DEEP LEARNING TECHNIQUES FOR IDENTIFYING KPIS IN LEAGUE OF LEGENDS: WIN PREDICTION, MAP NAVIGATION, AND VISION CONTROL

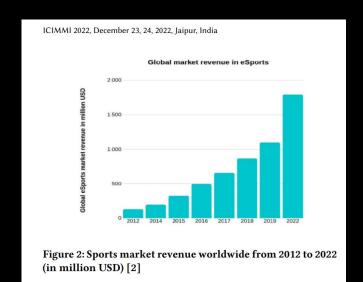
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LEAGUE OF LEGENDS, AND WHY IT MATTERS



GAME THEORY AND ESPORTS

- Branch of Mathematics dealing with zero-sum gains
- Now used for rational; decision making for animals, humans and computers
- Reinforced learning, Yao's principle, kserver problem and more!
- 100 million players on League of legends server in 2016.
- Popular at colleges



LEAGUE OF LEGENDS MAP

- Objective: destroy enemy nexus
- 3 progressive turrets per lane
- 3 types of minions march down the lane
- After 3rd tower an inhibitor is present. When destroyed a fourth "Super Minion" also spawns
- 2 extra turrets are must be destroyed before nexus can be damaged
- A jungle housing monsters that grant unique modifications to players once killed
- Positions are Top, Jungle, Mid, ADC and Support
- Fog of war covers the map limiting vision



LEAGUE OF LEGENDS CHAMPIONS

- 168 champions at the time of the study
- Unique playstyles
- Different win conditions
- Champions spike in overall power at different times
- Objects with user input
- Gain gold for items and XP for levels 1-18
- Auto attacks, 3 spells, and an ultimate.
- Values of AD, Armor, Armor p level, Mr, Mr per level etc.
- Different champions deal different damage, as interwoven into their kit
- Summoner spells



LEAGUE JARGON

- Map Awareness
- Skill floor and Skill ceiling
- Balance
- Champion pool
- Creep score(CS)
- Early/Mid/Late game
- Kite
- Main

- Meta
- Pathing
- Ping
- Skill-shot
- Smurf
- Wombo Combo
- Sweep
- Counter Pick

STUDY

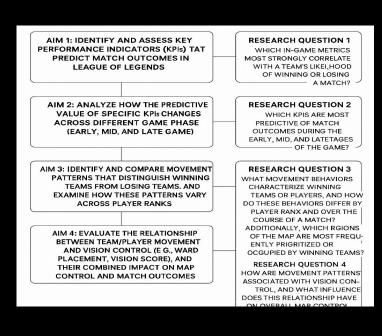
PREVIOUS LITERATURE IN THE FIELD

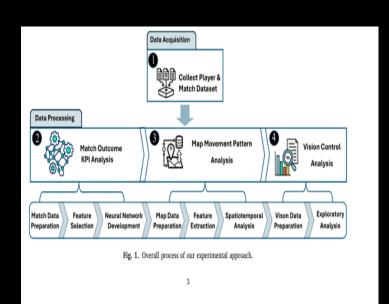
- Few studies have selected LoL specifically
- Player performance analysis (Hojaji et al., 2024; Smithies et al., 2021
- Previous studies have utilized Deep learning to predict match outcomes (Wilathgamuwa, 2024)
- Simple Vector Machine (SVM) and a tuned Recurrent Neural Network (RNN) were applied to early game only
- High Elo players were looked at

$$P_{A} = \frac{1}{1+10^{(R_{B}-R_{A})/400}}$$

$$R'_A = R_A + K \times (S_A - P_A)$$

4 STUDY QUESTIONS FLOW CHART





DATA ACQUISITION

- Riot games API
- EUW 14.1-14.7
- JSON 39,448
- Converted to Python csv file
- 1-minute intervals of stats, position, etc.
- Milliseconds of deaths, objectives, "significant occurrences"
- 3 datasets generated from combination, merged with rank

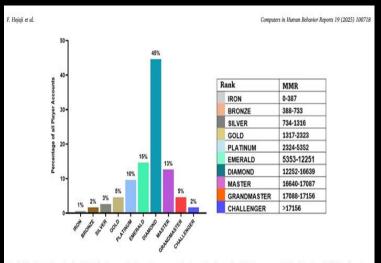


Fig. 2. The distribution of collected data in player ranks (percentages presented atop each bar) as well as MMR ranges associated with each rank division, from Iron to Challenger, based on 39,448 collected player accounts.

KPI AND FEATURE AIM 1

- 10 rows of resume data per match, averaged by team
- ->274,508 rows with 189 variables (from 137,316 unique valid matches)
- High level abstraction of player
- Game length normalized by / "features" from match-by-match duration
- First, Low Variance (LV) filtering applied to the match dataset
- Corr matrix between features ±0.8
- SKlearn to rescale 103 remaining features

NEURAL NETWORK MODEL 1

- Match resume for accuracy 30% 70%
- 102 neurons with two hidden 64 with RELU
- A dropout rate of 0.5 was applied to the hidden layers, and an L2 regularization penalty of 1e-5 was used.
- · Output layer with sigmoid
- 200 epochs optimized by ADAM and Binary Cross-Entropy loss function
- Evaluated using SHAP

