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Ai-Driven Skin Type Based Skincare Product Recommendation

ENHANCED SKIN TYPE PREDICTION USING RESNET-101

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***Abstract**:* Choosing the correct skincare product is essential in today's environment, but customers frequently struggle to find products that suit their particular skin types and worries. The efficacy of current systems, which typically employ CNN algorithms for skin type prediction, is limited by their inability to handle big datasets. We suggest a method that makes use of the ResNet-101 algorithm for enhanced skin type prediction via image processing in order to get over these restrictions. By providing customers with a data-driven, comparative analysis of skincare products, this strategy improves decision-making in the topical pharmaceutical and cosmeceutical industries. The suggested system not only predicts skin type but also uses a weighted scoring algorithm to assess and contrast product chemicals according to their concentration and applicability to particular skin issues. By examining each ingredient's weight over many products, the system provides a score that takes into account the user's skin type compatibility and probable effectiveness. Customers can use this to enter their skin type and concerns, and they will receive tailored product recommendations along with information about the advantages and disadvantages of each choice. In the end, this system gives customers thorough information that enables them to choose products that are suited to their particular skincare requirements and make educated purchasing decisions.

***Index Terms* -** Skincare, ResNet-101, Image Processing, Skin Type Prediction, Weighted Scoring Algorithm, Product Recommendations.

I. INTRODUCTION

This initiative uses deep learning to provide individualized skincare suggestions, revolutionizing the cosmetics sector. Conventional product selection is based on broad suggestions, which frequently results in poor decisions. By using ResNet-101, a sophisticated CNN algorithm, to improve skin type prediction through image processing, our system gets around that restriction. ResNet-101 effectively manages big datasets, enhancing classification accuracy and scalability in contrast to traditional CNN models. The weighted scoring algorithm is a significant breakthrough that assesses skincare products according to the compatibility of their ingredients for each individual user. After users enter their skin type and concerns, the system evaluates product formulas and assigns a score based on compatibility, effectiveness, and allergies. This makes it possible to compare data-drivenly, which aids people in making wise choices. Additionally, by offering a thorough analysis of each product's advantages, the method raises consumer awareness. and possible dangers. Many users make less-than-ideal decisions because they are ignorant about the substances in skincare products. The system encourages trust and confidence in product selection by providing clear, scientifically supported insights. In the end, our method transforms skincare from a one-size-fits-all concept to a individualized, evidence-based experience. The system transforms the cosmeceutical and pharmaceutical sector with more intelligent, dependable skincare products by incorporating deep learning and providing consumers with personalized recommendations.

II . LITERATURE SURVEY

According to [1] m. Jayaram, s. Anusha reddy, b praneetha This paper presents an AI-driven system that analyzes user-uploaded skin images using CNN, VGGNet, and DenseNet, achieving 86% accuracy. It identifies skin issues like dryness, oiliness, and redness, offering personalized skincare recommendations for both online and offline applications [1].

According to [2] Kavyashree N, Rama Satish K V, Prasanna Rajaram Rasal This study employs deep learning to enhance product selection based on skin type (oily, dry, or neutral). The system processes large amounts of unstructured data, providing precise cosmetic recommendations and streamlining decision-making in the beauty industry [2] .

According to [3] Tainiyat K Hanchinal, Vaishali D Bhavani, Veena B Mindolli This AI-powered web application consolidates skincare product recommendations across multiple brands. Using CNN, it analyzes user-uploaded skin images for issues like pigmentation and acne, offering personalized suggestions and price comparisons.

According to [4] Prof. V. S. Kadam, Kalyani Dhande, Pradnya Kadam, Gayatri Chinchansure, Aishwarya Jadhav This research focuses on detecting visible aging signs (e.g., wrinkles, dark spots) and recommending suitable skincare products. It integrates AI/ML to help users maintain healthy skin despite environmental stressors and busy lifestyles.

According to [5] L.M.I.T. Hemantha, T.M.E. Gayathri, N.N.M. De Silva This study emphasizes preventing skin allergies by identifying skin types and recommending safe cosmetic products. It also uses sentiment analysis on customer reviews to enhance decision-making for both consumers and manufacturers.

