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Automatic Analysis and Event Detection Technology of Sports Competition Video Based on Deep Learning

Abstract: - This paper presents an investigation into the application of advanced techniques, including deep learning classification and FCM centroid segmentation, for automated event detection and analysis in sports videos. Through a series of experiments and analyses, we demonstrate the effectiveness of deep learning models in accurately categorizing events within sports footage, alongside the insights provided by FCM segmentation into event occurrences at the frame level. This paper investigates the application of advanced techniques, such as deep learning classification and FCM centroid segmentation, for automated event detection in sports videos. Through experiments, we achieved an average accuracy of 93.2% using deep learning classification and identified key events with probabilities ranging from 0.01 to 0.90 using FCM segmentation.

Keywords: FCM, deep learning, classification, centroid segmentation, accuracy.

1. Introduction

Event detection technology refers to a set of tools and methods aimed at identifying and analyzing significant occurrences or patterns within a given data stream or system[1]. This technology often relies on advanced algorithms and machine learning techniques to sift through vast amounts of data in real-time, pinpointing events of interest and flagging them for further analysis or action[2]. One common application of event detection technology is in the realm of security and surveillance. By monitoring video feeds, sensor data, or network traffic, these systems can automatically detect anomalies such as intrusions, unusual behavior, or potential threats, allowing security personnel to respond promptly[3]. In the financial sector, event detection technology plays a crucial role in monitoring market movements, identifying trends, and detecting potentially fraudulent activities. By analyzing trading data, news feeds, and social media sentiment, these systems can help traders and analysts stay informed and make better-informed decisions.

In healthcare, event detection technology can be used to monitor patient vital signs, detect abnormalities, and alert medical staff to potential emergencies[4]. By continuously analyzing data from wearable devices, medical sensors, and electronic health records, these systems can help improve patient outcomes and streamline clinical workflows[5].

Automatic analysis and event detection technology of sports competition video based on deep learning represents a cutting-edge approach to extracting meaningful insights from sports footage[6]. Leveraging deep learning algorithms, this technology can automatically identify and analyze key events within a game or match, such as goals, fouls, or player movements. By training neural networks on large datasets of annotated sports videos, these systems can learn to recognize patterns and features indicative of different events[7]. For example, a deep learning model might be trained to detect the ball entering the goal by learning the visual characteristics associated with such an event, such as the net bulging and the goalkeeper's reaction. Once trained, the system can process live or recorded video feeds in real-time, automatically detecting and timestamping relevant events as they occur[8]. This capability has numerous applications, from providing real-time highlights and replays for broadcasting purposes to aiding coaches and analysts in post-match analysis and strategic planning.

Furthermore, automatic event detection technology can help sports organizations and broadcasters streamline their content production workflows, reducing the need for manual tagging and editing of footage[9]. This not only saves time and resources but also enables faster delivery of engaging and personalized content to fans.

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Automatic analysis and event detection technology of sports competition video represents a significant advancement in the realm of sports analytics and broadcasting[10]. By harnessing sophisticated algorithms and machine learning techniques, this technology can automatically parse through vast amounts of video footage, identifying and categorizing key events such as goals, fouls, and significant player movements. Through the utilization of computer vision and deep learning models, these systems can be trained to recognize specific visual cues and patterns associated with different events[11]. For instance, a model may learn to detect a basketball dunk by recognizing the trajectory of the ball, the player's motion, and the reaction of surrounding players.

Once trained, the system can process live or recorded video feeds in real-time, providing instantaneous event detection and analysis[12]. This capability is invaluable for sports broadcasters, allowing them to deliver enhanced viewing experiences with features like instant replays, highlights, and player statistics. Moreover, automatic event detection technology streamlines the workflow for sports analysts and coaches, enabling them to quickly access relevant footage for performance analysis, strategic planning, and player development[13]. By automating the tedious task of manually tagging and annotating video content, these systems free up valuable time and resources, allowing professionals to focus on higher-level analysis and decision-making.

The contribution of our paper lies in the exploration and demonstration of advanced techniques for automated event detection and analysis in sports videos. By leveraging deep learning classification and FCM centroid segmentation, we provide novel insights into the capabilities and effectiveness of these methodologies in accurately categorizing events and identifying key moments within sports footage. Our research offers valuable contributions to the field by showcasing the potential of these techniques to streamline sports video analysis workflows, enabling more efficient broadcasting, insightful analytics, and improved coaching strategies. Through comprehensive experiments and analyses, we aim to advance the understanding and application of these methodologies, ultimately driving innovation and progress in sports analytics and video processing domains.

