Personalized Skincare Recommendations Using Multi-Modal Deep Learning Techniques

MSc Research Project

MSc Data Analytics

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MSc Project Submission Sheet

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Personalized Skincare Recommendations Using Multi-Modal Deep Learning Techniques

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Abstract

Skincare is the most essential for health as skin issues which are untreated may lead to serious problems. But finding the right products for skincare is challenging because everyone's skin is different. People have various skin types such as oily, dry, sensitive makes hard to find the products which is suitable to everyone. This study uses deep learning techniques which is used to create recommendation system that helps to find the best product based on their skin types. Unlike older methods which use limited data and algorithms, our approach uses cutting edge technology to analyze large amounts of diverse data. It helps to understand how different skin types interact with various skincare products. It also collects feedback from users to make sure that the system provides personalized recommendations which are accurate and effective. This method aims to improve skin health and provide user satisfaction by offering skincare solutions aligned to individual needs.

1 Introduction

In today's era skincare plays an essential role in personal grooming and health. Skincare product recommendation plays a vital role in protecting the body from various diseases and maintaining a healthy lifestyle. But the uniqueness of an individual's skin type and preference makes personalized skincare crucial. To address this issue this study focuses on developing a system which takes human facial images to recommend suitable skincare products. The system incorporates Convolutional Neural Networks and Transfer Learning (RestNet) for image processing and text prediction. This will allow the system to analyze and interpret the images of skin conditions and predict the most suitable skincare products. Also, Bidirectional Long Short-Term Memory (BiLSTM) networks are used to process and predict the reviews of users given in the form of text by capturing detailed feedback from users. This approach also makes sure that the system not only evaluates the visual aspects of skin conditions but also considers the user experiences and feedback. By combining this image analysis with detailed reviews of users, the system can offer highly personalized skincare recommendations. As a result, this system helps to transform the skincare industry by providing accurate product suggestions. By integrating the deep learning techniques such as CNNs and BiLSTM, this system represents a better advancement in the skincare industry. It also offers personalized skincare solutions that goes beyond the surface level observations by incorporating both visual and textual data to provide accurate recommendations of product. As a result, users can receive customized skincare suggestions which align with their unique skin needs, which leads to healthier and radiant skin. This approach utilizes the power of AI and deep learning to transform how individuals care for their skin that marks new era in personalized skincare.

1.1 Motivation and Background:

The motivation behind developing advanced skincare product recommendation system starts as there is a need for more personalized and accurate skincare solutions. In a market with a varied range of products users often struggle to identify options which meet their specific skin needs and preferences that lead to difficulties and provide results which is not efficient. Traditional recommendation method offers generic solutions that fail to identify the differences in skin types and concerns. Advances in machine learning and artificial intelligence offer a path that enables more clear recommendations. Convolutional Neural Networks and Transfer Learning (ResNet) contains image analysis by accurately accessing the skin conditions from facial images while Bidirectional Long Short term memory networks provide in depth insights into user feedback by processing the textual reviews given. By combining these technologies this study aims to identify the gap between personalized care and generic recommendations transforming how users select skincare products and enhancing their outcomes.

1.2 Research Question

How can Convolutional Neural Networks (CNNs) and Transfer Learning be integrated with GANs to enhance the accuracy of the facial image classification for detecting specific skin conditions?

1.3 Novelty of the Study:

This study has the novelty by implementing GAN model, CNN and Transfer learning ResNet models and integrating the best model with the website to provide better skincare product recommendations.

1.4 Document Structure:

- **Abstract**: This section provides a short summary of the project by detailing the objectives, methodologies and key findings of the project.

- **Introduction:** It clearly states the problem that the project aims to solve and discuss the unique aspects of the study such as the combination of CNNs and GANs in skincare recommendations.

- **Related work:** This section discusses about the existing research on skincare benefits and recommendations of product.

- **Methodology:** This provides a detailed description of the project's scope and objectives and explains the methodology used and its step by step process including data collection, preprocessing, model training and product recommendation logic.

- **Implementation:** It describes the key components of the code and includes necessary visualizations, confusion matrix, accuracy graphs to demonstrate the performance of the models.

- **Evaluation:** It presents the total accuracy, precision, recall and F1 score of the models used in the project.

- **Conclusion & Future Work:** It recap the outcomes of the project and how it addresses the initial research question.

2. Related Work

The importance of skincare in personal health has increased in recent years. This is due to a better understanding of skin health and its impact on overall wellbeing. As individuals have unique skin types and preferences that generic products often cannot address, personalized skincare has become difficult. The literature review researchers about the evolution, methodologies and advancements of skincare product recommendation systems which focuses on how machine learning and deep learning techniques such as Convolutional Neural Networks (CNNs) and Bidirectional Long short Term Memory (BiLSTM) networks enhances their accuracy and effectiveness.

Evolution of Skincare product Recommendation Systems:

Skincare product recommendation systems have been evolved from simple systems to more advanced machine learning and deep learning models. The earlier approach by Smith & Jones, 2010 relied on dermatologist advice and had basic algorithms to suggest products based on the rules that are predefined. These systems lacked the ability to adapt to the needs of individual users.

