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Original Article

A Novel Strid CNN Model for Cosmetic Product Recommendation based on Skin Type and Tone

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Abstract *- In the last few years, consumer interest in cosmetic purchasing has increased globally, especially in skincare products. Traditionally, customers have used in-store advice from beauty experts for popular product purchases. However, due to the different skin types and skin tones of every individual, sometimes it is difficult to get the correct product that is suitable for them. This indicates the need for customized and effective methods for analyzing cosmetic products suitable for individual skin types and skin tones. This research proposes a novel cosmetic product recommendation system that addresses different consumer needs using a Strid Convolutional Neural Network (CNN). The proposed method identifies customers' different skin types (oily, normal and dry) and skin tones (medium tan, fair/light, and dark/deep). The proposed method takes the identified skin type and tone as input and then recommends the best-suited cosmetic or skincare product related to their skin tone and type. The dataset used to have 3152 images of different skin types and 1305 images of different skin tones. The overall dataset forms the basis of the proposed system, which identifies these parameters to offer customized recommendations that are most suitable cosmetic products like sun protection, eye creams, cleansers, face masks, and moisturizers, according to individual customer needs. The proposed Strid CNN architecture demonstrated excellent performance, achieving a validation accuracy of 98.8% and a validation loss of 0.0356, highlighting the model's enhanced capability to provide effective cosmetic product recommendations for different skin types and tones.*

Keywords - *Cosmetic product, Recommendation, Skin type, Skin tone, Deep Learning Techniques.*

1. Introduction

Skincare plays an essential role in promoting a balanced and healthy lifestyle. In recent years, the average age of consumers using cosmetic products has decreased, with rising interest among younger individuals, including both boys and girls and working professionals. These products not only enhance youthful appearance but also contribute to improved self-confidence. Numerous brands have introduced a wide range of skincare products to meet this growing demand. However, selecting the right product requires careful evaluation of individual skin types and tones. [25] Experts stress the importance of understanding one's unique skin characteristics to make informed product choices. While some skin types and tones are easy to identify, others require more detailed analysis, especially in cases of combination skin or varied skin tones. Over the past two decades, the skincare market has seen substantial growth, fueled by advancements in technology, particularly the integration of Artificial Intelligence (AI) into fields such as healthcare and cosmetics. With the increasing adoption of Deep Learning techniques, which enable computers to learn from data examples, AI-powered systems are now being utilized to provide personalized cosmetic product recommendations tailored to individual skin needs [34]. Even with advances in deep learning and artificial intelligence, research is still needed to integrate these technologies to provide customized cosmetic guidance. Current systems often fail to address the unique challenges posed by diverse skin conditions, particularly in handling complex or typical skin types. [29] While AI algorithms excel in analyzing large volumes of unstructured data, limited research has focused on creating user-friendly, comprehensive frameworks that combine skin diagnostics, product compositions, and real-time consumer preferences. Addressing that gap will allow for more precise and customized recommendations, increasing customer happiness and the beauty industry's capacity to effectively respond to customers' needs and demands [30]. Although deep learning algorithms have shown great promise in evaluating unstructured data to provide customized skincare advice, there is still a research gap in how to fully utilize these technologies to effectively treat various skin types [31]. Various skin types, including dry, oily, and neutral, cannot always be thoroughly analyzed by existing technologies and matched with appropriate cosmetic compositions. Moreover, there aren't many studies that focus on integrating user feedback, skin diagnostics, and algorithmic predictions into an integrated structure for decision-making. By filling this gap, the beauty industry will be better ready to meet the demands of each individual and offer effective, customized cosmetic advice, which will transform the consumer experience. Figure 1 shows a flow chart for any recommendation system for cosmetic products. The process starts with collecting raw data, which is collected from several kinds of data, including product details, user preferences, and purchase history. In order to make individualized suggestions, this data frequently includes characteristics like ingredients, skin types, skin tone, price, rank label, and brands. Data preprocessing is the following stage, including data cleaning, filling in missing values, standardizing formats, and transforming categorical data like product categories or user preferences into formats that may be used.

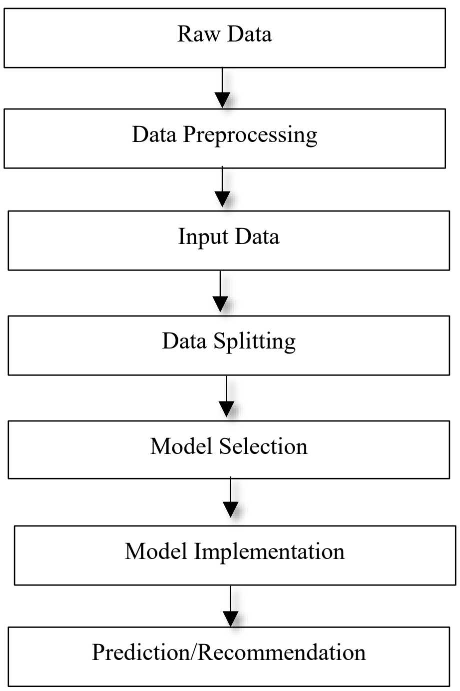


Fig. 1 Recommendation system

The model is trained and evaluated efficiently to ensure that, first, it starts by dividing the dataset into three parts: training, validation, and testing. Then, through the Model Selection stage, find the best algorithm for giving the best recommendations. Some frequent methods include content-based filtering, which focuses on the features of the products, and collaborative filtering, which discovers similarities between users or items. Some hybrid models combine both methods. For even improved model performance, we might use advanced techniques like neural networks. Once picked the right method is done, train the model using the equipped data and fine-tune it for the best performance and scalability in the Model deployment stage. Finally, in the last stage, Prediction/Recommendation, the trained model can provide personalized recommendations, such as recommending cosmetic products that match a user's skin type and tone or highlighting top picks among the same users. This progressive process ensures the recommendation system provides efficient and personalized product recommendations, enhancing user satisfaction and increasing sales.

This research aims to build a deep learning model that can classify a person's skin type like oily, dry, normal, or consolidated and their skin tone, such as fair/light, medium tan, or dark/deep. The model uses progressive image processing techniques to determine the skin's quality. Based on this analysis, it advises personalized cosmetic products that fit the user's definite skin needs. This way facilitates the process of picking skincare items, raises user satisfaction, and diminishes the chances of negative skin reactions by making sure that the recommended products are a great suitable for each individual's unique needs and requirements.

