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# Shapesense: Body Type Classification Using MediaPipe Pose Landmark Detection Model

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***Abstract***
*This project implements MediaPipe solutions to classify body types while overcoming various challenges like body shapes, clothing, and lighting conditions. For precise proportional analysis, MediaPipe's pre-trained models and pose estimation options are used to scan key body landmarks. The system successfully distinguishes body types (pear, apple, rectangle, hourglass) while maintaining user privacy. By offering actionable insights across domains, from fashion and fitness to health, it enhances user experiences with personalized recommendations and contextually relevant guidance. More safeguards and fallback methods will be built to strengthen this methodology. This encompasses but is not limited to novel error correction procedures, redundancy layers, and the implementation of rigorous fail-safes to maintain precision even in sub-optimal scenarios.*

**Keywords-** Body shape detection, Deep learning, Digital image analysis, Error correction algorithms, Personalized health tracking, Personalized services, Posture analysis, Shoulder-to-Hip Ratio (SHR), Waist-to-Hip Ratio (WHR)

## INTRODUCTION

Body type classification remains a topical issue within the research community (e.g. industry, fashion, health and fitness), since tailored recommendations strongly optimize user experience and customer satisfaction. Existing approaches to classify body types such as measuring anthropometric measurements require direct interactions with the individuals and are tedious and subjective. In addition, these techniques are not very suitable for extensive and automated applications. These limitations indicate the need for scalable and efficient solutions that can work with users from disparate demographics.

To strengthen the methodology, further safeguards and fallback mechanisms will be implemented. These include advanced error correction algorithms, redundancy checks, and integration of robust fail-safes to ensure accuracy even under non-ideal conditions. The developing interest in computer vision and machine learning has enabled the development of automated systems for body type classification, providing the potential to avoid the limitations of manual measurement [1]. The change from physical measurements to digital image analysis presents new opportunities for personalized services, allowing body types to be categorized efficiently and accurately. To intensify the methodology, further safeguards and fallback mechanisms will be implemented. These include advanced error correction algorithms, redundancy checks, and integration of robust fail-safes to ensure accuracy even under non-ideal conditions.

One important milestone in this space is MediaPipe, an open-source, cross-platform framework for building multimodal applied ML pipelines created by Google that provides a series of pre-trained models for a variety of tasks such as pose estimation (Cao et al., 2017) [2]. MediaPipe's pose estimation models (Fig. 1 and 2) can detect key body landmarks like shoulders, hips, and waist from images or video. These landmarks form the basis for measuring essential body ratios, including Waist-to-Hip Ratio (WHR) and Shoulder-to-Hip Ratio (SHR) fundamental principles in the classification of body types. By automating these tasks, MediaPipe helps in reducing the subjectivity and inconsistencies inherent in manual measurements.

