

Next-Generation Augmented Reality: A Deep Learning–Driven Framework for Intelligent Visual Perception and Interaction

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ABSTRACT

The rise of e-commerce has transformed the retail sector, providing customers worldwide with convenience. Nevertheless, one of the largest problems with online shopping is that customers cannot physically touch and feel products before purchasing them, particularly in the fashion retail sector. Most customers are reluctant to purchase accessories such as glasses, jewelry, hats, and shoes because they are not sure how they look when worn. This creates increased return rates, decreased customer satisfaction, and lost revenue for consumers. The Try Before Buy system is an on-the-go application that fuses Augmented Reality (AR) with AI-based recommendations to enable users to try fashion accessories virtually in real time. The system supports real-time face tracking, precise 3D object superimposition, and an AI-based recommendation engine to recommend accessories according to user choice. The application also enables users to post the outcome of their try-ons on social media, fostering engagement and interaction. This article presents the design, methodology, implementation, and testing of the system. The research also delves into existing AR-based try-on solutions, establishes their limitations, and shows how the Try Before Buy system enhances the online shopping experience. The proposed system massively lowers the uncertainty of online shopping, increases customer confidence, and reduces product returns.



Introduction

Through the integration of virtual objects with real-world surroundings, Augmented Reality (AR) has transformed digital interactions and provided immersive experiences across a range of domains. Before making a purchase, customers can virtually try on items like watches, hats, and glasses in the fashion business, which is one of the most promising uses of augmented reality [1]. The AR market is experiencing remarkable growth, with projections indicating it will reach \$38.6 billion by 2024 [2], while 57% of consumers report being more likely to make purchases after using virtual try-on experiences. Traditional online purchasing does not offer an interactive experience, making it challenging for customers to picture how trendy items will appear on them. AR-powered try-on apps have become more popular as a result of this disparity, giving consumers more confidence to make well-informed purchases. Major brands like Tommy Hilfiger and Coach are now leveraging AR mirrors and digital solutions both in-store and in window displays [3]. Fashion online shopping has increased manifold in the last decade, but amongst the key challenges is still the excessively high rate of product returns owing to size and fit.

Based on recent research, close to 30% of all web shopping for apparel is returned owing to inappropriate fitting or not liking the appearance of the actual product [4]. AR-powered virtual try-on solutions try to solve this problem by enabling consumers to see fashion products instantly using their smartphones or AR-compatible devices. Recent studies have highlighted the role of machine learning and hybrid models in forecasting [5,6,7].

Convolutional Neural Networks (CNNs) play a significant role in enhancing AR visualization by creating realistic fitting and texture mapping of virtual clothing. But in order to allow real-time execution on mobile devices, these models usually need a large amount of processing power [8]. Our study presents an AR-driven fashion try-on system that is optimized for face and body tracking using lightweight deep learning models in order to address these problems. COLMAP [8] is used for structure-from-motion 3D reconstruction, self-trained models are used for precise face and body identification, and Open3D and Maya3D are used for 3D modelling [9]. Low latency, smooth user interaction, and high-quality virtual garment rendering are all features of the system [10].

Deep learning and augmented reality have advanced, but real-time AR try-on apps still face significant obstacles. Current research addresses the longstanding challenge of online shopping, where customers grapple with uncertainties about fit. Emphasize the significance of real-time computation, perfect texture alignment, and compatibility with a variety of mobile devices. Occlusions are beyond the capabilities of the great majority of existing technologies [12,13,14].

Environmental adaptability has an impact on the accuracy of virtual fittings. Our technique is an adaptive AI model that learns user preferences and body shape, resulting in greater realism.

Main Objectives

- A robust AR framework that enhances virtual try-on experiences with high accuracy and minimal latency.
- A real-time deep learning pipeline optimized for facial and body recognition to improve user interaction and visualization.
- A scalable solution capable of running efficiently on smartphones and other portable AR devices, ensuring broad accessibility.

