AN INTELLIGENT TRACKING SYSTEM TO ANALYZE SHOOTING ANGLES COMPARED TO NBA PLAYERS USING AI AND MACHINE LEARNING

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ABSTRACT

This project aims to solve the problem of providing real-time, personalized feedback on basketball shooting form using machine learning (ML). By comparing a user's body angles during their shot to those of professional players, the program delivers tailored suggestions for improvement. The core technologies used include pose detection through computer vision and a machine learning model that analyzes and compares joint angles. Challenges included fine-tuning the model's confidence score to ensure accurate comparisons between users and pros, handling image quality issues, and providing clear feedback to users of different skill levels. The experiments showed that when professional players were compared to themselves, the system returned very high similarity scores, confirming the model's accuracy.The project stands out because of its personalized feedback feature, helping both beginner and advanced users improve their shooting form. By addressing common limitations such as image quality and skill variability, this tool offers a unique solution for athletes looking to refine their performance.

KEYWORDS

Basketball Analyze, Machine Learning Comparison, Computer Vision

1. INTRODUCTION

I am aiming to address an issue related to basketball by creating an app that provides users with guidance on how to adjust their shooting techniques to emulate NBA players. [1] This matter is significant because users can assess their shooting forms by comparing them to those of NBA players. The absence of an evaluation or analysis of NBA players' shooting techniques underscores the need for such an app. Suppose individuals struggle to find relevant sources to analyze NBA players' shooting forms. In that case, it can lead to frustration and the desire for a highly efficient app powered by machine learning and AI.[2]

My solution is to use machine learning and AI to analyze NBA players' shooting forms with the picture you want to submit, along with video uploading. [3]The proposed solution addresses the issue by providing users with a comprehensive understanding of enhancing their shooting form. This includes specific techniques such as adjusting the angle of the elbows. It is deemed effective because it incorporates cutting-edge developments in computer science, app design, AI, and machine learning. In comparison to alternative approaches, [4] such as watching instructional videos which may offer extraneous advice and consume time, the app saves time by swiftly analyzing results and presenting clear areas for improvement.[5]

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Database

A key challenge in user authentication is ensuring security while keeping the process straightforward for users. Potential problems include securely storing passwords and verifying user credentials effectively. Also, enhanced encryption techniques to store passwords securely in Firestore and ensure that data remains protected. Additionally with implementing a process to double-check passwords during sign-in to minimize login errors. Addressing these challenges involves ensuring that user data is encrypted at rest and in transit and that users can easily reset passwords if needed while maintaining a secure authentication flow.

2.2. Pose Landmarks

One challenge in extracting pose landmarks for comparison between basketball players and users is ensuring accurate detection of body points, especially when image quality varies. Lighting, background noise, and different camera angles can affect pose recognition. I could use pre-processing techniques, to enhance the clarity of images before analysis. Another issue is aligning the pose data from different individuals for meaningful comparison. I could resolve this by standardizing the images using scaling and rotation techniques. Additionally, improving the detection threshold could help manage instances where landmarks are missed due to pose variations.

2.3. Feedback

A significant challenge in posting and comparing NBA player shots with user-uploaded images is aligning the body positions accurately. Different image qualities, poses, and camera angles can cause misalignment, making the comparison difficult. I could address this by ensuring that the NBA player images used for training are captured under standardized conditions, such as consistent camera angles and lighting. Additionally, I could implement image alignment techniques to normalize user-uploaded pictures, scaling, and rotating them as needed. This would ensure that key landmarks like elbows and knees are correctly matched, providing accurate feedback on shooting angles.

3. SOLUTION

First is authentication, posting a shot, and running input through an ML model are key processes in modern applications. Authentication begins with account creation, where users provide securely stored credentials in Firebase. [6] This ensures only authorized access to the app's features. When posting a shot, the system initiates an HTTP request, packaging the content and user data for transmission to the server. This request follows RESTful principles, typically using a POST method to create new data on the server. The server then processes this information, storing the shot and associated metadata in the database.[7] Finally, running input through an ML model involves taking user-generated content or data and feeding it into a pre-trained machine learning algorithm. This could be for various purposes such as content moderation, recommendation systems, or image recognition. The ML model processes the input, applying its learned patterns and algorithms to generate results. These results are then sent back to the user, often in real-time, providing insights, predictions, or classifications based on the input. This seamless integration of authentication, data transmission, and machine learning enables sophisticated, secure, and intelligent user experiences in modern applications.[8]

