IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Sports Analytics using computer vision Performance analytics using Computer vision and analysis techniques

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Abstract: In the past few years, artificial intelligence (AI) has revolutionized how we watch and analyze sports. In addition to many other benefits, the use of AI in sports is multiplying and attracting greater interest from both the academic and business communities. Sports coaches have been utilizing data science to assist players to perform better. While statistics have always been crucial in the industry, sports-related AI has significantly impacted how the competition develops. The training process is becoming more effective and competitive as a result. More people now use AI to boost their performance by letting it analyze it, get suggestions for improving it, and much more.

***IndexTerms* - Sports analytics using computer vision, AI in sports training, improving performance using AI/ML, pose comparison, pose estimation, and analysis.**

I. INTRODUCTION

The fundamental components of technology are improving at an exponential rate that far exceeds our expectations. Nearly all of the standard sub-fields of artificial intelligence (AI) have made significant advancements in the last five years, including vision, speech recognition and generation, natural language processing (understanding and generation), image and video generation, multi-agent systems, planning, decision-making, and the integration of vision and motor control for robotics.
Furthermore, ground-breaking applications appeared in many different fields, including games, medical diagnosis, logistics systems, autonomous driving, language translation, and interactive personal support.

Sports analytics refers to computer vision techniques that detect human figures in images and videos. Today, widely used in many professional sports leagues to gain a competitive edge by analyzing player performance, game, strategies, player movements, and techniques during training and using patterns and trends of the player's performance using statistical and machine learning techniques. So the vision of sports analytics is to provide teams and organizations with the ability to make data-driven decisions that can improve performance and increase success.

II. BACKGROUND

Following the release of the 2011 movie Moneyball, in which Brad Pitt's character, Oakland Athletics general manager Billy Beane, heavily relies on the use of analytics to assemble a competitive team on a shoestring budget, the term "sports analytics" became widely accepted in mainstream sports culture. On-field and off-field analytics are the two main facets of sports analytics. On-field analytics aims to help teams and players perform better on the field. The business side of sports is covered by off-field analytics. Off-field analytics is focused on assisting a sports organization or body in uncovering trends and insights through data that would boost fan engagement, increase ticket and merchandise sales, etc. In essence, off-field analytics employs data to assist rights holders in making decisions that will result in greater growth and profitability[1].

Dr. Patrick Lucey the Chief Scientist at Stats Perform, created a robotic camera that moved to follow players' motions in a real-time sports broadcasting system. He recently discussed the usage of artificial intelligence in sports, what it entails, and how we may utilize AI to aid in the decision-making of coaches and analysts[2].

The usage of wearable devices has changed how coaching is often conducted. Wearable sleeves or sensor technologies for players can enhance their performance beyond fitness and agility. When wearables and technology are integrated, analytics will evaluate a player's mental and emotional makeup and how it connects to their performance on the field.

Introducing AI to improve player performance using apps like HomeCourt has an excellent opportunity to advance because these tools use computer vision and machine learning to evaluate their abilities. There are coaching platforms like Asensei that direct and correct individual workouts using motion capture sensors in everyday sports clothing. These performance indicators for athletes are reliable and give them a better idea of where they can thrive and where they still need to make improvements[3].

The sports business will continue to use AI for a very long time. The audience will enjoy a richer viewing experience as sensors, processors, and algorithms improve with the development of AI, which on the whole, will improve players' performance.

III. RELATED WORK

The capacity of AI is increasing to the point where we can now fairly precisely identify and monitor a human skeleton overlay of the human form. The capacity to analyze human (and animal) form in pictures for various purposes, which is frequently referred to as pose estimation, is remarkably potent. Over the past ten years, computer vision has made significant advancements in the interpretation of digital images and videos.

By tracking player movements and ball trajectories, businesses like Sportlogiq can provide coaches and players with a new kind of analysis and insightful data. Optimizing a runner's form, a golfer's swing or a soccer goalie's dives are just a few examples of how human pose analysis may be very useful in helping sportsmen find areas for improvement[4].

Some industries are analyzing the movement by using sensors such as accelerometers, gyroscopes, and magnetometers, wearable body sensors that can be worn on the body to track movement and provide position in real-time. The body's movement, speed, direction, range of motion, etc, can be tracked using these sensors[10]. But this research paper is based on sports analytics built using computer vision and other mathematical analysis techniques that capture specific body key points, track their position from videos, and then analyze the movement by identifying patterns and progress without any IoT sensors.

IV. CASE STUDY

There are so many people who are struggling to learn any sports, which can be due to insufficient resources or lag in the skills of coaches. Due to the enormous number of participants, there may be fewer instructors that can dedicate their attention to teaching each individual player. Trainers put in a lot of hard work to ensure that everyone can follow the technique in the best way possible, but they cannot provide training to anyone, anywhere and anytime. More precisely, The AI-powered assistant can offer in-the-moment feedback on a coach's approach, style, and other factors.

1. Problem Statement

The problem was to analyze the technique performed in the video uploaded by the player performing some defined activity and compare it with the professional trainer's video, along with providing insights to the user in the form of improvement KPIs and posture difference. This posture difference will help the user understand what has been done wrong. It will be done in a way where the user will be getting a visual comparison of his pose performing the main action of the technique and that of the trainer's pose doing the same. In this way, the user can easily differentiate and understand where exactly he is doing wrong. Also, some recommendations can be given to the user to improve and learn the techniques more efficiently.