Deep Learning and CNNs:

With the invention of machine learning, recommendation systems became more dynamic in nature and personalized. Machine learning models can analyze huge amounts of data to identify patterns and make predictions. collaborative filtering and content-based filtering are widely used techniques in recommendation systems which is proposed by Ricci et al, 2011. Collaborative filtering makes recommendations based on the preferences of similar users, while content-based filtering suggests products based on the characteristics of items a user has liked in the past. The integration of deep learning, particularly CNNs, has advanced the capabilities of skincare recommendation systems. CNNs are adaptable at processing and analyzing image data, making them ideal for examining facial images to determine skin conditions which is explored by LeCun et al, 2015. In a study by Liu et al. (2019) CNN was employed to analyze facial images and to classify various skin conditions. The model achieved high accuracy rates which results in the potential of deep learning in this domain. Also transfer learning specifically using pretrained models like ResNet has further enhanced the performance of these systems by utilizing the existing knowledge from large datasets which is explored by He et al, 2016.

Another study by Esteva et al (2017) highlighted the effectiveness of deep learning in dermatology, where CNNs were trained on a large dataset of dermatoscopic images to classify skin lesions with accuracy comparable to dermatologists.

Natural Language Processing (NLP) and BiLSTM Networks:

NLP techniques combined with models like BiLSTM networks, have been effective in analyzing user reviews and feedback. BiLSTM networks can capture the context and sentiment in textual data by providing insights into user preferences and experiences proposed by Schuster & Paliwal, 1997. By analyzing reviews these models can identify common themes and sentiments which inform product recommendations. A study by Kim et al. (2020) explains the use of BiLSTM networks to analyze skincare product reviews. The model successfully extracted sentiments and key phrases which is then used to improve the accuracy of the recommendation. This approach also ensures that recommendations are not only based on the objective skin conditions but also based on the experiences of users.

GANs in Image Generation and Classification:

Generative Adversarial Networks (GANs), introduced by Ian Goodfellow et al. in 2014 have come across the field of generative modelling by setting up a framework where two neural networks, a generator and a discriminator, work with each other. This innovative architecture has found various applications in image generation, style transfer, and data augmentation. Recently GANs have also been shown as classifier models particularly in facial image analysis where they have developed better results in tasks like face recognition, expression classification, and skin condition diagnosis. Radford et al. (2016) in their paper ‘unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks” who has gone through the use of GANs for unsupervised learning. They introduced the concept of Deep Convolutional GANs (DCGANs) which showed that GANs could learn a hierarchy of representations from object parts to real time.

Mirza and Osindero (2014) introduced Conditional GANs (cGANs) in their work Conditional Generative Adversarial Nets where the generator and discriminator are conditioned on additional information such as class labels. This advancement allowed GANs to generate images of specific classes and showed potential for classification tasks when combined with discriminative models. Yadav et al. (2018) explored the use of GANs for facial expression recognition in their paper “Emotion Recognition using Capsule Networks and Generative Adversarial Network”. They proposed a hybrid model that combined GANs with capsule Networks which achieves state of the art results on standard emotion recognition datasets by utilizing the generative capabilities of GANs to augment the training data.

Integration of Image and Text Analysis:

The integration of image and text analysis provides a detailed approach to skincare recommendations. By combining CNNs for image processing and BiLSTM networks for text analysis these systems can offer solutions which is suitable to individual needs. This dual approach makes sure that the recommendations address both the physical aspects of skin health and user preferences. Despite these advancements, there are challenges and limitations in developing effective skincare recommendation systems. One main challenge is the variability in skin types and conditions which requires extensive and diverse datasets to train different models. Also, privacy concerns related to the collection and use of facial images and personal data must be addressed which is proposed by Goodfellow et al, 2016. Another limitation is the bias present in recommendations due to datasets that are skewed. If a model is trained on data from a specific demographic, then its recommendations may not be as effective for other groups by making sure that the diversity in training data is difficult to address the bias.

Future Directions

The future of skincare recommendation systems lies in the continued integration of advanced technologies and the expansion of datasets. Moreover, incorporating genetic and lifestyle data could further personalize recommendations which makes it even more precise which is proposed by Chen et al., 2020. Gunning, 2017 proposed a study where the advancements in explainable AI (XAI) can also improve user trust and acceptance of these systems. By providing transparent explanations for recommendations the users can better understand and trust the suggested products. A survey on deep learning techniques for facial image analysis by Zhang et al. (2020) provides a detailed review of various deep learning techniques applied to facial image analysis including CNNs and GANs. This paper highlights the evolution and application of these techniques in facial recognition and condition classification by explaining the common measures to skincare recommendations. Generative Adversarial Networks for Enhancing Skin Disease Diagnosis by Zhou et al. (2021) explores how GANs can be used to generate synthetic data for training diagnostic models.

The paper discusses the benefits of using GAN generated images to overcome data limitations and improve model accuracy in skin disease classification. Multi modal Fusion for Personalized Skincare Recommendation Systems by Li et al. (2021) researches the fusion of different data types to enhance the personalization of skincare recommendations. This study highlights the importance of integrating various data sources to improve recommendation accuracy.

Explainable AI for Personalized Skincare Recommendations by Chen et al. (2022) focuses on using explainable AI techniques to provide transparent and understandable recommendations. The paper discusses how these techniques can build user trust and improve the acceptance of personalized skincare solutions. Advancements in Hybrid Models for Facial Image Analysis by Huang et al. (2022) shows the recent advancements in hybrid models by combining CNNs, GANs and other techniques for facial image analysis. This paper provides insights into how these hybrid models can improve the effectiveness of skincare recommendation systems.