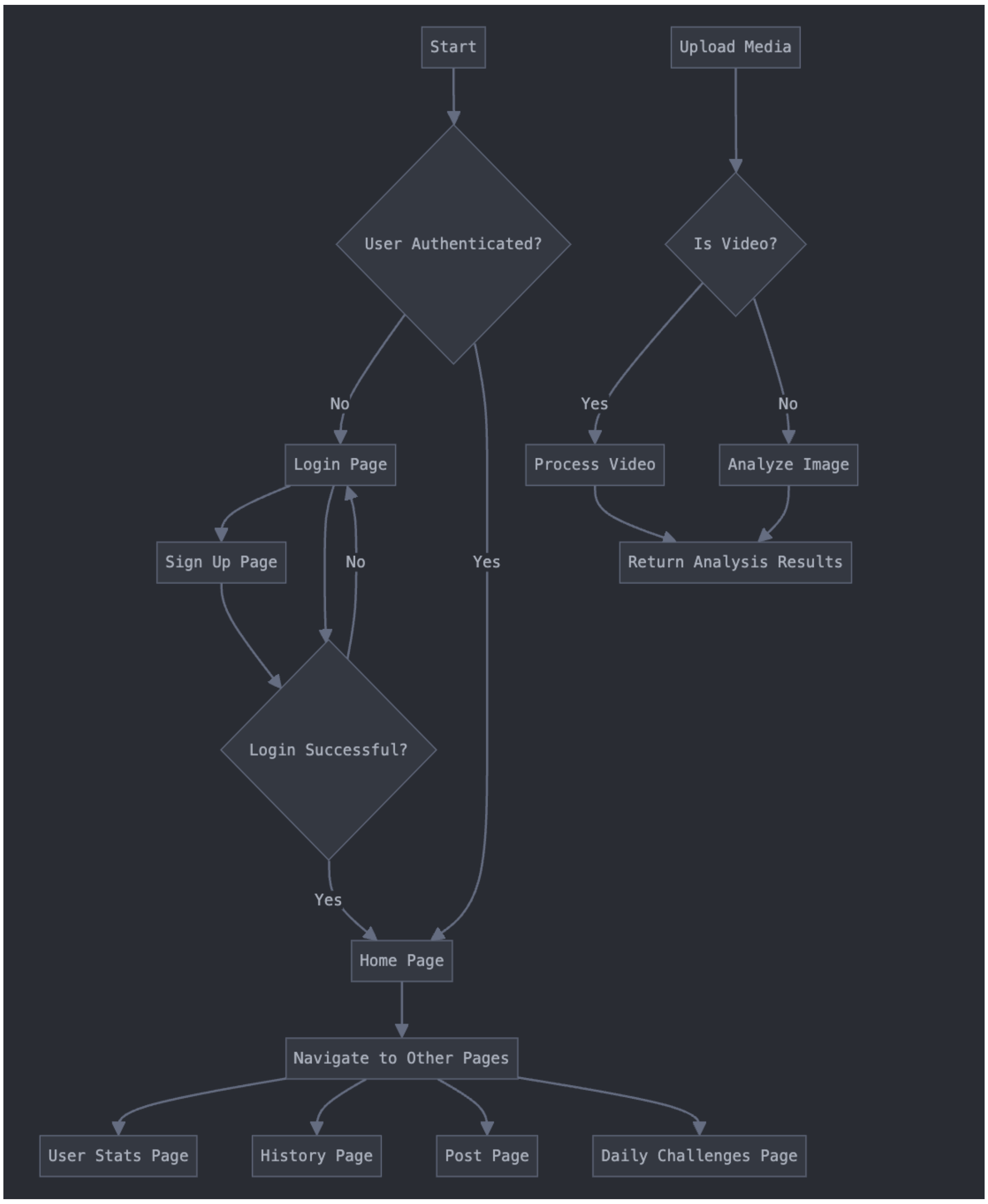


Figure 1. Overview of the solution

The authentication component allows users to create secure accounts by verifying and storing passwords in Firebase. It ensures that only authorized users can access the app's features. By providing a secure gateway, authentication protects user data and enables other processes, such as posting shots and interacting with the ML model.

