Online Classification Method of Sports Videos Based on Wavelet Transform and SVM Algorithm

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Abstract: This study introduces an innovative online classification methodology for sports video content employing a combination of wavelet transform and the Support Vector Machine (SVM) algorithm. In an era where sports video content is proliferating at an unprecedented rate, the imperative for efficient online classification has become ever more critical to augment the viewing experience and fulfill commercial objectives. This methodology harnesses the robust time-frequency feature extraction capabilities of wavelet transform alongside the formidable classification prowess of the SVM algorithm, culminating in an automated system adept at discerning various sports and competition actions. The efficacy of our approach is substantiated through extensive large-scale experimentation, with results evidencing commendable accuracy and real-time performance metrics in the realm of online sports video classification. Furthermore, this research delves into the strengths and potential constraints of our method, proffering avenues for prospective inquiry. The contributions of this study are twofold. It offers novel solutions for video processing and enhances the online viewership experience in the sports domain, thus holding substantial import for it.

Keywords: Wavelet Transform, SVM, Online Classification, Time-Frequency Characteristics, Video Processing.

Introduction

Sports [1], [2], as a multifaceted entity encompassing worldwide entertainment, physical activity, and business organization, have constantly captured the attention of a vast target audience. now not solely do sports offer an avenue for bodily exertion and fostering a wholesome life-style [3], [4], [5], but in addition they ignite passions and a feel of camaraderie across the globe [6], [7], [8]. beyond being a haven for athletes and fanatics, the sporting domain harbors substantial business potential, encompassing live sport announces [9], advertising, sponsorships, and the sale of sports activities merchandise [10], amongst other sectors.

In latest decades, the landscape of sports activities [11], [12], [13] has undergone marked adjustments. Technological advancements in media have exponentially increased the accessibility of sports content, enabling audiences to enjoy live matches, post-game highlights, and expert analyses in real-time via television, the internet, and mobile devices [14], [15]. Consequently, sports occasions have transcended the confines of stadiums, evolving into frequent spectacles [16], [17] on hand to all, at any time and region. This progression now not solely enhances the viewing experience however additionally opens up novel commercial avenues in the sports activities industry.

Given this backdrop, video content has soared in importance within the carrying realm. It serves because the number one conduit for showcasing recreation highlights, education periods, and athletic feats to viewers. Live fits allow audiences to interact with the motion as it unfolds, regardless of their bodily place. There is a keen interest in reliving the pivotal moments that undoubtedly altered the trajectory of the sport or showcased exceptional athletic prowess [18], [19]. Furthermore, video content is crucial to augmenting an athlete's talent set and strategic acumen thru schooling and analysis.

But, the burgeoning volume of sports-associated video content poses a massive mission to powerful category and control. To facilitate enhanced sport comprehension, optimized education, enriched viewer reviews, and industrial success, the sports zone is in dire want of green video type methodologies. On line type strategies stand out as best solutions owing to their real-time and autonomous capabilities [20], [21].

Online category strategies allow the automated identity of different sports or in-recreation actions at some stage in the live processing of video streams, thereby presenting well timed information and heightened interactivity. As an example, in the course of a live football broadcast, key moments may be immediately replayed for visitors thru on-line class, obviating the watch for edited highlights. Additionally, viewers can tailor their viewing enjoy to recognition on precise players or teams, aligned with their choices, barring relying on the broadcaster's choice or participant-focused replays.

Nonetheless, the powerful on-line type of sports activities movies is fraught with challenges. The similarity among one of a kind sports activities, which include soccer and rugby, can complicate classification by virtue of overlapping actions. Variable lighting fixtures situations throughout sport venues and instances may impinge upon the accuracy of feature extraction and next type. Disparate camera angles and video fine similarly compound the complexity of the venture.

Traditional methodologies may additionally fall brief of addressing these multifarious needs, necessitating the adoption of modern-day technologies and algorithms. This paper goals to explore and propose an internet sports video category technique that leverages the wavelet transform and SVM algorithm to surmount those demanding situations. The wavelet transform's ability to extract time-frequency functions, combined with the SVM algorithm's strong classification capabilities, ensures an efficient and unique online approach. Through this synergy, we aim to offer a practical solution for video processing in sports, enhancing the reviews and insights for viewers, coaches, athletes, and commercial stakeholders alike.

