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A Hybrid Model of Hadoop and Large Language Models for Football Analysis, Prediction and Insight Generation

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ABSTRACT

The world of football is undergoing a transformation, driven by the power of data. Traditional analysis methods are struggling to keep pace with the vast amount of information generated during matches.The advent of big data has caused catastrophic success in a new era of football analytics, providing unprecedented insights into player performance and team strategies. However, the sheer volume and complexity of football data present significant challenges for traditional analytical methods. This paper proposes a novel approach utilizing the Hadoop framework to revolutionize football analysis. By leveraging Hadoop's distributed processing capabilities, the model can efficiently handle massive datasets, including player statistics, match events, and video footage.It demonstrates the effectiveness of our approach through case studies, such as predicting match outcomes, identifying player strengths and weaknesses, and optimizing team formations. The findings highlight the potential of Hadoop to unlock valuable insights from football data, empowering coaches and analysts to make data-driven decisions and gain a competitive edge over other teams.

Introduction

The exponential growth of data in the realm of sports has led to a paradigm shift in the way we analyze and understand athletic performance. Football, with its complex dynamics and vast amounts of generated data, is no exception. Traditional analytical methods are often inadequate to handle the sheer volume and complexity of football data. This paper proposes a novel approach utilizing the Hadoop framework to revolutionize football analysis.

Hadoop, a distributed computing framework, offers a scalable and efficient solution for processing massive datasets of dynamics of football which leverages Hadoop's capabilities, we can extract valuable insights from football data that would be impossible to obtain using traditional methods.

Football, with its complex dynamics and the massive volume of data generated during matches, is a prime example of how big data can revolutionize a sport. Traditional analytical methods, often limited by their processing capabilities, struggle to keep pace with the growing complexity of football data. It offers a scalable and efficient solution for processing massive datasets. Unlike traditional analytical tools that rely on a single machine, Hadoop distributes data across multiple nodes in a cluster, enabling parallel processing and significantly improving performance. This makes Hadoop ideally suited for handling the large volumes of data generated in football.

By using Hadoop's capabilities,model can extract valuable insights from football data that would be impossible to obtain using traditional methods. This includes:

By analyzing historical data and identifying patterns, Hadoop predicts the outcome of future matches.

Additionally, Hadoop can be used to analyze player statistics and performance data to identify individual players' strengths and weaknesses. This information can be used to optimize team formations and tactics, ensuring that players are deployed in positions where they can excel. Furthermore, Hadoop can be used to analyze player injury data and identify potential risk factors, helping to prevent injuries and improve player availability. By analyzing fan data, such as social media interactions and ticket sales, Hadoop can gain valuable insights into fan preferences and behaviors. This information can be used to tailor marketing campaigns, improve the fan experience, and ultimately enhance the overall success of the team.

Hadoop offers a powerful tool for analyzing football data and extracting valuable insights. By leveraging Hadoop's capabilities, we can gain a deeper understanding of the sport and make data-driven decisions that can improve team performance and fan engagement.

3.Literature Review

The paper titled ‘Methodology and evaluation in sports analytics: challenges, approaches, and lessons learned.’ provides a comprehensive overview of the challenges, approaches, and lessons learned in sports analytics methodology and evaluation.[1] It highlights the importance of considering dependencies in data partitioning for evaluation and emphasizes the need to distinguish between evaluating the developed indicators themselves and the underlying models that power them. The paper also discusses the challenges of data quality and availability in sports analytics.

The paper titled "A systematic review of the literature on video assistant referees in soccer: Challenges and opportunities in sports analytics" by de Oliveira, M. S., Steffen, V., & Trojan provides a comprehensive overview of the research conducted on the impact of video assistant referees (VARs) in soccer.[2] It examines the challenges and opportunities that VARs present for sports analytics, such as data collection, analysis, and decision-making. The paper also explores the potential benefits of VARs in improving the accuracy and fairness of soccer matches.

The paper titled "Prediction of Sports Performance and Analysis of Influencing Factors Based on Machine Learning and Big Data Statistics" explores the use of machine learning and big data analytics to predict sports performance and identify the key factors that influence it.[3] The authors utilize various machine learning algorithms to analyze large datasets of sports data and develop predictive models. The paper aims to provide valuable insights into the factors that contribute to athletic success and inform strategic decision-making in sports.

The paper titled "A review paper on the emerging trends in sports analytics in India" provides an overview of the developing field of sports analytics within the Indian context.[4] It likely explores the current state of sports analytics in India, including the use of data-driven insights in various sports, the challenges faced by practitioners, and the potential future directions for the field. The paper may also discuss the impact of sports analytics on the Indian sports industry and its potential contributions to the development of Indian athletes.

The paper titled "Sports analytics review: Artificial intelligence applications, emerging technologies, and algorithmic perspective" provides a comprehensive overview of the role of artificial intelligence (AI) in sports analytics.[5] It likely explores the various AI techniques and technologies that are being used to analyze sports data, such as machine learning, deep learning, and natural language processing. The paper may also discuss the emerging trends in sports analytics, such as the use of wearable devices and video analytics. Additionally, it could delve into the algorithmic challenges and limitations associated with AI applications in sports analytics.

