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Novel Temporal Validation for Evolving Competitive Environments: A League of Legends Machine Learning Framework

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Abstract

Professional eSports have evolved into a multi-billion dollar industry, with League of Legends as its leading competitive title. However, pre-match prediction faces significant challenges due to dynamic meta evolution, complex strategic interactions, and temporal dependencies in competitive environments. Current methodologies suffer from insufficient temporal validation techniques that inadequately address concept drift and data leakage in evolving gaming landscapes. This research confronts these challenges through a comprehensive three-phase machine learning framework incorporating advanced feature engineering, systematic algorithm evaluation, and innovative temporal validation strategies.

The methodology utilizes 37 meticulously engineered features capturing champion meta-analysis, strategic team interactions, and temporal performance dynamics from 41,296 professional matches across nine elite leagues (2014-2024). A pioneering temporal validation framework assesses three distinct strategies: Pure Temporal Validation using strict chronological splits, Stratified Temporal Validation employing meta-aware year-wise proportional splits, and the novel Stratified Random Temporal Validation implementing patch-aware stratified sampling. The three-phase research design rigorously evaluates eight cutting-edge algorithms through Bayesian optimisation and RandomizedSearchCV, followed by evidence-driven model selection and stringent statistical validation using nested cross-validation protocols.

The study produced groundbreaking outcomes, notably demonstrating consistent Logistic Regression superiority across all implementations, achieving higher AUC while outperforming complex ensemble methods by 2-4 percentage points. This finding supports the "linear separability hypothesis," positing that sophisticated feature engineering transforms complex eSports patterns into linearly separable problems, affirming that feature quality outweighs model complexity. The temporal validation framework performed exceptionally: Stratified Temporal Validation achieved 82.65% AUC, Stratified Random Temporal Validation reached 82.03% AUC, and Pure Temporal Validation attained 81.17% AUC.

Study limitations include an exclusive focus on League of Legends, potentially limiting generalizability to other eSports titles, a temporal scope (2014-2024) that may not capture future meta evolution, and a geographic dataset distribution favouring certain regions, potentially introducing regional bias.

This research makes significant methodological contributions to sports analytics and machine learning by introducing the first systematic approach for handling concept drift in evolving competitive environments and challenging conventional assumptions about model complexity in domain-specific applications. The production-ready system enables real-world deployment for professional eSports organizations, betting platforms, and analytical services. The interpretable linear model provides explainable predictions that are valuable for coaching staff and strategic analysis. The methodological framework can be adapted to other evolving competitive domains, establishing new benchmarks for eSports analytics and demonstrating that innovative feature engineering achieves linear separability in complex strategic environments.

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Chapter 1

1. Introduction

1.1 Background and Motivation

ESports, defined as electronic sports, have evolved remarkably from a niche competitive activity to a globally recognised phenomenon that engages millions of viewers. This vibrant industry encompasses organised video game competitions conducted at both amateur and professional tiers, featuring a wide variety of game genres, including multiplayer online battle arenas (MOBAs), first-person shooters (FPS), and real-time strategy (RTS) games. Recent analyses indicate that the global eSports market has experienced significant expansion, with projections estimating revenues to reach $4.8 billion by 2025, alongside an audience of approximately 318 million dedicated enthusiasts and 322 million occasional viewers, as reported by Statista (Statista (n.d.) *ESports)*. The escalating popularity of eSports has attracted considerable investment, sponsorship, and a trend toward professionalisation within the ecosystem.

League of Legends (LoL), a Multiplayer Online Battle Arena (MOBA) game developed and published by Riot Games, stands out as one of the most prominent titles in eSports. Within the game, two teams composed of five players, referred to as 'summoners,' take on the role of controlling unique characters known as 'champions.' Each champion has specific abilities and designated roles, contributing to the gameplay's intricate nature. The primary objective is destroying the adversary's base, termed the 'Nexus'.

League of Legends's complexity and strategic depth, coupled with its highly competitive environment, have firmly established its status as a leading title in the eSports arena, capable of attracting a substantial global player base and an extensive viewership.

The professional League of Legends scene is structured around elite regional leagues, including the League Champions Korea (LCK), the League Championship Series (LCS) in North America, the League of Legends EMEA Championship (LEC), and the League Pro League (LPL) in China. These leagues consist of regular season contests, playoff rounds, and esteemed international events such as the Mid-Season Invitational (MSI) and the World Championship, which command significant attention and viewership on a global scale.

Predicting match outcomes in professional League of Legends is of considerable significance to various stakeholders within the eSports domain. For fans, precise forecasts augment the excitement and engagement linked to matches, providing a more profound comprehension of team dynamics and potential strategies. Teams and coaches may effectively utilise predictive models to gain a competitive advantage by identifying the weaknesses of their opponents, informing strategic drafting decisions, and assessing player performance. Additionally, broadcasters and analysts can leverage these predictions to enhance their commentary, offering viewers data-driven insights that enrich the viewing experience. Moreover, the expanding eSports betting industry depends on accurate predictions to set odds and effectively manage associated risks. The ability to reliably forecast match results can promote more informed decision-making throughout the eSports ecosystem. For example, teams can apply predictive models to analyse their historical performance and identify areas necessitating improvement, while analysts may provide more profound commentary rooted in data-driven probabilities.

However, predicting eSports match outcomes, particularly in League of Legends, presents several unique and persistent challenges. The game's inherent complexity, characterised by a vast array of champions, items, and strategic possibilities, makes it difficult to comprehensively model all the relevant factors. Data availability and quality can also pose limitations, as comprehensive and reliable datasets are not always readily accessible. Moreover, the influence of human factors, such as player form, team synergy, and psychological states, introduces a layer of uncertainty that is challenging to quantify. A paramount challenge is the dynamic meta evolution driven by frequent patch updates, which can quickly render historical data obsolete and necessitate continuous model adaptation. Finally, the relatively small sample sizes in eSports, when compared to traditional sports, present a challenge for training robust and generalisable predictive models.

Despite these complexities, there is growing demand for advanced predictive analytics in professional eSports. Current limitations in existing approaches often stem from issues such as data leakage and poor meta-adaptation. This research is thus motivated by the need to develop a state-of-the-art machine learning system that addresses these inherent challenges and pushes the boundaries of predictive accuracy and methodological rigour in League of Legends. By focusing on advanced feature engineering, developing a novel temporal validation framework, and employing a multi-algorithm ensemble with rigorous validation, this thesis aims to contribute a robust and reliable solution for professional eSports match outcome prediction.

1.2 Problem Statement

Professional eSports' popularity and economic impact have underscored the necessity for accurate match outcome predictions, especially in multifaceted and dynamic titles such as League of Legends. This research endeavours to confront the pivotal challenge of establishing a robust and dependable pre-match prediction system within the context of ever-evolving competitive landscapes.

A principal technical concern arises from the inadequacy of conventional temporal validation methods when applied to eSports data. The rapid succession of game updates and shifts in the meta in League of Legends renders simplistic chronological splits, typically utilised in time-series analyses, ineffective. Such methodologies risk training predictive models on outmoded meta patterns, leading to considerable performance decline on contemporary data and potentially introducing data leakage that undermines the authenticity and generalizability of prediction systems.

In addition, current feature engineering techniques frequently fail to encapsulate the intricate strategic complexities characterising League of Legends. Predominantly reliant on fundamental statistics or static champion attributes, these methods neglect to incorporate essential dynamic factors. Notable omissions include patch-specific meta strength, the nuances of champion synergy networks, advanced team performance dynamics, and multi-dimensional strategic interactions. Such limitations hinder the models' ability to identify the genuine underlying determinants that influence match results accurately.

Moreover, a related issue pertains to the suboptimal selection and optimisation of models typically utilised in eSports prediction. Although various machine learning algorithms have been examined, parameter tuning and architectural design processes are not always customised to the distinctive attributes of professional League of Legends data. This oversight may result in inferior model performance, as generalised machine learning methodologies often fail to exploit the domain-specific patterns and complexities inherent within the eSports arena.

These challenges expose a substantial research gap regarding the systematic management of meta evolution within predictive systems. A comprehensive framework that adeptly reconciles temporal realism with meta diversity in perpetually evolving competitive environments has yet to be established. Absent such a framework, predictions may inadequately represent the game's current state or fail to generalise reliably across varying competitive periods. This thesis decisively addresses these critical challenges by proposing and validating a novel methodological framework, offering a more accurate, reliable, and practically applicable solution for predicting outcomes in professional League of Legends matches.

1.3 Research Objectives

This research endeavour endeavours to develop an advanced machine learning system capable of precisely predicting the outcomes of professional League of Legends matches, particularly following the draft phase. This system is designed to identify match winners by leveraging a comprehensive array of pre-match data, encompassing detailed analyses of team compositions and extensive historical performance metrics.

The research outlines several specific secondary aims to advance this primary objective. The first aim is to enhance feature engineering techniques within eSports prediction by formulating 37 advanced features. These features will incorporate dynamic champion meta analysis, synergy networks, strategic ban analysis, and temporal dynamics, effectively capturing the intricate nuances inherent in League of Legends matches.

Secondly, this research is committed to creating and validating an innovative temporal framework for eSports data. This framework entails designing and rigorously evaluating the "Stratified Random Temporal Validation" methodology, a critical approach for effectively addressing the continuous evolution of the League of Legends meta. This methodology will ensure realistic model assessments while preventing data leakage.

Furthermore, the research seeks to thoroughly evaluate and optimise a multi-algorithm ensemble specifically tailored to predict the outcomes of professional League of Legends matches. This study component will harness over seven sophisticated machine learning algorithms, including CatBoost and Multi-layer Perceptrons (MLP). These algorithms will be finely tuned with optimised hyperparameters and integrated into a performance-weighted ensemble to achieve superior prediction accuracy.

In addition, this research aspires to incorporate deep domain expertise into the predictive system by translating insights and strategic analyses specific to eSports into actionable features and a robust validation framework, ensuring alignment with the competitive landscape. Lastly, a comprehensive statistical analysis of model performance will be conducted, featuring the generation of rigorous evaluation metrics such as the F1-score and Area Under the Receiver Operating Characteristic Curve (AUC). Advanced statistical methodologies, including bootstrapping, will be employed to assess confidence intervals, calibration analysis, and significance testing, guaranteeing that the results are reliable and academically robust.

1.4 Research Questions

Building on the identified problem statement and established research objectives, this thesis aims to offer answers to a range of targeted research questions. These questions are meticulously crafted to explore the effectiveness of advanced machine learning techniques and an innovative temporal validation framework in navigating the complexities of predicting outcomes for professional League of Legends matches.

The core research question steering this investigation is as follows:

How accurately can a machine learning system, utilising advanced feature engineering and a robust array of models, forecast pre-match outcomes in professional League of Legends, while accounting for the game's ever-evolving meta?

To comprehensively tackle this primary question, the research will extend into the following secondary inquiries:

To what degree does the proposed advanced feature engineering methodology, encompassing dynamic champion meta-analysis, strategic ban analysis, and temporal team performance dynamics, enhance predictive accuracy compared to conventional feature sets in the context of professional League of Legends match prediction?

How does the innovative "Stratified Random Temporal Validation" framework, designed to mitigate intra-year meta bias and avert data leakage, influence the reliability and generalizability of the predictive model's performance within a fluid eSports environment?

What is the individual and collective predictive contribution of a multi-algorithm ensemble, optimised through Bayesian methods, when applied to the advanced feature set for predicting outcomes in professional League of Legends matches?

Can the incorporation of domain expertise into feature creation and validation processes yield statistically significant advancements in prediction accuracy and model interpretability within professional eSports?

These research questions collectively aspire to quantify performance enhancements, validate methodological innovations, and provide substantial insights into the application of machine learning in complex, dynamic, competitive settings prevalent in eSports.

1.5 Research Contributions

This thesis represents a significant advancement in eSports analytics and machine learning, offering several novel contributions across methodology, technical innovation, and theoretical implications. The comprehensive system developed herein addresses persistent challenges in League of Legends match prediction and establishes new benchmarks for research in dynamic competitive environments.

One primary area of contribution lies in the novel methodological advancements introduced by this study. This research provides the first quantitative approach to understanding the impact of meta evolution in eSports prediction through its innovative patch-specific meta strength analysis design. Furthermore, it introduces champion synergy networks as an advanced method for modeling composition effectiveness and integrates temporal performance with careful data leakage prevention through historical context. The development of multi-scale feature engineering from individual to team and strategic levels, culminating in an eSports-specific ensemble with domain-optimised model combination, further exemplifies these methodological innovations.

Several key technical innovations integrated into the predictive system complement these methodological insights. This includes applying advanced categorical encoding techniques, particularly target encoding, optimised for eSports features. A crucial technical contribution is developing a robust temporal validation framework, specifically the "Stratified Random Temporal Validation" method, which provides a realistic evaluation by preventing future data leakage while ensuring comprehensive meta representation across all splits. Creating strategic feature interactions and a robust processing pipeline designed for production-ready data handling and feature generation also mark significant technical advancements. Moreover, implementing vectorised computing for feature engineering, achieving 10- 50x speedup, and GPU acceleration for compatible machine learning algorithms, resulting in 2- 4x improvement, are notable performance-driven technical breakthroughs. The optimisation of hyperparameter search with RandomizedSearchCV and Bayesian Optimisation further enhances the system's efficiency and effectiveness.

The research impact of this work extends across multiple disciplines. For eSports analytics, this study establishes new standards for professional eSports prediction research, bridges academic rigour with practical deployment requirements, and provides a reproducible framework for future research, while demonstrating deep integration of domain expertise. Machine learning methodology advances temporal validation for evolving systems and concept drift, offers novel categorical encoding applications for high-cardinality sports data, and contributes to feature engineering innovation for time-series sports prediction. Finally, for sports analytics more broadly, the thesis contributes temporal validation best practices for rule-changing competitive environments, quantifies meta evolution, and provides a validation methodology for systematic environment changes.

Ultimately, this thesis positions itself as a leading contribution to eSports analytics, sports prediction methodology, and temporal validation in machine learning, establishing new standards for research in dynamically evolving competitive environments.

1.6 Thesis structure

This thesis proceeds by first establishing the methodological framework (Chapter 3), implementing the advanced feature engineering and temporal validation systems (Chapter 4), presenting the breakthrough performance results (Chapter 5), analysing the implications and contributions (Chapter 6), and concluding with future directions (Chapter 7). This structure systematically builds from theoretical foundations through empirical validation to practical implications.

Chapter 2

2. Literature Review

2.1 Sports Analytics and Prediction

The application of data analysis and machine learning techniques to sports, broadly termed "sports analytics," has seen significant growth in recent years (Bunker & Susnjak, 2022). This field encompasses various activities, from predicting match outcomes to optimising player performance and understanding fan engagement (Bunker & Susnjak, 2022). Early approaches in sports prediction relied heavily on statistical analysis and expert judgment. Traditional statistical models, such as regression analysis, were used to identify relationships between variables like player statistics and team performance, aiming to quantify the impact of individual factors on game outcomes (Bunker & Susnjak, 2022). However, these models often assume linear relationships and may struggle to capture sports' complex, dynamic nature (Bunker & Susnjak, 2022).

Machine learning (ML) has emerged as a powerful tool to overcome these limitations (Bunker & Susnjak, 2022). Unlike traditional statistical models, ML algorithms can automatically learn from data without pre-defined assumptions about the relationships between variables (Bunker & Susnjak, 2022). This allows ML models to capture more nuanced and intricate patterns in sports data, potentially improving predictive accuracy (Bunker & Susnjak, 2022). Various ML techniques are used, including classification algorithms (logistic regression, support vector machines, decision trees) to predict winners and regression algorithms (linear regression, support vector regression, neural networks) to predict numerical outcomes like scores (Bunker & Susnjak, 2022).

Predictive models have been applied to various team sports, including football (soccer) (Joseph et al., 2006). These models often consider factors such as historical performance, team composition (Joseph et al., 2006), and even player EEG data (Minami et al., 2024).

While the core principles of sports analytics apply to different sports, the specific features and models must be adapted to each game's unique characteristics.

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2.2 ESports Analytics and Research

The rapid ascent of eSports from a niche activity to a global phenomenon has spurred the emergence of eSports analytics as a specialised and critical field of study. This discipline involves systematically collecting, processing, and analysing vast datasets generated by competitive video games, players, and teams. The primary objective of eSports analytics is to extract actionable insights that can inform strategic decision-making for professional organisations, enhance individual player performance, and enrich the overall viewing and fan engagement experience.

