Вестник РУДН. Серия: Инженерные исследования
RUDN Journal of Engineering Research

2024;25(2):162–172

ISSN 2312-8143 (Print); ISSN 2312-8151 (Online)
journals.rudn.ru/engineering-researches

DOI: 10.22363/2312-8143-2024-25-2-162-172
UDC 004.89
EDN: MURUAK

Scientific review / Научный обзор

The Role of Convolutional Neural Networks in Cricket Performance Analysis

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Article history

Received: March 27, 2024
Revised: May 11, 2024
Accepted: May 17, 2024

Conflicts of interest

The authors declare that there is no conflict of interest

Authors' contribution

Undivided co-authorship.

Abstract. Significant insights have arisen from an extensive review of the current literature, highlighting the importance of Convolutional Neural Networks (CNNs) in cricket performance analysis and mapping new directions for future research. Despite difficulties such as limited availability of data, processing difficulty, and interpretability issues, incorporating CNNs into cricket statistics is a potential effort made possible by advances in machine learning and deep learning methods. Instructors, players, and data analysts can use CNNs to better comprehend the game, extract meaningful information from video data, and improve decision-making processes. Key findings show that CNNs are effective tools for a variety of cricket analysis tasks involving batting, bowling, fielding, and player tracking. The use of CNNs represents an advancement in cricket analysis, promising to open up new aspects of performance and usher in a data-driven era of cricket genius. Augmenting data, the use of parallelization, explainable AI, and concerns about ethics, provide opportunities to address current challenges can be identified as future advances in sports analysis with CNNs. Embracing technological advancements and mapping out future research directions are critical steps towards realizing this revolutionary potential.

Keywords: artificial neural networks, cricket, deep learning, machine learning, sports analytics

For citation

Ranasinghe NK, Kruglova L.V. The role of convolutional neural networks in cricket performance analysis. *RUDN Journal of Engineering Research.* 2024;25(2):162–172. http://doi.org/10.22363/2312-8143-2024-25-2-162-172

Роль сверточных нейронных сетей в анализе результатов игры в крикет

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История статьи

Поступила в редакцию: 27 марта 2024 г.
Доработана: 11 мая 2024 г.
Принята к публикации: 17 мая 2024 г.

Заявление о конфликте интересов

Авторы заявляют об отсутствии конфликта интересов.

Вклад авторов

Нераздельное соавторство.

Аннотация. Обширный обзор современной литературы позволил сделать важные выводы, подчеркнув важность сверточных нейронных сетей (СНС) для анализа результатов игры в крикет и наметив новые направления для будущих исследований. Несмотря на такие трудности, как ограниченная доступность данных, трудности с обработкой и интерпретируемостью, включение СНС в статистику по крикету, — это потенциальная возможность, появившаяся благодаря достижениям в области машинного обучения и методов глубокого обучения. Инструкторы, игроки и аналитики данных могут использовать СНС для лучшего понимания игры, извлечения значимой информации из видеоданных и улучшения процессов принятия решений. Основные результаты показывают, что СНС являются эффективными инструментами для решения различных задач анализа крикета, связанных с отбиванием, боулингом, филдингом и отслеживанием игроков. Применение СНС представляет собой прогресс в анализе крикета, обещающий открыть новые аспекты производительности и ознаменовать эру совершенного крикета, основанного на данных. Расширение данных, использование распараллеливания, поддающийся объяснению искусственный интеллект и следование этическим принципам предоставляют возможности решения существующих проблем и определяют будущие успехи в области спортивного анализа с СНС. Внедрение технологических достижений и определение направлений перспективных исследований являются важными шагами на пути к реализации этого революционного потенциала.