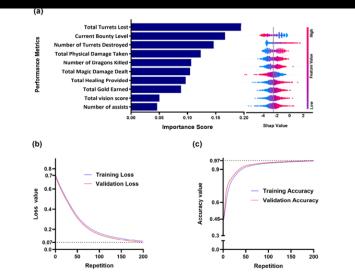
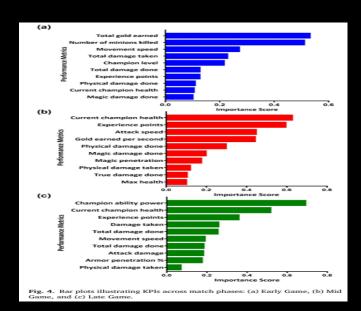


Fig. 3. (a) The bar graph and the scatter plot of the SHAP summary plot highlight the most important metrics and their effect on match outcomes as predicted by the neural network model. The scatter plot represents the relationship between the metric value and the predicted probability of the negative prediction impacts. The greater the value (red), the greater the probability of whining the match. (b) shows the occurred plot, illustrating the model's performance in predicting the correct class (win/oss) across training iterations. (c) presents the training and validation loss over iterations, demonstrating the model's progress in minimizing error during the training process. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

KPI EARLY, MID AND LATE AIM 2

- Data set split into 3 game phases
- 10 mins, to 20 mins, to Infinite
- Previous processing technique
- Removing minimal variance, remove redundant or irrelevant features, and "standardizing the data"
- 49 features for timeline data
- Same NN but with 48 neurons at the input layer



KPI MAP PREPARATION AND FEATURES, AIM 3

- Time series of 1 minute of players trajectories
- two datasets: one related to team player positions
- 35,001,035 samples
- And another with player rank data including 10,223,899 samples

- 3 types of movement
 - Total movement (Euclidian distance)
 - Minute by minute movement of different ranks
 - Movement by game phase
 - Movement in relation to teammates
- Split score
 - Player to their base at two points
 - Mean of these points multiplied by the angle

SPATIAL TEMPORAL ANALYSIS

- Trajectory plots
- Heatsmaps
- HDBSCAN
 - Building a density-based clustering hierarchy using a minimum spanning tree.
 - Extracting stable clusters from the hierarchy based on their persistence across different levels.
 - Differentiating noise from meaningful clusters by dynamically adjusting parameters like minimum cluster size.
- Davies-Bouldin Index for cluster compactness and separation, validating HDBSCAN

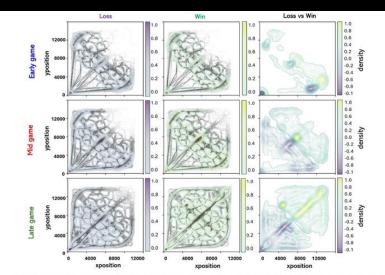


Fig. 7. Density heatmaps showing the movement patterns of players during different game phases. The right-side difference heatmap shows yellow areas indicating higher movement density for the vinning teams and purple areas indicating higher movement density for the losing teams. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

KPI VISION, AIM 4

- Resume, each player has 1 row per match
- 1,372,540 samples
- Merged with rank
- All ward destruction and ward placments
- 21,460,884 samples.
- VisionclearedPing, NeedvisionPings, VisionWardsBought, Ene myVisionPings, VisionScore, and WardPlaces. Features visionclearedPing and NeedvisionPings features included
- Vison score calculated form average of four "significant features"

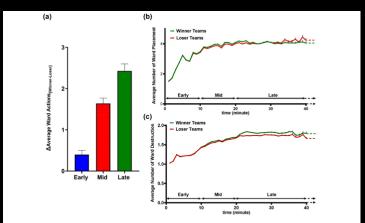


Fig. 8. (a) Bar plost illustrating the difference in total ward actions between winning and losing teams; (b) and (c) line graphs despiteing average number of ward placements and ward destructions per minute between winning and losing teams over the course of the game at different time intervals, respectively. Error brass represent pooled standard errors (SE), calculated using pooled standard deviations (SD) of winning and losing teams at each phase and conservatively using the smaller sample size (N) of the two groups. Winning teams, sepecially in the mid and late game, perform more ward placements and destruction, and higher-ranked players consistently achieve higher composite vision scores as well. The dotted line at the end of each line graph indicates the limited number of matches extending beyond 40 min (approximately 1.5 % of games).

RESULTS 1

- Accuracy of 97.42 % for Aim 1
- Reducing the number of turrets lost is the most important metric for predicting the results of matches
- Aim 2 accuracy 96.15 % for all game phases
- Early, gold (duh)
- Mid, current champion health and experience points
- Late, AP

RESULTS 2

- Aim 3, more movement Early († (1261558) = 21.39, p < .001, d = 0.06), Mid (†(1261435) = 101, p < .001, d = 0.4), and Late (†(1141508) = 351, p < .001, d = 0.4)
- Higher spread score, though rate decreases with rank
- Aim 4, more wards Early (†(189516) = 3.90, p < .001, d = 0.19), Mid († (189516) = 12.50, p < .001, d = 0.45), and Late (†(189516) = 13.80, p < .001, d = 0.36)
- High ranked players -> high composite vision score

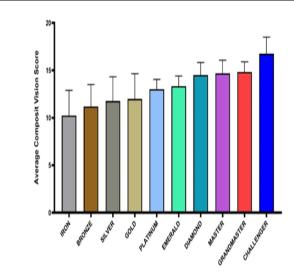


Fig. 9. Bar plot comparing average composite vision scores across different ranks. Higher-ranked players achieve consistently higher composite vision scores.

LIMITATIONS

- Small numbers on each tail
- EUW server only
- Champion
- 1 Minute intervals
- Patch
- Items





EASY CHAMPION EXAMPLE:

