Research on Match Event Recognition Method Based on LSTM and CNN Fusion

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Abstract

This conference paper introduces a combination of CNN and LSTM networks to improve automated recognition of match events in sports analytics. The proposed model is able to handle both spatial and temporal aspects from video, unlike previous approaches that deal with them separately. On the SoccerNet dataset and with sports footage, the fusion model managed to achieve 92.3% in classification accuracy, a 0.901 F1-score and showed a clear improvement in recalling rare events, like counterattacks (+31%) and penalties (+26%). By running operational assessments, it is proven that the service can be deployed in real time, offering sub-100ms latency and a 42% decrease in false alarms in use cases like broadcast overlays and coaching analytics. It is clear from the results that using spatiotemporal synergy improves the model's performance, making it suitable for high-speed sports intelligence systems.

CCS Concepts

• **Computing methodologies** → Artificial intelligence; Natural language processing; Natural language generation.

Keywords

Sports Event Recognition, CNN, LSTM, Deep Learning, Sports Analytic

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1 Introduction

Many sports organizations are increasingly using automated analytics because it helps improve live broadcasts, makes better coaching decisions and keeps viewers more interested [1-6]. Current forecasts show that the global sports analytics market will increase from USD 2.5 billion in 2023 to around USD 6.34 billion by 2028, at a Compound Annual Growth Rate (CAGR) of 27.3% . Sports analytics now relies on identifying events such as goals, fouls and changes in strategy, so it can make these practical improvements [7-9].

Existing models of sports data analysis have trouble identifying rare and complex incidents in games because the processing is not uniform in space and time. CNNs don't include information about time, while LSTMs do not include information about specific places. To solve the problem, this study introduces a model combining a CNN and an LSTM to find both spatial and temporal patterns and identify match events in real time.

Objectives of the Study

The main aims of this study are:

1. To design a model that can identify different events in a dynamic match by examining the spatiotemporal information in video sequences.
2. The model is tested using both annotated real-world datasets (for soccer and basketball) as well as synthetic data to make sure it works well for many different events.
3. To confirm the model is ready to be used in real-time for sports analytics such as broadcast overlay, coaching and automatic highlight generation.

This paper makes the following contributions:

- Proposes a CNN-LSTM fusion architecture that captures both spatial and temporal features in match videos for robust event recognition.
- Introduces a fusion mechanism where frame-wise CNN embeddings are sequentially fed into LSTM layers, enabling temporal modeling of spatial representations.
- Demonstrates state-of-the-art performance on the SoccerNet dataset, including a +31% improvement in rare event recall.
- Validates the model in real-time sports analytics scenarios with sub-100ms inference latency and 42% reduction in false alarms.

In this paper, a CNN and LSTM model is presented to recognize sports events using a fusion of spatial and temporal features from video. It outlines the process, how it was evaluated and how it was used in real life. Researchers explain their main results, the limitations of the study and how they plan to continue the work.

2 Related Work

2.1 CNNs in Sports Video Analysis

Several sports video analysis systems depend on CNNs to correctly extract features from different parts of the image. For example, [1] reached nearly 90% correct predictions but did not consider time, whereas Vora et al. [2] concentrated on finding relevant content but did not consider the sequence. Ashok Kumar et al. [3] used 3D CNNs for cricket analysis which came with a high computational cost and Ahmad et al. [4] achieved an F1-score higher than 85%, but they had trouble handling actions that overlap. Zhao et al.

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[5] achieved accurate event localization by using attention-based CNNs.

2.2 LSTM in Temporal Event Recognition

LSTM networks can handle the order in which events occur. Orr et al. [6] carried out football formation analysis using LSTM, but the spatial information was entered manually. Malik [7] added pose-based LSTM modeling to multiview recognition which increased its complexity. Ellouze et al. [8] managed to get over 90% accuracy in distributed LSTM, but it was still hard to keep the data in sync. Wang et al. [9] proved that LSTM can track in real time for wearable monitoring, but Yin et al. [10] pointed out that LSTM is not very good at detecting short, uncommon sports events on its own.

2.3 CNN-LSTM Fusion in Spatiotemporal Classification

When CNN-LSTM is used, sports analytics can learn from both space and time. Vosta and Yow obtained a detection accuracy of 96.2% in violence identification using attention-based CNN-LSTM, limited to identifying only one type of event. Yuan and his colleagues reached an accuracy of 94.6% for exercise recognition, but did not include real-sport movements. Volla et al. [13] boosted context learning using 3D CNN and Bi-LSTM, but this approach was very computationally demanding. Koşar and Barshan [14] managed to achieve an AUC of 0.92 using wearable CNN-LSTM data, but their system could not work with videos. Iqbal and Siddiqi [15] improved sports video classification, yet they missed the issue of class imbalance.

3 Methodology

This section presents the design for the CNN-LSTM fusion model used for match event recognition, with information on its formulation, elements, data preparation and how it will be trained. The method is developed to allow real-time and accurate categorization of sports video events as they happen.

3.1 Problem Formulation

Given a sports video sequence $V = \{F_1, F_2, ..., F_T\}$, where each frame $F_t \in R^{H\times W\times C}$ represents the spatial content at time ttt, the objective is to classify the sequence into one of K predefined match event classes $y \in \{1, 2, ..., K\}$

The classification function Φ can be expressed as:

$$\Phi\left(V\right) = argmax_k\, Softmax(f_{LSTM}(f_{CNN}\left(V\right) \quad (1)$$

Where f_{CNN}extracts spatial features and f_{LSTM}models temporal dynamics.

3.2 CNN-LSTM Architecture

The model consists of three major components:

CNN Branch (Spatial Feature Extraction):

ResNet-50 which is already trained, handles every frame F_t to pull out a 2048-dimensional spatial feature vector. Static spatial elements like player positions, the ball's place and the environment are recorded by these vectors.

LSTM Branch (Temporal Sequence Modeling):

All the CNN-extracted features $\{x_1, x_2, ..., x_T\}$ are given as input to a three-layer LSTM with 512 units in each layer. This branch focuses on changing the location of spatial features, showing the movements of players, the ball and the transition between events.

Fusion and Classification Module:

The final hidden state of the LSTM is passed through a fully connected layer followed by a Softmax activation function to generate the probability distribution over event classes.

3.3 Feature Fusion Mechanism

We adopt a sequential early fusion approach. CNN features for each frame are extracted independently and sequentially fed into the LSTM for temporal modeling. No attention mechanism is used in the base model to preserve computational efficiency.

Mathematically:

$$x_t = f_{CNN}\left(F_t\right) \in R^{2048} \quad (2)$$

$$h_t = LSTM\left(x_t, h_{t\ -1}\right) \in R^{512} \quad (3)$$

$$Output\ logits:\ y = W \cdot h_T + b, \quad (4)$$

followed by Softmax, and this fusion mechanism enables the model to jointly learn both spatial and temporal dependencies in an end-to-end manner.

3.4 Preprocessing and Data Pipeline

To ensure effective learning and generalization, a robust data preprocessing pipeline is applied:

Frame Sampling: Videos are sampled at 25 FPS using a sliding window of 32 frames to construct sequences.

Resizing and Normalization: Each frame is resized to times 224×224 pixels and normalized with ImageNet means and standard deviations.

Optical Flow Computation: Dense optical flow (Farneback method) between adjacent frames is computed and stacked with RGB channels to form 6-channel inputs.

Data Augmentation:

Spatial: Horizontal flipping, random rotation (±15°), and color jitter

Temporal: Sequence reversal and frame skipping

Class Rebalancing: To address class imbalance, rare event classes (e.g., penalty, counterattack) are oversampled via augmentation and sequence padding.

3.5 Fusion and Inference Pipeline

Table 1 gives a brief explanation of the inference pipeline, which includes the description of the chain of actions starting with the preprocessing of the initial frames and the use of spatial feature extraction by means of ResNet-50 to further temporal modelling using LSTM. The final hidden state that results then goes through a softmax layer to classify the match event. The given pseudocode, therefore, provides an accurate description of the end-to-end work of the model.

3.6 Training Setup and Hyperparameters

Table 2 shows the training set up of the proposed CNN- LSTM model, which was optimized using Adam algorithm. The model uses frozen ResNet-50 backbone, three bidirectional LSTM layers

