UNIVERZA NA PRIMORSKEM
FAKULTETA ZA MATEMATIKO, NARAVOSLOVJE IN INFORMACIJSKE TEHNOLOGIJE

Zaključna naloga
(Final project paper)

Napovedovanje in izbira strategij za izboljšanje napovedi športnih stavnic: pregledna študija

(Prediction and Strategy Selection for Outperforming Sport Betting Platforms: A Survey)

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Izvleček:
Z vedno večjo razpoložljivostjo športnih podatkov je strojno učenje doseglo široko uporabo na področju športa, od ekip, ki poskušajo optimizirati svojo igro, do stavnic, ki postavljajo svoje kvote in hazarderjev, ki poskušajo iz njih zaslužiti. V tem preglednem delu povzemamo obstoječe raziskave o uporabi strojnega učenja za pridobivanje dobička od športnih stav, napovedovanje izidov tekem in oblikovanje donosnih strategij stav. Najprej smo definirali postopek izbire člankov, nato smo izdelali taksonomijo izvlečenih podatkov in jih analizirali. Na koncu smo naredili zaključek z razpravo o rezultatih in pregledom bodočih raziskav.

Key words documentation

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Abstract: With the availability of more and more sport data, machine learning has become widely used in the field of sports, from teams trying to optimize their game to bookmakers setting their odds and gamblers trying to profit from them. In this review we survey existing research on using machine learning to profit from sports betting by predicting game outcomes and devising a profitable betting strategy. We begin with the study selection process, then we create a taxonomy of the extracted data and we analyze it. We end with discussion about the results and review the future research themes suggested by the surveyed literature.

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List of Abbreviations

i.e.	that is
e.g.	for example
ML	Machine Learning
H/D/A	Home/Draw/Away
H/A	Home/Away
BTTS	Both teams to score
O/U 2.5	Over/Under 2.5
AH	Asian Handicap
MCC	Majority Class Classifier
AMC	Average Market Classifier
FBC	Fairest Bookmaker Classifier
PM	Poisson Model
NB	Naive Bayes
LR	Logistic Regression
BOO	Boosting
RF	Random Forest
SVM	Suppoer Vector Machine
LINR	Linear Regression
H	Hybrid
BN	Bayesian Network
DT	Decision Tree
NN	Neural Network
PR	Probit Regression
RPS	Rank Probability Score
Uniform	Uniform strategy
UniformT	Uniform strategy with threshold
Dynamic	Dynamic strategy
DynamicT	Dynamic strategy with threshold
Kelly	Kelly criterion

MPT	Modern portfolio strategy
Variance	Variance adjusted strategy
HPF	Highest probability forms strategy
ROI	Return on investment
USD	United States dollar
GBP	British pound sterling

1 Introduction

1.1 Machine learning

Machine Learning was defined as building models using sample data in order to make predictions without being explicitly programmed, by Arthur Samuel in 1959 [38]. Tom M. Mitchell (1997) [30] provided a more formal definition: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E." Machine learning models have two goals, to classify the given data i.e., learn how an outcome occurs, and to make future predictions based on the experience. Machine learning approaches are normally split into three main categories, depending on the input and output data:

(i) Supervised learning: The model is given input and output data and needs to learn how inputs map to the outputs. There are classification and regression algorithms. Classification algorithms are used when the outputs are a limited set of values. Regressions are used when the outputs are numerical values within a range.

(ii) Unsupervised learning: The model is given only input data and needs to interpret and group or cluster the data.

(iii) Reinforcement learning: The model interacts with the environment and tries to maximise the rewards as is being rewarded for the right choices.

With a lot of sports data being available, machine learning has become widely used in the field of sports, from teams trying to optimize their game to bookmakers setting their odds and gamblers trying to profit from them. In this review we are addressing profiting from predictions by ML models. Sport outcome predictions are treated as classification problems e.g., predicting home win, draw or away win where each outcome is a class, or regression problems e.g., the total points scored. Hence, supervised learning is employed. The data set is usually split in training and test set. The training set is the larger part of the data set and is used for the model to learn. The test set is then used to evaluate the model's predictions.

1.2 Sports betting

The predictions from the ML models can be used for betting. There are different types of bets with different payouts offered by the betting houses also known as the bookmakers or bookies. In order to create the odds, the bookmakers are also using ML and their predictions are very accurate. The higher the probability of the outcome they predict the lower is the payout for that bet. There are European (decimal), UK (fractional) and American (money line) odds. The European odds are represented as the payout ratio. For example betting 10 units on a bet with odds 1.5 will return 10 * 1.5 = 15 units if guessed correct. The odds are reflection of the implied probability, e.g., if the probability for a home win is 80% the the odds will be 100% / 80% = 1.25. However, when the odds are converted to implied probability, adding them sums up to more than 100%. The extra percentage is called the margin. This way bookmakers make sure that they profit in the long run, e.g., if we have 2.0 odds for home win and 2.0 odds for away win (assume a draw cannot happen) we could bet 10 units on both outcomes and return the same amount we have placed. Now, if the odds are set to be 1.90 we would get 100/1.90 + 100/1.90 = 105.26%, with a margin of 5% betting 10 units on both outcomes would lose 1 unit. The UK odds are represented as the ratio of the amount won and the stake placed e.g., if the probability of the outcome is 10% the odds would be 9/1. Money line odds are the amount won by staking 100 units when positive, and the stake needed to win 100 when negative, e.g., +200 means bet 100 units to win 200 and -200 means bet 200 units to win 100. Taking into account the predictions by the model and the offered odds, a betting strategy needs to be devised in order to achieve some profit.

1.3 Goal of this work

In this work we present the results of a literature review exploring machine learning for sports betting. This work is novel since previous reviews only consider sports prediction accuracy and not profitability from betting. The goal of this work is to analyze sports studied, types of bets, ML models used, betting strategies and future research directions. We framed the following research questions:

1 What are the sport betting markets on which machine learning is used for making profit?

2 What types of bets are considered for profiting in the reviewed literature?

3 Which machine learning techniques are used for the predictions?

4 Which betting strategies are used?

5 What kinds of betting strategies are the best and how is the profitability evaluated?

6 Does profitability coincide with prediction accuracy?

The remainder of this study is structured as follows. In the following chapter (3) we present the related work surveying literature on this topic. Chapter 4 outlines the approach for the study selection. In chapter 5 we present and discuss the results of our review. We conclude our work with chapter 6 where we also review the future research themes suggested by the surveyed literature.

2 Related work

To our knowledge, machine learning techniques for sport forecasting are reviewed in four studies. Horvat and Job [17] analyzed papers covering American football, association football, basketball, baseball and cricket. They found that sport predictions are usually treated as a classification problem and that neural networks were the most used machine learning models. They suggest that future research should focus on discovering the best number of seasons, used features, and interconnection of different leagues and sports.

Langaroudi and Yamaghani [23] reviewed some ML models and provided short descriptions about relevant papers. They found that across different sports, mostly used features for prediction are the players age, players height, number of injuries, recent results and number of wins/loses. For future work they propose using in-game time-series approach which will reflect the changes in the match.

Hahghigat et al. [15] evaluate advantages and disadvantages of the ML models from previous research. They suggest trying ML techniques that have not been used for sport predictions but have yielded good results in other fields, using more features and using the same dataset so that the studies can be compared.

