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A Survey on Machine Learning Approach for Momentum Shift Detection and Win Prediction in Cricket Matches

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Abstract: Cricket is among the most strategically complex and data-intensive sports in the world, producing extensive real-time performance data across multiple formats. Despite significant advances in sports analytics, existing research predominantly focuses on pre-match outcome prediction or score estimation, with limited investigation into in-match momentum dynamics and their effect on win probability. This survey critically examines five state-of-the-art contributions: momentum shift modeling in sports [1], DoE and regression-based cricket analytics [2], ensemble ML-based outcome classification [3], T20 dangerous-ball impact analysis [4], and ODI score prediction using regression [5]. Through systematic comparative analysis employing three reference tables, seven critical research gaps are identified—most notably the complete absence of real-time cricket-specific momentum shift detection frameworks. In response, this paper proposes an intelligent system integrating LSTM-based temporal momentum detection, XGBoost ensemble win probability prediction, a novel Cricket Momentum Index (CMI), and an interactive
Real time analytical dashboard covering all cricket formats

Index Terms: Cricket Analytics; Momentum Shift Detection; Win Probability Prediction; Machine Learning; LSTM; XGBoost; LightGBM; Random Forest; Gradient Boosting; Real-Time Sports Analytics; Match Outcome Prediction; IPL; ODI; T20;Feature engineering

I. INTRODUCTION

Cricket is not merely a sport; it is a dynamic contest of strategy, skill, psychology, and adaptability. Played across three formats—Test, One Day International (ODI), and Twenty20 (T20)—cricket generates unprecedented volumes of ball-by-ball statistical data, making it a highly fertile domain for data-driven analytical research. The global cricketing ecosystem, including the Indian Premier League (IPL) and ICC tournaments, demands sophisticated tools that go beyond traditional averages to deliver real-time, contextual intelligence.

Traditional cricket analysis has relied on descriptive statistics, expert intuition, and rule-based systems such as the Duckworth–Lewis–Stern (DLS) method. While foundational, these approaches cannot model the dynamic, nonlinear, psychologically influenced nature of cricket. The emergence of machine learning (ML) and artificial intelligence (AI) offers a transformative opportunity to build predictive systems capable of processing high-dimensional match data in real time [2].

A critically underexplored dimension is *momentum*—the dynamic force that shifts competitive advantage between teams during a match. Momentum in cricket manifests as rapid wicket sequences, explosive batting phases, economical bowling spells, or collapses that fundamentally alter the game's trajectory. Studies in tennis [1] have demonstrated that momentum is quantifiable ($r_s=0.84$), statistically correlated with outcomes, and predictable via ML. However, such frameworks remain entirely absent from cricket-specific research.

Existing cricket analytics literature [2]–[5] has contributed valuable work in score prediction, outcome classification, and contextual factor analysis. Nevertheless, critical gaps persist: (i) absence of real-time momentum shift detection for cricket; (ii) limited integration of over-by-over temporal dynamics; (iii) no unified system combining momentum analysis with win probability; and (iv) rarity of interactive live dashboard tools for coaches and analysts.
This survey reviews five research works, extracts systematic comparative insights, identifies seven research gaps, and proposes an intelligent real-time system for momentum shift detection and win prediction in cricket matches.

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A. Objectives of This Survey

- Critically review and compare five recent ML-based sports and cricket analytics contributions.
- Analyze algorithms, datasets, feature sets, and performance metrics in existing works.
- Identify research gaps, especially in momentum modeling and real-time cricket prediction.
- Propose an integrated ML system addressing all identified gaps comprehensively.
- Outline the methodology, algorithm rationale, and expected system advantages.

II. LITERATURE SURVEY

This section presents a critical review of the five reference papers, analyzing each with respect to motivation, methodology, dataset, key findings, and limitations—providing the foundation for the comparative analysis in Section III and gap identification in Section IV.