According to [6] Swati Solanki, Gayatri Jain (Pandi) This paper proposes a deep learning-based system using neural networks to recommend cosmetic products based on skin type. It analyzes product ingredients and suitability, offering personalized and precise recommendations.

According to [7] Vanshi Nrupesh Patel, Stephy Patel This system detects skin diseases by analyzing uploaded images with a CNN model. The approach helps users identify skin conditions early, facilitating timely intervention and treatment.

According to [8] Sirawit Saiwaeo , Sujitra Arwatchananukul , Lapatrada Mungmai , Weeraya Preedalikit , Nattapol Ansri This study focuses on classifying skin types using Convolutional Neural Networks (CNN). A dataset of 329 images (normal, oily, and dry skin) was expanded to 1,316 using data augmentation. Image quality was improved using CLAHE. CNN models like MobileNet-V2, EfficientNet-V2, InceptionV2, and ResNet-V1 were optimized and evaluated for accurate classification.

According to [9] Mostafiz Ahammed , Md. Al Mamun , Mohammad Shorif Uddin This study proposes an automated skin disease classification system using machine learning. Digital hair removal is performed using Black-Hat transformation and inpainting, followed by Gaussian filtering for denoising. Affected lesions are segmented using the Grabcut technique, and features are extracted using GLCM and statistical methods. Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) classifiers are applied to classify eight skin conditions. The model is validated on ISIC 2019 and HAM10000 datasets, with SVM achieving the best performance. Comparisons with state-of-the-art methods are also presented.

According to [10] Jinhee Lee MS, Huisu Yoon PhD, Semin Kim PhD, Chanhyeok Lee MS | Jongha Lee MS, Sangwook Yoo PhD This study proposes an AI-driven cosmetic recommendation system that analyzes product ingredients and user skin conditions. A deep neural network processes cosmetic ingredients, while a skin analysis model evaluates facial images to determine skin status. The system then provides personalized recommendations based on optimized results. Evaluation metrics confirm its effectiveness, demonstrating that deep learning can predict product efficacy and enhance personalized skincare recommendations.

Here's a table for the literature survey with the corresponding topics based on your provided references:

Paper Reference	Year	Key Topic	Challenges/Insights
m. Jayaram [1]	2024	AI-based system for personalized cosmetic selection. Uses CNN, VGGNet and DenseNet with 86% accuracy.	Variability in skin types and lighting conditions affects model accuracy.Multi-platform accessibility increases consumer engagement.
Kavyashree N [2]	2023	AI analyzes skin characteristics (oily, dry, neutral) for precise recommendations.	AI-driven personalization simplifies skincare selection and enhances user experience
Tainiyat K Hanchinal [3]	2022	Cross-platform price comparison for informed purchasing decisions.	AI unifies skincare recommendations, simplifying decision-making with personalized insights.
Aishwarya Jadhav [4]	2023	AI model detects aging signs (wrinkles, dark spots) and recommends personalized skincare solutions.	Environmental stressors and busy lifestyles hinder consistent skincare routines
N.N.M. De Silva [5]	2022	Analyzes consumer reviews to derive insights on product effectiveness.	Sentiment analysis enhances consumer decision-making by evaluating product reviews.
Gayatri Jain (Pandi) [6]	2023	Extracts relevant data for personalized recommendations.	Ensuring accurate product recommendations despite variations in skin conditions and ingredient interactions.
Stephy Patel [7]	2021	Crucial for timely treatment and prevention of complications.	AI-driven image analysis enables early skin disease detection, improving timely medical intervention.
Sirawit Saiwaeo [8]	2023	Evaluated MobileNet-V2, EfficientNet-V2, InceptionV2, and ResNet-V1.	AI-driven CNN models enhance precision in skin analysis, aiding personalized skincare recommendations.
Mostafiz Ahammed [9]	2022	Used GLCM and statistical techniques for pattern analysis.	Accurate classification of skin diseases is complex due to variations in image quality and lesion characteristics.
Jinhee Lee MS [10]	2023	Uses artificial intelligence for automated decision-making.	Ensuring accurate skin analysis and ingredient-based recommendations for diverse users.