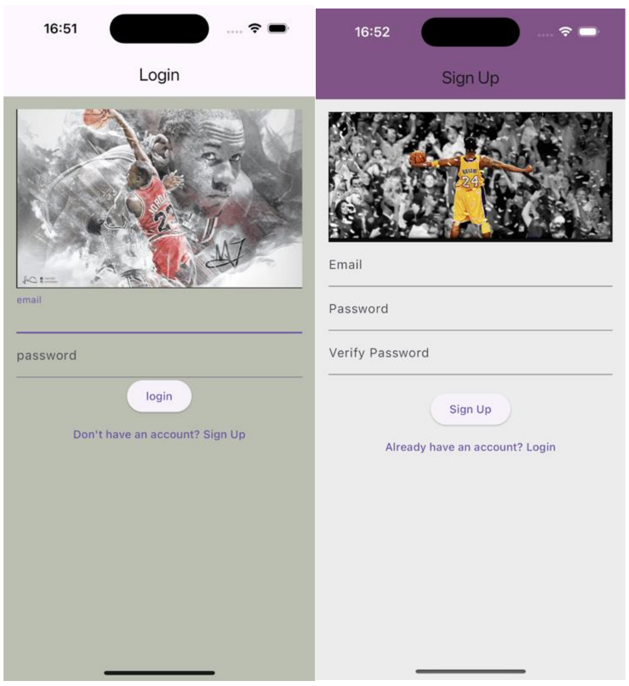
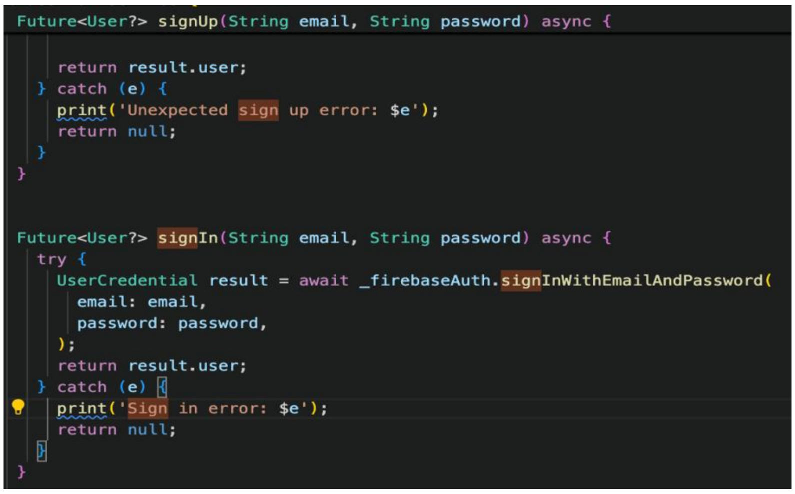


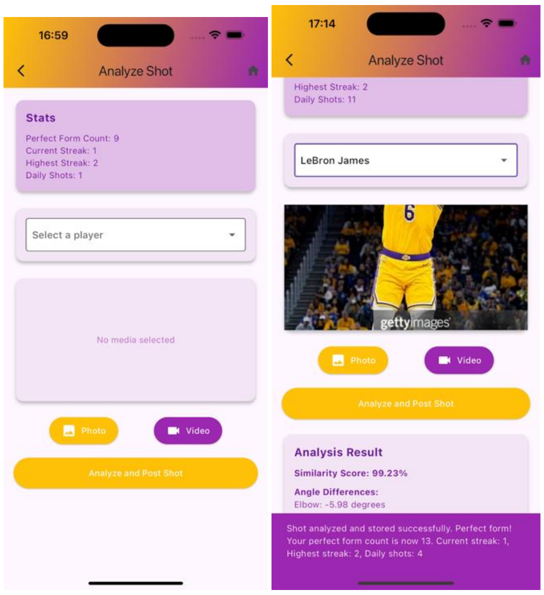
Figure 2. UI screenshot of the authentication component

The authentication process in my program involves a signup page stored in a separate folder, keeping the project structure clean and organized. When a user navigates to the signup page, they are prompted to enter a username, email, and password. The code checks that the password and its confirmation match to ensure accuracy before the information is submitted. Once validated, the user's credentials are securely sent to Firebase using an HTTP request, where they are stored for future authentication purposes. The variables username, email, and password are created to store the user's input. After the credentials are sent, Firebase handles processing and securely saving the data. If the signup is successful, Firebase returns a response confirming account creation, which is then displayed on the front end. In case of errors, such as a mismatched password or an existing account, the user is notified immediately, allowing them to correct the issues before proceeding.



```
Future<User?> signUp(String email, String password) async {

      return result.user;
    } catch (e) {
      print('Unexpected sign up error: $e');
      return null;
    }
}


Future<User?> signIn(String email, String password) async {
    try {
      UserCredential result = await _firebaseAuth.signInWithEmailAndPassword(
        email: email,
        password: password,
      );
      return result.user;
    } catch (e) {
      print('Sign in error: $e');
      return null;
    }
}
```