2. Solution Approach

This problem was solved using a pose estimation module, which gives body key points, an action detection module that detects action performed in the video, and an object detection module that detects the objects detected in the video uploaded by the user. For the calculation of posture difference, a further embedding approach introduced by Google is used in this project which no one has yet used till now. All these modules will be further used to analyze the user's performance and give some scores on it so that the user can understand the differences and learn the techniques more properly by practicing and checking every time he is improving or not.

3. Approaches used for performance analytics and posture difference analysis

Approaches used for performance analytics and posture difference analysis: The approach was to use deep learning frameworks to analyze the video. So the flow starts when the user uploads the video performing some defined activity.

3.1 Pose estimation module

Pose Estimation, a general problem in computer vision, is to identify the location and orientation of an item or human. In the case of Human Pose Estimation, this is typically accomplished by estimating the locations of various key points like hands, heads, elbows, etc. Rapid advancements have been made in deep learning-based approaches to address these problems, which typically take on the difficult task of utilizing convolutional neural networks. Vision transformers have recently demonstrated remarkable potential in a variety of vision tasks. Different vision transformer topologies have been implemented for the pose estimation problem due to their success[5].

The State of Art (SOTA) ML model has been used for detecting the pose of the human presence in the video, which returns the coordinates of the skeleton of the human in the form of key points. This gives 33 body key points which are of eyes, ears, nose, knees, feet, shoulders, etc.

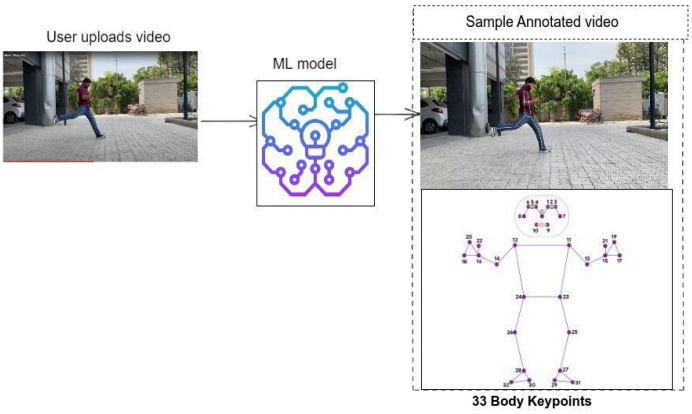

Fig 1: Overview of pose estimation module

This module takes video input and gives key points of the person detected in the form of 3d coordinates (x,y,z, and confidence score).

3.2 Action detection module

The learning of image representations for tasks like object recognition, image captioning, and semantic segmentation has empirically shown great effectiveness when using deep learning algorithms. Since it's crucial to comprehend videos, human action recognition has recently been a hot topic in research. In general, various modalities, including appearance, depth, optical fluxes, and body skeletons, can be used to identify human motion[6].

The action detection module uses the State of Art (SOTA) Tensorflow-based ML model to detect video action. This model is finetuned according to the actions that we want to detect. The features of the Action Detection module are noise reduction and improved accuracy of the overall pipeline.

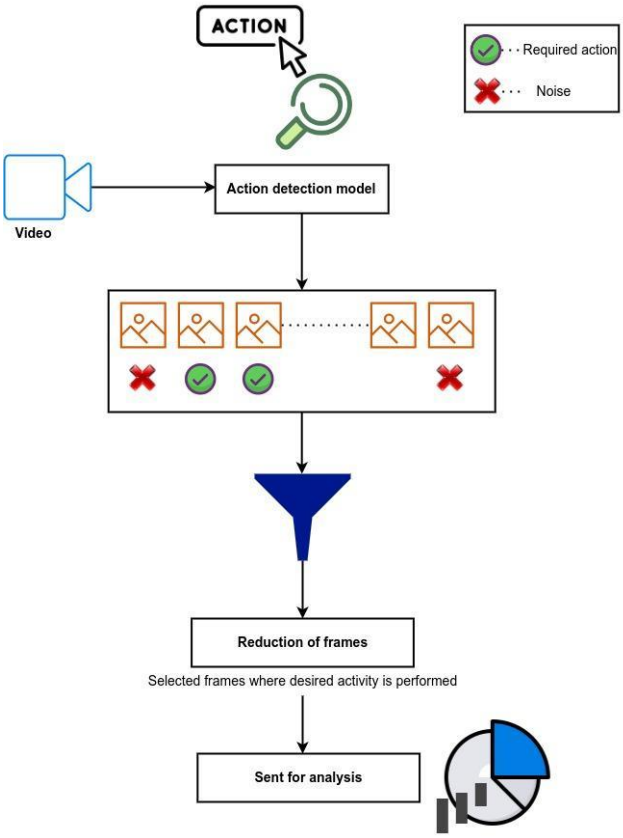

Fig 2: Overview of action detection module

This model basically detects which action is performed in the video and gives labels accordingly. Also, it stores the framewise output of video. It improves the accuracy as it filters out the unnecessary frames which are not required to be processed. For eg: if we want to analyze lunge activity rest of the frames where this model does not detect lunge action will be dropped while analysis.

