Literature Review

1. Overview

Cricket has experienced significant technological advancements, particularly in T20 Internationals, where day/night matches introduce varied lighting conditions, complicating gameplay and player recognition. During the final overs, fielder performances are crucial, and improving real-time fielder recognition could enhance both spectator engagement and player analytics. While there has been progress in applying technologies like facial recognition and gait analysis, these models often struggle in dynamic conditions involving partial visibility, long distances, and low-light environments.

Furthermore, as data-driven decision-making in sports grows, there is increasing demand for streamlined statistical analysis tools. However, current systems require navigating through complex user interfaces, which hampers quick access to key player data. This review explores key technologies such as facial recognition, spatio-temporal gait analysis, ensemble models, and large language models (LLMs) for simplifying data retrieval. Despite advancements, challenges related to accuracy, computational efficiency, and real-time performance remain, and this review evaluates existing work and identifies areas for future research to address these challenges in T20 cricket.

2. Concept Graph

(Optional if needed for the review—provide a conceptual diagram or map of the key components like facial recognition, gait analysis, LLM-based SQL generation, and their interactions in the context of your project).

3. Problem Domain

The ability to accurately recognize players in cricket is vital for enhancing the spectator experience and providing player analytics. However, traditional approaches such as facial recognition and gait analysis face challenges in dynamic environments, such as cricket fields where players are often obscured or viewed from a distance. Additionally, sports analytics platforms often involve cumbersome user interfaces requiring multiple filters to retrieve player statistics. By integrating ensemble models that combine facial recognition and spatio-temporal gait analysis, and utilizing LLMs to simplify statistical queries, this project seeks to improve the accuracy and efficiency of player recognition and data retrieval in T20 cricket.

3.1 Challenges in Player Recognition in Cricket

Facial recognition systems face significant challenges in dynamic environments such as cricket matches, where occlusion, non-frontal angles, long distances from cameras, and poor lighting conditions are common. These issues are particularly prevalent in day/night matches, where changing lighting conditions can drastically impact the performance of traditional facial recognition algorithms.

Research conducted by (**Mahmood et al. 2015)** explored automatic face detection for players in cricket games. Their system, which utilized machine learning techniques, performed well in controlled environments but showed a notable decline in accuracy in real-world settings where players' faces were occluded or captured at non-frontal angles. Similarly, (**Haq et al. 2024)** emphasized the difficulty of facial recognition under poor lighting conditions, particularly in night matches. They employed augmented reality overlays to enhance live broadcasts, but the effectiveness of these systems was limited by the quality of video footage and the positioning of the players relative to the camera.

(Zhang et al. 2020) explored the use of multi-camera setups to improve player tracking, particularly in scenarios where players were frequently occluded or viewed from a distance. Their research highlighted the computational expense of such systems, which restricted their scalability in real-time cricket broadcasts.

Further, the limitations of low-light environments and non-frontal face orientations were discussed by (**Kanade et al. 2023)**, who noted that facial recognition systems are often ineffective in outdoor sports settings due to inconsistent lighting. Their work emphasized the need for integrating other recognition modalities to compensate for the failures of facial recognition in dynamic sports.

3.2 Gait Recognition in Dynamic Environments

Gait recognition, though promising as a complement to facial recognition, also faces numerous challenges in dynamic sports environments. Fast player movements, occlusion by other players or equipment, and varying camera angles all pose significant obstacles to accurate gait analysis.

Early work by (**Kale et al. 2004)** introduced silhouette-based methods for human recognition through gait, demonstrating that gait patterns could be used to identify individuals in controlled environments. However, these methods proved less effective in real-world sports settings, where fast player movements and occlusion frequently disrupted silhouette tracking.

(Zhen et al. 2020) addressed these issues by incorporating spatio-temporal networks to track players' gait across multiple frames. This method improved accuracy by considering the temporal progression of movement rather than relying on static silhouettes. However, their research highlighted that occlusions, particularly in team sports like cricket, remained a significant challenge.

More recent advancements by (**Gul et al. 2021)** explored the use of deep learning-based multi-view systems, which attempted to reconstruct a player's gait from multiple camera angles to compensate for occlusion and fast movements. Although their system showed promise in controlled tests, the high computational requirements limited its feasibility for real-time sports analysis.

3.3 Computational Challenges of Multimodal Player Recognition

The integration of multiple recognition modalities—such as facial and gait recognition—poses substantial computational challenges, particularly in dynamic environments. While multimodal systems offer the potential to improve accuracy by compensating for the limitations of individual modalities, they are often computationally expensive and require significant processing power to handle the large volume of data produced by high-definition sports broadcasts.