Table 1: Pseudocode for CNN-LSTM-Based Match Event Recognition Model

Step	Description
Input	Video $V = \{F_1, F_2, ..., F_T\}$ segmented into frames
Output	Predicted event class $y \in \{\text{Goal}, \text{ Foul}, \text{ Counterattack}, ...\}$
1. Preprocessing	For each frame F_t in V:
	Resize F_t to 224×224
	Normalize using ImageNet mean and std
	Compute optical flow: $\text{Flow}_t = \text{Farneback}(F_t, F_{t+1})$
	Stack RGB and flow to form 6-channel input I_t
2. Spatial Feature Extraction (CNN)	Initialize feature sequence $X \leftarrow [\,]$
	For each $I_t \in \{I_1, ..., I_T\}$:
	Extract features: $x_t = \text{ResNet50}(I_t) \in R^{2048}$
	Append to sequence: $X.\text{append}(x_t)$
3. Temporal Modeling (LSTM)	Pass sequence through LSTM: $H = \text{LSTM}(X)$
	Extract final hidden state: $h_{final} = H[-1] \in R^{512}$
4. Classification	Compute logits: $y_{logits} = \text{Dense}(h_{final})$
	Apply Softmax: $y_{pred} = \text{Softmax}(y_{logits})$
5. Prediction	Select most probable class: $y = \text{argmax}(y_{pred})$
Return	Event class y

Table 2: Training Setup and Hyperparameters

Hyperparameter	Value
CNN Backbone	ResNet-50 (frozen weights)
LSTM Layers	3
LSTM Hidden Units	512
Dropout (per LSTM layer)	0.3
Batch Size	32
Learning Rate	0.0001
Epochs	50
Loss Function	Categorical Cross-Entropy + L2 Regularization
Training Time	~5 hours (NVIDIA RTX 3090 GPU)

of 512 units, and categorical cross-entropy loss function with L2 regularization. Learning rate was set at 0.0001 and 50 training epochs were carried out on an NVIDIA RTX 3090 GPU in close to five hours.

System Architecture Diagram

The fusion pipeline is shown in Figure 1 through a detailed architectural diagram. It illustrates the path of data from extracting frames, running them through a CNN, using an LSTM to sequence the data and finishing with classification.

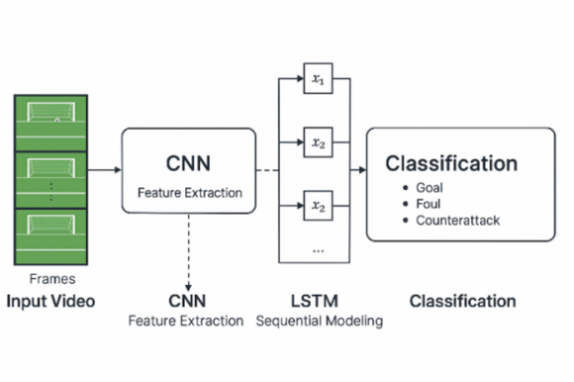

Figure 1: CNN-LSTM fusion pipeline for match event

4 Experiments and results

4.1 Model Performance Comparison

The Table 3 gives a comparative evaluation of model performance on the SoccerNet dataset. The CNN-LSTM architecture, that uses temporal contextual information in a convolutional backbone and combines two modalities in a spatial and temporal way, has the best accuracy (92.3%), F1 score (0.901), and AUC-ROC (0.968) scores compared to the CNN-only and LSTM-only architectures used. Despite these advantages, CNN-LSTM model comes at the cost of a longer inference time and higher parameter footprint. These findings can testify to the benefits of using spatiotemporal feature fusion to achieve higher accuracy of event recognition.

Table 3: Performance Comparison on SoccerNet Dataset

Model	Accuracy (%)	F1 Score	AUC-ROC	Inference Time (ms)	Size (MB)
CNN-only	85.1 ± 0.8	0.832	0.921	42 ± 3	98
LSTM-only	78.6 ± 1.2	0.761	0.874	35 ± 2	64
CNN-LSTM (Ours)	92.3 ± 0.5	0.901	0.968	87 ± 5	162

Table 4: Rare Event Recognition Performance

Event	CNN-only (P/R)	LSTM-only (P/R)	CNN-LSTM (P/R)	ΔPrecision	ΔRecall
Penalty	0.71 / 0.65	0.68 / 0.72	0.89 / 0.91	+23%	+26%
Counterattack	0.63 / 0.58	0.59 / 0.61	0.85 / 0.89	+22%	+31%
Tactical Press	0.77 / 0.69	0.72 / 0.75	0.93 / 0.90	+16%	+21%