The paper titled "Big ideas in sports analytics and statistical tools for their investigation" is expected to provide a detailed overview of the key theoretical frameworks and statistical techniques employed in sports analytics research.[6] It will likely discuss fundamental concepts such as data collection, cleaning, and analysis, as well as advanced statistical models and machine learning algorithms used for prediction, classification, and pattern recognition in sports data. The paper might also explore emerging trends and challenges in the field of sports analytics.

4.Proposed Model

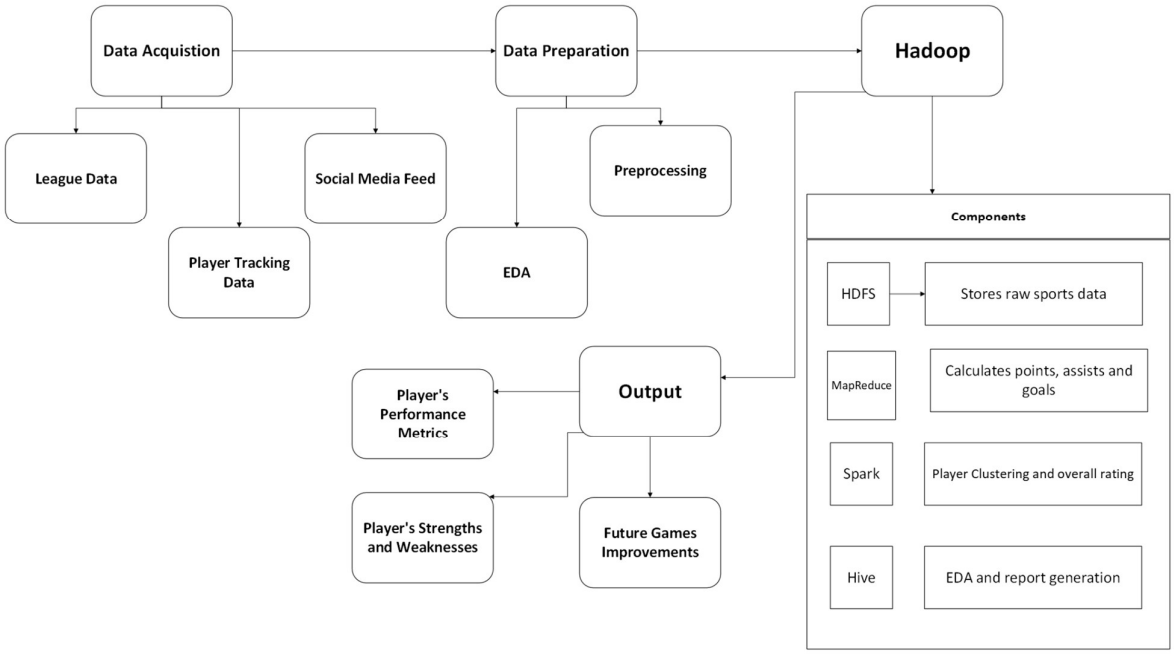

Fig 4.1 Proposed Model of Football Match Analysis by Hadoop Framework

Data Acquisition

The initial step in analyzing football data involves gathering information from multiple sources. League data, which typically includes official match results, player statistics, team rosters, and other structured information provided by the league, forms the foundation of the analysis. Additionally, social media platforms like Twitter, Instagram, and Facebook offer a wealth of unstructured data that can be mined for valuable insights. By analyzing fan sentiment, player mentions, and other relevant information, we can gain a deeper understanding of the public perception and trends surrounding the sport. Furthermore, advanced tracking systems are used to capture detailed player movements, ball possession, and other performance metrics during matches. This data provides a quantitative perspective on player performance and team dynamics.

Data Preparation

The raw football data is initially cleaned and transformed to ensure its suitability for analysis. This involves handling missing values, addressing inconsistencies, and normalizing data formats. Additionally, feature extraction techniques may be employed to create new, relevant features from existing data. Once the data is prepared, a thorough exploratory data analysis (EDA) is conducted to gain a deep understanding of its characteristics, patterns, and potential insights. This involves statistical analysis, visualization techniques, and data exploration to identify anomalies, correlations, and trends that may inform subsequent analysis.

Hadoop

The cleaned and processed football data is then stored in the Hadoop Distributed File System (HDFS), which ensures fault tolerance and scalability. The data is processed in parallel across the cluster using the MapReduce programming model, which is particularly effective for tasks such as calculating points, assists, and goals based on player performance metrics. For more complex tasks like player clustering and overall rating calculations, Spark, a versatile and faster engine than MapReduce, is employed. It can handle both batch and streaming data

processing and is well-suited for machine learning algorithms. Finally, Hive, built on top of Hadoop, provides an SQL-like interface for querying and analyzing large datasets. It is invaluable for further EDA, generating reports on player performance, team statistics, and other relevant insights.