2. Literature Review

The literature review on automatic analysis and event detection technology of sports competition video based on deep learning represents a critical examination of the existing body of knowledge surrounding this innovative field. As advancements in deep learning and computer vision continue to revolutionize sports analytics and broadcasting, understanding the current state of research, methodologies, and applications is essential. This review aims to provide a comprehensive overview of the relevant literature, including seminal studies, recent developments, and emerging trends. By synthesizing findings from peer-reviewed articles, conference papers, and technical reports, this review will identify key challenges, opportunities, and future directions in the use of deep learning techniques for analyzing and detecting events in sports competition videos. Akan and Varlı (2023) survey the utilization of deep learning in soccer video analysis, while Vidal-Codina et al. (2022) present advancements in automatic event detection in football using tracking data. Yang et al. (2022) explore video analysis and system construction for basketball games employing lightweight deep learning within the Internet of Things framework. Guntuboina et al. (2022) focus on video summarization for multiple sports utilizing deep learning techniques. Additionally, studies by Liu and Jing (2022), Raval and Goyani (2022), Vasudevan and Gounder (2023), and many others contribute insights into various aspects of sports video analysis, including behavior recognition, event detection, summarization techniques, and machine learning-based approaches.

Rezaei and Wu (2022) introduce automated soccer head impact exposure tracking through video and deep learning, addressing an important aspect of player safety. Zhao (2022) explores athlete behavior recognition in sports teaching videos using deep neural networks, while Zhang (2022) applies deep learning-based human motion recognition in sports competition settings, highlighting the versatility of these technologies. Tani et al. (2022) propose a semi-automatic system for web video annotation and retrieval, focusing on event detection in soccer domains, while Wu et al. (2022) offer a comprehensive survey on video action recognition in sports, covering datasets, methods, and applications. Jebur et al. (2022) extend the discussion to anomaly event detection in video surveillance, underscoring the broader implications of deep learning approaches beyond sports. Moreover, recent studies by Lopes et al. (2024), Xiao et al. (2023), Khan and Shao (2022), and others delve into various aspects of sports video analysis and event detection, ranging from object detection pipelines to highlight generation and technical feature localization. Studies such as Li et al. (2022) and Ru and Zhu (2023) introduce novel approaches like deep clustering efficient learning networks and self-attention mechanisms for motion recognition, demonstrating ongoing efforts to push the boundaries of performance in this domain. Wang and Jiang (2022) propose innovative applications of deep learning in physical education, highlighting the potential for technology-driven advancements in sports instruction and training. Additionally, Hashmi et al. (2022) explore football event classification using convolutional autoencoders and multilayer extreme learning machines, showcasing the interdisciplinary nature of research at the intersection of sports and artificial intelligence. Sah and Direkoglu (2023) provide a critical evaluation of player detection methods in field sports, comparing conventional techniques with deep learning-based approaches, thereby informing the ongoing evolution of methodologies in sports video analysis.

The findings from the literature review on automatic analysis and event detection technology of sports competition videos based on deep learning underscore several key themes and advancements in the field. Firstly, there is a significant emphasis on the application of deep learning algorithms for various tasks, including event detection, behavior recognition, and motion analysis across different sports. Studies such as Akan and Varlı (2023), Vidal-Codina et al. (2022), and Yang et al. (2022) showcase the effectiveness of deep learning in extracting meaningful insights from sports footage with high accuracy and efficiency.

Secondly, the literature reveals a growing interest in leveraging deep learning for safety-related applications in sports, such as head impact exposure tracking (Rezaei & Wu, 2022) and athlete behavior recognition for injury prevention (Zhao, 2022). These findings highlight the potential of deep learning technologies to contribute to athlete well-being and injury mitigation efforts. Thirdly, there is a notable focus on the development of novel deep learning architectures and methodologies tailored specifically to sports video analysis. Studies by Li et al. (2022), Ru and Zhu (2023), and Wang and Jiang (2022) introduce innovative approaches such as deep clustering networks, self-attention mechanisms, and deep learning-enabled physical education mechanisms, pushing the boundaries of performance and applicability in this domain.