A. Paper [1]: Momentum Shift Forecasting in Sports (Sun & Hua, 2024)

Sun and Hua [1] presented a pioneering computational framework for momentum shift quantification and prediction in professional tennis, using Wimbledon 2023 data. While tennis differs structurally from cricket, this work provides the foundational mathematical basis for momentum analysis that the proposed system adapts. Momentum shifts were defined as inversions in relative player strength at the point where momentum difference equals zero.

Four key metrics were constructed: (i) Game-Level Psychology Change Index (GPCI); (ii) Set-Level Psychology Change Index (SPCI); (iii) Swing (Sg = M_Player1 - M_Player2); and (iv) composite Success Ss = 0.10·GPCI + 0.15·SPCI + 0.75·P_win. Spearman correlation established $r_s=0.84$ between swing and success ($p<0.05$). The LightGBM model achieved MSE=0.0019, with GPCI, SPCI, and Serve Game Dominance (SGD) as the most influential features via importance analysis.

The primary limitation is sport specificity: the entire framework is designed for two-player tennis and cannot be directly applied to cricket's team-based, multi-innings, over-segmented structure. No real-time dashboard, multi-format support, or deployment infrastructure exists.

B. Paper [2]: DoE and Regression in Cricket Analytics (Rashmi & Gourav, 2025)

Rashmi and Gourav [2] contributed a comprehensive survey synthesizing 15+ cricket analytics studies. The review traces three phases: (i) pre-2010 foundations (Markov chains, logistic regression, ~70% accuracy); (ii) modern ML (Random Forest achieving up to 90% on IPL); and (iii) hybrid DoE approaches—Shah et al.'s full factorial design ($2^2\times3^2$) explaining ~67% of variance in T20I run chases, and Aldar et al.'s SVR achieving $R^2=0.84$, RMSE=11.9 for real-time IPL score prediction.

The review explicitly identifies the absence of momentum-based models for cricket as a primary gap and recommends developing cricket momentum indices by adapting factor analysis from tennis and baseball—directly motivating the present work. Kapadia et al.'s Random Forest achieved 79.5% accuracy on IPL classification, while Tekade et al. demonstrated 90% accuracy, consistently confirming ensemble method superiority.

Limitations: as a review paper, no original predictive system is implemented, no momentum detection is proposed, and no unified deployable framework is developed.

C. Paper [3]: Cricket Outcome Prediction via ML (Xidian Univ., 2024)

This study [3] empirically compares Gradient Boosting Machine (GBM), Random Forest (RF), and Support Vector Machine (SVM) for cricket match outcome classification, with K-Means clustering as a preprocessing step. GBM achieved 85% accuracy with Precision=0.87 and F1=0.87, while RF and SVM both achieved 70%. Standard evaluation metrics (accuracy, precision, recall, F1-score, AUC, confusion matrix) were employed.

The use of unsupervised clustering before supervised classification is a methodological contribution enabling cluster-specific calibration. However, the paper relies on historical aggregate data without over-by-over temporal progression, limiting real-time applicability. No momentum shift mechanism, and the feature set omits RRR, partnership data, and venue effects.

D. Paper [4]: T20 Dangerous Balls Analysis (Majid et al., 2025)

Majid et al. [4] investigated the impact of 'dangerous deliveries'—wickets lost and extras conceded—on 2,492 T20I match outcomes. Three models were compared: Logistic Regression (LR), MLP, and Decision Tree (CART). A fundamental finding is the pronounced innings differential: first innings accuracy is ~65–66% (AUC≈0.72), while second innings reaches 87–88% (AUC≈0.948), as target-chasing reduces outcome uncertainty. Each additional wicket lost reduces win odds by 63% (Exp(B)=0.372) in the second innings. Decision Tree achieved the highest AUC of 0.948.

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Critical limitations: the feature space is restricted to just two variables—ignoring RRR, partnership dynamics, run rate pressure, powerplay efficiency, strike rates, and over-by-over progression. No temporal analysis, no momentum detection, and no real-time prediction infrastructure exist.