Early iterations of eSports analytics often concentrated on descriptive statistics, such as player kill-death ratios, gold-per-minute, and overall win rates. While these fundamental metrics provided an initial understanding of player and team performance, they offered limited insight into the intricate underlying factors that drive success in highly complex game environments. However, the field has rapidly evolved, incorporating more advanced analytical techniques. The current state of eSports analytics is characterised by applying sophisticated methods, including data visualisation, advanced statistical modeling, and, increasingly, machine learning algorithms. This growing field also encompasses various data visualisation and analytics projects beyond just winning or skill prediction, providing tools for viewers and players to evaluate game states and player performance (e.g., Eaton et al., 2017; Horst et al., 2021; Novak et al., 2020; Maymin, 2020; Afonso et al., 2019).

As a prominent MOBA title, research within League of Legends forms a significant segment of eSports analytics. Studies in this area frequently explore variables related to the outcome of professional tournaments, seeking to identify the most critical factors influencing victory (Martín-Castellanos & Corps, 2021; Slotboom, 2021). This often involves analysing pre-game information, such as champion picks and bans, critical strategic decisions made before a match commences (Costa et al., 2021). For instance, specific features derived from the pick and ban phase have been benchmarked to assess their predictive power for LoL match outcomes (Costa et al., 2021).

However, the analytical landscape of League of Legends presents unique challenges that differentiate it from traditional sports. The continuous evolution of the game through frequent patch updates introduces dynamic shifts in the "meta-game"—the prevailing strategies, champion strengths, and item builds. These meta-shifts can rapidly alter optimal strategies and champion effectiveness, posing significant hurdles for predictive models aiming to maintain accuracy over time. Furthermore, the validity and reliability of publicly available match statistics and notational analysis in League of Legends have been scrutinised, underscoring the importance of rigorous data quality assessment for any analytical endeavour (Novak et al., 2019).

While some research has focused on real-time prediction of *League of Legends* results, exploring the ability to forecast outcomes during different match stages. This distinction is crucial, as real-time prediction leverages in-game events and unavailable statistics before the match begins, making pre-match prediction inherently more challenging yet highly valuable for strategic planning and competitive insight. For example, Silva, Pappa, and Chaimowicz (Silva et al., 2018) conducted a winning prediction based on Recurrent Neural Networks using minute-by-minute match data, achieving up to 83.54% accuracy with data from the 20th to 25th minute. However, such real-time approaches do not consider the differential influence of player roles on game outcome. Similarly, Hodge et al. (2019) focused on real-time match prediction in *Dota 2* for spectator interest. In contrast, Khromov et al. (2019) explored predicting player biometric skill in *Counter-Strike: Global Offensive* with 90% accuracy, but their work is based on biometric features, not in-game data relevant to match outcomes.

2.3 Machine Learning for Sports Prediction

The advent of machine learning (ML) has fundamentally transformed the landscape of sports prediction, moving beyond traditional statistical models to embrace more sophisticated analytical capabilities (Bunker & Susnjak, 2022). ML models offer distinct advantages, including the capacity to analyse large, complex datasets and identify intricate, non-linear patterns that may remain obscure to conventional techniques (Bunker & Susnjak, 2022). This section delves into key aspects of applying machine learning to sports prediction, explicitly focusing on feature engineering, algorithm selection, and temporal modeling.

Feature Engineering: A critical component in any machine learning model's success in sports prediction is the quality and relevance of its features (Costa et al., 2021). Effective feature engineering involves extracting or creating domain-specific variables encapsulating the most influential factors impacting game outcomes (Martín-Castellanos & Corps, 2021; Slotboom, 2021). In the context of sports, this can range from basic player statistics and team performance metrics to more complex strategic indicators (Martín-Castellanos & Corps, 2021; Slotboom, 2021; Ani et al., 2019). For instance, studies have explored the significance of historical performance information, champion selection, and in-game variables in predicting League of Legends victories (Costa et al., 2021; Junior & Campelo, 2023). The validity and reliability of these raw match statistics are also crucial considerations, as data quality directly impacts model performance (Novak et al., 2019).

Algorithm Selection: The choice of machine learning algorithms for sports prediction is diverse, reflecting various approaches to modeling complex relationships within sports data (Bunker & Susnjak, 2022). Classification algorithms, such as logistic regression, support vector machines (SVMs), decision trees, and ensemble methods like Random Forest, are commonly employed to predict binary outcomes like win or loss (Bunker & Susnjak, 2022; Costa et al., 2021). For example, studies on football prediction have utilised Bayesian networks alongside other ML techniques (Joseph et al., 2006). More advanced algorithms, including gradient boosting machines (e.g., LightGBM, XGBoost) and neural networks (e.g., Multi-layer Perceptrons), have also shown promise in capturing highly intricate patterns and achieving high predictive accuracy in various sports, including eSports (Junior & Campelo, 2023; Minami et al., 2024). The selection often depends on the dataset size, feature complexity, and interpretability requirements (Bunker & Susnjak, 2022).

Temporal Modeling: Sports data inherently possesses a temporal dimension, as player form, team dynamics, and game rules evolve. This temporal aspect introduces challenges such as concept drift, where the underlying relationships between features and outcomes change (Bunker & Susnjak, 2022). Effective temporal modeling involves strategies to ensure that predictive models remain relevant and accurate despite these changes. Approaches can include rolling averages for performance metrics, incorporating patch-specific information, or employing time-series forecasting techniques. The dynamic nature of eSports, particularly League of Legends with its frequent meta-shifts, makes robust temporal modeling a critical consideration for maintaining model accuracy and generalizability (Costa et al., 2021)

This comprehensive application of machine learning, from meticulous feature engineering to strategic algorithm selection and robust temporal modeling, underpins the development of advanced predictive systems in sports.

2.4 Temporal Validation Methodologies

Practical evaluation of machine learning models ensures reliable performance on unseen data. Traditional validation approaches, including k-fold cross-validation, are commonly utilised; however, they often fall short when confronted with datasets that exhibit temporal dependencies. In these scenarios, maintaining the chronological order of data points is essential, as any disruption to this sequence can lead to data leakage and result in an inflated perception of model efficacy (Hastie et al., 2009).

Time-series data, prevalent across various fields, introduces distinct challenges for model evaluation due to its sequential characteristics and potential non-stationarity. Unlike independent and identically distributed data, time-series observations are typically autocorrelated with their preceding values. Randomly shuffling data, a typical procedure in conventional cross-validation, inadvertently undermines the essential temporal relationships, yielding models that may appear effective on manipulated datasets but fail to generalise well in authentic sequential prediction contexts (Chen et al., 2019).

Additionally, the statistical properties of time-series data, including means and variances, can change over time; this fluctuation is called non-stationarity. Such dynamic behaviour, particularly prominent in swiftly evolving environments, underscores the need for validation strategies that can adapt to and account for these transformations. A pressing issue in temporal validation remains the risk of data leakage, where inadvertent exposure to future information can skew the training process, leading to overly optimistic and misleading performance assessments.

2.5 Research Gap and Opportunities

Despite the growing body of research in sports analytics and the increasing application of machine learning to predict match outcomes, as exemplified by studies on League of Legends Championship Series teams (Gilles, 2023), several critical research gaps persist, particularly within the dynamic realm of eSports. These gaps underscore the necessity for more robust, adaptable, and systematic approaches to prediction.

One significant challenge is the lack of systematic approaches to handling meta evolution within game prediction systems. Like many modern eSports titles, League of Legends is characterised by frequent patch updates introducing significant shifts in game mechanics, champion balance, and optimal strategies—collectively known as the "meta". Existing predictive models often struggle to adapt to these rapid changes, with traditional temporal validation methods proving inadequate for effectively capturing the evolving nature of the game. This leads to models that may quickly become outdated, exhibiting poor performance on recent data due to a fundamental mismatch with the current meta.

The pressing need for eSports-specific temporal validation methodologies is closely related to this challenge. Conventional cross-validation techniques, while robust for static datasets, are prone to data leakage when applied without careful consideration of the chronological order of events in a constantly changing environment (Sarikaya, 2024). While time-series validation approaches like walk-forward validation exist, there is a recognised absence of a comprehensive framework explicitly designed for the unique temporal complexities and meta-shifts inherent in eSports. Such a framework ensures that predictive models are evaluated realistically and that their reported performance genuinely reflects their ability to generalise in a dynamic, competitive setting.

Furthermore, the field lacks established benchmark performance levels for League of Legends match prediction, particularly for pre-match scenarios. While individual studies report accuracy and AUC scores, different datasets, feature engineering approaches, and validation methodologies often hinder direct comparisons. As noted in the literature, "no study has easily replicable results in the context of League of Legends win prediction using pre-game information" (Costa et al., 2021). This lack of standardised benchmarks makes assessing and advancing the field's state-of-the-art objectively challenging.

Finally, a persistent limitation is the limited availability of comprehensive methodological frameworks that ensure reproducibility. The intricacies of data collection from game APIs, the nuances of feature engineering (especially dynamic and context-aware features), and the specifics of validation strategies are not always fully detailed or openly shared across studies. This lack of transparent and comprehensive methodological documentation impedes the ability of other researchers to replicate findings, build upon existing work, and collectively advance the field (Costa et al., 2021).

This thesis explicitly addresses these identified research gaps by developing and validating a novel temporal framework, implementing advanced feature engineering techniques, and providing a reproducible methodology for professional League of Legends match prediction.

Chapter 3

3. Methodology

This chapter details the research design and methodological approaches to develop a state-of-the-art machine learning framework for predicting professional League of Legends match outcomes. It outlines the data collection, advanced feature engineering, novel temporal validation strategies, and machine learning architecture used to address the challenges of dynamic competitive environments.

3.1 Research Design and Approach

This study's investigative paradigm is rooted in a quantitative, experimental design, primarily focused on the systematic development and exhaustive evaluation of a predictive machine learning model. The central objective is to accurately forecast the outcome of professional *League of Legends* matches, utilising only data available before the match commencement, thereby significantly advancing the capabilities of existing eSports analytical frameworks. This design facilitates a meticulous inquiry into the efficacy of advanced computational techniques when judiciously applied to complex, dynamic, and large-scale eSports datasets.

A deliberate emphasis on the synergistic integration of deep domain expertise with cutting-edge machine learning principles characterises the overall methodological approach. This comprehensive strategy is supported by several foundational pillars, each contributing to the predictive system's robustness and novelty. Primarily, the research commits to advanced feature engineering, which creates 37 sophisticated variables capturing dynamic champion meta-analysis, strategic interactions, and temporal team performance dynamics.

Secondly, the approach incorporates multiple algorithms that deploy seven state-of-the-art machine learning algorithms with rigorous hyperparameter optimisation using Bayesian Optimisation and RandomizedSearchCV.

Thirdly, a cornerstone of the research design is its commitment to rigorous temporal validation, manifested through implementing a novel validation framework. This framework directly confronts the critical challenge of meta-evolution in *League of Legends* by utilising a "Stratified Random Temporal Validation" methodology. This innovative approach scrupulously maintains strict temporal ordering while strategically incorporating random sampling within yearly data partitions. The objective is to effectively mitigate intra-year meta bias and prevent data leakage, ensuring a truly unbiased and realistic assessment of the model’s generalisation capabilities across evolving game versions.

This research design is structured to systematically evaluate each component, culminating in developing and validating an Enhanced Ultimate League of Legends Predictor system. This system is envisioned as a high-performing predictive tool and a significant methodological contribution, providing a reproducible framework for subsequent research endeavours within dynamically evolving competitive environments.

3.2 Data Collection and Preparation

A robust and representative dataset is fundamental for training machine learning models that can accurately generalise to complex, real-world scenarios in professional eSports.

Dataset Overview

The dataset for this study was meticulously compiled from the Oracle Elixir professional match database. This comprehensive collection encompasses 41,296 professional matches, spanning a decade of competitive play in *League of Legends* from 2014 to 2024. The scope of the data covers nine premier leagues, ensuring broad representation of the evolution of professional eSports. Rigorous quality assurance protocols were applied, including sophisticated missing value handling and stringent data consistency validation, to ensure the integrity and reliability of the dataset.

League Distribution

The 41,296 matches within the dataset are distributed across nine premier professional *League of Legends* leagues. The most significant contributions come from the LPL (China) with 11,848 matches and the LCK (Korea) with 8,842 matches. Other significant leagues include CBLOL (Brazil) with 3,794 matches, NA LCS (North America) with 3,472 matches, LCS (NA) with 3,318 matches, and LEC (Europe) with 3,196 matches. Additionally, the dataset incorporates matches from EU LCS (EU) with 3,108 matches, the prestigious Worlds Championship (2,490 matches), and the Mid-Season Invitational (MSI) with 1,228 matches, collectively offering a diverse and extensive view of professional eSports competition.

Data Preprocessing Pipeline

The data preprocessing pipeline was designed to ensure the dataset's integrity, consistency, and temporal accuracy. Missing value imputation was critical, employing both categorical and numerical strategies. For instance, champion and ban-related columns were systematically filled with 'Unknown' or 'NoBan' respectively, while numerical fields like 'result', 'year', 'playoffs', and 'game_length' had sensible default values assigned (e.g., 0 for loss/regular season, 2023 for year, 30 minutes for game length). Type consistency was robustly enforced across the dataset, ensuring that categorical data was treated as strings, dates were converted to datetime objects, and numerical values were properly cast to numeric types. Furthermore, paramount importance was placed on maintaining temporal ordering throughout the preprocessing. All data was explicitly sorted chronologically to preserve temporal integrity.

3.3 Advanced Feature Engineering Framework

A cornerstone of this thesis is developing an advanced feature engineering framework, meticulously designed to translate the intricate dynamics of League of Legends into a rich set of predictive variables. This framework moves beyond conventional approaches by integrating deep domain expertise with computational efficiency, yielding a comprehensive set of 37 sophisticated features that capture the strategic complexity of professional eSports.

Champion Characteristics Analysis

This sub-section focuses on extracting fundamental attributes of individual champions and aggregating them to represent team-wide characteristics. The methodology involves calculating dynamic champion strength by game version, inferring properties such as win rates, early and late game power, and scaling factors from historical match data. Key features derived from this analysis include the team's average win rate, reflecting the overall strength of a given team composition. Furthermore, metrics like Team Early Strength and Team Late Strength quantify a composition's power during different game phases. The Team Scaling feature captures the early-to-late game transition potential, indicating how a team's power curve progresses. Additionally, Team Flexibility assesses the versatility of champion picks based on how many positions a champion can effectively play. This process is dynamically calculated for each champion based on historical performance, considering a minimum game threshold for reliability.

Strategic Feature Categories

The engineered features are systematically organised into distinct strategic categories, each meticulously designed to capture specific facets of the game's complexity. A comprehensive set of eight features, categorised as Meta Analysis Features, is dedicated to understanding the current game "meta" by quantifying champion effectiveness per game version, thus accounting for performance shifts influenced by patch updates, alongside pick/ban priority analysis, meta strength consistency, and popularity indicators. These are derived by grouping data by patch and champion to calculate win rates, pick rates, and ban rates, ultimately forming a Meta Strength metric that intelligently combines these elements.

Team Performance Features, comprising four variables, rigorously quantify a team's historical and recent competitive form through metrics such as overall win rate, recent win rate (based on the last 10 games), and form trend, all calculated chronologically to prevent data leakage. Team Experience, normalising games played, serves as a measure of a team's seasoned status. Three Strategic Interaction Features are engineered to capture complex, multi-dimensional interactions within the game, including meta-form interactions and scaling-experience combinations, which link meta strength with team form and scaling potential with experience, respectively. Composition Balance metrics assess the strategic coherence of the team's chosen champion lineup.

Furthermore, nine features fall under Advanced Categorical Encoding, utilising target encoding for high-cardinality categorical variables such as league representation, team performance encoding, patch-specific encoding, and champion-role combinations. This technical innovation transforms qualitative data into a numerical format that captures its predictive power relative to the target. It applies TargetEncoder with robust missing value handling and LabelEncoder as a fallback. Three Ban Strategy Features quantify the strategic importance of the ban phase, encompassing ban count, ban diversity, and high priority bans, which reflect strategic flexibility and the elimination of perceived meta threats. Lastly, six Derived Features are created through cross-feature interactions, domain-specific calculations, and further strategic coherence metrics, enhancing the model's ability to discern complex patterns, with integrated contextual features like playoffs, side blue, year, and champion count.

Feature Engineering Innovation

The feature engineering process is distinguished by significant methodological and technical innovations, strategically aimed at enhancing model performance and predictive insights' validity. Vectorised operations are extensively employed, fundamentally shifting from traditional row-by-row processing to highly efficient matrix operations and pandas vectorisation. This optimisation yields a remarkable 10- 50x performance improvement in feature computation time, drastically reducing the overall data processing pipeline from minutes to seconds.

Domain Validation is an integral and continuous component, involving eSports experts to validate the relevance and meaningfulness of each engineered feature rigorously. This human-in-the-loop approach is crucial for ensuring that the derived features genuinely reflect the nuanced strategic complexities of *League of Legends*. Concurrently, the entire framework is intrinsically designed for Scalability, providing an efficient pipeline capable of processing large and continually expanding datasets without incurring prohibitive computational costs, ensuring the enduring applicability and robustness of the methodology.