Bunker and Sisnjak [4] surveyed 31 papers covering nine sports. Their main findings are: artificial neural networks perform better than other machine learning models in terms of predictive accuracy. Successful studies had experimental approaches and tested a number of different training and validation data splits. Low scoring sports are harder to predict, but the prediction is also dependent on the competitiveness level of the match. Most common ways to evaluate a model's accuracy are comparing the accuracy with: match betting odds, expert opinions, rule that always selects the majority class, and random outcomes. Main future work theme was engineering additional richer features, listed in almost 90% of the papers.

To our knowledge there are no reviews of studies addressing profitability from sports betting using machine learning, therefore this survey fills this gap.

3 Methodology

This chapter outlines the methodological approach we used for the study selection relevant for our research questions.

The approach was inspired by the approach proposed by Kitchenham [24], which is designed for planning, conducting and reporting Software Engineering related reviews, and as a writing example for our methodology we used parts of the software engineering systematic review by Gasparic and Janes [13], where the authors evaluated software engineering recommendation literature.

Before conducting the systematic review we developed a review protocol specifying the methods for undertaking the review, which is followed during the execution. In the protocol we defined the research questions, the search strategy, the study selection criteria, the data extraction strategy and the data synthesis strategy.

On May 14th 2022 we queried the digital library Scopus and the scholarly literature Web search engine Google Scholar. We selected these libraries because they are widely used.

We framed our research questions as a hypothesis based on assumptions of what we could conclude from the existing literature since we could not find an applicable framework for our topic.

To obtain a sufficient number of results from both libraries we built the following queries:

For Scopus:

```
( beat AND bookies )
OR ( beat AND bookmakers )
OR ( machine AND learning AND sports AND income )
OR ( machine AND learning AND sports AND bet )
OR ( machine AND learning AND sports AND betting )
OR ( machine AND learning AND sports AND gambling )
OR ( machine AND learning AND sports AND profit )
OR ( machine AND learning AND betting ).
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For Google Scholar:

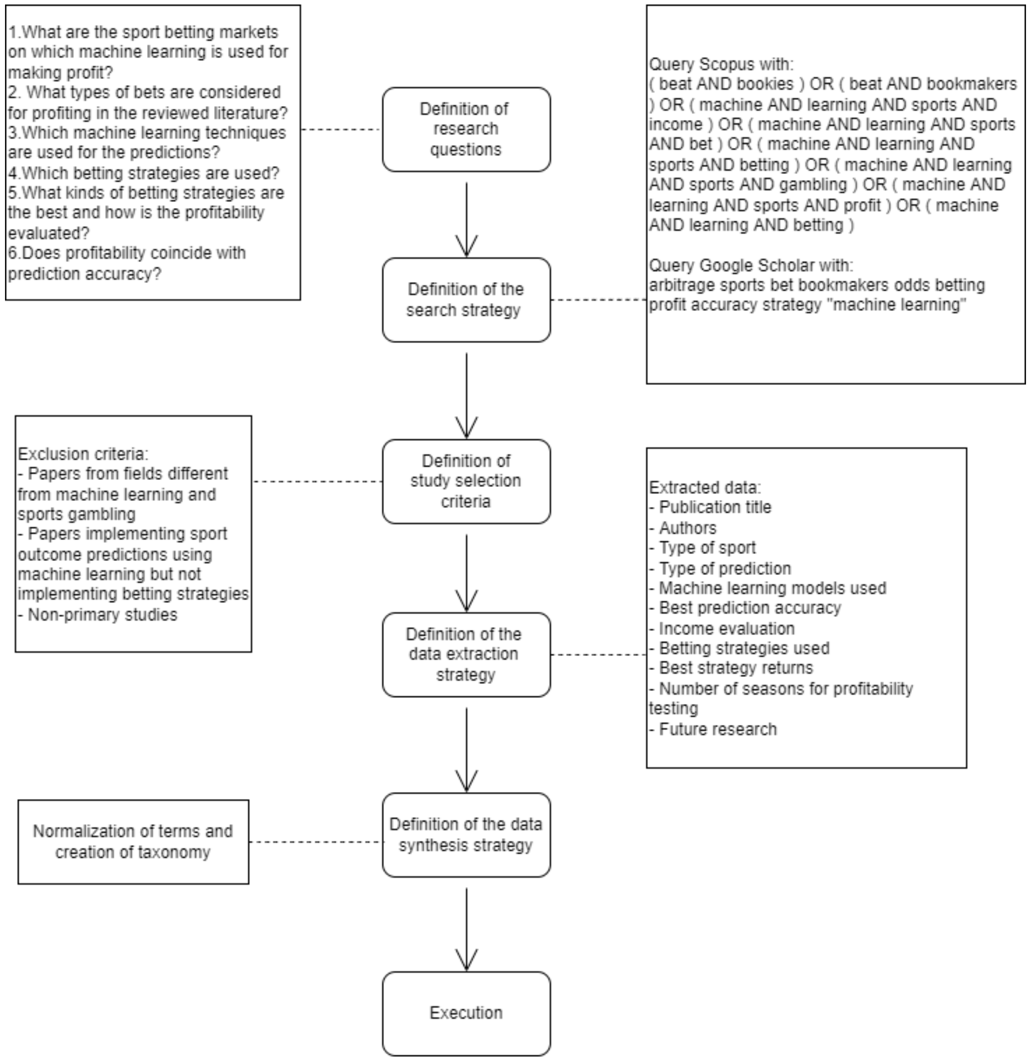

Figure 1: Research process.

`arbitrage sports bet bookmakers odds betting profit accuracy strategy "machine learning"`.

Scopus returned 100 and Google Scholar returned 197 results. We were interested in papers describing ML methods used for match outcome prediction and betting strategies used for generating profit from betting on the predicted outcomes, hence we defined the following exclusion criteria:

1. Papers from fields different from machine learning and sports gambling.
2. Papers implementing sport outcome predictions using machine learning but not implementing betting strategies.
3. Non-primary studies.

The exclusion criterion 1 serves for removing the papers that are out of context for our research. The second exclusion criterion serves for considering only the papers that put into use the models' prediction to generate some profit, since most of the literature on this topic is only about making predictions. We defined the third exclusion criterion because when doing a review, by default we want to asses only primary studies.

From the total of 297 search results, 275 turned out as unique. Based on our exclusion criteria, after reading the titles and abstracts of the papers, we excluded 230. We could not access 6 papers from the remaining that were left for full-text reading. We also excluded 5 other papers that were not written in English language because we could not evaluate them. From the 34 papers left for full-text reading we acquired 27 relevant papers for our study.

To answer our research questions we extracted the following data categories:

1. Publication title;
2. Authors;
3. Type of sport: what sport researchers tried to profit from;
4. Type of prediction: what outcomes researches tried to predict and bet on;
5. Machine learning models used;
6. Best prediction accuracy;
7. Income evaluation: what was the measure used for evaluation;
8. Betting strategies used;

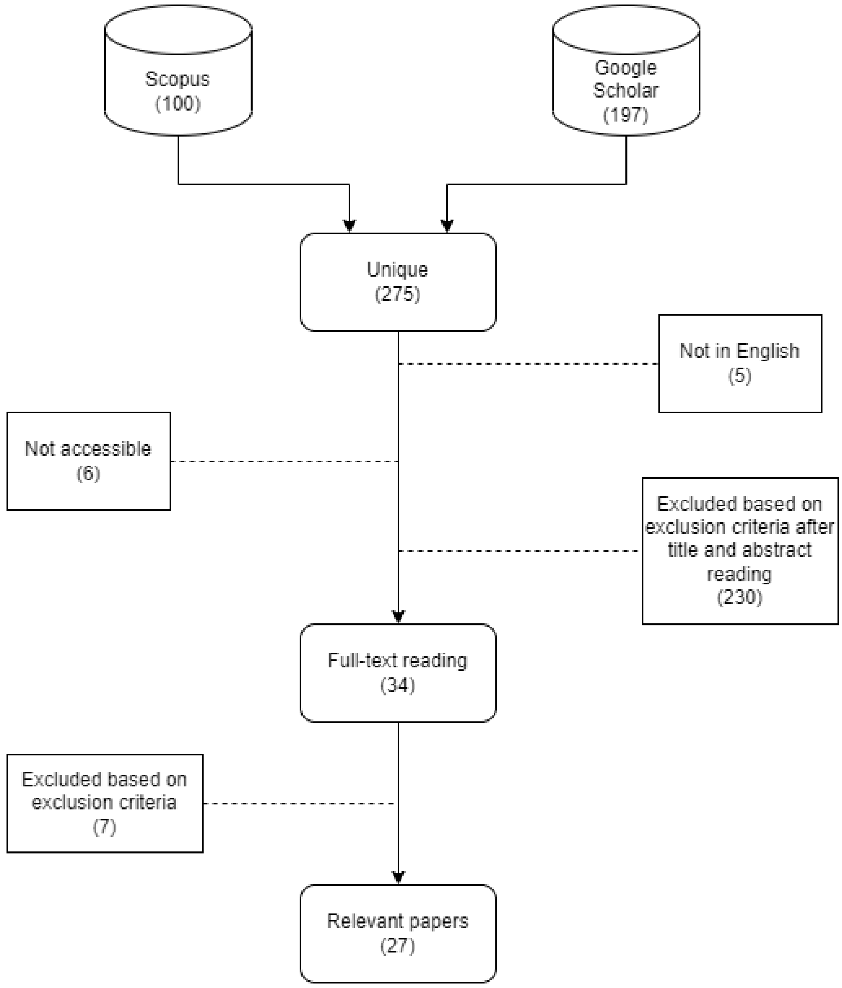

Figure 2: Filtering approach to filter 27 out of 275 papers.

9. Best strategy returns;

10. Number of seasons for profitability testing;

11. Future research: what the studies suggest could be done in the future.

We normalized the extracted terms that describe the same occurrence and we generalized similar sub-approaches under a general one which were used for the taxonomy. Extraction accuracy is not evaluated since every paper was read only by one author.

4 Results and Analysis

In this chapter we present and discuss the findings of our research.

4.1 Research Question 1: What are the sport betting markets on which machine learning is used for making profit?

The literature we surveyed covers 3 sports: football, basketball and tennis. Most of the literature covered football, counting 21 paper out of 27. Basketball and tennis were covered by 3 papers each. These results are due to the fact that football is the most popular sport in the world [46], and basketball and tennis are among the most popular sports too and there is a lot of data available for them, therefore their betting markets should be worth testing. This also leaves space for future research on profitability from betting on other sports.

4.2 Research Question 2: What types of bets are considered for profiting in the reviewed literature?

Among the papers covering football we distinguished 6 different types of bets and we labeled them as: H/D/A, H/A, BTTS, O/U 2.5, AH, WINNER 16. The meaning of each abbreviation is explained below.

By predicting H/D/A we refer to predicting whether the outcome of the match will

Sport	Papers
Football	[2, 3, 5–8, 10, 11, 20, 21, 25, 27, 32–34, 39–41, 43–45]
Basketball	[1, 18, 19]
Tennis	[9, 28, 49]

Table 1: Papers covering each sport.

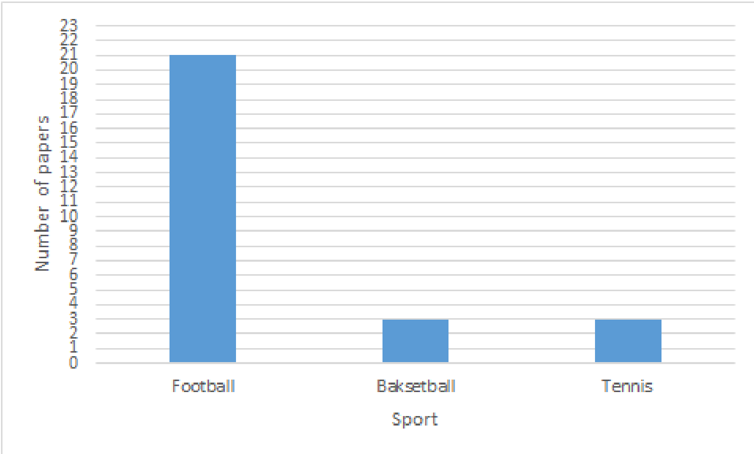

Figure 3: Distribution of papers according to the sport they cover.

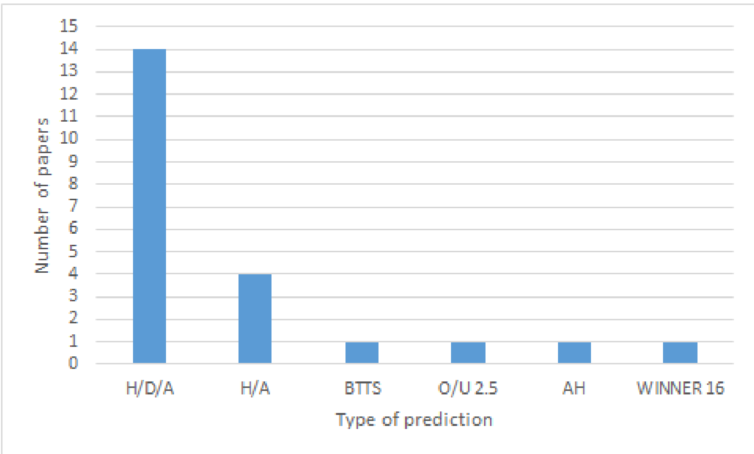

Figure 4: Distribution of football prediction types.

be a home win, a draw or an away win. This is the most dominant type of prediction present in 14 of the football papers. H/A is different in a way that the draw outcome is discarded. That is a consequence of the low occurrence of draw outcomes and low number of correct draw predictions since they are harder to predict. This type of prediction appears in 4 of the papers. The following 4 categories appear only in 1 paper each.

Costa et al. [10] investigate the case of BTTS (both teams to score) where both the home and away team have to score atleast 1 goal.

Wheatcroft [43] tries to generate profit by predicting whether there will be less than 3 or more than 2 goals between the 2 teams. We labeled this type of bet as O/U 2.5 (over/under 2.5 goals).

The Asian handicap(AH) type of bet is present in [6] where Constantinou studies differences and similarities between the AH and H/D/A bets. The AH bets increase or reduce the number of goals of a team to make the game more balanced. There are 3 types of AH bets:

Whole goal handicap: Here a team is given a whole goal handicap ($\pm$ 1, 2 and on) and in case of a draw, the bet is refunded.

Half-goal handicap: Here a team is given half a goal handicap ($\pm$ 0.5, 1.5, 2.5 and on) and the case of a draw is removed since no match can end up as a draw.