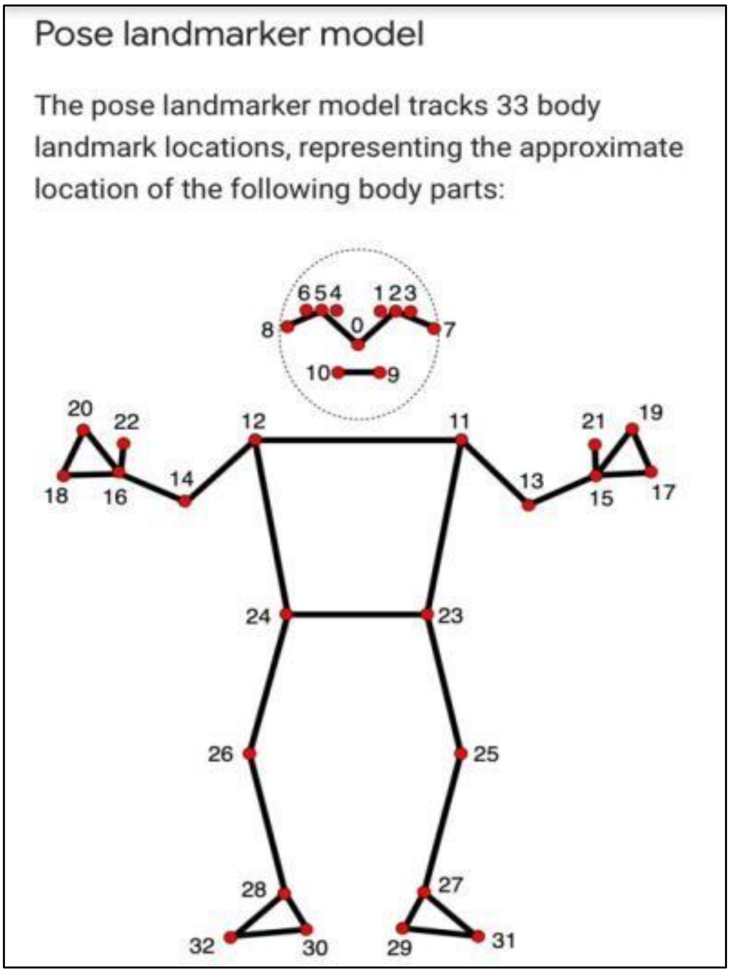


***Figure 1:*** *MediaPipe's pose landmark model.*

However, applying MediaPipe's solutions for body type classification presents several challenges. These include the diverse range of human body shapes, variations due to factors such as gender, ethnicity, and body composition, and the presence of issues like occluded body parts, poor lighting, and clothing variations (Priya Devarajan and Istook, 2004) [3]. To overcome these obstacles, this study proposes a methodology that utilizes MediaPipe's pose estimation capabilities to automate the extraction of key body landmarks and compute the relevant body proportions. The system categorizes body types into four primary groups: pear, apple, rectangle, and hourglass. Additionally, preprocessing techniques like normalization and augmentation are included to account for variations in body appearance, ensuring that the system works robustly across diverse conditions.

 

```
0 - nose
1 - left eye (inner)
2 - left eye
3 - left eye (outer)
4 - right eye (inner)
5 - right eye
6 - right eye (outer)
7 - left ear
8 - right ear
9 - mouth (left)
10 - mouth (right)
11 - left shoulder
12 - right shoulder
13 - left elbow
14 - right elbow
15 - left wrist
16 - right wrist
17 - left pinky
18 - right pinky
19 - left index
20 - right index
21 - left thumb
22 - right thumb
23 - left hip
24 - right hip
25 - left knee
26 - right knee
27 - left ankle
28 - right ankle
29 - left heel
30 - right heel
31 - left foot index
32 - right foot index
```

***Figure 2:*** *Mapping of points in MediaPipe's pose landmark model.*

The proposed website uses MediaPipe to inspect the key landmarks of the body and predicts the shape of the user's body. This approach utilizes leading edge models for pose estimation, following on research in medical imaging and deep learning. Some of these studies (e.g., Nandihal et al. [4]) for instance, Ant Colony Optimization (ACO) based preservation and segmentation techniques for medical images [5], and deep learning based diagnostic algorithms [6] demonstrate the effectiveness of ACO and DNNs in representing meaningful patterns from visual information. In addition, the research conducted in the field of glioma detection using artificial neural networks [4] highlights that the emerging methods in image base analysis emphasizing the need of methodologies in aspect this research has been performed on body shape detection in a completely non-medicinal sphere. Ethical considerations are also a vital part of the methodology. With increasing concerns over data privacy, this study emphasizes a privacy-conscious approach, processing user data locally instead of storing it in cloud databases, in compliance with regulations such as GDPR (TrueToForm, n.d.). This privacy-first strategy builds trust with users and ensures secure use of the system in a variety of contexts. This paper details the methodology for body type classification using MediaPipe, describing the challenges and presenting solutions for real-world applications in areas such as fashion, fitness, and health. This research proposes a MediaPipe-based framework for body type classification, leveraging its pose estimation capabilities to extract key landmarks and compute body proportions. The system categorizes body types into standard classifications (pear, apple, rectangle, and hourglass) and applies advanced preprocessing techniques to enhance robustness against data variations.

Furthermore, this approach supports potential applications in virtual try-ons, posture analysis, and personalized health tracking. By bridging traditional methods with modern, automated solutions, this study aims to provide a scalable, efficient, and privacy-focused framework for diverse user needs. To strengthen the methodology, additional safeguards and fallback mechanisms will be implemented. These include advanced error correction algorithms, redundancy checks, and integration of robust fail-safes to ensure accuracy even under non-ideal conditions.

