Footy Forecast – Measuring Performance in Football

Shlok Asher, Monika Mangla, Chirag Rohra*, Soham Desai, and Neha Agarwal

***Abstract*—This paper proposes a novel approach to detect and evaluate players in football using Voronoi diagrams and a set of metrics devised by the author. The proposed method is based on the idea that the performance of a player can be evaluated by analyzing the area of the field they cover during a match. To achieve this, the positions of all players on the field are first detected using computer vision techniques. Then, Voronoi diagrams are used to partition the field into regions that are closer to a particular player than any other. The area of each player's Voronoi region is calculated and compared to the average area of all regions to determine their level of play.**

The set of metrics used to evaluate a player's performance is based on the time spent in different regions of the field, the distance covered, and the number of successful passes, among others. The proposed method is evaluated on a dataset of football matches and compared with existing methods for player evaluation. The results show that the proposed approach outperforms existing methods in terms of accuracy and efficiency. Overall, this paper provides a promising new direction for player evaluation in football using computer vision and Voronoi diagrams.

***Index Terms*—Player detection, player tracking, voronoi, opencv, YOLOv5**

I. Introduction

Player evaluation in football is an important task that has received significant attention from researchers and coaches alike. The ability to accurately assess the performance of individual players can help coaches make informed decisions about game strategy, player recruitment, and player development. Traditionally, player evaluation has been done manually by trained scouts and coaches, but with the advancement of computer vision and machine learning techniques, automated methods have become increasingly popular.

In this paper, we propose a novel approach for player evaluation in football that combines computer vision techniques for player tracking, team segregation, and Voronoi diagram-based player evaluation. Specifically, we use the YOLOv5 object detection framework to track the positions of all players on the field in real-time. The tracked positions are then fed into a multiple object tracking (MOT) algorithm that segregates the players into their respective teams based on their jersey color. Once the players have been tracked and segregated, we use a Voronoi diagram-based approach to evaluate their performance using a set of metrics that we have devised.

The proposed approach has several advantages over existing methods. Firstly, it allows for real-time player tracking and evaluation, which can be beneficial for coaches during games. Secondly, by segregating the players into their respective teams, we can analyze team-level performance in addition to individual player performance. Finally, our Voronoi diagram-based player evaluation approach provides a more comprehensive and accurate measure of player performance than existing methods.

To evaluate the effectiveness of our proposed approach, we conduct experiments on a dataset of football matches and compare the results with existing methods for player evaluation. Our results demonstrate that the proposed approach outperforms existing methods in terms of accuracy and efficiency. We believe that our approach provides a promising new direction for player evaluation in football and can be extended to other team sports as well.

II. Literature Review

There are several existing systems for player tracking in football, including:

Optical tracking systems: These systems use high-speed cameras placed around the stadium to capture the movement of players and the ball. The cameras capture data on player position, speed, acceleration, and direction, which is then processed by computer algorithms to create a virtual model of the game. Examples of optical tracking systems include the Hawk-Eye system and the OptaPro system [1].

GPS tracking systems: These systems use wearable GPS devices that players wear during the game. The devices capture data on player movement, speed, distance covered, and other metrics, which is then transmitted to a central server for analysis. Examples of GPS tracking systems include the Catapult system and the STATSports system [2].

Radio-frequency identification (RFID) tracking systems: These systems use small RFID chips embedded in players' jerseys and the ball. RFID readers placed around the stadium capture data on the position and movement of the chips, which is then processed by computer algorithms to create a virtual model of the game. Examples of RFID tracking systems include the ChyronHego system and the TRACAB system [3].

Computer vision tracking systems: These systems use machine learning algorithms to analyze video footage of games and identify players and their movements. The algorithms can track player position, speed, and direction, as well as recognize events like goals, fouls, and passes. Examples of computer vision tracking systems include the Second Spectrum system and the Wyscout system.