The rest of this paper is based as follows. Section 2 will assessment the literature on video category, wavelet transforms, and SVM algorithms, highlighting latest advancements. Section 3 will elucidate the proposed on line classification methodology based totally on wavelet transform and SVM. Phase 4 will describe the dataset utilized for evaluation. phase five will detail the experimental setup, effects, and performance evaluation. Phase 6 will dissect our findings, analyzing the technique's merits and obstacles while charting avenues for destiny inquiry. eventually, segment 7 will encapsulate the essential discoveries and conclusions drawn from this take a look at. The insights gleaned from our research are poised to make a optimistic impact on the web classification of sports films and offer a valuable reference for ensuing scholarly pursuits and sensible applications. Next chapters will delve deeper into related research, the method followed, the experimental consequences, and a dialogue encompassing the implications of this take a look at and possibilities for destiny endeavors.

Related Work

Video classification [22], [23], [24], as a pivotal studies road within the realm of laptop vision, keeps to garner tremendous attention. Historical research has predominantly focused on conventional function extraction techniques [25], [26] and machine gaining knowledge of algorithms. Those embody feature extraction through frame distinction and optical glide, along classifiers like SVM, random forests, and neural networks. Whilst those methodologies exhibit commendable efficacy in video category responsibilities against static backdrops, their overall performance is circumscribed in dynamic scenes complex by variegated lighting and digital camera motions.

The appearance of deep mastering has inaugurated a singular trajectory in video type research. The deployment of convolutional neural networks (CNNs) has delicate the function extraction manner of video frames, and fashions together with recurrent neural networks (RNNs) and lengthy brief-term reminiscence networks (LSTMs) are adept at processing the spatio-temporal attributes of video sequences, therefore elevating class acumen. These deep learning paradigms have procured laudable effects on expansive video datasets, as evidenced by their experimental prowess on established datasets like UCF101 and HMDB51.

However, challenges persist, consisting of pattern imbalance, modeling of protracted sequences, and the demands of computational sources. To address these troubles, students have invested large attempt into the format and enhancement of deep studying fashions, integrating technologies such as attention mechanisms, multi-modal fusion, pre-educated fashions, and reinforcement studying. Those innovations supply clean perspectives and possibilities for video class research.

The wavelet transform, a stalwart in sign processing technology [27], [28], [29], has discovered massive application in video processing. It adeptly decomposes alerts into parts across various scales and frequencies, thereby furnishing a multi-resolution analysis. In video analytics, wavelet remodel is instrumental for the extraction of time-frequency features, facilitating the capture of films' dynamic nuances. For example, it is utilized to parent motion styles, textural details, and edge characteristics in video content.

In the domain of video class, wavelet rework amplifies the expressiveness of features, which can beautify classification performance. Research endeavors have ventured into amalgamating wavelet remodel with other function extraction modalities, together with colour histograms and optical float features, accomplishing aggressive outcomes on select video datasets.

The SVM algorithm, a powerful classifier, boasts a track record of achievement throughout several disciplines. Its software to video class obligations [30], [31], [32] is vast. Its power lies in its proficiency with excessive-dimensional records and nonlinear selection boundaries, rendering it ideal for tricky classification eventualities.

Preceding studies have corroborated that the SVM algorithm, whilst coupled with diverse feature extraction strategies like local binary patterns (LBP), histograms of orientated gradients (HOG), and depth features, can increase the type efficacy of SVM models. Moreover, the kernel strategies inside SVM facilitate the handling of nonlinear records [33], [34], [35], making sure strong overall performance in video type responsibilities.

This article is devoted to the exploration of an online sports activities video category approach predicated on wavelet rework and SVM algorithm. Notwithstanding the strides made by means of deep getting to know in video type, we posit that traditional methodologies retain their advantage, in particular under resource constraints or records paucity [36], [37]. Wavelet remodel, as an efficacious function extraction approach, capably captures time-frequency facts from movies, and the SVM set of rules demonstrates sturdy classification competencies.