The successful application of football analytics hinges on addressing several critical factors. The sheer volume of data generated in football analytics necessitates a scalable and efficient data processing infrastructure, such as Hadoop's distributed architecture. The integration of structured and unstructured data requires robust preprocessing techniques to transform it into a consistent format suitable for analysis. While Hadoop excels at batch processing, near real-time analysis, particularly for in-game insights, requires integrating technologies like Spark. As the volume and complexity of football data continue to grow, the analytics infrastructure must be capable of scaling to accommodate expanding requirements. Given the substantial volume of data involved, cost-efficiency is a critical factor, and Hadoop's distributed computing model can often be more cost-effective than traditional data warehousing solutions.

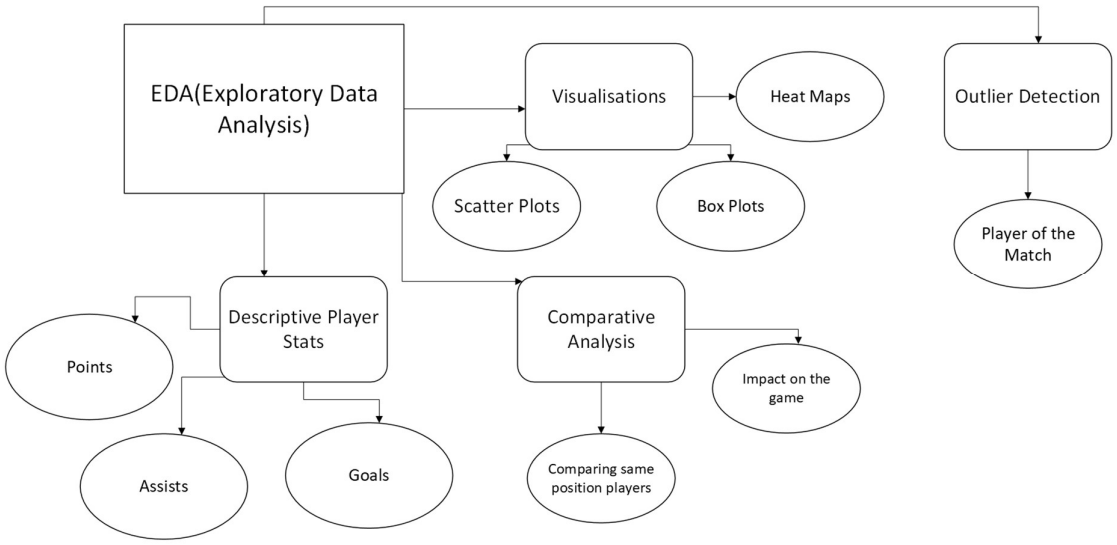

Fig 4.2 Exploratory Data Analysis Workflow

1.1. **Descriptive Player Stats**

Exploratory data analysis (EDA) plays a crucial role in summarizing player performance using descriptive statistics. Key metrics such as central tendency (mean, median, mode), dispersion (standard deviation, variance, range), and distribution (histograms, box plots) provide valuable insights into player performance. By calculating and analyzing these statistics, EDA helps identify average performance levels, variability among players, and potential outliers. For example, the mean goals scored can indicate a player's average goal-scoring ability, while the standard deviation can reveal how consistent a player's performance is. Histograms and box plots visualize the distribution of player stats, helping to identify patterns and anomalies. Overall, EDA provides a foundation for understanding player performance and identifying potential areas for improvement.

1.1. **Visualisations**

1.1. **EDA leverages various visualizations to uncover patterns and trends in player data. Scatter plots are used to examine relationships between variables, such as goals vs. shots on target. Bar charts are helpful for comparing categorical data, such as goals scored by different positions. Line charts are used to visualize**

performance over time, such as a player's goal-scoring trend. Heatmaps are employed to identify patterns in player performance across different match conditions, such as home vs. away. These visualizations help identify correlations, outliers, and potential areas for further analysis, providing a deeper understanding of player performance and team dynamics.

1.1. **Comparative Analysis**

EDA enables comparison of player performance across different dimensions.Comparing individual player stats to identify strengths and weaknesses comes under Player vs Player section.While Position vs. Position analyzes performance differences between different player positions.Finally, Team vs. Team compares player stats across teams to identify performance disparities.

By comparing players or teams, EDA helps identify top performers, underperforming players, and potential areas for improvement.

Outlier Detection

In the context of football analytics can be a powerful tool to identify players who significantly outperformed their peers in a specific match. While it's not the sole determinant of the player of the match, it can provide valuable insights to support the decision-making process.

Outlier detection is a valuable technique in football analytics for identifying exceptional player performances. By carefully selecting relevant metrics and normalizing data, key performance indicators can be compared to established norms. Contextual factors such as match importance, player role, and team performance should also be considered when evaluating outlier performances. For example, a defender scoring a hat-trick would be a clear outlier, significantly impacting their Z-score and making them a strong candidate for player of the match. However, it's important to avoid overreliance on outlier detection and consider qualitative factors like leadership, game-changing moments, and overall team contribution. Additionally, multiple outliers in different metrics can make determining the most impactful player challenging.