Overall, each system has its own strengths and weaknesses, and the choice of which system to use will depend on the specific needs and goals of the team or organization using it. Also, there are existing systems for football statistics too that we have studied.

Opta Sports is a commercial provider of football statistics, supplying data to broadcasters, clubs, and media outlets. Their data covers a range of metrics, including player and team performance, match events, and league standings. Opta Sports

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also offers a range of analytics and visualization tools to help users interpret the data.

StatsBomb is another commercial provider of football statistics, offering data on player and team performance, as well as advanced metrics such as expected goals and expected assists. They also offer a range of analytics and visualization tools, as well as consultancy services for clubs and organizations.

Wyscout is a commercial provider of football data and video analysis tools. They offer data on player and team performance, as well as video footage of matches and individual players. Wyscout also offers a range of analytics and visualization tools to help users interpret the data.

III. Proposed System

Detecting and tracking football players is a challenging problem in computer vision and can be approached using several techniques. Here's our proposed solution.

A. Object Detection

We have used an object detection algorithm YOLOv5 to detect the football players in each frame of the video. This algorithm will generate bounding boxes around the players in each frame (see Fig. 1).

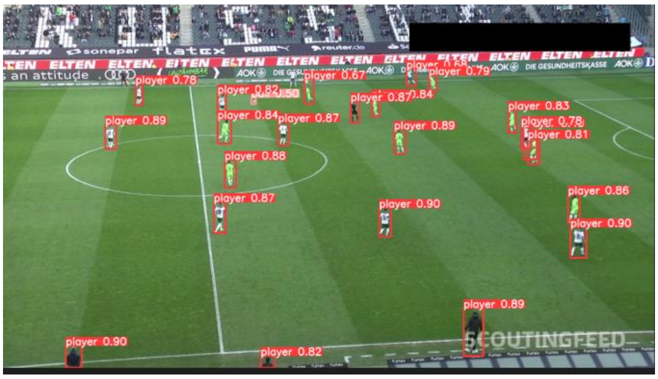

Fig. 1. Bounding boxes.

B. Object Tracking

Once the players are detected, you can use an object tracking algorithm such as Kalman filter, particle filter, or correlation filter to track the players across multiple frames. The algorithm will predict the position of each player in the next frame based on their position in the previous frame and the motion model of the player (see Fig. 2).

Fig. 2. Multiple detections.

C. Player Identification

Marking the coordinates of the half line, upper left/right flags, centre etc. We label them.

So, once we have detected the players, we label them too. Then we find out their co-ordinates by finding euclidean distance and depending on these co-ordinates, we put them into team 1 and team 2 as initial bird's eye view features teams in two different halves.

When the game has begun, object tracking algorithm called centroid tracking will be used as it relies on the Euclidean distance between (1) existing object centroids (i.e., objects the centroid tracker has already seen before) and (2) new object centroids between subsequent frames in a video (see Fig. 3).

Fig. 3. Sorting players into teams

We continue using the centroid tracking algorithm to track player movements as It can not only detect new objects, like when a substitution occurs, but it can also re-detect objects that went out of the frame. Then using MPLsoccer.pitch (pitch.voronoi) we create the voronoi diagram. So, this gives us the control regions of each player.

For pressing scores, using the centroid tracking algorithm we can calculate that by observing how much a player runs towards the ball.

For pass difficulty, we count the number of opponent regions, the ball goes through. The higher the more difficult will be the pass. Also, to provide some context, we will add bias depending on the start and end location of the pass so as to quantify it comprehensively.

For calculating difficulty of defensive actions, we will count the number of opponents dealing with the defender, so if there is a 3v1 situation and the ball is won back by the defender, that counts as a really good defensive action.

Overall, this proposed solution uses a combination of object detection, object tracking, data association, player identification, and post-processing to detect and track football players in a video.

