DOTA 2 match prediction through deep learning team fight models

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***Abstract*—Esports are complex computer games that are played competitively. *DOTA 2* is one of the most popular esports titles worldwide. Commentators, audiences, and players face tremendous challenges to keep up with events happening during live matches due to a rapidly evolving gameplay across a large virtual arena. This complexity leads to the question of whether esports analytics could detect important events and their subsequent impact on the match. One such important event is team fights, which can often determine the outcome of a match. Despite their significance across strategy, gameplay, and audience experience, team fights remain relatively unexplored in the literature. Their role and potential to support match prediction models are not well understood. This paper presents a novel definition of team fights in *DOTA 2* and proposes an algorithm to extract and quantify them for use in match prediction.**

***Index Terms*—Esports, Deep Learning, DOTA 2, Game Analytics, Recurrent Neural Networks, Prediction**

I. Introduction

Esports is a term used to describe video games that are played competitively [1], [2]. Esports are varied in their form and gameplay, and today attract audiences and players in the hundreds of millions worldwide [3]. Uniquely for esports, as compared with traditional sports, there is a large degree of overlap between audiences and players. As a sub-sector of the games industry, esports has grown immensely in recent years, and today comprise a multi-billion dollar sector [4]. Due to the high degree of innovation and technology adoption in the sector, and the detailed data available from many titles, esports has become a test bed for research across many domains, not the least data science [1], [5]–[7].

In recent years, esports has also become a focus for research on how to enhance sports broadcasting in the future, and how to utilize data to enhance the viewing experience, or provide interactivity [2], [7]. One of the most popular genre of esports games, in terms of audience numbers and academic research, is the Multi-Player Online Battle Arena (MOBA). This genre includes titles such as *DOTA 2* and *League of Legends*, each with major tournaments sporting price pools in the dozens of millions, often driven fully or partly by the community [8].

Similar to traditional sports, the tacit collaborations within each team are always the highlight of the game and at times can be the turning point for the match. For example, each team fight in MOBA game such as *DOTA 2* is significant since it might determine the landscape for the rest of the match [9]. The commentators could easily tell whether a team fight happens, but it requires years of experience to understand the impact of each team fight and convey it clearly to audiences [2]. Furthermore, although previous studies have focused on player encounter interactions [1], no detailed analysis exists that explores whether team fights can predict match outcome.

Previous research within esports analytics tends to focus on the whole game as a unit of analysis, as compared to investigating events occurring within matches [6]. The work here builds on previous analyses and extends it by focusing on the impact of team fights on match outcome prediction. With *DOTA 2* as the case study, a team fight detection algorithm is deployed, and match outcome predictions are made.

This paper analyzes the impact of individual team fights in a *DOTA 2* match to the match outcome. The purpose is not to build the most accurate real-time match predicting model, but to explore if team fights on their own provide a foundation for prediction models. These models will then contribute towards integrating machine learning and audience engagement, allowing for a context grounded approach to match outcome commentary and analysis.

II. Background: DOTA 2 Game-play

In *DOTA 2*, there are two opposing teams, named Radiant and Dire. These two teams fight against each other in a virtual arena, seeking to destroy the opposing teams' base (called the "ancient"), and protect their own ancient at the same time. Each team consists of five players and each player controls a different hero with unique abilities and skills to fight within this closed environment. The bases of both teams are distributed diagonally and the map is divided into different sections for each team[1]. There are three major lanes across the map and are designated as safe lane, mid lane, and off lane. Except for the three major lanes, there are jungle areas, including various properties (outposts, shops, effigy buildings), as well as neutral enemies, often referred to as neutral creeps or neutral monsters. There are also multiple towers protecting each team's ancients and lanes. Each team has to take down some of the towers in order to eventually destroy the base of the enemy team. At the home base of each team, there is a fountain where heroes would revive after being killed and waiting for the revive countdown.

At the time of writing, there are 121 heroes for players to choose from. Each hero possesses distinct abilities and skills. Different combinations of heroes would build a team with unique strengths and weaknesses. Each player would control their respective hero/units to engage in combat until the enemy ancient is exposed and destroyed. During the match, heroes would kill enemy creeps, heroes, or units to gain gold and experience. The gold enables players to buy more powerful items and the experience enables players to level up or learn new abilities so that they could outperform the enemy team.