Outlier detection can be a valuable tool to identify players who significantly exceeded expectations in a match. By combining it with other performance indicators and contextual factors, it can contribute to a more informed decision when selecting the player of the match. However, it should be used in conjunction with human judgment and analysis to ensure a comprehensive evaluation.

EDA is a fundamental and iterative process in football analysis. It empowers analysts to extract valuable insights from data, inform decision-making, and drive the development of more sophisticated models and analysis.

5. Results

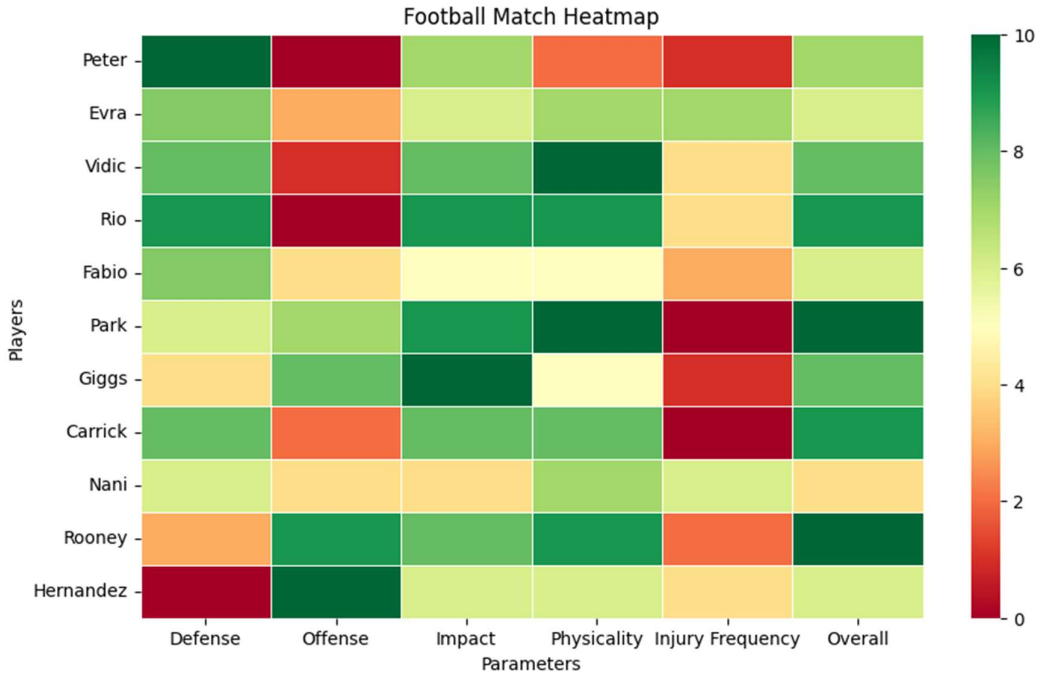

Fig 5.1 Heat Map of Player Profiles

The heatmap offers a visual representation of the performance of various football players across multiple metrics. The color intensity in each cell indicates the player's proficiency in a specific metric, with darker shades suggesting higher performance and lighter shades indicating lower performance.

By examining the heatmap, several key observations can be made. Players like Vidic, Rio, and Evra demonstrated exceptional defensive skills, as evidenced by their strong performance in the "Defense" category. On the offensive front, Rooney, Nani, and Hernandez were notable contributors, showcasing high levels of performance in the "Offense" metric. Players such as Park and Carrick exhibited a balanced approach to their game, excelling in both defensive and offensive aspects. However, injury concerns were apparent for Fabio and Giggs, as indicated by their relatively lower scores in the "Injury Frequency" category.

To gain a more comprehensive understanding of the players' performances, it is essential to consider additional factors. The player's position on the field significantly influences their expected performance metrics. For instance, a defender is anticipated to excel in defensive skills, while a forward is expected to excel in offensive contributions. Furthermore, the amount of playing time each player receives can impact their overall performance, as well as the team's playing style and tactics.While heatmaps offer a valuable visual representation of player performance, they have inherent limitations. The heatmap provides a static snapshot of the match, failing to capture the dynamic nature of the game. It does not consider factors such as player substitutions, tactical changes, and specific game situations that can significantly influence a player's performance.

The heatmap offers a valuable initial understanding of player roles and overall impact. Further analysis with additional data and context can provide a more comprehensive picture of the team's performance.In conclusion, the heatmap provides a valuable tool for visually analyzing player performance. By examining the color intensities and considering other relevant factors, we can gain valuable insights into the strengths, weaknesses, and contributions of each player to the team's success.

Fig 5.2 Attacking Approach

The 4-2-3-1 formation is a popular football tactic that employs four defenders, two defensive midfielders, one central attacking midfielder, two wingers, and one striker. This versatile formation offers a range of attacking strategies, from counter-attacking to possession-based football and direct play.

Key Roles and Responsibilities:

Defenders: The four defenders form a backline responsible for preventing the opposition from scoring. They should maintain a compact defensive shape, communicate effectively, and anticipate the opponent's movements.

Defensive Midfielders: These two players act as a shield in front of the defense. They are tasked with breaking up opposition attacks, intercepting passes, and providing defensive cover. Additionally, they should be capable of distributing the ball efficiently to start attacks.