Currently, cosmetics play a crucial role in enriching a person's looks and increasing confidence. However, with the number of skin care items and skin care products available and the variety of human skin types and tones, determining the perfect product can feel mind-blowing. This reinforces the need for a smart way to find the right cosmetics personalized to each person's unique skin quality. Fortunately, deep learning algorithms provide a promising solution since they excel at managing large amounts of unstructured data and delivering reliable, broad observations. The main goal of this research is to first label human frontal face images based on their skin type and tone. Then, develop a robust, AI-driven framework to recommend personalized skincare products, ensuring optimal consumer satisfaction and safety.

One of the key difficulties people encounter while selecting suitable skincare beauty products online is the lack of personalized recommendations. The impact of such products is mainly based on an individual's skin type, tone, and personal preferences. Regardless of the booming demand for customized cosmetic solutions, current online systems often fail to offer accurate and user-specific suggestions. There is a clear need for an immaculate and intelligent system capable of classifying skin type and tone effectively and efficiently and leveraging that information to recommend appropriate cosmetic products. Addressing this gap can significantly enhance user experience and decision-making in online cosmetic shopping. By successfully substituting the pooling layer seen in conventional CNNs, a Strid CNN can lower the overall complexity of the model.

2. Related Work

This section discusses different research papers based on cosmetic product suggestions, skin type classification, skin tone, and face shape identification using deep neural network models, specifically CNN. S. Umer (2020) here author [10] uses 40 different cosmetic products and clicks the image of the product using a mobile phone. The proposed algorithm takes input images and recognizes the product's brand, product and availability. They also perform some analytical tasks for brand and retail recognition. In another research, the author uses a deep neural network model. [16] That system suggests the makeup style on the user's facial image and also shows how that particular makeup looks on their face. Unlike other research, they use 961 females in an image database, one image before makeup and one after makeup. This large database makes this system more efficient.

R. Iwabuchi (2017) [18] On a number of websites, consumers give reviews. For example, when a person tries to search for skin products on the @cosme website, users read reviews from users with the same characteristics (such as age, skin type, etc.) to find products that align with the skincare routine she follows.

For example, a user with dry skin may seek out a lotion known for its hydrating properties, while someone interested in skin brightening will look for products with positive reviews regarding their whitening effects. Users often assume that the compatibility between themselves and a skincare product depends on its ingredients.

H. Gunaasighe (2016) [7] proposed a technique based on machine learning to identify face shapes for beauty-related activities like hairstyle, makeup, and eyeglasses. It is required to know about face shape. The author proposed a neural network that actually identifies the face shape of a person by taking a person's image. The author considers some types of face shapes, i.e. Diamond, Triangle, Inverted Triangle, and Oval, and oblong, square and round face shapes.

In C. L. Chin (2018) [14], the author suggested a deep learning approach using Convolution Neural Networks (CNNs) for the classification of facial skin images. It builds a system for skin image classification that aims to address some skin problems, such as whether skin quality is good or not, bad facial skin quality, and different makeup for the face.

It does this by using a smartphone and detects facial skin type. As per the result, a model with three convolution layers, three pooling layers, and four fully connected layers gets the maximum recognition rate, according to the results. When the system is finished, anyone can use it to improve their own facial skin problems. C. J. Holder (2019) [13] author in this paper author proposed a Siamese convolution neural network.

The main aim here of the system is to propose a vision-based system that can recommend cosmetic products. In the era of big data and deep learning, recommender systems like this are important to predict a person's preferences. Here, the author creates data from 91 persons, takes images of them, and crops the eye area because they mainly focus on mascara products. The system takes the eye area as input and, as a result, produces an output of a product preferred by the persons whose eyes are visually similar.

According to C. H. Hsia (2020), appearance matters to everyone. The primary researcher of the investigation recommended a system that evaluates the degree of acne and the skin on the face to provide product recommendations to customers. [24] In this instance, a camera takes a picture labeled and shows it in a window so that the customer can confirm that it shows the image in the right location. This paper's suggested method accurately determines skin type and detects acne on both cheeks. In addition, the system counts the quantity of acne scars after determining if the skin is normal, oily, or dry. It may include a chatbot that can interact with clients in the future. This aids customers in selecting the ideal cosmetic item.

B. Lokesh (2024) [34] The author discusses open-ended issues while contrasting approaches and theoretical frameworks. The study uses a certain research methodology, outlining the steps involved in data collecting and analysis. Although sample size, data availability, and potential biases are noted constraints, the dataset is supplied with reliability. By expanding on earlier research, the study adds fresh perspectives to scholarly discussions. It analyzes earlier research critically, pointing out patterns and discrepancies. Limitations point to potential directions for further study. The writers highlight the importance of their research while improving methods and putting forth fresh frameworks to further academic debates.

J. Lee [27] In order to promote skincare products, the author's work investigates Collaborative Filtering (CF) with Singular Value Decomposition (SVD). User ratings for five skincare categories are included in the dataset, which was gathered via web scraping Female Daily. Data preprocessing, SVD model training, RMSE-based validation, and hyperparameter adjustment are all part of the methodology. Although SVD predicts ratings well, it has drawbacks, such as sparse data and omitting skin type concerns. In contrast to previous CF approaches, the study validates the accuracy of SVD while pointing out possible biases in rating data that could impact tailored suggestions.

In modern times, cosmetics have a significant impact on the personal appearance of individuals. However, selecting the best skin care product is becoming challenging. Therefore, there is a requirement for a predictive approach that helps to understand which is the best product for which skin type and tone. To solve this problem, a deep learning algorithm will be used because it performs well under high volumes of unstructured data and generalizes with excellent results [30-32].

Kavitha et al. (2023) [29] introduced an AI model to analyze skin conditions and suggest cosmetics, though accuracy was not specified. Kavyashree et al. (2022) [30] developed a machine learning-based system with around 85% accuracy. Ray et al. (2022) [31] used deep learning for feature extraction, achieving about 90% accuracy. Bhuvana et al. (2022) [32] employed CNNs to classify skin types with 88% accuracy. Rajegowda et al. (2023) [33] combined AI with extended reality for personalized routines. Lee et al. (2024) [27] integrated ingredient analysis with deep learning, reaching 92% accuracy.

3. Dataset

3.1. Human Facial Image Dataset

The dataset consists of 3,152 frontal facial images of humans aged between 20 and 60 years. It is broken into three sections: training dataset, testing dataset, and validation purposes. For the training dataset, 1,000 images of oily skin, 1,104 images of normal skin, and 652 images of dry skin were used. The testing set includes 40 images of oily skin, 59 images of skin, and 35 images of dry skin.

For validation, 84 images of oily skin, 111 images of normal skin, and 71 images of dry skin were utilized. In total, the dataset comprises 1,274 normal skin types images, 1,120 oily skin types images, and 758 dry skin types images. Data augmentation strategies like rotation, scaling, flipping and color adjustment enrich the dataset. An augmented dataset consisting of 3408 images of human faces.