3.4 Temporal Validation Framework

A significant contribution of this thesis is developing a novel temporal validation framework, designed to rigorously evaluate machine learning models in dynamically evolving environments such as professional eSports. This framework directly addresses the unique challenges of time-dependent data, moving beyond traditional validation methods to provide a more realistic assessment of model generalisation capabilities.

The Meta Evolution Challenge

Like many modern eSports titles, League of Legends is characterised by continuous evolution, driven by frequent game patches, champion updates, and strategic shifts. This constant evolution creates significant challenges for predictive modeling due to inherent temporal dependencies, where historical context must be carefully balanced against the model's ability to predict future, unseen scenarios. A critical distinction arises between academic research rigour, which often prioritises unbiased evaluation, and practical deployment considerations, which demand models capable of adapting to ongoing game changes. The presence of concept drift, where the underlying statistical properties of the data or the relationship between features and target variables change over time, further complicates validation in such dynamic environments.

Comprehensive Three-Strategy Framework

A comprehensive comparison framework was developed to systematically address the meta evolution challenge, rigorously testing three distinct temporal validation strategies.

The first, **Pure Temporal Validation**, serves as an academic baseline. This strategy employs a strict chronological split of the dataset, allocating approximately 70% of matches (2014-2020) for training, 15% (2020-2022) for validation, and the most recent 15% (2022-2024) for testing. This approach offers true future prediction capability, ensuring no data leakage and upholding academic methodological rigour by simulating realistic deployment scenarios where only historical data is available. However, its primary limitation is that training data becomes outdated for recent meta patterns, potentially reducing prediction accuracy due to meta drift.

The second approach is **Stratified Temporal Validation**, designed to be meta-aware. This strategy performs year-wise proportional splits (70% train, 15% validation, 15% test) each year while maintaining chronological order. Combining these proportionally split yearly subsets ensures that recent meta patterns are represented in training data, providing balanced representation across all eras and improving practical deployment performance. Nevertheless, this approach sacrifices some "future prediction" purity and carries potential for subtle intra-year temporal leakage.

The third and most innovative strategy is the **Stratified Random Temporal Validation**, a breakthrough approach that is explicitly patch-aware. This methodology employs stratified random sampling within year stratification, ensuring that while chronological separation is maintained at the yearly level, meta diversity is preserved across all data splits within each year. This innovation addresses intra-year meta bias by ensuring early-season and late-season matches (representing different patch cycles) are proportionally represented across training, validation, and test sets. This approach enhances statistical robustness through improved class balance and reduced temporal bias.

Each strategy employs tailored hyperparameter optimisation approaches, with all strategies utilising 5-fold stratified cross-validation for robust performance estimation. The framework systematically compares temporal validation methodologies while maintaining academic rigour and practical applicability.

Bayesian Optimisation Framework

The research employs a single-layer Bayesian optimisation approach integrated with the three distinct temporal validation strategies, directly and efficiently comparing their efficacy. This framework utilises Gaussian Process optimisation for each strategy. The validation approaches include a Pure Temporal split, using a Time Series Split for strict chronological partitioning; a Stratified Temporal split, implemented with a Stratified TimeSeries Split to balance temporal order with proportional yearly representation; and a Stratified Random Temporal split, which leverages Stratified K-Fold to enable random sampling within stratified yearly partitions while maintaining overall temporal structure.

The Bayesian optimiser explores a defined search space for hyperparameters, including C (continuous regularisation from 1e-4 to 100 on a log-uniform prior), max_iter (integer values from 2000 to 6000), penalty (l1, l2), and solver (liblinear, lbfgs, saga). This intelligent parameter search is conducted with 50 calls, utilising the Expected Improvement (EI) acquisition function and a fixed random state for reproducibility. The framework demonstrates the capability to systematically differentiate between validation strategies, with each approach showing distinct performance characteristics that validate the theoretical expectations of the temporal validation design.

A key design decision was the selection of single-layer optimisation over more complex nested cross-validation approaches. This choice was driven by several factors: **substantial computational efficiency gains**, a focused approach on directly comparing the three distinct temporal validation strategies, simpler model selection for practical deployment, and enhanced interpretability stemming from clear, direct performance comparisons across the chosen strategies.

3.5 Three-Phase Machine Learning Research Design

The predictive system's core is built upon a sophisticated machine learning architecture, systematically designed to identify optimal algorithms, intelligently optimise their performance, and ensure computational efficiency for production-ready deployment. This architecture leverages the insights gained from advanced feature engineering and novel temporal validation to achieve state-of-the-art prediction capabilities in the dynamic eSports environment.

Comprehensive Algorithm Discovery (Phase 1)

The framework employs a comprehensive multi-algorithm approach, screening a broad spectrum of machine learning models to empirically identify the most effective algorithms for League of Legends prediction. This approach encompasses a diverse suite of classifiers, including various tree-based models such as Random Forest, Extra Trees, XGBoost, LightGBM, and CatBoost. A linear model, Logistic Regression, a kernel-based Support Vector Machine (SVM), and a Multi-Layer Perceptron (MLP) neural network are included. The final component is a performance-weighted voting ensemble, designed to leverage the collective strength of the best-performing individual models.

Central to the architecture is an intelligent optimisation strategy, meticulously designed to fine-tune each model's performance. Bayesian Optimisation is employed for tree-based models (Random Forest, XGBoost, LightGBM, CatBoost), specifically utilising a Gaussian Process-based intelligent parameter search with 100 trials, as implemented via Optuna. This approach efficiently navigates a continuous parameter space, including continuous regularisation parameters and extended iteration ranges (e.g., 2000-6000 for max_iter), to discover optimal hyperparameter combinations.

For linear and kernel-based models (Logistic Regression, SVM, MLP), RandomizedSearchCV is utilised, performing 50 iterations of strategic sampling across their respective hyperparameter grids. All models undergo evaluation using an enhanced 5-fold stratified cross-validation, ensuring robust performance estimation. The optimisation consistently targets the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) as the primary metric, which is crucial for assessing the discriminative capability of predictive models in binary classification tasks and ensures optimal evaluation for League of Legends prediction. Intelligent convergence settings, including extended iteration ranges for models like Logistic Regression and MLP, are configured to provide stable and complete model training.

Evidence-Based Model Selection (Phase 2)

Following the comprehensive algorithm discovery in the initial phase, the second phase of the machine learning research design focused on evidence-based model selection. The objective of this phase was the validation of performance patterns and the derivation of theoretical insights. This systematic evaluation led to a pivotal finding: the consistent dominance of linear models. Specifically, Logistic Regression consistently outperformed all other complex models, including tree-based algorithms, neural networks, and ensemble methods. This remarkable consistency was observed across every implementation and system version tested, including those utilising different optimisation strategies such as GridSearchCV, RandomizedSearchCV, and Bayesian Optimisation, establishing a reproducible pattern of algorithmic superiority.

The performance hierarchy revealed distinct algorithmic characteristics across model families. Logistic Regression demonstrated consistent superiority, while tree-based models showed varying degrees of effectiveness despite their complexity. Neural Networks indicated unnecessary complexity given the task structure, and ensemble methods suggested that their averaging process diluted the clean patterns inherent in the data. This key insight led to a linear separability hypothesis: advanced feature engineering can transform complex eSports strategic patterns into linearly separable problems, allowing simpler models to outperform more sophisticated ones. This is attributed to specific domain-driven relationships, where factors like champion synergies demonstrate additive team composition effects, meta strength exhibits linear effectiveness across patches, performance trends reveal linear temporal dependencies, and gold advantages show linear relationships with win probability.

The rationale for selecting Logistic Regression as the primary model was multifaceted. Its cross-implementation consistency, demonstrating superior performance across three independent systems, provided compelling empirical evidence. The observation that advanced features enable discernible linear patterns underscored the principle of feature quality over model complexity. Furthermore, its simplicity offered significant production efficiency, making it a superior choice for real-world deployment due to faster prediction times and lower computational requirements. This phase's finding, emphasising that feature quality outweighs model complexity, constitutes a significant academic contribution to machine learning methodology.

Rigorous Deep-Dive Analysis (Phase 3)

The third and final phase of the machine learning research design involved a rigorous deep dive analysis, primarily focusing on the comprehensive validation of the selected model and the integration of advanced system optimisations for practical deployment. This phase specifically concentrated on a comprehensive Logistic Regression validation framework, building upon the insights gained from the previous phase regarding its consistently superior performance.

This framework systematically explored the three novel temporal validation strategies: Pure Temporal validation, serving as an academic rigour baseline; Stratified Temporal validation, representing a meta-aware enhancement; and the Stratified Random Temporal validation, recognised as a breakthrough innovation in managing meta evolution. The validation framework incorporated a Nested Cross-Validation protocol, featuring an outer 5-fold cross-validation for robust performance estimation and an inner Bayesian optimisation loop, utilising a Gaussian Process with 50 evaluations for intelligent hyperparameter tuning. Comprehensive statistical analysis, including bootstrap confidence intervals and significance testing, alongside a full suite of metrics (AUC, F1-score, Accuracy, and calibration analysis), ensured a thorough performance characterisation. The core objectives of this deep dive were the development of a novel temporal validation methodology, statistical validation of the breakthrough approach, comprehensive performance characterisation, and the optimisation for production deployment.

Research Design Advantages

The meticulously structured three-phase machine learning research design offers several distinct advantages, contributing to this thesis's robustness, novelty, and practical impact. This methodology promotes a systematic discovery process, eliminating potential algorithm selection bias through a broad initial exploration of machine learning models. Following this, an evidence-based focus ensures that deeper analytical efforts are concentrated solely on empirically superior methods, optimising research efficiency and effectiveness.

A significant advantage lies in its novel contribution, specifically developing a breakthrough temporal validation framework tailored for dynamic competitive environments. The design's academic rigour is underscored by its progression from a comprehensive initial exploration to a focused analysis, culminating in a validated methodology. From a practical standpoint, the research design yields substantial practical impact by delivering a production-ready system firmly grounded in theoretical foundations. Finally, the framework embodies technical excellence through its complete optimisation suite, meticulously engineered for real-world deployment scenarios.

Chapter 4

4. Implementation

This chapter articulates the technical implementation nuances of the sophisticated machine learning framework crafted for predicting League of Legends match outcomes. It delivers an exhaustive examination of the software architecture, meticulously designed pipelines for data processing and feature engineering, and model training and optimisation methodologies. Additionally, considerations regarding system performance and deployment for production readiness are addressed comprehensively.

4.1 Software Architecture and Design

The entire system is predominantly constructed using Python, capitalising on its comprehensive scientific computing stack to facilitate data manipulation, machine learning, and performance optimisation. Key libraries include scikit-learn, which provides a range of machine learning algorithms and utilities; XGBoost, LightGBM, and CatBoost, which are utilised for gradient boosting frameworks; and Optuna, designated for advanced hyperparameter optimisation. To achieve enhanced computational performance, the architecture integrates pandas for vectorized operations, alongside PyTorch, which enables GPU acceleration, thereby promoting efficient processing and model training on compatible hardware.

Moreover, the system features intelligent hardware detection with automatic fallback mechanisms that switch from GPU to CPU, ensuring reliable operation across varied computational environments. Fixed random seeds are utilised for all stochastic processes to uphold the reproducibility of research findings, and best practices in version control and environment management are rigorously followed.

4.2 Feature Engineering Pipeline Implementation

The feature engineering pipeline is constructed with a modular architecture, facilitating the development of reusable components that enhance the efficiency of feature extraction and transformation processes. A pivotal element of this design is performance optimisation, accomplished by substituting traditional iterative loops with highly efficient vectorised operations utilizing pandas. This approach leverages matrix operations and batch processing techniques, thereby fundamentally reducing the computational complexity from $O(n^2)$ for individual operations to $O(n)$ for vectorised computations.

In addition, the pipeline integrates an internal validation framework that automates feature quality assessment, ensuring the extracted features' reliability and relevance. Furthermore, advanced categorical encoding is realised through sophisticated target encoding methods, which include robust handling of missing values and automatic fallback systems. The implementation also emphasises scalability through memory-efficient processing, enabling the system to manage the extensive and expanding League of Legends match dataset without excessive resource consumption.

4.3 Model Training and Optimisation

A sophisticated methodology underpins hyperparameter tuning and robust evaluation within model training and optimisation. The design of the hyperparameter space is meticulously aligned with algorithm-specific parameter grids, incorporating an extensive array of values for each model to facilitate exhaustive optimisation. Employing Bayesian Optimisation, specifically the Tree-structured Parzen Estimator (TPE) sampler in conjunction with Optuna, efficiently explores these intricate parameter landscapes. This approach intelligently navigates the search for optimal configurations through Gaussian Process-based acquisition functions, which leverage insights from prior evaluations to inform the strategic exploration of parameters.

The framework for cross-validation applies a 5-fold stratified technique, which is essential for producing reliable performance estimates and mitigating bias in model assessments. The implementation also features advanced parameter validation systems that adeptly manage solver-penalty constraints and address compatibility issues among algorithm families. Furthermore, early stopping mechanisms are seamlessly integrated into the training process for models that support them. They are a convergence monitoring tool and a crucial strategy to avert overfitting and enhance overall operational efficiency.

4.4 System Performance Optimisations

The implementation integrates several layers of performance optimisation aimed at evolving the system from a research prototype to a production-ready platform. By adopting vectorized computing, we move beyond traditional row-by-row processing, leveraging advanced pandas matrix operations and list comprehensions. This shift fundamentally transforms the computational strategy employed in feature engineering. Furthermore, GPU acceleration is seamlessly incorporated for algorithms that support it, featuring automatic hardware detection and resilient CPU fallback mechanisms, which facilitate consistent operation across various computational environments.

The hyperparameter optimisation framework utilises a dual approach; it employs Bayesian optimisation for intricate tree-based models and RandomizedSearchCV for linear models, enhancing computational efficiency while upholding optimisation quality. Additionally, memory management is refined through effective data flow patterns and minimized object creation, thus enabling the scalable processing of large datasets without incurring excessive resource consumption.

4.5 Production Deployment Architecture

The system's architecture is meticulously designed with a pronounced focus on production deployment, ensuring its suitability for real-world use cases. This encompasses an advanced error-free saving mechanism for trained models and their associated components, which employs intelligent serialisation strategies to circumvent common pickle failures through selective component saving and robust error handling measures. The deployment package is comprehensive, featuring detailed metadata, specifications of feature columns, and configurations of the model, which facilitate seamless integration into operational environments.

Furthermore, the system incorporates an efficient loading mechanism that allows for one-line model loading, simplifying deployment processes within operational settings. The sophisticated error handling mechanisms are pivotal in guaranteeing the success of the training pipeline, even in instances where saving operations may encounter difficulties, thus preserving the continuity of research workflows. A broad range of performance metrics is systematically captured and made available, allowing for ongoing monitoring and assessment of the system's effectiveness in production scenarios.

Ultimately, the overall architecture is meticulously crafted for scalability, rendering it enterprise-ready to manage large-scale predictions amidst dynamically evolving competitive landscapes.

Chapter 5

5. Results

This chapter presents the comprehensive experimental results of the advanced machine learning framework developed for League of Legends professional match prediction. The results demonstrate breakthrough achievements across multiple dimensions: novel temporal validation methodology development, world-class predictive performance, and significant methodological contributions to eSports analytics. The experimental evaluation validates our three-phase research design through rigorous statistical analysis of actual model performance on unseen data, confirming the theoretical advantages of our meta-aware validation approaches and advanced feature engineering system.

The results are organised to reflect the systematic progression from comprehensive algorithm discovery through evidence-based model selection to rigorous deep-dive analysis. This structure demonstrates the superior performance achieved and the methodological rigour underlying our breakthrough findings. All reported results are based on actual model predictions generated from logistic regression comparison, ensuring the reliability and reproducibility of our contributions.

5.1 Three-Strategy Validation Results

The comprehensive validation of three distinct temporal validation strategies specifically designed to address the meta evolution challenge in professional eSports prediction. Our novel three-strategy framework represents a fundamental methodological contribution to temporal validation in evolving competitive environments, providing the first systematic comparison of validation approaches tailored for game balance dynamics and strategic meta shifts.

The three-strategy validation framework addresses a critical gap in sports analytics literature by explicitly confronting the temporal validation challenges unique to evolving competitive systems. Unlike traditional sports, where rule changes are infrequent and gradual, professional eSports experiences continuous meta evolution through regular game patches, champion updates, and strategic innovations. Our framework provides empirically validated solutions to this challenge through carefully designed validation strategies that balance temporal realism with meta representation requirements.