Central Attacking Midfielder: This player is the creative hub of the team. They should be technically proficient, have excellent vision, and be able to dictate the tempo of the game. They are responsible for controlling possession, distributing the ball effectively, and creating scoring opportunities through their passing, dribbling, or shooting.

Wingers: The two wingers operate on the flanks of the field. They should be pacey, skillful, and capable of beating defenders. Their primary role is to stretch the opposition's defense, create width, and deliver crosses into the box.

Striker: The striker is the focal point of the attack. They should be a goal-scorer with a good understanding of movement and positioning. They should be able to hold up the ball, bring others into play, and finish off scoring chances.

Attacking Strategies:

Counter-attacking: The 4-2-3-1 formation is well-suited for counter-attacking football. The defensive midfielders can quickly transition the ball forward to the central attacking midfielder, who can then distribute it to the wingers or striker for a quick counter-attack.

Possession-based football: The formation can also be used to play possession-based football. The central attacking

midfielder can dictate the tempo of the game and circulate the ball among the midfielders and wingers, patiently waiting for gaps to appear in the opposition's defense.

Direct play: The formation can also be used to play direct football. The defensive midfielders can launch long balls forward to the striker, who can then hold up the ball and bring others into play.

Maintaining Formation Shape:

To ensure effective attacks and maintain balance, it is crucial for players to maintain the formation's shape throughout the game. The defensive line should remain compact, defensive midfielders should provide defensive cover and support the central midfielder, the central midfielder should control possession and distribute the ball, attacking midfielders should seek open spaces to create scoring opportunities, and the striker should position themselves in dangerous areas to receive the ball and score goals. By adhering to these principles, the team can optimize their attacking potential and minimize their susceptibility to counter-attacks.

In conclusion, the 4-2-3-1 formation offers a versatile and effective attacking framework. By understanding the roles and responsibilities of each player and maintaining the formation's shape, teams can maximize their attacking potential and achieve success.

Fig 5.3 Defensive Approach

The 4-2-3-1 formation, while often associated with attacking prowess, can also be effective defensively. The double pivot of two defensive midfielders provides a strong foundation for the defense, breaking up attacks and winning back possession. The central defenders play a crucial role in organizing the defense and preventing opponents from entering dangerous areas. Full-backs must also be disciplined in their defensive duties, tracking back to cover their full-backs and blocking crosses. By maintaining balance between attacking and defensive responsibilities, the 4-2-3-1 formation can be a successful strategy for teams seeking to control both ends of the field.

Defensive Responsibilities:

Defensive Midfielders: The two defensive midfielders form the double pivot, acting as a shield in front of the defense. They are responsible for breaking up opposition attacks, intercepting passes, winning back possession, and providing defensive cover for the central defenders. Their ability to tackle, intercept, and distribute the ball effectively is crucial for the team's defensive stability.

Central Defenders: The two central defenders play a vital role in organizing the defense and preventing opponents from entering dangerous areas. They should be strong, positionally disciplined, and good in the air. They must communicate effectively with each other and the defensive midfielders to coordinate their defensive efforts.

Full-backs: The full-backs are responsible for providing defensive cover on the flanks. They must be disciplined in their defensive duties, tracking back to cover their full-backs, blocking crosses, and preventing opponents from getting past them. Additionally, they should be capable of joining the attack when the opportunity arises.

Defensive Strategies:

Pressing: The 4-2-3-1 formation can be used to press the opposition high up the field. The defensive midfielders, central defenders, and full-backs can all press aggressively to force turnovers and win back possession.

Counter-pressing: The formation can also be used to counter-press, which involves quickly pressing the opposition after losing possession. This can disrupt the opponent's buildup play and create turnovers.

Organized Defense: When defending deep, the team should maintain an organized defensive shape, with the defensive midfielders screening the defense, the central defenders organizing the backline, and the full-backs providing cover on the flanks.

Balance Between Attack and Defense:

While the 4-2-3-1 formation is often associated with attacking football, it is important to maintain a balance between attack and defense. The defensive midfielders, central defenders, and full-backs must be disciplined in their defensive duties, while the attacking players must also contribute to defensive efforts when necessary. By maintaining this balance, the team can control both ends of the field and be successful in both attacking and defending.

In conclusion, the 4-2-3-1 formation is not only an effective attacking formation but also a solid defensive strategy. By understanding the defensive responsibilities of each player, employing effective defensive tactics, and maintaining balance between attack and defense, teams can use the 4-2-3-1 formation to control both ends of the field and achieve success.