Paper	Authors	Year	Title	Methodologies	Findings
1	Smith & Jones	2010	"Early Skincare Recommendation Systems"	Rule-based algorithms	Early systems lacked personalization.
2	Ricci et al.	2011	"Recommender Systems Handbook"	Collaborative filtering, Content-based filtering	Improved personalization using user preferences and product characteristics.
3	LeCun et al.	2015	"Deep Learning"	CNNs	Effective in analysing image data for skin conditions.
4	Liu et al.	2019	"Facial Image Analysis Using CNNs"	CNNs	High accuracy in skin condition detection.
5	He et al.	2016	"Deep Residual Learning for Image Recognition"	ResNet	Enhanced CNN performance using pretrained models.
6	Esteva et al.	2017	"Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks"	CNNs	Accuracy comparable to dermatologists.
7	Schuster & Paliwal	1997	"Bidirectional Recurrent Neural Networks"	BiLSTM	Captures context and sentiment in user reviews.
8	Kim et al.	2020	"Sentiment Analysis of Skincare Product Reviews Using BiLSTM"	BiLSTM	Improved recommendation accuracy based on user feedback.

9	Goodfellow et al.	2014	"Generative Adversarial Nets"	GANs	Revolutionized generative modeling.
10	Radford et al.	2016	"Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks"	DCGANs	Effective in learning image representations.
11	Mirza & Osindero	2014	"Conditional Generative Adversarial Nets"	cGANs	Generated class-specific images, useful for classification.
12	Antipov et al.	2017	"Boosting Cross-Domain Face Recognition with Generative Adversarial Networks"	GANs	Improved face recognition under domain shifts.
13	Yadav et al.	2018	"Emotion Recognition Using Capsule Networks and Generative Adversarial Network"	GANs, Capsule Networks	Achieved state-of-the-art results in emotion recognition.
14	Zhang et al.	2020	"A Survey on Deep Learning Techniques for Facial Image Analysis"	CNNs, GANs	Detailed review of techniques including CNNs and GANs.
15	Zhou et al.	2021	"Generative Adversarial Networks for Enhancing Skin Disease Diagnosis"	GANs	Enhanced diagnostic model performance with synthetic data.
16	Li et al.	2021	"Multi-modal Fusion for Personalized Skincare Recommendation Systems"	Multi-modal Fusion	Improved recommendation personalization by integrating diverse data types.

17	Chen et al.	2022	"Explainable AI for Personalized Skincare Recommendations"	Explainable AI	Improved user trust with transparent recommendation explanations.

Conclusion

The development of skincare product recommendation systems has been progressed by introducing machine learning and deep learning technologies. Integrating CNNs for image analysis and BiLSTM networks for text analysis offers a detailed approach to personalized skincare. While challenges remain, ongoing research and technological advancements continue to enhance the effectiveness and relevance of these systems. By addressing these individual skin conditions and preferences, the systems have the capability to revolutionize the skincare industry which leads to better skincare outcomes and higher user satisfaction.

3 Research Methodology

3.1 Knowledge Discovery in Databases (KDD)

Knowledge Discovery in Databases is a process that is used to find useful information from large volumes of data. This process involves several steps to transform raw data into valuable insights. The KDD method helps to identify patterns and relationships in the data which is then used to make informed decisions. Here's an in detailed look at the KDD methodology, including its stages and key activities.