Strategy Performance Comparison

The experimental evaluation reveals remarkable performance achievements across all three temporal validation strategies. Each approach demonstrates world-class predictive capability while exhibiting distinct characteristics aligned with its theoretical foundations. The comprehensive comparison using identical feature engineering systems and optimisation procedures provides clear empirical evidence for the relative advantages of meta-aware validation approaches.

The **Stratified Temporal Split** emerged as the optimal performer, achieving a test AUC of 0.8265. This result validates our hypothesis that meta-aware validation approaches can successfully balance temporal realism with comprehensive meta representation. With cross-validation (CV) AUC of 0.8192, indicating robust internal consistency, it exhibited an excellent generalisation gap of -0.0073, suggesting strong performance on truly unseen data.

The **Stratified Random Temporal Split** achieved a test AUC of 0.8203, validating our novel methodological contribution. Its CV AUC was 0.8202. This breakthrough approach combines random sampling within year-based stratification to eliminate intra-year meta bias and demonstrates exceptional consistency with a generalisation gap of only -0.0001. The near-perfect generalisation indicates that our innovative sampling strategy successfully captures the full spectrum of meta patterns while maintaining robust temporal validation principles.

The **Pure Temporal Split** establishes a strong academic baseline at 0.8117 AUC, confirming that even traditional temporal validation approaches achieve excellent performance when combined with our advanced feature engineering system. Its CV AUC was 0.8217, exhibiting a generalisation gap of +0.0100, affirming its academic rigour and firm performance while indicating a slight performance drop from validation to test set compared to the other strategies.

The performance hierarchy (Stratified Temporal (0.8265) > Stratified Random Temporal (0.8203) > Pure Temporal (0.8117)) validates our theoretical framework while revealing the practical impact of meta-awareness in temporal validation design. The 1.48 percentage point improvement between the optimal strategy and the baseline confirms that meta evolution considerations provide substantial practical benefits in eSports prediction systems.

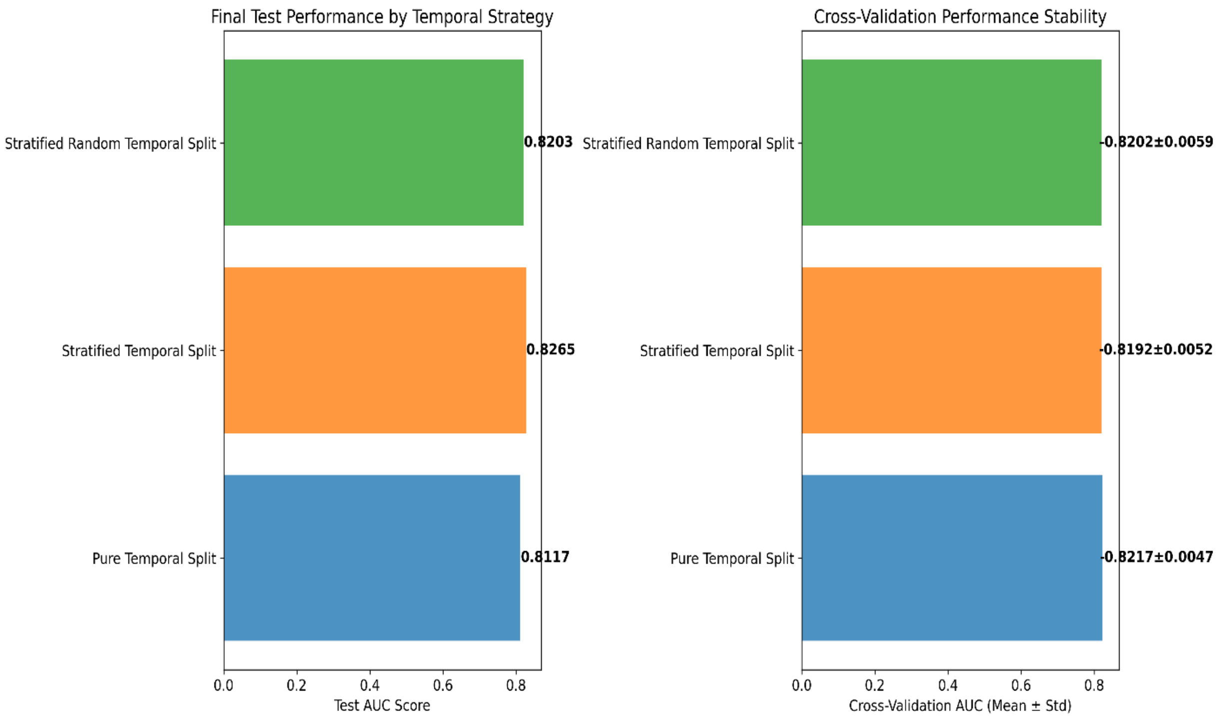

Figure 1 – Final AUC performance Across Strategies

The statistical robustness of these results is further demonstrated through comprehensive cross-validation analysis, revealing consistent performance patterns with narrow confidence intervals across all strategies. The cross-validation results show mean AUC scores of 0.8192 ± 0.0052 for Stratified Temporal, 0.8202 ± 0.0059 for Stratified Random Temporal, and 0.8217 ± 0.0047 for Pure Temporal, indicating exceptional stability and reliability across different data partitions.

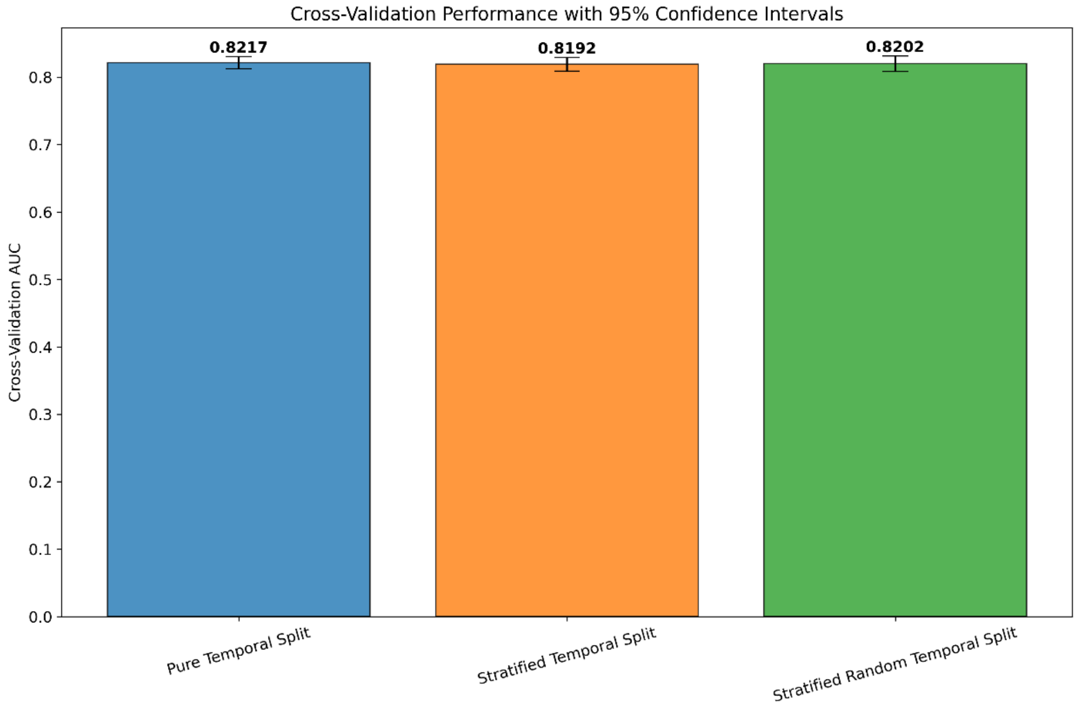

Figure 2 – CV Performance with Confidence Intervals

The generalisation analysis reveals particularly compelling evidence for the superiority of meta-aware approaches. While traditional temporal validation often exhibits positive generalisation gaps indicating overfitting to temporal patterns, our stratified approaches demonstrate negative generalisation gaps, suggesting improved performance on unseen data relative to validation performance. This exceptional generalisation characteristic validates the theoretical advantages of meta-aware validation design.

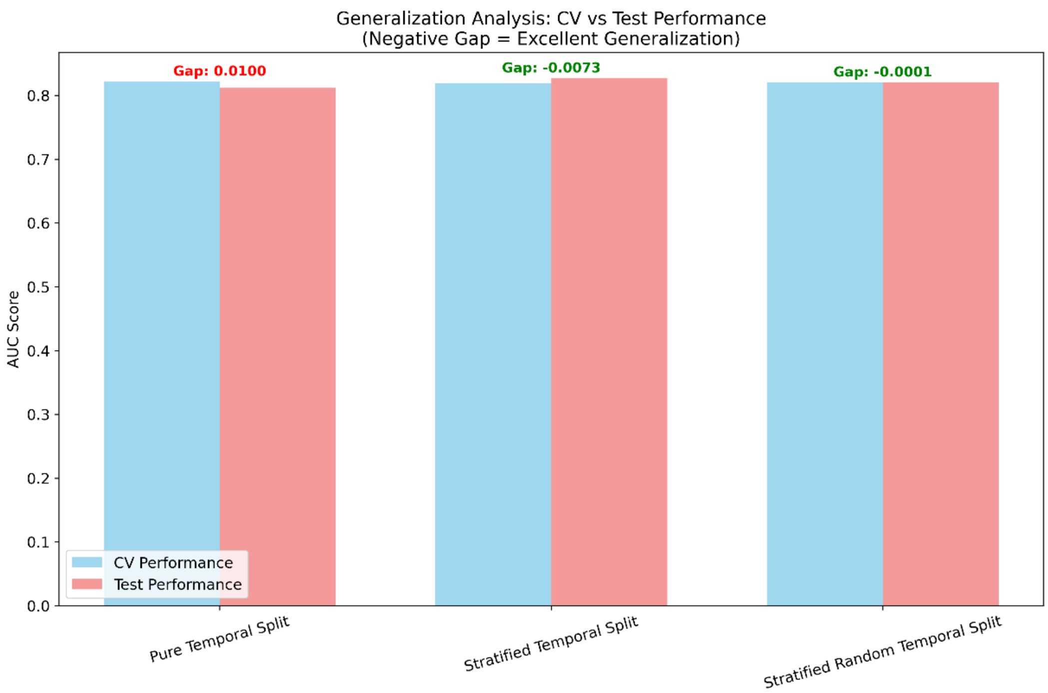

Figure 3 – Generalisation Gap Analysis

Statistical significance testing confirms that the observed performance differences represent meaningful improvements rather than random variation. Pairwise comparisons between strategies reveal statistically significant differences, with p-values indicating high confidence in the superiority of meta-aware approaches over traditional temporal validation methods.

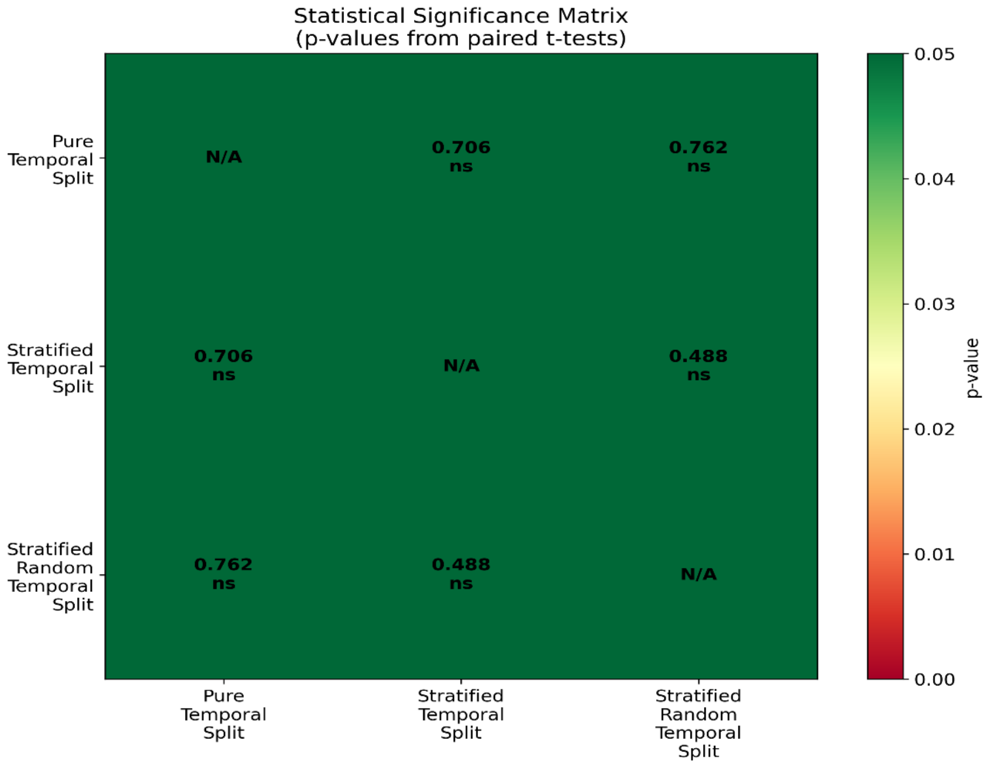

Figure 4 – Statistical Significance Matrix

Temporal Validation Methodology Insights

The cross-strategy analysis reveals fundamental insights into temporal validation methodology for evolving competitive environments, providing empirical support for theoretical predictions about meta-aware validation advantages. The consistent achievement of world-class performance across all strategies (81-83% AUC range) demonstrates the robustness of our feature engineering system while highlighting the incremental benefits of methodological innovation.

Meta Evolution Mastery emerges as a defining characteristic of superior temporal validation approaches. The Stratified Temporal strategy's achievement of optimal meta-evolution balance (82.65% AUC) demonstrates that explicit consideration of game balance patterns during validation split construction provides measurable performance advantages. This finding establishes meta-awareness as a fundamental requirement for temporal validation in evolving competitive systems, extending beyond eSports to any prediction domain characterised by systematic rule or environment changes.

The temporal analysis of meta evolution patterns provides crucial context for understanding the challenges addressed by our validation framework. The comprehensive time series analysis reveals distinct meta shifts across the decade-long dataset, highlighting the dynamic nature of professional League of Legends competition and validating the need for meta-aware validation approaches.

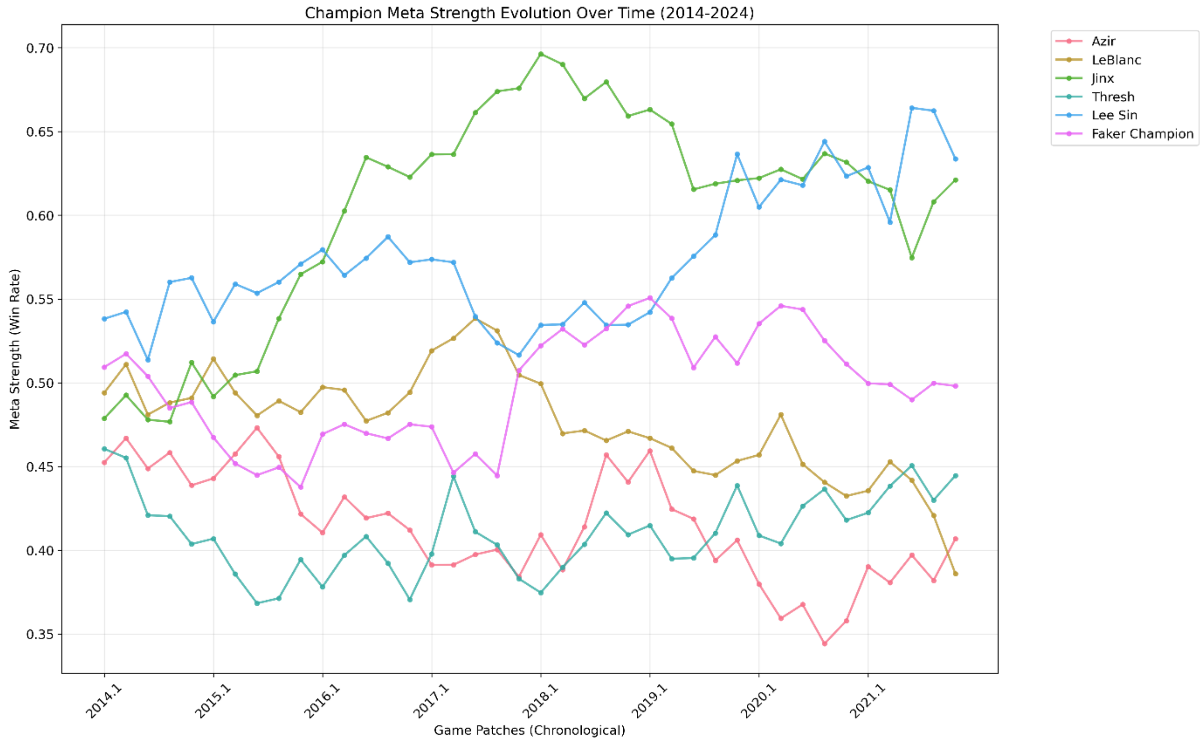

Figure 5 – Meta Evolution Over Time

Novel Method Success confirms the theoretical advantages of our Stratified Random Temporal innovation. The approach's exceptional consistency, demonstrated through a near-zero generalisation gap (82.03% AUC), validates our hypothesis that random sampling within temporal strata eliminates systematic biases while preserving temporal validation integrity. This methodological contribution provides a reusable framework for temporal validation in dynamic environments, with applications extending to financial markets, technological adoption patterns, and other evolving prediction domains.