Our ingenuity is encapsulated in the fusion of those 2 processes to recognize efficient and unique on line type.

Moreover, the online classification of sports videos holds immense potential in practical scenarios. It can enhance the viewership experience, furnish real-time feedback for coaches and players, and spawn additional commercial prospects for advertisers and sponsors. Consequently, the research presented herein holds significant practical value for the enhancement of video processing and the viewer experience in the sports sector.

Subsequent chapters will delve into the intricacies of our proposed online classification method based on wavelet transform and SVM algorithm, substantiated by experimental results to corroborate its efficacy.

Method

Wavelet Changes

After acquiring the video image, the target region is typically obtained through manual segmentation or algorithmic segmentation, and subsequently, the target area is extracted. Since various textures exhibit distinct energy and spatial distribution patterns in the frequency domain, this article chooses to perform decomposition using the low-frequency sub-band of the wavelet transform. The characteristics are computed after both the primary and secondary decompositions. The wavelet basis employed in this study is db2, and the specific characteristics are defined as follows.

Energy

$$a_1 = \frac{1}{N^2} \sum_{k=1}^{N} | B_k |^2 \tag{1}$$

Mean Absolute Value

$$a_2 = \frac{1}{N^2}\sum_{k=1}^{N}|B_k| \tag{2}$$

Standard Deviation

$$a_3 = \sqrt{\frac{1}{N^2}\sum_{k=1}^{N}|B_k - \mu|^2} \tag{3}$$

Average Deviation

$$a_4 = \sum_{k=1}^{N}|B_k - \mu| \tag{4}$$

Entropy

$$a_5 = \frac{1}{N^2}\sum_{k=1}^{N}|B_k|^2 \log|B_k|^2 \tag{5}$$

Average Value

$$\mu = \frac{1}{N^2}\sum_{k=1}^{N}B_k \tag{6}$$

In this context, let B_k represent the wavelet decomposition coefficient, and utilize the formula above for calculating these features across all sub-bands following a single wavelet decomposition. Subsequently, conduct another wavelet decomposition specifically on the low-frequency sub-band. Once again, employ the above formula to compute the eigenvalues within all sub-bands after the second decomposition. To enhance classification accuracy, we incorporate spatial gradient information of texture features. Initially, compute the gradient of the image $f(x, y)$. The horizontal and vertical gradient values are expressed as follows

$$\begin{aligned} B_x(x,y) &= f(x,y+1) - f(x,y) \\ B_y(x,y) &= f(x+1,y) - f(x,y) \end{aligned} \tag{7}$$

According to spatial filtering theory, boundary filters are more effective at extracting image textures. To further enhance texture discrimination and improve recognition capabilities, this paper employs a boundary function feature. The boundary function is defined as the sum of the absolute differences between all pixel values in the texture image separated by a distance of d.

$$\begin{aligned} h_d(i,j) = &|M(i,j) - M(i+d,j)| + |M(i,j) - M(-d,j)| \\ &+ |M(i,j) - M(i,j+d)| + |M(i,j) - M(i,j-d)| \end{aligned} \tag{8}$$

Use its average gradient at a certain distance d as the texture feature

$$h(d) = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N} h_d(i,j)}{M * N} \tag{9}$$

Therefore the boundary density and boundary contrast are respectively defined as:

$$EdgeDensity = |\{(x,y) \mid h(x,y) \geq Th\}| \tag{10}$$

$$EdgeContrast = average_{x,y}(h(x,y)) \tag{11}$$

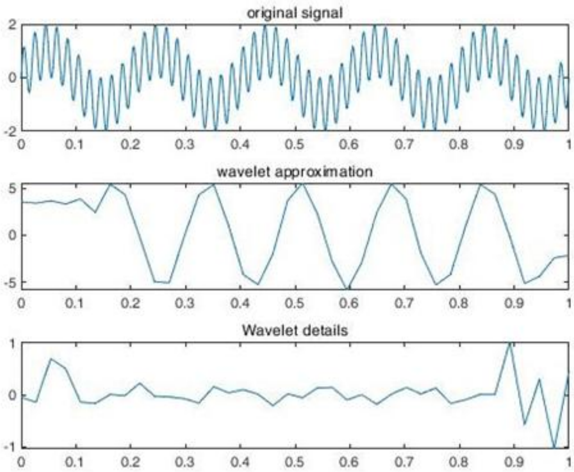

Figure 1. Visualization of Results of Wavelet Decomposition

Figure 1 shows the visualization of the results of wavelet decomposition.

