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Revolutionizing Fashion: Fashion Era's Deep Convolutional Neural Network for Outfit Recommendations

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Abstract: This article introduces a novel outfit recommendation system that leverages the user's physical appearance to provide tailored outfit suggestions. Employing a Deep Convolutional Neural Network (CNN) algorithm, the system accurately identifies the user's skin tone from input images, complemented by user-provided information like gender, age group, and size to curate personalized fashion choices aligned with the individual's body shape. The system's robustness is demonstrated through a 92% accuracy rate following model training, indicating its reliability in providing tailored suggestions. To facilitate user engagement, the system seamlessly integrates with IBM Assistant and NGROK application for efficient collection of user preferences and feedback. Looking forward, the system's roadmap includes an expansion to encompass all six types of skin tone identification based on the Fitzpatrick system. Moreover, plans involve integrating augmented reality for immersive try-on experiences, enhancing the user's interaction with suggested outfits. Additionally, the incorporation of audio chatbots aims to further optimize user convenience and engagement within the system, promising an enriched and personalized outfit recommendation experience.

Keywords: *Outfit Recommendation System, Convolutional Neural Network (CNN), IBM Assistant, Deep Learning*.

1. Introduction

In recent years, the fashion industry has seen a significant shift towards e-commerce and online shopping. With this shift comes the challenge of providing personalized recommendations to users based on their preferences and browsing history. One solution to this challenge is an outfit recommendation system using deep convolutional neural networks (CNNs). Deep CNNs have shown impressive performance in image recognition tasks, making them a promising approach for outfit recommendation. By training a CNN model on a large dataset of fashion images, the model can learn to extract features that capture the unique characteristics of different fashion items. These features can then be used to recommend items that are similar to those the user has shown interest in. In this article, we will explore the process of building a outfit recommendation system using a deep CNN. We will discuss the steps involved in collecting and preprocessing data, building and training a CNN model, and evaluating the performance of the system. Additionally, we will discuss the potential benefits and limitations of using a deep CNN for outfit recommendations and provide insights into future research directions in this field. This model proposes outfit recommendations by studying the physical appearance of the user, system identifies the skin tone of the user and gives outfit recommendations along with different body shapes. Researchers have identified that there are only six distinct skin tone categories present in India, which are determined by various factors. These skin tones are classified based on how the skin reacts to UV radiation, as shown in Fig. 1. The Fitzpatrick system is commonly used to classify skin tones into six types, as depicted in Figure 1. For the purpose of outfit recommendations, this model primarily focuses on three types of skin tones, namely Type-I (Extremely fair skin), Type-II (Olive skin), and Type-III (Markedly pigmented black skin). By considering these skin tone categories, a outfit recommendation system can provide more personalized outfit suggestions to users, catering to their unique skin tone characteristics.

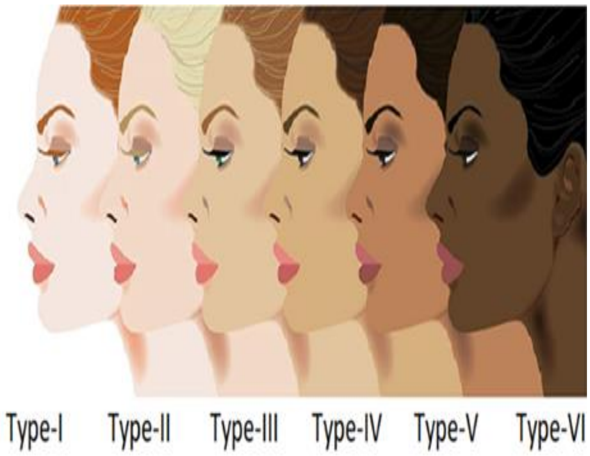

Fig.1. Human skin tone types according to Fitzpatrick System

An outfit recommendation system aims to provide more personalized fashion suggestions to users, taking into account their individual characteristics. This not only includes skin tone but also

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body shape. Research conducted by Mitch Calvert suggests that males have three distinct body shapes, namely Ectomorph, Mesomorph, and Endomorph, while females have five body shapes: Round/Apple, Pear/Triangle, Inverted Triangle, Rectangular/Athletic, and Hourglass, as illustrated in Figure 2.