## LITERATURE REVIEW

Body type classification has long been an area of interest due to its applications in personalized services across fitness, health, and fashion. Traditional methods have relied on manual measurements or expert assessments, which, while effective in controlled settings, are often impractical for large-scale or automated applications. The emergence of AI and machine learning has revolutionized this field, with frameworks like MediaPipe offering efficient and scalable solutions. This literature survey deals with the evolution of body type classification, focusing on the use of pose estimation technologies like MediaPipe and their advantages over earlier methods.

### Traditional Methods of Body Type Classification

Traditional methods rely on anthropometric measurements analyses such as waist-to-hip ratio (WHR), shoulder width, body mass index (BMI). With these measurements, body types were often categorized into shapes like pear, apple, rectangle and hourglass. Although these techniques were easy to understand, they were subjective, and thus, it was easy to make mistakes due to human interpretation and measurement inconsistency. Moreover, they relied on in- person interactions, which rendered them impractical for widespread implementation. Studies like those by Priya Devarajan and Cynthia L. Istook (2004) explored the use of anthropometric data for body type classification in apparel design. While these methods were accurate for specific applications, they lacked scalability and adaptability to diverse populations or real-world scenarios [3].

### Advancements with Pose Estimation Technologies

The introduction of pose estimation frameworks like MediaPipe has significantly advanced body type classification. MediaPipe, developed by Google, provides pre-trained models for detecting human body landmarks in real-time from images or videos. Unlike traditional methods, which rely on manual measurements, MediaPipe automates the extraction of critical body proportions, such as shoulder width, waist-to-hip ratio (WHR), and overall symmetry. MediaPipe’s capabilities have been successfully applied in various domains. For example, Zhe Cao et al. (2017) [2] demonstrated the use of pose estimation for human body analysis, providing a foundation for applications like fitness tracking and virtual try-ons [2]. Similarly, MediaPipe has been widely adopted for applications requiring accurate and real-time body landmark detection due to its efficiency and scalability.

### Challenges in Pose Estimation-based Body Type Classification

To strengthen the methodology, further safeguards and fallback mechanisms will be implemented. These include advanced error correction algorithms, redundancy checks, and integration of robust fail-safes to ensure accuracy even under non-ideal conditions. While MediaPipe provides a robust framework, several challenges remain in using pose estimation for body type classification. To strengthen the methodology, further safeguards and fallback mechanisms will be implemented. These include advanced error correction algorithms, redundancy checks, and integration of robust fail-safes to ensure accuracy even under non-ideal conditions. Dataset diversity are the public datasets like

COCO and MPII Human Pose that provide detailed images but may not sufficiently represent diverse body types, ethnicities, and demographics [7]. Custom datasets are often needed to ensure diversity and accuracy. Clothing and occlusions is the clothing that can hide key body landmarks, making it difficult to analyze accurate proportions. MediaPipe's robust detection algorithms mitigate this to some extent, but extreme occlusions remain challenging [8].Variability in poses and lighting are real-world images often include variations in pose and lighting, which can introduce noise into landmark detection. Data augmentation techniques are commonly used to simulate such variations and improve model robustness [9].

### Ethical and Privacy Considerations

The use of pose estimation technologies raises ethical and privacy concerns, especially when user images are involved. Regulations like GDPR and HIPAA mandate explicit consent, secure storage, and anonymization of data. MediaPipe-based systems address these concerns by enabling local processing of images, reducing the need for cloud storage and ensuring user privacy. Studies have emphasized the importance of ethical practices, such as anonymizing images by blurring faces or removing identifiable features, to foster user trust [10].

### Applications of MediaPipe in Body Type Classification

MediaPipe's real-time capabilities and lightweight implementation make it an ideal choice for body type classification. Applications includes fashion and e-commerce for virtual try-on systems use MediaPipe to analyze body proportions and recommend clothing that fits and flatters an individual's body type [11] and fitness and health for personalized workout plans can be generated based on body type, leveraging MediaPipe's ability to detect proportions accurately [2], and posture analysis for MediaPipe's pose estimation can be extended to assess posture, providing insights for ergonomic improvements and injury prevention [10].