An additional dataset-which contains 305 dark-deep frontal human face pictures, 500 medium-tone, and 500 fair-light pictures-is used for skin tone classification. The dataset is initially separated into 261 photos for testing and 1,044 images for training.

However, a data augmentation approach is applied because of the dataset's tiny dimensions. The dataset has been expanded with 2,088 pictures for training and 517 images for testing after being improved using the ImageDataGenerator program.

Features such as label, brand, name, price, rank, ingredients, skin type, and skin tone are all included in the dataset of cosmetic products. 298 moisturizers, 281 cleansers, 209 eye creams, 266 facial masks, 171 sun protection items, and 247 treatments are all included. This extensive dataset provides useful details on various skincare products, allowing for an analysis of their characteristics and effectiveness based on different requirements, like skin tone and type.

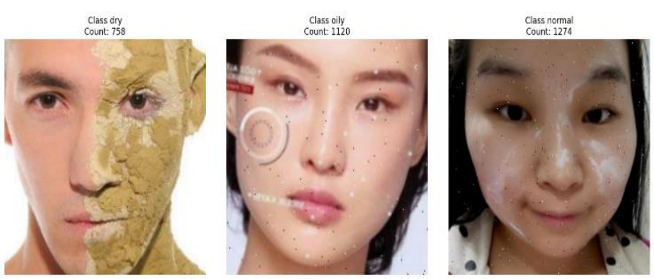


Fig. 2 Different skin types

Fig. 3 Different skin tone

4. Proposed Model

4.1 Proposed Recommendation System

Figure 4's flowchart provides an approach to detect skin tone and type to make customized product suggestions. The proposed system is a couple of databases and machine learning models to provide accurate results and efficient suggestions. Two key datasets were used: one for Skin Tone and another for Skin Type. Then, employ a significant machine learning model called Strid Convolutional Neural Network (Strid-CNN). The proposed model is trained on the above-mentioned datasets.

Convolutional neural networks that have been designed to help with the exclusion of dimensionality and the extraction of features from images are known as Strid convolutional neural networks or Strid-CNNs. The unique Strid convolution methods of Strid-CNNs basically distinguish them. These methods eliminate the need for an additional pooling layer by allowing the network to directly reduce the sample size of the maps of features throughout the convolution process.

One pixel at a time, with a step size (Strid) of 1, the convolutional layers of a typical CNN slide a filter, named a kernel, across the input features map. The Strid value in Strid-CNNs is set to a value larger than 1, like 2. This means the filter skips over pixels, effectively reducing the spatial dimensions of the feature map. For example, if the input feature map is 32x32 and the Strid is set to 2, the output feature map becomes 16x16. A facial image is entered into the system to begin the workflow. The technique separates the face from the backdrop by recognizing it in the image using the D-lib package. Bounding boxes are then used to crop the identified face to highlight the relevant area. The Strid-CNN model, which learns to categorize skin tone and type, is then trained using these cropped facial photos. The model is retained for use in the prediction step after it has been trained.

During the prediction stage, the system kicks off by loading the pre-trained Strid-CNN model to analyze a fresh facial image. Like in the training stage, first, detect the face and crop it to focus on the facial region. The trained model then inspects the cropped image to find the user's skin tone and type. This information is important because it describes key features of the user's skin, like tone and texture, that are important for making customized recommendation systems.