Quarter-goal handicap: Here values end with 0.25 or 0.75 and they cover various outcomes. Here is an example taken from [6]: If we bet 10 GBP on the away team to win given AH -0.25 with odds 2 (i.e., 50%), the stake would be divided between the nearest whole-goal and half-goal handicaps. That is, a 5 GBP bet will be placed on the away team to win given AH $\pm$ 0[2] with odds $\sim$ 2.5 (i.e., 40%) and another 5 GBP bet on the away team to win given AH -0.5 with odds $\sim$ 1.66 (i.e., 60%). Note that the odds for the quarter-goal handicap reflect the average payoff, in terms of probability, of the two nearest handicaps. Since this is a combination of two bets, each bet is executed independently. For example, a score of 0–0 would have resulted in voiding AH $\pm$ 0 (i.e., 5 GBP are returned) and winning AH -0.5 (i.e., 5 GBP $\times$ 1.66 = 8.3 GBP are returned).

Privandy et. al. [34] studied the WINNER 16, a lottery-like Israeli government game where participants need to guess the outcomes of a set of 16 matches. The rewards of WINNER 16 are cumulative gains from previous rounds and are split among winners.

For basketball we identified 2 types of bets that we labeled as: H/A and O/U. Same as the identically labeled football bet, betting on H/A means betting on the home or the away team to win. O/U stands for over/under where participants guess whether the total points in the game will be over or under a given value. The H/A prediction is studied by [18] and [19], the O/U prediction is studied by [1].

Table 2: Type of prediction studied by football papers.

Prediction type	Papers
H/D/A	[2, 3, 5–8, 11, 20, 21, 27, 32, 33, 40, 45]
H/A	[25, 39, 41, 44]
BTTS	[10]
O/U 2.5	[43]
AH	[6]
WINNER 16	[34]

In all 3 tennis papers a winner of the match is being predicted. We label this prediction type as W.

4.3 Research Question 3: Which machine learning techniques are used for the predictions?

We generalized all sub-types of same machine learning models and models with some modifications and additions. We identified 15 different machine learning techniques used in the surveyed papers and we labeled them for further use:

- Majority Class Classifier (MCC)
- Average Market Classifier (AMC)
- Fairest Bookmaker Classifier (FBC)
- Poisson Model (PM)
- Naive Bayes (NB)
- Logistic Regression (LR)
- Boosting (BOO)
- Random Forest (RF)
- Support Vector Machine (SVM)
- Linear Regression (LINR)
- Hybrid (H)
- Bayesian Network (BN)

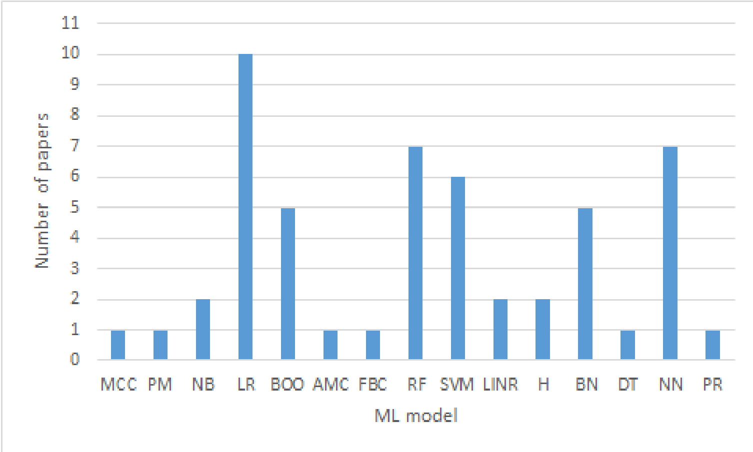

Figure 5: Frequency of models used.

- Decision Tree (DT)
- Neural Network (NN)
- Probit Regression (PR)

Here we briefly describe the ML techniques, for more detailed explanations check the references.

Majority Class Classifier (MCC) is tested in [10] for predicting whether both teams will score (BTTS) where it predicts "Yes" if most of the matches in the training set end up with both teams scoring a goal and "No" otherwise. Another custom classifiers tested in [10] are the Average Market Classifier (AMC) predicting outcomes based on the average bookmaker odds, and the Fairest Bookmaker Classifier (FBC) making predictions based on the bookmaker with lowest margin.

Poisson models (PM) are based on the model proposed by Maher [31], where goals scored by each team are treated as independent Poisson variables and are based on their attack and defence qualities. Dixon and Coles [12] improved Maher's model since the model could not predict low scoring outcomes, and they also considered the most recent matches as most important. Rue and Salvesen [36] extended their framework as they estimate the time-dependent skills of the teams and show how they vary trhough the season.

Naive Bayes (NB) [26] is from the family of naive simple classifiers that treat all features as independent.

Logistic Regression (LR) [42] is a classification model. It is more efficient for binary and linear classification problems but can be generalized to multiclass classification.

Boosting (BOO) [25] is an ensemble meta-algorithm for reducing bias and variance that merges more weak classifiers into a single strong classifier.

Random forest (RF) [25] is an ensemble learning method for classification, regression and other tasks that builds a variety of decision trees. For classification tasks, the output is the class selected by most trees and for regression tasks, the output is the mean or average prediction of the individual trees.

Support Vector Machine (SVM) [25] maps training examples to points in space creating classes with as wide as possible free area between the classes. New examples are then mapped into the classes.

Linear Regression (LINR) [50] is a linear approach for modelling the relationship between a scalar response and the explanatory variables.

We refer as Hybrid (H) to the models that are ensemble of more models. In [41] the hybrid model's prediction is the average of the predictions of the RF, BOO, SVM and LINR models. In [27] the model is a combination of linear algebra rating systems together with machine learning methods (Artificial Neural Networks, Decision Tables, Naive Bayes, Logistic Model Trees, Bagging, Stacking).

A Bayesian network (BN) [29] is a graphical model that measures the conditional dependence structure of a set of random variables based on the Bayes theorem.

Decision trees (DT) [35] are supervised learning algorithms, used for regression and classification tasks. They have a flowchart or tree structure and they structure the training dataset from the top down by selecting the best decision node to split first, and then after, based on measures of entropy and information gain.

Neural networks (NN) [9] are composed of layers. The input of each layer is the data itself or the output from a previous layer. Each layer applies a linear transformation to the data and then an activation function, which is typically nonlinear.

Ordered probit regression (PR) [14] is used to estimate match results directly instead of deriving them from goals predicted.

From Figure 5 we can see that the mostly used ML model in the surveyed papers is Logistic Regression (10 times), followed by Neural Network and Random Forest (7 times), Support Vector Machine (6 times), Bayesian Network and Boosting algorithm (5 times). The remaining models appear once or twice.

