A Systematic Literature Review in Machine Learning in Predicting Sports Outcome

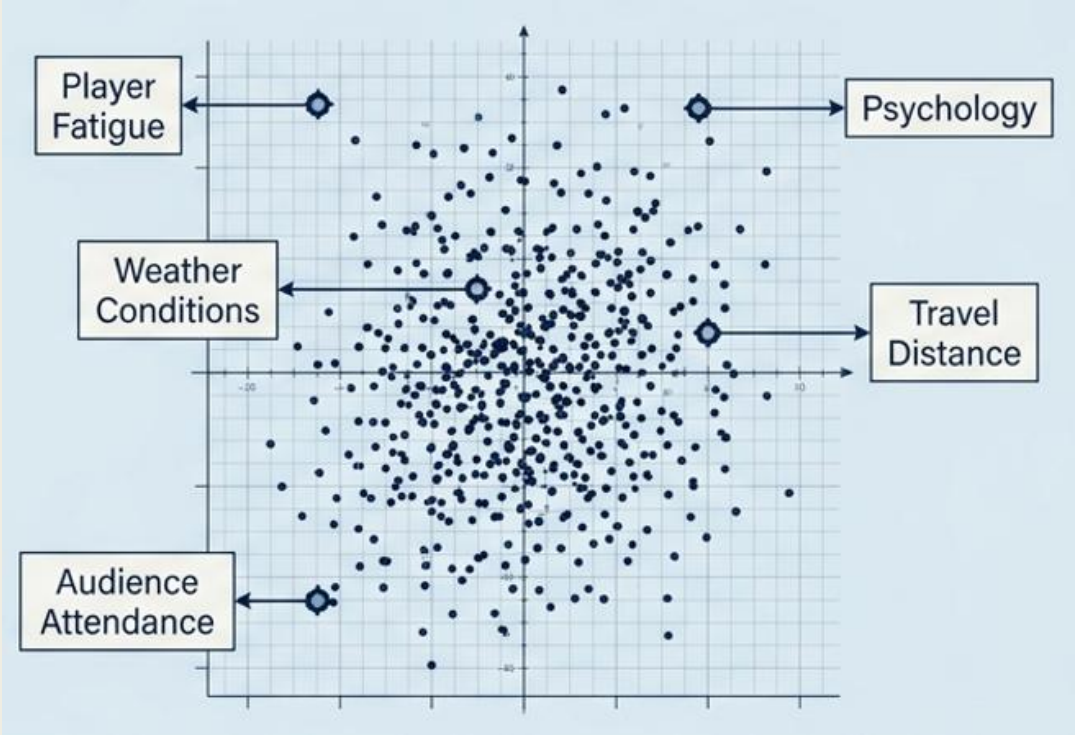
AmiEs-2026

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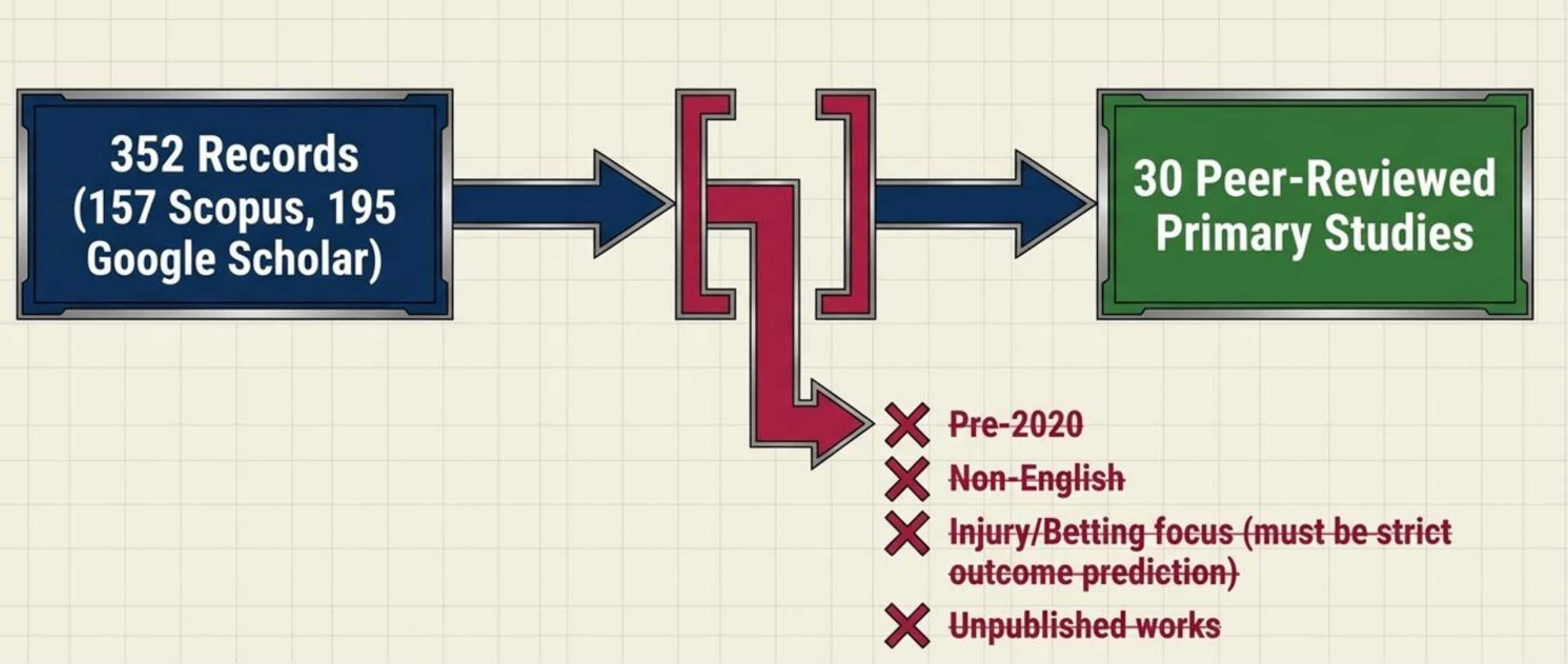