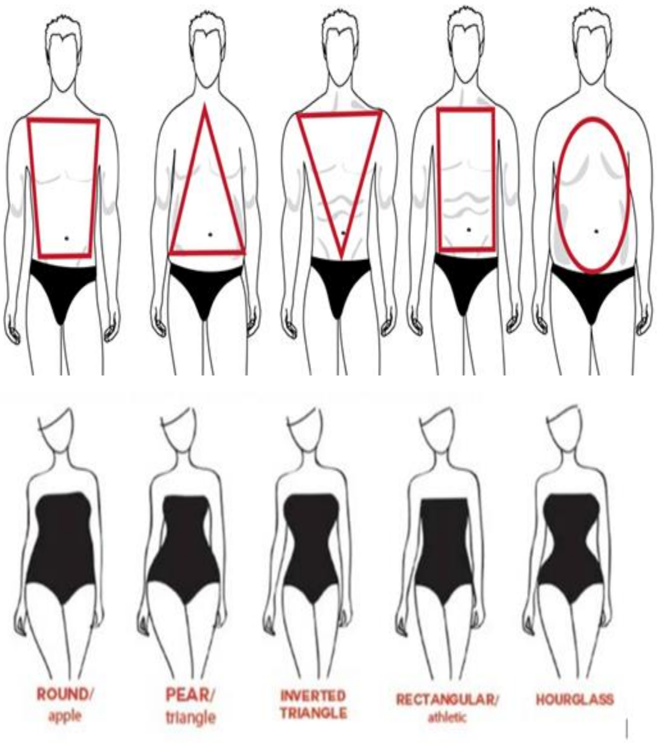


Fig.2. (a) Body shapes of female (b) Body shapes of male

By categorizing users into these body shape categories, a outfit recommendation system can suggest outfits that best suit their body type, enhancing their overall appearance and style. By incorporating these categories, the system can provide more targeted and personalized outfit recommendations that are tailored to the user's specific needs and preferences.

The main goal of the outfit recommendation system is to assist consumers in selecting outfits that best match their physical appearance. This system utilizes skin tone and body shape categories to recommend suitable outfits for each user, resulting in a more personalized shopping experience and reduced time consumption. By providing personalized outfit recommendations based on individual characteristics, the system can enhance user satisfaction and increase the likelihood of a successful purchase. This can lead to increased customer loyalty and satisfaction with the shopping experience. The outfit recommendation system aims to simplify the outfit selection process and provide users with a more efficient and enjoyable shopping experience.

2. Related work

A literature survey for outfit recommendation systems reveals a growing interest in this field, with numerous studies and research articles exploring various approaches and techniques for improving the accuracy and effectiveness of such systems. Some of the notable works in this area are Collaborative Filtering-Based Approach for Fashion Recommendation This study proposes a collaborative filtering-based approach for fashion recommendation [1], which combines user preferences and item characteristics to generate personalized recommendations. "Fashion Recommendation with Visual Explanations" [2] This study presents a novel fashion recommendation system that incorporates visual explanations, enabling users to better understand the reasoning behind each recommendation." [3] This paper proposes a deep learning-based approach for fashion recommendation and design, utilizing convolutional neural networks and generative adversarial networks to generate personalized fashion designs. "An Ensemble-Based Hybrid Fashion Recommendation System" by Zhang et al. (2021) [4] This study proposes an ensemble-based hybrid fashion recommendation system, combining content-based and collaborative filtering approaches to improve the accuracy of recommendations. [5] This paper presents a personalized fashion recommendation system based on social media data, utilizing deep learning techniques to analyze user preferences and generate personalized recommendations. In 2022, there have been some studies exploring new approaches to fashion recommendation systems. For example, a study by Song et al. proposed a novel method for fashion recommendation based on user visual preferences, utilizing a convolutional neural network to extract visual features from fa There are several online fashion applications that offer fashion recommendations based on factors such as prices, brands, discounts, and gender, among others. However, these applications do not consider the user's physical appearance, which can lead to user dissatisfaction [6]. Additionally, interacting with unwanted search results can waste a user's time when using current applications. Fashion choices are influenced by various factors such as demographics, geographic location, individual preferences, interpersonal influences, age, gender, season, and culture. The research work in [7,8] aims to help the user in deciding what colored clothing will best suit him or her on appropriate occasions by making choices based on different data-points using Decision Tree algorithm and K Means Clustering algorithm. In research work [9] a fashion recommendation system has been developed that provides outfit suggestions for female body. In the work carried out in [10] the researchers developed a recommendation system which suggests matching products to the consumer based on the past purchase behavior.