Table 3 shows the used machine learning models and the best accuracy achieved from the football papers. The accuracy for which we could not extract an exact value is labeled as "unknown". In most of the papers the accuracy is measured as a percentage of correct predictions. In 3 papers it is measured with the Rank Probability Score (RPS) error metric, and the AH prediction accuracy is measured with the Brier Score. RPS has values between 0 and 1, the lower the values the more accurate the predictions are. It is calculated as

$$RPS = \frac{1}{r-1}\sum_{i=1}^{r}\left(\sum_{j=1}^{i} p_j - \sum_{j=1}^{i} e_j\right)^2$$

Table 3: Used ML algorithms and the best achieved accuracy for football.

Paper	Type of prediction	Used models	Best accuracy
[10]	BTTS	MCC, PM, NB, LR, BOO, AMK, FBO	AMK:55.14% & FBO:55.14%
[25]	H/A	RF, BOO, SVM	RF:75.62%
[41]	H/A	RF, BOO, SVM, LR, H	H:81.77%
[5]	H/D/A	BN	BN:0.208256 RPS
[7]	H/D/A	BN	BN:unknown
[27]	H/D/A	H	H:73%
[43]	O/U 2.5	LR	LR:unknown
[21]	H/D/A	LINR	LINR:unknown
[32]	H/D/A	RF	RF:45.07%
[45]	H/D/A	LR	LR:0.2058 RPS
[34]	WINNER 16	LR, SVM, DT, RF, BOO	RF:unknown
[6]	H/D/A, AH	BN	H/D/A - BN: 0.195 RPS, AH - BN: 0.248 Brier score
[40]	H/D/A	NN	NN:55%
[11]	H/D/A	SVM	SVM: 60.09%
[2]	H/D/A	PR	PR: unknown
[3]	H/D/A	LR, RF, NN	NN: 49.89%
[8]	H/D/A	BN	BN:unknown
[33]	H/D/A	NN	NN:58.7%
[44]	H/A	LR	LR: unknown
[39]	H/A	NB	NB:50.49%
[20]	H/D/A	LOGITR	LOGITR: unknown

Table 4: Used ML algorithms and the best achieved accuracy for basketball.

Paper	Type of prediction	Used models	Best accuracy
[18]	H/A	NN	NN: 68.80%
[19]	H/A	NN	NN: 68.83%
[1]	O/U	BN	BN: 58.9%

Table 5: Used ML algorithms and the best achieved accuracy for tennis.

Paper	Type of prediction	Used models	Best accuracy
[28]	W	LR	LR: 77.2%
[49]	W	LR, NN, RF, BOO, SVM	BOO: 69.1%
[9]	W	LR, NN, RF, SVM	SVM: 69.9%

where r is the number of possible outcomes, p_j is the predicted probability of the outcome j and e_j is the real probability of the outcome j. Brier Score is calculated when we put $r = 2$ in the formula. The best known accuracy for each type of prediction is highlighted in green. We observe that for both H/D/A and H/A predictions, the best accuracy is achieved by hybrid models (81.77% and 73%), which indicates that integration of ML models improves the model in terms of accuracy. The best accuracy for H/D/A measured as RPS is achieved by a Bayesian Network (0.195). The BTTS prediction appears in only one paper and the accuracy is 55.14%. From table 4 (basketball) we observe that the best accuracy for the H/A prediction is 68.83% achieved by a Neural Network and the O/U prediction has 58.9% accuracy achieved by Bayesian Network. From table 5 (tennis) we can see that the best accuracy (77.2%) is achieved by a Logistic Regression.

4.4 Research Question 4: Which betting strategies are used?

A betting strategy is made of decisions when to place a bet and how much the bet should be. We categorized the betting strategies found in the surveyed papers into 8 main categories: Uniform strategy, uniform strategy with threshold, dynamic strategy, dynamic strategy with threshold, Kelly Criterion, Modern portfolio theory, Variance adjusted strategy and highest probability forms strategy.

The uniform strategy (Uniform) is a strategy where always the same amount bet (i.e. 1 unit, 5 units, 100 units etc.) is placed on the outcome predicted by the model.

The uniform strategy with threshold (UniformT) is a strategy where every bet has the same amount but it is placed on matches that satisfy a certain custom threshold. For example: betting on matches where the predicted outcome probability is higher than the probability offered by the bookmakers for some value.

The dynamic strategy (Dynamic) takes different custom valued bet sizes and they are placed on the predicted outcome. For example: always betting 1/1000 of the current capital, always betting the amount that would produce profit of 1 unit etc.

The dynamic strategy with threshold (DynamicT) is the same as the dynamic strategy except that bets are placed only on matches satisfying some threshold.

The Kelly Criterion [22, 47] is a mathematical formula for determining bet sizes based on probability of winning and it maximizes the profit on the long run. The Kelly formula:

$$f^* = p + \frac{p-1}{b}$$

where f^* is the fraction of the current capital to wager, p is the probability of a win,

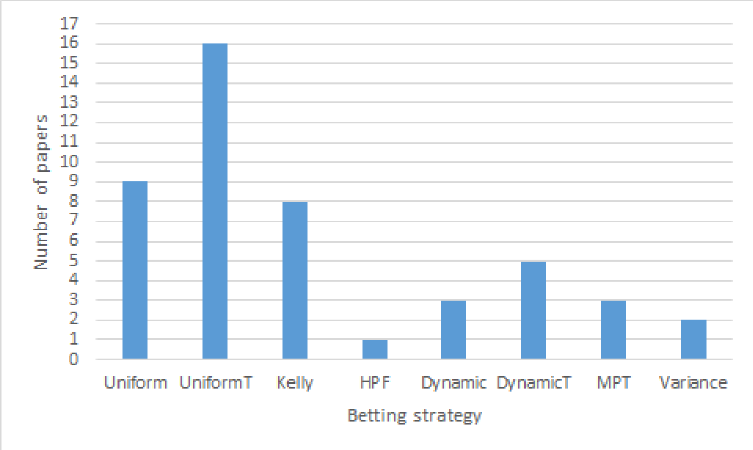

Figure 6: Frequency of betting strategies used.

b is the proportion of the bet gained with a win (if betting 10 USD on a 2-to-1 odds bet, (upon win 30 USD is returned, winning 20 USD), then b=20 USD/10 USD=2.0).

The Modern Portfolio Theory (MPT) [16, 48] is a mathematical model introduced by Harry Markowitz for balancing between the expected return and risk, choosing the portfolio with most favorable risk-expected return profile.

The Variance adjusted strategy [37] minimizes the difference between the expected profit and the variance of that profit.

Highest probability forms strategy is used only in [34] for the WINNER 16 bet and it consists of ranking the forms by probability of winning the big prize and submitting the top n probable forms.

From Figure 6 we can observe that the most betting strategies are the uniform strategy, the uniform strategy with threshold and the Kelly Criterion.

4.5 Research Question 5: What kinds of betting strategies are the best and how is the profitability evaluated?

Across the surveyed papers we identified 2 profitability measurements: return on investment (ROI) and profit. Return of investment is percentage returns relative to respective wagers calculated as

$$ROI = \frac{\text{End bankroll - Initial bankroll}}{\text{Cost of Investments}}$$

, while profit is the total net amount achieved after all bets minus the cost of investments. A betting strategy can be superior to another in terms of ROI but inferior in

Table 6: Distribution of papers by profitability evaluation.

Profitability evaluation	Papers
ROI	[2, 9, 18–20, 25, 28, 32, 33, 40, 41, 45, 49]
Profit	[3, 11, 27, 39]
ROI & Profit	[1, 5–8, 10, 21, 43]