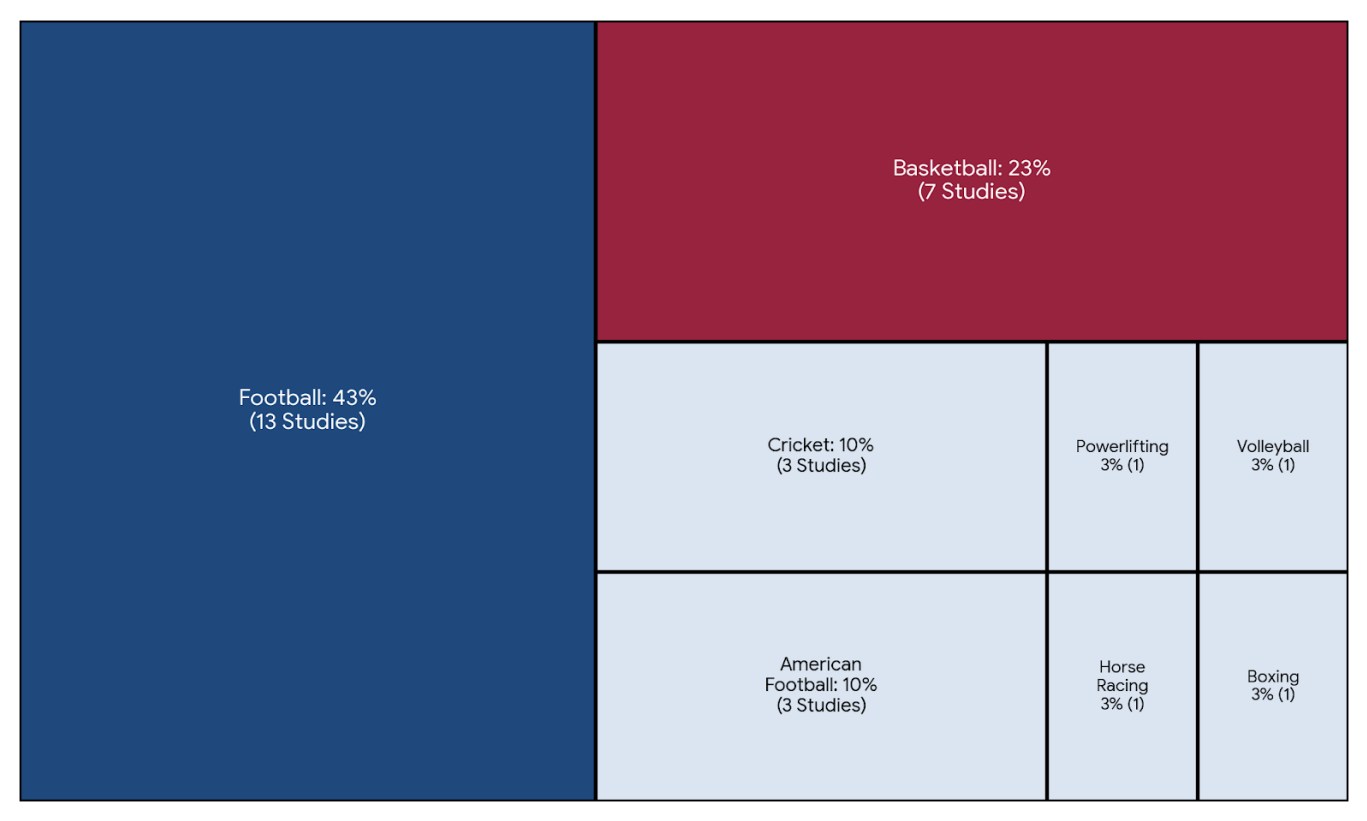
Introduction

- The prediction of sports outcomes constitutes an area of considerable intellectual inquiry and commercial value.
- The sports industry generates unprecedented volumes of non-linear, spatio-temporal data. The focus has shifted entirely from traditional statistics to complex Machine Learning (ML) to capture these dependencies.
- Can modern Machine Learning break the volatility barrier, or are human factors too unpredictable?
- A systematic literature review is essential to synthesize the broad spectrum of existing work.



Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA)