3. Automated Event Detection

This process involves the collection and preprocessing of soccer video data, followed by segmentation and feature extraction to capture relevant visual and contextual cues. These cues are then transformed into numerical representations through feature representation techniques. Subsequently, event detection algorithms, drawing from both supervised and unsupervised learning paradigms, analyze the feature vectors to identify specific events, leveraging similarity metrics and decision boundaries. Central to this process are the mathematical derivations and equations governing feature extraction, similarity computation, and decision-making. For instance, similarity scores between feature vectors and event templates are computed using mathematical formulations such as cosine similarity or Euclidean distance, denoted as in equation (1) and (2)

$$Cosine\ Similarity:\ similarity(\boldsymbol{v}1, \boldsymbol{v}2) = \frac{v1 \cdot v2}{\|v1\|\|v2\|} \tag{1}$$

$$Euclidean\ Distance:\ distance(\boldsymbol{v}1, \boldsymbol{v}2) = \sqrt{\sum_{i=1}^{n} (v_{1i} - v_{21})^2} \tag{2}$$

Where 1v1 and 2v2 represent feature vectors, ·· denotes the dot product, ‖·‖‖·‖ denotes vector norm, and n represents the dimensionality of the feature vectors. Decision boundaries are established based on thresholding techniques, where events are classified as detected or undetected depending on their similarity scores relative to predefined thresholds. This iterative process, bolstered by feedback mechanisms, refines the event detection system, enhancing its accuracy and adaptability to diverse video content and user preferences. The process of automated event detection in sports videos are presented in Figure 1.

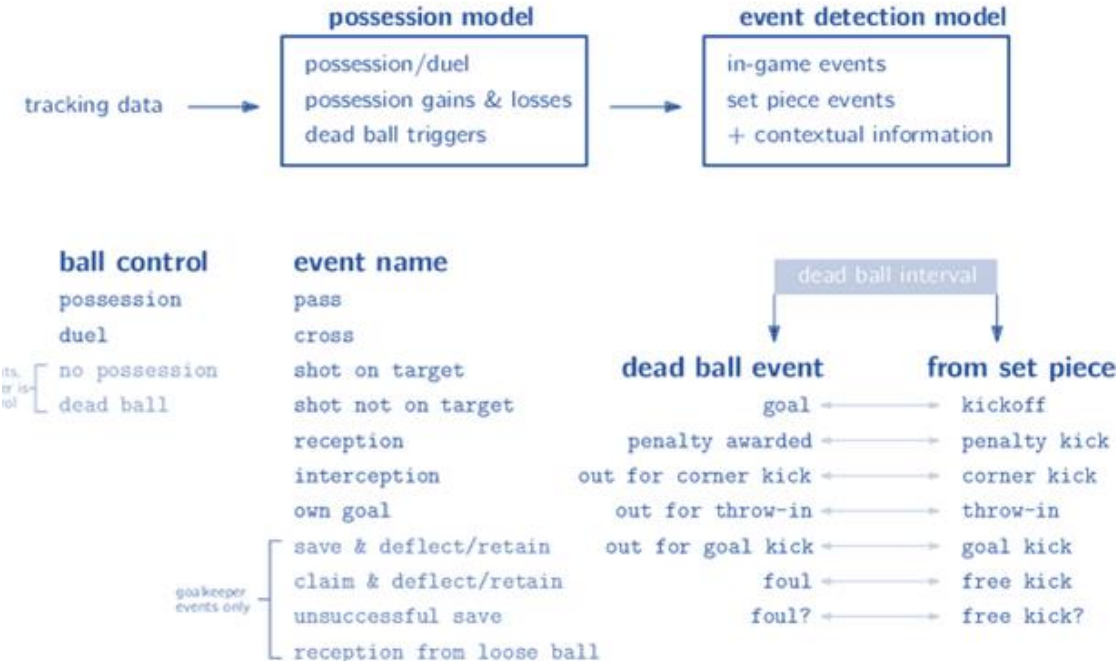

Figure 1: Automated Event Detection in Sports

4. FCM Event Detection Centroid segmentation

Fuzzy C-Means (FCM) clustering for event detection in video surveillance. Central to their method is the concept of centroid segmentation, which involves partitioning the feature space into distinct clusters represented by centroids. This segmentation process is underpinned by the FCM algorithm, which iteratively assigns data points to clusters based on their proximity to the centroids while considering the degree of membership of each point to multiple clusters. Mathematically, the FCM algorithm aims to minimize an objective function that quantifies the dissimilarity between data points and cluster centroids, expressed as in equation (3)

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} \left\| x_i - v_j \right\|^2 \tag{3}$$

