Research on Prediction Models for Alliance Matches Results in the FIRST Robotics Competition

Key Words: Transformer, LightGBM, FT-Transformer, win rate weighting , Accuracy, FIRST Robotics Competition

Abstract: This paper researches the predictive capability of commonly used machine learning algorithms in forecasting the result of FRC matches. By analyzing data characteristics, a win rate weighting method is designed to decouple the correlations of collaboration and competition among the six randomly assigned teams in matches, thereby improving prediction accuracy. When applied to the prediction models to playoff matches, the research explains the reasons for the decreased accuracy and proposes a regional prediction approach, which increases the prediction accuracy to over 91%. The research findings provide an effective auxiliary tool for team selection during Playoff Matches, helping teams achieve better competitive results.

1. Introduction

FIRST® Robotics Competition (FRC) is an international high-level robotics competition for teenagers aged 14-18 worldwide, well-known for its high level of challenge, professionalism, teamwork and innovation. In 2025, FRC attracted approximately 90,000 students from about 3,600 teams globally [1]。

The FRC competition adopts an alliance format, where three teams form one alliance, leading to Red and Blue Alliance matches. The competition consists of two stages: the qualification matches and the playoff matches. The qualification stage typically uses a round-robin format, where teams participate in multiple rounds. In each qualification match, the system randomly assigns three teams to form an alliance to compete against another alliance similarly formed from three randomly assigned teams. After the qualifications, the system calculates the rankings based on each team's total performance points across all matches to determine the seed ranking for the playoff stage. During the playoffs, the top-ranked team captains gain the right to sequentially select two other teams to form a fixed alliance and compete for the championship.

The round-robin mechanism in the qualifications ensures that all teams participate in matches; therefore, the qualification match data can be used to predict match outcomes between different team combinations and build a prediction model. Unlike the qualifications, where alliance teams are randomly assigned, the teams within an alliance in the playoffs are selectable. Thus, seeded teams can utilize this prediction model to assist in selecting the two most suitable teams for their alliance to achieve better final standings.

In a December 2020 study on prediction models for FRC matches[2], statistical methods were used to analyze and predict FRC match outcomes, and the study achieved a well prediction results. However, with the rapid development of machine learning in recent years, machine learning algorithms have been widely applied to prediction tasks and have shown excellent predicting accuracy. This paper will study the effectiveness of machine learning algorithms in predicting FRC match outcomes, seeks for suitable algorithms to build a prediction model, and apply the effective model to the team selection process during the playoff stage, thereby assisting teams in improving their competition rankings.

2. Data Features

The FRC game has a different theme each year. Although the themes vary annually, they typically require robots to complete a series of tasks, which can generally be categorized as shooting, collecting, climbing, collaboration, and other actions. Robots earn corresponding points for completing different tasks. The alliance's point is the sum of the points of its three teams, and the alliance with the higher point wins. This can be writed as:：

Result=f(B1,B2,B3,R1,R2,R3) **Equation(2.1)**

In the equation(2.1)，B1, B2, B3 are the three teams in the Blue Alliance, and R1, R2, R3 are the three teams in the Red Alliance.

The theme for the 2025 FRC season was REEFSCAPE. The match is divided into the Autonomous Period, the Teleoperated Period, and the Endgame.

- During the Autonomous Period, robots operate autonomously to complete tasks including Auto Leave, Autonomous Coral Transplantation, and Algae Collection.
- During the Teleoperated Period, operators remotely control the robots to complete Coral Transplantation and Algae Collection tasks.
- During the Endgame, operators maneuver the robots to climb to specific heights on the Coral Structure.

If any violations occur during the match, penalty points are assessed against the alliance, affecting the alliance's total score.

A example game field is shown in Figure 2-1. The scoring levels for the REEF and Coral are shown in Figure 2-2. The points for completing various tasks are listed in Table 2-1[1].