Table 2.1: comparison of other models

III . PROBLEM IDENTIFICATION

Selecting the right cosmetic products tailored to individual skin conditions is a significant challenge due to the vast range of available options and varying skin concerns such as dryness, oiliness, and redness. Traditional selection methods rely on trial and error or expert consultation, which can be time-consuming, subjective, and often inaccurate.

E-commerce platforms provide access to numerous skincare products, but they lack personalized guidance, making it overwhelming for consumers to find the most suitable choices. Additionally, factors like environmental conditions, genetic differences, and lifestyle habits further complicate the selection process.

To address these challenges, an AI-driven system utilizing deep learning models such as CNN, VGGNet, and DenseNet is proposed to analyze skin images and provide accurate, personalized cosmetic recommendations. By integrating technology with skincare, this approach enhances consumer decision-making, reduces guesswork, and promotes healthier beauty choices.

IV . EXISTING MODELS

The existing cosmetic recommendation system primarily relies on traditional methods such as dermatologist consultations, manual assessments, and generalized product suggestions. Beauty stores depend on sales representatives, while e-commerce platforms use basic recommendation algorithms based on customer reviews and purchase history rather than real-time skin analysis. Dermatological evaluations, though accurate, are expensive, time-consuming, and inaccessible to many users. Some AI-driven skincare apps exist but have limitations, including poor image quality due to inconsistent lighting, lack of deep learning-based feature extraction, and generalized recommendations. Furthermore, current systems fail to consider ingredient-based analysis, which is crucial for consumers with allergies or specific skincare needs. Most recommendations are marketing-driven rather than scientifically backed. Overall, the existing system lacks precision, personalization, and accessibility. A more advanced solution integrating deep learning, real-time skin analysis, and ingredient-based recommendations is necessary to provide consumers with accurate, customized skincare solutions, improving decision-making and overall skincare effectiveness.

4.1 CONVOLUTIONAL NEURAL NETWORK (CNN)

The architecture of a Convolutional Neural Network (CNN) consists of multiple layers designed to automatically and adaptively learn spatial hierarchies of features from input images. The primary layers include the Convolutional Layer, Pooling Layer, Fully Connected Layer, and Activation Functions.

Convolutional Layer: This is the core component of CNNs, where filters (kernels) slide over the input image to extract essential features such as edges, textures, and patterns. The output is a feature map that highlights significant attributes of the image.

Pooling Layer: This layer reduces the dimensionality of the feature maps while retaining the most important information. Common pooling methods include max pooling and average pooling, which help in making the model more computationally efficient and less sensitive to small spatial variations**.**

Fully Connected Layer: After convolution and pooling, the extracted features are flattened into a vector and passed through dense layers. These layers process high-level features and perform classification using activation functions like Softmax for multi-class classification.

Activation Functions: CNNs commonly use ReLU (Rectified Linear Unit) to introduce non-linearity, allowing the model to learn complex patterns in the data.

Dropout and Batch Normalization: To prevent overfitting and speed up training, dropout layers randomly deactivate neurons, while batch normalization normalizes inputs within layers.