unknown	[34, 44]

Table 7: Used betting strategies for football evaluated with ROI.

Paper	Used strategies	Best strategy & ROI
[25]	Uniform	5.42%
[41]	Uniform	1.58%
[32]	UniformT	-4.71%
[45]	UniformT, Kelly	Kelly: 4.88%
[40]	Dynamic, DynamicT	DynamicT: 8%
[2]	UniformT	1.73%
[33]	Uniform, Dynamic, Kelly, MPT, Variance	Variance: 18%
[20]	UniformT, DynamicT, Kelly	DynamicT: 0.95 units per bet

terms of profit and vice versa.
Here is an example from [8]: Suppose we have two football forecast models α and β. We want to compare their performance on the basis of profitability given the set of five match instances. Consider the following scenario where the stakes are 100 GBP and correct predictions pay double:

- Model α suggested two bets and both were successful (100% winning rate), returning a net profit of 200 GBP which represents a profit rate of 100% relative to total stakes.

- Model β suggested five bets and four of them were successful (80% winning rate), returning a net profit of 300 GBP which represents a profit rate of 60% relative to total stakes.

Here model α is better than model β in terms of ROI but worse in terms of profit, since it fails to recognize profitable bets for all matches. Model β makes riskier bets and ends up with a bigger profit than model α.

Even though gamblers should be interested in maximising profit, in most of the surveyed papers the profitability is measured as ROI.

All 3 tennis papers (Table 11) evaluate the profitability in terms of ROI, and only one basketball paper (Table 10) provides information about the profit from which the

Table 8: Used betting strategies for football evaluated with profit in units used by the corresponding paper.

Paper	Used strategies	Best strategy & Profit
[27]	Uniform	≈ 2000
[11]	Uniform, UniformT	UniformT: 42
[3]	UniformT	5184.7
[39]	Uniform	2704.63

Table 9: Used betting strategies for football evaluated with both ROI and profit.

Paper	Used strategies	Best strategy & profitability
[5]	Kelly	ROI: 1.09%, Profit: 65.38
[43]	UniformT, Kelly	UniformT - ROI: 0.8% , Profit: 535.01
[21]	UniformT	ROI: 8.5%, Profit: 957.5
[10]	Uniform, UniformT, Kelly	ROI - UniformT: 13.53% (38.32 Profit) Profit - UniformT: 61.97 (3.25% ROI)
[7]	UniformT	ROI: 9.48% (11.66 Profit) Profit: 14.19 (8.40% ROI)
[6]	UniformT	ROI: 26.69% (298.62 Profit) Profit: 393.36 (17.37% ROI)
[8]	UniformT, DynamicT	ROI - UniformT: 13.26% (23.74 Profit) Profit - UniformT: 47.71 (8.30% ROI)

Table 10: Used betting strategies for basketball.

Paper	Profitability evaluation	Used strategies	Best strategy & profitability
[18]	ROI	Uniform, MPT, Kelly	Kelly:2.33%
[19]	ROI	Uniform, Dynamic, DynamicT, MPT	MPT:1.74%
[1]	ROI & Profit	UniformT	ROI:10.04%, Profit: 2970.70

Table 11: Used betting strategies for tennis.

Paper	Profitability evaluation	Used strategies	Best strategy & profitability
[28]	ROI	UniformT	16.3%
[49]	ROI	UniformT, DynamicT, Kelly, Variance	DynamicT: 33.7%
[9]	ROI	UniformT	3.3%

ROI is calculated.

In Table 9 we have the football papers that used both economic metrics. The first 3 papers have the profit translated to ROI, while the remaining 4 papers show different performances in terms of the ROI and the profit metrics.

Costa et al. [10] achieved their best ROI (13.53%) using their most accurate AMK model and a strategy that falls into our UniformT category, but generated a profit of only 38.32 units. Using the same strategy with Logistic regression which was a little bit less accurate resulted in lower ROI (3.25%) but a higher profit of 61.97 units because the Logistic regression model recognized more matches as being worth betting on.

Constantinou et al. [7] used uniform betting strategy placing the same amount on matches where the discrepancy of the probability predicted by the model and the probability offered by the bookmakers was at least 5%. They considered 3 types of bookmaker odds for their profitability testing: maximum, average and most common. The maximum odds are the best available odds - ones that a experienced bettor would pick, the average are the odds someone would pick at random and the most common odds are the odds offered by the leading UK bookmaker William Hill - the ones a common UK bettor would pick. Betting on the common odds led to the highest ROI of 9.48% and a profit of 11.66 units, while betting on the maximum odds led to the highest profit of 14.19 units and a ROI of 8.40%. Here again the higher profit was achieved by betting on more matches. Another paper of them [8] introducing a better prediction model has a similar approach.

In his recent work [6], Constantinou found out that ROI and profit are maximised on different level thresholds. Profit maximises at 8% and 9% discrepancy, while ROI at 18% and 16%, for average and maximum odds respectively. Also both higher ROI and profit were achieved by betting on the H/D/A bets compared to the AH bets. Here again the higher profit for both H/D/A and AH bets was achieved by betting on more matches compared to when the highest ROI was achieved.

Note that the highest recorded ROI (33.7%) [49] from the surveyed papers, was achieved by betting on 0.2% of the available matches when a bet was placed only when all the used models agreed. This also questions the ROI as a good metric for betting profitability.

Now we cannot compare ROIs and profits from different studies due to many biases such as: stake sizes, leagues, seasons, number of matches, ML models used for prediction, bookmaker odds, currency used etc., but we can observe from tables 7, 8, 9 and 10 that for each study where the Uniform and Dynamic strategy were compared to other strategies, they never turned out to be superior (marked with red). Since these strategies have no thresholds, they are naively betting on every outcome predicted by the ML model and that leads to many missed bets. The more successful strategies are either some more complex money management systems such as the Kelly Criterion, Modern Portfolio Theory and Variance Adjusted strategy, or simple strategies with thresholds to avoid not so confident bets.