3.3 Object detection module

A computer vision technology called object detection enables us to recognize and pinpoint certain things in an image or video. Using this form of localization and identification, object detection can be used to count the items in a scene, as well as to locate and track them in real time while precisely labeling them.

Here are object detection modules using the State of Art (SOTA) Tensorflow-based ML model for detecting objects in a video. A pre-trained model of tensorflow is used for object detection, which is trained for around 20 labels (the label we needed was there). In case you need any label for which the model is not trained, then you can go for training the model on your custom dataset. For that, there will be a need for lots and lots of data and resources to train the model, and achieving good accuracy on the custom data is also a

risky task. One can follow approaches like Transfer Learning, LR Finder, Data Augmentation, and many other techniques to enhance accuracy.

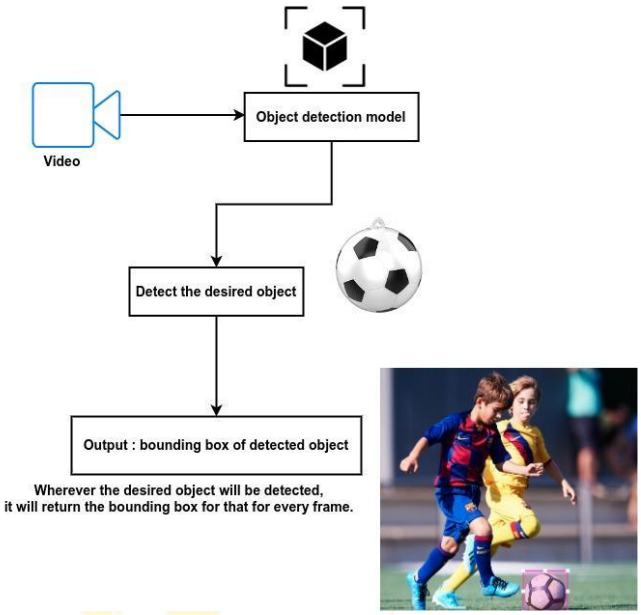

Fig 3: Overview of object detection module

According to our approach, the idea was to pick those frames where the object is detected successfully. The object detection results are always a bounding box as it is an object detection model.

3.4 Analytics module - for performance Analytics

Artificial Intelligence (AI) can be used to analyze the performance of players in various sports. One approach is to use computer vision techniques to analyze video footage of a player's performance, such as their movement patterns, speed, and coordination. This can be used for applications such as identifying areas of improvement or analyzing strategies used by opponents. Another approach is to use machine learning to analyze sensor data from devices worn by players, such as GPS trackers or accelerometers, to track metrics such as distance covered, speed, and acceleration. This can be used for applications such as monitoring player fatigue or identifying areas of improvement in their training regimen.

Additionally, AI-based analytics can be used to analyze the performance of teams by evaluating the collective performance of players and the plays they execute, to understand the team's strategies, strengths, and weaknesses, and to predict the outcomes of future matches[2].

Overall, AI-based performance analysis can provide valuable insights for coaches, players, and teams, helping them to improve their performance and make more informed decisions about training, tactics, and player selection. In the analytics module, we are mapping the pose of the trainer with the pose of the player. The general overview of the approach applied in the analytics module and their step-by-step instruction is also mentioned in this section.