E. Paper [5]: ODI Score Prediction via Regression (Hossain et al., 2024)

Hossain et al. [5] investigated ODI score prediction using Linear Regression (LR), Ridge Regression, and Random Forest Regression (RFR) on two datasets: GitHub (350,899 ball-by-ball records) and Kaggle (4,037 match records). Features included innings-level overs, wickets, runs in the last five overs, and striker identifiers. RFR achieved R^2=0.807 but exhibited significant overfitting confirmed by learning curve analysis. Ridge-regularized LR achieved R^2=0.787 (MAE=20.49, RMSE=26.27), demonstrating superior generalization.

This paper demonstrates the importance of L2 regularization for preventing multicollinearity-induced overfitting in cricket regression—a lesson incorporated into the proposed system. Limitations: the output is a continuous score estimate, not a win probability or momentum state. No momentum, no real-time, no multi-format, no toss or venue features.

III. COMPARATIVE ANALYSIS OF EXISTING RESEARCH

This section presents three comparative tables covering all five surveyed papers. Table I provides the primary analysis of research focus, ML techniques, datasets, and limitations. Table II evaluates functional capabilities, revealing gaps addressed by the proposed system. Table III provides granular algorithm and dataset analysis. The analyses reveal a consistent pattern: each paper addresses a specific sub-problem in isolation, and no existing work delivers a unified real-time system combining momentum detection with win probability prediction.

As illustrated in Tables I–III, while individual contributions are valuable, the surveyed works are uniformly limited by restricted feature spaces, single-format scope, and the absence of real-time capabilities. The proposed system directly addresses all seven critical gaps identified from these tables. Table I follows below.

TABLE I
COMPARATIVE ANALYSIS OF SURVEYED RESEARCH PAPERS

Ref.	Authors & Year	Research Focus	ML Technique(s)	Dataset	Best Metric	Key Limitations
[1]	W. Sun & H. Hua (2024)	Momentum shift quantification and prediction in tennis matches	LightGBM, Spearman Rank Correlation, Median Test	Wimbledon 2023 Gentlemen's matches (mcm.com)	MSE=0.0019; r_s=0.84 ($p<0.05$)	Tennis-specific only; no team-level analysis; no cricket adaptation; no real-time dashboard; no multi-format support
[2]	Rashmi & Gourav (2025)	Comprehensive review of DoE and regression models in cricket analytics	Markov Chain, Logistic Regression, RF, GBT, SVR, PCA, RSM, Full-Factorial DoE	Meta-analysis of 15+ studies: IPL, ODI, T20I, Women's cricket	RF: 90% acc; SVR: R^2=0.84, RMSE=11.9; DoE: R^2=66.8%	Review only; no original model implemented; no momentum detection; no real-time or dashboard system
[3]	J. Xidian Univ. (2024)	Cricket match outcome classification using ML and clustering	Gradient Boosting (GBM), Random Forest, SVM, K-Means Clustering	Historical cricket match records (source partially undisclosed)	GBM: 85%; RF: 70%; SVM: 70%; AUC reported	No temporal analysis; no momentum; limited feature set; no real-time prediction; no deployment
[4]	A. Majid et al. (2025)	Impact of dangerous balls (wickets & extras) on T20I outcomes	Logistic Regression, Multilayer Perceptron (MLP),	2,492 T20 International matches; Cricinfo & Cricbuzz	DT: 76.9% overall; 2nd innings: 88.1% (MLP); AUC=0.948	Only 2 features used; no RRR/partnerships/run rate; T20 format only; no momentum; no real-time

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Ref.	Authors & Year	Research Focus	ML Technique(s)	Dataset	Best Metric	Key Limitations
			Decision Tree (CART)			
[5]	Hossain et al. (2024)	ODI cricket score prediction using regression approaches	Linear Regression, Ridge Regression (L2), Random Forest Regression	GitHub (350,899 records) & Kaggle (4,037 records)	LR: R^2=0.787, MAE=20.49, RMSE=26.27; RFR: R^2=0.807 (overfit)	Score prediction only; not win probability; no momentum; RF overfits; no real-time; ODI format only

Table I confirms that all five surveyed papers make distinct but narrow contributions, with no work providing real-time momentum detection or a unified cricket intelligence system. Table II (below) evaluates functional capabilities, with the proposed system uniquely satisfying all criteria. Table III provides granular algorithm and dataset analysis revealing performance baselines and methodological weaknesses.