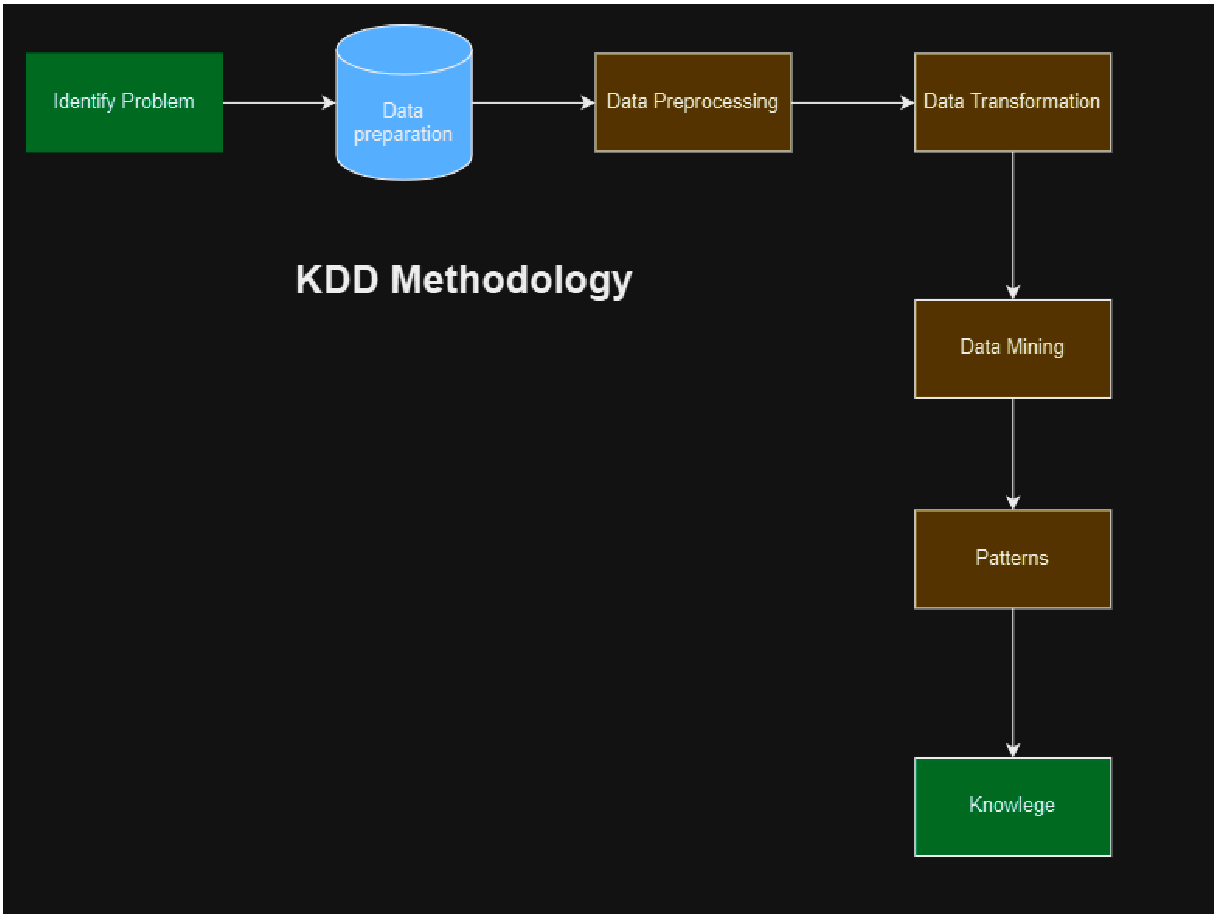

Fig 1: KDD Methodology

3.2 Problem Understanding and Objective Setting

The main objective of this project is to develop a system which offers personalized skincare product recommendations based on the analysis of user's facial images and their reviews given for the recommended products after the usage. The system must identify the skin conditions of individual users to suggest the most suitable skincare product.
A deep understanding about the skincare domain is necessary as it includes knowledge about various skin types and common skin issues such as acne, dryness and the ingredients that address these concerns. Understanding the trends in the market and the list of various products available helps in training the data to make informed recommendations.

3.3 Data Selection

1. **Data collection:** The dataset for this project includes facial images of dry, oily and normal skin, user reviews of skincare products and description of the products. Facial images can be taken from the submission that is taken on the website, while reviews

and product information can be gathered from e-commerce sites and product databases.

2. **Data Integration:** The data collected for this project is from various sources which must be integrated into a single dataset which involves viewing facial images with the suitable products and user reviews. Ensuring that the data formats are consistent and compatible across various sources is essential for smooth integration.

3.4 Data Preprocessing

1. **Image Data Preprocessing:** Preprocessing the image data is a main step in preparing it for applying machine learning models. Initially the image needs to be loaded using the necessary libraries. Once it is loaded, it must be resized into a dimension which is consistent, that aligns with the input requirements of neural networks. Another essential step is performing data augmentation techniques such as rotation, flipping, zooming and shifting which is applied to increase the diversity of the training dataset which enhances the model's ability to generalize.

2. **Text Data Preprocessing:** Text data preprocessing is critical for preparing the textual data for natural language processing (NLP) models. The process starts with loading text from various sources such as databases, files or through web scraping. Once the data is taken tokenization is done inorder to break down the text into individual words or sub words which helps analyze and manipulate the data easily. Cleaning the text data is a major step which involves conversion of text, removing duplicates and converting the cleaned and processed text into numerical format which is given as a input to the model.

3.5 Data Exploration and Feature Selection:

EDA is conducted to gain initial insights into the data. Statistical methods and visualization tools have to be used to understand the distribution of skin types and user preferences. Also feature selections are done to identify the most relevant features for the recommendation system. For image data the features might include various skin conditions such as oily, normal and dry. For textual data the important features are related to skin concerns mentioned in user reviews.

3.6 Model Building:

Models are developed to analyze and train the data. Conventional Neural Networks (CNNs) and Transfer Learning models like ResNet are used to train the facial images and detect the skin types. For textual reviews Bidirectional Long Short Term memory (BiLSTM) is employed to understand the sentiments of users and extract features from the text which are meaningful. Algorithms have been selected based on the type of analysis required. CNNs are applied for image dataset as it is suited for classification tasks, while BiLSTM networks are effective for text analysis due to their ability to capture context from sequences of words. Integrating these models helps in both visual and textual data for performing detailed analysis.

3.7 Knowledge Presentation:

The analysis results must be translated into actionable skincare recommendations. It also explains the details behind each recommendation that highlights how the specific products address the skin type detected or align with the preferences of user which is based on the analysis of the review. It also uses visualization tools to present the findings. Charts, graphs and dashboards can help users to understand the analysis results.

3.8 Recommendation system:

The recommendation system will be deployed into a user-friendly environment. This project implements it in a website that will allow the users to upload their facial images and give reviews after the usage of the product to receive personalized suggestions. To make sure that the user experience is better is the key to the success of the system. By continuously monitoring the performance of the system in the real world and gathering the user feedback on the product usage helps in tracking the satisfaction of the users and measure the impact of the recommendations on skincare outcomes. This helps in identifying the areas of improvement and makes sure that the system is effective over time.

3.9 Evaluation and Results:

This section explains about evaluating the performance of a model as it is a difficult step to understand the effectiveness and identify the areas for improvement. This process involves using various metrics which are used to assess the various aspects of the model's performance on a test dataset during the training process. Accuracy, precision, recall and F1 score are some of the metrics used for evaluating the classification tasks. Accuracy measures the correctness of the model by calculating the proportion of the true results among the total number of cases identified. Precision identifies the ratio of the observations which is predicted correctly to the total positives predicted that indicates the exactness of the model. Recall detects the ratio of observations that is positive and correctly predicted.