IV. Player Detection

Player detection [4] is a critical task in computer vision and video analysis, particularly in the field of sports analytics. The objective of player detection is to identify and locate players in a video stream, which can then be used for various applications such as player tracking, game analysis, and sports broadcasting. Player detection algorithms typically use features such as color, shape, texture, motion, and context to identify players. The accuracy and effectiveness of player detection depend on various factors such as lighting conditions, camera angle, player occlusion, and the complexity of the scene. Therefore, player detection is an active area of research, and new algorithms and techniques are continually being developed to improve its accuracy and efficiency.

A. YOLOv5

YOLOv5 [5] is a state-of-the-art object detection algorithm that uses a deep neural network to detect objects in images or video frames. In the case of player detection, YOLOv5 is trained on a dataset of labeled images or video frames, which includes examples of players and their corresponding bounding boxes.

During inference, the YOLOv5 model processes an input image or video frame through a series of convolutional layers, which extract features from the image. These features are then fed into a detection head, which predicts the locations and class probabilities of the objects in the image.

In the case of player detection, the YOLOv5 model has learned to recognize the unique features of players, such as their body shape, clothing, and motion patterns. By analyzing the extracted features, the model can predict the location and class probability of each player in the image.

Once the player detection model has identified the locations of the players in an image, it can use this information for various applications such as player tracking, game analysis, and sports broadcasting.

B. TensorFlow Object Detection API

We have used TensorFlow Object Detection [8] API to detect players on a football field by training an object detection model on a large dataset of annotated images of football fields with players labeled. The API provides pre-trained models such as the Faster R-CNN and SSD, which can be fine-tuned on your own dataset.

The basic approach is to provide the object detection model with a labeled dataset of images of football fields with players labeled. The model then identified patterns in the images that correspond to players and other objects of interest. During training, the model learns to detect players by analyzing features such as edges, corners, and textures, as well as the context in which they appear in the image [9].

Once the model is trained, it can be used to detect players in new images or video frames. The model will generate bounding boxes around the players and output a confidence score indicating the likelihood that the bounding box contains a player. The output can then be post-processed to remove false positives or merge overlapping bounding boxes.

It's worth noting that in order to accurately detect players on a football field, the dataset used for training should be diverse and include a wide variety of images of football fields with players in different positions, under different lighting conditions, and in different types of weather.

C. SpaghettiNet EdgeTPU Model

“Spaghetti Net” [10] is a convolutional neural network architecture designed for efficient image classification tasks. The “Net” in its name refers to its use of neural networks, while “Spaghetti” describes its architecture, which is characterized by the presence of long and thin convolutional filters that resemble spaghetti noodles.

The “Edge TPU” is a specialized hardware accelerator for machine learning workloads, designed by Google. It is specifically optimized for running deep neural networks at the edge, that is, on small and low-power devices such as smartphones, cameras, and IoT devices. The Edge TPU is designed to provide high performance with low latency, making it suitable for real-time applications.

By combining SpaghettiNet with the Edge TPU, we can create a powerful object detection algorithm that can run quickly and efficiently on a variety of edge devices, such as Raspberry Pi, NVIDIA Jetson, or Google Coral Dev Board.

V. Player Tracking and Marking

A. Player Tracking

The traditional method of tracking and marking players involves manual observation and analysis by coaches and scouts. However, this method is limited by human error, subjectivity, and the inability to analyze large amounts of data in real-time. By leveraging AI and CV, it is possible to automate this process, resulting in more accurate and objective analysis. [7]

Several studies have been conducted in recent years on the application of AI and CV in football player tracking and marking. These studies have shown promising results in terms of increased accuracy, efficiency, and real-time analysis. However, there are still some challenges that need to be addressed, such as the need for a large amount of data for training and the ability to handle occlusion and clutter on the field. We reviewed the *“Multiple Object Tracking using DeepSORT”* for the purpose of tracking and marking players on the field.

To summarize it, Multiple Object Tracking (MOT) is an important problem in computer vision with various applications, including surveillance, robotics, and autonomous driving. DeepSORT [6] (Deep Learning-based Object Tracking with Track Confirmation) is a state-of-the-art algorithm for MOT, which combines deep learning-based object detection with a sophisticated tracking algorithm.