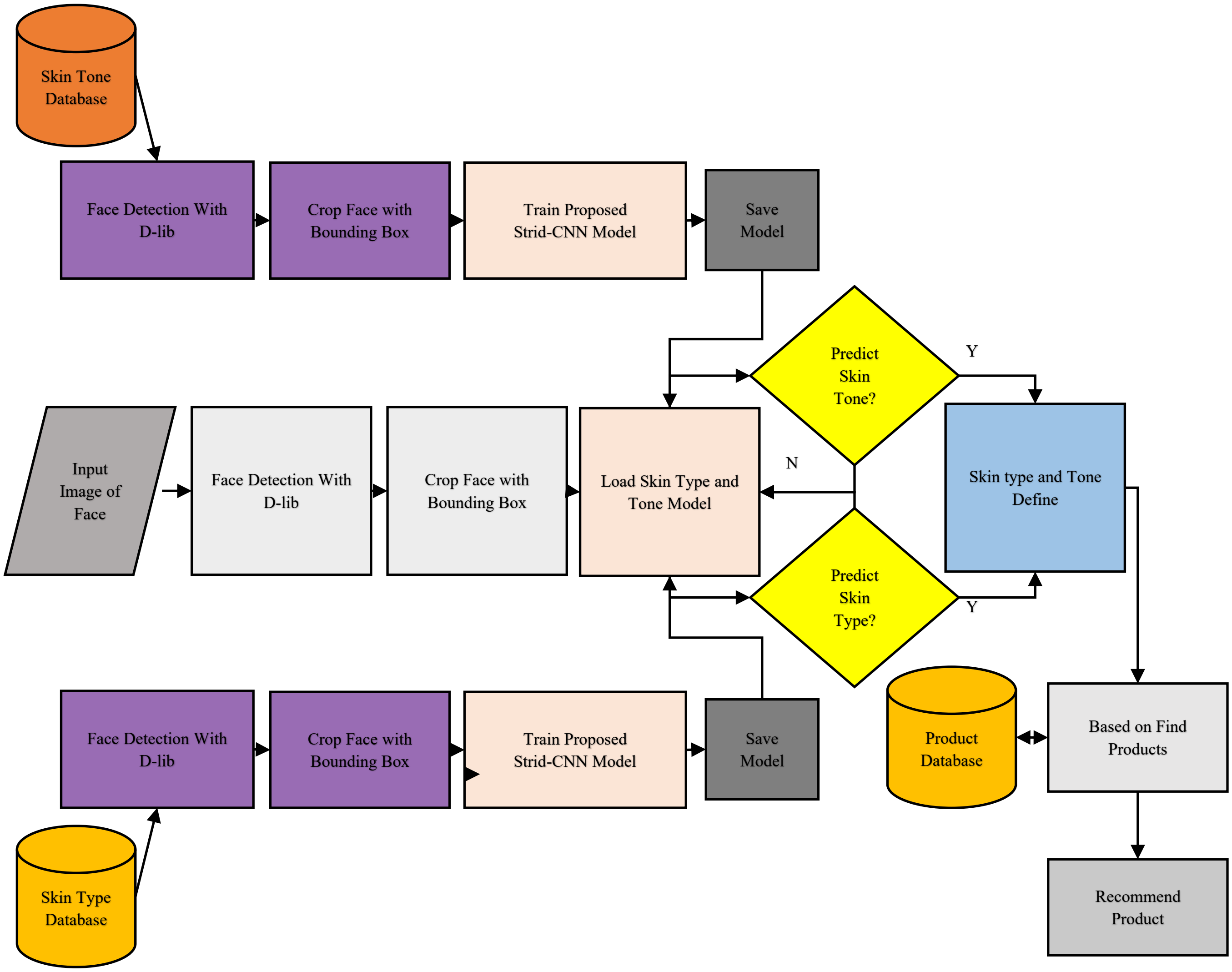


Fig. 4 Proposed model architecture using Strid CNN

Once the system predicts a human's skin tone and type, it will check the list of available products. Features such as label, brand, name, price, rank, ingredients, skin type, and skin tone are all included in the dataset of the cosmetic products system, which selects products that fulfil your particular needs by contrasting your anticipated skin characteristics with the database. Finally, it recommends these items, providing a personalized and appropriate experience.

The proposed model uses specific datasets for skin tone, skin type and cosmetic products and advanced deep learning algorithms to provide correct predictions and personalized suitable product recommendations. First, it will detect the face and, using the D-lib library, detect features that are needed for analysis. This approach enhances the model's overall accuracy, helping it analyze all facial images efficiently. The comprehensive Product Database includes even more value. The algorithm then matches this database with the predicted skin features to recommend products personalized to individual user's needs. The main aim of this research is to classify frontal human face images based on skin type and tone and finally build a robust system to suggest skincare products, ensuring customer satisfaction and safety.

4.2. Strid CNN Architecture

TensorFlow and Keras libraries build a Strided Convolutional Neural Network (CNN). The model uses a Conv2D layer featuring 128 filters and a kernel size [7, 11]. The model employs a stride of [2, 2] and padding set to the same to keep the original spatial dimensions of the input image intact.

After introducing non-linearity with a LeakyReLU activation function (set to an alpha of 0.1), added a MaxPooling2D layer was used to reduce spatial dimensions. The next layers consist of several Conv2D and LeakyReLU pairs to dig deeper into feature extraction. Also included more convolutional layers with filter sizes of [5, 5] and [1, 1]. To downsample the feature maps after these layers, and again used MaxPooling2D. The Conv2D layers in this model use both [1, 1] and [3, 3] kernel sizes to pull out features, along with ReLU activation and pooling operations to enhance the design. After going through several convolutional and pooling layers, use a flattened layer to simplify the output. Then, have two Dense layers that work with this flattened output. The first of these layers has 4096 units and employs a ReLU activation function. To help combat overfitting, there's a Dropout layer set at a rate of 0.5. Finally, the last Dense layer, designed for multi-class classification, has three units and uses a Softmax activation function. Adam optimizer is used to build a model, which works great for tackling multi-class classification problems. It runs on a learning rate 0.0001 and relies on categorical cross-entropy for measuring loss. Use accuracy as a metric to track how well the model is performing. This setup allows us to process and categorize complex image data into three distinct groups. The model architecture overview below will show you the number of parameters and how the layers are configured. Thanks to its strong performance and ability to scale, this model is perfect for a wide range of computer vision tasks that involve multi-class categorization.

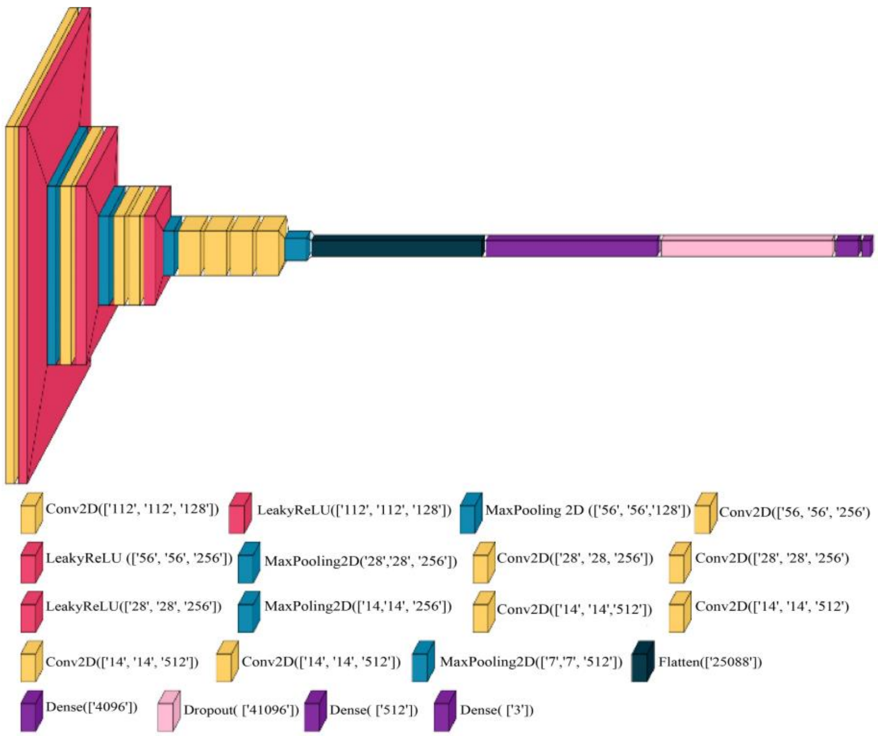


Fig. 5 Strid CNN architecture

A Strid CNN architecture designed for image classification or similar tasks is depicted in Figure 5. After processing an input image, the network uses convolutional layers to extract features, pooling layers to reduce dimensionality, and dense layers to make decisions.

4.3. The Model's Architecture Looks Like This

4.3.1. Input Layer

The network begins with an input image, likely sized 112×112x112 \times 112x112×112, as indicated by the first convolutional layer.

4.3.2. Convolutional Layers

Each Conv2D block applies a set of filters to extract features from the input image. These layers increase in depth (e.g., 128, 256, 512 filters) as the network progresses, capturing increasingly complex features. The convolutional layers operate with the Rectified Linear Unit (ReLU) or LeakyReLU activation functions, introducing non-linearity to enhance feature learning.

4.3.2. Activation Layers

LeakyReLU layers follow the convolutional layers to mitigate the "dying ReLU" problem, ensuring gradients flow even for small input values.

4.3.4. Pooling Layers

MaxPooling2D layers are interspersed to downsample the spatial dimensions of feature maps (e.g., reducing from 56×5656 \times 5656×56 to 28×2828 \times 2828×28). This operation reduces computational cost and emphasizes the most prominent features.