Problem Statement

Online fashion retail platforms have transformed the way people shop, offering convenience and a wide range of products. However, one major limitation remains: customers cannot try accessories, such as glasses, watches, and hats, before making a purchase. This lack of an interactive shopping experience creates uncertainty, as buyers are unable to visualize how an item will look on them in real life. As a result, many shoppers order multiple sizes, styles, or colors to compare options at home, ultimately returning the items that do not meet their expectations. This practice, known as "bracketing," has become common in online fashion shopping but comes with significant drawbacks for both consumers and retailers. Increased Return Rates & Revenue Loss:

- Up to 30–40% of fashion items are returned because they don't fit, fit, or match in style, which makes it a difficult market for internet retailers.
- There are extra shipping and restocking costs associated with processing these returns.
- Product returns may result in lost inventory and lower profitability. Additionally, ruined goods might not be as valuable when sold, which would reduce company earnings.
- Customers will delay purchasing because they are not aware that an item will suit them.
- They are hesitant to buy contemporary fashion products and accessories through the Internet due to fit, color representation, and general appeal problems.
- Due to the uncertainty, most customers abandon their carts, lowering the sales conversion rates of e-commerce businesses.

Proposed Solution

The Try Before Buy solution brings together artificial intelligence (AI) and augmented reality (AR) into a live, interactive mobile application that will revolutionize the online purchase. The solution allows customers to virtually try fashion accessories in real time, allowing customers to visualize how wristwatches, hats, and eyeglasses will fit them prior to purchasing. Utilizing advanced face tracking and augmented reality visualization, the solution provides a realistic and accurate depiction, removing all doubt when engaged in online shopping. Guesswork in online fashion shopping is removed as customers are able to choose accessories with certainty that fit their features.

The Try Before Buy solution maximizes personalization via AI-driven recommendations that select the most appropriate accessories according to user preference, like gender, skin tone, and face shape. For further optimization of user engagement, the system allows users to post their virtual try-on on social media via a social media share feature. The interactive and immersive process maximizes consumer satisfaction, boosts confidence in online shopping, and finally lowers the percentage of merchandise returns. Both consumers and retailers benefit through an improved, engaging, and enjoyable shopping process via the Try Before Buy solution, ending the major defects in online fashion shopping.

The Try Before Buy project tries to revolutionize online shopping by developing a virtual try-on smartphone system based on AR. It will allow customers to view how they appear in hats, glasses, and watches in real-time on their smartphones. The system will utilize high-end 3D modeling and real-time rendering to offer as realistic and accurate a fit as possible, so that the purchaser will feel at ease about the purchase. With a single click, you don't have to question whether that hat will fit you or whether that pair of glasses would look good on your face. The primary intention is to create a helpful tool.

The system will also employ recommendations driven by AI to personalize the purchasing experience. Through an analysis of your tastes, skin tone, and facial shape, the AI will recommend the ideal accessories for you. By including social media sharing capabilities, the project seeks to increase user engagement by enabling users to tell friends and followers about their virtual try-on experiences. Furthermore, in addition to making shopping more fun, this fusion of AR, AI, and social sharing will lessen the annoyance of returns. Online purchasing will be enhanced by the project's integration of these elements [15].

Scope of Project

The main focus of the Try Before Buy method will be fashion items, including watches, caps, and eyewear. The main components of the virtual try-on experience will be these objects, which will let customers view how they appear in real time on their own features [16]. The system will not include full-body virtual garment try-ons since these require more sophisticated body tracking methods and are more involved than the project can handle at this time. Giving these particular attachments a smooth and precise experience will be the main priority for the time being [17].

Literature Review

Augmented Reality in Fashion Retail

Augmented Reality (AR) is revolutionizing online shopping by enabling virtual fashion try-ons [18]. Major brands like Nike and Gucci have implemented AR technology to provide customers with immersive shopping experiences. Gucci has been particularly innovative, adding AR sneaker try-ons to its mobile app and later unveiling global shoe try-on experiences in Snapchat. The luxury brand has also experimented with virtual-only sneakers that can only be worn in AR, partnering with AR platforms like Wanna. fashion to expand their digital product offerings

AI-Powered Fashion Recommendations

AI-powered recommendation engines are transforming the way that customers locate fashion items. The greatest fashion accessories are suggested by these systems using machine learning algorithms based on user preferences and personal information, like style, color, in addition to prior purchases [19]. Modern retail innovations leverage AI for personalized shopping experiences, with sports apparel retail leading this transformation in 2024. AI-powered shopping assistants have been shown to increase conversion rates by up to 35% when compared to traditional product listings. These AI programs improve the shopping experience by offering tailored suggestions based on the individual interests of each customer [20]. Businesses see an increase in revenue and consumer satisfaction as a result.