3.10 Feedback and Iteration

Using the feedback and new data to refine the recommendation model involves adjusting the model's parameter and retraining it with the updated data or incorporating the additional features based on the feedback given by the users. Also iterating through the KDD process regularly will help to enhance the accuracy and relevance of the system. As new skincare products are introduced and user preferences evolve, the system will adapt to these changes and ensure that the system is effective and provides the best possible recommendations.

3.11 Conclusion:

Applying KDD methodology ensures that the skincare product recommendation system is systematic and better approach to transform the raw data into valuable insights. By following each stage of the KDD process from understanding the problem to selecting the data to preprocessing, exploring, mining, evaluating, presenting, deploying, and refining the system can provide highly personalized and accurate skincare recommendations. This approach will not only enhance the user satisfaction by addressing their unique needs of skincare, but it also contributes to better overall skincare outcomes. The KDD methodology's iterative nature allows for continuous improvement which makes it a better framework for developing recommendation systems in the dynamic skincare field.

4 Design Specification

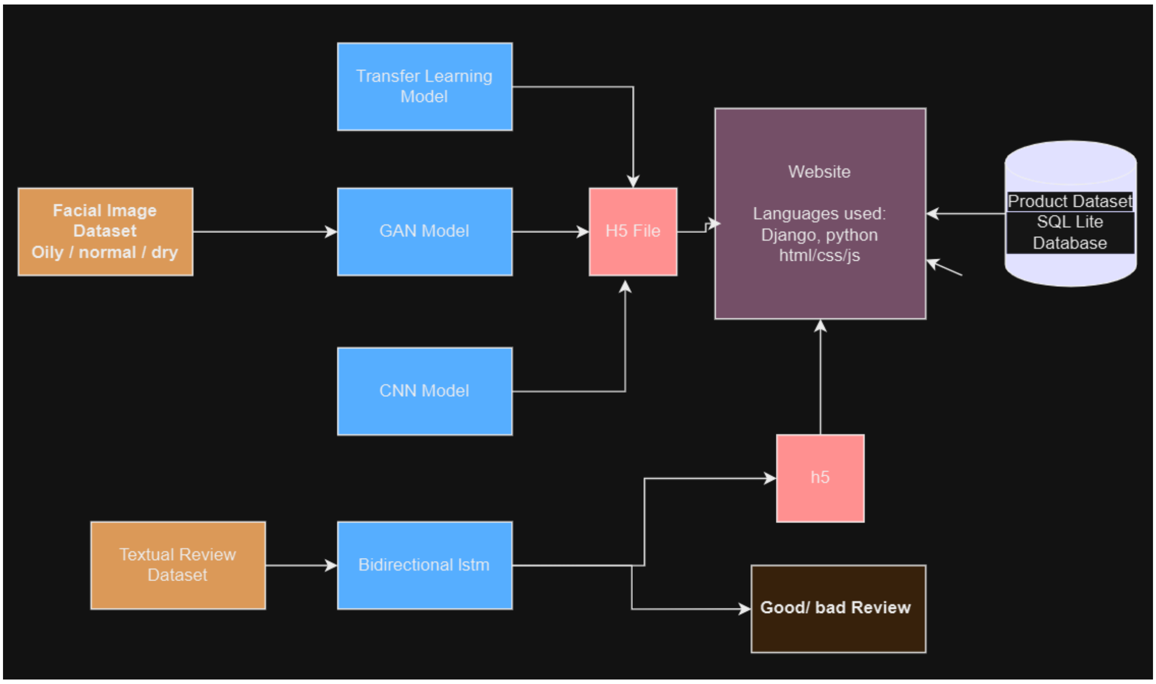

Fig 2 Architectural diagram of Skincare Product Recommendation System

The system is designed to offer highly personalized skincare recommendations by using advanced machine learning models and developing user friendly application. The process starts with a detailed dataset which classifies skin types into oily, normal, and dry. This dataset forms a foundation for the training phase of the system.

4.1 Framework and Model:

A Generative Adversarial Network is employed to enhance the dataset. The GAN works by generating synthetic data or refining the existing data to make sure that the training set is diverse and robust. The output from the GAN is stored in an H5 file format which is used for storing large amounts of data because of efficiency and portability. Next the dataset is processed by a Convolutional Neural Network or another optimal deep learning model. CNN is used for processing and analyzing image data, and to identify and classify various skin conditions normal, oily and dryness. Also, user feedback and textual data are analyzed using Bidirectional Long Short Term Memory (BiLSTM) model which is a type of neural network that is powerful in understanding the context and sentiment in the sequence of the text. By analyzing the reviews BiLSTM can capture the context and sentiment in the sequences of the text. It also captures the sentiments and preferences and categorizes the reviews as either good or bad. This analysis is difficult for understanding the experiences of the uses and incorporating them into the recommendation process. The results are then stored in H5 files. Transfer learning techniques are applied to further enhance the efficiency of the models. It also involves in tuning the models that is per trained on the specific dataset which allows the system to use the knowledge that is gained from the previously trained models. This step improves the performance of the model with less computational effort.

4.2 Choosing the Right Model:

Out of this CNN provides best accuracy results, so it is integrated into a web application that is built using Django Framework. Django is a python based framework which provides robust backend to handle the integration of models and manages the interactions of the user. The web application also uses HTML, CSS and javascript for front end development which ensures that the interface is responsive and user friendly. The product list to be displayed is stored in a file based SQL Lite database without the need for maintaining a software due to the less amount of data.