Ключевые слова: искусственные нейронные сети, крикет, машинное обучение, глубокое обучение, спортивная аналитика

Для цитирования

Ranasinghe N.K., Kruglova L.V. The role of convolutional neural networks in cricket performance analysis // Вестник Российского университета дружбы народов. Серия: Инженерные исследования. 2024. Т. 25. № 2. С. 162–172. http://doi.org/10.22363/2312-8143-2024-25-2-162-172

Introduction

In the dynamic world of modern sports, data analytics integration has become increasingly important, revolutionizing how athletes, coaches, and analysts perceive and improve performance. Cricket, a sophisticated and nuanced sport, is not immune to this revolutionary wave. Cricket performance analysis has always depended on manual observation, subjective assessments, and basic statistical metrics. However, the introduction of advanced technology, particularly machine learning and deep learning techniques such as Convolutional Neural Networks (CNNs), has created new opportunities for profound insights and predictive capacities in cricket performance monitoring.

This literature review seeks to investigate the critical significance of CNNs in cricket performance analysis, offering light on their evolution, uses, advancements, problems, and future directions. The review is motivated by an awareness of the critical need to use cutting-edge approaches to extract relevant insights from the massive and complex datasets produced by current cricket matches [1; 2] By evaluating the existing research, this review aims to provide a complete picture of how CNNs are changing the landscape of cricket analytics.

The literature is obtained from multiple databases by employing a range of keywords, such as "Convolutional Neural Networks in sports analytics," "data science in sports," "cricket performance analysis,' and "deep learning in cricket performance analysis." Figure 1 shows the procedure of literature selection for a review, commencing with preliminary searches carried out using Google Scholar, Semantic Scholar, and Scopus. An initial selection of 21 articles is made based on these sources. Subsequently, the snowballing technique is utilized, wherein the references of the first chosen papers are studied to discover supplementary literature that is relevant. This process results in the inclusion of an extra 24 articles in the selection. Afterward, a total of 13 articles are rejected for reasons such as lack of relevance, poor quality, or duplication. The final literature selection is obtained by merging the initial and subsequent selections and subsequently excluding the rejected articles, yielding a total of 32 articles.