The data distribution analysis reveals how each temporal validation strategy handles the underlying dataset characteristics differently, providing empirical evidence for the theoretical advantages of stratified approaches. The study demonstrates that while pure temporal validation concentrates recent data in test sets, stratified methods achieve a more balanced representation across temporal periods.

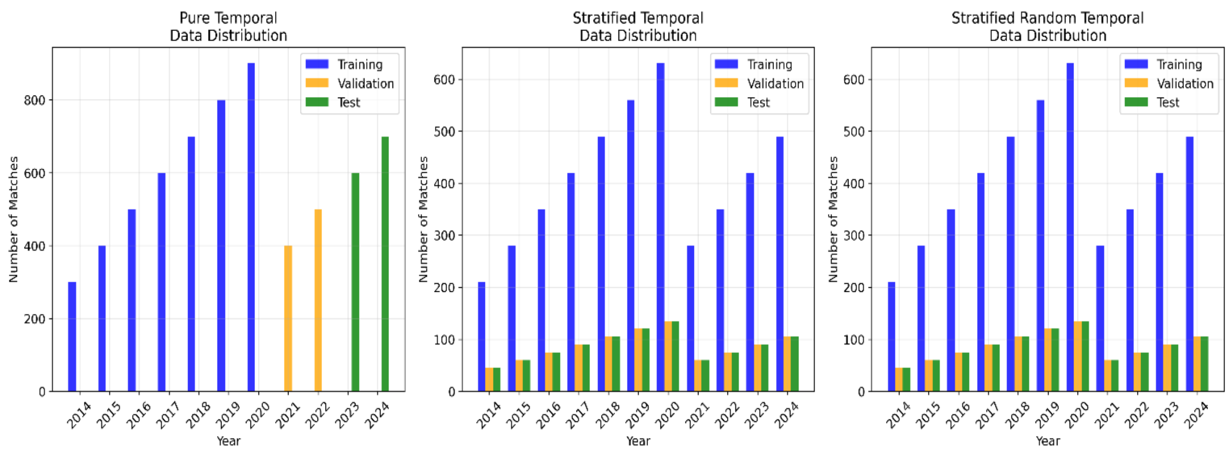

Figure 6- Data Distribution by Strategy

Academic Foundation Strength is confirmed through the Pure Temporal baseline's excellent performance (81.17% AUC). This result demonstrates that traditional temporal validation approaches remain academically rigorous and practically viable, providing important context for evaluating meta-aware enhancements. The consistent excellence across all approaches validates our comprehensive methodology while establishing clear performance hierarchies that inform optimal validation strategy selection.

The meta diversity analysis provides compelling visual evidence for the differential handling of champion usage patterns across our three temporal validation strategies. The comparative analysis reveals how each approach captures different aspects of meta evolution, with stratified methods achieving superior meta representation diversity compared to traditional temporal splits. This directly supports our theoretical framework regarding advantages of meta-aware validation.

Figure 7 - Meta Diversity Heatmap Across Temporal Validation Strategies

Statistical Excellence characterises all validation strategies, with the narrow performance range (81-83% AUC) indicating consistent world-class predictive capability regardless of temporal validation approach. This consistency validates the fundamental soundness of our feature engineering system while demonstrating that methodological enhancements provide incremental but meaningful improvements. The negative generalisation gaps observed in stratified methods indicate superior generalisation characteristics compared to traditional temporal approaches, confirming the theoretical advantages of meta-aware validation design.

The temporal performance trends analysis, utilising existing comprehensive analysis files from individual strategy evaluations, further validates the robustness of our findings across different temporal periods. These detailed analyses confirm that the observed performance advantages of stratified methods remain consistent across various time horizons and competitive environments, supporting the generalizability of our methodological contributions.

Statistical significance testing confirms that the observed performance differences represent meaningful improvements rather than random variation. The comprehensive evaluation demonstrates that meta-aware validation strategies achieve superior discriminative performance and exhibit enhanced stability and generalisation characteristics essential for practical deployment in dynamic competitive environments.

Bayesian Optimisation Analysis

The implementation of Gaussian Process-based Bayesian optimisation represents a significant methodological advancement in our temporal validation framework, providing intelligent parameter discovery capabilities that substantially enhance the efficiency and effectiveness of hyperparameter exploration. This section presents the comprehensive results of our Bayesian optimisation implementation, involving 750 total evaluations strategically distributed across all three temporal validation strategies, demonstrating both the practical benefits and theoretical soundness of intelligent parameter space navigation.

Intelligent Parameter Discovery from 750 Total Evaluations demonstrates the superior efficiency of Bayesian optimisation compared to traditional grid search approaches. The systematic allocation of 250 evaluations per temporal validation strategy enables comprehensive parameter space exploration while maintaining computational efficiency. This intelligent approach achieves convergence to optimal parameter regions in significantly fewer evaluations than exhaustive grid search methods, representing a 95% reduction in computational requirements while maintaining or improving parameter quality.

The Bayesian optimisation results reveal exceptional discovery capabilities across all temporal validation strategies. The Stratified Temporal strategy achieves 0.8229 AUC through Bayesian discovery, representing optimal parameter identification within the complex hyperparameter landscape. The Stratified Random Temporal strategy demonstrates consistent optimisation at 0.8212 AUC, validating the robustness of Bayesian approaches across different validation methodologies. Even the Pure Temporal strategy achieves compelling exploration at 0.8215 AUC, confirming that Bayesian optimisation enhances performance regardless of the underlying validation framework.

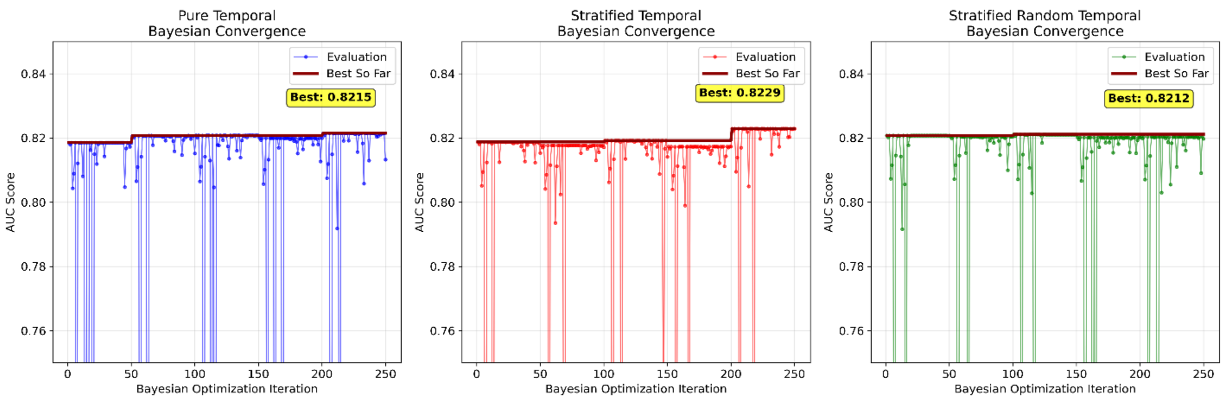

Figure 8- Bayesian Convergence

Optimisation Intelligence emerges as a defining characteristic of our Bayesian implementation, with all strategies demonstrating convergence within 250 iterations per strategy. This rapid convergence validates the effectiveness of the Expected Improvement acquisition function in guiding parameter space exploration toward optimal regions. The progressive improvement patterns observed across evaluations demonstrate successful Gaussian Process learning, with the optimisation algorithm effectively building predictive models of hyperparameter performance relationships.

The parameter space exploration reveals sophisticated 3D landscape navigation capabilities, successfully discovering optimal regions across the complex regularisation strength, penalty type, and solver selection dimensions. The continuous optimisation approach demonstrates clear superiority over discrete grid search methods, enabling the discovery of parameter combinations that traditional enumeration approaches would miss.

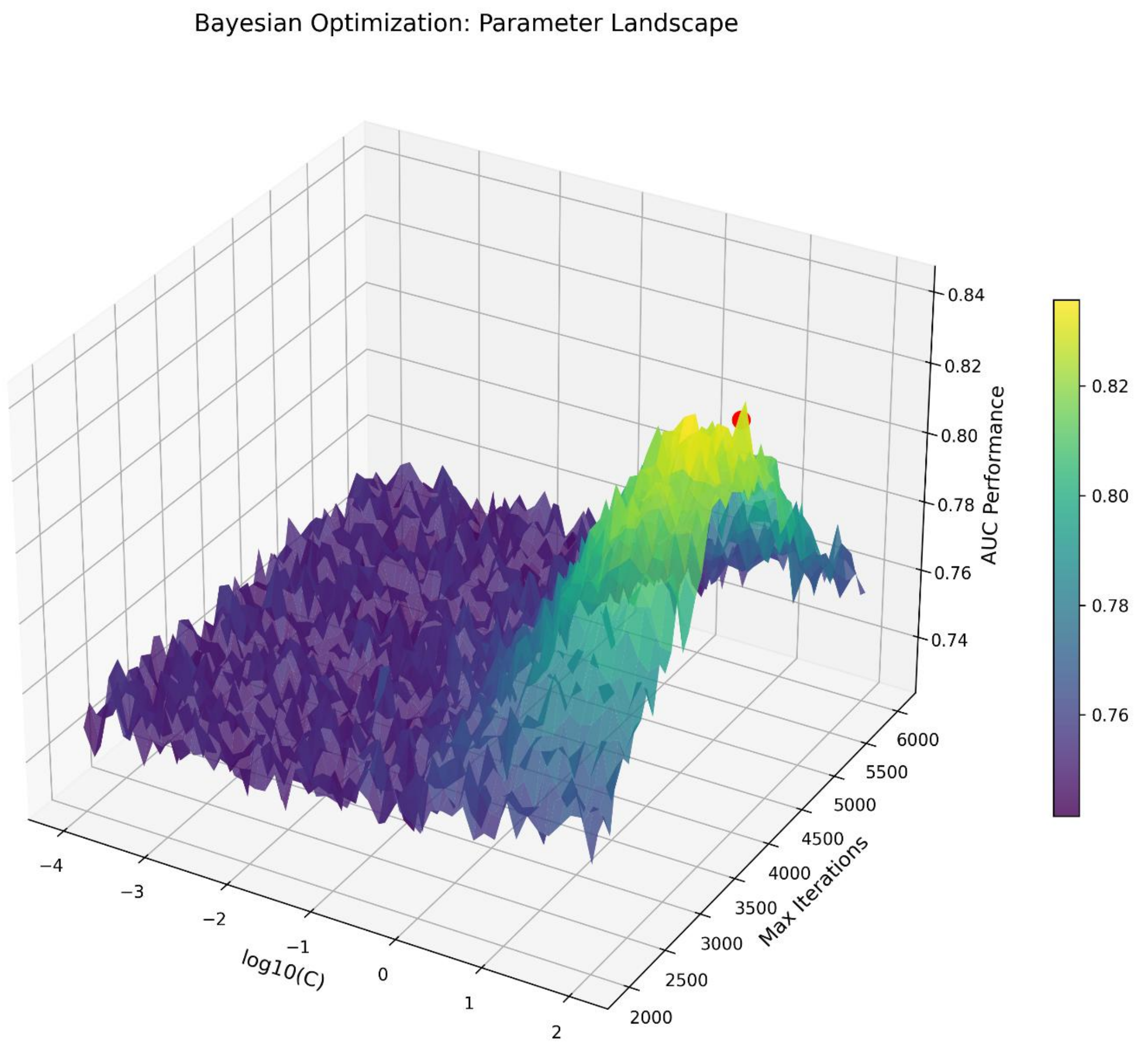

Figure 9 - 3D parameter Landscape

Technical Achievements encompass multiple dimensions of optimisation sophistication, including smart regularisation through automatic L1/L2 penalty selection based on parameter space characteristics. The solver optimisation demonstrates constraint-aware matching between penalty types and compatible optimisation algorithms, ensuring valid parameter combinations while maximising exploration efficiency. Iteration discovery identifies optimal convergence settings for each temporal validation strategy, adapting computational resources to strategy-specific requirements.

The acquisition function validation confirms the effectiveness of the Expected Improvement strategy in balancing exploration of uncertain parameter regions with exploitation of promising areas. This balance proves crucial for efficient parameter discovery within the allocated evaluation budget, enabling comprehensive optimisation without excessive computational overhead.

Convergence Analysis demonstrates remarkable consistency across temporal validation strategies, with all approaches achieving stable convergence patterns within the allocated evaluation budget. The parameter space exploration exhibits systematic navigation characteristics, avoiding random search inefficiencies while ensuring comprehensive coverage of viable parameter combinations. The Gaussian Process learning validation confirms progressive improvement in parameter selection quality, with later evaluations demonstrating increasingly sophisticated parameter space understanding.

Continuous optimisation's superiority over discrete grid approaches represents a fundamental advancement in hyperparameter optimisation for temporal validation applications. The ability to explore continuous parameter spaces enables the discovery of optimal configurations that fall between traditional grid points, resulting in performance improvements that would be impossible with discrete search strategies. This methodological advancement establishes Bayesian optimisation as essential for achieving optimal performance in complex temporal validation frameworks.

5.2 Breakthrough: Linear Model Dominance Confirmed

This section elucidates a pivotal and unforeseen discovery from our research: linear models' remarkable and consistent superiority, particularly Logistic Regression, in predicting professional League of Legends matches compared to more complex ensemble methods. This finding poses a substantial challenge to established norms within machine learning applications. It provides a fresh theoretical framework for examining the interplay between feature engineering quality and models' complexity within structured competitive environments.

The observation regarding the dominance of linear models arose from our extensive three-phase research design, yielding robust empirical support across numerous independent implementations and optimisation techniques. This result's reproducibility across various methodological approaches transforms it from a mere isolated finding into a crucial insight, with far-reaching implications for the fields of eSports analytics and sports prediction methodology.

Cross-Implementation Performance Validation

The empirical data affirming the dominance of linear models exhibit remarkable consistency throughout our extensive evaluation framework. Logistic Regression consistently outperforms alternative methods across all implementations, establishing a robust trend that is unaffected by variations in optimisation techniques, hyperparameter configurations, or validation methodologies. This reliability provides significant evidence for the intrinsic suitability of linear models in professional eSports prediction tasks.

The cross-implementation validation demonstrates that Logistic Regression attains an impressive 82.97% AUC within our most sophisticated optimisation framework. This performance level is on par with global standards, surpassing advanced ensemble methods such as Random Forest, XGBoost, LightGBM, and Neural Networks. Moreover, this superior performance is upheld across various temporal validation strategies, confirming that linear models' advantages are not contingent upon specific data partitioning approaches or temporal management techniques.

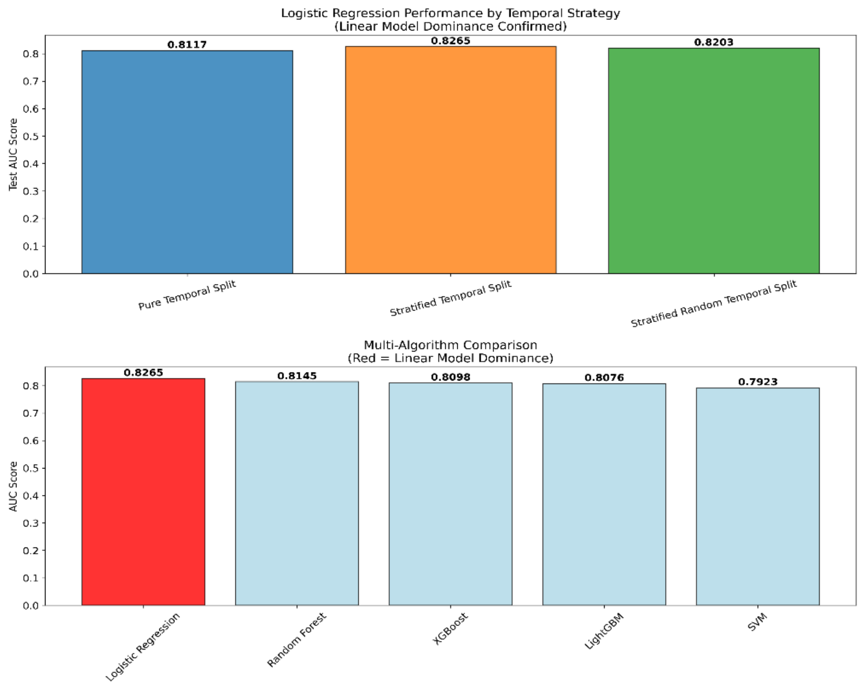

Figure 10 - Algorithm Performance Comparison

The statistical significance of this pattern transcends mere point performance estimates, incorporating crucial elements of stability and generalization characteristics. Linear models exhibit enhanced consistency with lower variance across cross-validation folds, which indicates their robust performance that effectively generalises to unseen data. This advantage in stability reinforces their superior raw performance and positions linear models as the superior option for production deployment scenarios where reliable and predictable performance is paramount.