### Future Directions

Future research should focus on addressing the limitations in pose estimation-based systems. This includes developing more diverse and representative datasets, improving adaptiveness to clothing and pose variations, and integrating 3D pose estimation for enhanced accuracy. Furthermore, combining MediaPipe with advanced machine learning classifiers can further refine body type classification systems, ensuring they remain scalable and adaptable to real-world conditions. Collaborative efforts between researchers and industries can also accelerate the development of user-friendly applications, enhancing accessibility for non-technical users [7]. To strengthen the methodology, furthermore safeguards and fallback mechanisms will be implemented. These include advanced error correction algorithms, redundancy checks, and integration of robust fail-safes to ensure accuracy even under non-ideal conditions.

## METHODOLOGY

### Methodology for Body-type Classification Using MediaPipe Solution

The MediaPipe solutions come with a pre-trained pose estimation model that can be used to extract the body key point landmarks. We develop a systematic pipeline that is efficient, flexible, and accurate, and that tackles challenges including body diversity, clothing complexity and lighting conditions. To enhance the robustness of the methodology, supplementary safeguards and fallback mechanisms will be integrated. Such methods involve even more sophisticated error correction algorithms, redundancy checks, and implementing strong fail-safes to guarantee precision, in spite of non-ideal conditions under which data must be operating.

While preprocessing is essential for maintaining the data types and attributes of the input information for analysis, the pose estimation model of MediaPipe is dependent on varied high-quality datasets, starting from determining data sources of publicly available datasets like COCO and MPII Human Pose, which has annotated data with body landmarks. Moreover, controlled photoshoots or crowdsourcing platforms are used in the former case to generate custom datasets that includes a range of body types, genders, and ethnicities. Images are interpreted and categorized based on body type classifications (e.g., pear, apple, rectangle, hourglass) derived from extracted proportions. Privacy and ethical considerations are paramount, with explicit user consent obtained and identities unclassified to comply with data protection regulations. It is employed to detect and extract body parts like shoulder width, waist, and hip ratios from images. Body part coordinates are normalized to account for variations in resolution and scale, and synthetic transformations like rotations are applied to landmarks for data augmentation, simulating real-world diversity and enhancing model adaptability. Feature extraction uses the pre-trained MediaPipe models, so you do not have to do the manual engineering; the models can find every key point on a particular body part automatically. Other criteria that provide more data for such classification are key metrics which include waist-to-hip ratio (WHR) used to identify the two body types, these being the pear and apple body types, as well as the Shoulder-to-Hip Ratio (SHR) used to identify rectangular and hourglass shapes; overall contour and symmetry. The model is evaluated and fine-tuned by testing it on a separate dataset to assess its performance. Misclassifications are analyzed to refine the model, with adjustments made to feature thresholds or furthermore landmark-based metrics included as necessary. Finally, the system is deployed as a scalable application, allowing users to upload images for analysis. MediaPipe processes these images locally or on secure servers, ensuring privacy while outputting the predicted body type and offering actionable insights, such as personalized clothing or fitness recommendations.

To create a website that can accurately identify a user’s body type—whether hourglass, pear, rectangle, or apple a thoughtful and innovative methodology was developed, leveraging the capabilities of MediaPipe’s pose landmark detection model. MediaPipe, a powerful tool for real-time human pose estimation, serves as the backbone of this system by identifying key body points such as shoulders, waist, hips, and torso. These landmarks are mapped with precision, allowing the system to capture a detailed representation of the user’s body proportions.

Once the body points are identified, the website processes the data to calculate essential metrics such as Shoulder-to-Hip Ratio (SHR), Waist-to-Hip Ratio (WHR), and overall body symmetry. These measurements are used to classify the user into one of the four body type categories. The classification process relies on well-defined algorithms that compare the user’s proportions to standard characteristics of each body type. For example, an hourglass body type typically shows balanced shoulder and hip measurements with a narrower waist, while a pear shape is characterized by hips that are noticeably wider than the shoulders. The website is designed to be user-friendly, offering a seamless interface where individuals can upload a photo. This approach ensures accessibility and convenience for users, making the experience both engaging and intuitive. By integrating MediaPipe’s advanced machine learning capabilities, the methodology ensures a high level of accuracy, allowing users to receive personalized insights. This system is not only a technical solution but also a tool that empowers users in various aspects of their lives. It can help individuals make informed decisions about clothing styles that complement their body shapes, guide fitness planning to target specific areas for health and wellness, and even provide ergonomic suggestions for better posture and comfort. By combining advanced technology with practical applications, this methodology bridges the gap between science and everyday life, offering a comprehensive, reliable, and human-centered solution. The flowchart of the body type detection process is shown in Fig. 3.