4.6 Research Question 6: Does profitability coincide with prediction accuracy?

At first, intuitively it makes sense that the more accurate our prediction model is, the more profit we will make, but that is not necessarily true. Since bookmakers already have highly accurate forecasts and they set the odds based on those forecasts we don't have much use of a highly accurate model that predicts almost the same outcomes as the ones predicted by the bookmakers because their odds are low. What we need is a model that predicts some outcomes where the bookmakers predicted wrong. Even if our model is less accurate it may lead to a higher profitability due to the higher odds of the outcomes missed by the bookmakers.

In figures 8 and 9 we have shown the best ROI and profit and the prediction accuracy of the model which they were achieved with from the surveyed papers. Here are presented only values that could be extracted for both, accuracy and ROI/profit. From figure 8 we can observe that the accuracy from all studies that measured their profitability as ROI is above 45%. From the studies that measured the total profit (figure 9), only one achieved accuracy of less than 45%. We can also see that profitability and prediction accuracy do not correlate but the figures are biased since in different studies different leagues, seasons, betting strategies, stake sizes, bookmaker odds etc. were used. But we already mentioned [10] in the previous research question, where the higher profit (61.97) was achieved by a model that had 53.77% accuracy and the most accurate model with 55.14% accuracy earned a profit of 38.32 units. We have a few more examples of achieving higher profitability with not the most accurate model under the same environment from same studies excluding the aforementioned biases.

Schumaker et al. [39] performed twitter sentiment analysis that outperformed wagering on odds- favorites, with higher profit (2704.63 USD compared to odds-only 1887.88 USD) but lower accuracy, a trade-off from non-favorite wagering.

In [11] the highest profit was achieved from betting on Bundesliga matches using a model that had a prediction accuracy of only 33.58% for that league and the most accurate model for that league had 51.80% accuracy. The same betting strategy was used. The high profit was obtained due to predicted draws. Also for the Premier League the highest prediction accuracy was 60.09% but the highest profit was made with a model of 58.4% accuracy.

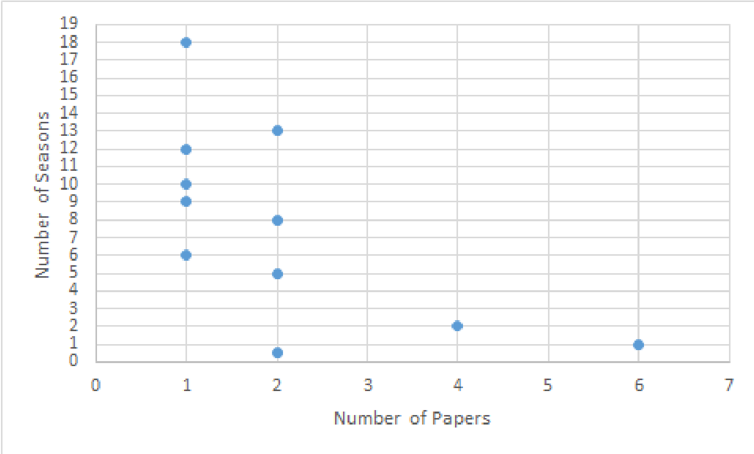

Figure 7: Number of seasons tested where positive income was achieved trough simulation across surveyed papers.

Hubáček et al. [18, 19] introduce decorrelation techniques to reduce correlation between the predicted outcomes from their ML model and the predictions offered by the bookmakers to maximise profitability. The decorrelation has values between 0 and 1. They achieve best prediction accuracy when incorporating the bookmaker odds as a feature with 0 decorellation. In [18] they achieve the best accuracy of 68.83% using bookmaker odds as a feature with 0 decorrelation resulting in 0.89% ROI, but achieve the best ROI of 1.74% using no odds with 0.4 decorrelation and the accuracy is 67.15%. In [19] with 0 decorrelation and using odds as a feature they achieve accuracy of 68.80% and end up with -0.09% ROI. The best ROI of 2.33% is generated with no odds as a feature and 0.4 decorrelation (67.15% accuracy) and same with odds as a feature and 0.6 decorrelation (66.5% accuracy).

These results imply that in order to make a good profit other than a good betting strategy we need to predict correct what the bookmakers miss even if we predict less correct outcomes.

From our results and analysis, so far we've seen in all papers except [32] a positive income over some period (Figure 7) whether it was evaluated as ROI or profit suggesting that the betting market can be exploited by the bettors using machine learning. But the results from all studies were obtained through simulation and not real betting except for [21]. Kaunitz et al. achieved 3.5% ROI (98,865 USD) over a ten year simulation showing promising long run returns. Then they applied their strategy to real betting, in 5 months they achieved 8.5% ROI (957.50 USD). Few months after they started betting with real money the betting house started to limit their bet amounts and reduced the number of matches they could bet on to compensate for the market's

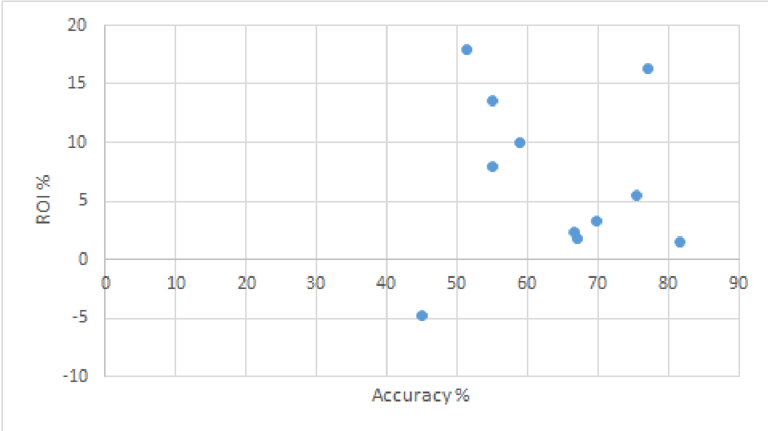

Figure 8: Plot of prediction accuracy and ROI

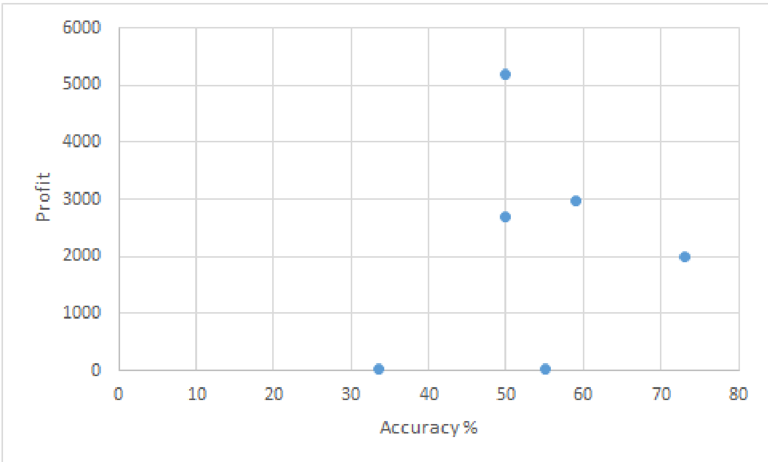

Figure 9: Plot of prediction accuracy and profit

inefficiency. According to the simulations, the betting market can be exploited by the bettors over a longer term, but more research should be done on real money betting to conclude that this can be done only for a shorter term since we don't know if all the betting houses are compensating their loses through discriminatory practices.

5 Conclusion

In this work we reviewed studies that implemented machine learning models for sports outcome predictions and devised betting strategies for exploiting the betting markets. We went over several aspects of the reviewed studies such as: the sports covered, types of outcomes predicted, ML models tested and the highest accuracy achieved, betting strategies devised and their profitability, and number of seasons tested.