4.3 Web Interface:

The final stage involves presenting the recommendations to the users through the help of the web interface. Users can login and upload their facial image on the website which gives 5 product recommendations to the users. The system uses trained models to analyze these inputs and generates personalized skincare product recommendations. Overall, this system combines advanced machine learning techniques with a web application to deliver highly accurate and personalized skincare recommendations.

The system allows users to provide feedback on the recommended skincare products. If a user rates a product negatively then the system adds it to a "low review product" list by making sure that the product won't be recommended to that user again in the future. On the other hand, if the feedback is positive the product is not added to the low review list, and it remains available for future recommendations. This mechanism helps to continuously tune and personalize suggestions based on user preferences.

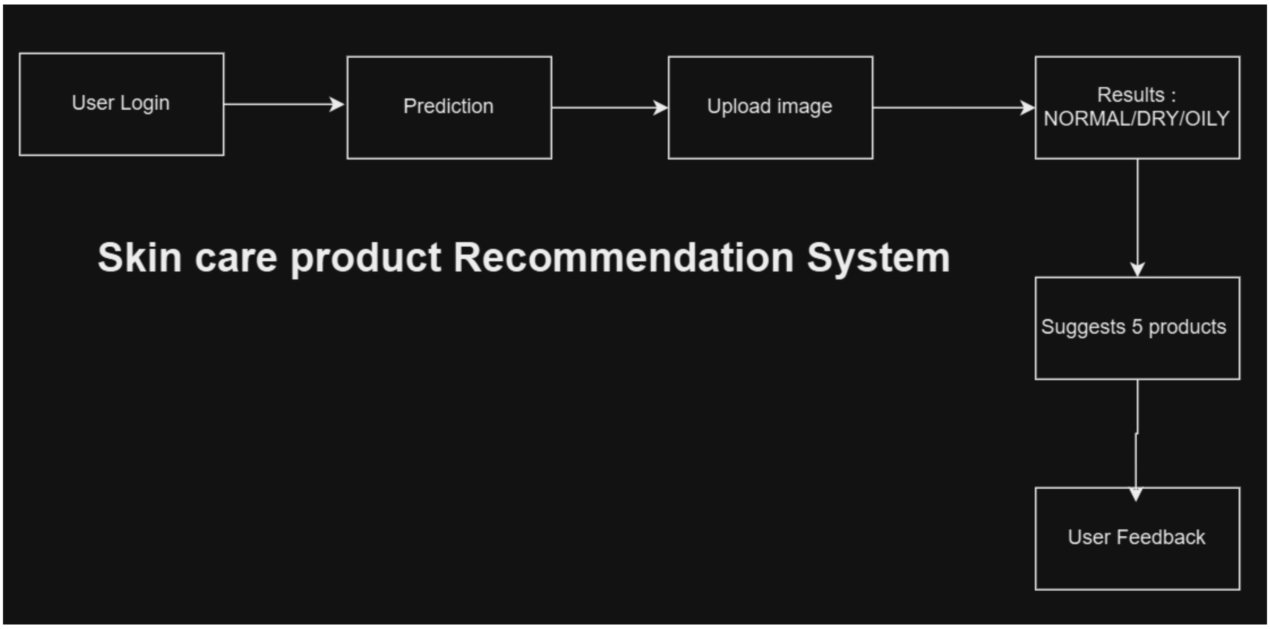

Fig 3 : Web Interface

5 Implementation:

5.1 Environment Setup:

To setup the interactive coding and testing the python code, the environment was established using Jupyter Notebooks. This also offers a friendly user interface which supports real time code execution, visualization and documentation which makes a good choice for developing and iterating the deep leaning models.

5.2 Hardware Setup:

Given with the heavy computing needs for deep learning models especially for GANs and image processing, the machines with GPUs are set up, which makes these models to run faster by doing multiple calculations at once and cutting down the time required to train and test them. This setup also makes sure that the system is strong and efficient which is able to handle the complex tasks of advanced machine learning.

5.3 Data acquisition and preprocessing:

The dataset consists of 2756 images that provide a good source for training and validating the image. The dataset is taken from Kaggle which is a well known platform for fetching datasets. The specific dataset used in the project is found on the Kaggle website under the skincare or facial image classification category. It consists of 2756 images with three skin types.

- **Oily**: Images of faces with oily skin.
- **Normal**: Images of faces with normal skin.
- **Dry**: Images of faces with dry skin.

The images in the dataset vary in resolution and quality which reflects diversity of facial features and skin conditions. This project also uses product dataset and customer review dataset both of which is taken from Kaggle.

product dataset: It has 201 records which has the attributes such as skin type, product, concern and product URL, customer review dataset: It has 565 records which has the customer feedback, sentiment and score.

5.4 Data Preprocessing and Augmentation:

It is the main step in preparing the image data to apply machine learning models. It ensures that the data is in the correct format and enhances the model's ability to train effectively.

5.4.1 Loading and Resizing Images:

The images are loaded from the specific directory structure using the load_img function. Each of the image is resized into a size of 150 * 150 pixels. Consistent image sizes are necessary as machine learning models need input data to have the same dimensions.