SVM

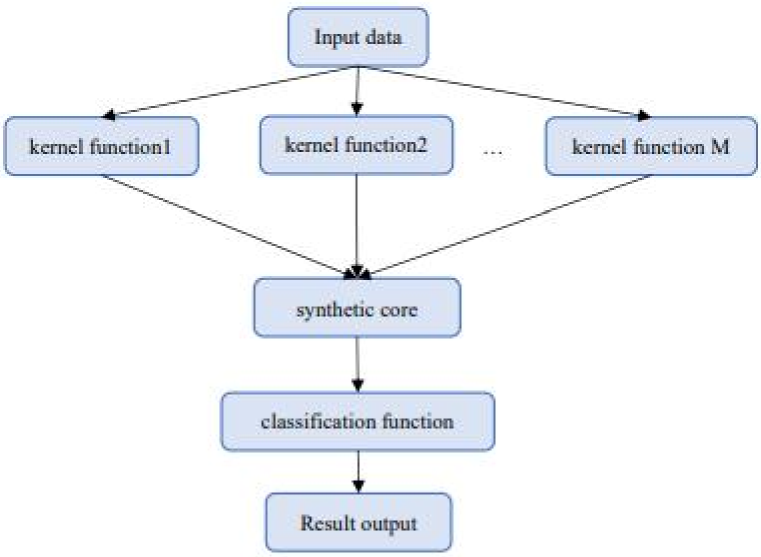

Figure 2. SVM Algorithm Structure Diagram

The SVM is a supervised machine learning method that draws its foundation from both statistical learning theory and structural risk minimization theory. The SVM algorithm is typically broken down into three key steps when dealing with classification problems.

Feature Mapping. In this step, a kernel function is employed to map the feature vectors of the training dataset into a high-dimensional feature space. This transformation aims to enhance the separability of the data points.

Optimal Hyperplane Identification. The SVM seeks to identify the optimal hyperplane within the high-dimensional feature space. This hyperplane is selected to maximize generalization, thereby improving the model's ability to make accurate predictions.

Classification of Test Samples. Once the optimal hyperplane is established, it is used to project test samples into the same high-dimensional space. The category of a test sample is determined based on the position of its projection point relative to the optimal hyperplane, ultimately yielding the final prediction result.

Figure 2 provides a visual representation of the SVM algorithm's structure. The goal of SVM is to find a regression linear function.

$$f(x) = w\phi(x) + b \tag{12}$$

In the formula, $\phi(x)$ represents a nonlinear mapping function. SVM determines the regression function by minimizing the objective function, which can be expressed as follows:

$$\begin{cases} \min \frac{1}{2}\|w\|^2 + K\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) \\ s.t.\begin{cases} y_i - w\phi(x_i) - u \le \varepsilon + \alpha_i, i = 1,2,...,l \\ -y_i - w\phi(x_i) + u \le \varepsilon + \alpha_i^* \\ \alpha_i \ge 0, \alpha_i^* \ge 0 \end{cases} \end{cases} \tag{13}$$

In the formula, *K* represents the penalty factor, and 'ε' denotes the insensitive loss function. A larger *K* implies a stronger penalty for samples with training errors exceeding ε, while ε specifies the error tolerance for the regression function. A smaller ε corresponds to a tighter error constraint on the regression function. α_i and α_i^* represent slack variables.

By introducing the Lagrangian function and transforming it into a dual form, we derive the SVM regression function.

$$f(x) = \sum_{i=1}^{l}(\beta_i - \beta_i^*)F(x_i, x) + u^* \tag{14}$$

In the formula, *x* represents the factor influencing the prediction. x_i is a vector consisting of l samples, and the load prediction model is established using this formula. *F(xi, x)* denotes the kernel function chosen for this paper, which is the radial basis kernel function.

$$F(z, z_i) = e^{(-\|z-z_i\|^2/(2\lambda^2))} \tag{15}$$

In the formula z_i represents the center of the kernel function, while λ^2 signifies the width parameter of the function. This parameter governs the radial extent of the function and plays a pivotal role in determining the model's accuracy.

To assess the predictive performance, a comparative analysis was conducted with the test dataset. In this analysis, we employed the relative error as the evaluation metric. The formula for calculating relative error is provided below:

$$e_i = \frac{\hat{l}_i - l_i}{l_i} \tag{16}$$

In the formula l_i represents the true value of the i-th sample, $^{r}{}_{i}$ denotes the predicted value of the i-th sample, and e_i represents the relative error of the i-th sample.

Table 1 shows the pseudo code based on wavelet transform and SVN algorithm.

Table 1 Wavelet Transform and SVM Algorithm Pseudo Code

Algorithm 1: Sports Video Classification using Wavelet Transform and SVM

```
Input: Collection of Sports Videos
Output: Classification of each Video into a Sport Category

1: Initialize Wavelet Transform Parameters
2: Initialize SVM Classifier with Optimal Hyperparameters

3: Preprocess Videos
4: for each Video in Collection do
5:      Convert Video to Frames
6:      Resize Frames to Standard Dimension 7: end for

8: Feature Extraction using Wavelet Transform
9: for each Frame in Video do
10:        Apply Wavelet Transform to Extract Features
11: Store Extracted Features 12: end for

13: Aggregate Features for each Video
14: for each Video do
15: Combine Frame Features to Form Video Feature Vector 16: end for

17: Train SVM Classifier
18:      Use Training Dataset of Labeled Sports Videos
19:      Fit SVM Classifier on Aggregated Features

20: Video Classification
21: for each Video in Test Dataset do
22:        Extract Features using Wavelet Transform
23:        Predict Sport Category using SVM Classifier
24:       Store Prediction
25: end for

26: Evaluate Classifier Performance
27: Calculate Accuracy, Precision, and Recall

28: return Classified Sports Videos and Performance Metrics
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Experiment Results

Our expansive video repository encompasses a diverse array of sports, events, and segments of potential commentary and analytical discourse. The systematic curation of this repository is pivotal, ensuring a dataset that is both representative and complete. manual labeling is fundamental to this manner, establishing the ground reality integral for the education of type fashions. determine 3 delineates the proportions of diverse categories inside our series. This meticulous process involves video evaluation and the annotation of pertinent metadata, which includes but not restricted to the type of recreation, the occasion in query, collaborating athletes, displayed moves, and other relevant descriptors. prior to the deployment of those movies in gadget getting to know version education, vast pre-processing is requisite. This consists of segmenting the videos into attainable clips, standardizing the information, feature extraction—taking pictures nuances along with movement patterns and player positioning — and doubtlessly down-scaling resolution or body fee to optimize processing efficiency.