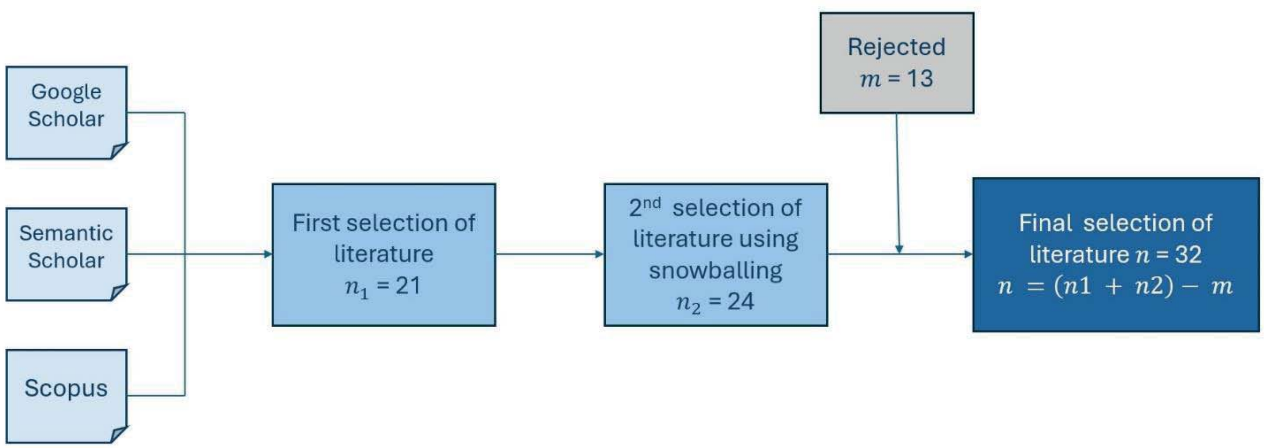

Figure 1. Selection process of literature review
Source: made by N.K. Ranasinghe

The evolution of sports analytics provides context for understanding the advent of CNNs in cricket. From basic statistical studies to advanced machine learning algorithms, the trip demonstrates a gradual change towards data-driven decision making and performance optimization [2]. Within this environment, CNNs have emerged as a powerful tool, making use of their ability to learn hierarchical representations from raw data, particularly in image and video processing. Recent research has emphasized the potential of CNNs in image and video processing, particularly its ability to learn hierarchical representations from unprocessed data [3]. These representations are created from grid data, such as photos and videos, and can be applied to a variety of applications other than typical image and video processing, such as optimal control, flow cytometry, and molecular simulations [4]. Furthermore, Convolutional Neural Network (CNN) feature maps can be used with different models of machine learning, such as Random Forests and Support Vector Machines, to improve classification performance [5].

Cricket, with its diverse nature that includes batting, bowling, fielding, and strategic intricacies, provides a unique and fruitful environment for the use of CNNs. Traditional techniques of performance analysis frequently fail to capture the nuances of cricketing moves and strategy, resulting in restricted insights. CNNs, on the other hand, present a viable answer because they allow for automatic, data-driven examination of numerous elements of cricket play [6]. CNNs have shown exceptional efficacy in deriving meaningful information from cricket data, ranging from assessing hitting approaches and bowler actions to recognizing fielding patterns and tracking player mobility [2].

As CNN-based cricket analytics evolves, it faces new hurdles. Data scarcity, computational complexity, and interpretability are key challenges that necessitate novel solutions. Furthermore, ethical concerns about player privacy and data fairness need cautious navigation in the quest of advanced analytics. Despite these problems, CNNs have enormous potential for cricket performance analysis. Future research directions show potential for future innovation, such as real-time analysis via wearable technologies, multimodal data integration, and the discovery of novel learning paradigms [1; 7].

This literature study aims to investigate the transformative effects of CNNs on cricket performance analysis. By synthesizing existing findings and recommending future research objectives, it hopes to contribute to a better understanding of how CNNs are changing the way we perceive and analyze cricket excellence.

1. Convolutional Neural Networks: Foundations and Basics

Convolutional Neural Networks (CNNs) have emerged as a key tool in deep learning, particularly for computer vision, speech recognition, and time series analysis [8]. These networks are artificial neural networks that excel at pattern recognition and inference [9]. They have been effectively used for a variety of applications, including natural language processing (NLP) [8]. CNNs have also been used to high-dimensional irregular domains like social networks and brain connectomes, using spectral graph theory [10]. This modification enables the effective development of localized convolutional filters that operate on graphs while maintaining the computational as well as learning complexity of classic CNNs [10].

Two innovative Convolutional Neural Network (CNN) structures are presented in distinct articles, both representing notable advancements in the field. The study [11], introduces a CNN structure that takes inspiration from quasi-linear hyperbolic systems, which are a type of partial differential equations (PDEs). This novel design enables weight adjustment by means of a continuous symmetry group, which deviates from the fixed structures and weights commonly observed in traditional models. Although this architecture takes an alternative approach, it obtains performance that is comparable to typical models on image classification tasks. This highlights the importance of internal symmetry in neural networks.

On the other hand, the following research [12], presents the Inception architecture, which sets a new benchmark in classification and detection for the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). Inception effectively utilizes computer resources in the network by simultaneously expanding the depth and width, all while keeping the computational budget constant. The Inception framework, specifically the GoogLeNet form with 22 layers, showcases remarkable efficacy in classification and detection tasks.

According to [13], there has been a growing trend toward utilizing deeper neural networks to enhance accuracy. On the other hand, a new and broader design for Convolutional Neural Networks (CNNs) is suggested, taking inspiration from multicolumn deep neural networks and Network in

Network (NIN). The goal is to achieve more accuracy without altering the input data. The proposed architecture, referred to as “CNN in Convolution” (CNNIC), applies convolution to a small CNN instead of using the original generalized linear model (GLM)-based filters. This little CNN serves as a kernel for the original picture and a feature extraction layer. A global average pooling layer and a softmax layer perform further categorization. They have utilized dropout and orthonormal initialization to mitigate training challenges such as slow convergence and overfitting.

