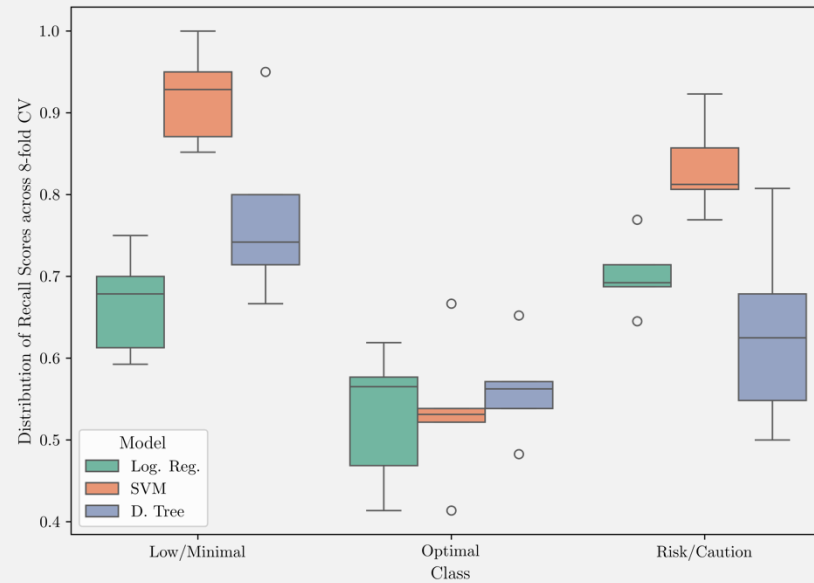
# RESULTS ANALYSIS

# PERFORMANCE METRICS

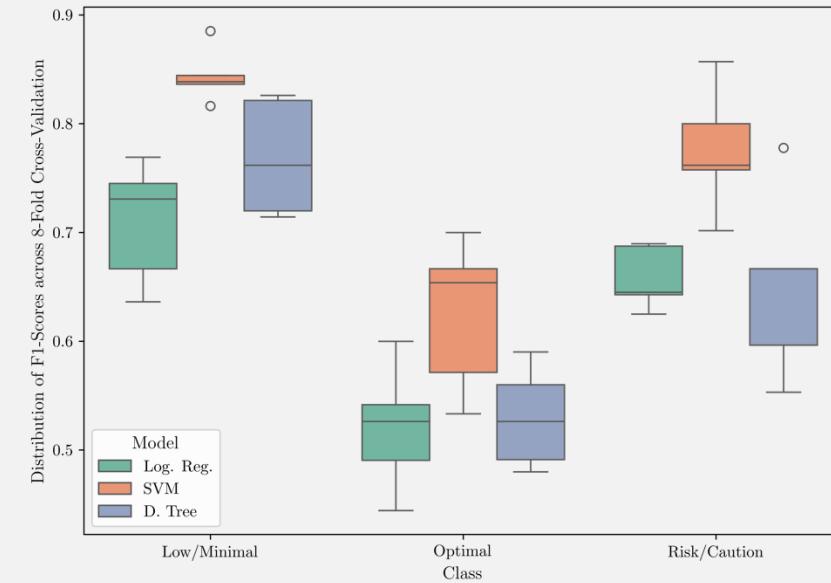
Precision Distribution Across 8-Fold CV



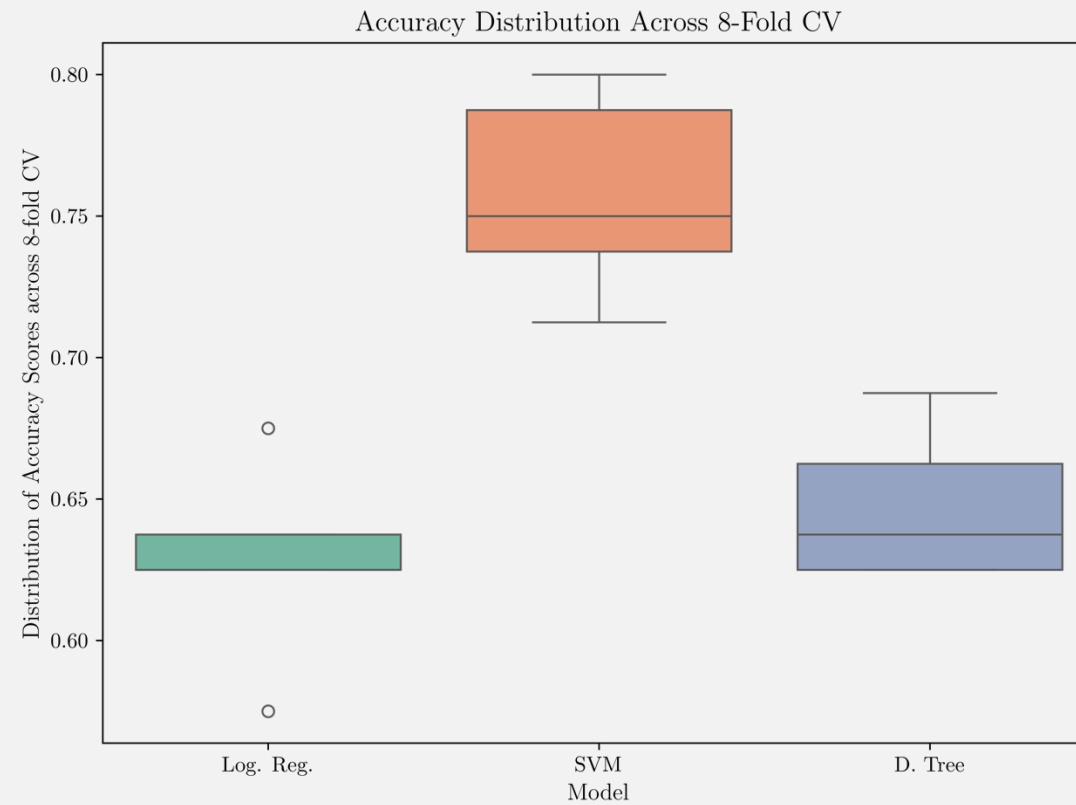
Recall Distribution Across 8-Fold CV



F1-Score Distribution Across 8-Fold CV

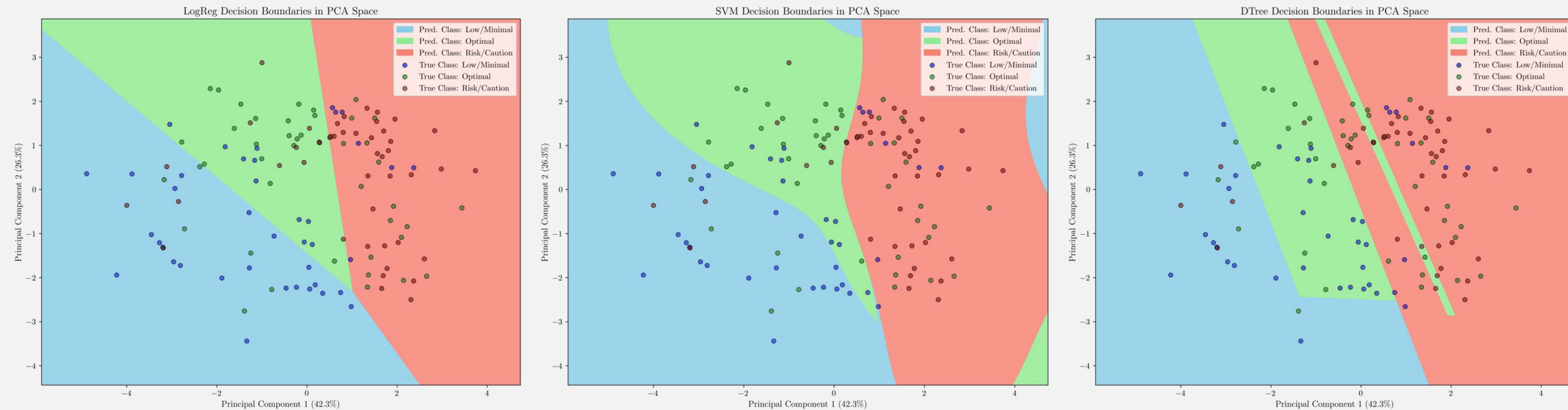


# PERFORMANCE METRICS



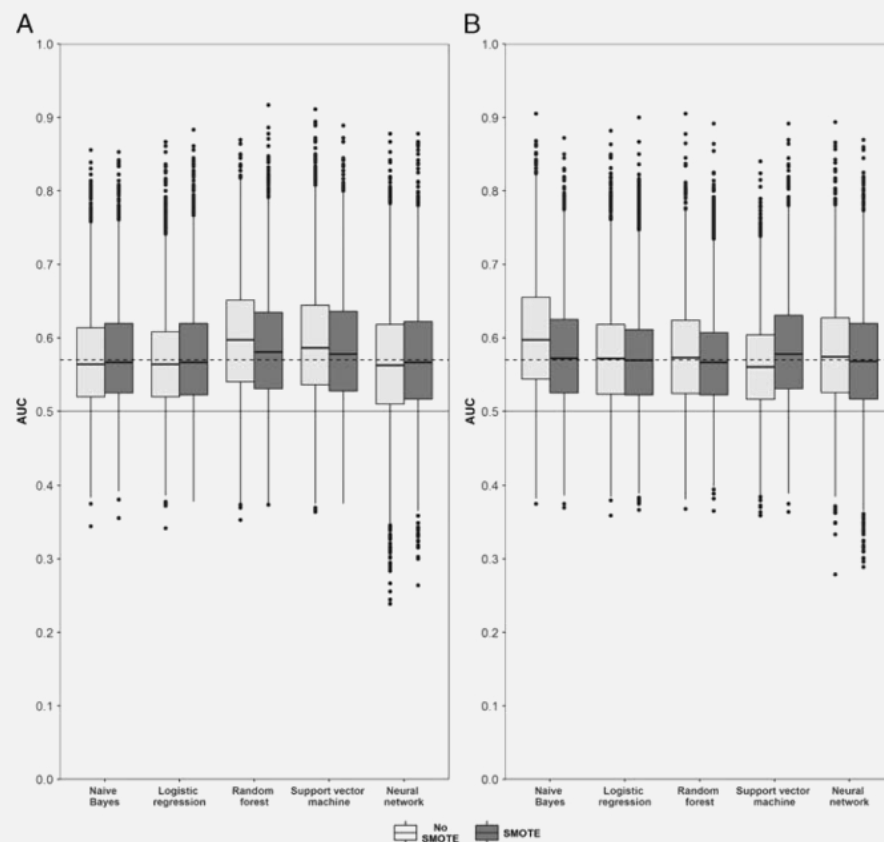
# DECISION BOUNDARIES

PCA was applied to approximate the decision boundaries of each model within a 2D space, where 31% of the variance was lost due