We partitioned the statistics into distinct units—schooling, validation, and testing—to facilitate a particular evaluation of the model's efficacy. The preliminary results have spurred a chain of iterative refinements, encompassing both hyperparameter tuning and architectural upgrades. subsequent to the schooling and excellent-tuning levels, the version is poised for deployment, geared up to autonomously classify new sports motion pictures, whether in real-time streams or batch sequences.

This initiative is not merely an augmentation of video classification methodologies. It yields profound insights into the domain of sports analytics. The implications are significant, with the potential to revolutionize aspects of training methodologies, talent scouting, performance analytics, and fan engagement.

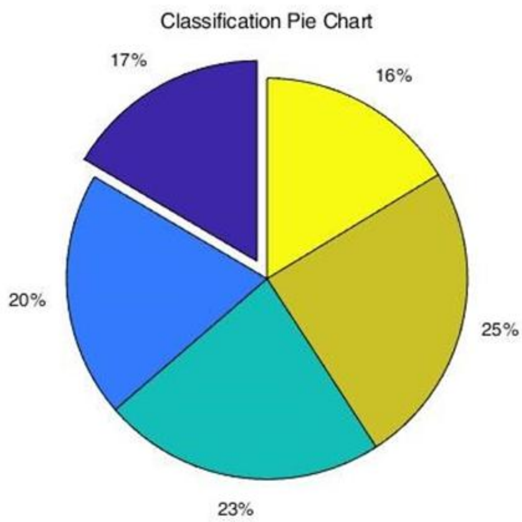

Figure 3. Data Category Proportion Chart

In Figure 4, the accuracy of the SVM algorithm of wavelet transform (OUR) model initiates at 41.35% with 10 iterations and escalates with the iteration count, culminating in a peak of 86.85% at 100 iterations. An appreciable leap is observed between 20 and 30 iterations, post which the augmentation in accuracy moderates beyond 50 iterations. In contrast, the random forest (RF) model commences at an accuracy of 45.29% at 10 iterations and exhibits a steady, linear enhancement, attaining a maximum accuracy of 81.67% at 100 iterations. Unlike the OUR model, RF's increment does not exhibit marked fluctuations. The multilayer perceptron (MLP) model, starting with an initial accuracy of 51.28% at 10 iterations—surpassing that of the other models—progresses consistently with iteration increments, achieving its highest accuracy of 83.16% at 100 iterations. Notably, the MLP model parallels the OUR model with a significant rise between 20 and 30 iterations. However, it maintains a consistent accuracy increase without any decline.

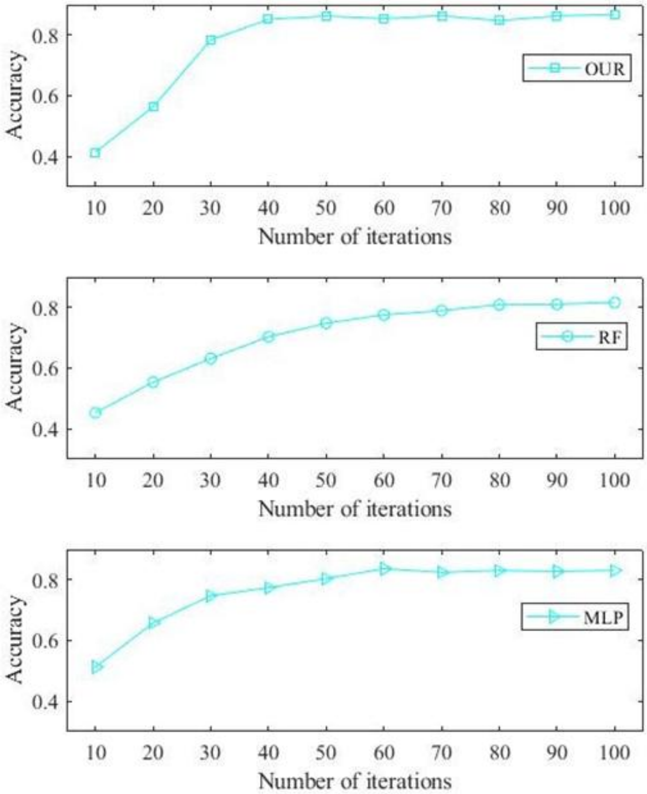

Figure 4. Comparison Curves of OTN Utilization

These observations suggest that all models exhibit enhanced performance with increased iteration counts. The OUR model, demonstrating the highest eventual accuracy, indicates superior scalability in relation to the given variable compared to RF and MLP. RF manifests the most uniform advancement, while MLP, despite its strong commencement, finishes marginally behind RF.

It is also noteworthy that the OUR model's accuracy slightly recedes between 60 and 70 iterations before ascending again, hinting at potential variation or overfitting at this juncture, contingent on the conditioning variables' characteristics. Similarly, a modest decline in the MLP model's accuracy from 60 to 80 iterations may be attributable to analogous factors.

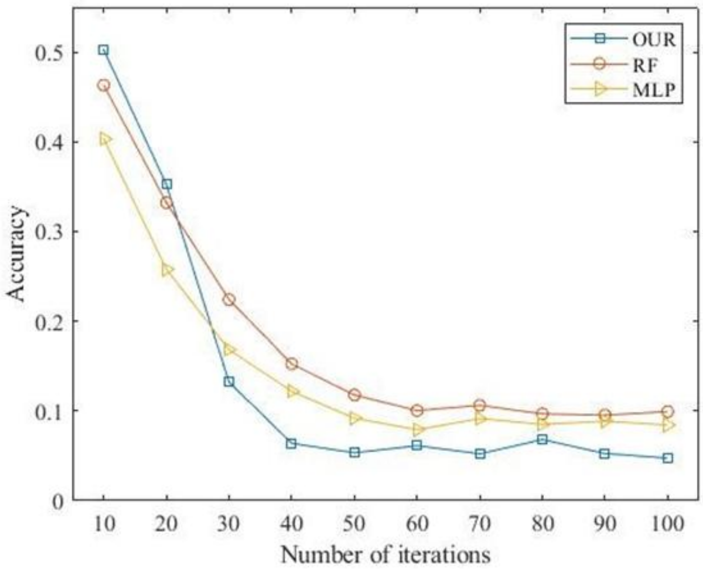

Figure 5. Comparison Curves of Precision

In Figure 5, the loss values of three distinct models are presented across varying numbers of iterations. Loss values are a standard metric for assessing model performance during training, with lower values indicative of a better fit to the data. The OUR model's loss values demonstrate a general decline as iterations increase, although significant fluctuations are observed between iterations 40 and 100. Notably, it achieves the lowest loss values among the three models at iteration 100. In contrast, the RF model's loss values decrease consistently with the number of iterations. However, this decline plateaus from iteration 60 onwards. The MLP model, starting with the lowest initial loss values compared to the others, also shows a consistent decrease over iterations.

