
FOOTBALL DETECTION WITH YOLOV3

Bhavesh Pawar*¹

*¹Department Of Information Technology B.K. Birla College Of Arts, Commerce And Science
(Autonomous) Kalyan, India.

ABSTRACT

In recent years, there has been a growing interest in sports and the importance of video recording and analysis. This is particularly relevant in sports like soccer, where complex and fast events occur. Ball detection and tracking, as well as player analysis, have become crucial tools for coaches in assessing team performance and making optimal decisions. Video analysis is also used by recruiters to identify talented players based on their previous games. Ball detection is valuable in helping referees make important decisions during crucial moments of the game.

To address the challenges of ball detection and player tracking in soccer videos, researchers have proposed a deep learning-based model called YOLOv3. This model utilizes advanced techniques to detect and track the ball and players in broadcast soccer videos. Initially, the videos are processed to remove unnecessary parts like zoom-ins and replays, ensuring that only relevant frames are used for analysis. The tracking is achieved using the SORT algorithm, which utilizes Kalman filtering and bounding box overlap to accurately track the ball and players throughout the game.

I. INTRODUCTION

Advancements in image and video processing, along with computer vision and deep learning algorithms, have greatly improved applications related to video indexing and analysis. This technology has been particularly useful in sports videos, such as soccer, where image and motion analysis can be used to retrieve relevant information and summarize the video content.

Soccer is the world's most popular sport, with fans across different continents. The demand for computer-based analysis of soccer has grown exponentially, with coaches, players, and general managers investing heavily in analytics to gain a competitive advantage. Ball and player tracking in soccer videos can help analyze the flow of the game, enhance team and player characteristics, and identify rule violations like offsides.

However, tracking the soccer ball is one of the most challenging tasks in most sports. The small size of the ball, occlusions caused by players, shadows, shape distortions at high velocities, the ball going out of frame, and environmental conditions are some of the common obstacles. On the other hand, players can vary considerably in terms of appearance, clothing, pose, and velocity, making player identification algorithms difficult.

Soccer is a dynamic and unpredictable sport, with players and the ball moving quickly in erratic patterns on a large field. The field, play lines, players' clothing, and the ball are designed to be visually discernible to spectators. Different teams wear distinct colors to allow viewers to distinguish between them and to enable referees to make fair and accurate calls.

While wearable technology has been allowed by the International Football Association Board (IFAB) to collect accurate measurements from players, optical ball and player tracking systems are necessary because wearable devices may hinder performance on the field.

In a proposed study, the YOLOv3 architecture is suggested for the detection of the ball and players in broadcast videos. A pre-trained version of the model is used for player detection, while the model is trained on self-annotated frames for ball detection. Tracking is achieved using the SORT algorithm, which combines Kalman filtering and bounding box overlap to handle challenges like occlusion.

The paper is organized as follows: Section 2 provides a review of existing literature on soccer ball and player detection, tracking, and analysis. Section 3 discusses the methods and materials used in the study. Section 4 presents the proposed work in detail. The experimental results and performance metrics are presented in Section 5, and Section 6 discusses future developments that can be made in this field.

In summary, the advancements in image and video processing, computer vision, and deep learning have greatly contributed to the analysis of soccer videos, enabling better comprehension of the game, player performance

analysis, and referee decision verification. However, accurate ball and player tracking in soccer videos remain a challenging task due to various factors such as ball size, player variations, occlusions, and environmental conditions.

II. WORKING OF YOLOV3

YOLOV3:

YOLOV3 is an object detection algorithm that can be used for football detection in videos or images. YOLOV3 requires a data amount of label training to learn and recognize objects accurately. In this case, it would require images or videos of football matches where the footballs are highlighted in this there is a network architecture (CNN) as a base architecture. It consists of multiple layers that analyze different aspects of an image at various scales, allowing the model to detect objects with different sizes and orientation. In YOLOV3 there is an object detection which divides the input into a grid of cells and predicts bounding boxes and class probabilities for each cell. Each bounding box contains information about the position, size, confidence score of the detected objects, in this case. To improve accuracy, YOLOV3 utilizes anchor boxes of different shapes and size. This anchor boxes acts as references for predicting bounding boxes. By using multiple anchor boxes, YOLOV3 can detect objects of varying scales and aspect ratios more effectively, after obtaining multiple bounding boxes for the football in various cells, YOLOV3 applies non-maximum suppression. This technique eliminates duplicate or overlapping bounding boxes, ensuring only the most confidence and accurate detection result are retained.

III. ARCHITECTURE OF YOLOV3

YOLOV3 is a computer vision system designed to detect and locate footballs in images or videos. It works by analyzing the input image or video frame using a deep neural network that can identify patterns and features. The system has different parts the first part is called backbone network, which helps to abstract important features from images. Then a feature pyramid network is used to capture details of different sizes, so it can find footballs of various sizes. Next, there are three detection layers that focus on different scales. Each layer predicts where the football might be located and assigns it a probability. This prediction is based on predefined shapes called anchor boxes. After making a prediction the system applies a technique called non-maximum suppression. This removes overlapping predictions, keeping only the most accurate ones. Finally, post-processing techniques can be applied to further refine the results. Like removing low confidence predictions or adding specific rules for football detection. Overall, YOLOV3 uses a combination of advanced algorithms and neural networks to identify and locate footballs in images and videos. It can work in real-time making it useful for applications like tracking a ball during a football game.