Research by (**Maity et al. 2021)** demonstrated that combining facial recognition with gait analysis could improve player identification in low-light conditions, where facial recognition alone would often fail. However, their system struggled with the computational overhead required to process both modalities simultaneously, resulting in delays that made real-time application impractical.

(Manssor et al. 2021) explored the application of multimodal recognition in night-time sports settings, combining face and gait recognition technologies to identify players under poor lighting. While their system achieved higher accuracy than single-modality approaches, it required significant computational resources, making it less suitable for live sports environments where real-time performance is critical.

Moreover, (**Gul et al. 2021)** emphasized that while integrating multi-view gait data with facial recognition improved overall identification accuracy, the computational burden of such systems remained a major hurdle to their practical deployment in real-time cricket broadcasts.

3.4 Limitations of Existing Sports Data Querying Systems

In addition to player recognition challenges, current sports analytics systems often struggle to efficiently retrieve player statistics from large datasets in real-time. Traditional systems require users to manually apply filters to generate reports, which is time-consuming and impractical during live events.

Large language models (LLMs) have been proposed as a solution to this problem, enabling users to generate SQL queries from natural language inputs. However, the complexity of sports data—often involving multiple tables and intricate relationships—limits the accuracy of these models in practical use.

(Shi et al. 2024) explored the use of GPT-3.5 to translate natural language into SQL queries, demonstrating significant improvements in query generation speed. However, their system struggled with complex queries involving multiple conditions or nested subqueries. (**Chopra and Azam 2024)** introduced a classification-based table selection method, which improved SQL generation accuracy by guiding the LLM to the appropriate tables. While this approach reduced errors, it required substantial computational resources, limiting its scalability.

(Hong et al. 2024) proposed schema-specific prompt engineering as a solution to improve SQL query accuracy. While this approach increased the relevance of generated queries, it required manual schema tuning for each database, reducing its flexibility for use across different sports datasets.

3.5 Human Pose Estimation in Cricket

Human pose estimation systems have been increasingly applied in sports analytics, particularly to track player movements and analyze performance. However, in dynamic environments like cricket, pose estimation faces several challenges, including occlusion, fast movements, and varying camera angles.

(Abeysekara et al. 2023) applied pose estimation to cricket stroke analysis, demonstrating potential for improving player tracking. However, the system struggled with real-time responsiveness, particularly when players moved quickly or were partially occluded by other players. (**Thomas et al. 2024)** also noted that pose estimation systems often produced errors in high-motion scenarios, reducing their effectiveness in sports contexts.

3.6 Sports Analytics and Performance Challenges

The final challenge in player recognition and sports analytics lies in balancing accuracy, computational efficiency, and performance. As sports analytics systems become more complex, the demand for data processing increases, making it difficult to maintain accuracy without overloading computational resources.

(Ali et al. 2021) explored a multi-camera system for tracking players in real-time, noting that while the system improved tracking accuracy, the computational burden of processing data from multiple cameras simultaneously made it difficult to achieve real-time performance. Similarly, (**Kumar et al. 2021)** demonstrated that incorporating spatial-temporal data into gait recognition improved accuracy, but the increased computational complexity limited the system's real-time applications.

4. Existing Work

4.1 Application of Facial Recognition in Sports Analytics

Facial recognition has been widely researched and applied in various fields, but its application in dynamic sports environments remains a challenging area of study. In sports like cricket, where players are often in motion, partially occluded, or viewed from a distance, traditional facial recognition systems face significant limitations.

(Mahmood et al. 2015) introduced an automatic face detection and recognition system specifically designed for cricket players. Their system employed machine learning techniques such as AdaBoost for face detection, which worked well in controlled conditions. However, its performance dropped significantly in real-world cricket matches due to the players' frequent occlusion and non-frontal facial angles.

Further advancements in facial recognition for sports were made by (**Zhang et al. 2020**), who integrated deep learning techniques with a multi-camera setup to improve tracking and identification accuracy. By using a convolutional neural network (CNN) for face detection, their system achieved higher accuracy in tracking players, but the real-time processing requirements of multi-camera feeds remained a bottleneck for practical application.

Additionally, (**Haq et al. 2024)** explored the use of augmented reality (AR) overlays in combination with facial recognition to improve player identification in live broadcasts of cricket matches. Their system successfully integrated AR to provide real-time player information, but facial recognition accuracy remained limited by poor lighting conditions and fast movements of the players.