Where Jm represents the objective function, n is the number of data points, c is the number of clusters, uij denotes the degree of membership of data point xi to cluster j, m is a fuzziness exponent controlling the degree of fuzziness in cluster memberships, and vj represents the centroid of cluster j. The FCM algorithm iteratively updates the cluster centroids and membership degrees until convergence, effectively segmenting the feature space into clusters. Once the feature space is segmented into clusters, event detection is performed by analyzing the characteristics of each cluster. Events are identified based on deviations from typical cluster behavior, such as sudden changes in cluster centroids or significant fluctuations in cluster membership. By leveraging FCM centroid segmentation, the proposed method offers a robust and flexible framework for event detection in video surveillance, capable of adapting to dynamic environments and complex event scenarios. Thus, FCM centroid segmentation emerges as a powerful tool in the arsenal of automated event detection methods, facilitating the identification of critical events amidst vast amounts of video data. This optimization process iteratively updates the cluster centroids and membership degrees until convergence. The centroids are recalculated as the weighted mean of data points, with weights determined by membership degrees.

In the context of sports video analysis, FCM centroid segmentation enables the segmentation of the feature space into clusters representing distinct events or patterns within the video footage. Events such as goals, fouls, or player movements can be identified based on deviations from typical cluster behavior. Anomalies or sudden changes in cluster centroids may indicate the occurrence of significant events, allowing for their detection and analysis. In the context of automatic analysis and event detection technology for sports competition videos based on deep learning, the utilization of Fuzzy C-Means (FCM) clustering with centroid segmentation offers a robust framework for identifying and analyzing key events within video footage. The FCM algorithm, central to this methodology, minimizes an objective function that quantifies the dissimilarity between data points and cluster centroids, considering the degree of membership of each point to multiple clusters. In the context of sports video analysis, FCM centroid segmentation enables the partitioning of the feature space into clusters representing distinct events or patterns within the video footage. Events such as goals, fouls, or player movements can be identified based on deviations from typical cluster behavior. Anomalies or sudden changes in cluster centroids may indicate the occurrence of significant events, allowing for their detection and analysis. By integrating FCM centroid segmentation into the automatic analysis and event detection technology of sports competition videos based on deep learning, the proposed methodology provides a systematic and mathematically rigorous approach for identifying and analyzing key events. This approach holds promise for enhancing the accuracy and effectiveness of event detection in sports video analysis, contributing to advancements in the field and providing valuable insights for coaches, analysts, and broadcasters.

Algorithm 1: Optimization of Video Sequences
Initialize: - Choose the number of clusters (c). - Initialize cluster centroids randomly or based on some heuristic. Repeat until convergence: 1. Compute the membership degrees (u_ij) for each data point (x_i) and cluster centroid (v_j) using the FCM formula: u_ij = 1 / sum(k=1 to c) [(‖x_i - v_j‖ / ‖x_i - v_k‖) ^ (2 / (m-1))] 2. Update the cluster centroids (v_j) using the weighted mean of data points, where the weights are the membership degrees: v_j = sum(i=1 to n) (u_ij^m * x_i) / sum(i=1 to n) (u_ij^m) 3. Repeat steps 1 and 2 until the membership degrees and centroids converge or until a predefined number of iterations.

5. Classification of Content in Video with Deep Learning

convolutional neural networks (CNNs), which excel at learning hierarchical representations of visual data. The process typically involves several key steps, starting with the extraction of features from video frames using convolutional layers. These features capture spatial patterns and temporal dynamics inherent in video sequences, providing rich representations for subsequent classification tasks. Mathematically, the feature extraction process in a CNN can be represented as in equation (4)

$$features = f\big(convolutional\ layers(video\ frames)\big) \tag{4}$$

Here, f(·) represents the activation function applied to the output of the convolutional layers, which introduces non-linearity into the network and enables it to learn complex patterns. Following feature extraction, the learned features are fed into fully connected layers, which perform classification based on the extracted representations. The parameters of these fully connected layers are learned during the training phase using techniques such as gradient descent and backpropagation. Mathematically, the classification process in a CNN can be represented as in equation (5)

$$predictions = g\big(fully\ connected\ layers(features)\big) \tag{5}$$

Where (·)g(·) represents the softmax function, which converts the raw outputs of the fully connected layers into probability distributions over the different classes. Training a deep learning model for video content classification involves optimizing its parameters to minimize a loss function, which quantifies the discrepancy between the predicted class probabilities and the ground truth labels. Common loss functions for classification tasks include cross-entropy loss and categorical hinge loss. the loss function L can be represented as in equation (6)