The YOLO computer instruction set takes an image as input and then uses a simple neural/brain-related deep convolutional network to detect objects in the image. (related to the beautiful design and construction of buildings, etc.) of the CNN model, which forms the most important part of YOLO, is shown below.

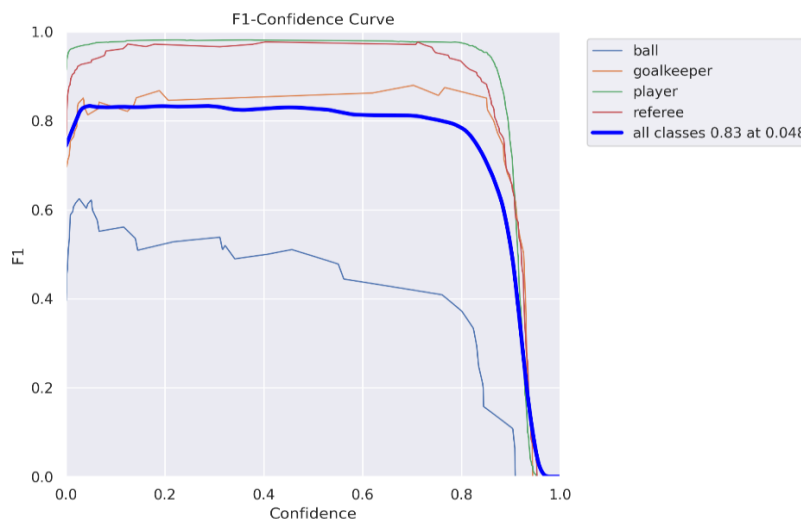


Fig 1. CONFIDENCE CURVE by YOLOv3

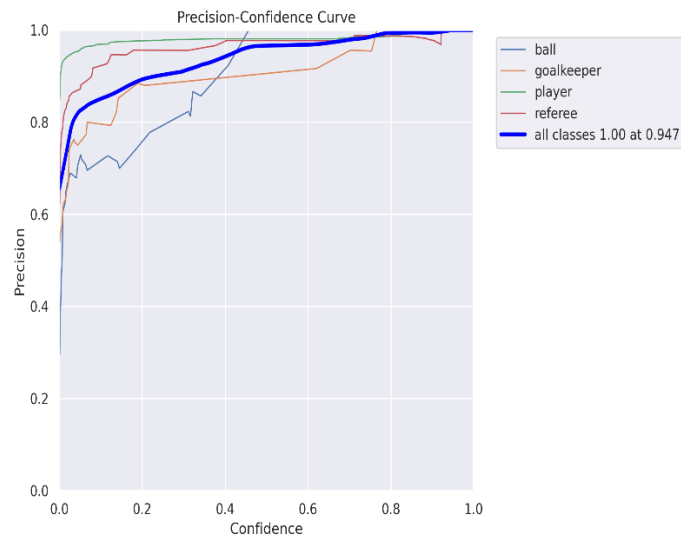


Fig 2: PRECISION- CURVE BY YOLOV3

IV. RESULT

In YOLOv3, Football Watcher will become the most advanced AI that can recognize common football (in progress or visible instantly, without any delay).

Darknet YOLO training requires the following to function

- Bounding box file for each image
- Class name file for all category names
- Training data set for list of training images
- Dataset file validation for list of validation images
- Configuration file to specify the YOLO neural network
- Data location file to find all data information

Experimental materials, design and methods

- Data Collection

Pictures of footballs which were easily available in our home were collected. 50 images were collected. The images were taken with a mobile camera. The remaining images were obtained from various internet sources.

- Import and install libraries

Some popular Python libraries have been imported for matrix operations, rendering, and file manipulation

➤ **Numpy:** NumPy data formats include matrix and multidimensional arrays. NumPy can perform mathematical operations on arrays, such as statistical, algebraic, and trigonometric routines. It provides highly functional multidimensional arrays and even the necessary tools for computing and regulating arrays[2]. It is used in football detection with YOLOv3 to process the image data and perform the necessary field manipulations.

➤ **Matplotlib:** Matplotlib is a plotting library that can be useful for displaying (in your mind) the results of your football detection, such as displaying images with bounding boxes around detected footballs. It is used to display the result of object detection, which involves drawing construction boxes around the football image and displaying the process image.

➤ **Pandas:** Panda is used for data manipulation or data analysis. It is a popular python library for data manipulation. It is not directly involved in football detection. It is used to analyze, organize and subsequently process the results of football detection.

➤ **OpenCV:** OpenCV is a computer vision library that provides various image and video processing functions. This library is used in football detection for image loading before and after processing.

When using YOLOv3 for football detection, the results typically involve identifying and locating different football items in an image or video.