Through our findings we demonstrate that the surveyed literature covers the sports football, basketball and tennis, mostly being focused on football (more than 2/3 of the papers). Among the surveyed papers the most popular types of predictions are the final outcome predictions H/D/A and H/A. Mostly applied ML models used for outcome predictions are Logistic Regression, Neural Network, Random Forest and Support Vector Machine. The prediction accuracy is mostly measured as percentage of correct forecasts and the best accuracy for football is achieved by hybrid models. Mostly tested betting strategies were the Uniform strategy, the Uniform strategy with threshold and the Kelly Criterion. The strategies that placed bets on every predicted outcome by the ML model without any thresholds never turned out to be superior over the other betting strategies. The profitability was evaluated as return on investment and total profit and these two metrics do not coincide. We also found out that profitability does not coincide with prediction accuracy due to the fact that bookmakers already possess highly accurate ML models to set the odds. Exploiting the betting market over a longer period was demonstrated only as a simulation and real money betting could be put to good use for future research.

In Figure 10 there are shown the most common future research themes mentioned by the surveyed papers. The most mentioned future research direction is improving the prediction accuracy. There are different new features which are not tested that might gain prediction power to the models. Also collecting more data and having more computational power can be of use for some models. To increase profitability, the betting strategies should be optimized too, for example having more flexible bet sizes which is already implemented by some papers. Also real-time betting and different types of bets can be tested. So far we have identified only 3 sports covered by the surveyed literature. In the future more sports can be targeted using the existing frameworks from the papers. An interesting field for research would be how the bookmakers form

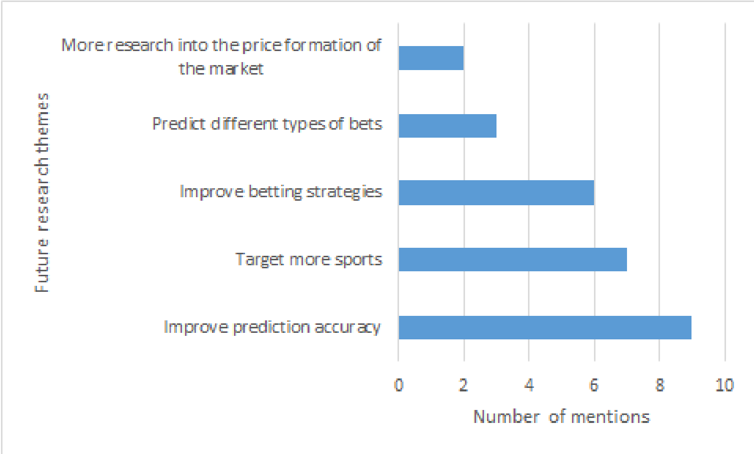

Figure 10: Most frequent future research themes mentioned by the reviewed papers.

and change the prices and do they become more efficient over the years.

6 Povzetek naloge v slovenskem jeziku

V tem preglednem delu smo pregledali obstoječe raziskave o uporabi strojnega učenja za ustvarjanje dobička pri športnih stavah z napovedovanjem izidov tekem in oblikovanjem donosne stavne strategije. Obstoječi pregledni članki, povezani s športnimi napovedmi in strojnim učenjem, zajemajo le raziskave o napovedovanju izidov tekem. Namen te raziskave je zapolniti raziskovalno vrzel o člankih, o napovedovanju donosne stavne strategije.

Pred izvedbo študije smo zastavili protokol pregleda literature, v katerem smo definirali metode za pregled obstoječih del. V protokolu smo opredelili raziskovalna vprašanja, strategijo iskanja, merila za izbiro obstoječih del, strategijo pridobivanja podatkov in strategijo sinteze podatkov.

Naša raziskovalna vprasanja so naslednja:

1. V katerih športih se strojno učenje uporablja za ustvarjanje dobička?
2. Katere vrste stav se v pregledani literaturi obravnjava za ustvarjanje dobička?
3. Katere tehnike strojnega učenja se uporabljajo za napovedi?
4. Katere stavne strategije se uporabljajo?
5. Katere vrste stavnih strategij so najbojlše in kako se ocenjuje donosnost?
6. Ali donosnost sovpada z natančnostjo napovedi?

Poizvedovali smo v zbirkah Scopus in Google Scholar ter pridobili 275 zadetkov. Ko smo uporabili naša merila za izključitev zadetkov iz študije, nam je ostalo 27 ustreznih člankov za našo raziskavo.

Da bi odgovorili na naša raziskovalna vprašanja, smo iz člankov izvlekli naslednje kategorije podatkov:

1. Naslov publikacije;
2. Avtorji;

3. Vrsta športa: na katerem športu so raziskovalci poskušali zaslužiti;
4. Vrsta napovedi: katere rezultate so raziskovalci poskušali napovedati in na katere staviti;
5. Uporabljeni modeli strojnega učenja;
6. Najboljša natančnost napovedi;
7. Ocena prihodka: katero merilo je bilo uporabljeno za oceno;
8. Uporabljene stavne strategije;
9. Najboljši donos strategije;
10. Število sezon za testiranje donosnosti;
11. Prihodnje raziskave: kaj bi bilo po mnenju študij mogoče storiti v prihodnosti.

Izvlečene izraze, ki opisujejo enak ali podoben pojav, smo normalizirali in posplošili podpristope v enega splošnega. Te normalizirane izraze smo uporabili za taksonomijo.

Naši rezultati kažejo, da pregledana literatura zajema športe nogomet, košarko in tenis, pri čemer se večinoma raziskave osredotočajo na nogomet (več kot 2/3 literature). Med pregledanimi članki so najbolj priljubljene vrste napovedi napovedi končnega izida H/D/A in H/A. Največkrat uporabljeni modeli strojnega učenja, ki se uporabljajo za izid so logistična regresija, nevronska omrežja, naključni gozd in metoda s podpornimi vektorji. Natančnost napovedi se večinoma meri kot odstotek pravilnih napovedi. Najboljšo natančnost za nogomet dosegajo hibridni modeli. Najpogosteje preizkušene stave so bile enotna strategija, enotna strategija s pragom in Kellyjev kriterij. Strategije, ki so stavile na vsak izid, ki ga je napovedal algortitem brez praga, se nikoli niso izkazale za boljše od drugih stavnih strategij. Donosnost je bila ocenjena kot donosnost naložbe (ROI) in skupni dobiček, vendar ti dve metriki ne sovpadata. Ugotovili smo tudi, da se donosnost ne ujema z natančnostjo napovedi, ker imajo stavnice že zelo natančne napovedne modele za določanje kvot. Izkoriščanje stavnega trga v daljšem obdobju je bilo prikazano le kot simulacija, stave s pravim denarjem pa bi bilo mogoče dobro izkoristiti za prihodnje raziskave.

Najbolj omenjena smer prihodnjih raziskav je izboljšanje natančnosti napovedi. Obstajajo različne nove funkcije, ki niso bile preizkušene in bi lahko povečale moč napovedovanja modelov. Tudi zbiranje več podatkov in večja računska moč sta lahko koristna za nekatere modele. Za povečanje donosnosti bi bilo treba optimizirati tudi stavne strategije, na primer z bolj prilagodljivimi velikostmi stav, kar se v nekaterih raziskavah že izvajajo. Preizkusiti je mogoče tudi stave v realnem času in druge vrste stav. Do zdaj smo v pregledani literaturi odkrili le tri športe. V prihodnosti se lahko z uporabo obsoječih okvirov iz člankov osredotočimo na več športov. Zanimivo področje za raziskovanje bi bilo kako stavnice oblikujejo in speminjajo cene ter ali z leti postajajo učinkovitejše.

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