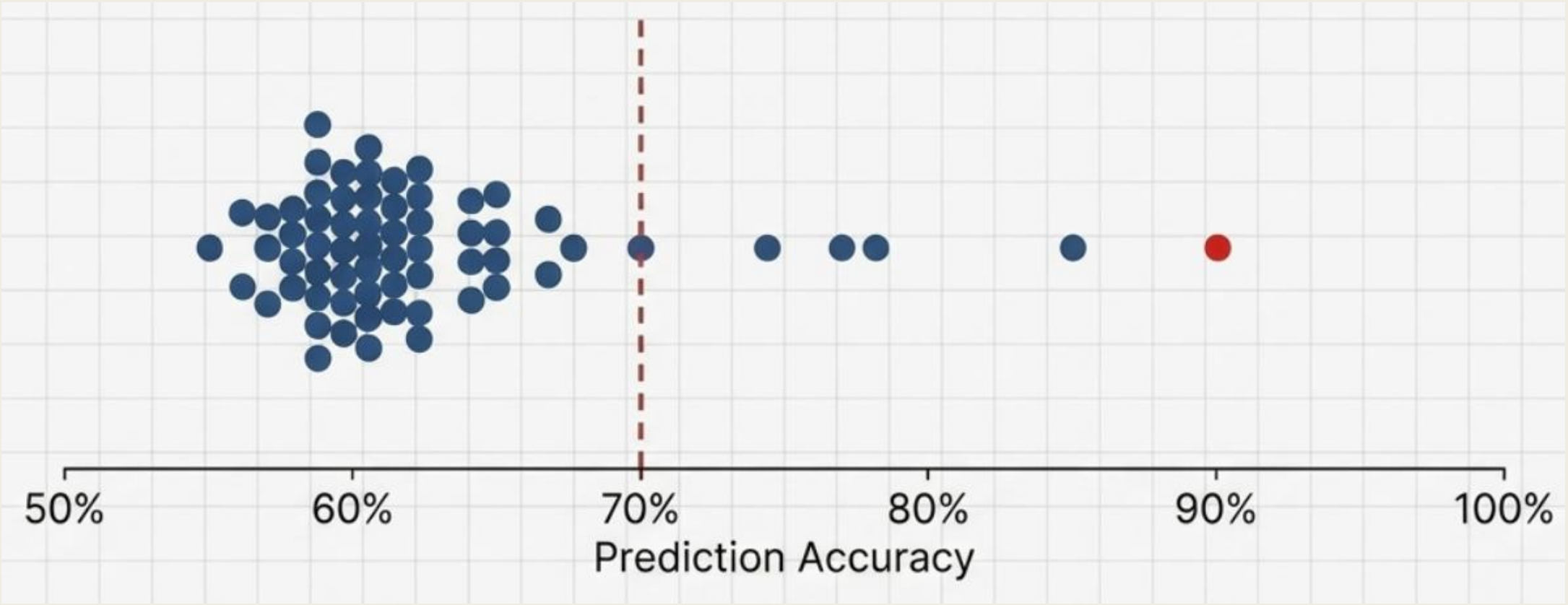


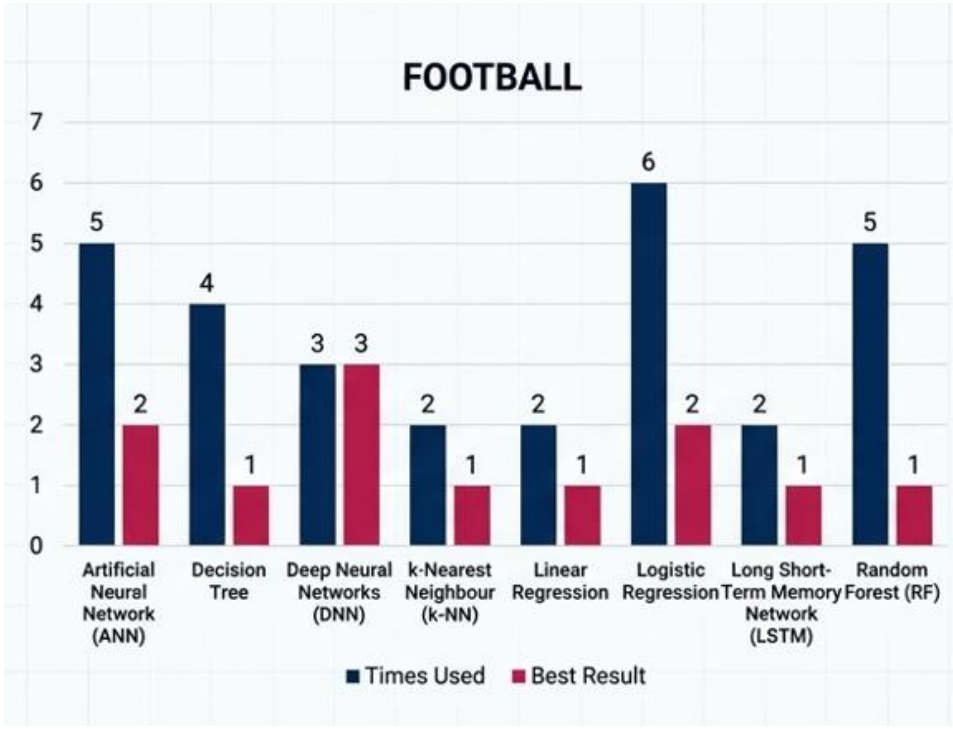
- Research is highly concentrated. Football and Basketball provide the primary proving grounds for testing ML classification models due to data availability, though their inherent dynamics require vastly different algorithmic approaches.