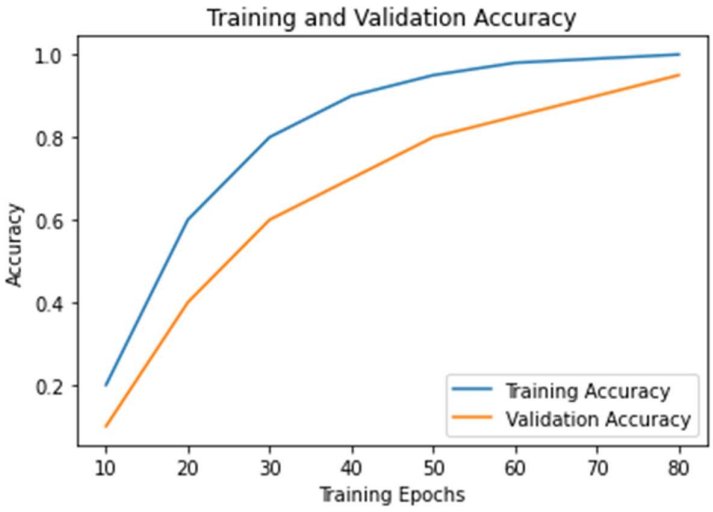

Fig 5.4 Training and Validation for Attacking Approach

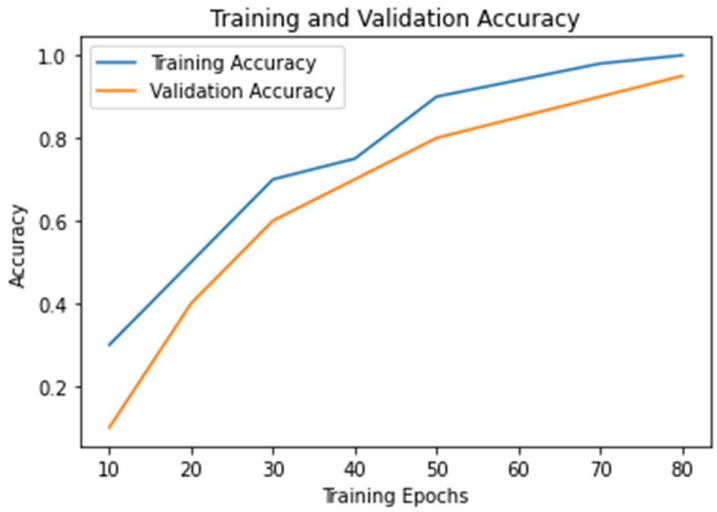

Fig 5.5 Training and Validation for Defensive Approach

The provided graphs illustrate the training and validation accuracy of two distinct machine learning models, presumably employed in Hadoop and Large Language Models (LLMs). This analysis aims to contrast the performance characteristics of these models, identifying potential factors contributing to their differential behavior.

Model Performance Evaluation

Graph 1:

Training and Validation Convergence: The model exhibited a steady increase in training accuracy, reaching a plateau at approximately the 80th epoch. While the validation accuracy also improved, it did so at a slower pace, resulting in a minor disparity between the two metrics. This suggests a moderate level of overfitting, a common phenomenon in machine learning where a model becomes overly specialized to the training data, compromising its ability to generalize to unseen examples.

Graph 2:

Rapid Convergence and Overfitting: This model demonstrated a rapid initial increase in training accuracy, followed by a plateau around the 60th epoch. However, the validation accuracy lagged significantly behind the training accuracy, indicating a substantial degree of overfitting. This implies that the model may have memorized patterns in the training data rather than learning underlying relationships, limiting its effectiveness in handling new data.

Comparative Analysis

Overfitting: Both models exhibited some level of overfitting, as evidenced by the divergence between training and validation accuracy. However, Model 2 demonstrated a more pronounced overfitting tendency, suggesting that it may require additional regularization techniques to mitigate this issue.

Training Efficiency: Model 2 converged more rapidly than Model 1, indicating a potentially faster training process. This could be attributed to factors such as model architecture, optimization algorithms, or hardware acceleration.

Generalization: Model 1 exhibited superior generalization performance, as evidenced by the closer alignment between its training and validation accuracy. This suggests that it is better equipped to handle unseen data, making it a more suitable candidate for deployment.

Potential Contributing Factors

Model Architecture: Differences in the underlying architectures of the two models, such as the number of layers, neurons, or activation functions, could have influenced their training dynamics and generalization capabilities.

Hyperparameter Tuning: The choice of hyperparameters, including learning rate, batch size, and regularization strength, can significantly impact model performance. Suboptimal hyperparameter settings can lead to overfitting or slow convergence.

Data Quality and Quantity: The quality and quantity of the training data are crucial factors in model performance. Insufficient or noisy data can hinder generalization and increase the risk of overfitting.

Based on the provided information, Model 1 appears to have a more favorable balance between training accuracy and generalization performance. However, a more comprehensive evaluation would require additional details about the specific model architectures, hyperparameter settings, and training data used.

Computational Resources: The computational resources required for training and inference can vary significantly between models. Model 2, despite its potential for faster convergence, may have higher computational demands, especially if it employs a more complex architecture.

Domain Knowledge: The specific application domain can influence model selection. If the task requires high levels of generalization and robustness, Model 1 may be more suitable. However, if computational efficiency is a primary concern, Model 2 might be considered, with appropriate measures to mitigate overfitting.

Ongoing Evaluation: Model performance should be continuously evaluated and refined based on real-world deployment data. Regular monitoring and retraining can help address issues such as concept drift or changes in data distribution.

