Player Classification from Badminton Game Data: A Game Theory Assignment Report

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***Abstract*—This report details the process of solving a player classification problem in a badminton game dataset. The task involves segregating player images into four individual player classes from top and bottom court halves. The objective is to optimize the classification in real-time using computer vision techniques, specifically MobileNetV2 for feature extraction, and clustering with DBSCAN for class separation. We present two approaches, one based on deep learning and the other using classical image processing methods, evaluating their effectiveness in distinguishing players during gameplay.**

I. Introduction

The task of classifying players from images of a badminton game presents a unique challenge due to the dynamic nature of sports and the variability in camera perspectives. The dataset provided contains two folders representing players on the top and bottom halves of the court. The objective is to classify these images into four individual player classes. Given the constraints of execution time and the requirement for real-time performance, efficient methods for feature extraction and clustering were essential.

II. Problem Understanding

The dataset comprises:

- **top_two_players**: Images of the two players from the top half of the court.
- **bot_two_players**: Images of the two players from the bottom half of the court.
- **court_image**: The court background image, which can help model background color and assist in segmenting the players.

The goal is to segregate these images into four player classes (two from the top and two from the bottom).

III. Proposed Solutions

A. Approach 1: Deep Learning-Based Solution Using MobileNetV2

1) Idea: MobileNetV2, a lightweight convolutional neural network, was chosen for feature extraction due to its efficiency and suitability for real-time applications. The features extracted from each image are used to cluster the images into four classes using a density-based clustering algorithm (DBSCAN).

2) Implementation Steps:

- **Pretrained Model Selection**: We use MobileNetV2 for extracting deep features from player images.
- **Feature Extraction**: Images are resized and processed through MobileNetV2 to obtain feature vectors for each player.
- **Dimensionality Reduction**: Since high-dimensional features may cause clustering noise, PCA was applied to reduce the feature space to 50 dimensions.
- **Clustering with DBSCAN**: DBSCAN, a density-based clustering algorithm, was applied to group similar images into four clusters, corresponding to the four players.
- **Image Segregation**: The clustered images were saved into four distinct folders, each representing a different player.

3) Advantages and Challenges:

- **Advantages**: The MobileNetV2 model provides a robust feature representation, allowing the clustering algorithm to separate players effectively based on their pose and appearance.
- **Challenges**: The primary challenge was tuning the DBSCAN parameters (eps and min_samples) for optimal clustering. Variations in lighting and player pose sometimes caused noisy predictions.

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+------------------+      +--------------+       +--
| Input Images     | ---> | MobileNetV2  | --->  | C
+------------------+      +--------------+       +--
        (top and bottom players)               Feature e
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B. Approach 2: Classical Image Processing Approach

1) Idea: In an alternative approach, classical computer vision methods such as background subtraction and contour detection were considered. The idea was to segment players from the court using color difference between the background court and the players.

2) Implementation Steps:

- **Background Subtraction**: The court image was used as a reference for background subtraction. Any deviations from the background were considered potential player regions.
- **Contour Detection**: Contours were extracted to isolate the player regions from the segmented images.

- **Feature Matching**: Features such as color histograms were extracted from the player regions and used for clustering.

3) Advantages and Challenges:

- **Advantages**: This method is computationally inexpensive and performs well under controlled conditions.
- **Challenges**: It struggles with dynamic lighting and players blending into the background.

IV. Conclusion

In conclusion, the deep learning approach utilizing MobileNetV2 proved to be effective in classifying players based on visual features extracted from the images. DBSCAN clustering allowed us to segregate players into four distinct classes with reasonable accuracy. The classical image processing approach, while efficient, was less effective due to the variability in the dataset.

The key to improving performance in future implementations would be to fine-tune the clustering algorithm parameters and to explore advanced techniques such as transfer learning or generative augmentation to enhance player classification under varying game conditions.

V. Future Work

- **Enhancing Data Augmentation**: Using advanced augmentation techniques such as synthetic rain or generative models to simulate diverse playing conditions.
- **Transfer Learning**: Leveraging pretrained models on similar datasets to improve the generalization of player classification.
- **Real-time Optimization**: Further optimizing the feature extraction and clustering processes to ensure real-time classification performance.

VI. References

References

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