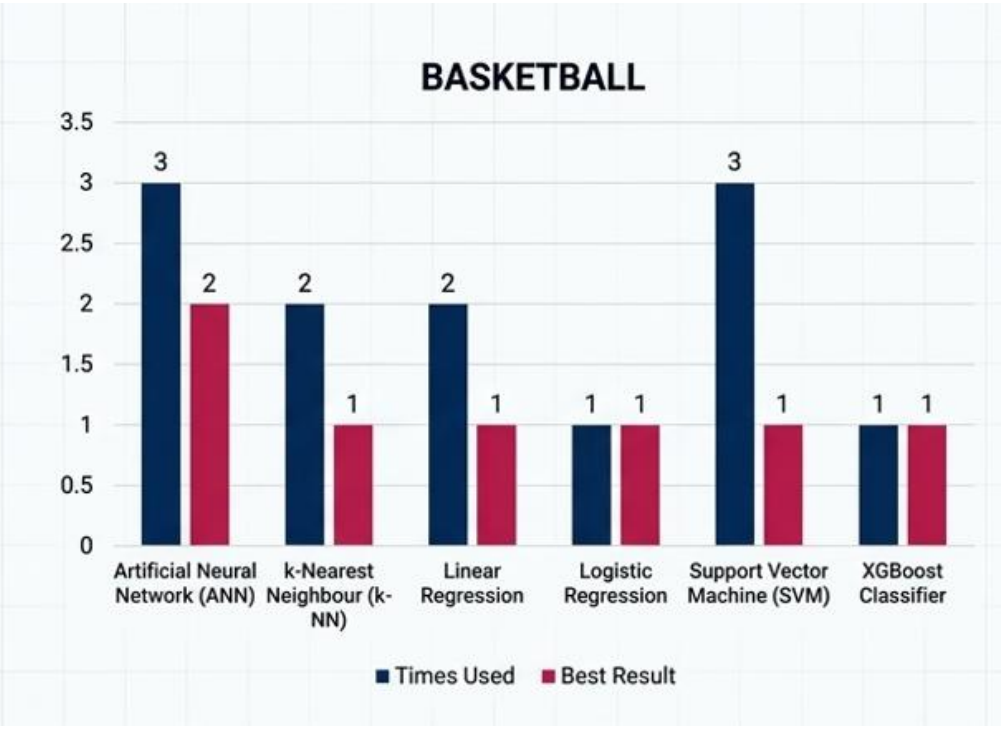
Football – Basketball Dynamics

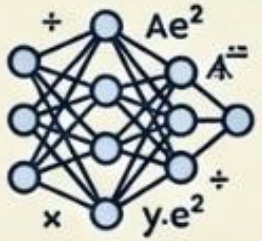
	FOOTBALL	BASKETBALL
	Highly Volatile. Low scoring, highly unpredictable spatio-temporal dynamics.	Highly Structured. High scoring, distinct relational variables.
Algorithmic Approach	Researchers tested 15 different algorithms across 41 instances searching for an edge.	Researchers focused on 10 algorithms across 21 instances.
Standalone Deep Learning Performance	DNN/LSTM models hover around an underwhelming 60-63% accuracy.	Standard ANNs successfully capture non-linear interactions, achieving 67-77% accuracy.

Low-scoring sports like football exhibit extreme natural volatility. Consistently breaking the 70% accuracy threshold remains a critical challenge for standalone algorithms.




FOOTBALL
7
6
5
4
3
2
1
0
5
2
4
1
3
3
2
1
2
1
6
2
2
1
5
1
Artificial Neural Network (ANN)
Decision Tree
Deep Neural Networks (DNN)
k-Nearest Neighbour (k-NN)
Linear Regression
Logistic Regression
Long Short-Term Memory Network (LSTM)
Random Forest (RF)
Times Used
Best Result


BASKETBALL
3.5
3
2.5
2
1.5
1
0.5
0
3
2
2
1
2
1
1
1
3
1
1
1
Artificial Neural Network (ANN)
k-Nearest Neighbour (k-NN)
Linear Regression
Logistic Regression
Support Vector Machine (SVM)
XGBoost Classifier
Times Used
Best Result

Standalone Deep Learning (High Complexity)	**Domain-Specific Hybrids** (High Context)
	
1D CNN + Transformer (Gao et al.) ➔ 55% Accuracy	k-NN + Poisson Regression (Adebisi & Alabi) ➔ 93% Accuracy
LSTM Network (Rahman) ➔ 63% Accuracy	
DNN + Elastic Net (Anfilets et al.) ➔ 61% Accuracy	Extended Team Efficiency Index (Horvat et al.) ➔ 78% Accuracy

Dimensionality Reduction