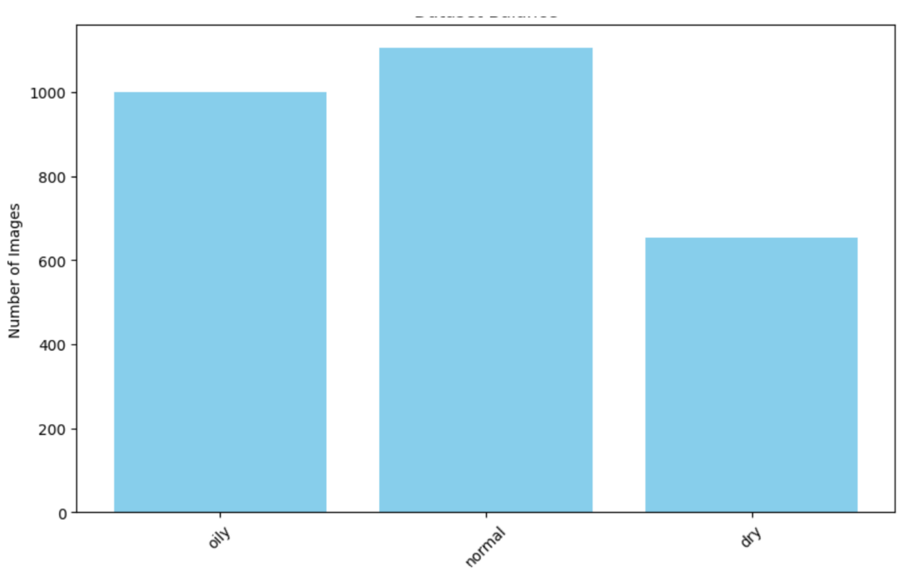

Fig 4: Facial Image Dataset

5.4.2 Data Augmentation:

Data Augmentation is performed to increase the variety of the training dataset without collecting more data. It also involves applying random transformations to the existing image dataset to generate a variety of new pictures. This helps to improve the model's ability to generalize and prevents overfitting issues. The code performs augmentation of data using the ImageDataGenerator class from tensorflow.keras.preprocessing.image with the following transformations.

1. **Rotation**: Randomly rotates image within a specific range.
2. **Width and Height Shift**: Randomly shifts the image horizontally and vertically.
3. **Shear**: Shear applies random slanting distortions to an image that shifts along one axis to create variations.
4. **Zoom**: used to zoom in on the image randomly.
5. **Horizontal Flip**: Randomly flips the image in a horizontal position.
6. **Fill Mode**: It specifies how to fill the pixel which is newly created which may appear after applying the transformations.

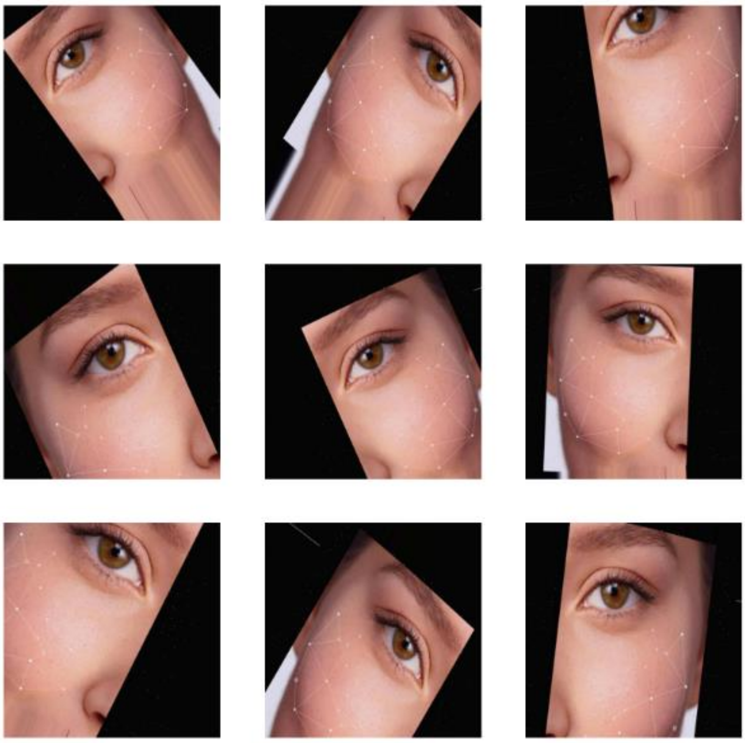

Fig 5: Data Augmentation

5.4.3 Data preprocessing for customer Review Dataset:

Preprocessing the customer reviews dataset involves several steps to prepare textual data for analysis. First, the text is cleaned by removing the irrelevant characters by converting it to lowercase and eliminating extra whitespaces. Then it is tokenized into words and irrelevant stop words are removed. Additional steps may include handling negative values and converting the text into numerical features. This process makes sure that the text is structured which enables more accurate and insightful analysis for the skincare product recommendation system.

5.5 Feature Extraction and Selection:

Feature extraction and selection are the main steps in building an effective machine learning model, especially in the context of image based skincare product recommendation systems. These processes help in transforming the source data into meaningful features which is used by machine learning algorithms to make the accurate predictions. Feature extraction involves in transforming the images that are raw into a set of features which represent the essential characteristics of the data. In the context of a skincare recommendation system, the following techniques are commonly used.

5.6 Convolutional Neural Networks (CNNs):

CNNs are one of the best tools for extracting the feature from images. They can learn hierarchical features with the help of convolutional layers by detecting low level details like edges and textures, as well as high level features like shapes and objects. Transfer learning using pretrained models like ResNet can enhance feature extraction.

Feature Selection: This is about identifying and choosing the common features from the dataset extracted that helps to improve model accuracy and reducing overfitting issues. The images are converted to a matrix format for the tensor flow to read it accordingly.