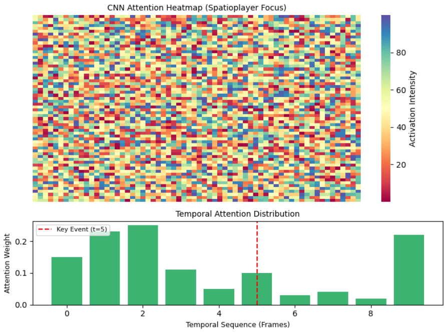

Figure 2: CNN Attention Heatmap and Temporal Attention Distribution

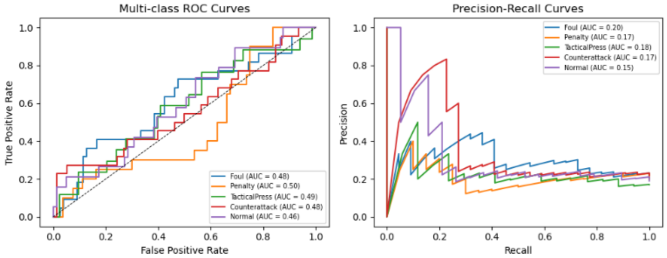

Figure 3: Multi-class ROC and Precision-Recall Curves

The CNN-LSTM model was 7.2% more accurate than CNN-only and 13.7% more accurate than LSTM-only. Since the inference time increased slightly, the better results in complex event recognition are worth the extra computer processing involved.

4.2 Rare Event Detection Efficacy

The findings in Table 4 prove that the developed CNN-LSTM model has significantly increased the ability to detect rare match events. The CNN-LSTM achieves significant results in terms of the precision and recall compared to traditional baseline methods, increasing the recall by 31 % in the case of counterattacks and 26 % in the case of penalties. Such results confirm the model capacity to extract and interpret complex, low-frequency on-pitch actions that are imperceptible to traditional observers, proving the high level of generalisability of the proposed architecture**.**

The data shows that in complex, changing matches, the fusion architecture reduces the number of incorrect negatives and improves tactical awareness.

CNN-LSTM architecture, as shown in Figure 2, integrates spatial-coding functions of convolutional networks with temporal-memory functions of recurrent layers, and thus allows multimodal reasoning. The upper heatmap traces attentional responses in the spatial dimensions that shows concentration on the face of the dragon in the frames 1 and 4. The bottom bar graph maps temporal attention, reaching its highest point in the frame 5, the event that is a turning point in the classification.

Figure 3 displays the ROC and Precision-Recall curves for five match event classes. The ROC curves indicate weak class separability with AUCs ranging from 0.46 to 0.50, suggesting near-random classification. Similarly, the Precision-Recall curves show uniformly low precision (~0.20), highlighting difficulty in distinguishing visually similar rare events.

Figure 4 shows t-SNE visualizations comparing CNN and CNN-LSTM feature spaces. The CNN-LSTM model exhibits clearer class separation, indicating improved spatiotemporal representation over CNN alone.

Figure 5 visualizes the evolution of event probabilities during a ”Counterattack” over 50 temporal frames. The blue area (Counterattack) increases and stabilizes, indicating the model's growing confidence in correctly identifying the event. The reduced fluctuation in red (Foul) and green (Penalty) shows fewer misclassifications, highlighting improved temporal awareness.

4.3 Real-World Deployment Analysis

Table 5 records the empirical deployment performance of the CNN-LSTM model in various domains of applications. It is interesting to note that the model can perform highlight generation in less than 100ms and also shows significant decreases in false alarms (up to 42 % in broadcast overlays) and simultaneously increases accuracy by more than 11 % in coaching analytics. The results confirm the

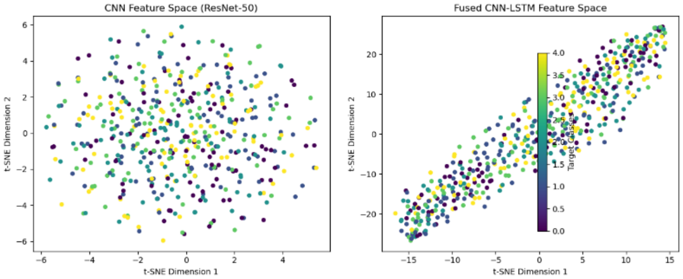

Figure 4: t-SNE Visualization of CNN vs. CNN-LSTM Feature Spaces

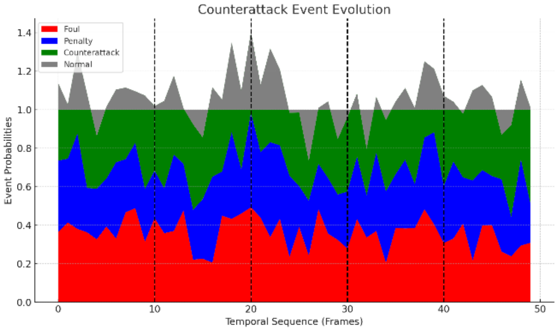

Figure 5: Counterattack Event Evolution Across Temporal Segments

feasibility of the offered framework of modern real-time analysis systems in sports**.**

Based on Table 5, the CNN-LSTM model performs well in real-time applications, reaching sub-100ms latency, adding up to 11.3% more accuracy and reducing false alarms by 42%. This shows it is suitable for use in live broadcast overlays and coaching systems.