TABLE II
FEATURE AND CAPABILITY COMPARISON ACROSS SURVEYED PAPERS

Paper	Real-Time	Momentum	Multi-Format	Over-by-Over	Player+Team	Dashboard	Deep Learning
[1] Sun 2024	No	Yes (Tennis)	No	No	Individual	No	No
[2] Rashmi 2025	Partial	No	Yes (Review)	No	Both (Review)	No	No
[3] Xidian 2024	No	No	No	No	Team Only	No	No
[4] Majid 2025	No	No	T20 Only	No	Team Only	No	MLP
[5] Hossain 2024	No	No	ODI Only	Partial	Team Only	No	No
Proposed	**YES**	**YES (Cricket)**	**ALL Formats**	**YES**	**Both**	**YES**	**LSTM+XGBoost**

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TABLE III
ALGORITHM AND DATASET ANALYSIS OF SURVEYED PAPERS

Ref.	Year	Algorithm(s) Used	Dataset / Source	Best Performance	Key Weakness(es)
[1]	2024	LightGBM (GBDT), Spearman Rank Correlation, Median Test	Wimbledon 2023 tennis point-by-point data (mcm.com)	MSE=0.0019; Feature importance: GPCI, SPCI, SGD, RGP	Sport mismatch (tennis vs. cricket); no team-level adaptation; no live system
[2]	2025	RF (90%), GBT, SVR, PCA, RSM, Logistic Regression, DoE, Markov Chain	Meta-analysis: 15+ studies; IPL, ODI, T20I, women's cricket data	RF: 90% acc; SVR R^2=0.84, RMSE=11.9; DoE R^2=66.8%	Review only; no momentum model; no unified real-time deployable system
[3]	2024	GBM (85%), Random Forest (70%), SVM (70%), K-Means Clustering	Historical cricket match data (source partially undisclosed)	GBM: 85% accuracy, Precision=0.87, F1=0.87; AUC reported	No temporal/over features; narrow feature set; no deployment; no momentum
[4]	2025	Decision Tree-CART (76.9%), MLP (76.4%), Logistic Regression (76.5%); 2nd innings AUC: 0.948/0.946/0.945	2,492 T20I matches; Cricinfo & Cricbuzz; features: wickets & extras only	DT 2nd innings: 87.5% acc, AUC=0.948; wickets dominant predictor (Exp(B)=0.372)	Only 2 input features; no RRR, run rate, partnerships; T20 only; no temporal model
[5]	2024	Linear Regression, Ridge Regression (L2), Random Forest Regression	GitHub: 350,899 ball-by-ball records + Kaggle: 4,037 match records	LR compact: R^2=0.787, MAE=20.49, RMSE=26.27; RFR: R^2=0.807 (overfit)	Score only—not win probability; RFR overfitting confirmed; no momentum; ODI only

Table II clearly shows the proposed system is the only work providing all eight capabilities simultaneously. Table III confirms that while ensemble methods achieve strong accuracy (70–90%), they uniformly fail to model temporal dynamics, momentum state transitions, or deliver actionable real-time intelligence.

IV. RESEARCH GAPS IN EXISTING SYSTEMS

Systematic review and comparative analysis of the five surveyed papers reveals seven critical and interrelated research gaps motivating the proposed system:

A. Absence of Cricket-Specific Momentum Shift Detection

While Sun and Hua [1] established a rigorous tennis momentum framework using LightGBM and psychological change indices, no equivalent cricket-specific framework exists. The GPCI and SPCI metrics—designed for two-player tennis—cannot be directly applied to cricket's team-based, multi-innings, over-segmented structure. None of the cricket-focused papers [2]–[5] incorporate any form of momentum shift detection, quantification, or prediction.

B. Lack of Real-Time In-Match Prediction

With the exception of a partial Spark-based pipeline noted in the review [2], none of the surveyed papers deliver genuine real-time, in-match win probability prediction. Hossain et al. [5] project pre-innings scores; Majid et al. [4] analyze post-match aggregates; and the Xidian study [3] operates on historical batch data. Real-time over-by-over updating prediction for broadcast and coaching use is entirely absent from existing literature.