This study in research work [11] describes a collaborative filtering recommendation system developed for Korean fashion company which sells products based on fashion in online and offline mode. The work in [12] is referred for study of CNN for Face Recognition. In the study carried out in [13] they have proposed adaptive hierarchical network structure composed of DCNNs that can grow and learn and recommends when recent data is available. The skin tone-based recommendations and detailed report is described in the paper [14]. The work [15, 16] is referred for detailed study and implementation of CNN using Python with Keras and TensorFlow. The research paper [17] throw light on detailed survey on deep learning-based outfit recommendation system. In the research work done in [18] they have designed algorithms that automatically recommend users' attire based on their own fashion tastes. The papers [19, 20] shows that by recommending items that are likely to appeal to the user, fashion recommendation systems can help retailers increase sales and customer satisfaction. In the review paper [21] a detailed review is made on different fashion recommendation systems. In the work [22, 23] similarity-based fashion recommendation systems are developed and tested. The paper [24] elaborates Personalized outfit generation for fashion recommendation at Alibaba iFashion. In paper [25] a detailed study on the relative importance of convolutional neural networks in visually-aware recommender systems is done. In the paper [26] a Recommendation system is developed for fashion retail e-commerce.

3. CNN Architecture for Skin Tone Identification and Model Performance Analysis

3.1 CNN Architecture

A Convolutional Neural Network (CNN) is a specialized deep learning algorithm used for analyzing images, such as image recognition, object detection, and segmentation. The architecture of a CNN consists of different layers that transform the input volume into an output volume using a differentiable function which is shown in Fig. 3.

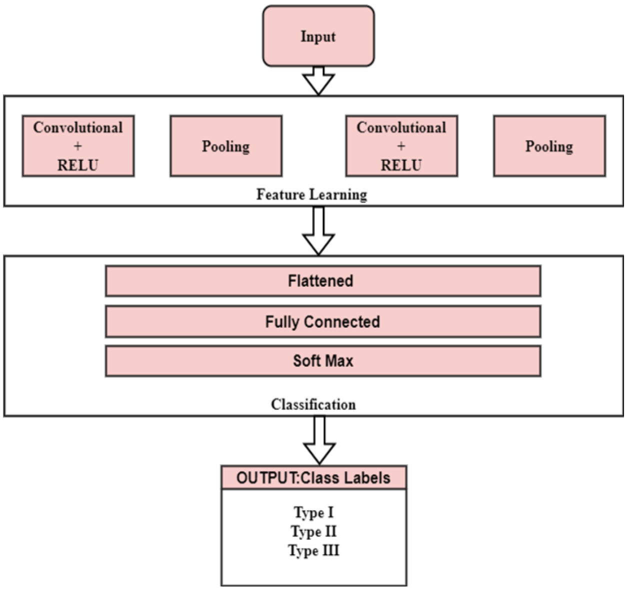


Fig.3. CNN Architecture

The core building block of a CNN is the convolutional layer, which extracts various features of the input images. The output from this layer is a feature map that is further analyzed by other layers to study the details of an input image.

The pooling layer follows the convolutional layer and decreases the computational power of data processing. It classifies into two types: max pooling, which takes the maximum value of the local cluster of neurons, and average pooling, which takes the average value of each local cluster of neurons from the feature map. The fully connected layer is placed before the output layer and connects neurons between two different layers. The activation layer, present before the pooling layer, is used to learn about the continuous and complex relationships between variables of the network. In a CNN, every image is represented as an array of pixel values. The image is divided into a matrix format according to its color pixel values, and these pixels are sent to the input layer. The hidden layer performs feature extraction and identifies patterns in the image by convolutional operation. The classification layer, presented as a fully connected layer, identifies the object in the image, such as the type of skin tone, and provides the prediction as the result.