The article by [14], introduces two architectures, namely the selection graph neural network (GNN) and the aggregation GNN, which are designed to extend the capabilities of Convolutional Neural Networks (CNNs) for analyzing signals on graphs. The GNN selection replaces linear time-invariant filters with linear shift-invariant graph filters and redefines pooling as a nonlinear subsampling stage, while preserving the positions of sampled nodes for computations in deeper layers. The aggregation Graph Neural Network (GNN) propagates signals across the graph, capturing diffused components that are detected by specific nodes. This enables the utilization of Convolutional Neural Network (CNN) convolution and pooling stages. An aggregate Graph Neural Network (GNN) variant is presented, specifically designed for handling large-scale networks with multiple nodes. Both designs can be simplified to typical convolutional neural networks (CNNs) when applied to temporal signals on circulant graphs.

In image processing, Convolutional Neural Networks (CNNs) have shown to be incredibly successful, especially for tasks like feature learning and picture classification [15; 16]. The practical applications of CNNs in image processing are highlighted in both [3] and [17]. Hidalgo [17] concentrates on style transfer, denoising, and deep dreaming, while Sharma and team [3] present an improved CNN model that uses state-of-the-art preprocessing and augmentation techniques to improve image readability and simplify the learning process. All these experiments demonstrate how flexible and effective CNNs are for a range of image processing applications.

Image classification is one of the most crucial and fundamental fields for computer vision applications [18]. The CNN architecture used for classification of images is displayed in Figure 2. Fully connected layers, pooling layers, and convolutional layers make up CNN. It convolves the entire image and creates intermediate feature maps using different kernels in the convolutional layers to produce different feature maps.

The purpose of the pooling layers is to minimize the size of feature maps and the parameters of the network. It functions as a CNN classifier and is often found at the final stage of each CNN architecture for the entirely connected layers. The result, as illustrated in Figure 2, can be utilized for image classification after all layers have been connected or as illustrated in Figure 3, can transmit the output to the derived Deep Neural Networks (DNN).

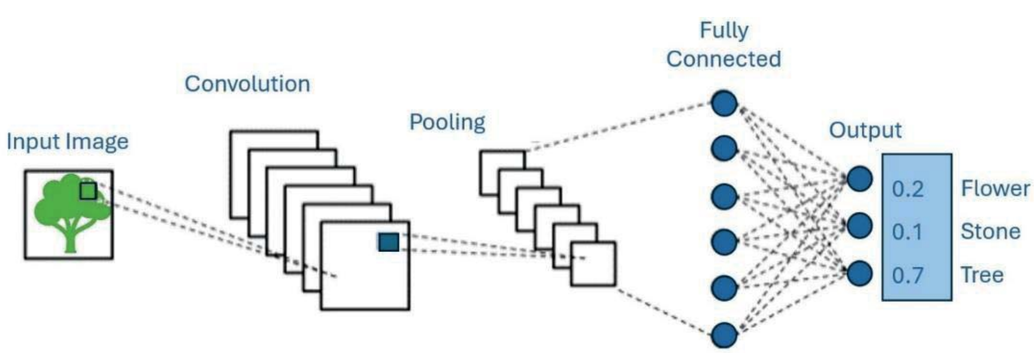

Figure 2. A basic CNN Architecture for Image Classification
Source: made by N.K. Ranasinghe