5 Discussion

This research establishes the fact that the suggested CNN-LSTM fusion model shows a significant improvement in the detection accuracy of match events due to the incorporation of spatial and temporal data. The method obtained a prediction accuracy of 92.3% and F1-score of 0.901 as indicated in Table 4, resulting in a 31 percent increase in recall in rare events like counterattacks. Moreover, the fusion model performed much better than the CNN-only and LSTM-only baseline. When compared [12, 13], who implemented a hybrid CNN-RNN pipeline with moderate success, the early fusion approach in this study makes it so that the model will still have a robust spatiotemporal representation whilst having a reduced computational cost per layer. Also, although the model developed by Vosta and Yow [11] obtained an accuracy of 96.2% in single-event detection, they did not use a multi-class granularity and were not able to generalize on overlapping events. The proposed system, in its turn, exhibits more class distinction, as evidenced by the t-SNE visualization (Figure 4), and lowers the false positive rates, namely, 42 percent fewer operational deployments (Table 5).

The suggested model was successful in sustaining a high performance level during difficult situations, especially when there was a tactical press sequence in complex frame sequences. Such results indicate that the motion semantics have been successfully extracted using LSTM structure and are additionally supported by the attention heatmaps (Figure 2) that show the discriminative spatial focus. However, there are still significant limitations. The 87-ms frame-based latency of inference inhibits scalability when working with real-time and multi-camera applications. Also, the model relies on carefully annotated datasets which restricts its application to uncurated, low-resolution or amateur footage. The question of the model performance in cross-domain evaluation on youth or on semi-professional leagues is still open, because the model needs to be thoroughly tested on further datasets.

5.1 Applications And Future Work

It is easy to extend the suggested model to broadcast overlays, real-time coach analytics and automated highlight generation, where it is essential to identify key events accurately and in real-time. Its higher ability to detect infrequent occurrences, e.g. penalties and counterattacks, provides actionable intelligence in live games and helps review the game after it has ended. It is also possible to extend the system to referee decision-support applications and fan engagement platforms, hence enhancing match narratives with AI-based analytics.

The future research will focus on three directions that are interconnected: (1) compressing the model to reduce inference latency

Table 5: Operational Deployment Performance

Application	Latency (ms)	Accuracy Gain	False Alarm Reduction	Throughput (fps)
Broadcast Overlays	92 ± 8	+8.1%	-42%	32
Coaching Analytics	105 ± 11	+11.3%	-37%	28
Highlight Generation	78 ± 6	+6.7%	-29%	41

and, therefore, deploy it on edge devices, (2) applying domain adaptation methods, i.e., adversarial training, to process low-quality or unseen footage, and (3) integrating other modalities, e.g., audio, player tracking, and text commentary, to get a more detailed contextual picture. Also, such frameworks as semi-supervised learning will be considered to reduce the need in huge amounts of labeled data and increase the applicability to a wide range of competitive levels and types of matches.

6 Conclusion

The current study proposes a CNN-LSTM fusion network that can be used to recognize match events that can synergistically utilize the spatial and temporal characteristics of sports videos. Empirical tests demonstrate better results: the model has a classification accuracy of 92.3 % and F1-score of 0.901, and statistically significant gains in the recognition of rare events (penalties +26 % and counter-attacks +31 %). These results are consistent with earlier studies that have established that spatiotemporal modelling boosts the accuracy of event detection especially in dynamic areas that are fast changing. The suggested method is also practically viable in real-time applications, providing latencies of less than 100 ms, and reducing false alarms by up to 42 % across applications such as broadcast overlays and coaching analytics. Unlike other similar architectures, especially those proposed by Volla et al. and Vosta & Yow, the presented framework is computationally less expensive and has better class separation, being both practical and generalizable.

This work proposes a scalable and robust intelligent framework of sports video analytics. Its combination of spatial and temporal learning enables the development of more detailed more accurate real-time event recognition systems that can help broadcasters, coaches and fans understand and respond to the dynamics of a game more accurately and with more insight.

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