to dimensionality reduction, providing a rough visualization of the models' performance.

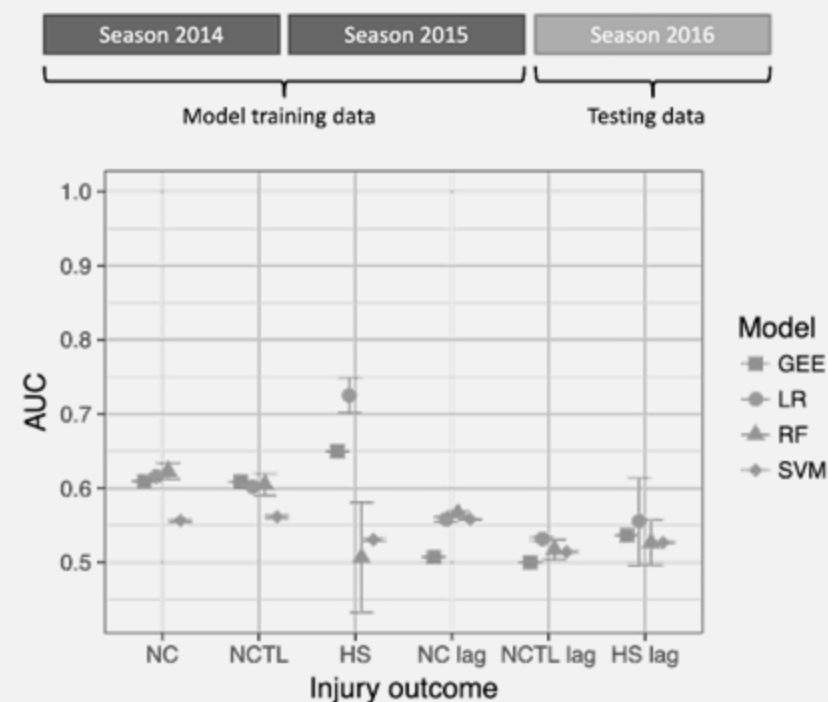


# LITERATURE BENCHMARK

“Predictive modeling of hamstring strain injuries in elite Australian footballers,” 2017, Rudy et al.



“Predictive modelling of training loads and injury in Australian football”, 2018, Carey et al.



- Most literature focus on injury prediction
- Performance criteria not directly comparable: most of the problems are binary (injury or no injury)
- Models developed are well aligned with those in the literature.

# CONCLUSIONS

- Despite the reduced dataset, it was possible to implement and assess different machine learning models.
- Of the three models tested (LogReg, SVM, DTree), the support vector machine model stood out as being the most consistent across the board.
- The model's performance aligns closely with published results.
- The model will be implemented in Excel format and shared with the Head Coach Daniel Tavares.
- Future work: follow-up on the implementation and improve data collection for further refinement.