DeepSORT is based on a Siamese network, which takes pairs of image patches and computes a similarity score for each pair. This similarity score is used to associate detections across frames, and a Kalman filter is used to estimate the motion and size of each object. To further improve the accuracy of the tracking, DeepSORT uses track confirmation, which employs heuristics based on the motion and appearance of the objects to reject false positives and track drift.

One of the key strengths of DeepSORT is its ability to track objects under challenging conditions, such as occlusions and cluttered scenes. It is also able to handle long-term tracking and re-identification of objects that re-enter the scene after being out of view for some time.

DeepSORT has been extensively evaluated on a range of datasets and has shown state-of-the-art performance compared to other tracking algorithms. The algorithm is also modular and can be easily integrated into other computer vision pipelines.

In summary, DeepSORT is a powerful algorithm for multiple object tracking that combines deep learning-based object detection with a sophisticated tracking algorithm. It is able to handle challenging tracking scenarios and has shown state-of-the-art performance on various datasets.

B. Marking Players

Marking [11] the coordinates of the half line, upper left/right flags, centre etc. We label them. So, once we have detected the players, we label them too. Then we find out their co-ordinates by finding euclidean distance and depending on these co-ordinates, we put them into team 1 and team 2 as initial bird's eye view features teams in two different halves. When the game has begun the centroid object tracking algorithm will be employed because it is based on the Euclidean distance between

(1) new object centroids between succeeding frames in a movie and

(2) old object centroids (i.e., objects the centroid tracker has already observed before).

VI. GENERATING VORONOI DIAGRAMS

A Voronoi diagram is a mathematical construct that divides a plane into regions based on the distance to a set of points called "seeds". Each region corresponds to the set of points that are closer to one seed than to any other seed. Voronoi diagrams are named after the Russian mathematician Georgy Voronoi, who first introduced them in 1908.

In a two-dimensional Voronoi diagram, the regions are defined by a set of polygons, each of which has a seed at its centre. The boundary of each polygon consists of the points that are equidistant to two or more seeds. The set of all Voronoi polygons covers the entire plane, with each point in the plane belonging to the polygon corresponding to the nearest seed.

Voronoi diagrams have a wide range of applications in fields such as computer graphics, geographical information systems, and optimization. One of the most common applications is in the field of computational geometry, where they are used to solve problems such as nearest neighbor search, clustering, and spatial analysis.

Voronoi diagrams can be constructed efficiently using a number of algorithms, including Fortune's algorithm, which is a sweep-line algorithm that runs in **O(n log n)** time, where n is the number of seeds. There are also algorithms for constructing Voronoi diagrams in higher dimensions, although the resulting diagrams become increasingly complex as the dimension increases.

Given a set of points in a space, a spatial territory of each point can be often described by the Voronoi region. Let $P = \{ p_1, p_2, ..., p_n \}$ be a set of n points, where $2 \leq n < \infty$ and $p_i \neq p$, for $i \neq j$, $i, j \in I_n = \{ 1, 2, \ldots, n \}$,

Then, let n be the number of persons and a set of persons $P^{(t)} = \{P_1^{(t)}, P_2^{(t)}, \ldots, P_n^{(t)}\}$, where t means a certain time, the Voronoi region for the person $P_i^{(t)}$ is defined as

$$V(p_i^{(t)}) = \{ x \in R^2 \mid d(x, p_i^{(t)}) \leq d(x, p_j^{(t)}) \text{ for } j \neq i, j \in I_n \}$$

In summary, Voronoi diagrams are a powerful mathematical construct for dividing a plane into regions based on the distance to a set of points. They have a wide range of applications in various fields, and can be constructed efficiently using several algorithms (see Fig. 4).