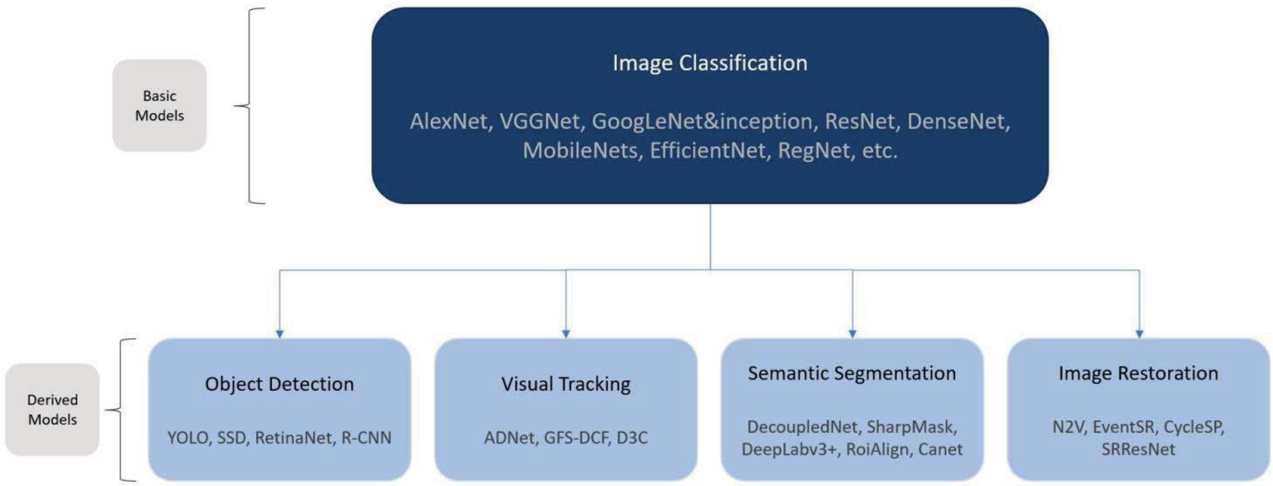

Figure 3. CNN basic models and derived models
Source: made by N.K. Ranasinghe

Historically, sports analysis was based mainly on subjective observations, rudimentary statistics, and unreliable evidence [1]. However, the environment began to change with the introduction of increasingly sophisticated data collection and analysis techniques.

2. Evolution of Sports Analytics

The development of machine learning and deep learning techniques in recent decades has catapulted sports analytics into a new age. Machine learning algorithms, which can extract patterns and insights from large datasets, have transformed the way teams and players approach training, strategy, and performance evaluation [6]. Deep learning, a subset of machine learning distinguished by neural networks with numerous layers, has broadened the possibilities by allowing the extraction of complex characteristics and representations from raw data.

One of the most notable advancements in this progression has been the incorporation of Convolutional Neural Networks (CNNs) into sports analytics. CNNs, which were originally created for image identification tasks, have been shown to be extremely versatile and effective across a wide range of sports. By learning hierarchical representations from raw data, CNNs can analyze visual data with unparalleled precision and efficiency [19].

The possibility of using pre-trained CNNs and hybrid optimization algorithms to enhance the precision and efficacy of sports video categorization and player performance analysis is emphasized by both [20] and [21]. By integrating CNNs for classification of sports in serial frames, [22] improves this even further and achieves a high classification accuracy. K. Dixit, A. Balakrishnan [23] uses CNNs to classify cricket ball-by-ball outcomes, and he achieves an astounding 80% accuracy rate. All of this research highlights how important CNNs are to improving sports analytics.

CNNs have been used in sports like soccer, basketball, and tennis to follow player movements, analyze game tactics, and forecast outcomes with amazing accuracy. CNNs have enabled coaches, analysts, and athletes to make better judgments and optimize performance plans by automating labor-intensive processes and revealing hidden patterns in data.

As technology advances and datasets become more complex, the role of CNNs in sports analytics is anticipated to grow, revealing new insights and opportunities for the success of the game and the players [1].

3. CNN Applications in Cricket Performance Analysis

Cricket, a sport renowned for its complexity and delicacy, has witnessed an increase in the use of advanced technologies such as CNNs to improve performance analysis. CNNs, which were originally created for image recognition tasks, have proven to be extremely effective at extracting useful insights from the huge and diverse datasets generated by cricket matches. This section looks into the various applications of CNNs in cricket performance analysis.