4.3.5. Flatten Layer

The flattened layer reshapes the final feature map into a 1D vector, preparing it for fully connected layers.

4.3.6. Fully Connected Layers

Two dense layers with 4096 and 512 neurons, respectively, process the flattened feature vector. Dropout is applied to prevent overfitting during training. The final dense layer with 3 neurons corresponds to the output classes, making predictions based on the learned features.

4.4. Flow of Data

- The input undergoes sequential transformations through convolution, activation, pooling, and flattening.
- The spatial resolution decreases progressively while the depth (number of filters) increases, ensuring robust feature extraction.
- The fully connected layers aggregate the extracted features to produce class probabilities or scores.

This architecture is used for applications like image classification, where feature extraction and hierarchical abstraction are essential. It works well with high-dimensional picture data because it strikes a compromise between computing efficiency and the ability to recognize intricate patterns. To strengthen the novelty claim, the article should explicitly define the architecture shown in Figure 5, referred to as the 'Strid CNN' model. This architecture must be clearly distinguished from traditional CNNs regarding structure and performance enhancements. Figure 5 illustrates a Strid CNN architecture designed for deep feature extraction and robust classification.It consists of multiple Conv2D layers with increasing depth (from 128 to 512 filters), paired with LeakyReLU activations to handle negative gradients and prevent dead neurons. Strategic MaxPooling2D layers reduce spatial dimensions and computational load while maintaining key features. A Dropout layer follows the fully connected Dense layer with 4096 units to reduce overfitting. Finally, the network includes two additional Dense layers for further abstraction and classification, ending in a 3-class output (as seen in Dense [3]), likely corresponding to skin types or tones.

4.5. Annotated Novel Contributions

- Customized strides and pooling: The repeated pattern of convolution followed by pooling at progressively smaller spatial resolutions (e.g., from 112×112 down to 7×7) enables hierarchical feature abstraction with controlled dimensionality.
- Use of LeakyReLU: Enhances gradient flow compared to ReLU, reducing the risk of dead neurons in deeper layers.
- Deep fully connected block (Dense [4096] + Dropout [4096]): Offers a strong regularization mechanism and powerful feature representation before classification.
- Balanced depth and complexity: With a total of over 250,000 flattened features and deep, fully connected layers, the model leverages deep learning capacity while incorporating regularization techniques to prevent overfitting.

5. Result Analysis

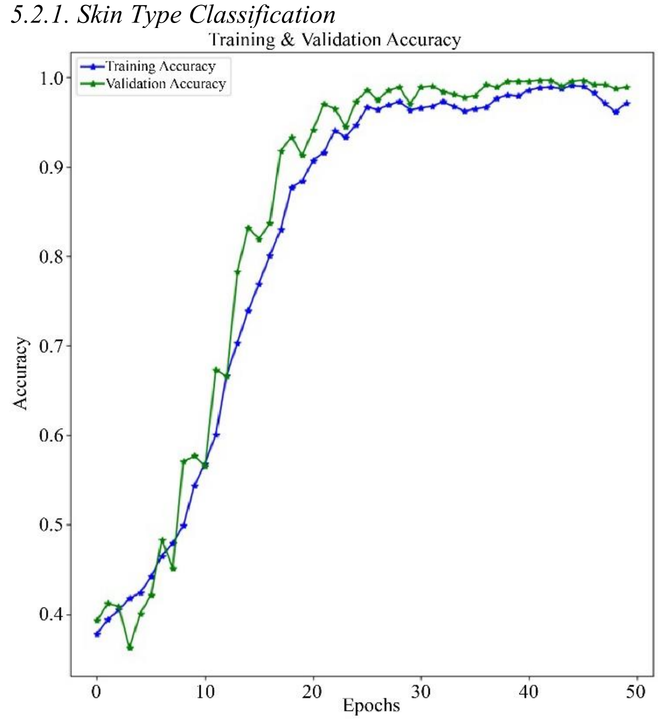
5.1. Experimental Setup

The proposed model uses Google Colab, a cloud-based platform that gives us access to powerful hardware. Using an NVIDIA Tesla T4 GPU, which really speeds up the model training by allowing for parallel processing in deep learning tasks. For building and training models, use TensorFlow 2.x, which is totally compatible with Keras and offers an easy-to-use, high-level API. Coding is done in Python 3.x, version 3.7, to guarantee it works seamlessly with modern libraries and frameworks. The environment is all set up with hardware accelerators like the GPU, which increases computational efficiency, especially when training large neural networks. Using GPU, it will be easy to handle large datasets and perform tasks like image classification with deep convolutional networks much more efficiently and quickly.

The images used to train the model are sorted into three main skin types: normal, dry, and oily. Each type is further divided by specific skin tone characteristics, like medium-tone, fair-light, and dark-deep. This classification helps the model analyze and recognize different skin tones and types from the photos. There's a recommendation system focused on cosmetic products that suggests the best items for various skin types and tones. By pinpointing these traits, the model can provide personalized recommendations for skincare and makeup products, so users get suggestions that really fit their unique skin profiles. This method ensures more accurate and relevant product recommendations, improving the cosmetic industry's customer experience.

5.2. Results

5.2.1. Skin Type Classification



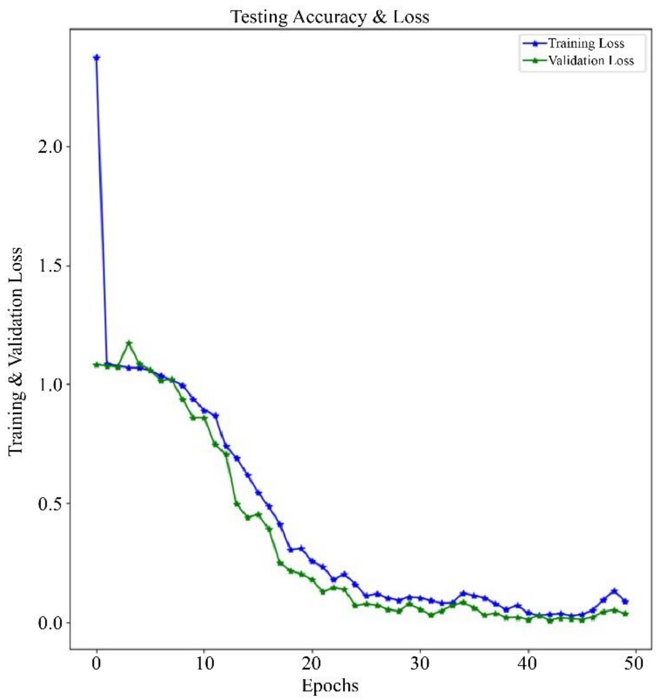
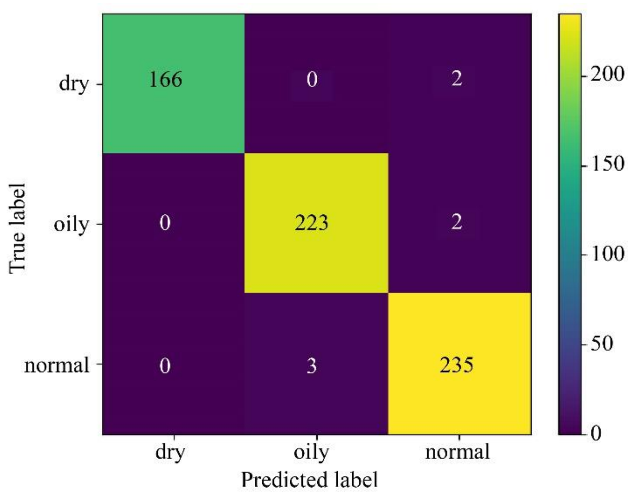