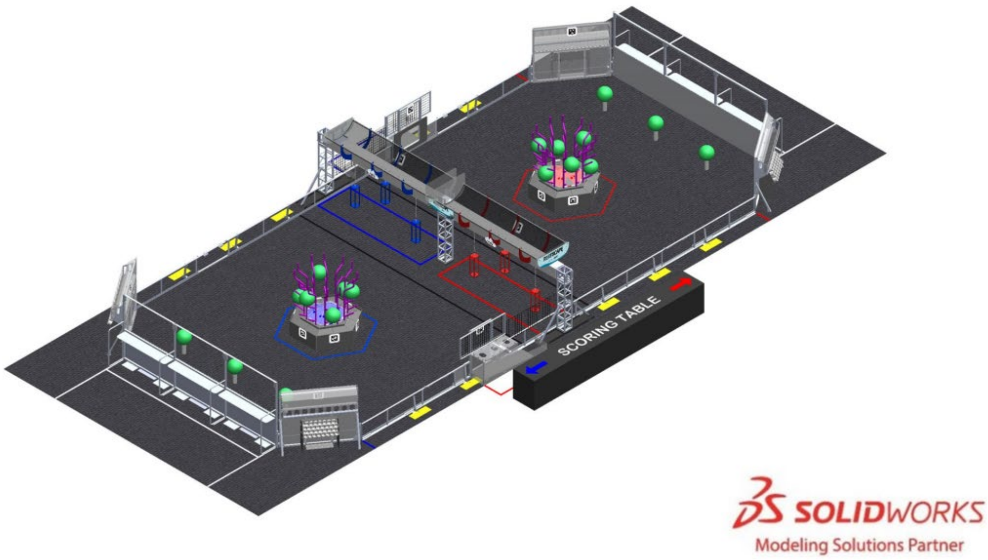

Figure 2-1 REEFSCAPE Field

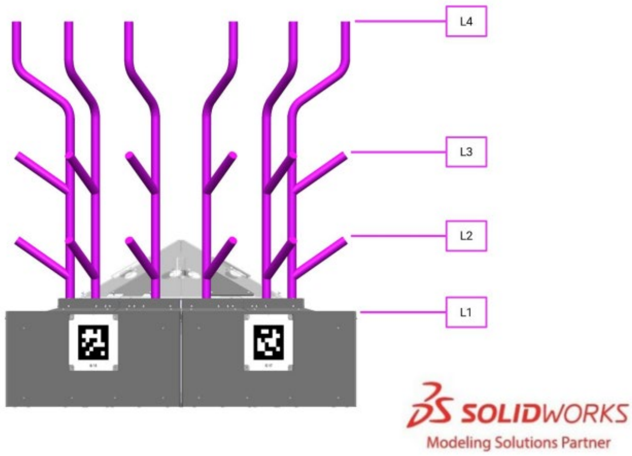

Figure 2-2 Scoring Level on REEF

		MATCH points	
		AUTO	TELEOP
LEAVE		3	
CORAL	CORAL scored in trough (L1)	3	2
	CORAL scored on L2 BRANCH	4	3
	CORAL scored on L3 BRANCH	6	4
	CORAL scored on L4 BRANCH	7	5
ALGAE	scored in PROCESSOR	6	6
	scored in NET	4	4
BARGE	PARK in the BARGE ZONE		2
	off-the-ground via shallow CAGE		6
	off-the-ground via deep CAGE		12

Table 2-1　REEFSCAPE point values

For more specific game details, please refer to the “2025 FIRST® Robotics Competition Game Manual”[1]。

During the Autonomous Period, robots primarily rely on programs to execute tasks, reflecting the team's technical capabilities. The Teleoperated Period tests the robot's stability and the operators' skill. The Endgame challenges the robot's ability to perform difficult tasks. Therefore, different scoring items reflect different strengths of the teams. So, all the items points should be used as the feature data.