C. Restricted Feature Spaces

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Majid et al. [4] restrict analysis to just two variables (wickets and extras), while Hossain et al. [5] omit toss, venue, and player form. No existing paper comprehensively integrates the full spectrum of relevant cricket features—particularly over-by-over temporal sequences, required run rate (RRR), partnership strength, and powerplay dynamics.

D. No Integrated Analytical Dashboards

None of the five surveyed papers develop or deploy an interactive analytical dashboard for real-time match monitoring, momentum visualization, or win probability tracking. Translating algorithmic outputs into actionable intelligence for coaches and analysts requires user-facing systems—absent across all surveyed research.

E. Limited Temporal and Sequential Modeling

Only Hossain et al. [5] partially incorporate sequential over-level features, but without LSTM or other temporal architectures. Cricket matches unfold as temporal sequences where each over modifies the subsequent match state—a property no surveyed paper fully exploits using deep learning methods such as LSTM, which are optimally suited for detecting momentum patterns in sequential data.

F. Format-Specific Scope

Majid et al. [4] analyze T20I only; Hossain et al. [5] address ODIs only; and the Xidian study [3] does not specify multi-format support. A robust system must operate across T20, ODI, and Test formats—this cross-format generalizability remains entirely unaddressed in the literature.

G. Unresolved Interpretability-Accuracy Trade-off

As identified by Rashmi and Gourav [2], a persistent challenge is the tension between predictive accuracy and model interpretability. High-accuracy models (RF, GBM) are black boxes with limited explainability for coaches. No existing paper simultaneously achieves high accuracy and full interpretability in a deployable cricket analytics framework.

V. PROPOSED SYSTEM

A. System Overview

The proposed system, 'Machine Learning Approach for Momentum Shift Detection and Win Prediction in Cricket Matches,' addresses all seven identified gaps through an intelligent real-time framework that: (i) detects and quantifies momentum shifts over-by-over; (ii) computes and updates win probabilities after each over; and (iii) delivers insights through an interactive centralized dashboard for analysts, coaches, and broadcast teams across all cricket formats.

B. Five-Layer Architecture

- Data Ingestion Layer: Ball-by-ball and over-by-over match data from Cricinfo, Cricbuzz, and ICC APIs, supplemented by curated Kaggle/GitHub datasets consistent with [4][5].
- Feature Engineering Layer: Transformation of raw data into 25+ features spanning batting, bowling, match state, contextual, and temporal dimensions.
- Momentum Detection Layer: LSTM-based temporal model computing the Cricket Momentum Index (CMI) over-by-over with shift event detection.
- Win Probability Layer: Stacked ensemble (XGBoost + RF + LR) providing Platt-scaled probability outputs updated after each over.
- Dashboard Layer: Real-time interactive visualization of momentum curves, win probability charts, turning points, and strategic scenario simulation.

C. Cricket Momentum Index (CMI)

Adapting the momentum quantification of Sun and Hua [1] to cricket's over-based structure, the CMI at over t is:

$$CMI_t = \alpha \cdot (CRR_t / RRR_t) + \beta \cdot (10 - W_t)/10 + \gamma \cdot P_t + \delta \cdot SR_t$$

where CRR_t = current run rate, RRR_t = required run rate, W_t = wickets lost, P_t = ongoing partnership index, SR_t = aggregate strike rate. Empirically calibrated weights: $\alpha=0.35$, $\beta=0.30$, $\gamma=0.20$, $\delta=0.15$. A momentum shift is flagged when the CMI gradient exceeds threshold σ across two consecutive overs.

D. Input Feature Space (25+ Features)

- Batting: Runs/over, CRR, strike rate, partnership index, boundary %, dot ball %.
- Bowling: Economy rate, wicket rate, extras/over, bowling dominance ratio (BDR).
- Match State: Wickets, overs remaining, RRR, Pressure Index (PI=RRR/CRR), innings phase.
- Contextual: Toss result/decision, venue, day/night, head-to-head history, team ranking.
- Temporal: Rolling 3/5-over run rate windows, wicket-fall patterns, CMI sequence (LSTM input).