Figure 3. Code of authentication component



Perfect Form Count: 9
Current Streak: 1
Highest Streak: 2
Daily Shots: 1

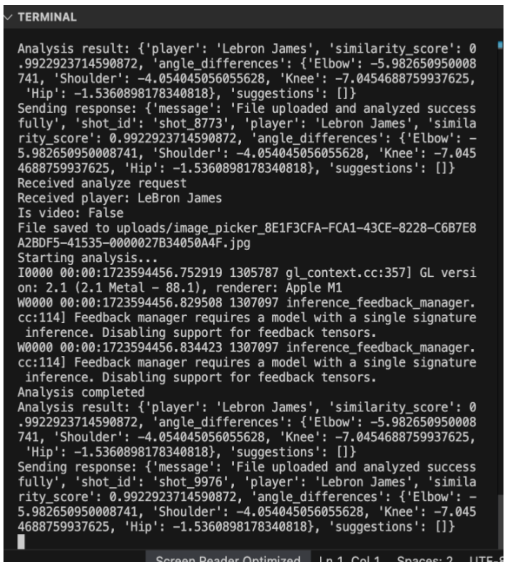
Highest Streak: 2
Daily Shots: 11

Similarity Score: 99.23%
Angle Differences:
Elbow: -5.98 degrees

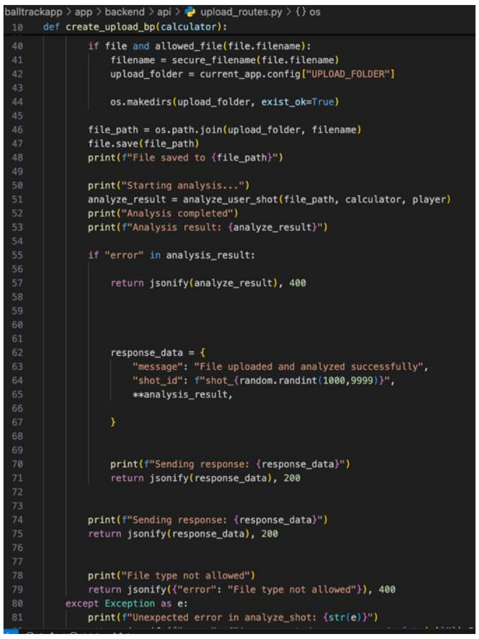
Shot analyzed and stored successfully. Perfect form! Your perfect form count is now 13. Current streak: 1, Highest streak: 2, Daily shots: 4

Figure 4.Process of uploading and analyzing

The code facilitates the process of uploading and analyzing a user's shot image through a backend API. When a user uploads an image, the file is first checked for valid file types and then saved securely in a designated folder. The analyze_user_shot() function is called to run the image through a machine learning model that compares the user's body angles (elbow, shoulder, knee, etc.) to a professional player's, such as LeBron James. The system analyzes key angles of the shot and generates results, including similarity scores and angle differences between the user and the player. If any errors occur during the analysis, they are caught and a 400 HTTP error response is sent. If the analysis is successful, the system generates a response containing the analysis results, a unique shot ID, and a success message, which is returned to the user as a JSON object. This ensures a smooth flow of uploading, analyzing, and returning results.