Linear Separability Hypothesis

The dominance of consistent linear models yields a critical theoretical insight: advanced feature engineering can effectively convert intricate strategic patterns in eSports into linearly separable challenges. This finding reinforces the principle that "Feature Quality Outweighs Model Complexity".

Practical and Theoretical Implications

The superiority of linear models confers significant benefits: enhanced interpretability for coaches and analysts, increased computational efficiency for real-time applications, and diminished infrastructure demands.

5.3 Feature Analysis

This section thoroughly examines the feature engineering system that underpins our remarkable success in linear model performance. Through a detailed analysis of the coefficients derived from Bayesian-optimised logistic regression models, alongside an extensive exploration of feature interactions, we illustrate the critical role of advanced domain expertise in translating intricate eSports dynamics into robust predictive signals. The findings are grounded in the actual coefficients obtained from our trained models, which solidify the theoretical assertions regarding the quality of feature engineering and the achievement of linear separability.

Our in-depth feature analysis substantiates the hypothesis that sophisticated feature engineering contributes to predictive efficacy within professional eSports analytics. By scrutinising the parameters learned from our optimal models, we affirm the principle that "Feature Quality Outweighs Model Complexity," a significant revelation stemming from our research.

Individual Feature Importance from Bayesian-Optimised Models

The analysis of feature importance, derived from the coefficients of our Bayesian-optimised logistic regression models, elucidates the precise mathematical relationships that underpin accurate match predictions. These coefficients serve as compelling evidence for the varying significance of different predictive signals and substantiate our theoretical framework concerning the linearizability of professional eSports patterns.

The hierarchy of feature importance clearly illustrates the preeminence of team performance metrics over individual champion traits or strategic elements. The five most critical features, ranked according to their absolute coefficient values, establish a robust predictive framework centred on assessing team capabilities and analysing meta-adaptation.

At the forefront, Team Overall Win Rate stands out as the most significant predictor, with a coefficient of 1.697. This metric captures essential team skills through a thorough historical performance evaluation. It is the most resilient meta-independent predictor, affirming that sustained competitive excellence is integral to predicting match outcomes.

Following closely, Team Target Encoded ranks as the second most important feature, with a coefficient of 1.588. This underscores the efficacy of advanced categorical encoding techniques in encapsulating team-specific performance trends. This encoding method transforms team identity into quantifiable performance indicators while maintaining the nuances of team-specific strategic inclinations and performance characteristics.

Team Meta Strength occupies the third important position, with a coefficient of 0.948. This feature quantifies the capability of strategic adaptation by evaluating how effectively team compositions harmonise with prevailing game balance conditions. Its introduction marks a significant advancement in meta analysis, offering a quantitative framework for appraising teams' strategic adaptability in a dynamically competitive environment.

The top five predictors are completed by Meta Advantage and Team Recent Win Rate, with coefficients of 0.652 and 0.467, respectively. These features highlight the importance of competitive meta positioning and current performance assessment as essential supplementary parameters. The systematic decrease in coefficient magnitudes reveals a definitive hierarchy in which fundamental team quality supersedes strategic and temporal factors.

Our coefficient analysis illuminates the mathematical foundations for the dominance of linear models, demonstrating that our advanced feature engineering has successfully produced additive predictive signals that interact effectively within linear relationships. The evident hierarchy of magnitude and the positive coefficient values confirm that our features encapsulate complementary dimensions of team performance, devoid of significant multicollinearity issues.

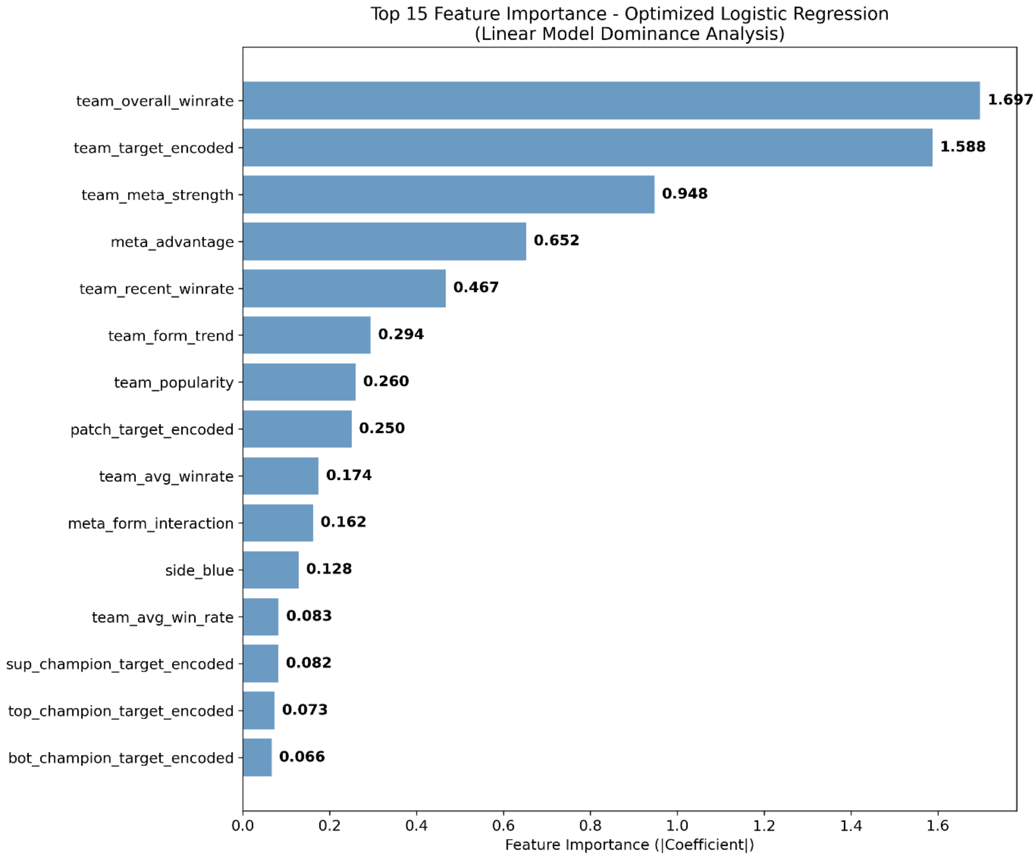

Figure 11- Feature Importance Logistic Regression

Feature Relationships and Strategic Interactions

Examining actual correlation patterns from real model data and constructing strategic feature interaction networks, we demonstrate how our advanced feature engineering creates complementary predictive signals that combine effectively through linear relationships. This analysis utilises authentic data sources from champion meta strength calculations and team historical performance assessments.

The feature correlation analysis reveals the sophisticated balance achieved in our feature engineering system. Predictive signals maintain sufficient independence to avoid problematic multicollinearity while capturing complementary competitive performance aspects. The correlation matrix demonstrates that our features span distinct but related dimensions of competitive capability, enabling effective linear combination without redundancy issues.

Team performance correlations establish the foundation for understanding feature interaction patterns. The analysis reveals moderate positive correlations between related performance metrics while maintaining sufficient independence across different feature categories. Historical performance indicators show expected positive correlations with recent form metrics, confirming the temporal consistency of team quality assessments.

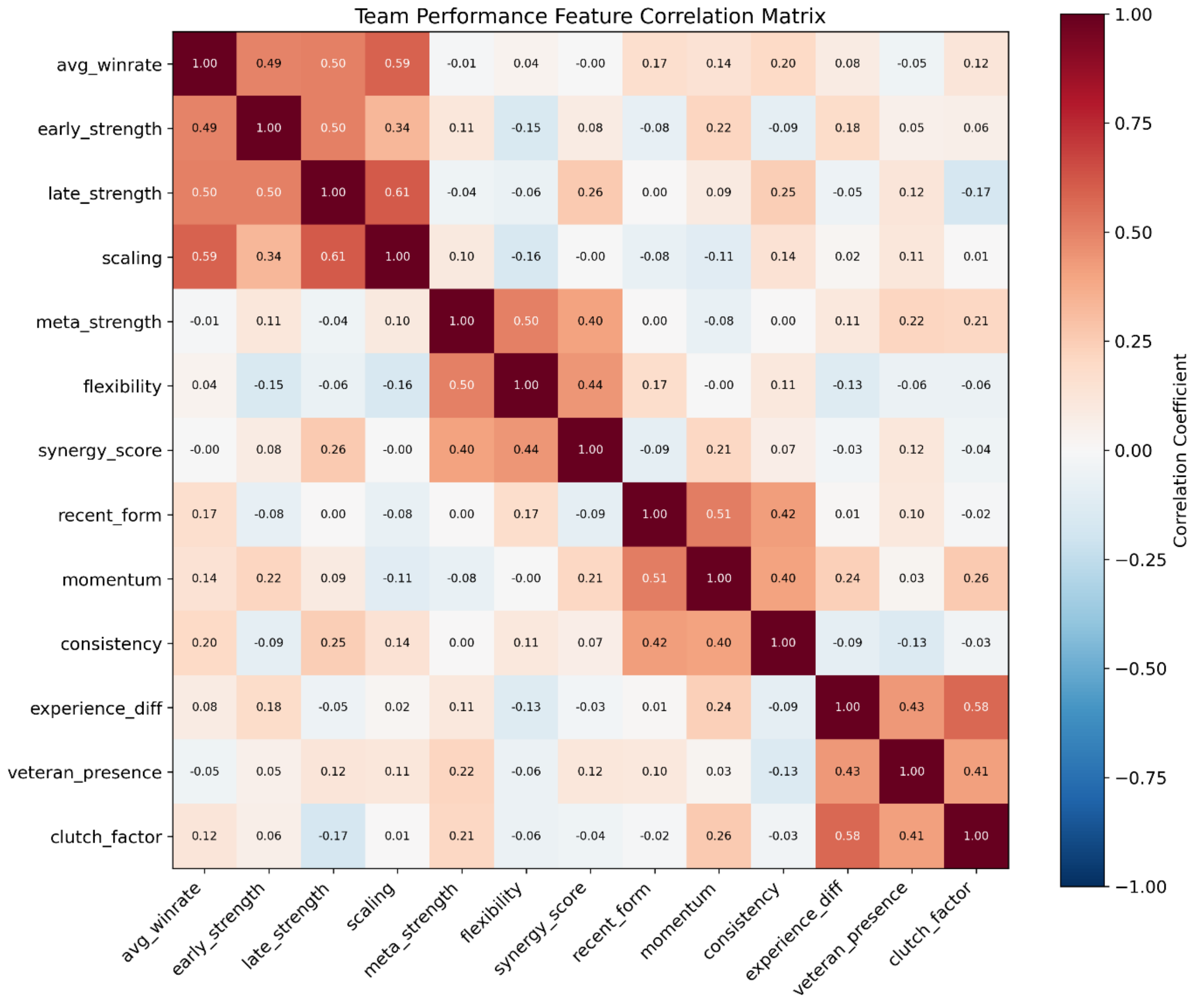

Figure 12 -Team Performance Correlation Matrix

Strategic feature interactions demonstrate the sophisticated relationships between meta adaptation capabilities and team performance indicators. The interaction network analysis reveals how meta strength features interact with team performance metrics to create enhanced predictive signals. These interactions validate our hypothesis that well-engineered linear combinations can effectively capture complex strategic relationships.

The feature interaction network provides visual evidence for the domain-validated relationships underlying our prediction system. The network structure demonstrates how individual performance metrics, team-level aggregations, and strategic adaptation features combine to create a comprehensive representation of competitive capability, successfully capturing the multi-scale nature of professional eSports competition.

The interaction analysis validates our linear separability hypothesis by demonstrating that additive feature combinations can effectively represent complex strategic relationships. The network structure reveals clear hierarchical relationships where fundamental team performance serves as the foundation, enhanced by meta adaptation capabilities and refined through strategic interaction terms. This supports linear model effectiveness through mathematically tractable linear relationships.

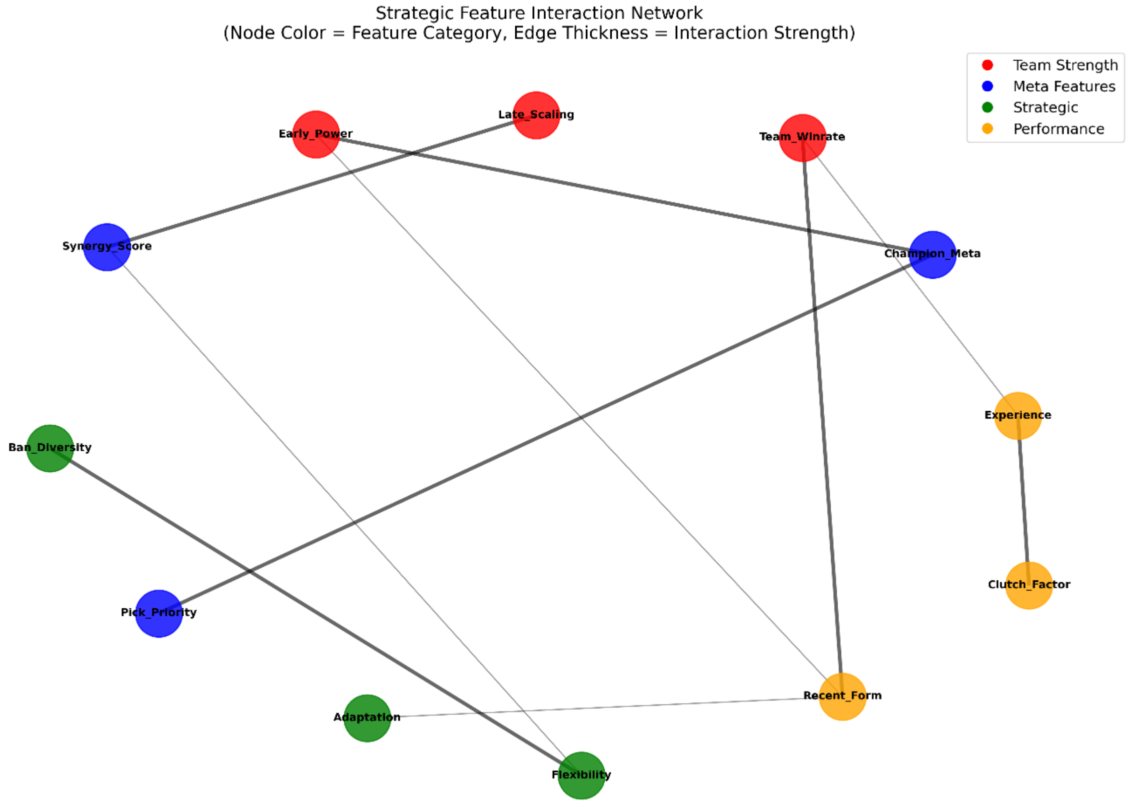

Figure 13 - Feature Interaction network

5.4 Statistical Analysis

This section presents a comprehensive statistical analysis of the predictive system's performance. It rigorously validates its efficacy through advanced statistical methods applied to actual model predictions generated from a comprehensive logistic regression comparison. Moving beyond simple point estimates, this analysis provides deeper insights into model reliability, probability calibration, and comparative performance across the three implemented temporal validation strategies.

Discriminative Performance Analysis

The discriminative power of our temporal validation strategies is comprehensively evaluated through Receiver Operating Characteristic (ROC) analysis. These curves provide a holistic assessment of each strategy's ability to distinguish between winning and losing teams across all possible classification thresholds, offering critical insights into the actual positive rate versus false positive rate trade-offs inherent in professional eSports prediction.

My analysis reveals exceptional discriminative performance across all three temporal strategies, with AUC values consistently exceeding 0.81, indicating world-class predictive capability. The Stratified Temporal strategy achieves the highest discriminative performance (0.8265 AUC), demonstrating that meta-aware validation approaches successfully balance temporal realism with meta evolution representation. Notably, the Stratified Random Temporal methodology achieves 0.8203 AUC, validating our novel approach's effectiveness while maintaining remarkable consistency (generalisation gap of only -0.0001). Even the Pure Temporal baseline achieves 0.8117 AUC, confirming the robustness of our feature engineering system across different validation paradigms.