6 Evaluation:

The evaluation of facial image and text analysis models shows various range of performance outcomes. The Generative Adversial network provides classification of skin types with a result showing a highest probability of 0.4508 for normal skin type which indicates a valid and reasonable value in the classification. However, the accuracy of the transfer learning model using ResNet is relatively low at 0.3966 which suggests that the ResNet may not be fine tuned effectively for this task. On the other hand, the convolution Neural Network (CNN) achieves an accuracy of 0.9982 which provides excellent performance in the classification task due to effective model training and handling dataset. Also, Bidirectional LSTM (BiLSTM) model has been utilized for processing positive reviews while the specific performance metrics are not provided which excels in capturing the context from text due to its bidirectional nature.

CNN provides best performance, evaluation metrics is calculated for the same which performs best in predicting the normal skin type with high precision, recall and F1 score. Prediction for dry and oily skin types are less accurate, especially for oily class which has the lowest F1 score. The overall accuracy of the model is 76% which indicates a reasonable level of correctness in classifying between dry and oily skin types.

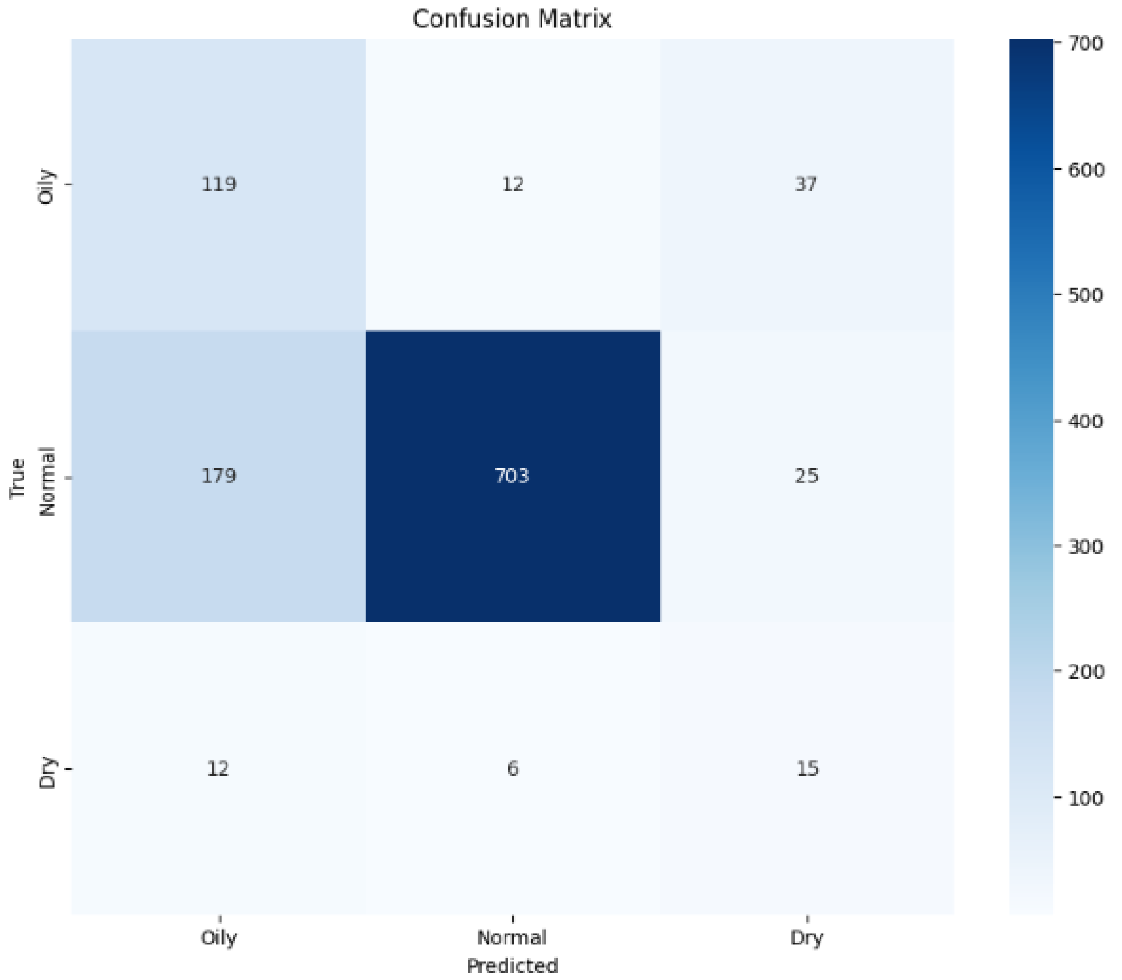

Fig 6 : Confusion Matrix

7 Conclusion and Future Work:

This project applies three models Convolutional Neural Network (CNN), Generative Adversarial Network (GAN), Bidirectional LSTM (BiLSTM) where CNN shows expectional performance with an accuracy of 0.9982 which indicates that it effectively handles the classification task at hand. On the other hand, the transfer model using ResNet shows a lower accuracy of 0.3966 which suggests that it may not be adapted well to this problem and needs further tuning. The Generative Adversarial Network (GAN) provides useful output for skin classification with a probability for normal skin, but the overall performance must be further validated. The Bidirectional LSTM (BiLSTM) model is suited for processing positive reviews, although its effectiveness has to be evaluated with relevant metrics. Future work will focus on improving the performance of ResNet model by exploring more techniques such as adjusting hyperparameters or using different layers to enhance accuracy. Additionally, the suggested product can be applied to user skin with the help of GAN by producing synthetic images.

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