In CNN, every image is represented in the form of an array of pixel values. When the image is given to the CNN model as input it divides the image into a matrix format according to its color pixel values. Further, these pixels will be sent to the input layer as shown in Fig. 4. In the CNN architecture, the hidden layer is given after the input layer. This layer performs the feature extraction, with some calculation and manipulation, and also performs a matrix filter where the module will identify the pattern in the image by convolutional operation. In the classification layer, it is found that a fully connected layer is presented which identifies the object in the image i.e., the type of skin tone, and gives the prediction as the result. The dataset used for building the machine learning model for skin tone identification contains different images of Indian and foreign people classified into three categories: Type-I, Type-II, and Type-III. Colored images contain unwanted features and require a lot of power to load the model. However, using colored images for training the model is considered in this research. The proposed model was also built on Teachable Machine Learning, a Google Creative Lab service, and achieved an accuracy of 93%. The accuracy graph, loss graph, and confusion matrix were derived from Teachable Machine Learning.

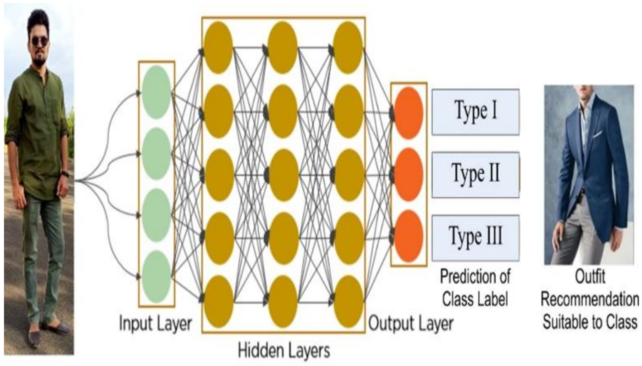


Fig.4. Working model architecture of CNN

3.2 Employing CNN In Outfit Recommendation: Model Framework

The developed image classification model can detect the skin tone of a user from the given image input. The model is built using Convolutional Neural Network (CNN), a specialized type of neural network that uses convolution instead of general matrix multiplication in at least one of its layers. The architecture of the model follows the block diagram in Figure 5, which consists of distinct layers that transform the input image into an output volume using a differentiable function. To make the application user-friendly, a web interface is designed where users can interact with the basic functionality of the application.

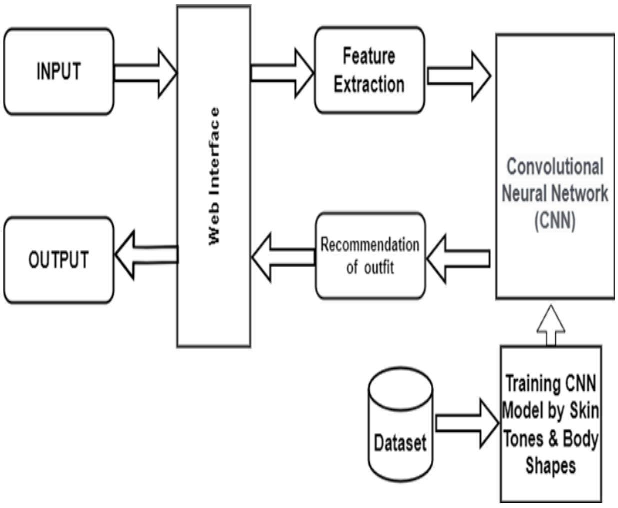


Fig.5. Framework for CNN based Recommendation

An IBM assistant is integrated into the web application to understand the user's needs regarding the outfit they are looking for. NGROK, a cross-platform application, is used to expose the local server ports to the internet and send all user responses securely to the system. The user is required to answer some basic questions posed by the IBM assistant before submitting their image as input. The image is then sent to the CNN model for prediction, which predicts the skin tone for the given input using the train and test dataset used during the building model. Under the result analysis stage, the user responses from NGROK and the model prediction results are processed together to give outfit recommendations as the output on the web interface. The algorithm used for fashion recommendation is given in algor 1 below. It is important to note that the dataset used for building the machine learning model contains images of Indian and foreign individuals classified into three categories: Type-I, Type-II, and Type-III. The images are in color, which contains unwanted features and requires a lot of power to load the model. However, converting the images into grayscale reduces the model load but may lead to unpredictable prediction fluctuations. The proposed model was also built using Teachable Machine Learning, a web-based tool provided by Google Creative Lab. The model achieved an accuracy of 92%, and the accuracy graph, loss graph, and confusion matrix from the proposed method were derived from Teachable Machine Learning.