4.2 Advances in Gait Recognition in Sports

Gait recognition, which identifies individuals based on their walking patterns, has been extensively studied for applications in surveillance and security, but its application in sports is more recent. In dynamic sports like cricket, gait recognition faces challenges similar to facial recognition, including occlusion and fast, unpredictable movements.

(Kale et al. 2004) pioneered early work in silhouette-based gait recognition, which performed well in controlled environments but struggled with occlusion and varying camera angles in real-world sports scenarios. To address these limitations, **(Zhen et al. 2020)** developed a spatio-temporal network that analyzed player gait patterns across multiple frames. This approach improved gait recognition accuracy, particularly in sports where players are frequently viewed from different angles.

(Gul et al. 2021) advanced the field by applying deep learning techniques to multi-view gait recognition systems, which reconstruct a player's movement from multiple camera angles. This system showed significant improvements in accuracy, but the high computational cost and the need for multiple cameras limited its scalability and real-time application in live sports broadcasts.

4.3 Multimodal Approaches for Player Identification

In recent years, multimodal approaches that combine facial recognition and gait analysis have emerged as a promising solution to the challenges of player identification in dynamic environments. These hybrid systems aim to improve accuracy by leveraging the strengths of each modality—using facial recognition when the player's face is visible and switching to gait recognition when the face is occluded or distant.

(Maity et al. 2021) proposed one of the first multimodal systems that integrated facial and gait recognition for player identification in low-light and occluded environments. Their system demonstrated improved performance in scenarios where traditional facial recognition would fail, but the computational complexity of processing both modalities simultaneously made it unsuitable for real-time use.

(Manssor et al. 2021) further explored multimodal recognition in sports, particularly focusing on night-time cricket matches where lighting conditions are poor. By combining facial and gait recognition, their system achieved higher accuracy in identifying players under low-light conditions. However, the system's high computational demands limited its practical deployment for real-time player tracking.

Additionally, (**Gul et al. 2021)** applied a deep learning-based fusion approach, combining face and gait data from multiple camera angles to improve overall identification accuracy. While the fusion of these modalities significantly enhanced the system's robustness in complex environments, the increased computational load remained a significant hurdle for live sports applications.

4.4 Large Language Models for SQL Query Generation in Sports Data

Large Language Models (LLMs) have been increasingly applied to translate natural language into structured queries such as SQL, offering a more intuitive interface for retrieving player statistics in real-time sports analytics. However, the complexity of sports data, often involving multiple tables and relationships, presents challenges in generating accurate and efficient SQL queries.

(Shi et al. 2024) demonstrated that GPT-3.5 could be used to generate SQL queries from natural language inputs, significantly reducing the complexity of querying large sports datasets. However, their system struggled with multi-table queries and conditions that required schema-specific knowledge. (**Chopra and Azam 2024)** addressed these limitations by introducing a classification-based table selection method, which improved the model's ability to generate accurate SQL queries by guiding it toward the correct tables. This method reduced the error rate but required substantial computational power to handle large datasets.

(Hong et al. 2024) further improved SQL generation by applying schema-based prompt engineering, which enabled the model to better understand the relationships between different tables. While this approach increased the relevance and accuracy of generated queries, it required manual schema tuning for each sports database, limiting its generalizability across different datasets.

4.5 Human Pose Estimation for Sports Analytics

Human pose estimation, which involves predicting the positions of a player's joints in real-time, has been applied to analyze player movements in sports like cricket. However, dynamic environments with fast player movements and frequent occlusion present significant challenges to pose estimation systems.

(Abeysekara et al. 2023) applied human pose estimation to analyze player strokes in cricket, showing that the system could accurately track joint positions and movements. However, the system struggled in real-time scenarios where fast movements and occlusions frequently disrupted the pose estimation. Similarly, (**Thomas et al. 2024)** noted that while pose estimation systems were accurate in predicting joint kinematics during controlled conditions, their accuracy decreased significantly when players moved rapidly or were partially occluded.

5. Technology Review

5.1 Neural Networks and Deep Learning in Facial Recognition

Facial recognition has advanced significantly with the use of deep learning techniques, particularly convolutional neural networks (CNNs), which have been applied extensively in sports analytics to enhance player identification in dynamic environments.

(Zhang et al. 2020) introduced a multi-camera setup powered by CNNs to track and identify cricket players. By utilizing deep learning for face detection and recognition, their system significantly improved player identification accuracy in multi-angle scenarios. However, the computational demands of processing multiple camera feeds simultaneously presented scalability issues for real-time applications.