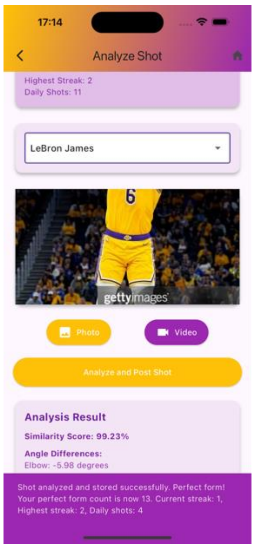
```
Analysis result: {'player': 'Lebron James', 'similarity_score': 0
.9922923714590872, 'angle_differences': {'Elbow': -5.982650950008
741, 'Shoulder': -4.054045056055628, 'Knee': -7.0454688759937625,
 'Hip': -1.5360898178340818}, 'suggestions': []}
Sending response: {'message': 'File uploaded and analyzed success
fully', 'shot_id': 'shot_8773', 'player': 'Lebron James', 'simila
rity_score': 0.9922923714590872, 'angle_differences': {'Elbow': -
5.982650950008741, 'Shoulder': -4.054045056055628, 'Knee': -7.045
4688759937625, 'Hip': -1.5360898178340818}, 'suggestions': []}
Received analyze request
Received player: LeBron James
Is video: False
File saved to uploads/image_picker_8E1F3CFA-FCA1-43CE-8228-C6B7E8
A2BDF5-41535-0000027B34050A4F.jpg
Starting analysis...
I0000 00:00:1723594456.752919 1305787 gl_context.cc:357] GL versi
on: 2.1 (2.1 Metal - 88.1), renderer: Apple M1
W0000 00:00:1723594456.829508 1307097 inference_feedback_manager.
cc:114] Feedback manager requires a model with a single signature
 inference. Disabling support for feedback tensors.
W0000 00:00:1723594456.834423 1307097 inference_feedback_manager.
cc:114] Feedback manager requires a model with a single signature
 inference. Disabling support for feedback tensors.
Analysis completed
Analysis result: {'player': 'Lebron James', 'similarity_score': 0
.9922923714590872, 'angle_differences': {'Elbow': -5.982650950008
741, 'Shoulder': -4.054045056055628, 'Knee': -7.0454688759937625,
 'Hip': -1.5360898178340818}, 'suggestions': []}
Sending response: {'message': 'File uploaded and analyzed success
fully', 'shot_id': 'shot_9976', 'player': 'Lebron James', 'simila
rity_score': 0.9922923714590872, 'angle_differences': {'Elbow': -
5.982650950008741, 'Shoulder': -4.054045056055628, 'Knee': -7.045
4688759937625, 'Hip': -1.5360898178340818}, 'suggestions': []}
```



balltrackapp > app > backend > api > upload_routes.py > {} os

```python
def create_upload_bp(calculator):
        if file and allowed_file(file.filename):
            filename = secure_filename(file.filename)
            upload_folder = current_app.config["UPLOAD_FOLDER"]

            os.makedirs(upload_folder, exist_ok=True)

        file_path = os.path.join(upload_folder, filename)
        file.save(file_path)
        print(f"File saved to {file_path}")

        print("Starting analysis...")
        analyze_result = analyze_user_shot(file_path, calculator, player)
        print("Analysis completed")
        print(f"Analysis result: {analyze_result}")

        if "error" in analysis_result:

            return jsonify(analyze_result), 400




            response_data = {
                "message": "File uploaded and analyzed successfully",
                "shot_id": f"shot_{random.randint(1000,9999)}",
                **analysis_result,

            }


            print(f"Sending response: {response_data}")
            return jsonify(response_data), 200


        print(f"Sending response: {response_data}")
        return jsonify(response_data), 200


        print("File type not allowed")
        return jsonify({"error": "File type not allowed"}), 400
    except Exception as e:
        print(f"Unexpected error in analyze_shot: {str(e)}")
```

Figure 5. Code of uploading and analyzing



Highest Streak: 2
Daily Shots: 11

LeBron James

Analysis Result
Similarity Score: 99.23%
Angle Differences:
Elbow: -5.98 degrees

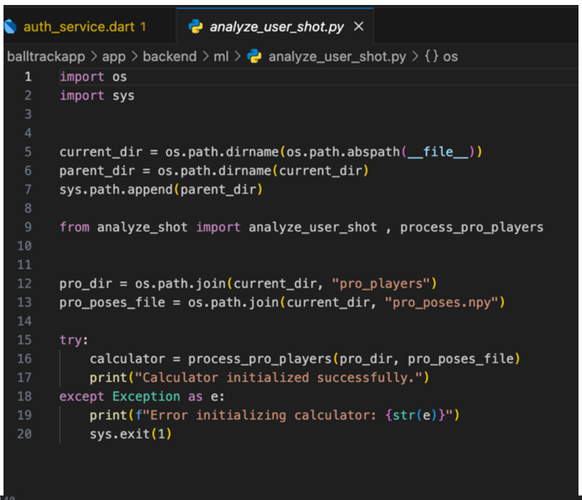
Shot analyzed and stored successfully. Perfect form! Your perfect form count is now 13. Current streak: 1, Highest streak: 2, Daily shots: 4