Comparison of Existing Virtual Try-On Solutions

Several virtual try-on platforms have emerged in the market, each offering unique features to enhance the online shopping experience. For example, Wanna. Fashion provides an AR-based try-on experience for shoes; however, it lacks AI-driven product recommendations and offers a limited product range [21]. Similarly, some platforms enable virtual try-ons for clothing but do not incorporate face-tracking technology for accessories, which reduces their effectiveness for items such as glasses or hats. Other applications focus primarily on AR-based footwear and eyewear experiences but fail to include social media sharing features, which could significantly enhance user engagement [22]. Although these platforms offer valuable capabilities, they still face notable limitations that restrict their potential to deliver a truly immersive and intelligent virtual shopping experience.

Gaps in Existing Systems

Even with the developments in AI and augmented reality, there are still a number of shortcomings in the current virtual try-on systems. One significant drawback is the absence of personalization, since many platforms do not provide AI-driven styling recommendations tailored to each user's particular tastes or bodily attributes [23]. Furthermore, there is a noticeable lack of social features that might greatly improve user engagement, such as the option for consumers to post about their virtual try-on experiences on social media. A wider audience cannot use certain systems due to persistent device compatibility concerns, such as the fact that they are only available on particular platforms like iOS [24]. The field of virtual try-ons could benefit from these gaps, which also draw attention to the need for a more individualized and inclusive solution.

Our Contribution

- The Try Before Buy system aims to address these gaps and enhance existing models by incorporating several key features:
- AI-driven personalized recommendations to offer style suggestions tailored to the user's preferences.
- Broad device compatibility, ensuring the system works seamlessly on both Android and iOS devices.

Methodology

Due to differences in user facial features, lighting circumstances, and positioning in real-time augmented reality (AR) environments, it is still difficult to efficiently and accurately virtual test on fashion products like watches, caps, glasses, and headwear [25]. Additionally, lightweight models are necessary for real-time processing in order to guarantee seamless and engaging mobile experiences. In this study, we tackle these issues by optimizing an AR-based model that improves the responsiveness and accuracy of virtual try-ons. The suggested approach is reliable and lightweight, offering accurate user alignment of fashion items and real-time visualization.

The work presented consists of two major components: 3D Model Preparation and Customization, and an AR-Based Virtual Try-On System. The initial module focuses on creating and optimizing 3D models of fashion products, ensuring accurate texture mapping and realistic rendering [26]. The second module is an AR-based virtual try-on framework that uses real-time face detection and tracking to correctly overlay 3D models onto the user's face or body [27]. This module is divided into two sub-modules: the first implements face identification and tracking techniques, while the second conducts AR rendering and user interaction in real time. Figure 1 depicts a flow diagram of the proposed methodology.

The flow diagram shows the procedures for the AR-based virtual try-on system. It begins by using the device's camera to take a picture of the user's face. Key facial landmarks are then identified by the system using face identification and tracking algorithms [28]. To guarantee accurate placement of virtual objects, extracted critical feature points are analysed using a lightweight deep learning model. Finally, the AR rendering engine overlays the selected fashion items onto the user's image, enabling real-time visualization and interactive adjustments. The user experience is improved, and smooth alignment is guaranteed by the trained model for virtual fashion try-on applications.