Algorithm illustrating Outfit recommendation

Input: Human image
Output: Outfit recommendation.

Training Phase

1. Start
2. Pre-process the images
3. Train the CNN Model with different skin tones of males and female image dataset.
4. Train the model with various shapes of Men and Female image dataset.
5. Calculate the accuracy with different epochs.
6. Save the trained model with satisfactory accuracy.

Classification and Recommendation Phase

7. Input the image through any source like webcam or camera.
8. Image is feeded into trained Conventional Neural network Model from input.
9. Model will classify the Image into three categories as Type:1 Type:2 and type:3 based on skin tone and body fit.
10. Based on Type the best suitable outfit is recommended.
11. Stop

Algorithm 1. Algorithm illustrating Outfit recommendation.

4. Results and Discussion

4.1 Experimental Setup

IBM has developed an intelligent assistant that can recommend outfits to users based on their preferences and other parameters. The system interacts with the user through a series of questions designed to understand their requirements. The first question asks the user about the type of outfit they are looking for, with options such as Season Outfits, Corporate Industry Outfits, Wedding Outfits, Army Outfits, and Festival Special Outfits. The user can select any one option from the drop-down menu. The next question is about the user's gender, which is necessary for the system to provide appropriate recommendations. To avoid any confusion regarding the user's age, the application has categorized age groups into 5 categories: Kid (0-5), Teen (6-17), Young Adult (18-27), Adult (28-45), and Elder (45+). The user can select their age group to receive outfit recommendations tailored to their age. The third question is about the user's size, which is essential for the system to recommend outfits that fit the user correctly. The system provides possible sizes based on the user's age group. Finally, the system requests the user to upload an image for skin tone identification, which allows the system to suggest outfits that match the user's skin tone. An example scenario is provided where a user is looking for a Festival Special Outfit, is male, falls under the Young Adult age group, has size L, and has Type-I skin tone. Based on these parameters, the system provides outfit recommendations that are displayed in a snapshot of Fig. 6. Overall, IBM's intelligent assistant provides an efficient and convenient way for users to receive outfit recommendations tailored to their requirements and preferences.

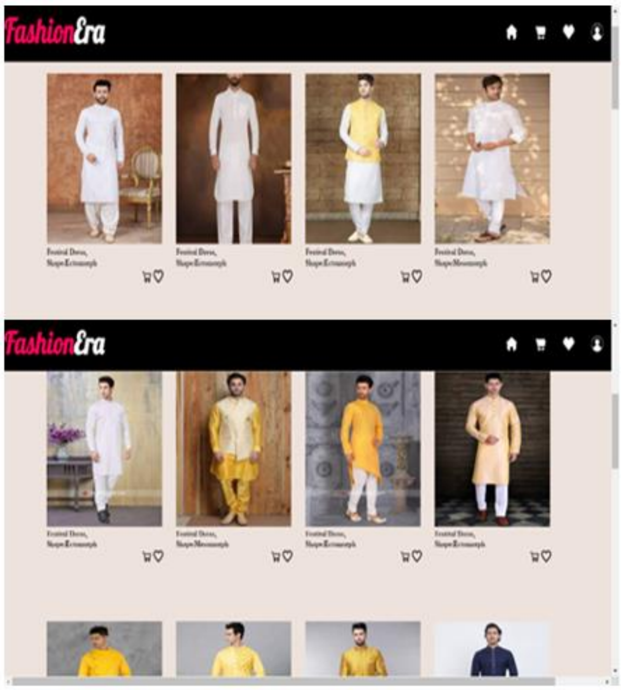


Fig.6. Experimental Results

4.2 Result and Discussion

The accuracy trend depicted in Figure 7 illustrates a consistent increase in accuracy throughout the training epochs. Initially starting at 88%, the accuracy steadily climbs with each epoch's execution, eventually stabilizing at 92% after a certain number of epochs. This trend signifies a progressive improvement in the model's performance, reaching a consistent and satisfactory accuracy level of 92% following a sequence of training iteration