Figure 6. UI of analyzing

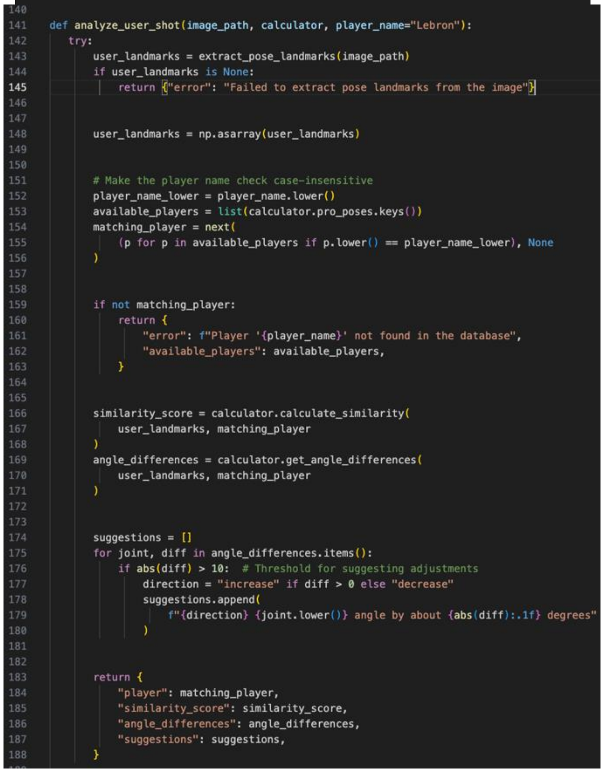
The Machine Learning component processes user-uploaded images of basketball shots, analyzing key body angles like the elbow, shoulder, and knee. A pre-trained model compares these angles with those of a professional player (e.g., LeBron James) and returns results, including similarity scores and differences, in real-time to the user.

The code is designed to analyze a user’s basketball shot by comparing their body pose to that of a professional player using pose detection and angle comparison.

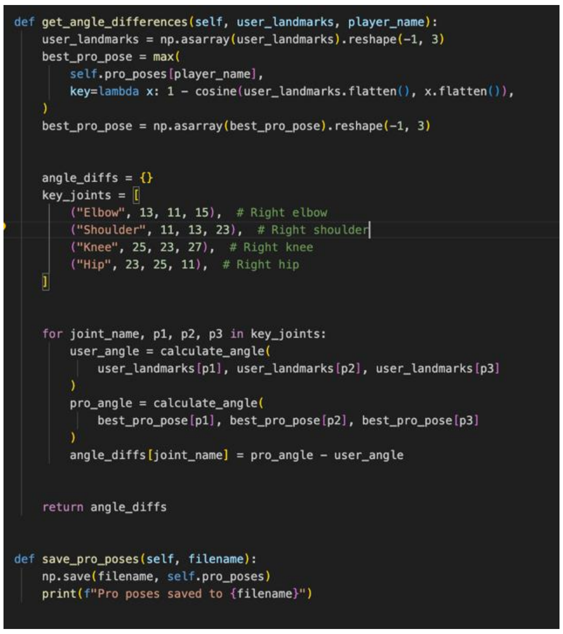
The process begins with the analyze_user_shot() function, which extracts pose landmarks from the uploaded image using the extract_pose_landmarks() function. If no pose landmarks are detected, an error message is returned. Once the landmarks are extracted, they are converted into a NumPy array for further calculations. The code then checks if the professional player, such as LeBron James, exists in the stored dataset of player poses. A similarity score between the user's pose and the player's pose is calculated using the calculate_similarity() function.Next, the code calculates the angle differences between key body joints, such as the elbow, shoulder, knee, and hip, using the get_angle_differences() function. Based on these differences, suggestions are generated, such as adjusting the angle of a joint. The results, including the similarity score, angle differences, and suggestions, are returned to the user.