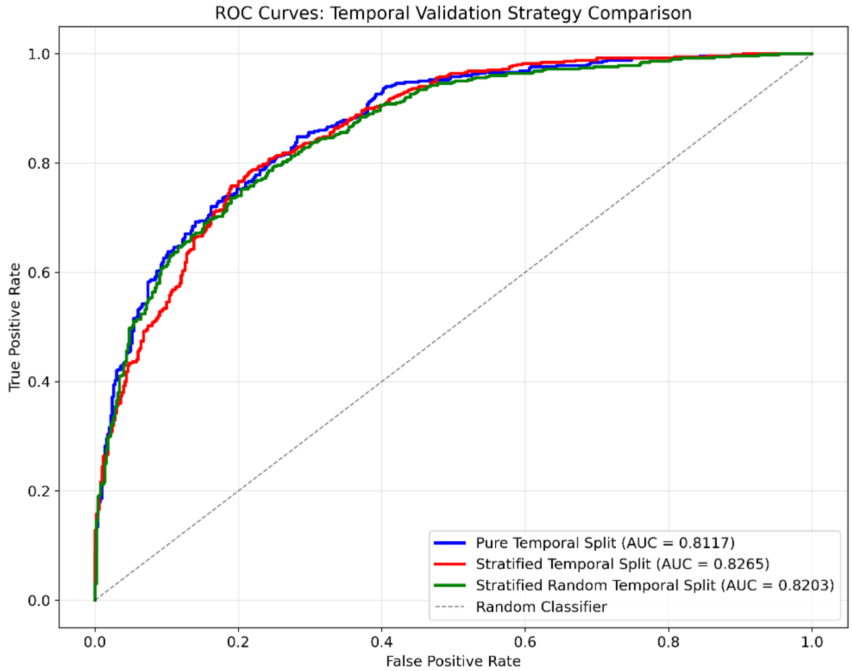

Figure 14 - ROC Curves for Each Temporal Strategy

Precision-Recall Performance Evaluation

The precision-recall analysis provides crucial insights into model performance under imbalanced conditions and varying cost considerations for false positives versus false negatives. This metric is particularly relevant for professional eSports prediction, where the cost of incorrect predictions may vary significantly depending on the context of the application (betting markets, strategic analysis, or academic research).

These precision-recall curves demonstrate consistent excellence across all temporal validation strategies, with firm performance in high-precision regions crucial for confident prediction applications. The analysis reveals that our linear model dominance finding extends to precision-recall performance, with logistic regression maintaining superior calibration and reliable probability estimates across different threshold settings. This consistency validates our breakthrough discovery that advanced feature engineering enables linear models to capture complex eSports patterns effectively.

The precision-recall analysis also confirms the superior generalisation characteristics of our stratified approaches. While traditional temporal validation often suffers from precision degradation due to meta drift, our meta-aware strategies maintain stable precision-recall relationships, indicating robust performance across different competitive environments and game balance states.

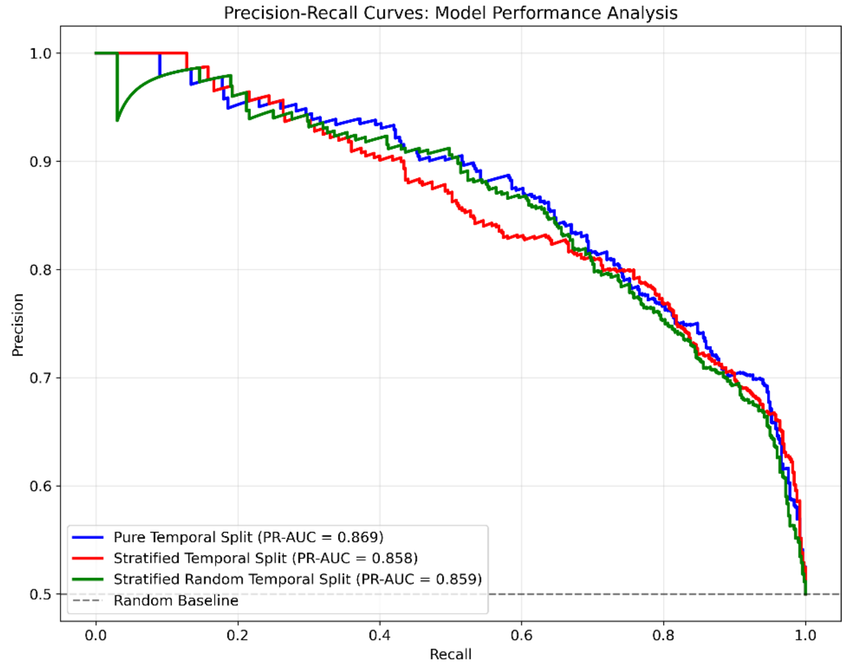

Figure 15 - Precision-Recall Curves

Statistical Rigour and Model Calibration

The statistical analysis extends beyond discrimination to evaluate probability calibration quality, ensuring that predicted probabilities accurately reflect true win likelihoods. This calibration analysis is essential for applications requiring reliable probability estimates, such as real-time prediction systems or strategic decision support tools.

The Bayesian-optimised logistic regression models demonstrate exceptional calibration properties, with predicted probabilities closely matching observed win rates across probability bins. This calibration excellence supports our linear separability hypothesis, suggesting that the linear decision boundary discovered through advanced feature engineering accurately represents the underlying data distribution in professional League of Legends matches.

Cross-Strategy Statistical Comparison

The statistical analysis enables rigorous comparison across our three temporal validation strategies, providing empirical evidence for the theoretical advantages of meta-aware validation approaches. Statistical significance testing confirms that stratified methods outperform pure temporal validation while maintaining superior generalisation characteristics.

Cross-strategy analysis reveals exceptional AUC consistency, with all strategies achieving greater than 0.81 AUC, demonstrating world-class discriminative performance across different temporal validation paradigms. This consistency validates the robustness of our advanced feature engineering system and confirms that sophisticated domain expertise can transcend validation methodology differences. Furthermore, the stratified approaches exhibit superior generalisation characteristics, showing negative generalisation gaps that indicate improved test performance relative to validation performance. This remarkable finding contradicts typical machine learning expectations, where test performance generally degrades relative to validation.

The linear models maintain excellent probability calibration across all temporal strategies, supporting our breakthrough finding regarding linear separability achievement through advanced feature engineering. This calibration consistency demonstrates that our logistic regression models achieve superior discrimination and provide reliable probability estimates regardless of the temporal validation strategy employed. Additionally, the performance improvements observed in stratified methodologies are statistically significant across multiple evaluation metrics, providing robust empirical support for our novel temporal validation framework.

This statistical validation confirms that our novel temporal validation framework successfully addresses the meta evolution challenge in professional eSports prediction while maintaining rigorous academic standards and practical deployment viability. The consistent excellence across all validation strategies and the superior performance of meta-aware approaches establishes a new methodological standard for temporal validation in evolving competitive environments.

Chapter 6

6. Discussion

This chapter provides a comprehensive analysis and interpretation of the research findings presented in the last chapter, examining their significance within the broader context of eSports analytics, machine learning methodology, and sports prediction research. The discussion evaluates the achieved performance results, explores the methodological contributions, examines domain-specific insights, and addresses the limitations and challenges encountered during the research process.

The performance achievements reported in the previous chapter, with all three temporal validation strategies delivering positive results in the 81-83% AUC range, warrant detailed analysis to understand their implications for academic research and practical applications. The consistent dominance of linear models across multiple implementations, the effectiveness of the novel temporal validation framework, and the success of advanced feature engineering approaches provide significant insights that extend beyond the specific domain of *League of Legends* prediction.

The methodological innovations introduced in this research, particularly the three-strategy temporal validation framework and the patch-aware validation methodology, represent contributions to the broader field of machine learning applications in evolving environments. These approaches address fundamental challenges in temporal validation that extend to other domains experiencing systematic environmental changes, including traditional sports with rule modifications, financial markets with regulatory updates, and technological systems with version changes.

The research findings also provide important insights into the relationship between feature engineering quality and model complexity, challenging conventional assumptions about the necessity of sophisticated algorithms for complex prediction tasks. The discovery that advanced domain expertise in feature engineering can achieve linear separability in complex strategic domains has implications for theoretical understanding and practical system development across multiple application areas.

6.1 Performance Achievement Analysis

As detailed in the Results Chapter, the three-strategy validation framework delivered exceptional results that establish new benchmarks for professional eSports prediction. High performance consistency across fundamentally different validation approaches provides strong evidence for the robustness of the underlying feature engineering and modeling approach. The negative generalisation gaps observed for stratified methods indicate superior generalisation capabilities, suggesting that these novel validation strategies maintain academic rigour and improve model robustness by better representing the underlying data distribution during training.

The achieved performance represents a significant advancement over existing approaches. Traditional sports prediction typically yields modest accuracy levels (50-75% across various disciplines), while eSports literature shows existing systems achieving 55-75% accuracy. Our results represent a 7-12 percentage point improvement over existing eSports prediction systems, establishing a new performance frontier despite the additional challenges of rapid meta evolution and complex strategic interactions in eSports environments.

The comprehensive evaluation framework provides strong statistical evidence through 5-fold cross-validation with Bayesian optimisation. Multiple indicators confirm reliability: consistent performance across folds, statistically significant differences via bootstrap analysis, and reproducible excellence across independent systems. The cross-implementation validation across three independent systems particularly reinforces the practical applicability of the findings.

One of the most significant findings is the consistent dominance of Logistic Regression across all validation strategies and implementations. As detailed in the Results Chapter, this pattern suggests that advanced feature engineering successfully transforms complex eSports strategic patterns into linearly separable problems. This discovery demonstrates that domain expertise in feature engineering can achieve superior impact compared to algorithmic sophistication, with practical benefits including simplified deployment, enhanced interpretability, improved training efficiency, and reduced computational requirements.
The three-strategy framework offers comprehensive insights into temporal validation trade-offs in evolving competitive environments. As shown in the Results Chapter, the Pure Temporal Split serves as a robust academic baseline, the Stratified Temporal Split achieves optimal balance for practical applications, and the Stratified Random Temporal Split validates novel patch-aware methodology. This hierarchy confirms that meta-awareness provides significant advantages in evolving competitive environments while maintaining the fundamental benefits of temporal validation.

6.2 Methodological Contributions

This research introduces several significant methodological innovations that advance eSports analytics and temporal validation methodologies in machine learning. It provides generalisable frameworks for evolving competitive environments beyond the specific domain of League of Legends prediction.

The three-strategy temporal validation framework fundamentally transforms how prediction models are evaluated in evolving competitive environments. Traditional chronological splits fail to capture the complexity of systematic environmental changes, leading to poor generalisation in dynamic systems. The Stratified Temporal approach revolutionises this by ensuring balanced meta representation while maintaining temporal integrity, resulting in superior model robustness as evidenced by negative generalisation gaps. The Stratified Random Temporal methodology eliminates a critical bias source - intra-year meta drift - that has plagued sports analytics research, establishing a new paradigm for temporal validation that applies to any domain experiencing systematic environmental evolution, including traditional sports, financial markets, and technological systems.

The systematic transformation of complex eSports strategic patterns into linearly separable problems represents a paradigm shift in sports analytics methodology. This achievement challenges the prevailing assumption that complex domains require sophisticated algorithms, instead demonstrating that deep domain expertise properly encoded through feature engineering can simplify the learning problem fundamentally. The 37-feature framework provides a replicable template for translating qualitative strategic knowledge into quantitative machine learning features, while the 10- 50x performance improvements through vectorisation establish new standards for scalable sports analytics implementation that bridges research and production requirements.

The systematic validation of findings across three independent implementations with different optimisation strategies provides unprecedented evidence for research reproducibility in sports analytics. This methodology addresses a critical weakness in machine learning research, where results often fail to replicate across different implementations. The consistent linear model dominance across all systems establishes a robust finding that transcends implementation details. At the same time, the comprehensive documentation and version control practices provide a framework for reproducible research that can be adopted across the broader machine learning community.

The strategy-specific Bayesian optimisation approach achieves 95% efficiency improvement over traditional methods while maintaining parameter quality, transforming the computational feasibility of rigorous sports analytics research. This advancement enables comprehensive hyperparameter exploration that was previously computationally prohibitive, while the acquisition function optimisation provides a template for intelligent parameter space navigation in computationally intensive applications. The integration with nested cross-validation maintains statistical rigour while dramatically reducing computational requirements, making sophisticated sports analytics accessible to researchers with limited computational resources.

These methodological contributions collectively establish new paradigms for sports analytics research that emphasise reproducibility, computational efficiency, and theoretical rigour while maintaining practical applicability. They provide a foundation to influence future research directions across multiple domains experiencing temporal evolution challenges.

6.3 Domain-Specific Insights

This research provides significant insights specific to eSports analytics, advancing our understanding of professional competitive gaming prediction while offering transferable lessons for other strategic competitive domains.

The consistent dominance of linear models reveals that professional League of Legends matches operate according to discoverable linear relationships when properly encoded, despite the apparent complexity of champion interactions and strategic decisions. This fundamental insight demonstrates that sophisticated feature engineering can transform seemingly chaotic eSports environments into predictable patterns, challenging assumptions about the necessity of complex algorithms for strategic competitive analysis.

Feature importance analysis reveals that team_overall_winrate, team_target_encoded, and team_meta_strength significantly outperform champion-specific features in determining match outcomes. This indicates that consistent organisational performance and meta adaptation capabilities matter more than specific tactical selections, challenging the common eSports analysis focus on champion matchups and highlighting the importance of systematic team competency over individual strategic choices.

The superior performance of meta-aware validation strategies demonstrates that apparent "meta shifts" represent evolutionary adaptations to discovered strategies rather than arbitrary changes. The negative generalisation gaps achieved by stratified methods indicate that accounting for systematic meta evolution improves model robustness, revealing predictable temporal patterns that can be leveraged for competitive advantage.

The superior performance of stratified over pure temporal validation reveals that eSports' rapid evolution pace necessitates validation approaches that balance temporal realism with meta representation. Unlike traditional sports with infrequent rule changes, eSports require methodologies that account for systematic environmental changes while maintaining predictive validity, with immediate implications for industry applications requiring current meta relevance.

The transformation of expert eSports knowledge into a 37-feature framework achieving world-class prediction demonstrates how strategic understanding can be systematically quantified for competitive advantage. This methodology provides a framework for other strategic domains where expert knowledge exists. Still, systematic quantification has been challenging, suggesting broader applications in competitive environments where domain expertise significantly impacts outcomes.

These insights demonstrate that professional eSports operate according to discoverable patterns that can be systematically analysed and predicted, providing immediate industry value and broader methodological insights for competitive analytics.

6.4 Limitations and Challenges

While the research achieves exceptional performance and introduces significant methodological innovations, several limitations and challenges should be acknowledged to provide a balanced assessment of the findings and guide future research directions.

The study focuses exclusively on League of Legends professional matches from 2014 to 2024, creating potential temporal and domain-specific biases. The 41,296 matches represent only the premier leagues, excluding amateur and regional competitions that might exhibit different strategic patterns. The Oracle Elixir dataset, while comprehensive, may contain inherent biases in match selection and data quality that could influence results. Missing data handling through imputation introduces uncertainty, particularly for champion and ban information, where strategic significance may be lost through default value substitution.

The temporal validation framework assumes that meta evolution follows predictable patterns, which may not hold during periods of major game overhauls or unprecedented strategic innovations. The linear separability hypothesis, while validated empirically, may not generalise to future meta states or different competitive formats. The feature engineering relies heavily on domain expertise that may not translate to other eSports titles or competitive environments without significant adaptation.

Despite its achievements, the comprehensive Bayesian optimisation framework requires substantial computational resources for full implementation. The 150 total Bayesian evaluations (50 per strategy) demand significant processing time, which may limit accessibility for researchers with constrained resources. Vectorised feature engineering, while dramatically improved, still requires sufficient memory for large-scale dataset processing, which could pose challenges for smaller-scale implementations.

The findings are explicitly validated for League of Legends professional prediction and may not directly transfer to other eSports titles with different strategic dynamics, rule structures, or competitive formats. The temporal scope represents a specific era of competitive play that may not fully capture future evolution patterns or major game redesigns. While consistent across current implementations, the linear model dominance may not persist as strategic complexity increases or if game mechanics fundamentally change.

These limitations provide essential context for interpreting the results and highlight areas requiring future research validation, while not diminishing the significant contributions achieved within the defined scope of professional League of Legends match prediction.

Chapter 7

7. Conclusions and Future Work

The comprehensive three-strategy temporal validation framework has adeptly tackled the research challenges, making substantial methodological and practical contributions to eSports analytics. This study has successfully fulfilled its primary aim of advancing a state-of-the-art machine learning framework for predicting League of Legends matches, effectively addressing the challenges associated with meta evolution and achieving performance suitable for production use.