Fig. 6 Skin type classification performance graph



	precision	recall	fl-score	support
dry	1.00	0.99	0.99	168
oily	0.99	0.99	0.99	225
normal	0.98	0.99	0.99	238
accuracy			0.99	631
macro avg	0.99	0.99	0.99	631
weighted avg	0.99	0.99	0.99	631

Fig. 7 Skin type classification confusion matrix

5.2.2. Skin Tone Classification

The skin type and tone classification model is not overfitting, as observed from the training and validation accuracy and loss graphs [Figures 6 and 8]. Both accuracy curves converge and remain closely aligned throughout training, reaching high accuracy (~1.0) without divergence. Similarly, the training and validation losses decrease steadily and stay close to each other, indicating good generalization to unseen data. The training accuracy, loss curves, and performance on an independent test set indicate that the model is well-generalized. The training and validation accuracy curves rise steadily and remain closely aligned, suggesting effective learning without overfitting.

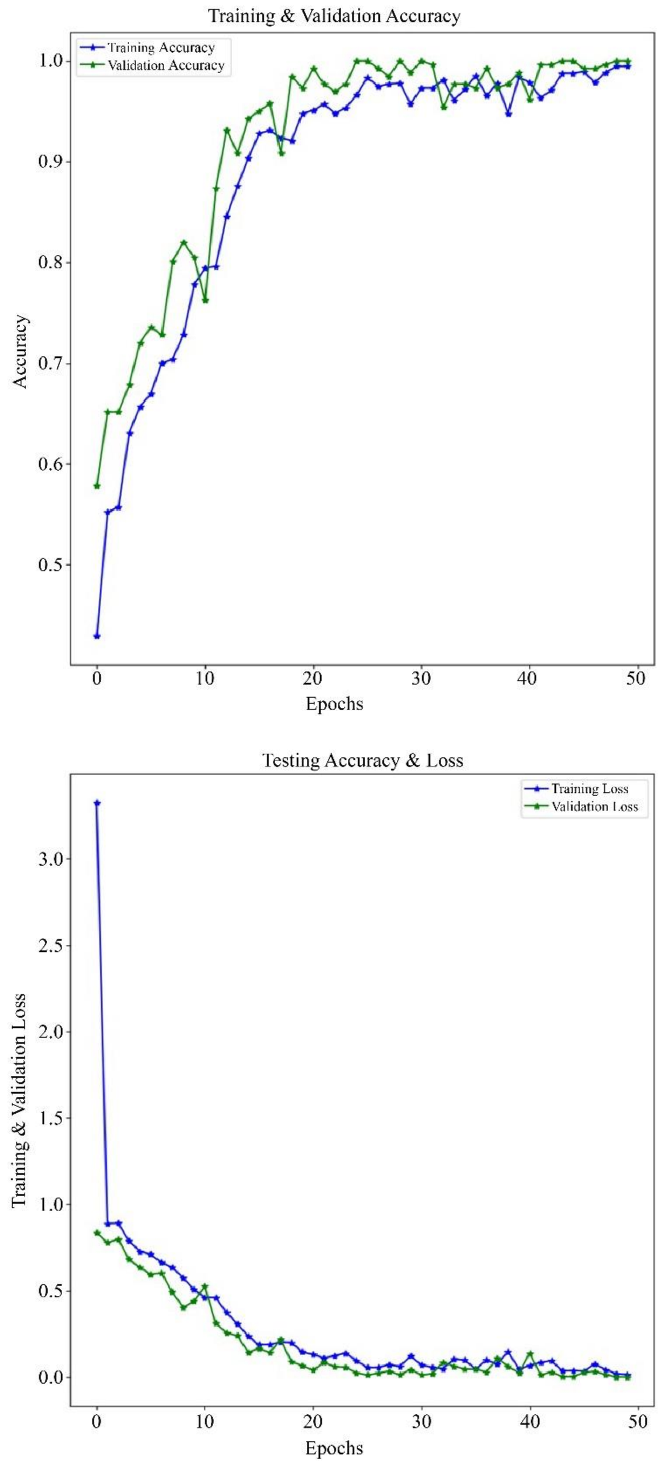
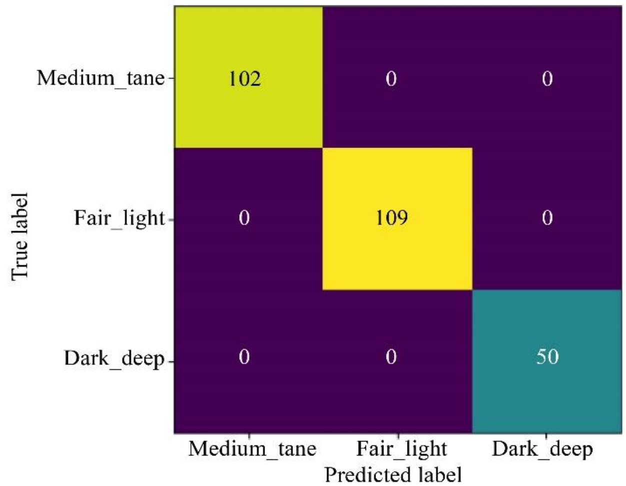


Fig. 8 Skin Tone classification performance graph



	precision	recall	f1-score	support
Medium_tane	1.00	1.00	1.00	102
Fair_light	1.00	1.00	1.00	109
Dark_deep	1.00	1.00	1.00	50
accuracy			1.00	261
macro avg	1.00	1.00	1.00	261
weighted avg	1.00	1.00	1.00	261