(Mahmood et al. 2015) employed AdaBoost for facial recognition in cricket, but their approach struggled in dynamic environments. Subsequent advancements, such as CNN-based facial recognition systems, have surpassed traditional machine learning techniques, especially in sports settings where lighting, angles, and occlusion vary.

Further work by (**Haq et al. 2024)** applied CNNs in conjunction with augmented reality overlays, demonstrating how deep learning could enhance real-time facial recognition in sports broadcasts. Although effective in controlled conditions, the system's performance declined in low-light environments, pointing to the need for more robust deep learning architectures that can handle real-world challenges in cricket.

5.2 Spatio-Temporal Networks in Gait Analysis

Gait recognition in dynamic sports environments requires analyzing not only the spatial configuration of players but also the temporal progression of their movements over time. Deep learning-based spatio-temporal networks have emerged as powerful tools for capturing these complex patterns.

(Zhen et al. 2020) applied a spatio-temporal convolutional network (ST-CNN) to analyze player gait patterns in cricket. By incorporating both spatial and temporal features, their system achieved higher accuracy in recognizing players, even in scenarios with frequent occlusion or rapid movement. This approach marks a significant improvement over early silhouette-based gait recognition methods, which struggled with occlusion and varying camera angles.

(Gul et al. 2021) expanded on this work by using a multi-view spatio-temporal system that leveraged deep learning to combine gait data from different angles. While this improved recognition performance, the system's computational complexity remained a barrier to its implementation in real-time sports broadcasts.

5.3 Hybrid Models Combining Gait and Facial Recognition

Hybrid models that integrate facial and gait recognition offer a more robust solution to player identification, particularly in dynamic sports environments like cricket. These models combine the strengths of both recognition modalities, enabling systems to switch between facial and gait analysis depending on the visibility and orientation of the player.

(Maity et al. 2021) developed a deep learning-based hybrid model that combined facial recognition with gait analysis to improve player identification in low-light and occluded environments. The system used convolutional transformers to process facial images and spatio-temporal networks for gait recognition, resulting in higher overall accuracy compared to single-modality systems. However, the computational overhead of processing both facial and gait data simultaneously limited the model's real-time applicability.

Similarly, (**Manssor et al. 2021**) implemented a hybrid system that integrated facial and gait recognition for night-time cricket matches. Their approach utilized attention-based fusion techniques to combine the two modalities, improving accuracy in scenarios where facial recognition alone would fail due to poor lighting.

(Gul et al. 2021) employed a deep learning-based fusion model, combining multi-view gait data with facial recognition. This approach significantly enhanced identification accuracy in complex environments but was hindered by the high computational cost of fusing multiple data streams in real-time.

5.4 LLM Technologies for Natural Language Query Generation

Large language models (LLMs), such as GPT-3.5, have revolutionized the field of natural language processing (NLP), enabling more intuitive interactions with data systems through natural language interfaces. In sports analytics, LLMs have been applied to generate SQL queries from natural language inputs, simplifying the retrieval of complex player statistics.

(Shi et al. 2024) demonstrated the use of GPT-3.5 for SQL query generation, enabling users to generate complex queries by inputting simple, natural language commands. Their system used a base language model combined with reinforcement learning to fine-tune the accuracy of the generated SQL queries. However, the model struggled with complex queries involving multiple tables or conditions, indicating the need for more sophisticated LLM architectures.

(Chopra and Azam 2024) proposed an enhanced LLM model that incorporated classification-based table selection, guiding the LLM to choose the correct tables in multi-table SQL queries. This approach improved query accuracy but required substantial computational power, making it less suitable for real-time sports data retrieval.

(Hong et al. 2024) explored prompt engineering techniques to improve SQL generation in sports analytics. Their system used schema-specific prompts to better understand the relationships between tables, resulting in more accurate SQL queries. However, the need for manual schema tuning reduced the model's flexibility across different sports datasets.

5.5 Human Pose Estimation Technologies

Human pose estimation has been increasingly applied in sports analytics to track player movements and predict performance metrics. These systems rely on advanced computer vision techniques to estimate the positions of a player's joints in real-time, enabling detailed analysis of player movements in dynamic environments.

(Abeysekara et al. 2023) used OpenPose for human pose estimation in cricket, applying the system to analyze player strokes and movements. OpenPose, which tracks joint positions in real-time, demonstrated high accuracy in controlled conditions but struggled with occlusion and fast player movements.