The following four pictures (Fig. 4–7) show the sample output of our website.

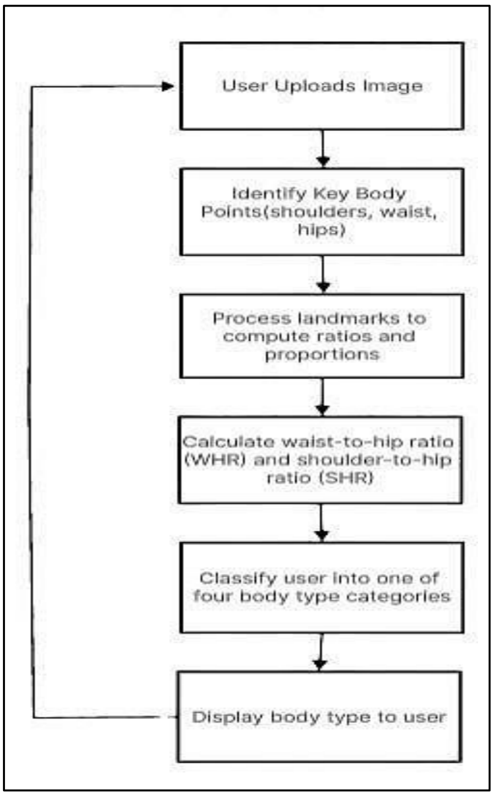


***Figure 3:*** *Flowchart of the body type detection process.*

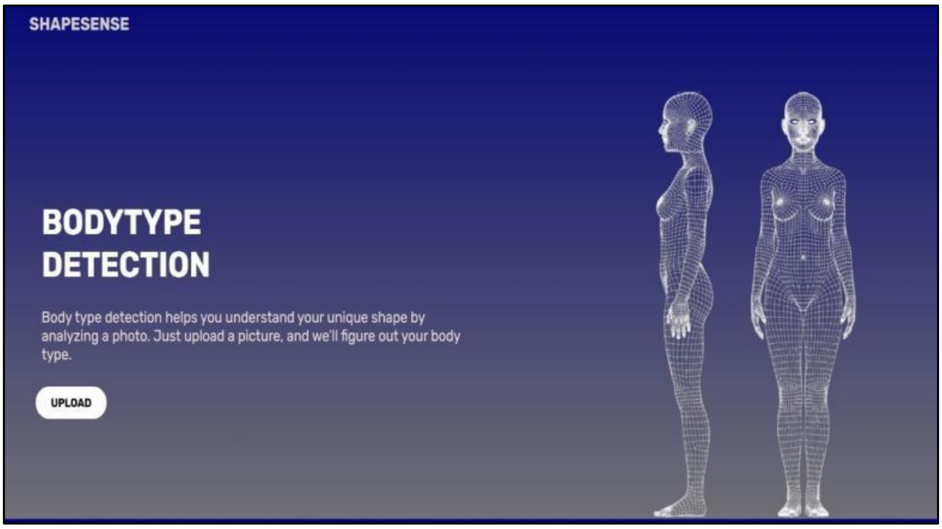