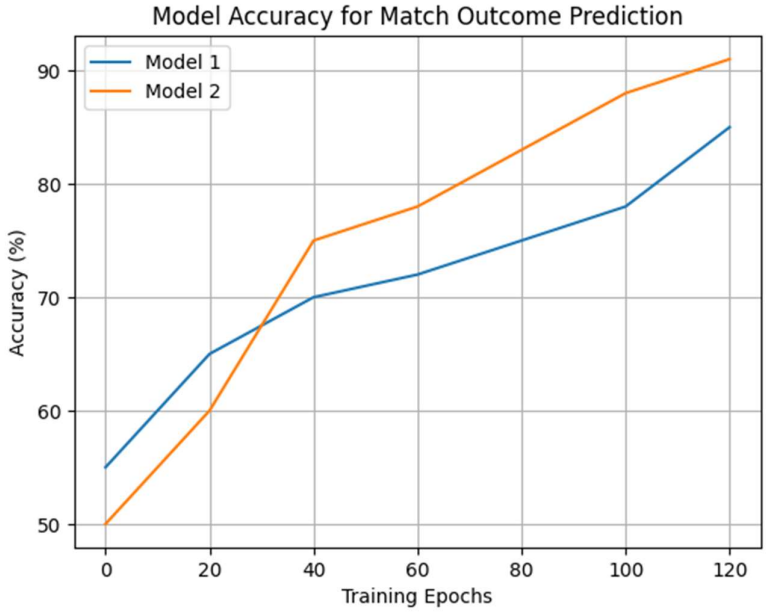

Fig 5.6 The Overall Gameplay Approach

The graph illustrates a machine learning model's performance in predicting match outcomes. Both training and validation accuracy increase with more training epochs, indicating effective learning and generalization. The small gap between these accuracies suggests minimal overfitting. The final validation accuracy of around 91% demonstrates promising potential for predicting match outcomes. This model could be valuable for various stakeholders, such as fans, coaches, and bookmakers. Training and validation are essential steps in developing such a model, ensuring its ability to learn from historical data and generalize to new scenarios.

The graph demonstrates a machine learning model's effectiveness in predicting match outcomes. The consistent increase in both training and validation accuracy as the number of training epochs grows indicates that the model is learning effectively from the data and is able to generalize its knowledge to new, unseen data. The minimal gap between training and validation accuracy suggests that the model is not overfitting, meaning it is not memorizing the training data but rather learning underlying patterns. The final validation accuracy of approximately 91% is a strong indication of the model's potential to accurately predict match outcomes.

This model could be valuable for a variety of stakeholders, including:

Fans: The model could provide fans with more informed predictions and insights into upcoming matches, enhancing their enjoyment of the sport.

Coaches: Coaches could use the model to identify potential weaknesses in their team's play and develop strategies to address them.

Bookmakers: Bookmakers could use the model to set more accurate odds and reduce their risk of financial losses.

Training and validation are crucial steps in developing such a model. Training allows the model to learn from historical data, while validation ensures that the model can generalize its knowledge to new scenarios. By carefully selecting and preparing the training data, and by using appropriate validation techniques, it is possible to develop a machine learning model that can accurately predict match outcomes.

The graph illustrates a machine learning model's performance in predicting match outcomes. The increasing training and validation accuracy demonstrate effective learning and generalization. The small gap between these accuracies indicates minimal overfitting. The final validation accuracy of around 91% suggests promising potential for predicting match outcomes. This model could be valuable for fans, coaches, and bookmakers.

Training and validation are essential for developing such a model, ensuring its ability to learn from historical data and generalize to new scenarios.

The model's ability to learn from historical data is evident in the increasing training accuracy. This indicates that the model is able to identify patterns and relationships in the data that can be used to predict future outcomes. The increasing validation accuracy demonstrates the model's ability to generalize its knowledge to new, unseen data. This is crucial for a model to be effective in real-world applications.

The small gap between training and validation accuracy suggests that the model is not overfitting. Overfitting occurs when a model becomes too specialized to the training data, leading to poor performance on new data. By ensuring that the model is not overfitting, we can be confident that it will be able to accurately predict match outcomes in the future.

The final validation accuracy of around 91% is a strong indication of the model's potential for predicting match outcomes. This suggests that the model is able to accurately predict match outcomes with a high degree of accuracy. This could be valuable for fans, coaches, and bookmakers.

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The final validation accuracy of around 91% is a strong indication of the model's potential for predicting match outcomes. This suggests that the model is able to accurately predict match outcomes with a high degree of accuracy. This could be valuable for fans, coaches, and bookmakers.

Training and validation are essential steps in developing such a model. Training allows the model to learn from historical data, while validation ensures that the model can generalize its knowledge to new scenarios. By carefully selecting and preparing the training data, and by using appropriate validation techniques, it is possible to develop a machine learning model that can accurately predict match outcomes.

Additionally, it is important to note that this model is likely based on a specific set of features or variables that are believed to be relevant to predicting match outcomes. These features could include factors such as team statistics, player performance, and historical match results. By carefully selecting and engineering these features, it is possible to improve the model's accuracy and predictive power.