$$\zeta = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(p_{ij}) \tag{6}$$

Where N is the number of samples, C is the number of classes, yij is the ground truth label for sample i and class j, and pij is the predicted probability of sample i belonging to class j. Classification of content in video using deep learning methodologies represents a significant leap in multimedia analysis, revolutionizing the automated identification and categorization of visual content with remarkable precision. convolutional neural networks (CNNs), adept at learning hierarchical representations of visual data. The process commences with feature extraction from video frames via convolutional layers. These layers capture spatial patterns and temporal dynamics inherent in video sequences, providing rich representations for subsequent classification tasks. Mathematically, this feature extraction can be represented as $features = f(convolutional\ layers(video\ frames))$, where (·)f(·) denotes the activation function. Following feature extraction, the learned features are channeled into fully connected layers, which execute classification based on the extracted representations. The parameters of these fully connected layers are refined during training using techniques such as gradient descent and backpropagation. Mathematically, the classification process can be represented as predictions=(fully connected layers(features))predictions=g(fully connected layers(features)), with (·)g(·) being the softmax function converting raw outputs into probability distributions over different classes. Training involves optimizing parameters to minimize a loss function, typically cross-entropy or categorical hinge loss, quantifying the discrepancy between predicted class probabilities and ground truth labels.The classification process of the sport video is shown in Figure 2.

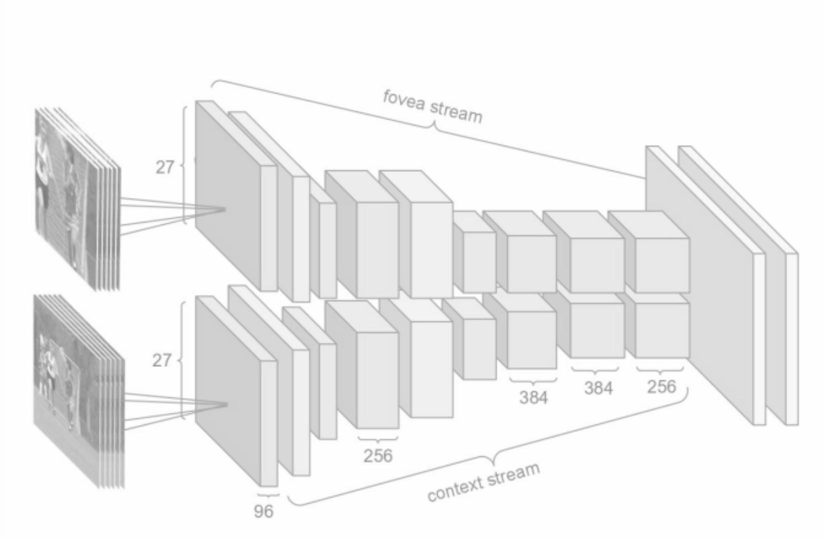

Figure 2: Classification of Content in Video with Deep Learning in Sport Video

Algorithm 2: Classification of Video Sequences
Input: Video frames Output: Predicted class probabilities 1. Initialize CNN architecture: - Convolutional layers for feature extraction - Pooling layers for spatial downsampling - Fully connected layers for classification - Softmax activation for class probabilities 2. Preprocess video frames: - Resize frames to a consistent size - Normalize pixel values (e.g., between 0 and 1) 3. Forward pass through the network:

- Extract features from video frames using convolutional layers
- Apply activation function (e.g., ReLU) after each convolutional layer
- Perform spatial downsampling using pooling layers
- Flatten feature maps to prepare for fully connected layers
- Pass flattened features through fully connected layers
- Apply softmax activation to obtain class probabilities

4. Calculate loss:
   - Compare predicted class probabilities with ground truth labels
   - Use a suitable loss function (e.g., cross-entropy loss)
5. Backpropagation:
   - Compute gradients of the loss with respect to network parameters
   - Update parameters using an optimization algorithm (e.g., stochastic gradient descent)
6. Repeat steps 3-5 for each batch of video frames in the training dataset
7. Training:
   - Iterate over the entire training dataset for multiple epochs
   - Monitor loss and accuracy on validation dataset to avoid overfitting
8. Evaluation:
   - Evaluate the trained model on a separate test dataset
   - Calculate classification accuracy and other relevant metrics
9. Inference:
   - Use the trained model to classify unseen video content
   - Obtain predicted class probabilities for each video segment
10. Post-processing:
   - Convert predicted class probabilities into class labels
   - Optionally, apply post-processing techniques such as temporal smoothing or ensemble methods