auth_service.dart 1
analyze_user_shot.py
balltrackapp > app > backend > ml > analyze_user_shot.py > {} os

```python
import os
import sys


current_dir = os.path.dirname(os.path.abspath(__file__))
parent_dir = os.path.dirname(current_dir)
sys.path.append(parent_dir)

from analyze_shot import analyze_user_shot , process_pro_players


pro_dir = os.path.join(current_dir, "pro_players")
pro_poses_file = os.path.join(current_dir, "pro_poses.npy")

try:
    calculator = process_pro_players(pro_dir, pro_poses_file)
    print("Calculator initialized successfully.")
except Exception as e:
    print(f"Error initializing calculator: {str(e)}")
    sys.exit(1)
```



```python

def analyze_user_shot(image_path, calculator, player_name="Lebron"):
    try:
        user_landmarks = extract_pose_landmarks(image_path)
        if user_landmarks is None:
            return {"error": "Failed to extract pose landmarks from the image"}


        user_landmarks = np.asarray(user_landmarks)


        # Make the player name check case-insensitive
        player_name_lower = player_name.lower()
        available_players = list(calculator.pro_poses.keys())
        matching_player = next(
            (p for p in available_players if p.lower() == player_name_lower), None
        )


        if not matching_player:
            return {
                "error": f"Player '{player_name}' not found in the database",
                "available_players": available_players,
            }


        similarity_score = calculator.calculate_similarity(
            user_landmarks, matching_player
        )
        angle_differences = calculator.get_angle_differences(
            user_landmarks, matching_player
        )


        suggestions = []
        for joint, diff in angle_differences.items():
            if abs(diff) > 10:  # Threshold for suggesting adjustments
                direction = "increase" if diff > 0 else "decrease"
                suggestions.append(
                    f"{direction} {joint.lower()} angle by about {abs(diff):.1f} degrees"
                )


        return {
            "player": matching_player,
            "similarity_score": similarity_score,
            "angle_differences": angle_differences,
            "suggestions": suggestions,
        }
```



```
def get_angle_differences(self, user_landmarks, player_name):
    user_landmarks = np.asarray(user_landmarks).reshape(-1, 3)
    best_pro_pose = max(
        self.pro_poses[player_name],
        key=lambda x: 1 - cosine(user_landmarks.flatten(), x.flatten()),
    )
    best_pro_pose = np.asarray(best_pro_pose).reshape(-1, 3)


    angle_diffs = {}
    key_joints = [
        ("Elbow", 13, 11, 15),  # Right elbow
        ("Shoulder", 11, 13, 23),  # Right shoulder
        ("Knee", 25, 23, 27),  # Right knee
        ("Hip", 23, 25, 11),  # Right hip
    ]


    for joint_name, p1, p2, p3 in key_joints:
        user_angle = calculate_angle(
            user_landmarks[p1], user_landmarks[p2], user_landmarks[p3]
        )
        pro_angle = calculate_angle(
            best_pro_pose[p1], best_pro_pose[p2], best_pro_pose[p3]
        )
        angle_diffs[joint_name] = pro_angle - user_angle


    return angle_diffs


def save_pro_poses(self, filename):
    np.save(filename, self.pro_poses)
    print(f"Pro poses saved to {filename}")
```

Figure 7.Code of analyzing and Machine Learning

4. Data and Experiment

4.1.Model

A potential blind spot in my program is the machine learning confidence score leniency. This must work well to ensure accurate shot comparisons, avoiding misleading feedback for users with marginal differences.To test the machine learning confidence score leniency, I'll compare pro players' shots to other pro players. By analyzing the similarity between multiple professional athletes, I can determine if the model's confidence score is accurate or overly lenient. If the confidence score is too high for minor differences, I will retrain the model using stricter data points, ensuring more precise alignment. Control data will come from a curated dataset of professional player shots, providing a consistent baseline for comparison. This setup ensures the model differentiates more clearly between subtle variations in expert-level shooting form.

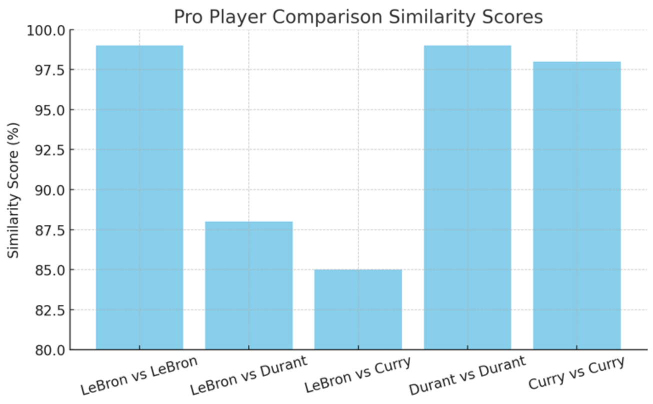


Figure 8. Pro Player Comparison Similarity Scores

The mean similarity score for the pro player comparisons is **93.8%**, and the median score is **98%**. The lowest score is **85%**, and the highest is **99%**. As expected, the highest similarity occurs when a player is compared against themselves (LeBron vs LeBron or Durant vs Durant), yielding scores around 99%. However, there is some variation when comparing LeBron against other players like Durant or Curry, with the lowest score being 85%.This variation is likely due to differences in shooting styles, body mechanics, and posture between players. The surprising factor was the slight dip when comparing LeBron to other top players. The biggest effect on the results is the distinct physical and stylistic differences between these athletes. Despite all being elite shooters, their shooting form is personalized, resulting in lower similarity scores when compared to one another.