In a typical *DOTA 2* match, each player would "farm" by collecting gold and gaining experience by killing enemy creeps in their respective lane in the early game. As the game progresses, players tend to gather together and fight against the enemy team in a group. We call this type of group fight a team fight. Team fights are always the highlights for both players and audiences since the effects of group spell casting are splendid and the winning team in the team fight would gain huge advantages, especially in the late game. This is one of the reasons we chose to focus this research on team fights. Most of the time, team fights would have a tremendous impact on the game and the result of a team fight might change the landscape of the entire match [9]. While team fights are one of the most important game events, they are not the only event that can lead to teams gaining a large advantage. Other engagements such as small skirmishes (2-on-1 or 1-on-1 trades) or health trades that send an opponent from the lane, can be significant and be the start of one team gaining an advantage (i.e a snowballing event). Although significant we decided to scope our work to start with team fights, with a plan to explore the impact of other game events on overall match outcome in future work.

[1] *DOTA 2* Map - https://dota2.fandom.com/wiki/Map

III. Related Work: Esports Analytics

The domain of esports analytics emerged over the past decade, and has expanded rapidly since. The literature contains a broad area of work and has seen an accelerating pace of publications in recent years [10]. Esports analytics was defined by Schubert et al. [1] as: "the process of using esports related data, ... to find meaningful patterns and trends in said data, and the communication of these patterns using visualization techniques to assist with decision-making processes." The definition of Schubert et al. [1] highlights a fundamental challenge in esports, namely making complex and fast-paced games comprehensible to players and audiences alike.

Thanks to the readily available data of esports games from public API systems provided by game publishers, esports analytics has become a fertile ground for research in machine learning, AI, and sports, with high-dimensional and high-volume data across amateur to professional levels being utilized [6], [11], [12].

Predicting the result of esports matches has emerged as a key topic in esports analytics. Not only does such predictions provide interesting material for broadcasting and audience engagement [2], [7], but are also of use to inform players and teams for the purpose of training.

Prior studies demonstrated the application of machine learning algorithms in *DOTA 2* match analysis. Demediuk et al. [11] utilized an unsupervised machine learning algorithm to classify the role of players in *DOTA 2* games, while Eggert et al. [9] used supervised learning algorithms instead to identify player roles in *DOTA 2*. Sifa et al. [13] detected outliers occurring during a game for improving the commentator-driven storytelling experience. Drachen et al. [14] investigated the relationship between team skill and spatio-temporal behavior of the team using time series clustering. Katona et al. [10] utilized a feedforward neural network with shared weights to predict the probability of a player hero being killed within a five second window. Yang et al. [15] modeled *DOTA 2* games using graphs and constructed Decision Trees using extracted patterns to predict the match outcome with 80% accuracy. Semenov et al. [12] experimented with the possibility of predicting *DOTA 2* match outcome from draft picks using Factorization Machines (0.66 AUC) and XGBoost classifier (0.65 AUC).

More relevant to our research, Yang et al. [16] performed real-time match outcome prediction using individual players' match history and real-time features. Hodge et al. [6] also examined real-time game result prediction for *DOTA 2* using standard machine learning models.

Past literature has dealt with different aspects of an esports match. Although various researches focus on match prediction and analysis [6], [12], none have dealt with the influence of team fights directly, which are important events that could drastically alter the outcome of an entire match [9]. Our work aims to bridge this gap in the existing literature and does so by focusing on real-time game outcome prediction for *DOTA 2*. However, different from prior research, our prediction models are based on the concept of *team fights* adapted from *encounter* components defined by Schubert et al. [1]. The goal of our work is to provide an innovative way of retaining spectator engagement by providing match outcome predictions after each team fight. This framework would generate data-driven insights to assist commentators and augment the audience experience [7].