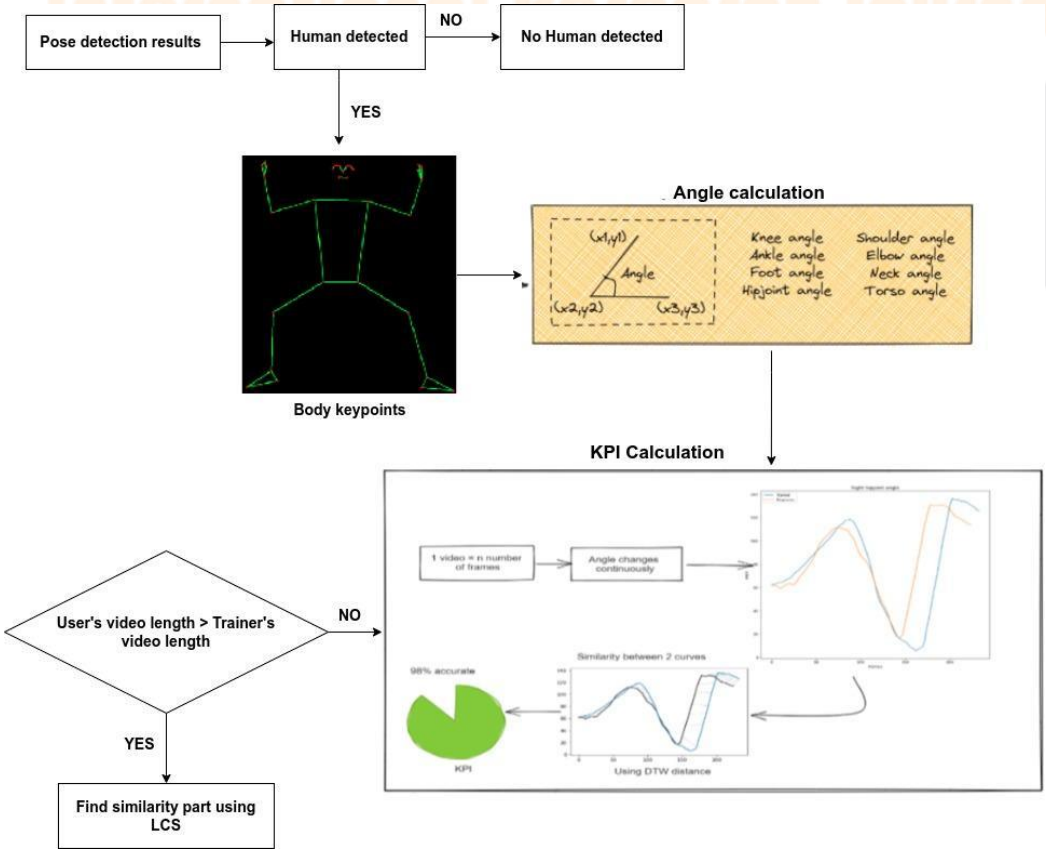

Fig 4: Brief working of analytics module

1. **Extracting Data from Model:** Whenever a user uploads his video After video quality checks, the video is sent to the open pose model for pose estimation. The model gives the output in JSON format. The JSON file consists of (x,y) coordinates of 25 body key points. We use these coordinates for further analytics.
2. **Human Detection:** The analytics module checks if the human is detected in the video or not. When no human is detected in the frame of video, then the model gives an empty list for that frame of video, and the analytics model gives the result as "No Human Detected."
3. **Angle Calculation:** We are calculating different body angles for the comparison. For each angle calculation, three key points coordinates are required. For example, for the calculation of the right knee angle, three key points (right hip-joint coordinates, right knee coordinates, right ankle coordinates) are required. Similarly, we can calculate all the necessary angles required for KPI calculation.
4. **Action Detection:** When a user uploads a video, there may be a noise in the video (like walking, sitting, or any other activity than kicking). To remove this type of noise and compare only the necessary part, LCS (Longest common subsequence) is used[8].
5. **Kicking leg detection:** It is very important to find the kicking leg of a person, whether it is right or left. To find the kicking leg, the variance of key points has been calculated (as the variance in the kicking leg will be more than the non-kicking leg because it is stable). The leg with more variance is considered as a Kicking leg.

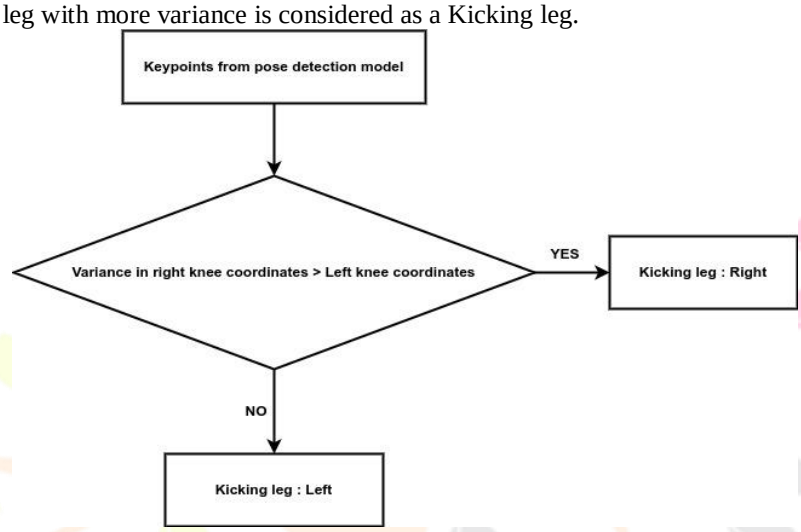

Fig 5: Approach to detect kicking leg

6. **KPI Calculation:** In KPI calculation, we calculate the various KPIs which give performance results to the user.
   For KPI calculation, DTW is used, which gives the similarity between 2 curves of different lengths. Here, the angles on different frames are used for comparison. When one starts analyzing the angles in every frame for a particular joint, then it actually forms a sequence, and this sequence length varies, due to which it's very hard to compare them. One approach for determining the degree of resemblance between two temporal sequences, which may differ in pace, is dynamic time warping (DTW). DTW has been used to analyze temporal sequences of video, audio, and graphic data; in fact, DTW can analyze any data that can be converted into a linear sequence. The similarity obtained by DTW is converted into a score. After calculating the KPIs (Kicking Leg, Non-Kicking Leg, Kicking food, Non-Kicking foot, Upper Body), the overall score is calculated by giving weightage to different KPIs according to their importance[9].

3.5 Posture difference module

Artificial Intelligence (AI) can be used to detect and analyze posture differences in various ways. One approach is to use computer vision techniques to analyze images or video of a person's posture and compare it to a reference posture. This can be used for applications such as monitoring posture in physical therapy or ergonomics. Another approach is to use machine learning to analyze sensor data from devices worn on the body, such as accelerometers or gyroscopes, to detect posture differences. This can be used for real-time applications such as monitoring posture to prevent injury or alert users to poor posture.