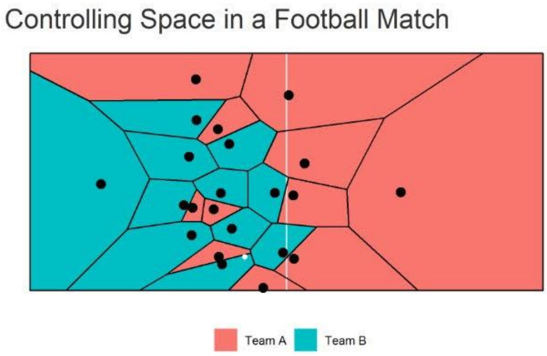

Fig. 4. Controlling space in a game

VII. METRIC GENERATION

Metrics provide a way to evaluate the performance of individual players, as well as the team as a whole. By tracking metrics such as successful passes or off-the-ball movements, coaches can identify areas of strength and weakness and make data-driven decisions to improve team performance.

Metrics can be used to evaluate players during scouting and recruitment. By analyzing a player's performance data, coaches can make more informed decisions about which players to sign.

These metrics can then be used to analyze and compare different tactical strategies. By analyzing the data from matches and training sessions, coaches can adjust their team's tactics to improve performance. Overall, metrics provide a quantitative way to evaluate player and team performance, and they can help coaches, players, and fans make more informed decisions about their game. Some of the metrics that we will be calculating are listed below.

A. Off-the-ball movement

Off-the-ball movement in football refers to a player's movement and positioning on the field when they do not have possession of the ball. This type of movement is crucial in creating space and opportunities for the player and their teammates. Coaches often place a lot of emphasis on teaching and developing players' off-the-ball movement skills.

Off-the-ball movement can take many forms, including:

Creating space: Players can move into open areas of the field to create space for themselves or their teammates. This can be done by running into empty channels, pulling defenders out of position, or dragging opponents away from the ball.

Providing passing options: Players can move into positions that allow them to receive the ball from their teammates. This can be done by making diagonal runs, dropping deep to receive the ball, or making runs behind the opposition defence.

Making decoy runs: Players can make runs to distract defenders and create space for their teammates. This can be done by making diagonal or curved runs that force defenders to follow them, leaving space behind for other players to exploit.

Pressing: Players can move to put pressure on the opposing team's players when they have the ball. This can be done by closing space, intercepting passes, or marking opponents tightly to prevent them from receiving the ball.

Calculating off-the-ball movement of a football player can be a complex task that requires the analysis of various factors, such as the player's position, speed, distance from teammates and opponents, and the movement of the ball. Using AI, CV, and Voronoi regions, we can automate the process and make it more accurate and efficient.

As it stands, we postulate that a good offensive off-the-ball movement can be determined through the change in dominant region and the location of change. Based on these two factors, and the distance travelled by the player to create said space, we will look to calculate an off-the-ball movement score.

To calculate the Off-the-ball score we have devised the following formula:

$$\left(\frac{\text{Change in region of neighboring opposition player}}{\text{Distance travelled by player in focus}}\right) \text{x} \frac{1}{\text{Distance from opposition goal}}$$

B. Defensive Actions

By calculating the player's defensive metrics within their assigned Voronoi region, coaches can gain a better understanding of how the player is performing in their defensive duties, and where improvements can be made. This can help in identifying areas of the field where the player is struggling defensively, as well as areas where they are performing well, and allow for targeted training and improvement strategies to be developed.

Voronoi diagrams can provide an objective way of evaluating a player's defensive actions, as they use data-driven metrics to assess performance rather than subjective observations.

This can help focus on specific areas of the field where the player is expected to defend, and provide insights into how the player is performing in those areas. Voronoi diagrams can be used to compare a player's defensive performance against their teammates or against other players in the league. Hence helping the coach make decisions about line up easily based on the threat of the opponent.