IV. Data Collection and Preprocessing

In this study, a dataset comprising a total of 1,493 professional-level *DOTA 2* matches, from patch 7.27, were gathered using the OpenDota API [17]. The data contains all behavioral telemetry of each player during the matches, the replay files are detailed enough for the game client to provide a full replay of the matches, providing highly granular data. The Clarity Analyzer Library was used to parse match replay files into JSON format [18]. Spatio-temporal information was extracted on a per-second level.

We first parsed the raw JSON data using SQL queries into a tabular format and removed games that were only partially recorded. The remaining data consisted of 1,456 games with 747 won by the Radiant and 709 won by the Dire. Each row consisted of a hero action and/or performance at a certain time within the game. This data was then fed into our team fight detection algorithm.

V. Feature Engineering for Game Prediction

We detected all team fights in our data, using the team fight detection algorithm defined and explained in Section VI-B, and created an output table. We then joined the processed data with the output table to label each row of the data based on the following rules: First, if the data entry is during a team fight, label it with a team fight number in the order the fight happened in that specific game. For example, if it is the first team fight that occurred in a game, label it as 1. Second, if the data entry is not during a team fight, the label will be Null. Once we have successfully labeled the entire data set with the appropriate team fight number, we filtered out the rows that were labeled as Null because we only need team fight relevant data for our subsequent use.

Next, we aggregated the data set by team fight for each of the 1,456 unique *DOTA 2* games and summarized team fight statistics. To build predictive models that can predict the final winner of the game (the Radiant team or the Dire team), we performed another level of aggregation to summarize team fight statistics by faction. More specifically, for each team fight, we calculated the number of hero kills, assists, deaths, total damage dealt during a team fight, total gold obtained during a team fight, and the number of players who participated in the team fight for both the Radiant and the Dire teams [19]. Besides these general statistics, we also generated additional features from the data, that can be helpful for our predictive models:

1) Total Crowd Control Time: The total time effects that cause affected players to partially or fully lose control of their heroes[2].

2) Total Spell Damage: The total amount of damage that is caused by player spells for each team.

3) Total Auto Attack Damage: The total amount of damage that is caused by player auto attacks for each team.

4) Total Item Damage: The total amount of damage that is caused by player items for each team.

5) Total Distance Traveled: The total displacement of each hero in the *DOTA 2* arena for each team during a team fight.

6) Number of Buildings Destroyed: The number of buildings on the map that deplete to zero health during a team fight.

As we discussed in Section II Background: DOTA 2 Gameplay, players have to destroy the ancients of the opposing team as well as the buildings protecting the ancients to win the game. One of the goals when engaging in a large scale team fight in a *DOTA 2* match is to destroy one or more of the enemy buildings. Thus, the number of destroyed enemy buildings during a team fight has a strategic influence on the final match outcome and therefore we want to include this feature in our predictive models.

VI. Methodology

This research aims to create a model that is capable of predicting a *DOTA 2* match outcome using only features within team fights. To achieve this goal, we first developed a team fight detection algorithm to identify team fights. We then utilized this algorithm to extract and aggregate features used in our supervised prediction modeling. This section describes our team fight detection algorithm and match outcome predictions.

A. Team Fights

Although the specific details vary across definitions, team fights occur when players from opposing teams meet within the arena of *DOTA 2*. Team fights are viewed as important to determining the outcome of matches [9] and also form central components of the narrative developed by commentators and casters [2]. However, while team fights have been utilized conceptually in multiple esports research publications [9], [20], a formal definition has not been widely agreed upon in the esports community [1]. In this section, we attempt to provide a flexible, broadly applicable definition and model of team fights that takes into account the spatio-temporal nature of *DOTA 2* as highlighted by previous work, e.g. Schubert et al. [1] and Eggert et al. [9].

Past research utilized rules based algorithms to detect hero encounters within *DOTA 2* [1]. In our research, we referenced this paper's definition of encounter as the basis for our team fight definition and constructed our approach for identifying team fights by further enhancing the encounter detection algorithm as described in Section VI-B Team Fight Definition.

[2] *DOTA 2* Crowd Control - https://dota2.fandom.com/wiki/Disable

B. Team Fight Definition

We define a team fight as an encounter of player units from both teams with one side of the encounter having at least two players from the same team, and at least one killing event happened during the encounter. This definition filters out 1-on-1 and 2-on-1 trades, while focusing on fights that have a more significant impact on both teams.