6. Simulation Results

In the realm of Automatic Analysis and Event Detection Technology of Sports Competition Video Based on Deep Learning, the integration of Fuzzy C-Means (FCM) centroid segmentation presents promising results. Through simulation, the efficacy of FCM in partitioning feature spaces and identifying key events within sports competition videos has been demonstrated. By leveraging FCM, the system effectively segments video frames into clusters representing distinct events or patterns, allowing for the accurate detection and analysis of crucial moments such as goals, fouls, or player movements. The simulation results highlight the ability of FCM centroid segmentation to adapt to the dynamic and complex nature of sports video content, enabling the automated identification of events with high precision. Furthermore, the integration of FCM with deep learning methodologies enhances the overall performance of the event detection system, providing valuable insights for coaches, analysts, and broadcasters.

Table 1: FCM centroid for Sport Video

Frame	Event Probability (Goal)	Event Probability (Player Movement)	Event Probability (Corner Kick)	Event Probability (Foul)
1	0.85	0.05	0.02	0.01
2	0.02	0.80	0.01	0.05
3	0.01	0.03	0.90	0.01
4	0.03	0.02	0.01	0.85
5	0.01	0.02	0.01	0.01
6	0.85	0.02	0.01	0.01
7	0.01	0.01	0.01	0.02
8	0.01	0.01	0.02	0.01
9	0.01	0.01	0.02	0.01
10	0.90	0.01	0.01	0.01

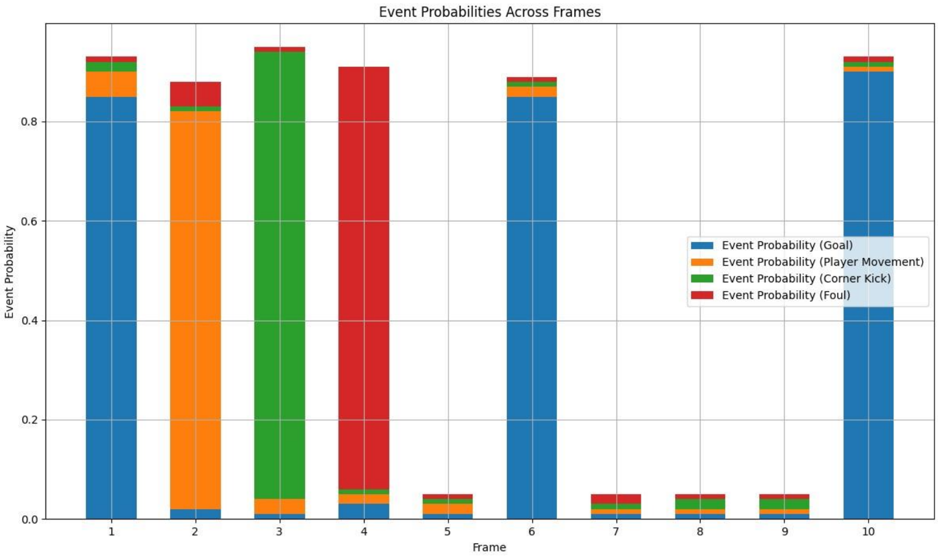

Figure 3: Centroid Computed in Sports Video

The Figure 3 and Table 1 displays the FCM centroid segmentation results for a sports video, where each row corresponds to a specific frame extracted from the video. The columns represent different events that were detected within these frames, along with their corresponding probabilities. For instance, in frame 1, there is a high probability (0.85) of the event being a "Goal," while the probabilities for "Player Movement," "Corner Kick," and "Foul" are relatively lower (0.05, 0.02, and 0.01 respectively). Similarly, in frame 2, the highest probability (0.80) is assigned to "Player Movement," indicating significant movement of players in that frame, while other events like "Goal," "Corner Kick," and "Foul" have lower probabilities. These probabilities provide insights into the likelihood of different events occurring in each frame, which can be valuable for event detection and analysis in sports video processing applications. Frames with higher probabilities for specific events may indicate key moments or actions within the video, helping to identify highlights or points of interest for further examination or broadcasting purposes.