3.1. Batting Performance Analysis:

CNNs have been used to analyze batting approaches and performance in cricket. CNNs can discover significant features of batsmen's performances by analyzing video footage [22]. These insights enable coaches and analysts to provide batsmen with specific feedback, allowing them to improve their methods and performance at the crease.

3.2. Bowling Action Assessment

Assessing bowling movements is critical for detecting biomechanical problems and improving performance. Using a VGG16 model that had already been trained, [24] cut out the last layer, and then built three extra dense layers and an output layer for their classification. They kept the weights of the first 14 layers unchanged, using their dataset to train the subsequent layers. CNNs may analyze video footage of bowlers to discover minute differences in their movements, such as arm angle, release point, and follow-through [25]. CNNs help bowlers improve their performance on the pitch by identifying areas for improvement.

3.3. Fielding Pattern Recognition

Fielding is an important component of cricket, and CNNs can help analyze fielding trends and methods. CNNs can detect trends and patterns in field placements, outfield coverage, and throwing accuracy by analyzing video footage of fielding positions and motions [22; 26]. This information enables teams to optimize their fielding strategies and respond dynamically to match situations.

3.4. Player Tracking and Motion Analysis

Tracking player motions and analyzing motion patterns is critical for understanding game dynamics and performance. CNNs can interpret video footage from cricket matches to correctly track player motions and analyze their motion patterns over time [25; 26]. This data allows coaches and analysts to evaluate player fitness, workload, and positional techniques, resulting in more informed decisions about team selection and game tactics.

CNNs have emerged as useful tools for cricket performance monitoring, with applications spanning batting, bowling, fielding, and player tracking. Teams and sportsmen can gain a competitive advantage and improve their performance on the pitch by exploiting CNNs ability to analyze video data and extract relevant insights. As technology advances, the importance of CNNs in cricket analytics is projected to grow further, opening new avenues for understanding and improving performance in the sport.

4. Challenges and Potential Solutions

Cricket performance analysis, powered by Convolutional Neural Networks (CNNs) and other modern technologies, faces various hurdles that must be overcome in order to reach its full potential [29]. Furthermore, identifying future directions and developing trends is critical for advancing the discipline and meeting changing demands. This section looks at the obstacles, potential solutions, and future directions for CNN-based cricket performance analysis.

4.1. Challenges

4.1.1. Data Scarcity

Despite the quantity of cricket matches, gathering high-quality, labeled data for training CNNs remains difficult. Limited availability of annotated datasets impedes the development and validation of robust models.

Summary of few papers which used CNN in cricket analytics

Paper	Main findings	Year	Methodology
[19]	Deep neural networks have yet to be explored in analyzing sports data. The proposed model, "Shot-Net," demonstrated great accuracy while maintaining a low cross-entropy rate.	2018	The technique introduced and employed in the paper is a 13-layer convolutional neural network known as "Shot-Net."
[23]	A comparison of three alternative convolutional neural network designs for predicting ball-by-ball outcomes in cricket videos. Reporting on the performance of each architecture and investigating their benefits and drawbacks for this area. The best model achieved an accuracy of about 80% on the validation set.	2016	Three distinct convolutional neural network architectures were used.
[24]	The concept of a method for recognizing bowlers from bowling action photographs, the potential benefit to broadcasters, scorers, and team managers, and the model's outstanding performance with a test set accuracy of 93.3% and an F1 score of 93.2%.	2019	The study's specific algorithm is the pre-trained VGG16 model, which has been altered by dropping its final layer and integrating three more dense layers as well as a classification output layer.
[27]	The use of neural networks to predict cricketers' future performance based on past performance, as well as the utility of neural networks in providing valuable decision support throughout the team selection process.	2009	The study used neural networks to predict cricketer performance and recommend players for the World Cup.
[28]	The proposed approaches for predicting cricket match outcomes based on team performance, which used player-category correlations and a shallow Convolutional Neural Network (CNN) architecture, outperformed baseline approaches significantly. The shallow CNN architecture outperformed the proposed feature encoding-based technique. — The outcome of a match can be predicted with greater than 70% accuracy.	2019	The study's specific techniques include the feature-encoding-based approach and the shallow Convolutional Neural Network (CNN) architecture.