We first define the two teams are T_1 and T_2, each with five player units, which are represented as u_i. We also define a function called $D(u_i, u_j)$ to calculate the distance of two player units. In addition, we define a player link $L(u_i, u_j)$ to describe the player units relationships. There are three kinds of player links we think are essential in defining a team fight, which are combat link, support link, and kill link.

1) Combat Link: We define a combat link as a player units relationship where the two player units are from different teams and the distance between them are within the general attack range ϵ_a (700 units) of player units in *DOTA 2*. It is represented as a $L_c(u_i, u_j)$ where $u_i \in T_1$ and $u_j \in T_2$ and $D(u_i, u_j) <= \epsilon_a$.

2) Support Link: We define a support link as a player units relationship where the two player units are from the same team and the distance between them are within the general healing range ϵ_h (400 units) of player units in *DOTA 2*. It is represented as a $L_s(u_i, u_j)$ where $u_i \in T_1$ and $u_j \in T_1$ and $D(u_i, u_j) <= \epsilon_h$.

3) Kill Link: We define a kill link as a player units relationship where the two player units are from different teams and one player unit kills the other player unit. It is represented as a $L_k(u_i, u_j)$ where $u_i \in T_1$ and $u_j \in T_2$ and u_i has killed u_2.

4) Encounter Component: We define an encounter component EC_t as a subset of player units where each player unit is connected to all other units via a path that consists of combat and support links. For an encounter component, there should be at least one combat link and one support link, which indicates that there are at least two player units from the same team and at least two player units from different teams, shown in Figure 1. An Encounter Component depicts a kind of cross-team interaction of player units at a specific time tick t. We represent an encounter component as a graph called $G(U, E)$ where U is a set of nodes or player units and E is a set of edges or player links. For player units, there $\exists u_i \in U$ from T_1 and $\exists u_j \in U$ from T_2; for player links, there $\exists e_i \in E$ is L_c and there $\exists e_j \in E$ is L_s.

5) Successor: We define a successor $EC_{t+\Delta t}$ as a subsequent encounter component to a sequence of encounter components whose last component is EC_t. The time difference between the successor and the last previous encounter component Δt should not exceed a time threshold τ. And an additional requirement is that there should $\exists u_i \in EC_t$ from T_1 such that $u_i \in EC_{t+\Delta t}$ and $\exists u_j \in EC_t$ from T_2 such that $u_j \in EC_{t+\Delta t}$.

6) Encounter: We define an encounter as a sequence of encounter components where each encounter component at time tick t is a successor of a previous encounter component.

Fig. 1: Illustration of Combat Link (red) and Support Link (blue) during Encounter. When there exists at least one Combat Link and at least one Support Link, the algorithm detects it as one encounter Component [21].

An encounter is dynamic in terms of its components, since player units can join and leave during the entire time span of an encounter.

7) Team Fight: Finally, we define a team fight as an encounter which contains at least one kill link, or to say a team fight should be a special form of encounter which involves killing activity. The reason for making this definition is that team fights with kills are more consequential than non-kill team fights. If someone dies in a fight, there is a clear punishment to the team – gold and experience (XP) gain to the other team as the most direct consequence. While there can be many ”encounters”, we believe the ones that involve killing have a more tangible impact on the game and can provide us with useful information for making predictions on game result.

C. Algorithm Design

After defining team fights, we followed and implemented an algorithm outlined in the paper Esports Analytics Through Encounter Detection [1] to automatically detect encounter components from raw game data. We then added an extra constraint of requiring a kill event to happen during the encounter to classify it as a team fight.

The algorithm works by reading in a stream of player unit positions, and at each tick, we constantly updated the position and the distance, and identified the possible combat components. Then, we identified the possible predecessors of the combat components, and try to link components together as encounters based on specific conditions described above. Finally, we filtered out the encounters that contain one or more kill links and identified them as team fights. A list of team fight encounters is outputted by the algorithm.