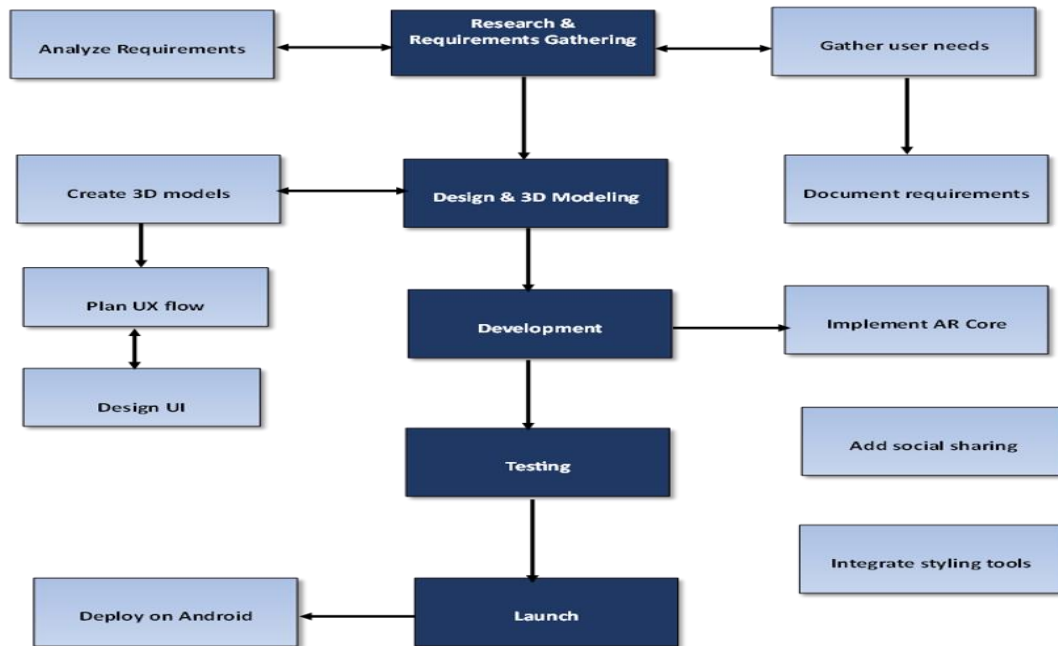


Figure 2: illustrates the flow diagram of the proposed methodology

Dataset Overview

Face Shape Classification Dataset

The Face Shape Dataset is a publicly accessible dataset used to categorize human faces into various shape groups. This dataset is especially helpful in domains such as personalized facials, haircare selection, eyewear advice, and cosmetics. evaluation. To enable automated face shape classification, machine learning models can be trained using a dataset that comprises labelled photos divided into various facial shapes.

Applications that require the ability to recognize a person's face shape, such as virtual try-on systems for glasses, AI-based cosmetics advice, and personalized styling recommendations, depend heavily on this dataset. Using deep learning and machine learning methods, the dataset aids in the creation of models that can accurately classify a person's facial shape.

Dataset Composition and Classes

The collection includes seven face shape groups, each reflecting a common facial structure found in human faces.

Oval Face: Characterized by balanced proportions, slightly broader cheekbones, and rounded jawline.

Round Face - Has a soft, curved contour with almost equal breadth and height. A square face is distinguished by a large forehead and a strong, angular jawline.

Heart Face – Recognized by a wider forehead and a narrow chin, resembling the shape of a heart

Diamond Face: Features high cheekbones and a thin jawline, and forehead.

Triangle Face: This type of face has a wider jawline than forehead, creating a triangle.

Oblong Face –A longer, rectangular face that appears elongated is called an oblong face. The way that various accessories, haircuts, and cosmetics fit a person depends greatly on each of

these face forms. Each face shape is represented in the dataset in a balanced manner, guaranteeing that the machine learning model is trained equally across all categories.

Format and Structure of the Dataset

The dataset is organized into directories, with pictures from each folder representing a certain group of face shapes. This arrangement facilitates simple retrieval.

Training Data Directory

Contains the majority of the dataset and is used to train the deep learning model.

Testing Data Directory

A subset of photos used to assess the accuracy and generalization of the model may be found in the Testing Data Directory.

Preparation and Enhancement of Data

The dataset is subjected to many preprocessing and augmentation procedures to enhance its quality and diversity prior to machine learning model training. These procedures ensure that the model captures strong characteristics and performs effectively when applied to new data. Image Resizing

Resizing: 100 x 100 pixels (MobileNetV2 optimized [30]) When deep learning models are being trained, this standardization aids in lowering computing complexity.