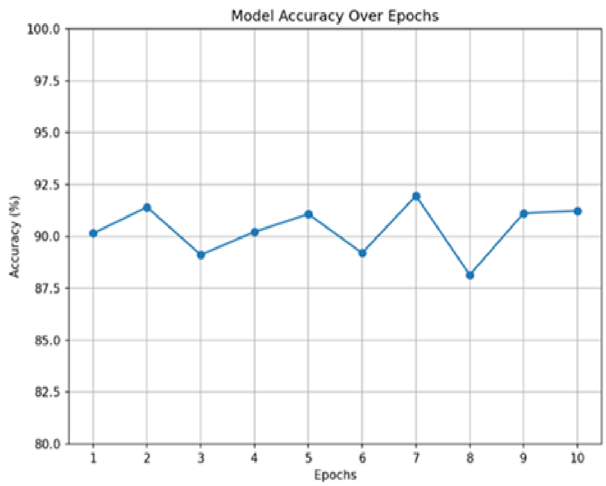


Fig.7. Accuracy vs Epochs graph

The results discussion revolves around precision, a key metric showcasing the model's accuracy in correctly identifying positive instances within specific categories. Highlighted in Figure 8, precision scores illustrate the model's effectiveness in differentiating and accurately predicting positive cases across diverse classes. It's emphasized that while precision is crucial, a comprehensive assessment integrating multiple metrics is essential for a holistic understanding of the model's performance, especially in scenarios with imbalanced data or varying class distributions.

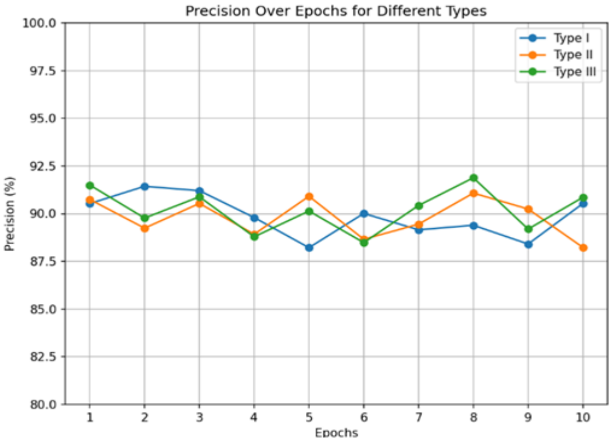
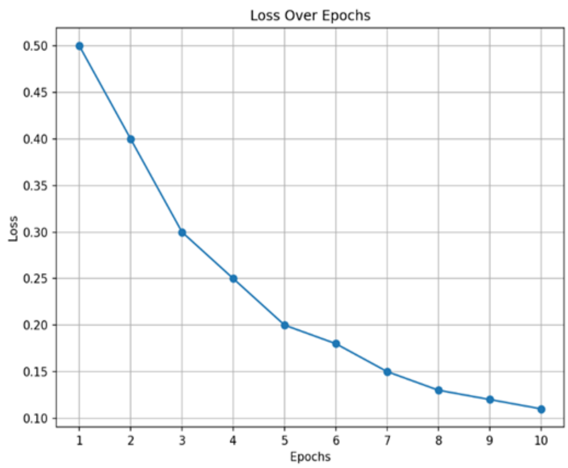


Fig.8. Precision over Epochs for different types

In the visual representation presented as Figure 9, the graph illustrates the relationship between the loss and the number of training epochs. It vividly demonstrates that as the training progresses through each epoch, there is a consistent and continuous decrease in the loss values. The loss, serving as a scalar metric, embodies the value that the model aims to minimize during its training phase. A declining loss trajectory, as depicted in the graph, signifies that the model's optimization process is effectively minimizing this value with each epoch's iteration. This progressive reduction in loss values indicates the model's improved ability to make more accurate predictions as it learns from the training data. The downward trend observed in the loss graph reinforces the notion that the model is progressively converging towards an optimal state, enhancing its predictive capabilities. As the loss decreases, it signifies that the discrepancies between the model's predictions and the actual ground truth are diminishing, aligning with the model's learning objectives