***Figure 4:*** *Select upload to upload the image.*

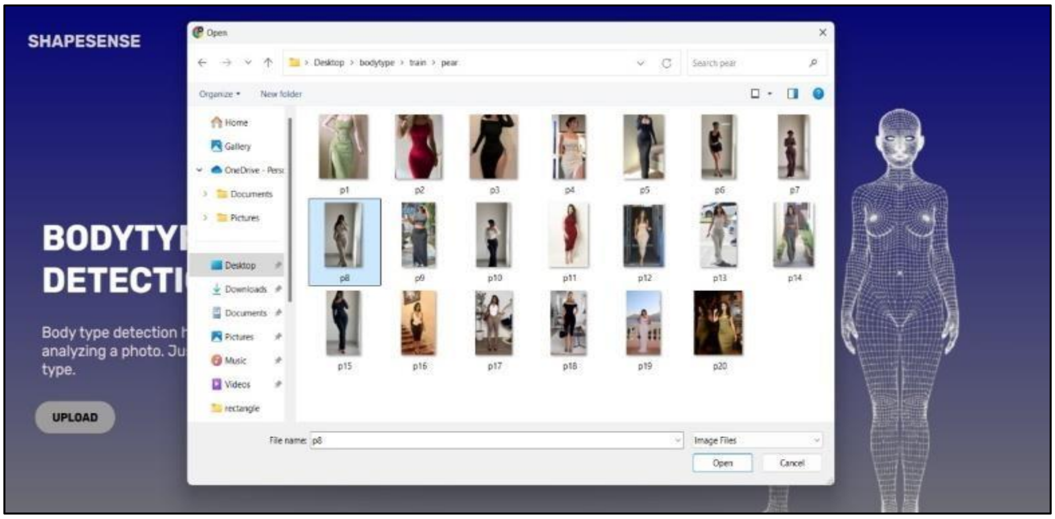

***Figure 5:*** *Choose the image that needs to be detected.*

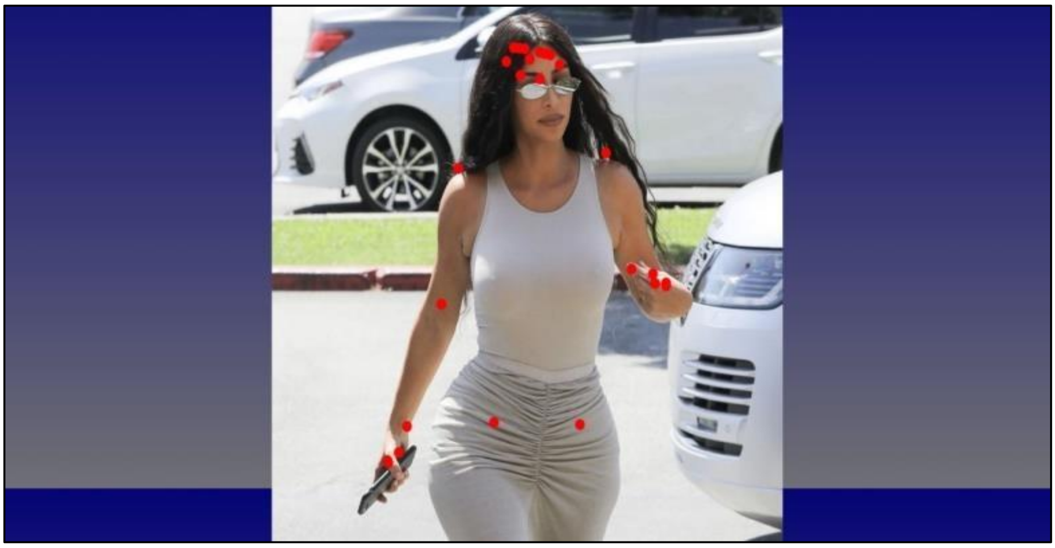
***Figure 6:*** *Landmarks of the uploaded picture.*