Normalization

The model's convergence during training is enhanced by scaling the 0–255-pixel values to a range of 0-1. Values of pixels [0,1] (Optimal TensorFlow Practices)

Normalization improves model stability and guarantees constant illumination conditions.

Methods of Data Augmentation Used:

- Rotation: To increase the resilience of the model, images are randomly rotated within a predetermined angle range.
- Zooming: To replicate various camera viewpoints, random zooming is used.
- Flipping: To address orientation variances, flipping is done both horizontally and vertically.
- Brightness Adjustment: The model can adjust to various lighting situations with the use of random brightness variations.
- Brightness: $\pm 20\%$ range (Khoshgoftaar & Shorten, 2019)
- Rotation/Zoom: Using Keras Image Data Generator

Dataset Splitting

To guarantee that the model learns efficiently, 80% of the photos are used for training. 20% of the photos are used for testing in order to assess generalization and performance. These preprocessing methods guarantee that the model is not skewed towards particular image orientations, lighting scenarios, or angles.

Table 1: The methodology is divided into five main stages

Stage	Component	Purpose
1	Data Acquisition	Capture visual and sensory input from the environment
2	Preprocessing	Prepare the data (resize, clean, normalize)
3	Deep Learning–Based Visual Perception	Detect and recognize objects, gestures, or scenes
4	AR Rendering & Interaction Module	Overlay virtual elements and manage real-time interactions
5	Evaluation	Measure system accuracy, latency, and user satisfaction

Procedure for Training and Classifying Models

A Convolutional Neural Network (CNN) with a deep learning foundation is utilised to categorise the facial forms in the dataset. CNNs are perfect for classifying face shapes because of their well-known capacity to extract significant characteristics from photos.

Selection of the Base Model

The MobileNetV2 model is selected as the foundational architecture for the classification model's training. MobileNetV2 is incredibly well-suited for embedded and mobile vision applications. Giving it a strong but portable option for facial shape recognition.

The deep learning model receives the dataset and proceeds as follows:

- Important facial traits like forehead proportions, cheekbone breadth, and jawline structure are extracted using MobileNetV2's convolutional layers.
- Images are classified into one of the seven facial shape groups using Fully Connected (Dense) layers. A SoftMax activation function is used by the final output layer to calculate the probability distribution for each class.
- Optimizer: Adam Optimizer is used to enhance model learning efficiency.
- Loss Function: Categorical cross-entropy is applied to measure classification accuracy.
- Accuracy is measured to determine how well the model classifies face shapes.
- Precision and Recall are calculated to assess model reliability in identifying different face shapes.

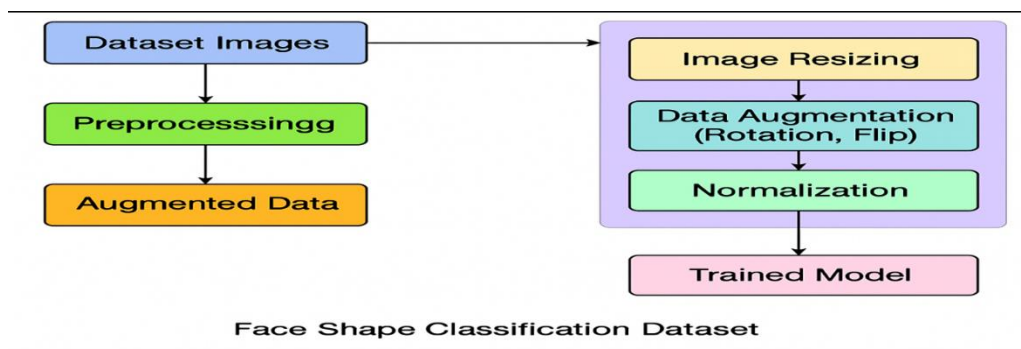


Figure 3: A visual overview of the Face Shape Classification Dataset methodological flow, illustrating each stage from data preprocessing to model training and evaluation.