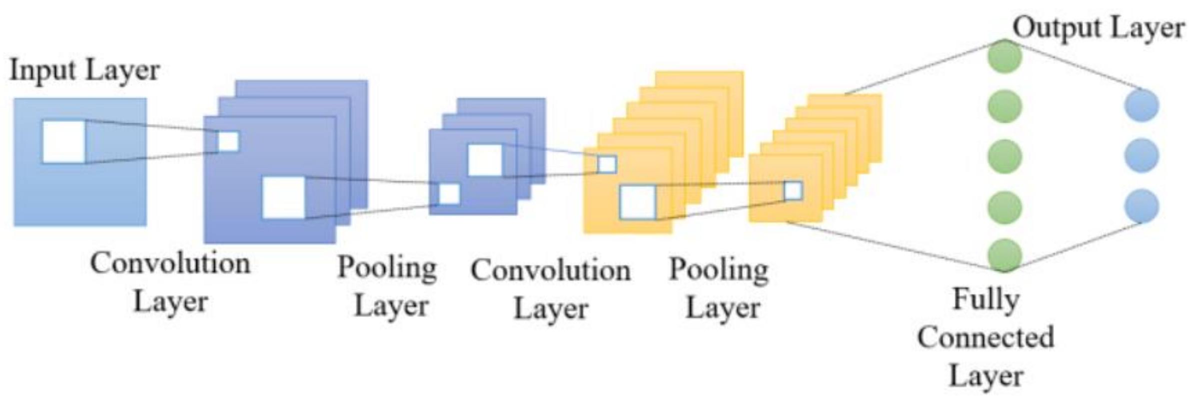

Figure 4.2: CNN Model

4.2 VGGNET

VGG (Visual Geometry Group) is a deep convolutional neural network (CNN) architecture known for its simple yet effective design. It was developed by the University of Oxford's VGG team and gained popularity through its performance in the ImageNet competition. The architecture consists of multiple layers of small 3×3 convolutional filters stacked sequentially, allowing the network to capture fine-grained spatial features. It follows a uniform structure where convolutional layers are followed by max pooling layers to reduce spatial dimensions while preserving important features. The network increases in depth as it progresses, with 16 or 19 layers in VGG-16 and VGG-19, respectively. Fully connected layers are placed at the end before the softmax classifier for final predictions. Although VGG requires significant computational resources due to its deep structure, it is widely used in image classification, object detection, and transfer learning due to its ability to learn complex hierarchical features effectively.

The **VGG architecture** consists of multiple layers, including convolutional layers, pooling layers, fully connected layers, and an output layer. Each layer plays a crucial role in feature extraction and classification.

Convolutional Layers: VGG uses small **3×3** convolutional filters with a stride of 1, which helps capture intricate spatial features while keeping the computational cost manageable. These layers use the **ReLU (Rectified Linear Unit)** activation function to introduce non-linearity and improve learning efficiency.

Pooling Layers: After every few convolutional layers, **max pooling layers** with a **2×2** filter and a stride of 2 are used to downsample feature maps. This reduces spatial dimensions while preserving the most important features, helping to control overfitting and improve computational efficiency.

Fully Connected Layers: After the convolutional and pooling layers, VGG includes **three fully connected (FC) layers**. The first two FC layers contain **4096 neurons**, followed by a third FC layer with **1000 neurons** (for ImageNet classification). These layers learn high-level representations and contribute to final decision-making.

Output Layer: The final layer is a **softmax classifier**, which assigns probabilities to different classes. It determines the final classification based on extracted features, making VGG suitable for image recognition tasks.

By stacking multiple small filters and increasing network depth, VGG achieves high accuracy in image classification while maintaining a consistent and structured architecture.