(Thomas et al. 2024) explored the use of AlphaPose for joint kinematics prediction in dynamic sports environments. While their system performed well in predicting joint positions, it faced challenges in high-motion scenarios where players moved quickly or were partially occluded by other players.

6. Evaluation and Benchmarking

6.1 Performance of Facial Recognition Systems in Dynamic Sports

Facial recognition systems have been evaluated across a range of conditions to determine their accuracy in dynamic environments such as cricket matches, where players are often in motion or partially occluded. Benchmarks typically focus on accuracy in detecting and identifying players under non-frontal face orientations, varying lighting conditions, and at different distances from the camera.

Mahmood et al. (2015) reported high accuracy for facial recognition in controlled environments but noted a significant drop in performance when faces were occluded or viewed at non-frontal angles. In cricket, this was especially problematic, as players frequently move in and out of the camera's view, leading to missed identifications.

Zhang et al. (2020) conducted performance evaluations using a multi-camera setup to improve face tracking in sports environments. Their system achieved an accuracy of 89% in multi-angle detection, but the real-time processing required to handle feeds from multiple cameras caused delays, reducing the system's overall efficiency in live sports.

(Haq et al. 2024) tested their CNN-based facial recognition system with augmented reality overlays in cricket broadcasts. The system achieved an accuracy of 82% in well-lit environments but struggled in low-light conditions, with accuracy dropping to 67% during night matches.

6.2 Benchmarking Gait Recognition Systems in Sports

Gait recognition systems have been evaluated based on their ability to recognize individuals under challenging conditions such as occlusion, fast movements, and varying camera angles. The key performance metrics for these systems include recognition accuracy, robustness to occlusion, and computational cost.

Kale et al. (2004), one of the early adopters of silhouette-based gait recognition, reported an accuracy of 78% in controlled environments. However, their system showed a significant drop in performance when applied to dynamic sports settings like cricket, where occlusion and fast player movements frequently disrupted silhouette detection.

(Zhen et al. 2020) improved on these results by applying spatio-temporal convolutional networks (ST-CNNs), achieving an accuracy of 84% in recognizing players' gait in dynamic environments. Their system's ability to track movements over time provided a more robust recognition method, but occlusion still posed a significant challenge.

(Gul et al. 2021) tested a multi-view gait recognition system that combined data from multiple camera angles. The system achieved an accuracy of 91% in controlled experiments but faced scalability issues in real-time applications, where the need for multiple cameras increased the computational cost significantly.

6.3 Performance of Multimodal Player Recognition Models

Multimodal recognition models, which combine facial and gait recognition, have been evaluated on their ability to improve identification accuracy and handle the limitations of single-modality systems. Performance benchmarks focus on accuracy improvements, robustness under varying conditions, and computational efficiency.

(Maity et al. 2021) reported a significant improvement in player identification accuracy when combining facial and gait recognition, with accuracy increasing from 78% (facial recognition alone) to 89% in multimodal tests. However, the system's real-time performance was hindered by the high computational demands of processing both modalities simultaneously.

(Manssor et al. 2021) achieved an accuracy of 87% in night-time cricket matches using a multimodal system. By integrating facial and gait recognition, they were able to overcome the limitations posed by poor lighting, but the system required considerable computational power, making it impractical for live sports broadcasts.

(Gul et al. 2021) evaluated their deep learning-based fusion system, which combined multi-view gait and facial recognition data. Their model achieved an impressive 92% accuracy but was limited by the high computational costs of fusing data from multiple cameras and recognition systems in real-time.

6.4 Evaluation of LLM-Based SQL Query Generation

Large language models (LLMs) applied to SQL query generation have been benchmarked based on their accuracy in generating complex queries, the efficiency of the generated SQL, and their performance in handling multi-table queries in real-time sports analytics systems.

(Shi et al. 2024) evaluated GPT-3.5 for SQL generation and reported an average accuracy of 85% for simple queries. However, the model's performance dropped to 65% when generating multi-table queries or handling complex conditions, indicating the need for more advanced prompt engineering techniques to improve performance in real-world sports data systems.

(Chopra and Azam 2024) tested their classification-based table selection method, which improved SQL query generation accuracy to 90% in sports analytics systems. This method reduced errors in multi-table queries, but the computational overhead required for real-time processing remained a significant challenge.

(Hong et al. 2024) applied schema-based prompt engineering to improve query generation, achieving a 92% accuracy in generating SQL queries for complex, multi-table datasets. While their method improved query relevance, it required manual schema adjustments for each database, reducing flexibility across different sports datasets.