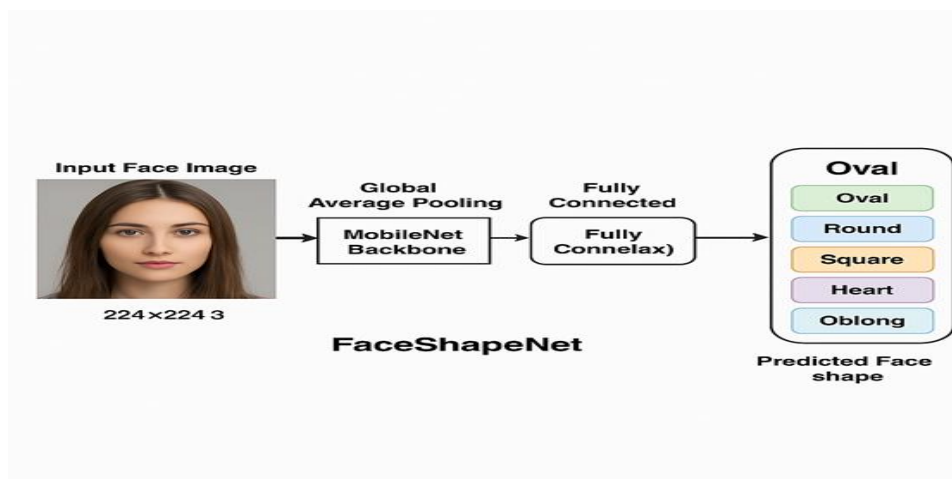


Figure 4: Proposed FaceShapeNet architecture for face shape classification

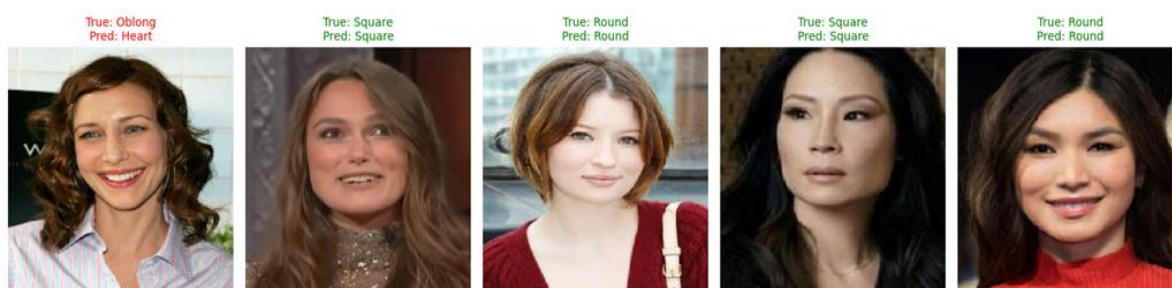


Figure 5: Face shape classification results on real-world celebrity images

As shown in Figure [5], the proposed deep learning-based AR framework has the capability of visual perception, in which the system recognizes and categorizes various shapes of human faces under natural, real-life environments. The picture depicts five sample inputs, and five predicate labels are obtained by the AR camera module, accompanied by the actual label (actual face shape) and the predicted label (model output). The model has undergone training to classify facial geometries, i.e., Oblong, Heart, Square, and Round, with convolutional and transformer-based feature extraction layers.

According to the graph, the model is accurate in presenting a number of face types (e.g., True: Square, Pred: Square, and True: Round, Pred: Round), which proves that it is a highly accurate model in learning a variety of faces and performing generalization among individuals. Nonetheless, there are also some misclassifications (e.g., True: Oblong, Pred: Heart), which demonstrate the difficulty of homogeneous geometric resemblance between categories of faces. These small mistakes are usually brought about by overlapping characteristics such as the jawline curve or the forehead width.



Figure 6: Face Shape Data Distribution for Training, Validation, and Testing. This figure illustrates the distribution of images across different datasets: Training, Validation, and Testing.

Such visual outputs prove that the deep learning perception system achieves real-time face recognition, which allows the AR system to fit virtual overlay (e.g., glasses, accessories, or emotion-based filters) to the face of users correctly. This kind of intelligent perception improves user experience in augmented settings - this is how personalization is supported, how responses may be based on emotions, and how AR visualization may be realistically shown in Figure 6.