Images and videos include 2D data about a section of the 3D world that was photographed by a camera. An image of a person, for instance, offers a singular perspective of that person, whereas two images taken by two separate cameras can be radically different. It is necessary to learn a view-invariant representation to be able to detect a particular 3D posture from various photos that capture the position from various angles. Researchers from Google suggest using a probabilistic model trained on a collection of 2D key points to learn such representations or embedding spaces. Their strategy was founded on the idea that perspective invariance and ambiguity would not be adequately captured by a direct 2D-keypoint-to-3D mapping[7].

The model they introduced takes a set of 2D key points as input (which may originate from any pose detection model) and returns the mean and variance of the pose embedding or a sample from a Gaussian distribution.

The combined data from existing multi-view image datasets and 2D projections of 3D poses were used to train the suggested model. A pose similarity score is calculated as the similarity across distributions when the 2D postures are transformed into a probabilistic embedding, or a multivariate Gaussian distribution[7].

So we used this approach to just get Probabilistic embeddings of the 2d key points.For posture difference, the trainer's four main frames were frozen, and pose similarity was calculated for the filtered-out frames. The best four frames will be extracted from the user's uploaded video to show him the differentiation of his pose from that of the trainer's pose.

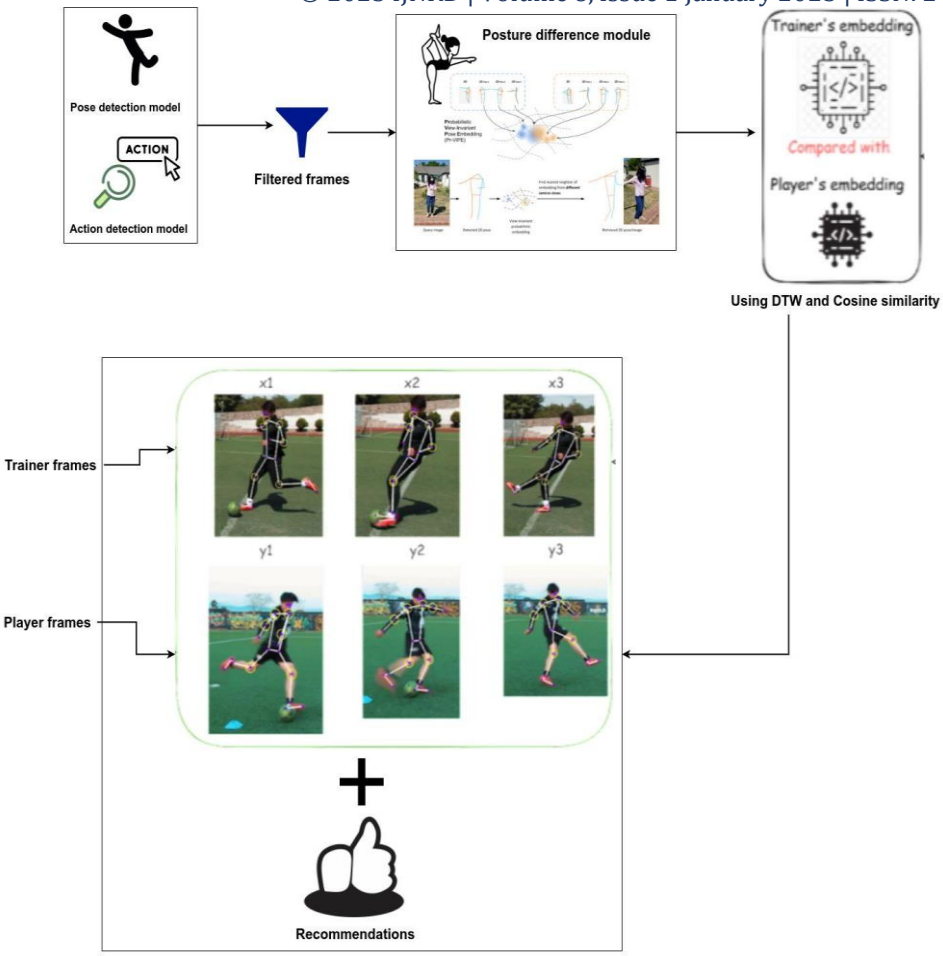

Fig 6: Overview of posture difference module

- To calculate pose similarity, the View Invariant Probabilistic Embeddings approach has been used as the noise has been already removed using action detection, and the required frames are filtered out.
- Now, the embeddings will be created from the human key points using this approach. The embeddings are basically the vectors made from 16 defined key points using Google's PrVIPE for the human pose approach mentioned here.
- These embeddings are created for the trainer and user(both).
- The embeddings of the player and user have been compared to find the best matching frames with 3 fixed frames of a trainer using DTW on vectors and cosine similarity (in case of more than 1 matched frame).
- The matched frame will be annotated that is shown on UI to the user.
- For each user, recommendations will be shown for every technique performed.

4. Overall architecture for performance analysis

For the performance analysis the architecture was in the following way.