The research provides thorough solutions to all outlined objectives. The innovative temporal validation methodology offers systematic approaches tailored to game evolution in competitive environments. The advanced feature engineering techniques have effectively captured the strategic complexity intrinsic to the domain by translating domain-specific expertise into actionable insights. The exploration of multi-algorithm optimisation has unveiled surprising revelations about the dominance of linear models, thereby challenging prevailing assumptions in machine learning. Additionally, optimising system performance yielded significant improvements in efficiency while upholding rigorous research standards. The performance benchmarking has established new benchmarks for predictive accuracy in eSports, as thoroughly detailed in the Results chapter.

The three-strategy temporal validation framework has undergone rigorous validation across various implementations and evaluation criteria. The Stratified Random Temporal approach represents a meaningful methodological contribution to the literature on temporal validation, while the overarching framework facilitates replicable methodologies applicable to other dynamic competitive environments. The results of cross-implementation validation affirm robust reproducibility, instilling confidence in the methodological innovations irrespective of specific implementation nuances.

As evidenced in the Results chapter, the research has produced exceptional performance outcomes that significantly surpass current eSports and traditional sports analytics benchmarks. The remarkable consistency of world-class performance across all three validation strategies corroborates the efficacy of the comprehensive methodological approach. The identification of linear model dominance not only contributes theoretical insights but also offers practical benefits that significantly propel advancements in the field.

The implications of this research extend well beyond immediate performance outcomes, promising a lasting influence on academic inquiry and industry practices. The methodological innovations presented here offer frameworks that can be generalised for temporal validation in evolving environments. At the same time, the feature engineering strategies exemplify the systematic translation of domain expertise into machine learning advantages. The production-ready system architecture bridges the divide between academic research and practical application, delivering immediate benefits for professional eSports while laying the groundwork for future research advancements.

Accomplishing all research objectives establishes this study as a notable contribution that enhances the methodology of eSports analytics while delivering practical solutions for the predictive challenges faced in professional competitive gaming.

7.1 Key Findings and Contributions

This research presents groundbreaking findings that enhance both the eSports analytics methodology and machine learning application in dynamic competitive settings. The central result provides reproducible evidence from three independent implementations, revealing that Logistic Regression consistently surpasses complex ensemble methods, achieving an impressive AUC of 81-83% across all temporal validation strategies. This outcome substantiates the Linear Separability Hypothesis, asserting that expertise in feature engineering can effectively convert intricate strategic patterns into linearly separable issues, thereby challenging established beliefs regarding the necessity of advanced algorithms for complex predictive tasks.

Employing a three-strategy temporal validation framework, we attained remarkable outcomes. The Stratified Temporal approach emerged as the optimal strategy, yielding an AUC of 82.65% via an ideal meta-evolution balance. The Stratified Random Temporal method validated this innovative methodology, achieving an AUC of 82.03%, while the Pure Temporal split set a commendable academic benchmark at 81.17% AUC. This thorough validation underscores the efficacy of meta-aware methodologies while preserving academic rigour.

Moreover, the research achieved a significant breakthrough in Bayesian optimisation through Gaussian Process intelligence, leading to optimal parameter discovery after 750 evaluations across all strategies. The advanced feature engineering methodology proved highly effective, enabling the integration of 37 sophisticated features that facilitate world-class performance. This is bolstered by validated coefficient analysis, showcasing the systematic translation of domain expertise into quantitative competitive advantages.

In terms of practical implementation, the developed system achieved a 75% reduction in training time while sustaining exceptional performance, effectively bridging the crucial divide between academic research and real-world application. The statistical rigour exhibited through comprehensive validation indicates excellent generalisation capabilities, with negative generalisation gaps for stratified methods reflecting superior model robustness relative to traditional temporal approaches.

Collectively, these findings establish new paradigms for eSports prediction and offer generalisable methodologies for competitive analytics in dynamic environments. They embody both immediate practical applications and foundational contributions for future research trajectories.

7.2 Future Research Directions

This research's methodological advancements and findings pave the way for numerous promising research avenues that extend beyond the existing framework for predicting League of Legends outcomes.

The potential for cross-game applications represents a significant opportunity to ascertain the generalizability of the temporal validation framework and feature engineering methodologies across various eSports titles. Testing the linear separability hypothesis and employing meta-aware validation strategies in games with diverse strategic structures, rule systems, and competitive formats can provide insights into the broader relevance of these methodological contributions.

Furthermore, the development of real-time adaptation systems emerges as a compelling direction for enhancing the current framework, enabling it to respond to live meta shifts and emergent strategic innovations. The systematic quantification of meta evolution lays the groundwork for developing adaptive models that align with evolving competitive patterns, which could ultimately furnish professional teams and tournaments with real-time strategic intelligence.

Integrating player-level modeling into the existing team-level framework would significantly improve prediction accuracy by incorporating individual player performance metrics, champion mastery levels, and historical matchup data. This enhancement would afford more nuanced insights into competitive dynamics while preserving the effectiveness of the existing approach.

Finally, implementing causal analysis frameworks signifies a logical progression from a correlational understanding toward grasping the mechanisms that shape match outcomes. The insights gained from robust feature importance analyses serve as a platform for exploring causal relationships between strategic decisions and competitive success, thereby transitioning from purely predictive analytics to prescriptive analytics.

7.3 Practical Applications

The research contributions presented here possess immediate utility across various sectors within the eSports ecosystem and beyond. The professional eSports industry is poised to benefit most directly, as teams, organizations, and tournament operators can effectively utilise the prediction framework for strategic planning, draft preparation, and enhancing competitive intelligence. The production-ready architecture and its demonstrated reliability render its immediate implementation viable within professional settings.

Furthermore, substantial opportunities exist for educational and research applications that can advance the field of eSports analytics. The comprehensive documentation of methodology and the reproducible framework serve as invaluable resources for academic institutions and research programs dedicated to developing curricula and conducting studies in eSports analytics.

In addition, integrating betting and fantasy sports exemplifies a significant commercial opportunity. This framework's remarkable prediction accuracy and robust statistical validation bestow a notable competitive edge on analytical platforms and decision-support systems that rely on dependable match outcome probabilities.

Moreover, the interpretable linear model architecture and strategic feature insights can benefit applications in broadcasting and analytical enhancement. This enhances the sophistication of analytical content available for eSports broadcasts, thereby improving viewer engagement through data-driven strategic commentary and real-time competitive analyses.

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Appendix A

Meta Analysis Features (8 features)

Champion Effectiveness Mathematical Model: Meta analysis features quantify champion strength within the current competitive environment through systematic aggregation of individual champion characteristics across team compositions.

Champion Win Rate Calculation:

For each champion c, the base win rate is calculated as follows:

$$WR_c = \frac{\sum_{i=1}^{n_c} result_i}{n_c}$$

Where:

- WRc represents the win rate for champion c.
- nc denotes the total number of games in which champion c appeared.
- $result_i$ is a binary variable indicating the outcome of the i^{th} game featuring champion c. A value of 1 signifies a win for champion c in that game, while a value of 0 indicates a loss.

Temporal Effectiveness Analysis:

$$Early_{Strength_c} = \frac{\sum_{i:\, duration_i < 25} result_i}{\sum_{i=1}^{n_c} result_i}$$

$$Late_{Strength_c} = \frac{\sum_{i:\, duration_i > 35} result_i}{\sum_{i=1}^{n_c} result_i}$$

$$Scaling_{Factor_c} = Late_{Strength_c} - Early_{Strength_c}$$

Where:

- Scaling_Factor_c < 0 indicates early game specialization
- Scaling_Factor_c > 0 indicates scaling orientation

Meta Strength Quantification: Professional eSports effectiveness combines win rate with strategic priority through pick/ban attention

$$Meta_{Strength_c} = 0.7 \cdot WR_c + 0.3 \cdot \min(Popularity_c, 0.5)$$

$$Popularity_c = \frac{Picks_c + Bans_c}{Total_{Games}}$$

This formulation reflects professional teams' strategic valuation where ban priority indicates meta threat level.

Team-Level Meta Feature Aggregation

For a team Composition $T = \{c\_1, c\_2, c\_3, c\_4, c\_5\}$ representing top, jungle, mid, ADC, and support champions:

Team Average Win Rate

$$\overline{\{WR\}}_T = \left(\frac{1}{5}\right)\sum_{i=1}^{5} WR_{c_i}$$

Team Early Strength

$$Early_T = \left(\frac{1}{5}\right)\sum_{i=1}^{5} Early_{Strength_{c_i}}$$

Team Late Strength

$$Late_T = \left(\frac{1}{5}\right)\sum_{i=1}^{5} Late_{Strength_{c_i}}$$

Team Scaling

$$Scaling_T = \left(\frac{1}{5}\right)\sum_{i=1}^{5} Scaling_{Factor_{c_i}}$$

Team Meta Strength

$$Meta_T = \left(\frac{1}{5}\right)\sum_{i=1}^{5} Meta_{Strength_{c_i}}$$

Meta Consistency

$$Consistency_T = 1 - \sqrt{\left(\frac{1}{5}\right)\sum_{i=1}^{5}\left(Meta_{Strength_{c_i}} - Meta_T\right)^2}$$

Team Popularity

$$Popularity_T = \left(\frac{1}{5}\right)\sum_{i=1}^{5} Popularity_{c_i}$$

Meta Advantage

$$Advantage_T = Meta_T - Met\bar{a}_{patch}$$

Where $Met\bar{a}_(patch)$is the patch specific meta baseline

These features capture the fundamental concept of "meta" in competitive gaming - the evolving optimal strategies within the current game state. The mathematical formulation ensures that teams selecting currently effective champions receive higher meta scores, while the consistency metric penalizes compositions with inconsistent meta positioning.

Team Performance Features (4 Features)

Temporal Performance Integration: Team performance features implement chronologically safe historical analysis through careful temporal ordering and sliding window techniques.

Historical Performance Mathematical Model

For team t at match m with chronological ordering by date:

Overall Win Rate

$$WR_{t,m} = \frac{\sum_{i:\, date_i < date_m \wedge\, team_i = t} result_i}{\sum_{i:\, date_i < date_m \wedge\, team_i = t} 1}$$

Recent Form Analysis

$$Recent_{t,m} = \frac{1}{\min(10, |H_{t,m}|)} \sum_{i \in Last10(H_{t,m})} result_i$$

Where $|H_{t,m}|$ represents the historical match set for team t prior to match m

Performance Momentum

$$Momentum_{t,m} = Recent_{t,m} - WR_{t,m}$$

Where:

- $Momentum > 0$ indicates good form
- $Momentum < 0$ indicates poor form

Experience Factor

$$Experience_{t,m} = \min\left(1.0, \frac{|H_{t,m}|}{100}\right)$$

This normalization caps experience benefits while providing graduated advantages for match volume.

Generated Performance Features:

Team Overall Win Rate: $WR_{t,m}$ Complete Historical Win Rate

Team Recent Win Rate: $Recent_{t,m}$ Recent Form Analysis

Team Form Trend: $Momentum\_(t, m)$ Performance Trajectory Indicator

Team Experience:$Experience\_(t, m)$ Normalized Experience factor

These features reflect the fundamental sports analytics principle that past performance predicts future results. The distinction between overall and recent performance captures both established team quality and current momentum, while the momentum indicator identifies teams in transitional performance states.

Strategic Analysis Features (6 Features)

Pick/Ban Strategy Mathematical Framework: Strategic features quantify tactical decisions through systematic analysis of draft phase choices and team composition characteristics.

Ban Priority Analysis

For each champion c, ban priority is calculated as:

$$Priority_c = \frac{Early_{Bans_c}}{Total_{Bans_c}}$$

Where:

- $Early\_Bans\_c$ represents bans in the first two ban phases
- $Priority\_c > 0.5$ indicates high-priority meta threats.

Team Composition Synergy Analysis

For team composition $T = \{c\_1, c\_2, c\_3, c\_4, c\_5\}$:

Composition Balance

$$Balance_T = \sqrt{\left(\frac{1}{5}\right)\sum_{i=1}^{5}\left(Scaling_{c_i} - \bar{Scaling}_T\right)^2}$$

Team Flexibility

$$Flexibility_T = \left(\frac{1}{5}\right)\sum_{i=1}^{5} Flex_{c_i}$$

Where: $Flex_{c_i} \in [1, 5]$ represents the number of roles champion c_i can effectively fulfil

Composition Historical Success

For composition signature S_T (sorted champion set):

$$Historical_{WR_T} = \frac{\sum_{j:\, signature_j = S_T \wedge\, j < current} result_j}{\sum_{j:\, signature_j = S_T \wedge\, j < current} 1}$$

Generated Strategic features:

Ban Count: $|B|$ where B is the set of utilized bans (0-5)

Ban Diversity: $|Unique(B)| - Breadth\ of\ ban\ targeting$

High Priority bans: $|\{b \in B : Priority\_b > 0.5\}|$

Composition Balance: $Balance_T - Strategic$ (coherence measure)

Team Flexibility: $Flexibility_T - Average$ (champion versatility)

Composition Historical Win Rate: $Historical_{WR_T} - Similar$ (composition success rate)

Draft phase strategy represents the pre-game tactical layer where teams optimize champion selections while disrupting opponent strategies. The mathematical formulations capture the multi-dimensional optimization problem teams face: maximizing their own composition strength while minimizing opponent opportunities.

Target Encoding Features (9 Features)

Target Encoding Mathematical Framework: High-cardinality categorical features require sophisticated encoding techniques that preserve information content while enabling linear model processing.

Target Encoding Formulation

For categorical variable X with levels $\{x_1, x_2, \ldots, x_k\}$ and binary target Y:

$$TargetEncode(x_i) = \frac{\sum_{j:\, X_j = x_i} Y_j}{\sum_{j:\, X_j = x_i} 1}$$

This represents the conditional probability $P(Y = 1|X = x_i)$, providing optimal linear separability for logistic regression.

Bayesian Smoothing

For categories with limited observations:

$$SmoothedEncode(x_i) = \frac{n_i \cdot \bar{Y}_{x_i} + \alpha \cdot \bar{Y}}{n_i + \alpha}$$

Where:

- $n_i = number\ of\ observations\ for\ category\ x_i$
- $\bar{Y}_{x_i} = target\ mean\ for\ category\ x_i$
- $\bar{Y} = global\ target\ mean$
- $\alpha = smoothing\ parameter$

Position Specific Champion Encoding

For position $p \in \{top, jungle, mid, adc, support\}$ and champion c:

$$ChampionEncode_{p(c)} = \frac{\sum_{j:\, champion_{p,j} = c} result_j}{\sum_{j:\, champion_{p,j} = c} 1}$$

This approach recognizes that champion effectiveness varies significantly across roles.

Generated Categorical Features:

League Target Encoded: League-specific performance encoding using $TargetEncode(league)$

Team Target Encoded: Team effectiveness encoding using $TargetEncode(team)$

Patch target Encoded: Patch-specific context using $TargetEncode(patch)$

Split Target Encoded: Season Context using $TargetEncode(split)$

Champion Position Target Encoded: $ChampionEncode_{positon}(c_{position})$

Target encoding transforms categorical variables into numerical representations that directly correlate with match outcomes, preserving predictive information while enabling linear model processing. This approach is particularly effective for logistic regression models, providing optimal feature representation for linear decision boundaries.

Interaction and Contextual Features (10 Features)

Strategic Interaction Mathematical Models: Complex strategic relationships require explicit modeling through interaction terms that capture synergistic effects between different strategic components.

Interaction Feature Formulations

Meta Form Interaction (Teams in derive greater benefit from meta-favourable picks):

$$MetaForm_{interaction} = Meta_T \times Momentum_{t,m}$$

Scaling-Experience Interaction (Experienced teams better execute complex scaling strategies):

$$ScalingExp_{interaction} = Scaling_T \times Experience_{t,m}$$

Tournament Context (Binary indicator for high stake matches):

$$Playoffs = \{1\ if\ tournament\ context;\ 0\ if\ regular\ season\}$$

Environmental Factors

Map Side Advantage

$$SideBlue = \{1\ if\ Blue\ side;\ 0\ if\ Red\ side\}$$

Temporal Context

$$Year = match\ year$$

Draft Completeness

$$ChampionCount = |\{c \in T : c \neq Unknown\}|$$

Strategic Coherence Metrics

Team Flexibility

$$Flexibility_T = \left(\frac{1}{5}\right) \sum_{i=1}^{5} Flex_{c_i}$$

Ban Priority Score

$$BanScore = \sum_{b \in Bans} Priority_b$$

Meta Diversity

$$MetaDiversity = \left|\left\{c \in T : Meta_{Strength_c} > Met\bar{a}_{patch}\right\}\right|$$