- Researchers actively avoid complex mathematical Dimensionality Reduction algorithms to preserve model interpretability and speed.
- Algorithms like PCA is reserved for massive datasets.
- Preserving explicit real-world variables.
- Seems that game specifIc features matter more than mathematical transformations.



Conclusion

- Findings
  - *Used Robust Base Architectures.*
  - *Smart Feature Engineering is dominating.*
  - *Fusing standard ML with non-parametric sports statistics, like Poisson distribution or Data Analytics.*
  - *Better results given by embedding Deep Learning inside hybrid solutions. E.g. rather than deploying standalone Neural Networks, pair traditional statistical sports forecasting with modern Machine Learning (1D CNN alongside a Transformer).*
- Key Concerns
  - *Volatility : Standalone models struggle to break 70% accuracy; low-scoring sports remain highly resistant to raw computational power.*

Future Work

- The future of sports AI lies not in larger datasets, but in dynamic feature integration and predicting something more than win loss classification.
- Move beyond static historical statistics. Models must integrate dynamic, real-world constraints such as player fatigue estimates, weather volatility, travel distance and psychological momentum indicators.
- The true value of Deep Learning architectures lies in predicting real-time micro match momentum swings throughout the duration of an event. Despite the big data narrative, high-quality datasets remain restricted.
- Future ML frameworks must be resilient enough to train accurately on fragmented, heavily constrained sports data. This is where advanced Deep Learning (LSTMs, Transformers) can finally outshine traditional statistics.





Question Time


THANK YOU
FOR YOUR ATTENTION