D. Team Fight Detection Results

The output of our team fight detection algorithm given a single *DOTA 2* game is a list of team fight encounters as defined in Section VI-C Algorithm Design. This list is a homogeneous list of Encounter objects, i.e. the team fight encounters that we detected from a given *DOTA 2* game. We can convert the list of team fights into an output table as comma-separated values. The output table has N number of rows with respect to the total number of team fights we detected from the input *DOTA 2* game. Each row has the following attributes: team fight number (first team fight of the game, second team fight of the game, etc.), team fight start time and end time, a list of players who participated in the team fight, and whether there is any death during the team fight. We can then use the generated output table for our predictive models.

The cleaned data were further aggregated by game, team fight number, and team faction. The resulting data containing the generated features discussed previously were then used to classify the overall outcome of the match. Our approach detected around 20 to 25 team fights in most games, with the majority of the fights falling within the first 30 minutes.

E. Recurrent Neural Networks

We first investigated the ability of DOTA 2 team fights in predicting match outcome through simple models: logistic regression and random forest. However, the sequential nature of team fights and their non-linear relationship with the overall match outcome makes these non-deep learning models less suitable for our purposes. Accuracy from these models did not surpass 66%.

We then investigated the use of Recurrent neural networks (RNN). RNN's are a type of deep learning model that retains the memory of previous inputs within the network's internal state [22]–[24]. This construction allows past inputs or contextual information to influence the model's output. This makes RNNs some of the best deep learning algorithms to model sequential data [25].

However, RNN models suffer from the problem of vanishing gradients. The influence of an input would decay or explode exponentially as the RNN model trains. To address this issue, we have chosen to utilize two different algorithms that extend the simple RNN model [22], [23].

1) Bidirectional RNNs: Bidirectional RNNs are a type of RNN that allows the model to access both past and future context. The input data sequence is fed to two separate recurrent hidden layers that are connected to the same output layer [22]. In terms of *DOTA 2*, the use of a bidirectional construction allows the model to utilize team fight information in the past and future. Bidirectional model constructions also work with RNN extensions such as LSTM and GRU.

2) Long Short-Term Memory: Long Short-Term Memory (LSTM) is a neural network that is similar to an RNN, but replaces summation units in the hidden layers with memory blocks, which are a type of recurrently connected subnets. Multiplicative gates within LSTM memory cells allow the algorithm to store and utilize information over long periods of time [22]. LSTM is able to decide whether the content derived from an input should be overwritten at each time step. Thus, it is better able to retain important features over a long distance [23].

3) Gated Recurrent Unit Networks: A gated recurrent unit (GRU) is a recurrent unit that can adapt and capture dependencies from different time scales. GRUs also have gating units similar to LSTM, but they do not have separate memory cells. Thus, GRUs do not control the exposure of hidden memory content. Other units in the network can use the full content within the memory. GRUs are simpler in design compared to LSTM without sacrificing model performance [23]. Past research has also revealed that GRUs require less time to train compared to LSTM [26].

TABLE I: RNN model performance with all available team fight data in training and test set

Model Type	GRU 1	GRU 2	LSTM 1	LSTM 2
Regular	0.712	0.759	0.711	0.753
Bidirectional	0.734	0.792	0.738	0.742

Note: Training sample size: 2,622. Test sample size: 290. Value shown are the average test accuracies over 10 runs.

VII. Results

We applied four different RNN models to our data: LSTM, GRU, bidirectional LSTM, and bidirectional GRU. These four models were also tested using two different architecture variants with either one layer or two layers. All features were standardized to between 0 and 1 before modeling. The model consisted of an initial layer with 256 nodes. If the architecture tested had two layers, the output of the first layer was then fed into a second layer with 128 nodes. This was followed by a fully connected layer with softmax activation. Loss was calculated using categorical entropy with an Adam learning rate optimizer. Early stopping was applied if the model's validation accuracy did not improve in 10 epochs. All models were trained up to a maximum of 60 epochs using a batch size of 256. Ten percent of the entire data was used as the holdout test set. The remaining training data was further split into training and validation sets (90:10).