Fig. 9 Skin tone classification confusion matrix

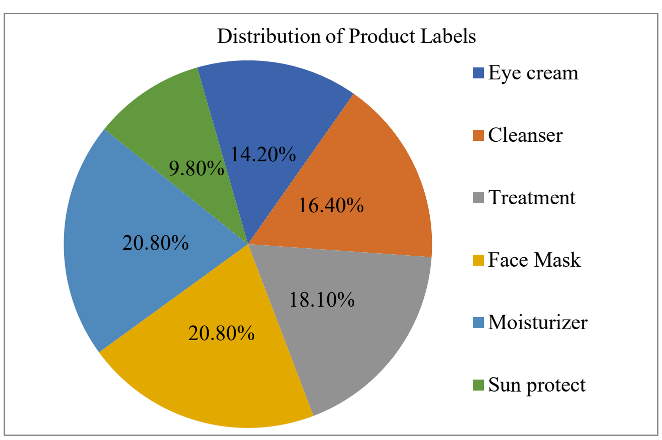
5.2.3. Predict & Recommendation

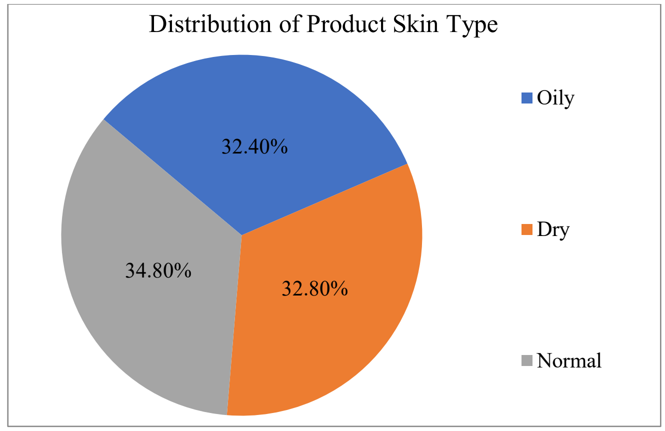
Cosmetic Product Dataset used here is

	Label	Brand	Name	Price	Rank	Ingredients	SkinType	SkinTone
0	Moisturizer	LA MER	Crème de la Mer	175	4.1	Algae (Seaweed) Extract, Mineral Oil, Petrolat...	Dry	Medium
1	Moisturizer	SK-II	Facial Treatment Essence	179	4.1	Galactomyces Ferment Filtrate (Pitera), Butyle...	Dry	Medium
2	Moisturizer	DRUNK ELEPHANT	Protini™ Polypeptide Cream	68	4.4	Water, Dicaprylyl Carbonate, Glycerin, Ceteary...	Dry	Dark
3	Moisturizer	LA MER	The Moisturizing Soft Cream	175	3.8	Algae (Seaweed) Extract, Cyclopentasiloxane, P...	Dry	Medium
4	Moisturizer	IT COSMETICS	Your Skin But Better™ CC+™ Cream with SPF 50+	38	4.1	Water, Snail Secretion Filtrate, Phenyl Trimet...	Dry	Medium
...	...	...	...	...	...	...	...	...
4403	Sun protect	MOROCCANOIL	After-Sun Milk Soothing Body Lotion	28	4.7	Water, Caprylic/Capric Triglyceride, Glycerin,...	Oily	Dark
4404	Sun protect	SUPERGOOP!	Perfect Day 2-in-1 Everywear Lotion Broad Spec...	19	4.8	-Homosalate 10%, Octinoxate 7.5%, Octisalate 5...	Oily	Dark
4408	Sun protect	IT COSMETICS	Anti-Aging Armour™ Super Smart Skin-Perfecting...	38	4.1	Water, Cyclopentasiloxane, Butyloctyl Salicyla...	Oily	Medium
4411	Sun protect	KORRES	Yoghurt Nourishing Fluid Veil Face Sunscreen B...	35	3.9	Water, Alcohol Denat., Potassium Cetyl Phospha...	Oily	Medium
4415	Sun protect	DERMAFLASH	DERMAPROTECT Daily Defense Broad Spectrum SPF 50+	45	0.0	Visit the DERMAFLASH boutique	Oily	Medium

2758 rows × 8 columns

Fig. 10 Recommendation dataset





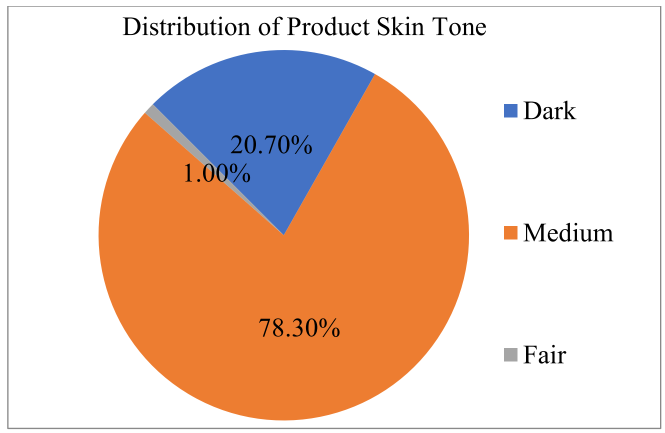
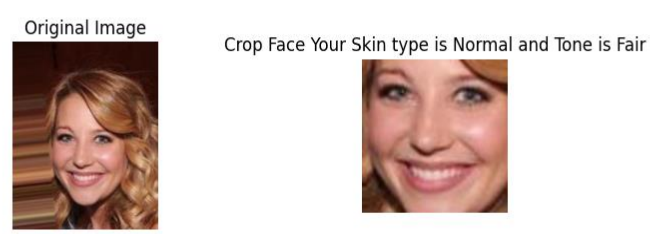
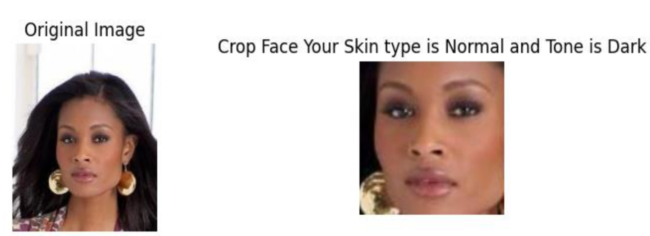


Fig. 11 Dataset distribution




```
Available Product Labels:
Moisturizer, Cleanser, Treatment, Face Mask, Eye cream, Sun protect

Please enter the product label you want: Moisturizer

Available Brands for the selected Label:
DRUNK ELEPHANT, BELIF, FRESH, IT COSMETICS, OLEHENRIKSEN, TARTE, BOBBI BROWN, HERBIVORE, GLAMGLOW, AMOREPACIFIC, SMASHBOX, KIEHL'S SI

Please enter the brand you want: FRESH

Final Filtered Products:
```