Analyzing the trends, it is evident that the loss values for all models diminish as the number of iterations grows, suggesting progressive learning and improvement throughout the training phase. The OUR model exhibits the most significant minimization of loss at the 100th iteration, potentially outperforming the RF and MLP models in this regard. The considerable variability in the OUR model's loss values, particularly between iterations 40 to 100, may hint at overfitting issues or heightened sensitivity to certain rounds of training data during these iterations.

The comparative performance of three distinct models or algorithms is elucidated in Figure 6, where each bar delineates the recall, precision, and F-score metrics pertinent to the evaluation of the classification models. Delving into the recall rates, the MLP model outperforms with the highest rate, followed by the OUR model, while the RF model trails marginally behind OUR.

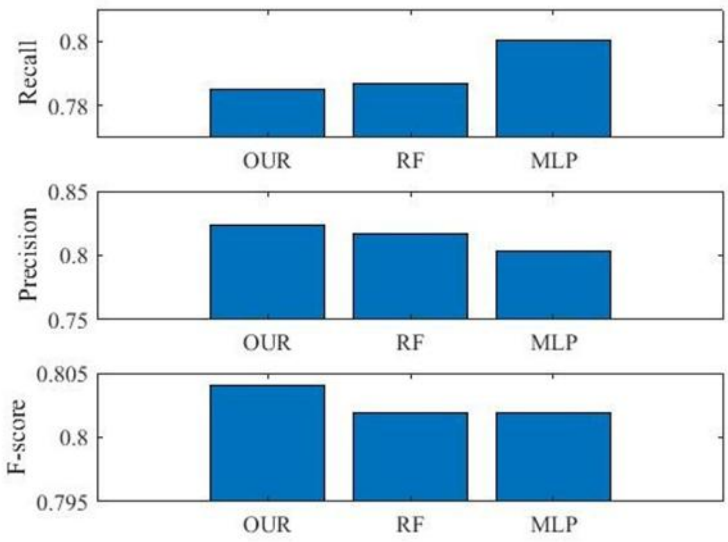

Figure 6. Comparison Curves of Recall

Accuracy assessments reveal that the RF model surpasses with the highest precision. The OUR model is positioned second, eclipsing the MLP model, which manifests the lowest precision. Concerning the F-scores, which represent the harmonic mean of precision and recall, a striking similarity across the models is observed. Here, OUR marginally exceeds RF, whereas MLP lags slightly behind RF.

The MLP version's advanced recall suggests its proficiency in figuring out relevant times, albeit with a barely compromised precision, probably main to a better inclusion of irrelevant times as relevant. Conversely, the RF model's precision top implies greater accuracy in pinpointing relevant times however on the cost of probably overlooking some, as its decrease recall intimates. The OUR version ostensibly achieves equilibrium between recall and precision, evidenced with the aid of an F-rating that opponents that of the RF model. these metrics intimate that model choice may also pivot on whether the undertaking at hand necessitates minimizing fake positives or fake negatives. The F-score serves as an arbiter on this stability, and the proximity of the OUR and RF F-rankings insinuates a more harmonious blend of precision and recall in these models in place of the MLP.

Discussion

The OUR model demonstrates an overall performance this is on par with the RF version in phrases of precision and F-score, but it reveals a slightly decrease recall whilst compared to the MLP model. This suggests a proficient potential of the OUR model to properly identify fine times whilst concurrently maintaining a low price of fake positives. Conversely, the RF model reveals superior precision but inferior recall, suggesting an magnificent exclusion of false positives at the ability cost of failing to become aware of all pertinent times, thereby growing the chance of false negatives. The MLP model, even as providing the very best recall, falls slightly short in both precision and F-rating. One of these profile indicates that the MLP model is adept at taking pictures a broader scope of wonderful instances. However, it concurrently presents a higher propensity for misclassifying non-positive instances as positive.