We first tested all models using the complete training and test data. Results can be seen in Table I. All eight models were re-trained 10 times and their performance on the hold out test set was calculated. It can be seen that the bidirectional GRU model with two layers outperformed all other models with an average test set accuracy of 79.2%. However, this accuracy is achieved only with the complete training and test data available.

DOTA 2 games can vary widely with some games filled with frequent but inconsequential skirmishes, and others dominated by a few game changing team fights. To ensure that our models are not dominated by outliers, we also trained each model on either a filtered training set or the entire training set. All models were then compared using the holdout test set accuracy. The holdout test set was also filtered accordingly to simulate incomplete real time match data. This allows us to analyze the performance of each model when limited by only using data up to a certain point in the match. In the first part of each analysis, we trained models using the complete training data set, but tested them using a hold out test set that has been filtered according to different criteria. We then trained the same models again, but this time also using incomplete training data filtered according to the same criteria as the test set. The goal of this evaluation is to identify weaknesses within the models if they were given incomplete match data to train with. This is especially important for predicting match outcomes immediately after patch changes to *DOTA 2*.

We start with the number of team fights as the filter/cut-off criteria. In Figure 2a test data sets were filtered according to the number of team fights. Only matches that have at least the corresponding number of team fights will be included in the model predictions. The eight lines within the figure are the prediction accuracy for the test set by various RNN models. The y-axis indicates model accuracy on the test set. X-axis values indicate the cutoff for each model's train and/or test datasets, using either minutes of game time or the number of team fights. Each model is trained and evaluated at every data cutoff. Results revealed that by ensuring only games with two or more team fights are used in the holdout test, the accuracy for all models would be increased to 69% or higher. However, this benefit does not increase if we were to limit our predictions to only games with a high number of team fights.

In Figure 2b both training and test data sets were filtered according to the number of team fights. Only matches that have at least the corresponding number of team fights will be included in the model predictions. Results revealed that by ensuring only games with two or more team fights are used in the holdout test, the accuracy for all models would be increased to 73% or higher. However, this benefit did not result in large increases if we were to limit our predictions to only games with a high number of team fights.

Next, we evaluated each model using game time as the cut-off criteria. Performances of the eight models tested using team fights that started before a certain game time are shown in Figure 2c. Performances for all eight models increased drastically as the number of minutes increased. As more team fight data is added into model training, accuracy changes from lower than 50% to over 70%. Most model performances were similar, although the two layer bidirectional GRU model had the highest performance when all team fights up to the 32 minute mark are included for the test data. The 32 minute mark was selected as the approximate average match time of DOTA 2 is between 30-35 minutes.

Performances of the eight models trained and tested using team fights that started before a certain game time are shown in Figure 2d. Similar to the models trained using the full data set, performances for all eight models increased drastically as the number of minutes increased. As more team fight data is added into model training, accuracy changes from lower than 50% to slightly over 70%. Most model performances were also similar, but the two layer bidirectional GRU model had the highest overall performance when team fights up to the 20 minute mark are included for both the training and test data.

Results in Figures 2a and 2c indicated that having both a team fight number cutoff combined with a game time cutoff would result in a model that is best able to generalize to future matches. Thus, we conducted additional tests using test data filtered by game time and containing at least two team fights. Although the addition of the two team fight filter reduced the number of available samples, this resulted in stronger initial performance compared to Figure 2c, but similar performance afterward until the 20 minute game time cutoff with the requirement of also having at least two team fights. Best model performances at 32 minutes of game time increased to over 72%. The same is also true when filtering both training and test data by game time and by having at least two team fights. We also tested the same model configurations but with data filtered by game time and containing at least three team fights. The resulting model performances were almost identical to when the data was filtered by game time and containing at least two team fights.

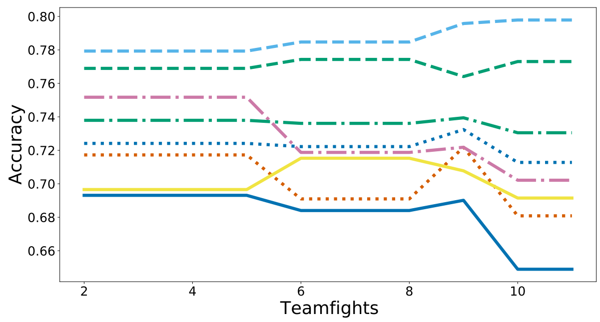
Overall, results in Figure 2 indicate that single layer models tend to achieve higher accuracy with less data. However, two layer models are able to provide better results as more training and/or test data becomes available.