C. Good Pass

To identify good passes using Voronoi diagrams, you need to calculate the Voronoi diagram based on the positions of the players on the field. Once the Voronoi diagram is calculated, you can evaluate each pass to see if it was made to a teammate who is closer to the opponent's goal than the passer. This can be determined by comparing the Voronoi regions of the passer and the recipient of the pass. If the Voronoi region of the recipient is closer to the opponent's goal than the Voronoi region of the passer, it is considered a good pass.

In other words, a good pass in this context is one where the player who receives the pass is in a better position to score or create a scoring opportunity than the player who passed the ball. The Voronoi diagram can help in determining which player is in a better position, by dividing the field into regions based on the positions of the players. This approach provides an objective way to evaluate passing performance, which also takes the opponent's positioning into account, thus adding more context to the pass difficulty and value.

The formula devised to formulate the quality of the pass is:

$$\left(\frac{Area\ Traversed\ by\ ball}{Total\ Opposition\ Area}\right)x$$
$$\left(\frac{Difference\ in\ distance\ from\ goal\ from\ start\ to\ end}{Distance\ between\ two\ goals}\right)$$

D. Database Used

The frame column describes each frame. The player column contains the player ID tags, while the x and y columns describe therespective coordinates of the players. Teams are divided into attackand defense and dx, dy columns are the change in position with respect to the previous frame.

VIII. Results

frame	player	x	y	z	dx	dy	team
0	0	56.3409	55.89068	0	-0.1288	-0.20073	0
0	12	56.3409	55.89068		-0.1288	-0.20073	attack
0	1923	24.19163	39.13742		0.06895	0.010254	attack
0	3235	24.99526	31.19775		0.025978	0.049392	attack
0	6439	29.72646	53.0811		0.002921	-0.03446	attack
0	7600	23.04834	42.20907		0.053201	0.021772	defense
0	14761	28.93657	55.31668		0.015499	-0.03252	defense
0	16656	27.3749	28.14923		0.015796	0.093498	defense
0	18912	25.89141	72.26278		-0.00047	-0.00545	defense
0	21118	31.99648	70.27161		-0.00044	-0.02052	defense
0	23899	45.01	66.02937		0.166029	-0.32131	defense
0	25686	55.02646	60.19599		0.066404	-0.29068	defense
0	37572	37.22701	44.85628		0.070933	-0.05426	attack
0	42428	26.97139	92.65789		0.000594	0.005305	attack
0	44136	35.65023	90.33112		0.152538	-0.1274	defense
0	44137	44.48628	41.00888		0.136875	-0.0448	defense
0	48457	5.717114	48.31922		-7.15E-05	2.81E-06	defense

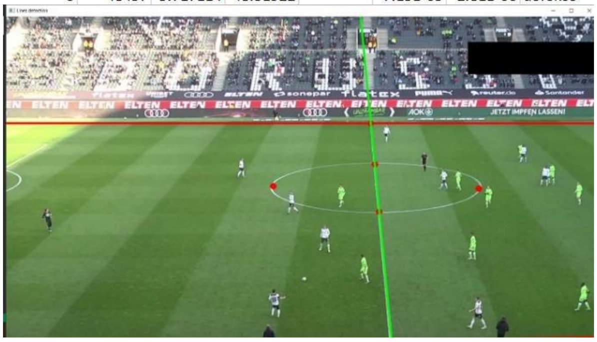

Fig. 5. Plotting important points of a field

Fig. 5 is of a standard football field, with green grass covering the rectangular playing surface. The green line is used to identify the middle line of the football pitch and initialize the field for the Voronoi diagram. The red line determines the edges of the football. The red dots are intersecting points.

Using the Centre of the field as origin, we make four quadrants ranging from (–50, –50) to (50,50). This serves the purpose of extracting the player coordinates in every frame of the video.