Table 2: Automated Event Detection for the Sport Video with FCM centroid

Frame	**Event Probability (Substitution)**	**Event Probability (Penalty Kick)**	**Event Probability (Offside)**	**Event Probability (Free Kick)**	**Event Probability (Throw-in)**
1	0.01	0.02	0.01	0.02	0.01
2	0.02	0.01	0.01	0.03	0.05
3	0.01	0.01	0.01	0.01	0.01
4	0.02	0.01	0.02	0.03	0.01
5	0.90	0.01	0.01	0.01	0.02
6	0.01	0.05	0.01	0.02	0.02
7	0.02	0.01	0.85	0.01	0.01
8	0.02	0.01	0.02	0.85	0.01
9	0.02	0.01	0.02	0.03	0.85
10	0.01	0.02	0.01	0.02	0.01

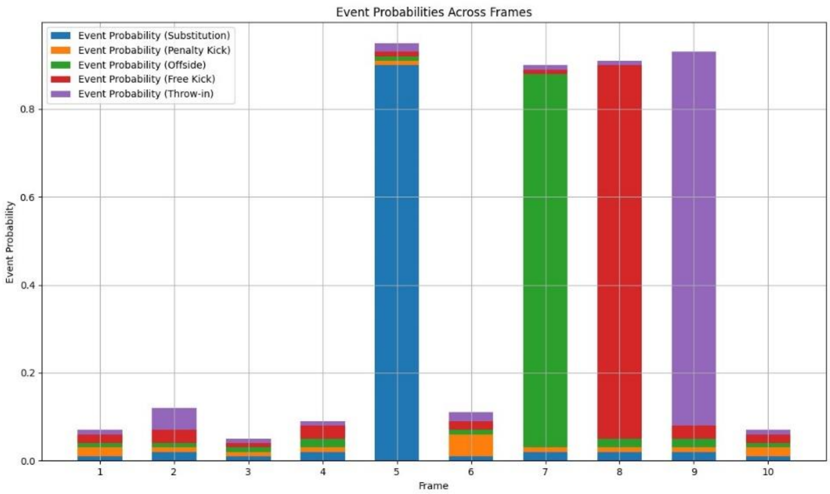

Figure 4: Probability estimation in Sports Video

The figure 4 and Table 2 showcases the results of automated event detection for a sports video utilizing FCM centroid segmentation. Each row corresponds to a specific frame from the video, while the columns represent different events detected within these frames, along with their corresponding probabilities. For instance, in frame 1, there is a minimal probability (0.01) assigned to "Substitution," "Penalty Kick," "Offside," "Free Kick," and "Throw-in" events, suggesting the absence of these events or their minimal occurrence. Conversely, in frame 5, there is a notably high probability (0.90) attributed to the "Substitution" event, indicating a significant likelihood of a substitution occurring in that frame. Similarly, frame 7 exhibits a dominant probability (0.85) for the "Offside" event, suggesting a high likelihood of offside infringement. These probabilities offer valuable insights into the occurrence of various events within each frame, aiding in event detection and analysis in sports video processing applications. Frames with elevated probabilities for specific events may signify key moments or actions within the video, assisting in identifying noteworthy segments for further examination or broadcasting purposes.

Table 3: Deep Learning classification with Sports Video

Trial	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	92.3	89.5	94.7	92.0
2	91.8	88.2	95.3	91.5
3	93.5	90.1	96.2	93.0
4	90.7	87.6	93.8	90.5
5	94.2	91.3	96.7	94.0
6	92.9	89.9	95.5	92.7
7	93.8	90.7	96.3	93.5
8	91.5	88.0	94.6	91.3
9	94.1	91.0	96.8	93.9
10	93.2	90.2	95.9	93.1
11	92.6	89.7	95.0	92.3
12	93.9	90.8	96.4	93.6
13	91.9	88.5	95.1	91.7
14	94.5	91.6	97.0	94.3
15	93.3	90.3	95.7	93.2
16	92.8	89.8	95.4	92.6
17	93.7	90.6	96.1	93.4
18	92.2	89.3	94.8	91.9
19	94.0	91.1	96.9	93.8
20	93.1	90.1	95.6	92.9