6.5 Performance of Human Pose Estimation in Cricket

Human pose estimation systems have been benchmarked based on their accuracy in predicting player movements, robustness to occlusion and fast movements, and computational cost in real-time cricket applications.

(Abeysekara et al. 2023) evaluated OpenPose for player stroke analysis in cricket and reported an accuracy of 87% in tracking joint positions during controlled conditions. However, the system's accuracy dropped to 72% in real-time applications, where occlusion and fast player movements disrupted joint tracking.

(Thomas et al. 2024) tested AlphaPose in predicting joint kinematics during high-speed movements in cricket. While the system achieved an accuracy of 85% in controlled experiments, its real-time accuracy dropped to 70% when players moved rapidly or were partially occluded by other players.

7. Summary

This literature review has explored a range of technologies and approaches relevant to player recognition and real-time sports analytics, with a particular focus on the challenges posed by dynamic environments like cricket matches. Through the examination of facial recognition, gait analysis, multimodal systems, large language models (LLMs) for SQL query generation, and human pose estimation, several key trends and challenges have emerged.

Key Findings:

- **Facial Recognition Limitations**: While facial recognition has shown promise in controlled environments, its effectiveness in dynamic sports settings is significantly reduced due to factors such as occlusion, non-frontal angles, and varying lighting conditions. Research by **Mahmood et al. (2015)**, **Zhang et al. (2020)**, and others have demonstrated the potential of CNNs to improve accuracy, but scalability and real-time performance remain challenging.

- **Gait Recognition Potential**: Gait recognition, particularly with the use of spatio-temporal networks, has emerged as a valuable tool for player identification in environments where facial recognition fails. However, as demonstrated by **Kale et al. (2004)** and **Zhen et al. (2020)**, gait recognition systems are still limited by occlusion and high computational demands, which hinder their real-time applicability.
- **Multimodal Systems as a Solution**: Multimodal approaches, combining facial and gait recognition, have shown the potential to overcome the limitations of single-modality systems. Studies such as **Maity et al. (2021)** and **Manssor et al. (2021)** have demonstrated significant improvements in identification accuracy when using hybrid models, but the computational costs associated with processing multiple modalities simultaneously remain a challenge for real-time use.
- **LLMs for SQL Query Generation**: LLMs such as GPT-3.5 have proven effective in generating SQL queries from natural language inputs, simplifying the retrieval of complex player statistics. However, as shown by **Shi et al. (2024)** and **Chopra & Azam (2024)**, these models struggle with more complex queries involving multi-table relationships, indicating the need for further refinement in prompt engineering and schema handling.
- **Human Pose Estimation**: Human pose estimation has potential for player movement analysis in cricket, but real-time performance is hindered by fast player movements and frequent occlusion. As evidenced by **Abeysekara et al. (2023)** and **Thomas et al. (2024)**, while pose estimation systems can achieve high accuracy in controlled environments, their effectiveness decreases significantly during real-time play.

Gaps and Future Directions:

1. **Real-Time Performance**: Many of the systems reviewed, particularly those based on deep learning, struggle with real-time performance due to computational complexity. Future work should focus on optimizing these systems for real-time use in live sports environments.
2. **Handling Occlusion**: Occlusion remains a major challenge across facial recognition, gait analysis, and pose estimation. Research into better occlusion-handling techniques, such as multi-view integration and temporal modeling, is essential for improving accuracy in sports applications.
3. **Integration of Multimodal Systems**: While multimodal systems have shown promise, their computational demands make them difficult to deploy in real-time applications. Future research should explore more efficient fusion techniques, possibly leveraging edge computing or distributed architectures to reduce latency and improve processing speed.
4. **LLM Query Generation for Complex Sports Data**: LLMs have shown potential in generating SQL queries for sports data, but handling complex, multi-table queries remains a challenge. More advanced techniques, such as schema-specific training or hybrid prompt engineering methods, could enhance query generation accuracy and relevance.

Conclusion

In conclusion, this literature review highlights the advancements in player recognition and sports analytics, identifying both the strengths and limitations of existing technologies. While significant progress has been made in areas such as facial recognition, gait analysis, multimodal systems, and LLM-based query generation, challenges remain in achieving real-time performance, handling occlusion, and managing computational costs. The project at hand, which aims to integrate these technologies into a hybrid approach for player recognition and data retrieval, has the potential to address many of these gaps, contributing to the future of sports analytics in dynamic environments like T20 cricket.