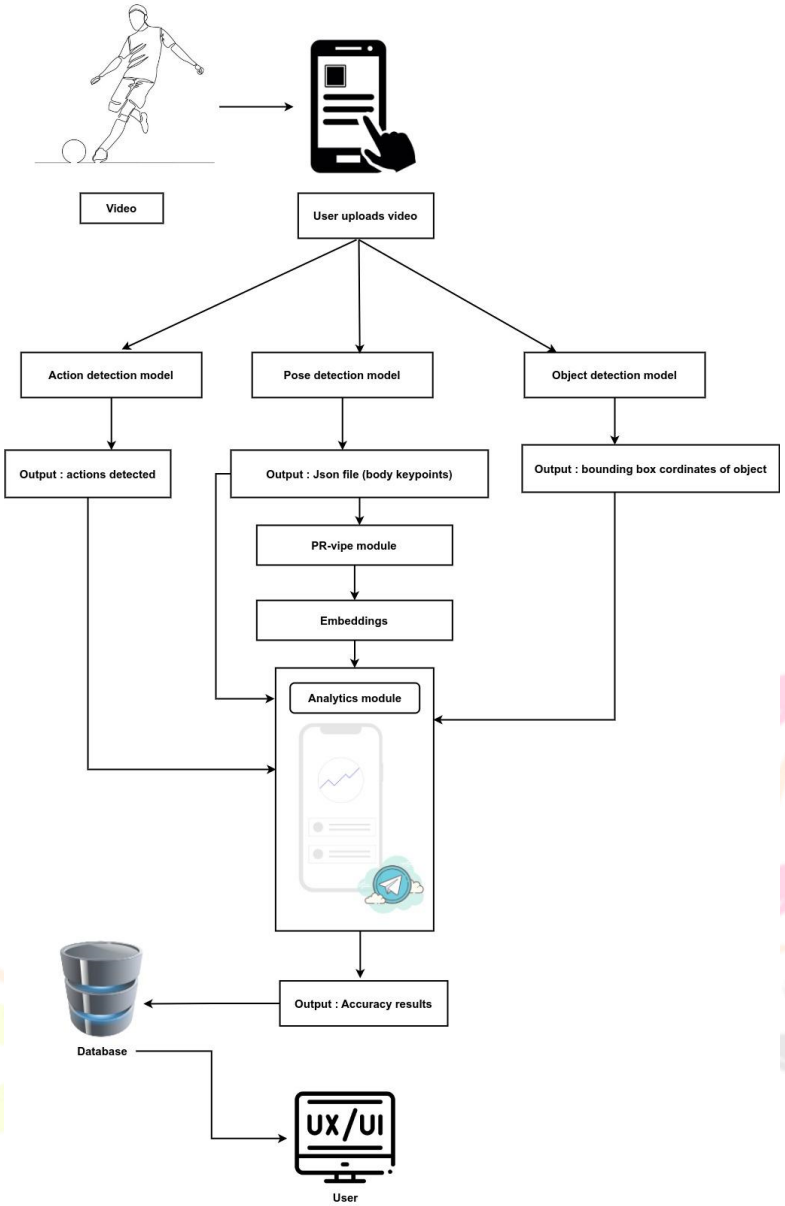

Fig 7: Architecture of performance analytics

- First of all, the video uploaded by the user should be given to the posing estimation model, which will give output in the form of key points of the person detected.
- This video will be passed from the action detection model which will detect the actions performed in the whole video on a frame basis. This will basically help to remove the noise from the video.
- Also, the video will be passed to the object detection module, which will detect the required object.
- The idea was to pick those frames from the whole video where the object is detected, and the action we are looking for is actually performed. Then we need to analyze the pose of humans only in those selected frames.
- The pose detection results are used to make embeddings which are used in the analytics module for making the results more concrete and accurate. Action annotation approach using embedding (a mathematical approach to convert 2d points given by the pose detection model into vectors). A similarity metric is calculated between player embeddings and trainer embeddings. These similarity metrics are used in the calculation of accuracy KPIs to increase the accuracy of these KPIs.
- The output of all the three models used above along with the embeddings will be analyzed using only those selected frames from the whole video.
- For performance analysis, an analytics module was developed which gives performance KPIs, which will tell the accuracy score of the technique performed by the user.

5. Overall architecture for posture difference

For the posture difference module, the architecture was in the following way.