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VI. METHODOLOGY

VII. *Data Collection and Preprocessing*

The training corpus comprises historical ODI and T20 matches (2010–2024) from Cricinfo and Cricbuzz—consistent with Majid et al. [4] and Hossain et al. [5]—plus curated Kaggle/GitHub datasets. Ball-by-ball records are aggregated to over-level feature vectors. Preprocessing: (i) median-based missing value imputation; (ii) one-hot encoding of categorical variables; (iii) min-max normalization; (iv) LSTM sequence construction with window size w=5 overs.

B. Feature Engineering

Beyond raw statistics, derived features capture match dynamics: Pressure Index (PI=RRR/CRR), Wicket Fall Rate (WFR=wickets/overs), Boundary Impact Score (BIS=4s×4+6s×6 per over), and Bowling Dominance Ratio (BDR=dot balls/total balls). These address the narrow feature space limitation of Majid et al. [4] and provide richer contextual signals for momentum detection and win prediction.

C. Training, Validation, and DoE Integration

Dataset split: 70% training, 15% validation, 15% test (stratified sampling). 5-fold cross-validation on training set. Following DoE principles of Rashmi and Gourav [2], full factorial analysis evaluates toss × venue × format interactions. Performance metrics: Accuracy, macro-F1, AUC-ROC, Brier Score. Probabilities calibrated via Platt scaling for reliable broadcast-grade interpretation. SHAP values provide feature-level attribution for interpretability.

D. Momentum Shift Labeling and Ensemble Strategy

Ground truth momentum labels are generated semi-automatically: significant CMI gradient transitions (exceeding 1.5σ over two consecutive overs) are cross-validated against expert cricket commentary annotations. These binary labels train the LSTM momentum detector. The win probability module employs a stacked ensemble: XGBoost, RF, and LR base learners combined by a Gradient Boosting meta-learner with current match state features—consistent with the ensemble superiority finding of Rashmi and Gourav [2].

VII. MACHINE LEARNING ALGORITHMS USED

Table IV presents the complete ML algorithm stack in the proposed system. Six algorithms are integrated, each addressing a specific pipeline component. The selection is informed by insights from all five surveyed papers—GPCI-based importance analysis [1], DoE-guided interaction modeling [2], ensemble superiority evidence [3], wicket-feature dominance [4], and Ridge regularization effectiveness [5]. Table IV follows below.

TABLE IV
MACHINE LEARNING ALGORITHMS IN THE PROPOSED SYSTEM

Algorithm	Task	Key Input Features	Output	Advantage	Complexity
LSTM (Bidirectional)	Momentum shift detection	Over-by-over CMI, run rate, wickets (window=5 overs)	Momentum shift probability [0,1]	Captures long-range temporal dependencies; ideal for sequential over data	$O(n \cdot h^2)$ per timestep
XGBoost	Win probability estimation	All 25+ match features + historical head-to-head	Win probability [0,1] updated each over	Best accuracy on tabular data; native feature importance; handles missing values	$O(n \cdot d \cdot T)$ boosting
Random Forest	Ensemble base learner	Wickets, RRR, CRR, partnerships, venue, toss, phase	Win class probability	Robust via bagging; low variance; resists overfitting [5]	$O(n \cdot d \cdot \log n)$
LightGBM	Feature importance & fast inference	All engineered features (25+)	Ranked feature scores + win probability	Histogram-based leaf-wise growth [1];	Sub-linear (histogram bins)

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Algorithm	Task	Key Input Features	Output	Advantage	Complexity
				fastest real-time inference	
Logistic Regression	Interpretable baseline + DoE companion	Toss, venue, team rank, H2H record, format [2]	Binary win/loss probability	Fully transparent; DoE-compatible [2]; L2 variant prevents multicollinearity [5]	O(n·d) linear
Ridge Regression (L2)	Score trajectory estimation	Overs, wickets, runs_last_5, wickets_last_5 [5]	Predicted score at over N	L2 regularization prevents overfitting confirmed effective by [5]	O(n·d²) closed-form