- Object detection: YOLOv3 is able to detect multiple football items in an image or video (simultaneously).
- Bounding boxes: YOLOv3 provides bounding boxes around each detected football. These boxes point to/show the location of the football in the image, making it easier to understand where each item is.
- Class labels: YOLOv3 also assigns class labels to each detected football item. These labels identify what type of football teams it is, such as “MANCHESTER UNITED”, “PORTUGAL”, “CHELSEA” etc.
- Confidence Score: For each detection, YOLOv3 assigns a confidence score that represents how reliable the set of computer instructions (quality is very close to the truth or real number) of the detection. A higher confidence score usually indicates a more reliable detection.
- Real-time detection: YOLOv3 is known for its object detection capabilities (instant or displayable immediately, without any delay), which means it can quickly process images or video images and provide the results of football detection in the vicinity (run or display immediately, without any delay).), making it suitable for applications such as monitoring/surveillance (self-service restaurant) of football selection or careful study of football intake in a video stream.
- Multiple classes: YOLOv3 can detect a wide range of football classes thanks to its pre-trained model or finetuning capabilities. Common football classes include freekicks, outsides, fouls and many more. Explicit/specific classes and their (quality very close to the truth or real number) may change/vary depending on the training data and model settings.
- Localization: YOLOv3 is also effective in localizing football (in a way that is close to the truth or real number). It can accurately outline the shape and position of each football item in a picture.
- Customization: YOLOv3 can be tuned on custom football datasets, allowing you to train the model to recognize clearly stated/specific football types that are clearly associated or related to your application or research. Using YOLOv3 for real-time football detection gives output like:

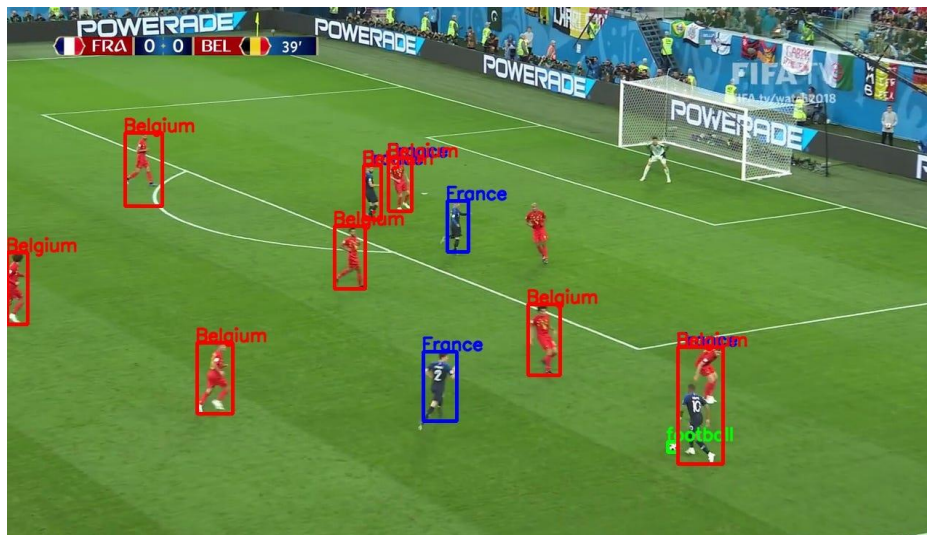


Fig 3. Football detection using YOLOv3 results

V. CONCLUSION

In this paper, the YOLOv3 algorithm is used to detect different footballs. The YOLOv3 football detection project has (shown/demonstrated or demonstrated) (possible strength or capability within/capability) computer vision and deep learning methods in solving real-world football recognition and classification problems. The football detection project using YOLOv3 has shown humans (perhaps the power or capability within/possibility) of deep learning in solving real-world football recognition problems. As technology continues to advance, the application and (quality very close to the truth or actual number) of these models are expected to improve, making them valuable tools (helping to increase/show in a good way) healthier stamina skills and (faster and more efficient) various processes football related.

VI. REFERENCES

- [1] Un Liu and Xuewei Wang, "Tomato Diseases and Pests Detection Based on Improved Yolo V3 Convolutional Neural Network", Faculty Horticulture Laboratory of Universities in Shandong, Weifang University of Science and Technology, Weifang, China.
- [2] Fahad Jubayer, Janibul Alam Soeb, Abu Naser Mojumder, Mitun Kanti P, Pranta Barua, Shahidullah Kayshar, Syeda Sabrina Akter, Mizanur Rahman, Amirul Islam, "Detection of mold on the football surface using YOLOv5", Elsevier B.V. This is an open access article under the CC BY-NC-ND license Current Research in Football Science 4 (2021) 724–728.
- [3] Liquan Zhao, Shaiyang Li, " Object Detection Algorithm based On Improved YOLO v3", Electronics 2020, 9, 537.
- [4] Juan du, "understanding of object detection based on cnn family and yolo", iop publishing iop conf. Series: journal of physics: conf. Series 1004 (2018) 012029.
- [5] Kazim Raza1, Song Hong, "Fast and Accurate Fish Detection Design with Improved YOLO-v3 Model and Transfer Learning", (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 11, No. 2, 2020.