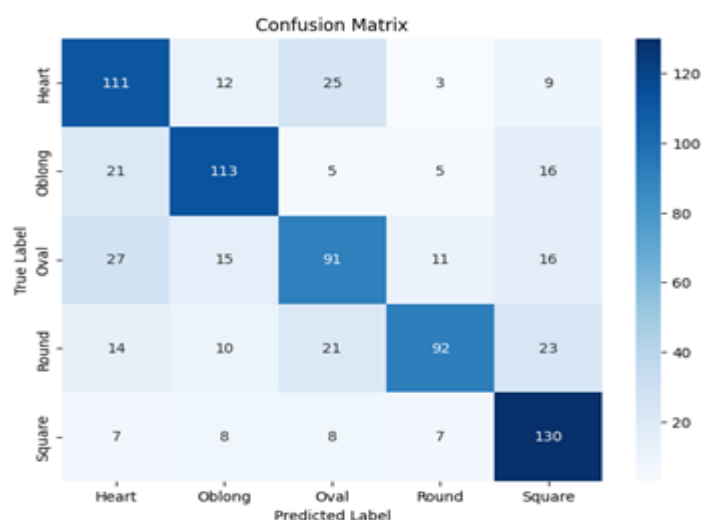


Figure 7: Confusion matrix for face shape classification using FaceShapeNet. The matrix compares true labels (rows) with predicted labels (columns) across five face shape categories: Heart, Oblong, Oval, Round, and Square.

The deep learning based visual perception model that drives the intelligent aspect of the proposed Augmented Reality (AR) framework is shown in Figure [8] in terms of training and validation performance. The model was trained using a large-scale image dataset with various object and face categories so that it could have a strong understanding of scenes and interact. The graphs show the accuracy and loss of the model as the number of epochs was increased to 40 throughout the training process.

In the Model Accuracy graph (left), the training accuracy (blue curve) and the validation accuracy (orange curve) exhibit a steady positive trend with an increase in the number of epochs. The first few epochs increase the training accuracy steeply and level off to about 85-88 percent, whereas the validation accuracy flattens to about 70-72 percent. This enhancement demonstrates that the model gradually acquired discriminative visual characteristics and was thus able to identify and interpret complex visual images like human faces, gestures, and objects of the environment in real-time AR situations. The fact that there is a little distance between the training and validation curve indicates that there is not much overfitting, that is, the model is very generalizable to unknown data.

Model Loss graph (right) is a plot of the resultant decrease in training loss (blue line), as well as validation loss (orange line), as the model becomes more efficient at minimizing the prediction errors. The beginning of both curves has a relatively smaller loss (around 1.8) that gradually decreases and levels off to 0.6 during training and to 1.1 during validation in 40 epochs. The declining trend of the value of losses indicates that the model was able to achieve optimality in its parameters with the help of backpropagation and gradient descent, which increased the recognition accuracy and stability of the model.

These findings verify that the deep learning perception part of the proposed AR framework effectively learns meaningful spatial and semantic representations of real-world scenes. The system can ensure accurate detection and tracking of physical elements, which are essential to creating smart visual overlays and facilitating natural human-computer interaction in augmented space, because of its high accuracy and low loss.