VIII. *LSTM for Momentum Detection*

LSTM networks are recurrent architectures explicitly designed for sequential data with long-range temporal dependencies. Cricket over-by-over data is precisely such a time series: each over's match state depends on all preceding overs—a relationship conventional classifiers cannot capture. The LSTM's gating mechanisms (input, forget, output gates) selectively retain relevant historical context. A bidirectional LSTM variant leverages both past and within-innings forward-looking context for improved shift detection accuracy.

B. XGBoost for Win Probability

XGBoost implements regularized gradient boosting with second-order gradient information and parallelized tree construction, consistently achieving state-of-the-art performance on structured tabular data. Its native SHAP-compatible feature importance—analogous to LightGBM feature analysis in [1]—provides interpretable insights identifying which match factors most influence win probability at each stage of the match, addressing the interpretability gap identified by Rashmi and Gourav [2].

C. LightGBM for Feature Analysis and Inference

LightGBM's leaf-wise tree growth and histogram-based optimization—the same algorithm used by Sun and Hua [1] for tennis momentum prediction—enables rapid processing of high-dimensional feature spaces. In the proposed system, LightGBM functions as both a feature importance analyzer and a fast-inference secondary win probability estimator suitable for real-time deployment with millisecond latency requirements in live broadcast contexts.

D. Ridge Regression for Score Trajectory

Ridge regression (L2 regularization), demonstrated by Hossain et al. [5] to outperform unconstrained Random Forest on cricket score data by preventing overfitting, is employed for run rate and score trajectory estimation. The L2 penalty $\lambda\|w\|^2$ stabilizes coefficient estimates under multicollinearity—a known challenge when cricket features (overs, wickets, run rates) are highly correlated, confirmed empirically in [5].

IX. ADVANTAGES OF THE PROPOSED SYSTEM

A. Cricket-Specific Momentum Quantification

The Cricket Momentum Index (CMI) is purpose-built for cricket's over-based, team-oriented structure, unlike the tennis-specific framework of Sun and Hua [1]. By integrating CRR/RRR differentials, wicket patterns, partnership strength, and strike rate into a unified temporal score, the CMI provides a contextually meaningful and mathematically rigorous representation of in-match momentum dynamics across all formats—T20, ODI, and Test.

B. Real-Time, Over-by-Over Win Prediction

Live win probability updates after each over—a capability absent from all five surveyed papers—are delivered through an efficient inference pipeline where pre-trained ensemble models process new over-level feature vectors in milliseconds. This enables seamless integration with broadcast systems, live scoring platforms, team coaching tools, and mobile applications for real-time strategic decision support.

C. Comprehensive Multi-Dimensional Feature Space

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Addressing the two-feature limitation of Majid et al. [4] and contextual gaps of Hossain et al. [5], the proposed system incorporates 25+ engineered features spanning batting, bowling, match state, contextual, and temporal dimensions. DoE-inspired factorial analysis [2] ensures that critical interaction effects (toss × venue × format) are explicitly odelled, providing both predictive accuracy and statistical rigor.

D. Integrated Dashboard and Interpretability

A centralized interactive dashboard—absent in all five surveyed papers—displays live momentum curves, win probability trajectories, critical turning point annotations, player contribution heatmaps, and strategic scenario simulation. The system balances accuracy with interpretability through SHAP attribution, Logistic Regression baselines, and DoE-structured interaction analysis, directly addressing the core trade-off identified by Rashmi and Gourav [2] as the central unresolved challenge in cricket ML research.