The Blue Alliance provides task point data for each match in the 2025 season[3] . This research selects 13 task points (Auto Leave, Auto Coral L4, Auto Coral L3, Auto Coral L2, Auto Coral L1, Teleop Coral L4, Teleop Coral L3, Teleop Coral L2, Teleop Coral L1, Processor Algae, Net Algae, Endgame, Fouls) as the feature data for Machine Learning. Since The Blue Alliance provides alliance-level task points for each match, this feature data represents the combined performance of the three teams within each alliance. However, during the qualification stage, alliance teams are randomly selected, leading to random combinations of strong and weak teams. Therefore, during the data preprocessing stage, before building prediction model, it is necessary to decouple the various task points of the participating teams from the aggregated alliance task points.

Furthermore, due to the FRC competition format in the qualification stage, the three teams within an alliance collaborate with each other while competing against the three randomly assigned teams in the opposing alliance. Consequently, the outcome of a match depends on the collaborative effectiveness of the three randomly assigned teams within the alliance and their competitive ability against the three randomly assigned teams in the opposing alliance. This relationship can be represented as:

$$\begin{cases} Corr\ (\mathrm{B1}, \mathrm{B2}, \mathrm{B3}) > 0 \\ Corr\ (\mathrm{R1}, \mathrm{R2}, \mathrm{R3}) > 0 \\ Corr\ (\{\mathrm{B1}, \mathrm{B2}, \mathrm{B3}\}, \{\mathrm{R1}, \mathrm{R2}, \mathrm{R3}\} < 0 \end{cases}$$ **Equation(2.2)**

In the equation(2.2), Corr() is the correlation function.

The collaborative and competitive relationships described above are implicitly reflected in the result of that particular match, with no independent feature data available to represent them directly. The collaborative ability between teams and their competitive capability must be discovered during the training process of the prediction model.

3. Algorithm Selection

With the rapid advancement of AI technology, deep learning and ensemble learning algorithms have become mainstream in prediction model applications. Based on the data feature analysis in Chapter 2, we can construct tabular data for FRC matches by using feature values as columns and individual matches as rows. According to the Kaggle 2024 Report[4], LightGBM accounts for 62% of usage in tabular data, while Transformer-based models have grown by 35%. Therefore, we will consider selecting LightGBM and Transformer as the algorithms for our research.

LightGBM (Light Gradient Boosting Machine) is an open-source gradient boosting decision tree (GBDT) framework. It discretizes continuous feature values into "buckets" and then finds the optimal split points based on these buckets (histograms), thereby reducing computational load and memory consumption. Furthermore, unlike the traditional level-wise growth strategy, LightGBM uses a leaf-wise strategy where it selects the leaf with the largest splitting gain from all current leaves for splitting each time. Thanks to the leaf-wise growth strategy, LightGBM often achieves higher accuracy with the same or lower error rates in multiple comparative experiments.

Transformer was initially designed for NLP tasks. Its "self-attention mechanism" enables it to efficiently capture long-range dependencies between elements in the data. The encoder-decoder structure of the Transformer is also highly flexible, and its versatility allows it to be easily adapted to various different types of tasks. Transformers have expanded from NLP to a wide range of domains, embodying the trend of "Transformers for everything."

Despite the rapid development of Transformers, their application to tabular data faces challenges due to characteristics such as "irregular patterns in the target function, uninformative features, and non rotationally-invariant data where linear combinations of features misrepresent the information"[5]. In contrast, "tree-based models more easily yield good predictions, with much less computational cost"[5]. Therefore, LightGBM should also be included as an algorithm in this research.

The FT-Transformer (Feature Tokenizer + Transformer) is an optimized variant of the Transformer architecture specifically designed for structured/tabular data. This algorithm provides insights into feature importance through its attention weights. The FT-Transformer is challenging the dominance of gradient boosting trees in the tabular data domain and often shows superior performance, particularly in scenarios involving complex feature interactions. So, this paper also includes the FT-Transformer as one of the researched algorithms.

The MLP (Multi-Layer Perceptron) is the most fundamental feedforward artificial neural network architecture. With just a single hidden layer containing a sufficient number of neurons, an MLP can approximate any complex continuous function with arbitrary precision, indicating its potential to solve a wide variety of complex problems. For many simple to moderately complex tasks, it remains the preferred baseline model. Thus, this paper also includes the MLP as one of the algorithms for comparative research.