VIII. Discussion

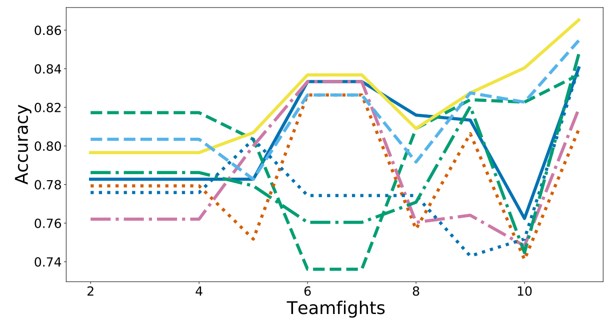
Match outcome prediction results revealed that RNN models were able to predict the outcome of an ongoing *DOTA 2* match. Our results indicate that it is possible to utilize deep learning models in predicting the outcome of real-time ongoing matches. Accurate predictions also do not necessitate the use of all game related data, but only features related to team fights. By leveraging only team fight performance in the first 5 minutes of a match, our models were able to achieve over 50% accuracy in predicting final match outcome. If an additional filter requiring a specific number of team fights to be included were added, the model's accuracy would improve to over 50% using only the first 5 minutes of data.

The performance of all eight models was similar in terms of accuracy. No model performed best in all scenarios. GRU models, especially two layer bidirectional GRUs were able to achieve slightly higher performance when there were more data due to game time cutoffs. This is especially evident when both training and test data were filtered according to game time. However, all eight models had less than 1% difference in accuracy when only 5 minutes of data were included. This indicates that if ample computation resources are available, all eight models could be used to create a more accurate prediction. Different models should be deployed for different stages of the game to maximize the advantages of each given limited data. Based on our results, to achieve the highest possible prediction accuracy, both a one layer model and a two layer model should be employed. The one layer model would be used to predict match outcome if less than 10 minutes of data is available. Once the match has progressed beyond 10 minutes a two layer model, preferably a two layer bi-directional GRU model, should be used.

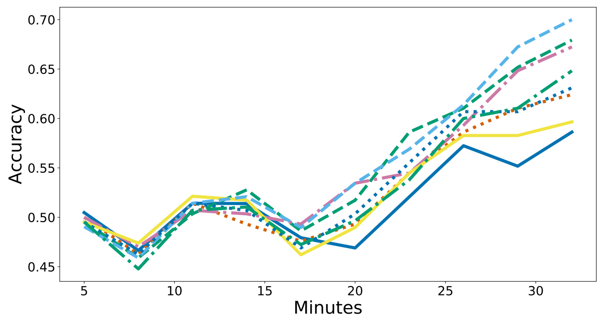
The implications of our results are twofold. First, we have established that it is possible to build a real-time prediction system for ongoing *DOTA 2* matches using RNN models only trained on team fight data. The accuracy improves as the



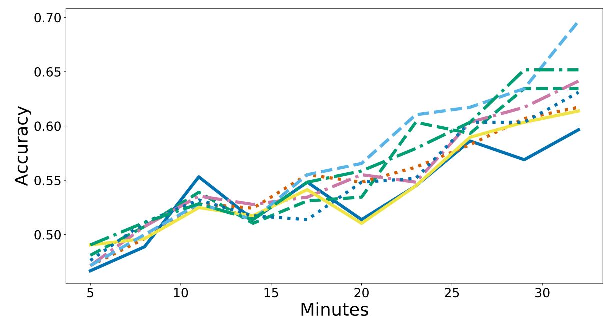
(a) RNN model performance using the number of team fights as cutoff for test data



(b) RNN model performance using the number of team fights as cutoff for training and test data