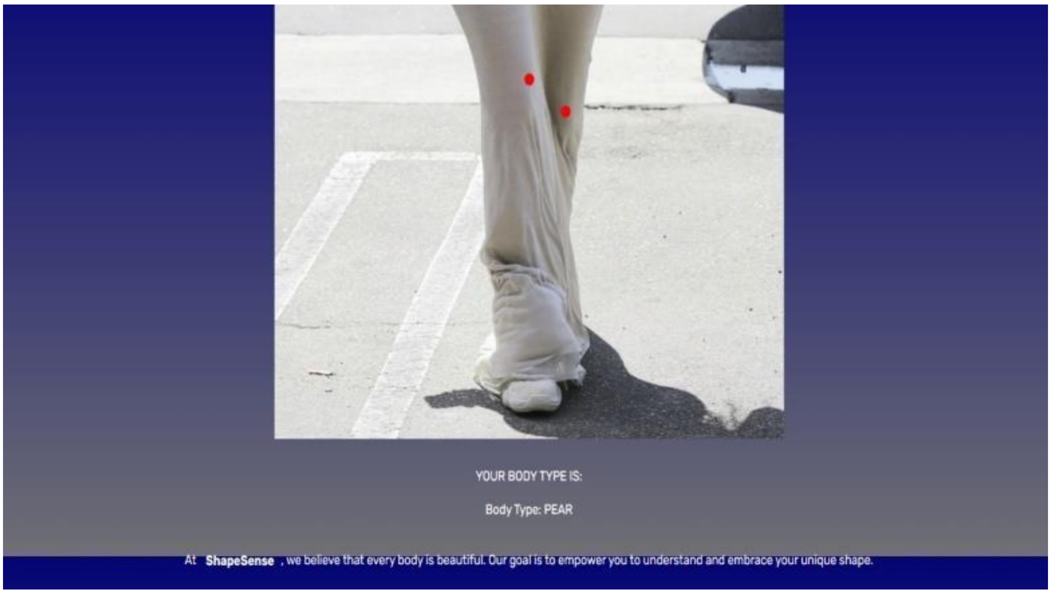

***Figure 7:*** *Detected body type is shown as the output.*

**Pose Landmark Detection Accuracy**

The model shows different rates of accuracy depending on body type. The accuracy and reliability of the pear and hourglass body types are higher than that of other classifications. But, the accuracy decreases a lot specifically for rectangle body type which suggests that it is not able to distinguish this type much properly. Apple body types get a moderate level of accuracy, indicating some dependability but not perfect. This discrepancy in performance indicates areas for further refinement, particularly improving the model's capacity to accurately identify.

Improving the accuracy of body type detection, especially for rectangle and apple body shapes, requires a well-rounded approach. Expanding the dataset to include more diverse images capturing variations in posture, clothing, and camera angles helps the model better understand real-world scenarios. Adding new metrics like torso length, shoulder shape, and abdominal contours gives the model more detailed information to differentiate between body types. Using advanced data augmentation techniques, such as adjusting lighting, perspectives, and backgrounds, makes the model more robust and adaptable .To avoid training errors and ensure reliable predictions, it is important to accurately label body types. This improves the performance of the model (fine-tuning the algorithm, using different classifiers, hyper-parameter tuning). Feedback loops where user corrections are fed back into the system make continuous improvement over time possible. Establishing thresholds and leveraging the use of newer techniques, such as landmark-based measurements, is another level of refinement. Adaptation of pre-trained MediaPipe models to this specific task provides further efficiency and reliability. To make the system practical for real-world use, it integrates MediaPipe's pre-trained pose estimation models for fast and accurate processing, making real-time applications possible. It calculates key body ratios, such as waist-to-hip and shoulder-to-hip, which are essential for body type classification. By using diverse datasets like COCO and MPII, along with custom datasets created through photoshoots or crowdsourcing, the system ensures it works well for people of all body types, genders, and ethnicities. User privacy is protected through unclassified and explicit consent, meeting standards like GDPR. Synthetic data augmentation and pose correction techniques handle variations in image quality, while fallback rules estimate missing data, ensuring the system stays reliable even in challenging cases. This system has wide-ranging applications. In fashion, it can provide personalized clothing recommendations. In fitness, it helps design tailored workout plans, and in healthcare, it can support ergonomic assessments. Thanks to its lightweight design, it delivers real-time performance for a seamless user experience. Future improvements will focus on enhancing 3D pose estimation, expanding the dataset even further, and refining how it handles rare or tricky cases. These efforts ensure the system remains accurate, adaptable, and ready to meet the needs of its users [5].

## CONCLUSION

With MediaPipe, poses are detected based on one of the pre-trained pose estimation models that maps out the major body landmarks. Body ratios such as waist-to-hip and shoulder-to-hip can be measured from these landmarks. Such method could minimize the measurement errors and therefore make 3D body reconstruction accessible and accurate. It preprocesses the input dataset in such a way (using data normalization, data augmentation) that the system you build is efficient. This ensures it works well even under suboptimal circumstances. It is well suited to wide usage in this respect because everything it does can be done at real time and with lightweight algorithms. Local data processing not only solves privacy issues (like those proposed in laws such as GDPR), it suggests recommendations while keeping user data safe. The system, for example, requires a wider variety of datasets that accurately capture different body types, ethnicities, and poses. Situations like occlusions or extreme poses can affect classification accuracy, though advancements like 3D pose estimation and larger datasets are helping overcome these hurdles.

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