In summary, this paper will conduct a comparative study on the performance of prediction models trained using MLP, LightGBM, Transformer, and FT-Transformer to determine the most suitable machine learning algorithm for FRC match prediction.

4. Perdiction Models

4.1 Building Prediction Models

Based on the analysis in Section 2, we adopt Auto Leave, Auto Coral L4, Auto Coral L3, Auto Coral L2, Auto Coral L1, Teleop Coral L4, Teleop Coral L3, Teleop Coral L2, Teleop Coral L1, Processor Algae, Net Algae, Endgame, and Fouls as the features of the data to represent a team's technical capability and operational skill. Therefore, Equation 2.1 can be further expressed as:

Result= f({Auto Leave$_{B1}$,Auto Coral L4$_{B1}$,Auto Coral L3$_{B1}$,Auto Coral L2$_{B1}$,Auto Coral L1$_{B1}$,Teleop Coral L4$_{B1}$,Teleop Coral L3$_{B1}$,Teleop Coral L2$_{B1}$,Teleop Coral L1$_{B1}$,Processor Algae$_{B1}$,Net Algae$_{B1}$,Endgame$_{B1}$,Fouls$_{B1}$}

,{Auto Leave$_{B2}$,Auto Coral L4$_{B2}$,Auto Coral L3$_{B2}$,Auto Coral L2$_{B2}$,Auto Coral L1$_{B2}$,Teleop Coral L4$_{B2}$,Teleop Coral L3$_{B2}$,Teleop Coral L2$_{B2}$,Teleop Coral L1$_{B2}$,Processor Algae$_{B2}$,Net Algae$_{B2}$,Endgame$_{B2}$,Fouls$_{B2}$}

,{Auto Leave$_{B3}$,Auto Coral L4$_{B3}$,Auto Coral L3$_{B3}$,Auto Coral L2$_{B3}$,Auto Coral L1$_{B3}$,Teleop Coral L4$_{B3}$,Teleop Coral L3$_{B3}$,Teleop Coral L2$_{B3}$,Teleop Coral L1$_{B3}$,Processor Algae$_{B3}$,Net Algae$_{B3}$,Endgame$_{B3}$,Fouls$_{B3}$}

,{Auto Leave$_{R1}$,Auto Coral L4$_{R1}$,Auto Coral L3$_{R1}$,Auto Coral L2$_{R1}$,Auto Coral L1$_{R1}$,Teleop Coral L4$_{R1}$,Teleop Coral L3$_{R1}$,Teleop Coral L2$_{R1}$,Teleop Coral L1$_{R1}$,Processor Algae$_{R1}$,Net Algae$_{R1}$,Endgame$_{R1}$,Fouls$_{R1}$}

,{Auto Leave$_{R2}$,Auto Coral L4$_{R2}$,Auto Coral L3$_{R2}$,Auto Coral L2$_{R2}$,Auto Coral L1$_{R2}$,Teleop Coral L4$_{R2}$,Teleop Coral L3$_{R2}$,Teleop Coral L2$_{R2}$,Teleop Coral L1$_{R2}$,Processor Algae$_{R2}$,Net Algae$_{R2}$,Endgame$_{R2}$,Fouls$_{R2}$}

,{Auto Leave$_{R3}$,Auto Coral L4$_{R3}$,Auto Coral L3$_{R3}$,Auto Coral L2$_{R3}$,Auto Coral L1$_{R3}$,Teleop Coral L4$_{R3}$,Teleop Coral L3$_{R3}$,Teleop Coral L2$_{R3}$,Teleop Coral L1$_{R3}$,Processor Algae$_{R3}$,Net Algae$_{R3}$,Endgame$_{R3}$,Fouls$_{R3}$}) **Equation(4.1)**

In the equation(4.1), the collaboration and competition relationship function Corr() for B1, B2, B3 and R1, R2, R3 is implicitly expressed within the function f. The process of building the prediction model is the training the model to approximate the FRC match result function f as closely as possible.