	Label	Brand	Name	Price	Rank	Ingredients	SkinType	SkinTone
1495	Moisturizer	FRESH	Black Tea Firming Overnight Mask	92	4.1	Water, Glycerin, Butylene Glycol, Jojoba Ester...	Normal	Dark



```
Available Product Labels:
Moisturizer, Cleanser, Treatment, Face Mask, Eye cream, Sun protect

Please enter the product label you want: Treatment

Available Brands for the selected Label:
DRUNK ELEPHANT, SUNDAY RILEY, DR. DENNIS GROSS SKINCARE, GLAMGLOW, OLEHENRIKSEN, KIEHL'S SINCE 1851, HERBIVORE, MURAD, KATE SOMERVILLE, PETER THOM

Please enter the brand you want: DRUNK ELEPHANT

Final Filtered Products:
```

	Label	Brand	Name	Price	Rank	Ingredients	SkinType	SkinTone
2051	Treatment	DRUNK ELEPHANT	C-Firma™ Day Serum	80	4.1	Water, Ethoxydiglycol, Ascorbic Acid, Glycerin...	Normal	Dark
2062	Treatment	DRUNK ELEPHANT	B-Hydra™ Intensive Hydration Serum	52	4.2	Water, Coconut Alkanes, Ammonium Acryloyldimet...	Normal	Dark
2081	Treatment	DRUNK ELEPHANT	D-Bronzi™ Anti-Pollution Sunshine Drops	36	4.5	Water, Hydrogenated Polyisobutene, Glyceryl Ol...	Normal	Dark

Original Image

Crop Face Your Skin type is Normal and Tone is Medium

```
Available Product Labels:
Moisturizer, Cleanser, Treatment, Face Mask, Eye cream, Sun protect

Please enter the product label you want: Eye cream

Available Brands for the selected Label:
ESTĒE LAUDER, SHISEIDO, WANDER BEAUTY, FRESH, DIOR, BELIF, KATE SOMERVILLE, AMOREPACIFIC, ERNO LASZLO, DR. BRAN

Please enter the brand you want: FRESH

Final Filtered Products:
```

	Label	Brand	Name	Price	Rank	Ingredients	SkinType	SkinTone
2636	Eye cream	FRESH	Lotus Eye Gel	48	3.8	Sea Water, Butylene Glycol, Caprylic/Capric/Su...	Normal	Dark

Original Image

Crop Face Your Skin type is Dry and Tone is Fair

```
Available Product Labels:
Moisturizer, Cleanser, Treatment, Face Mask, Eye cream, Sun protect

Please enter the product label you want: Eye cream

Available Brands for the selected Label:
DRUNK ELEPHANT, SHISEIDO, KIEHL'S SINCE 1851, OLEHENRIKSEN, FRESH, BELIF, ORIGINS, TATCHA, CLINIQUE, SATURDAY SKIN, IT COSMETICS, SK-II, DR.

Please enter the brand you want: OLEHENRIKSEN

Final Filtered Products:
```

	Label	Brand	Name	Price	Rank	Ingredients	SkinType	SkinTone
1097	Eye cream	OLEHENRIKSEN	Banana Bright Eye Crème	38	4.2	Water, Simmondsia Chinensis (Jojoba) Seed Oil,...	Dry	Medium
1155	Eye cream	OLEHENRIKSEN	Uplifting Transformation™ Eye Crème	42	3.9	Visit the OLEHENRIKSEN boutique	Dry	Medium

Original Image

Crop Face Your Skin type is Oily and Tone is Dark

```
Available Product Labels:
Moisturizer, Cleanser, Sun protect

Please enter the product label you want: Cleanser

Available Brands for the selected Label:
BELIF

Please enter the brand you want: BELIF

Final Filtered Products:
```

	Label	Brand	Name	Price	Rank	Ingredients	SkinType	SkinTone
3422	Cleanser	BELIF	Problem Solution Toner	28	4.3	Water, Dipropylene Glycol, Butylene Glycol, 1,...	Oily	Fair

5.2.4. Result Analysis

Table 1. Performance comparison of existing methods and proposed Strid CNN

Method_Name	Accuracy	Precision	Recall	F1_score
Collaborative Filtering [35]	80%	0.75	0.70	0.72
Deep Neural Network [36]	83%	0.578	0.574	0.575
XR (Extended Reality) [37]	93%	0.878	0.8	0.83
CNN [38]	97%	0.93	1.0	0.96
Proposed Strid CNN	98.8%	1.00	0.99	0.99

The above table shows the result analysis between the existing system and the proposed Strid CNN model. On the parameters of Accuracy, Precision, Recall and F1-score the proposed model performance is better than the existing systems.

6. User Experience

Nowadays, everyone uses different e-commerce platforms to make purchases online. This has a lot of information, and users utilize that knowledge to buy the products. They found selecting the ideal skin care product challenging because it completely depended on the user's preferences and skin type. The proposed method is easy for the end user to use; they can enter a face photograph, and the model will recognize their skin type as normal, dry, or oily. After learning their skin type, the user can choose a cosmetic product based on skin tone and type. In contrast to other models, the suggested model is effective for both male and female users. Additionally, sensitive personal information like a user's skin appearance, medical history, lifestyle details, etc., is frequently needed for AI-powered skin care products.

7. Conclusion

Recommending the finest skincare products requires accurately detecting and anticipating skin type and tone. This study investigates many transfer learning models for classifying skin tone and type. Compared to current models, the suggested Strid CNN model showed noticeably higher accuracy and dependability, suggesting possibilities for accurately identifying human skin types (normal, dry, and oily) and skin tones (medium tan, fair/light, and dark/deep).

The suggested model serves Individual needs and preferences, which provides more individualized skincare advice. This study emphasizes how crucial model refinement is to getting better outcomes. Future research will incorporate more algorithms into the suggested Strid CNN models to increase the accuracy of the suggestions for beauty products. A more thorough grasp of each person's skincare requirements will be possible as a result, and users will receive product recommendations that are optimized. In the end, research advances customized skincare treatments and improves the user experience while choosing cosmetic products.

7.1. Future Research Direction

Future models with more features, such as skin texture and hydration level, maybe more accurate. It is also possible to incorporate other demographic parameters.

Researchers can use hybrid models, such as vision transformers, to enhance the entire model's performance and efficiency. Also, future researchers can increase the cosmetic product dataset by adding more brands, and different products can be more usable for the end users.

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