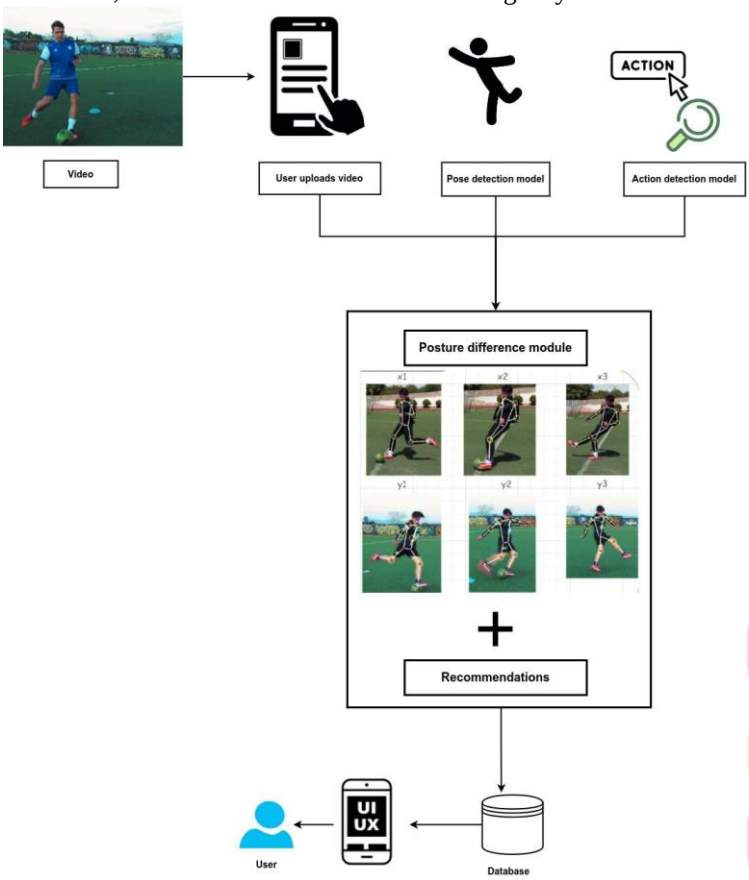

Fig 8: Architecture of posture difference

- First of all the video uploaded by the user should be given to the posing estimation model and action detection model.
- The input for the posture difference module is three things.
  - Video uploaded by the user
  - Output of pose detection model
  - Output of action detection model
- After calculating pose similarity with respect to the trainer's freeze frames we will be getting the most similar frames of the player.
- Next task is to read the frames from the video and draw a bounding box on the frames.
- This can be done using outputs of the pose detection models and the whole recommendation can be done based on the three frames selected.
- The annotated frame data and the recommendation messages can be saved to the database.
- Now UI can fetch this data from the database to show it to the user.

V. RESULTS AND DISCUSSION

The sport chosen for the project was soccer and the data set was in the form where we had some videos for beginner, intermediate, and advanced level players which were used for the testing of this developed architecture. On the other hand, we had the trainer's video which was assumed to be the most accurate of all. This was considered as a baseline and every uploaded video was compared to the trainer's video. Also, we have considered four techniques of soccer i.e. Push-pass, Control and shoot, Volley-pass, and shooting. Benchmarking of the results was done for both performance analytics and posture difference.

We have tested the performance analytics module on various scenarios, based on the testing of the module on various techniques following are the benchmarking of the accuracy numbers for the four techniques. This benchmarking is based on the intuition that advanced accuracy should be more than that of a beginner and intermediate. The intermediate accuracy should lie between advanced and beginner. The accuracy of beginners should be the lowest among the three of them.

Table 1: Accuracy results for performance analytics

Soccer Techniques	**Category**	**Accuracy**
Push pass	Advanced	80.09%
	Intermediate	80.43%

	Beginner	82.11%
Shooting	Advanced	78.87%
	Intermediate	77.60%
	Beginner	73.37%
Control and shoot	Advanced	78.55%
	Intermediate	88.81%
	Beginner	75.40%
Volley pass	Advanced	84.12%
	Intermediate	79.67%
	Beginner	82.26%

The overall accuracy of performance analytic module lies between 80-85% as seen from the tested videos.
Some scenarios where the user will get real-time suggestions on some random cases:

1. **No Human is Present in the Video:** Proper message is given when no human is detected in the uploaded video.

```
{'recommendation': 'Human not detected in the video.'}
```

2. **When Ball is not Present:** No ball-detected message will be given to the user.

```
{'kicking_leg': 0, 'non_kicking_leg': 0, 'kicking_foot': 0, 'non_kicking_foot': 0, 'upper_body': 0, 'overall_score': 0, 'recommendation': 'Results may not be accurate! It seems that your ball is not detected.'}
```

3. **When a player performs a technique from the incorrect side :** Side correction suggestions will be given to the user.

```
{'kicking_leg': 0, 'non_kicking_leg': 50, 'kicking_foot': 0, 'non_kicking_foot': 62, 'upper_body': 56, 'overall_score': 40.0, 'recommendation': 'Results may not be accurate! Ensure that the kick is performed from the same side as of trainer.'}
```

4. **When No action is performed by the user :** Suggestions to perform the action will be given.

```
{'kicking_leg': 81, 'non_kicking_leg': 81, 'kicking_foot': 49, 'non_kicking_foot': 90, 'upper_body': 42, 'overall_score': 60.0,'recommendation': "Results may not be accurate! Please see the trainer's video again and perform the correct technique."}
```

5. **When KPIs show a 0 score:** Suggestions to perform the action will be given.

```
{'kicking_leg': 81, 'non_kicking_leg': 81, 'kicking_foot': 49, 'non_kicking_foot': 90, 'upper_body': 42, 'overall_score': 60.0,'recommendation': "Results may not be accurate! Please see the trainer's video again and perform the correct
```

technique."}

We have tested the posture difference module on various scenarios; based on the testing of the module on various techniques following are the benchmarking of the accuracy numbers.

Table 2 : Accuracy results for posture difference module

Soccer Techniques	**No of test cases**	**Accuracy**
Push pass	15	78.01 %
Shooting	15	75.42 %
Control and shoot	15	70.46 %
Volley pass	15	68.29 %
Overall Accuracy		**70-75%**

The overall accuracy for posture difference module was around 65-70% which is a better start. In future one can work on further improving this accuracy. Also, some points should be kept in mind to get accurate results which are:

- It is recommended to use landscape mode for better posture difference visuals.
- The user needs to upload the video in the same technique he wants to analyze for the results to make sense.
- Also, it is recommended to upload the video that is played from the same side as that of the trainer.