In the match data, except for the feature values Auto Leave and Endgame, the data for all other feature values are assigned to the alliances. Since the feature values of individual teams cannot be directly obtained, it is necessary to decouple the alliance points to derive the feature values for each team. The most straightforward decouple method is to average each alliance feature value (except for Auto Leave and Endgame) across the three teams in the alliance, as given by the formula:

$$\begin{cases} \text{Auto Coral L4}_i = \text{Auto Coral L4}/3 \\ \text{Auto Coral L3}_i = \text{Auto Coral L3}/3 \\ \text{Auto Coral L2}_i = \text{Auto Coral L2}/3 \\ \text{Auto Coral L1}_i = \text{Auto Coral L1}/3 \\ \text{Teleop Coral L4}_i = \text{Teleop Coral L4}/3 \\ \text{Teleop Coral L3}_i = \text{Teleop Coral L3}/3 \\ \text{Teleop Coral L2}_i = \text{Teleop Coral L2}/3 \\ \text{Teleop Coral L1}_i = \text{Teleop Coral L1}/3 \\ \text{Processor Algae}_i = \text{Processor Algae}/3 \\ \text{Net Algae}_i = \text{Net Algae}/3 \\ \text{Fouls}_i = \text{Fouls}/3 \end{cases} \quad i = 1,2,3 \qquad \textbf{Equation(4.2)}$$

A total of 13,772 qualification matches from around the world in 2025 season were selected. After preprocessing the data as described above, the input feature values required for model construction were obtained. The dataset was split in an 80%-20% ratio, creating a training dataset and a testing dataset. The MLP, LightGBM, Transformer, and FT-Transformer prediction models were trained respectively, and the test results are shown in Table 4-1.

Algorithms	DataSet	Accurancy	F1-Score	AUC
MLP	Training Set	0.8158	0.8151	0.8608
	Test Set	0.7957	0.7950	0.7583
LightGBM	Training Set	0.8828	0.8828	0.9703
	Test Set	0.7860	0.7854	0.7593
Transformer	Training Set	0.8668	0.8661	0.9412
	Test Set	0.7793	0.7787	0.7410
FT-Transformer	Training Set	0.7981	0.7963	0.7894
	Test Set	0.7835	0.7823	0.7863

Table 4-1 Prediction Results

4.2 Win Rate Weighting

Using four different algorithms to train models and validate them on the test dataset, it was found that the prediction accuracy of all models on the test set did not exceed 80%. This suggests a potential issue with the data. Further optimization of the data features must be done.

Considering the randomness of alliance selection, strong and weak teams can be grouped into the same alliance. Since the alliance's various points are the sum of the three teams' points, using a simple averaging method would lead to an underestimation of the strong team's capability and an overestimation of the weak team's capability. Consequently, when building the model, the feature values of the teams do not accurately reflect their actual strength, leading to a decrease in prediction accuracy.

As seed teams only have the opportunity to select their alliance partners during the playoff stage, and the prediction model can utilize match results from the entire qualification process, a win rate weighting method is introduced to differentiate the strength between strong and weak teams. A team's win rate is defined as its win rate across all matches it participated in during the qualification stage, namely

:

$$\text{Win Rate}_i = \frac{\text{Win Count}_i}{\text{Count}_i} \quad i = 1,2,3 \qquad \textbf{Equation(4.3)}$$

In the equation, Win Rate_i represents the win rate of team i, Win Count_i is the number of wins achieved by team i during the qualification matches, and Count_i is the total number of matches team i participated in during the qualification stage.

The weights used for decoupling the alliance feature values for each team are derived by calculating the win rate ratio of the three teams within the alliance:

$$\text{Weight}_i = \frac{\text{Win Ratei}}{\text{Win Rate1+Win Rate2+Win Rate3}} \quad i = 1,2,3 \qquad \textbf{Equation(4.4)}$$

In equation, Weight_i represents the decoupling weight for the alliance feature values of team i.