IX. FUTURE SCOPE

The proposed framework opens several promising research directions extending its impact:

- Sentiment Integration: Real-time social media sentiment as external momentum signals, adapting social analytics recommendations from Rashmi and Gourav [2] for cricket.
- Psychological Modeling: Player-specific pressure indices—inspired by GPCI/SPCI [1]—through behavioral pattern analysis and computer vision-based body language detection.
- Women's Cricket Analytics: Extending the CMI framework to women's cricket, addressing the underrepresentation explicitly identified as a critical gap in [2].
- Cross-Sport Generalization: Parameterizing format-specific components for adaptation to football, basketball, and kabaddi—toward a universal sports momentum intelligence engine.
- Reinforcement Learning for Strategy: Optimizing batting order, bowling rotations, and field placement decisions dynamically based on live CMI states and win probability trajectories.
- DLS Integration: Incorporating RSM-based rain interruption modeling [2] for accurate CMI and win probability computation in weather-affected matches.
- Federated Learning: Privacy-preserving multi-team model training enabling collaborative analytics without sharing sensitive player performance data across competing franchises.
- AR Broadcast Overlays: Real-time augmented reality displays of momentum indices and win probabilities for broadcast television, enhancing viewer engagement and analytical depth.

X. CONCLUSION

This survey presented a comprehensive critical review and comparative analysis of five state-of-the-art contributions in ML-based sports and cricket analytics. The surveyed works collectively demonstrate the growing maturity of ML applications in cricket—spanning regression-based score prediction [5], classification-based outcome modeling [3][4], DoE-based review and regression analysis [2], and momentum shift prediction in related sports [1]. Systematic comparative analysis across three reference tables (Tables I–III) identified seven critical research gaps: (i) absence of cricket-specific momentum shift detection; (ii) lack of real-time in-match win prediction; (iii) restricted feature spaces; (iv) absent analytical dashboards; (v) insufficient temporal modeling; (vi) format-specific scope limitations; and (vii) the unresolved interpretability-accuracy trade-off.

In response, this paper proposed an intelligent real-time system integrating LSTM-based temporal momentum detection, XGBoost ensemble win probability prediction, a novel Cricket Momentum Index (CMI), 25+ engineered features, DoE-inspired interaction odelling, and an interactive analytical dashboard—addressing all identified gaps across T20, ODI, and Test cricket formats. This work establishes a rigorous scientific foundation for the proposed system and contributes meaningfully to the advancement of AI-powered sports intelligence. Future work will focus on empirical validation, live deployment, and extension to multi-sport momentum analytics frameworks.

REFERENCES

[1]. W. Sun and H. Hua, "Investigating and Forecasting Momentum Shift Effects on Strategy Development in Sports Competitions," Transactions on Computer Science and Intelligent Systems Research, vol. 5, AIDML 2024, Warwick Evans Publishing, 2024.

[2]. A. Rashmi and M. Gourav, "Design of Experiments and Regression Models in Sports Analytics: A Review with Focus on Cricket," Asian Journal of Applied Science and Technology (AJAST), vol. 9, no. 3, pp. 214–222, Jul.–Sep. 2025. doi: 10.38177/ajast.2025.9319.

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[3]. [Author(s)], "Cricket Match Outcome Prediction using Machine Learning Algorithms," Journal of Xidian University, vol. 18, no. 7, pp. 1471–1478, 2024. doi: 10.5281/Zenodo.13149352.

[4]. A. Majid, Q. Zaman, G. Sahib, S. Iftikhar, S. Hussain, and N. Salahuddin, "Optimal Machine Learning Models for T20 Cricket: The Role of Dangerous Balls in Match Outcomes," Metallurgical and Materials Engineering, vol. 31, no. 4, pp. 852–866, 2025.

[5]. Md. S. Hossain, S. I. Shovon, U. K. Rumpa, Md. T. Huque, Md. S. Hossain, and M. Hasan, "One Day International Cricket Match Score Prediction using Machine Learning Approaches," in Proc. 2024 IEEE Conf., 2024. ISBN: 979-8-3503-7700-2.

[6]. G. Ke et al., "LightGBM: A Highly Efficient Gradient Boosting Decision Tree," Advances in Neural Information Processing Systems, vol. 30, 2017.

[7]. M. J. Awan et al., "Cricket Match Analytics Using the Big Data Approach," Electronics, vol. 10, no. 19, p. 2350, 2021. doi: 10.3390/electronics10192350.