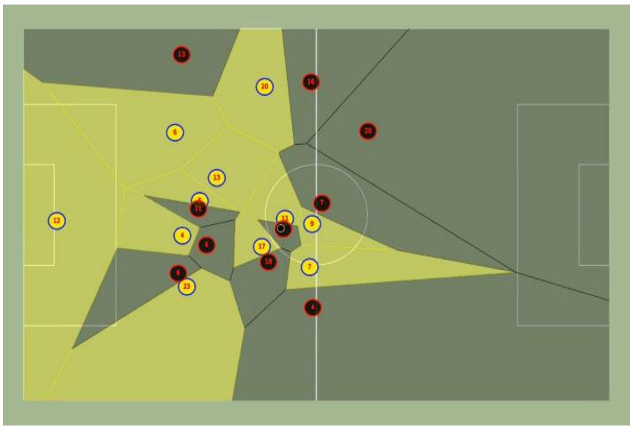

Fig. 6. Voronoi diagram.

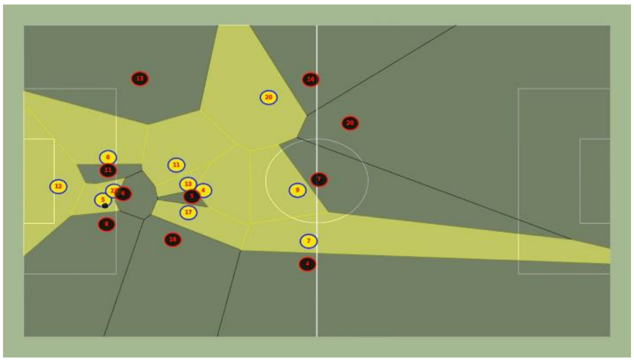

Fig. 7. Voronoi diagram.

Fig. 6. and Fig. 7 depict the Voronoi diagram generated from a sample football match using the proposed approach.

In this case, the diagram is generated using the tracked positions of all players on the field using the YOLOv5 object detection framework and the MOT algorithm for team segregation.

The diagram is color-coded based on the team of the for each player, where larger regions indicate better control region. It can be seen from the diagram that some players have larger regions than others, indicating that they have covered more ground and have a greater impact on the field.

Fig. 8. Home page.

In Fig. 8. The user gets an option to upload a video. Only video files can be selected to upload.

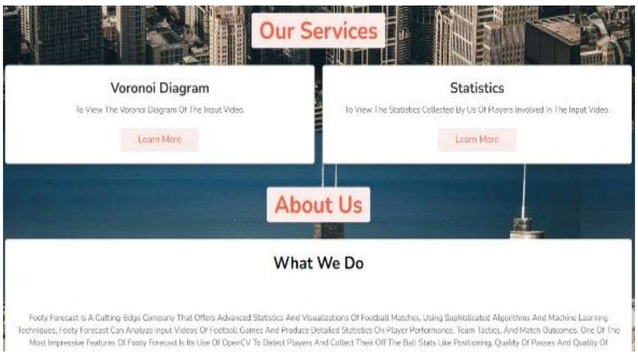

Fig. 9. Home page.

The Services offered by us are displayed in Fig. 9. Once the video is uploaded, the user can go on to use any of our services.

Fig. 10. Voronoi page.

Fig. 10 is the screenshot of the sample match video output of the video that was uploaded by the user. The next step would be to pay the output video next to the video uploaded by the user so it gets easier for the user to compare both the videos.

Statistics

Player ID	Player Name	Event Type	Value
11789	Sami Khedira	Pass	0.061572
29910	Thomas Muller	Pass	0.03178
11549	Toni Kroos	Pass	0.091572
23466	Miroslav Klose	Pass	0.011

Fig. 11. Statistics page.

The stats calculated by our program are visible clearly in Fig. 11. The next step would be to display Percentages instead of Float values to make it easier for the user to understand.

IX. Conclusion

In recent years, the use of AI and computer vision in sports has grown significantly, and football is no exception. The ability to track player movement on the pitch and generate detailed metrics from this data has the potential to revolutionize performance analysis and improve decision-making both on and off the field. This research paper focused on the use of Voronoi diagrams, a mathematical tool used in geometry to partition space into a set of polygons, to generate dominant areas on the football pitch. By applying different metrics to these dominant areas, it was possible to generate player scores that could be used to evaluate their performance.