Using the decoupling weights for each team, the various feature values for a team can be derived from the according alliance points:

$$\begin{cases} \text{Auto Coral L4}_i = \text{Auto Coral L4 x Weight}_i \\ \text{Auto Coral L3}_i = \text{Auto Coral L3 x Weight}_i \\ \text{Auto Coral L2}_i = \text{Auto Coral L2 x Weight}_i \\ \text{Auto Coral L1}_i = \text{Auto Coral L1 x Weight}_i \\ \text{Teleop Coral L4}_i = \text{Teleop Coral L4 x Weight}_i \\ \text{Teleop Coral L3}_i = \text{Teleop Coral L3 x Weight}_i \\ \text{Teleop Coral L2}_i = \text{Teleop Coral L2 x Weight}_i \\ \text{Teleop Coral L1}_i = \text{Teleop Coral L1 x Weight}_i \\ \text{Processor Algae}_i = \text{Processor Algae x Weight}_i \\ \text{Net Algae}_i = \text{Net Algae x Weight}_i \\ \text{Fouls}_i = \text{Fouls x } (1 - \text{Weight}_i)/2 \end{cases} \quad i = 1,2,3 \qquad \textbf{Equation(4.5)}$$

Special considerations are as follows:

1. The calculation logic for Fouls differs from other feature values because it represents a negative point.
2. The feature values Auto Leave and Endgame for each team in a match can be obtained directly and do not require decoupling.

After preprocessing the data using the win rate weighting method, the prediction results of the models for each algorithm are shown in Table 4-2:

Algorithms	DataSet	Accurancy	F1-Score	AUC
MLP	Training Set	0.8582	0.8575	0.8786
	Test Set	0.8452	0.8445	0.8438
LightGBM	Training Set	0.9186	0.9186	0.9839
	Test Set	0.8432	0.8426	0.8333
Transformer	Training Set	0.8947	0.8939	0.9538
	Test Set	0.8284	0.8277	0.8691
FT-Transformer	Training Set	0.8498	0.849	0.8391
	Test Set	0.8491	0.8484	0.8319

Table 4-2 Prediction Results, by win rate weighting

Compared to Table 4-1, after applying the win rate weighting method, the test set accuracy shows an improvement of 5%-7%, basically reaching around 85%. A horizontal comparison of the algorithms reveals that the training effectiveness of the four algorithms during the qualification stage is generally similar.

4.3 Playoff Match Prediction

Playoff matches data is not used in training. Since the prediction for playoff matches involves forecasting before the actual games, the feature values from the actual playoff matches cannot be used for prediction. Therefore, the prediction for playoff matches utilizes the average of the "win rate weighting" feature values from each team's matches in the qualifying rounds as the capability feature value for the team. The predictive model is expressed as:

$$
\begin{aligned}
\text{Prediction}=f(\{ & \overline{\text{Auto Leave}}_{B1},\overline{\text{Auto Coral L4}}_{B1},\overline{\text{Auto Coral L3}}_{B1} \\
& ,\overline{\text{Auto Coral L2}}_{B1},\overline{\text{Auto Coral L1}}_{B1},\overline{\text{Teleop Coral L4}}_{B1} \\
& ,\overline{\text{Teleop Coral L3}}_{B1},\overline{\text{Teleop Coral L2}}_{B1},\overline{\text{Teleop Coral L1}}_{B1} \\
& ,\overline{\text{Processor Algae}}_{B1},\overline{\text{Net Algae}}_{B1},\overline{\text{Endgame}}_{B1},\overline{\text{Fouls}}_{B1}\} \\
,\{ & \overline{\text{Auto Leave}}_{B2},\overline{\text{Auto Coral L4}}_{B2},\overline{\text{Auto Coral L3}}_{B2} \\
& ,\overline{\text{Auto Coral L2}}_{B2},\overline{\text{Auto Coral L1}}_{B2},\overline{\text{Teleop Coral L4}}_{B2} \\
& ,\overline{\text{Teleop Coral L3}}_{B2},\overline{\text{Teleop Coral L2}}_{B2},\overline{\text{Teleop Coral L1}}_{B2} \\
& ,\overline{\text{Processor Algae}}_{B2},\overline{\text{Net Algae}}_{B2},\overline{\text{Endgame}}_{B2},\overline{\text{Fouls}}_{B2}\} \\
,\{ & \overline{\text{Auto Leave}}_{B3},\overline{\text{Auto Coral L4}}_{B3},\overline{\text{Auto Coral L3}}_{B3} \\
& ,\overline{\text{Auto Coral L2}}_{B3},\overline{\text{Auto Coral L1}}_{B3},\overline{\text{Teleop Coral L4}}_{B3} \\
& ,\overline{\text{Teleop Coral L3}}_{B3},\overline{\text{Teleop Coral L2}}_{B3},\overline{\text{Teleop Coral L1}}_{B3} \\
& ,\overline{\text{Processor Algae}}_{B3},\overline{\text{Net Algae}}_{B3},\overline{\text{Endgame}}_{B3},\overline{\text{Fouls}}_{B3}\} \\
,\{ & \overline{\text{Auto Leave}}_{R1},\overline{\text{Auto Coral L4}}_{R1},\overline{\text{Auto Coral L3}}_{R1} \\
& ,\overline{\text{Auto Coral L2}}_{R1},\overline{\text{Auto Coral L1}}_{R1},\overline{\text{Teleop Coral L4}}_{R1} \\
& ,\overline{\text{Teleop Coral L3}}_{R1},\overline{\text{Teleop Coral L2}}_{R1},\overline{\text{Teleop Coral L1}}_{R1} \\
& ,\overline{\text{Processor Algae}}_{R1},\overline{\text{Net Algae}}_{R1},\overline{\text{Endgame}}_{R1},\overline{\text{Fouls}}_{R1}\} \\
,\{ & \overline{\text{Auto Leave}}_{R2},\overline{\text{Auto Coral L4}}_{R2},\overline{\text{Auto Coral L3}}_{R2} \\
& ,\overline{\text{Auto Coral L2}}_{R2},\overline{\text{Auto Coral L1}}_{R2},\overline{\text{Teleop Coral L4}}_{R2} \\
& ,\overline{\text{Teleop Coral L3}}_{R2},\overline{\text{Teleop Coral L2}}_{R2},\overline{\text{Teleop Coral L1}}_{R2} \\
& ,\overline{\text{Processor Algae}}_{R2},\overline{\text{Net Algae}}_{R2},\overline{\text{Endgame}}_{R2},\overline{\text{Fouls}}_{R2}\} \\
,\{ & \overline{\text{Auto Leave}}_{R3},\overline{\text{Auto Coral L4}}_{R3},\overline{\text{Auto Coral L3}}_{R3} \\
& ,\overline{\text{Auto Coral L2}}_{R3},\overline{\text{Auto Coral L1}}_{R3},\overline{\text{Teleop Coral L4}}_{R3} \\
& ,\overline{\text{Teleop Coral L3}}_{R3},\overline{\text{Teleop Coral L2}}_{R3},\overline{\text{Teleop Coral L1}}_{R3} \\
& ,\overline{\text{Processor Algae}}_{R3},\overline{\text{Net Algae}}_{R3},\overline{\text{Endgame}}_{R3},\overline{\text{Fouls}}_{R3}\}) \qquad \textbf{Equation(4.6)}
\end{aligned}
$$

The predictive models trained by each algorithm were applied to 3,238 global playoff matches for validation, yielding the prediction results shown in Table 4-3:

Algorithms	DataSet	Accurancy	F1-Score	AUC
MLP	Playoff	0.7576	0.7537	0.7647
LightGBM	Playoff	0.7474	0.7476	0.7710
Transformer	Playoff	0.7193	0.7213	0.6051
FT-Transformer	Playoff	0.7452	0.7485	0.7801

Table 4-3 Playoff Matches Prediction Results

Comparing the results in Table 4-2, the prediction accuracy of all algorithmic models dropped significantly by approximately 10% when applied to playoff matches.