Source: compiled by N.K. Ranasinghe

4.1.2. Computational Complexity

Training and deploying CNN models can be computationally intensive, particularly when working with large-scale video collections [30]. This complexity poses issues in terms of infrastructure, time, and resource management.

4.1.3. Interpretability Issues

CNNs are sometimes regarded as "black box" models, making it difficult to understand the reasoning behind their predictions [30]. Coaches, players, and stakeholders may be hesitant to trust and implement a system that is difficult to interpret.

4.2. Potential Solutions

4.2.1. Data Augmentation

By creating more training examples, techniques like data synthesis and augmentation can help alleviate data scarcity difficulties [31]. This method improves model generalization and robustness without the use of large, annotated datasets.

4.2.2. Parallelization and Optimization

Using parallel computing architectures and optimizing CNN algorithms can reduce computational complexity and speed up training and inference operations. Model pruning, quantization, and distributed training are all important techniques for improving efficiency.

4.2.3. Explainable AI (XAI)

Combining explainable AI techniques with CNNs can improve interpretability by providing information about model predictions [32]. Attention mechanisms, saliency maps, and feature visualization are all useful tools for understanding how CNNs make decisions.

5. Future directions

5.1. Integration with Wearable Technology

Combining CNN-based analytics with wearable sensors provides real-time information about player performance indicators such as heart rate, movement patterns, and fatigue levels. This real-time analysis allows coaches to make data-driven judgments throughout games and training sessions.

5.2. Incorporation of Multimodal Data Sources

By combining video analysis with other data modalities such as sensor data (e.g., GPS, accelerometers) and physiological measurements, the analysis is enhanced and provides a more complete picture of player performance [6]. Integrating multiple data sources improves the granularity and accuracy of performance assessments.

5.3. Exploration of Transfer Learning and Domain Adaptation

Transfer learning approaches allow knowledge to be transferred from pre-trained CNN models to cricket-specific tasks, minimizing the requirement for large amounts of labeled data. Domain adaptation approaches help models adjust to different cricketing circumstances and playing styles, improving model robustness and generalization.

5.4. Ethical Considerations

As CNN-based analytics become more prevalent in cricket, ethical concerns about player privacy, data security, and fairness become critical. Establishing norms and regulations for data gathering, utilization, and distribution ensures ethical practices while also protecting player rights and welfare.

Conclusion

In conclusion, this literature study has shed light on the significance of CNNs in developing cricket performance analysis. Several major discoveries have emerged from a review of the literature, emphasizing the importance of CNNs and recommending future research avenues in this field.

CNNs have developed as strong tools for cricket performance analysis, with applications spanning batting, bowling, fielding, and player tracking. The evolution of sports analytics, together with advances in machine learning and deep learning techniques, has cleared the road for the incorporation of CNNs into cricket statistics. Data scarcity, processing complexity, and interpretability concerns all pose challenges to the mainstream use of CNN-based cricket performance analysis.

However, future solutions like data augmentation, parallelization, explainable AI, and ethical considerations provide opportunities to overcome these issues and advance the area.

The value of CNNs in improving cricket performance analysis cannot be emphasized. Coaches, players, and sports analysts can obtain a better understanding of the game by harnessing CNNs ability to analyze video footage, extract actionable insights, and improve decision-making processes. CNNs enable stakeholders to unlock new dimensions of cricket performance excellence by refining batting skills and evaluating bowling actions, as well as optimizing fielding strategies and tracking player movements.

The application of CNNs to cricket performance analysis marks a paradigm shift in how the sport is understood, analyzed, and optimized. By embracing technology developments, tackling difficulties, and setting future research routes, the field is on track to usher in a new era of data-driven cricket brilliance.

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