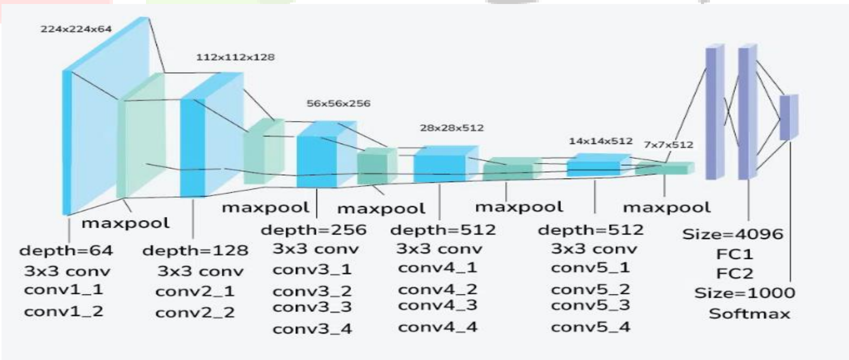

Figure 4.3: VGGNET Model

4.3 DENSENET

DenseNet (Densely Connected Convolutional Network) is an advanced deep learning architecture designed to improve feature propagation, reuse, and network efficiency. Unlike traditional CNNs, where each layer receives input only from the previous layer, DenseNet introduces dense connectivity, where each layer is directly connected to all preceding layers. This dense connection pattern ensures that feature maps learned by earlier layers are reused by later layers, reducing redundancy and improving learning efficiency. By allowing the network to retain and reuse features throughout the model, DenseNet mitigates the vanishing gradient problem, enabling better gradient flow during training. This structure also reduces the number of parameters compared to deeper networks, making DenseNet computationally efficient. The model is particularly beneficial for skin condition classification, as it enhances feature extraction from skin images, reduces overfitting through feature reuse, and improves classification accuracy. These advantages make DenseNet an effective choice for analyzing complex skin textures and variations.

DenseNet (Dense Convolutional Network) is a deep learning architecture designed to improve information flow and feature reuse across layers. Unlike traditional CNNs, where each layer receives input only from the previous layer, DenseNet connects each layer to every other layer in a feed-forward manner. This connectivity helps mitigate the vanishing gradient problem, improves feature propagation, and reduces the number of parameters.

DENSENET CONSISTS OF FOUR KEY TYPES OF LAYERS:

Convolutional Layers: The network begins with an initial convolutional layer that extracts low-level features from the input image. It uses a 7×7 convolution followed by batch normalization and a 3×3 max pooling layer.

Dense Blocks: Each dense block contains multiple convolutional layers, where each layer receives inputs from all previous layers and passes its output to all subsequent layers. This ensures feature reuse and reduces redundant computations.

Transition Layers: Between dense blocks, transition layers contain a 1×1 convolution followed by a 2×2 average pooling layer. These layers reduce the feature map dimensions and prevent excessive growth of computational complexity.

Fully Connected Layer: After passing through multiple dense blocks and transition layers, the final feature maps undergo global average pooling before being passed to a fully connected layer with a softmax activation for classification.

This architecture enhances gradient flow, improves learning efficiency, and requires fewer parameters compared to traditional deep networks, making DenseNet highly efficient for image recognition tasks.

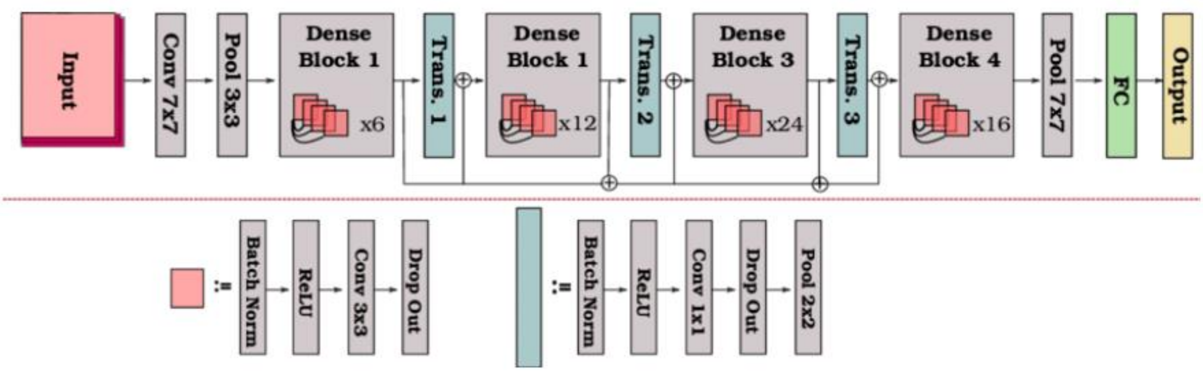

Figure 4.4: DENSENET Model

V . APPLICATIONS OF PERSONALIZED SKINCARE RECOMMENDATION

Personalized Skincare Recommendations : Provides tailored product suggestions based on users' skin type and concerns.