(c) RNN model performance using match time as cut-off for test data



(d) RNN model performance using match time as cut-off for training and test data

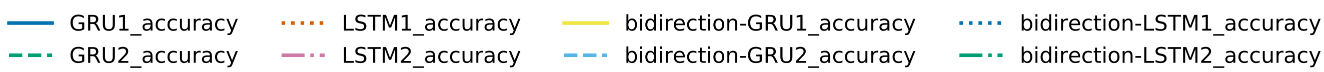


Fig. 2: RNN model performance with restricted data by number of team fights and game time

match unfolds and more team fights occur, similar to the result obtained by Hodge et al. [6]. Although our models did not achieve better accuracy compared to past research [6], these results do indicate that team fights serve as an important data point for predicting overall match outcomes.

The model presented could be repeatedly updated in real time to provide an esports audience and/or commentator with progressively more accurate predictions of the overall match outcome, similar to models proposed by others, e.g. Hodge et al. [6] and Schubert et al. [1].

Due to the varied nature of *DOTA 2* matches, restricting the model to only utilize games with up to a certain number of team fights would result in overfitting, due to the smaller sample size. Restricting the model to only using the features within a certain number of fights would also result in lower accuracy. This implies that it does not matter how many team fights a match contains, what matters are the features within the fights, the match time at which they are fought, and the order they are in.

A limitation of our research is the exclusive use of aggregated data. By aggregating all team fight performance data to the faction and team fight level, we were able to ensure that our models were trained efficiently. However, a more granular approach to the modeling, by focusing on player level performance could potentially increase the overall accuracy of our model [6], [11], [12], [19].

Previous prediction models, to the best knowledge of the authors, did not integrate team fights as a factor. As shown here, team fights alone provide a signal for match prediction, and therefore appear to be a contender for inclusion in match prediction models as a novel feature. Therefore, to improve match prediction models in esports analytics, a potential venue for future exploration could be the integration of both in-game player team fight performance with traditional performance statistics [6]. Another area that could be explored to enhance prediction systems are player physiological characteristics [27]. This could be further expanded upon through the use of identification of players/heroes with exceptional contributions within team fights. By leveraging player role identification and individual player performance to enhance our existing models [11]. The influence of team hero combinations could also be added to enhance the performance of our models [12].

IX. Conclusion and Future Work

In this research, we identified and defined the core concept of team fights in *DOTA 2* esports, and show that team fights are an important element of an esports match that can be a decisive factor of match outcome. We utilized data from team fights in the esports game *DOTA 2* to explore the potential use of team fight information in real-time match prediction models in such multi-player online battle arena games. We then employed the resulting data to train eight different types of RNN models to predict overall match outcome. Our models were able to achieve an accuracy of over 70% when including all team fight data up to 32 minutes into a match. Model performances were over 50% when trained on the first 5 minutes of each match and the game having at least 2 team fights. These results indicate that team fights alone contain a signal useful for predicting match winners. As would be expected, model performance in a team fight-based prediction model increases as more match time elapses. By adding our team fight model to existing prediction models, such as Hodge et al. [6] it is possible to further increase performance and accuracy. Future studies could thus extend previous work, and the work presented here, by integrating team fights data with player level performance features [6], [12], [27], hero role identification [11], and individual player performance [19].

Furthermore, the deep learning models presented here can be utilized in real-time, allowing commentators to note the impact of each team fight on the overall match outcome. To implement this approach for real-time use, we could embed the team fight prediction model to existing platforms such as Echo [2], a production tool that can monitor data from a live match. Esports commentators can easily tell whether a team fight happens, but it requires years of experience to understand the impact of each team fight and convey it clearly to audiences [2]. Integrating the team fight prediction model with production tool like Echo allows the commentators to display the potential consequences of each team fight to the audience directly. Currently, there is no quantitative way for measuring the influence each team fight has over the whole match. Our models, by solely leveraging team fight information, allow any prediction updates in live matches to be a direct reflection of the last team fight. Hence, the focus on only team fight information allows the RNN model predictions to be intimately tied to game context, which makes any changes to the predicted overall match outcome easily interpretable by commentators and audiences alike.

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