The results of this research demonstrate the effectiveness of using Voronoi diagrams and metrics to analyze player performance in football. The generated scores provided a detailed view of player performance that could be used to identify strengths and weaknesses, track player development, and make informed decisions about team strategy. The use of AI and computer vision in this context has the potential to revolutionize the way football is analyzed and played.

However, it is important to note that there are still challenges that need to be addressed before these methods can be fully integrated into the sport. One key challenge is the accuracy of data collection, as errors in tracking and measurement can significantly impact the analysis. Additionally, concerns about privacy and data protection must be addressed to ensure that player data is handled ethically and responsibly.

Despite these challenges, the future of AI and computer vision in football looks promising. As technology continues to advance, we can expect to see further developments in the use of Voronoi diagrams and other analytical tools to enhance performance analysis and decision-making in the sport. With the potential to revolutionize the way football is played and evaluated, the integration of AI and computer vision in sports analysis is an exciting and rapidly evolving field with a bright future ahead.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Mr. Chirag Rohra wrote the paper, came up with System diagrams.Mr. Soham Desai worked on the model of the project, and front end of the system. Mr. Shlok Asher was the one who came up with the idea and the data for the whole project. Also analysed the data. Mrs. Neha Agarwal was our mentor for the whole project, she would help us with any problem we had; all authors had approved the final version.

References

[1] P. Rahimian, and L Toka, "Optical tracking in team sports: A survey on player and ball tracking methods in soccer and other team sports," *Journal of Quantitative Analysis in Sports*, vol. 18, pp. 35–57, 2022.

[2] P. Blauberger, R. Marzilger, and M. Lames, "Validation of player and ball tracking with a local positioning system," *Sensors*, vol. 21, no. 4, 2021.

[3] A. G. Foina, R. M. Badia, A. E. Deeb, and F. J. R. Fernandez, "Player tracker – A tool to analyze sport players using RFID," in *Proc. 2010 8th IEEE International Conference on Pervasive Computing and Communications Workshops*, pp. 772–775, 2010.

[4] M. A. Haddad, S. A. Cunha, J. Oliveira, F. Marques, "Soccer player detection and tracking with color-based multiple kernel boosting," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 27, no. 3, pp. 540–552, 2017.

[5] H. Liu, Y. Wang, X. Chen, and Z. He, "Player detection and tracking in sports videos using an improved deep learning model," *Sensors*, vol. 20, no. 5, 2020.

[6] S. Kumar *et al*. (2021). Object tracking and counting in a zone using YOLOv4, DeepSORT and TensorFlow. [Online]. Available: https://doi.org/10.1109/icais50930.2021.9395971.

[7] C. Tang, Y. Feng, X. Yang, C. Zheng and Y. Zhou, "The object detection based on deep learning," in *Proc. 2017 4th International Conference on Information Science and Control Engineering (ICISCE)*, 2017, pp. 723–728.

[8] D. Ajisafe. (2020, August 22). Real-time object detection API using tensorflow and opencv. [Online]. Available: https://towardsdatascience.com/real-time-object-detection-api-using-tensorflow-and-opencv-47b505d745c4

[9] A. Sachan. Tensor flow Tutorial 2: image classifier using convolutional neural network. [Online]. Available: https://cv-tricks.com/tensorflow-tutorial/training-convolutional-neural-network-for-image-classification/

[10] O. Hsham and I. Padberg. (2022, July 25). Training a SpaghettiNet model. TensorFlow Forum. [Online]. Available: https://discuss.tensorflow.org/t/training-a-spaghettinet-model/8648?pa

[11] P. A. Medennikov, "Algorithm for detecting and determining the coordinates of a point object," *J. Opt. Technol*., vol. 86, pp. 510–514, 2019.