VI. CHALLENGES

The following are the challenges that we have faced during the implementation of this:

- Motion blur handling while recording the video is a challenge that one can face. For this, a video check module can be set up to check the parameters like blur, stability, and dark detection, and once it passes the video check module, you can proceed further.
- Occlusions due to viewing angle and background can cause various problems in detecting the joints and further analysis can be impacted very highly.
- Difficulty in tracking small and barely visible joints. So if one wants to detect small joints very precisely. It is possible only if a video is recorded from a very close distance.
- One may face challenges in choosing the right model for pose detection because there is always an accuracy and runtime tradeoff in deep learning models for pose detection.
- Detection for third dimensions in most of the CPU-based models are estimated key points of the 2d key points. The output of the 3D pose estimation model may be inaccurate if the 2D detector sets key points in the wrong place.

Fig 9: Image depicting the problem of the side of the player/user

- The accuracy of your analysis also gets affected by the view(side) from where the video is recorded(fig 9) so make sure the views of both the videos should be almost same. If in case they are different, this can have a great impact on the results. To avoid this, one can use the Pr-Vipe approach of google to create left and right-side embeddings and then check the similarity of the uploaded video with both the embeddings using cosine or any other similarity metrics. The embeddings with which the uploaded video matches more can be considered further for analysis.

VII. FUTURE SCOPE OF STUDY

It is encouraging to see artificial intelligence being used in India. It is, however, still in its infancy at the moment. While some sectors, such as IT, manufacturing, automobiles, etc., are making use of AI's abilities, there are still many others where its potential is untapped.

1. The integration of KPIs scores for each frame chosen to visualize posture difference with the posture difference itself can be done so that the users can receive more thorough ratings and advice as a result.

2. The Posture Difference Module might need some work to solve the issues like user and player side matching and identification. So that if a particular user uploads a video from a different side as well, our module can analyze it and give recommendations accordingly.
3. Further if we want to make the module for more sports or exercise, the analytics module needs human intervention for fine-tuning it. So we can work on automating performance analysis such that user first has to upload one video with which he wants to compare his video and then user will upload his own video of performing the same activity and performance will be analyzed based on that.
4. Using your smartphone as a virtual coach in your pocket seems like a fantastic idea because there are models that are portable enough to run on it.

VIII. CONCLUSION

Artificial Intelligence is the future, it is crystal clear now. Artificial intelligence provides more robustness, and accuracy and decreases error-prone conditions. In simple words, artificial intelligence can make decision-making more efficient and accurate. What if this particular quality of AI can provide the same benefits in different areas? In Indian Primer League (IPL), Kolkata Knight Riders used Sports analytics in various departments such as player selection, performance analysis, and even in the live game. They reached the finale (in 2021) of such highly competitive tournaments, not taking away anything from the players and their performances, but it is certain that analytics and AI played a vital role in their game. Now other sports and sports organization also wants to follow the same trend, which provides AI and analytics a vital position in sports, this research work is a small attempt in the same direction.

REFERENCES

[1] Sharda, R. and Delen, D. 2020 in *ANALYTICS, DATA SCIENCE, & ARTIFICIAL INTELLIGENCE SYSTEMS FOR DECISION SUPPORT* . E L E V E N T H.

[2] Arastey , G.M. 2021 "Artificial Intelligence (AI) in Sports," *SPORT PERFORMANCE ANALYSIS*, February. Available at: https://www.sportperformanceanalysis.com/article/artificial-intelligence-ai-in-sports.

[3] Chemi, E. 2019 "SPORTS How artificial intelligence is making better basketball shooters, with just your iPhone," *CNBC*. Available at: https://www.cnbc.com/2019/04/17/how-artificial-intelligence-is-making-better-basketball-shooters-with-just-your-iphone.html.

[4] Bakken 2022 "Improving your Tennis Game with Computer Vision," December. Available at: https://medium.com/bakken-b%C3%A6ck/improving-your-tennis-game-with-computer-vision-863969743024.

[5] Shakhadri, S.A.G. 2021 *Pose estimation opencv: How to estimate pose using opencv, Analytics Vidhya*. Available at: https://www.analyticsvidhya.com/blog/2021/05/pose-estimation-using-opencv/.

[6] Vrigkas, M. 2015 "A Review of Human Activity Recognition Methods," November. Available at: https://www.frontiersin.org/articles/10.3389/frobt.2015.00028/full.

[7] Sun, J.J. *et al.* 2020 "View-invariant probabilistic embedding for human pose," *Computer Vision – ECCV 2020*, pp. 53–70.

[8] *Longest common subsequence. Longest Common Subsequence - tslearn 0.5.3.2 documentation*. Available at: https://tslearn.readthedocs.io/en/stable/auto_examples/metrics/plot_lcss.html.

[9] Giorgino, T.dot. *Welcome to the Dynamic Time Warp Suite!, Home - The DTW suite*. Available at: https://dynamictimewarping.github.io/.

[10] Ancans, A. *et al.* 2021 "Wearable sensor clothing for body movement measurement during physical activities in Healthcare," *Sensors*, 21(6), p. 2068.