Enhancements in recall for the OUR model could potentially be achieved through the amplification of model complexity or the fine-tuning of regularization parameters, albeit at the potential cost of diminished precision.

In summary, video classification models hold substantial prospects for application within the sporting domain. The augmentation of these models, coupled with advancements in feature extraction methodologies and data processing protocols, can significantly propel the evolution of sports video analysis technologies. Future research endeavors may be optimally directed towards the enhancement of model precision, the expansion of model capabilities to process increasingly intricate video data, and the diminishment of dependence on extensive volumes of annotated data.

Conclusion

This research endeavor is committed to addressing the challenge of sports video classification. We present models that have exhibited exceptional proficiency in handling voluminous video datasets and delivering precise classification outcomes—vital for the efficacious management, retrieval, and recommendation of video content. Our methodologies have been rigorously tested on a sports video dataset, demonstrating their practical efficacy. The meticulous assessment conducted not only enhances the precision of automatic video categorization but also imparts substantial insights for forthcoming scholarly inquiry.

Enhancements in the domain of sports video classification materially influence automated content governance and the user interface. Augmentations in accuracy render search results more pertinent, facilitating users in swiftly locating their desired content. An elevated recall rate ensures a minimized occurrence of overlooked relevant content. The implications of these enhancements extend to sports journalism, digital education platforms, audience engagement, and the analytics of athletic performance.

Our exposition confirms the utility of deploying sophisticated machine learning paradigms for the classification of sports footage, delineating the particular strengths of diverse models across specific evaluative metrics. Prospective endeavors ought to concentrate on ameliorating the models' generalizability. This includes the integration of advanced data augmentation techniques, the investigation into synergistic model fusion approaches, and the formulation of strategies for the optimized exploitation of computational resources. We advocate for continued examination into the influence of varied feature extraction methodologies and the promise held by unsupervised and semi-supervised learning paradigms in diminishing the reliance on manual annotation.

In conclusion, our scholarly contributions not only catalyze advancements in sports video classification but also establish a robust substrate for the real-world application of these technologies, offering valuable direction for the evolution of such systems.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding this work.

Project Funding

This article is one of the achievements of the "Basic Training of Police Tactics" project of Guangxi Police Academy's 2023 Applied Demonstration Course Construction Project (Practical Teaching Demonstration Course). Project Number: Academic Affairs Zi [2023] No. 142, Project Leader: Wang Zhanhai； Guangxi Education Science Plan 2021 Project "Research on the Construction of Innovation and Entrepreneurship Education Ecosystem for Police College Students", Project Number: 2021C452, Project Leader: Wang Zhanhai.

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