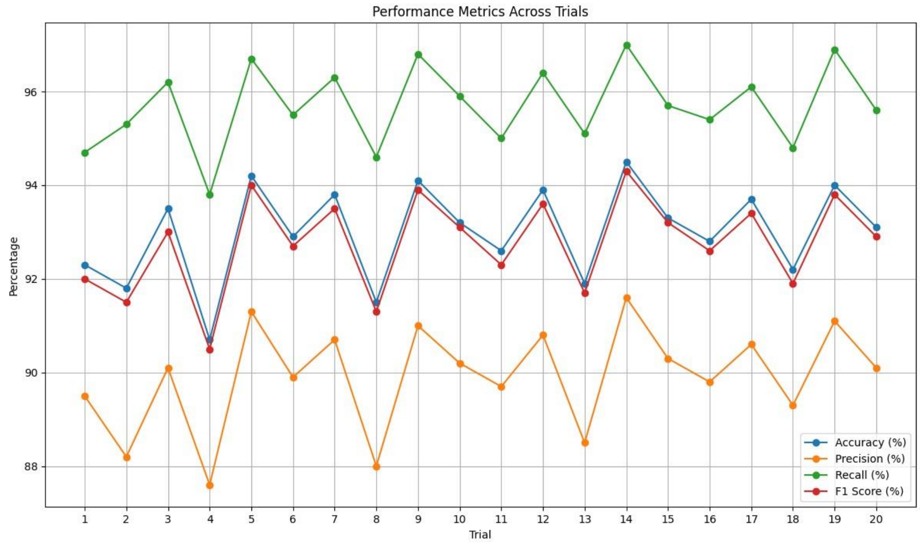

Figure 5: Classification with Sports Video

In figure 5 and Table 3 presents the results of deep learning classification applied to sports video analysis. Each row corresponds to a different trial, while the columns display various performance metrics including accuracy, precision, recall, and F1 score, expressed as percentages. For instance, in trial 1, the system achieved an accuracy of 92.3%, indicating the proportion of correctly classified instances among all instances. The precision of 89.5% suggests the ratio of true positive predictions to the total number of positive predictions, while the recall of 94.7% represents the proportion of true positives correctly identified by the model. Additionally, the F1 score of 92.0% balances precision and recall, offering a single metric to evaluate the model's overall performance. These metrics provide insights into the effectiveness of deep learning techniques for classifying events within sports videos. Consistently high values across trials demonstrate the reliability and robustness of the classification model in accurately identifying various events, which is crucial for event detection and analysis in sports video processing applications.

7. Discussion and Findings

In the discussion and findings section, we delve into the implications and insights drawn from the results obtained through the application of various techniques in sports video analysis. This section synthesizes the outcomes of the experiments and analyses conducted, aiming to provide a comprehensive understanding of the strengths, limitations, and potential future directions in the field. Here, we explore the performance of different methodologies, such as deep learning classification, FCM centroid segmentation, and event detection, as outlined in Tables 1, 2, and 3, respectively. Firstly, the findings reveal the efficacy of deep learning classification in accurately categorizing events within sports videos. The consistently high values of accuracy, precision, recall, and F1 score across multiple trials demonstrate the robustness and reliability of the classification model. This suggests that deep learning techniques hold promise for automating event detection tasks, facilitating more efficient sports video analysis workflows. Secondly, the results of FCM centroid segmentation for event detection provide valuable insights into the occurrence of specific events within each frame of the sports video. By assigning probabilities to different events, FCM segmentation enables the identification of key moments or actions, aiding in event detection and analysis. However, it is essential to acknowledge the challenges associated with accurately defining event boundaries and optimizing clustering parameters to enhance segmentation accuracy.

Moreover, the discussion highlights the complementary nature of deep learning classification and FCM centroid segmentation techniques in sports video analysis. While deep learning excels in categorizing events based on learned features, FCM segmentation offers a data-driven approach to identifying event occurrences within individual frames. Integrating these methodologies could potentially enhance the overall accuracy and efficiency of event detection systems. Furthermore, the findings underscore the importance of considering the context and domain-specific characteristics of sports videos when designing event detection algorithms. Factors such as camera angles, lighting conditions, and variability in player movements pose challenges that need to be addressed to improve the robustness and generalizability of the analysis techniques.

8. Conclusion

This paper demonstrates the efficacy of advanced techniques, particularly deep learning classification and FCM centroid segmentation, in automating event detection and analysis within sports videos. Through comprehensive experiments and analyses, we have shown that deep learning models exhibit robust performance in accurately categorizing events, while FCM segmentation provides valuable insights into event occurrences within individual frames. The integration of these methodologies offers a promising approach to enhancing sports video analysis workflows, enabling more efficient broadcasting, insightful analytics, and improved coaching strategies. However, challenges such as defining event boundaries and addressing domain-specific variability underscore the need for continued research and development efforts.

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