9. loss vs Epochs

Figure 10 displays a confusion matrix, a graphical representation summarizing a machine learning model's performance. It showcases the model's predictions for different classes in a matrix format, indicating correct and incorrect predictions made across various categories. This matrix, obtained post-model training, aids in assessing accuracy. The matrix structure consists of rows and columns representing actual and predicted classes respectively. Correct predictions align along the diagonal elements, while incorrect ones appear off-diagonal. Analyzing this matrix allows us to gauge the model's accuracy by calculating the ratio of correct predictions to the total.

In our results, the confusion matrix, in below figure, highlights the model's effectiveness, revealing a commendable 92% accuracy. This visual aid offers comprehensive insights into the model's performance across multiple categories, enabling a detailed evaluation of its strengths and weaknesses in differentiating classes.

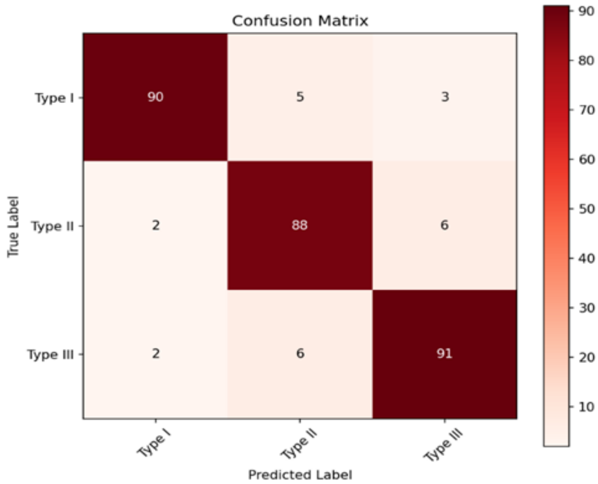


Fig.10. Confusion Matrix

5.Conclusion

In culmination, this research paper pioneers a groundbreaking solution in the realm of outfit recommendations by leveraging the distinctive physical attributes of users, particularly focusing on the identification of their skin tone. The system's innovative approach facilitates the delivery of highly personalized and tailored outfit recommendations, thereby significantly enhancing the user's shopping experience. The system's prowess in accurately identifying skin tones through input images has been instrumental in achieving a noteworthy accuracy rate of 92%. This high level of accuracy underscores the system's precision and reliability in providing recommendations that align with users' unique preferences and physical attributes. Looking ahead, the research team aims to expand the system's capabilities by encompassing all six skin tone types defined by the Fitzpatrick system. This expansion seeks to further refine and enhance the accuracy and inclusivity of the system, catering to a broader spectrum of users with diverse skin tones. Moreover, the integration of Augmented Reality (AR) technology into the system's framework marks an innovative step forward. This addition will allow users to virtually try on outfits, offering a realistic and immersive experience before making purchase decisions. This feature has the potential to revolutionize the way users shop for clothing, providing a more engaging and confident purchasing journey. Additionally, the inclusion of audio chatbots signifies the system's commitment to user convenience and accessibility. By offering a seamless and interactive interface, users can easily navigate the platform, receive personalized recommendations, and seek assistance, thereby further enhancing their shopping experience. In summary, the holistic advancements outlined in this research hold the promise of transforming the traditional approach to outfit selection. The system's precision, coupled with the integration of cutting-edge technologies like AR and user-friendly interfaces, anticipates a future where shopping for outfits becomes an efficient, personalized, and immersive experience for users across diverse demographic.

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Author contributions

Author 1 Contributes Conceptualization, Methodology, Writing - Original Draft Preparation. Author 2 Contributes Data curation, Formal analysis, Investigation. Author 3 Contributes Software, Visualization, Methodology. Author 4 Contributes implementation & Validation. Author 5 Contributes, Funding acquisition, Project administration. Author 6 Contributes Conceptualization, Writing - Review & Editing, Visualization.

Conflicts of interest

The authors declare no conflicts of interest.

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