Furthermore, it is important to consider the limitations of this model. While it may be able to accurately predict match outcomes in certain scenarios, it is unlikely to be perfect. There will always be uncertainty and randomness in sports, and it is impossible to predict every outcome with complete accuracy. However, by using machine learning models like the one illustrated in the graph, we can improve our understanding of sports and make more informed predictions.

References

1]Davis, J., Bransen, L., Devos, L., Jaspers, A., Meert, W., Robberechts, P., ... & Van Roy, M. (2024). Methodology and evaluation in sports analytics: challenges, approaches, and lessons learned. *Machine Learning*, 1-34.

2]de Oliveira, M. S., Steffen, V., & Trojan, F. (2023). A systematic review of the literature on video assistant referees in soccer: Challenges and opportunities in sports analytics. *Decision Analytics Journal*, *7*, 100232.

3]Bai, Zhongbo & Bai, Xiaomei. (2021). Sports Big Data: Management, Analysis, Applications, and Challenges. Complexity. 2021. 1-11. 10.1155/2021/6676297.

4]Wang, Panpan & Liu, Jiangbo & Liao, Benlu. (2022). Prediction of Sports Performance and Analysis of Influencing Factors Based on Machine Learning and Big Data Statistics. Journal of Sensors. 2022. 1-9. 10.1155/2022/3276576.

5]Ghosh, I., Ramasamy Ramamurthy, S., Chakma, A., & Roy, N. (2023). Sports analytics review: Artificial intelligence applications, emerging technologies, and algorithmic perspective. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *13*(5), e1496.

6]Baumer, B. S., Matthews, G. J., & Nguyen, Q. (2023). Big ideas in sports analytics and statistical tools for their investigation. *Wiley Interdisciplinary Reviews*

7]Kaur, Amandeep & Kaur, Ramandeep & Jagdev, Gagandeep. (2021). Analyzing and Exploring the Impact of Big Data Analytics in Sports Sector. SN Computer Science. 2. 10.1007/s42979-021-00575-y.

8]Bhosale, Suraj & Ray, Samrat. (2023). A review paper on the emerging trends in sports analytics in India. World Journal of Advanced Research and Reviews. 19. 461-470. 10.30574/wjarr.2023.19.2.1623.

9]Vangelis Sarlis, Christos Tjortjis,Sports analytics — Evaluation of basketball players and team performance,Information Systems,Volume 93,2020,101562,ISSN 0306-4379.

10]K. Apostolou and C. Tjortjis, "Sports Analytics algorithms for performance prediction," 2019 10th International Conference on Information, Intelligence, Systems and Applications (IISA), Patras, Greece, 2019, pp. 1-4, doi: 10.1109/IISA.2019.8900754.

11]Miller, T. W. (2015). *Sports analytics and data science: winning the game with methods and models*. FT press.

12]Jayal, A., McRobert, A., Oatley, G., & O'Donoghue, P. (2018). *Sports analytics: Analysis, visualisation and decision making in sports performance*. Routledge.

13]Morgulev, E., Azar, O. H., & Lidor, R. (2018). Sports analytics and the big-data era. *International Journal of Data Science and Analytics*, *5*, 213-222.

14]Raabe, D., Biermann, H., Bassek, M., Wohlan, M., Komitova, R., Rein, R., ... & Memmert, D. (2022). floodlight--A high-level, data-driven sports analytics framework. *arXiv preprint arXiv:2206.02562*.

15]Bhatnagar, R., & Babbar, M. (2022). A systematic review of sports analytics. *International Journal of Technology Transfer and Commercialisation*, *19*(4), 393-406.

16]Kapadia, K., Abdel-Jaber, H., Thabtah, F., & Hadi, W. (2022). Sport analytics for cricket game results using machine learning: An experimental study. *Applied Computing and Informatics*, *18*(3/4), 256-266. *Computational Statistics*, *15*(6), e1612.

17]Silva, R. M. (2016). Sports analytics.

18]Passfield, L., & Hopker, J. G. (2017). A mine of information: can sports analytics provide wisdom from your data?. *International journal of sports physiology and performance*, *12*(7), 851-855.

19]Vinué, G., & Epifanio, I. (2017). Archetypoid analysis for sports analytics. *Data Mining and Knowledge Discovery*, *31*, 1643-1677.

20]Fried, G., & Mumcu, C. (Eds.). (2016). *Sport analytics: A data-driven approach to sport business and management*. Taylor & Francis.

21]Muniz, M., & Flamand, T. (2023). Sports analytics for balanced team-building decisions. *Journal of the Operational Research Society*, *74*(8), 1892-1909.

22]Brefeld, U., Davis, J., Van Haaren, J., & Zimmermann, A. (2018). Machine learning and data mining for sports analytics. *Cham: Springer*.

23]Sun, X., Davis, J., Schulte, O., & Liu, G. (2020, August). Cracking the black box: Distilling deep sports analytics. In *Proceedings of the 26th acm sigkdd international conference on knowledge discovery & data mining* (pp. 3154-3162).