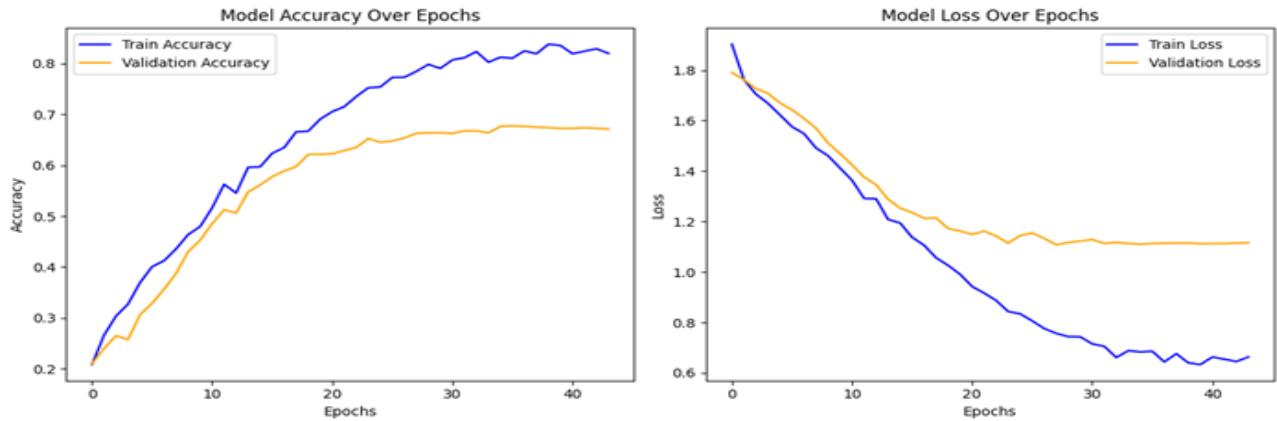


Figure 8: Model Accuracy and Loss Over Epochs. This figure shows the training and validation accuracy (left) and loss (right) as a function of epochs.

Ai-Based Face Shape Recommendation System

This system integrates a pretrained deep learning model (stored in Keras format) for automatic face shape classification. A pre-trained Keras model is loaded from Google Drive using TensorFlow's model loading API. This model is trained to classify facial shapes into five categories: Heart, Oblong, Oval, Round, and Square.

- Reads the input image using OpenCV
- Converts BGR to RGB

Resizes the image to 224x224 (matching the model's input shape). Normalizes pixel values to the [0,1] range.

Prediction Functionality: After preprocessing, the image is passed through the model to predict the most likely face shape. The output probabilities are mapped to their corresponding class labels.

Recommendation Integration (optional future scope): This feature can be extended to recommend accessories, hairstyles, or glasses based on detected face shape.

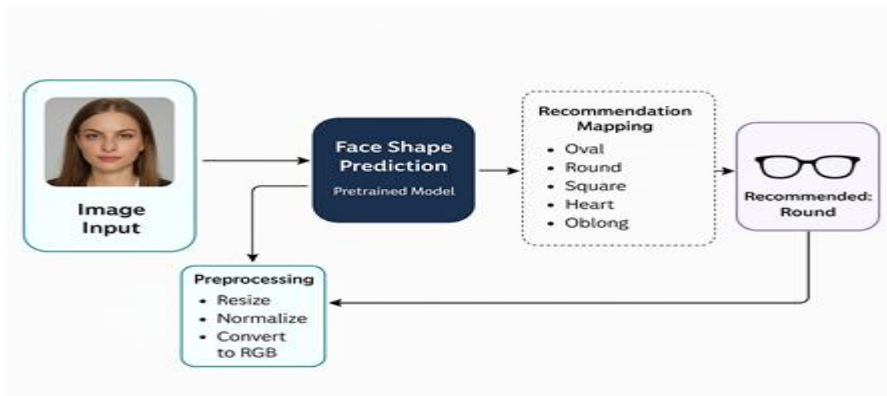


Figure 9: Face Shape-Based Recommendation System Architecture.

Conclusion

This diagram outlines the workflow of the AI-driven face shape recommendation system. The process begins with an input image, which undergoes preprocessing (resizing, normalization, and RGB conversion). The image is then passed to a pretrained model for face shape prediction. Based on the predicted face shape, the system performs recommendation mapping and outputs personalized suggestions, such as recommended accessories. This study examines the Try Before Buy idea using the application of Augmented Reality (AR) and Artificial Intelligence (AI) to provide users with an immersive and interactive experience. The system that is suggested enables users to experiment with fashion accessory items such as hats, glasses, and watches in an internet context, ultimately building confidence among users and allowing for more knowledgeable purchasing decisions. There has been considerable advancement in the integration of AR modelling with 3D models, taking on an AI-powered facial recognition system, making and designing the user interface (UI/UX), and releasing the initial version of the virtual try-on feature. However, there are some developments in process. These like enhancing the facial recognition and object alignment capabilities of AI, making more realistic and diverse 3D models, increasing overall user experience (User Experience), and enhancing features. Further, efforts are being placed on the following: towards maximum system performance and reduced response time, followed by last testing and iterative refinement based on real user feedback. This ongoing work is intended to deliver a robust, customer-centric, and highly personalized virtual try-on solution to modern digital retail.

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