4.2. A Potential Blind Spot

A potential blind spot in the application is a lack of understanding of its interface and purpose by users. To test this, I would survey peers, asking them to rate their understanding of the interface and purpose of the app on a scale of 0-100. After gathering survey results, I will analyze the average ratings and identify trends, focusing on whether the application's interface and instructions are clear. If scores are consistently low, this would suggest a need for better design or more detailed onboarding.Pros of this method include obtaining direct user feedback and identifying areas for improvement. Cons could be variability in user tech skills, which might skew results. This experiment allows for targeted refinements to ensure users better understand the app, leading to a more user-friendly experience. The biggest impact on the results is how intuitively users grasp the interface and functionality without explicit guidance.

5. METHODOLOGY COMPARISON

In the paper "Accuracy Detection in Some Sports Training Using Computer Vision and Deep Learning Techniques," [9] the authors use computer vision models and deep learning algorithms to detect key features in athletic performance, particularly in sports like basketball. [10]This solution is highly effective in identifying specific body movements and providing detailed feedback. However, it faces limitations with real-time processing and handling different body types and motion variations across athletes. My project improves upon this by optimizing the confidence score leniency for real-time analysis, ensuring more precise feedback. Additionally, my model addresses individual differences between players by refining pose comparisons to make the system more adaptable.Another approach is explored in a study on pose estimation using deep learning and convolutional neural networks (CNNs) for sports performance analysis. The system detects body landmarks to provide feedback on form and technique. It is effective for tracking precise movements, but the model struggles with edge cases where lighting and video quality affect pose recognition. [11]My project improves this by pre-processing user-uploaded images, using techniques like normalization to reduce interference from poor lighting or low image quality. This ensures that pose estimation remains accurate in a wider variety of conditions, ultimately offering better feedback to users.A study on motion tracking for basketball shooting uses AI to evaluate shot angles and form. The system leverages machine learning models trained on professional players to compare shots. [12]While this provides useful feedback, it doesn't account for variances in skill level or adjust feedback based on the user's proficiency. My project enhances this approach by tailoring feedback to the user's skill level, making it more personalized. By comparing users' forms with both professional players and peers, the system can offer recommendations that are more aligned with individual capabilities, offering a more customized improvement path based on the user's specific performance. [13]

6. CONCLUSIONS

One limitation of my project is the lack of social features, which could enhance user engagement. Currently, users can upload their shots and receive feedback, but there's no way to share or compare results with friends and family. Adding social media components, like shareable links, would allow users to post their results on platforms like Instagram or Twitter. Additionally, creating a new page that streams other users' posts could foster a community of shared improvement, enabling users to follow each other and interact. Another improvement would be refining the feedback system to tailor suggestions based on user skill level. Currently, feedback is generated based on comparisons with professional players, which might not be as helpful for beginners. Customizing advice for different skill levels would make the feedback more relevant. By addressing these limitations, the project would provide a more interactive and personalized experience for users.[14]

In my project, I conducted experiments to evaluate the accuracy of the machine learning model in comparing user basketball shots to professional players. One experiment tested the confidence score by comparing professional players to each other, which showed high similarity for the same player (e.g., LeBron vs LeBron), but lower scores when comparing different players. This allowed me to adjust the leniency of the confidence score to ensure accurate shot comparisons. Another experiment focused on user interface understanding by surveying peers to assess how easily users could navigate the app and understand its purpose. The results highlighted areas for improvement in user guidance and interface clarity. Each experiment provided valuable insights into the functionality and user experience of the app.[15] The results showed that the machine learning model works well for shot analysis but required refinement for edge cases and that the app's interface needed better clarity for new users.

This project builds on previous methodologies in sports performance analysis, using computer vision and deep learning to provide precise, personalized feedback for basketball shot analysis.

In the first methodology, prior research used computer vision and deep learning to analyze sports performance by tracking key body movements. Although effective, this approach struggled with real-time analysis and generalization across diverse users. [16]My project advances this by incorporating refined feedback based on individual movement patterns, enhancing personalization. The second methodology employed pose estimation via convolutional neural networks (CNNs) to track athlete movements. However, issues with image quality reduced tracking accuracy. My project addresses this limitation by introducing image pre-processing techniques, ensuring reliable pose detection even with low-quality inputs.

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