An analysis of the reasons reveals: During playoff matches, seeded teams select alliance members, which widens the power disparity between different alliances. Moreover, the active teams selection strengthens collaborative synergies within each alliance. When use the global dataset, it contains implicit regional cluster relationships. So, when a unified global prediction model is established, differences in alliance strength across regions interfere with the effectiveness of the trained predictive model.

4.4 Regional prediction approach

Based on the analysis of implicit regional cluster relationships within the competition data, a regional prediction approach has been designed. The specific method involves making the implicit regional cluster relationships explicit, training the model using qualification match data segmented by region, and validating the model's performance with playoff match data from the corresponding regions.

In 2025, two regional competitions were held in the P.R. China: the Shanghai competition and the Sanya competition. For these two regional events, the regional prediction approach was applied to build prediction models. The prediction results are presented in Table 4-4 and Table 4-5.

Algorithms	DataSet	Accurancy	F1-Score	AUC
MLP	SH Playoff	0.8000	0.8063	0.8864
LightGBM	SH Playoff	0.7333	0.6205	0.4318
Transformer	SH Playoff	0.8000	0.7520	0.8864
FT-Transformer	SH Playoff	0.9333	0.9300	0.9333

Table 4-4 Shanghai Playoff Matches Prediction Results

Algorithms	DataSet	Accurancy	F1-Score	AUC
MLP	SY Playoff	0.6667	0.6458	0.5143
LightGBM	SY Playoff	0.6667	0.5926	0.6571
Transformer	SY Playoff	0.9167	0.9172	1.0000
FT-Transformer	SY Playoff	0.9167	0.9148	0.8286

Table 4-5 Sanya Playoff Matches Prediction Results

Comparing with the prediction results in Table 4-3, the accuracy of MLP regional prediction model decreases by an average of 2.4%, the accuracy of LightGBM regional prediction model decreases by an average of 4.7%, the accuracy of Transform regional prediction model increases by an average of 13.9%, and the accuracy of FT-Transformer regional model increases by an average of 18.0%. It can be observed that Transformer and FT-Transformer show significant performance improvements, while MLP and LightGBM perform worse.

The analysis suggests that when adopting the regional prediction approach, the substantial reduction in regional competition data volume impacted the performance of the algorithms. In FRC predictions, MLP and LightGBM are more sensitive to data volume and struggle to adequately uncover underlying patterns with smaller datasets. In contrast, the Transformer algorithm family remains relatively effective even with limited data, achieving better results. FT-Transformer, an optimized version of Transformer for tabular data, demonstrated even stronger performance under the regional prediction approach, showing an average improvement of 4.1% over the standard Transformer.

5. Conclusion and Discussion

Based on the performance evaluation of the MLP, LightGBM, Transformer, and FT-Transformer prediction models, it has been found that in FRC competitions, the win rate weighting method can effectively decouple the feature values of stronger and weaker teams within alliances, as well as their collaborative and competitive capabilities. Under the regional prediction approach, Transformer and FT-Transformer achieve excellent prediction results. Specifically, for the small-data scenario of FRC regional matches, FT-Transformer performs most prominently.

In comparison, a study on FRC match prediction models conducted in December 2020 employed statistical prediction algorithms. The best-performing algorithms in that study, WMPRC1 and WMPRC2, achieved average estimated accuracies of 90.5% and 88%, respectively, for the 2018 Houston Championship, and 90.3% and 88.6% for the 2018 Detroit Championship[2]. In contrast,using FT-Transformer prediction models, the prediction accuracies for the 2025 Shanghai competition reached 93.3%, and for the 2025 Sanya competition, 91.7%. This represents an improvement of approximately 3 percentage points over the 2020 statistics-based prediction models.

Based on the above research, participating teams can now apply the win rate weighting method to decouple data according to each scoring tasks of the season's theme. They can use FT-Transformer and follow the regional prediction approach to train prediction models, ultimately developing a model tailored to the current season's theme. During the playoff matches, seeded teams can use this prediction model to experiment with various alliance combinations and select the optimal team formation strategy, thereby achieving better competitive results.

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