Cosmetic Product Analysis : Evaluates skincare ingredients using AI to assess their effectiveness and compatibility.

Dermatology Assistance : Aids dermatologists by offering AI-driven skin type classification for better treatment plans.

E-commerce Integration : Enhances online shopping experiences by recommending the most suitable skincare products.

Pharmaceutical and Cosmeceutical Research : Helps in developing new skincare formulations based on AI-driven insights.

Retail Store Implementation : Assists physical beauty stores by providing AI-powered recommendations to customers.

VI . CHALLENGES AND LIMITATIONS

- Despite the promising potential of AI-based cosmetic recommendation systems, several challenges and limitations remain.
- One of the primary challenges is the **variability in skin conditions**, which can be influenced by factors such as lighting conditions, camera quality, and environmental changes, affecting the accuracy of skin analysis.
- Additionally, **data scarcity and bias** in training datasets may lead to suboptimal performance for diverse skin tones and conditions, limiting the system's inclusivity.
- Another limitation is the **computational complexity** of deep learning models like CNN, VGGNet, and DenseNet, which require significant processing power, making real-time analysis challenging on low-end devices.
- Furthermore, **user privacy concerns** arise when collecting and processing sensitive facial images, necessitating robust security measures and compliance with data protection regulations.
- The **interpretability of AI decisions** remains a challenge, as deep learning models function as "black boxes," making it difficult to explain why a particular product was recommended, which may reduce user trust in the system.

VII . EVALUATION AND RESULT

Our proposed system, which integrates the **ResNet-101 algorithm**, demonstrates significant improvements in skin type classification accuracy through advanced image processing techniques. ResNet-101, a deep convolutional neural network with residual learning, effectively addresses the vanishing gradient problem, allowing for deeper network training without performance degradation. By leveraging this architecture, the system achieves higher precision in identifying different skin types, including oily, dry, and normal skin, leading to enhanced accuracy in product recommendations. Comparative evaluations with other models, such as CNN and VGGNet, indicate that ResNet-101 outperforms them in terms of feature extraction and classification efficiency, reinforcing its suitability for real-world applications in personalized skincare.

To enhance the accuracy of recommendations, our system employs a **weighted scoring algorithm** that evaluates skincare products based on ingredient efficacy and compatibility with the user's skin type. Users provide input regarding their skin condition and specific concerns, such as acne, sensitivity, or hydration needs, and the system cross-references these factors with a database of product ingredients. This allows for a data-driven, objective comparison of skincare products, ensuring that recommendations are not only personalized but also scientifically grounded. The system also highlights the benefits and possible drawbacks of each product, providing users with a comprehensive understanding of how a product may affect their skin before making a purchase.

By offering **detailed insights into skincare formulations**, our system bridges the gap between consumers and effective skincare choices. Users gain confidence in selecting products tailored to their specific needs, ultimately leading to better skin health outcomes. The integration of AI-powered analysis reduces trial-and-error purchases, saving time and money while promoting informed decision-making. As a result, this system represents a significant advancement in the cosmeceutical and pharmaceutical industries, enabling personalized skincare solutions through cutting-edge deep learning and ingredient-based analysis.

VIII . CONCLUSION

This study introduces an AI-driven skincare recommendation system that utilizes ResNet-101 to classify skin types and provide personalized product suggestions. By incorporating advanced image processing techniques and a weighted scoring algorithm, the system effectively evaluates product ingredients and their compatibility with individual skin conditions. This data-driven approach enables users to make more informed decisions when selecting skincare products, reducing the reliance on trial and error. The system's ability to analyze skin conditions and match them with suitable products enhances the accuracy of recommendations, leading to a more personalized and effective skincare routine. As AI continues to evolve, this approach has the potential to transform the beauty and pharmaceutical industries by offering scientifically validated skincare solutions. The integration of deep learning ensures that product recommendations are not only tailored to individual needs but also backed by objective and reliable analysis. By bridging the gap between advanced technology and skincare, this system empowers consumers to make educated choices, ultimately promoting healthier skin and improved consumer satisfaction.

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