ONTOLOGY BASED MACHINE LEARNING APPROACH FOR FACIAL SKINCARE PRODUCTS RECOMMENDATION

M. H. Maduri Hansanie

208526J

Degree of Master of Science in Artificial Intelligence

Department of Computational Mathematics

Faculty of Information Technology

University of Moratuwa

Sri Lanka

April 2023

ONTOLOGY BASED MACHINE LEARNING APPROACH FOR FACIAL SKINCARE PRODUCTS RECOMMENDATION

M. H. Maduri Hansanie

208526J

Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Artificial Intelligence

Department of Computational Mathematics

Faculty of Information Technology

University of Moratuwa

Sri Lanka

April 2023

DECLARATION

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature: Date:

The above candidate has carried out research for the PhD/MPhil/Masters thesis/dissertation under my supervision. I confirm that the declaration made above by the student is true and correct.

Name of Supervisor:

Dr. Thushari Silva

Signature of the Supervisor: Date:

DEDICATION

I would like to dedicate this thesis to my beloved parents, teachers and lecturers who have helped me and guided me throughout the journey of life.

ACKNOWLEDGEMENT

I would like to express my heartfelt gratitude to my supervisor Dr. Thushari Silva for providing guidance, comments, feedback, and vital support throughout the entire research in order to make it a success.

Furthermore, I would like to express my sincere gratitude to consultant dermatologist Dr. D.M. Amaratunga and Dr. Dilsha Chathuri for the help and support provided to get dermatological expertise knowledge.

Lastly, I would like to thank my parents, fellow colleagues, and all the lecturers of the Department of Computational Mathematics for their help and support throughout the research.

ABSTRACT

The need to preserve facial skin health and improve attractiveness has become more widespread in the modern world. There has been competition among skincare companies to research and create new products. The dynamic skincare market creates a wide range of skincare products to treat various skin disorders and skin types. Therefore, selecting the best skincare products suitable for a consumer’s skin type and condition is not an easy task. Consumers tend to seek suggestions from their friends, doctors, or favorite bloggers and frequently purchase expensive products that don't deliver the desired results. A user's skin impairment could worsen if products are utilized that contain ingredients that are inappropriate for the user's skin type and condition. In this study, we describe a unique system architecture for recommending facial skincare products that combine ontological and machine learning advantages. Our system hypothesizes that facial skincare product recommendations can be created as an AI solution using machine learning for identifying skin conditions, which was selected as acne severity since it is one of the most prevalent skin conditions dermatologists treat. A CNN model was developed to identify acne severity based on the user's facial image. As well as an ontology for modeling user profiles, skincare information, and skincare product information integrated from multiple sources using the Protégé ontology editor with hierarchical relationships. A user interface is also created that takes user inputs to allow for product customization and the recommendation of facial care products. The developed system had an accuracy of 87.5% based on the evaluation of the recommended products by a survey carried out with 24 participants. Additionally, medical experts reviewed the system's knowledge base to ensure reliable performance. Therefore, the proposed ontology-based ML approach is effective and accurate for facial skincare product recommendations.

Keywords: Ontology, ML, CNN, facial skincare products

TABLE OF CONTENTS

Declaration i
Dedication ii
Acknowledgement iii
Abstract iv
Table of Contents v
List of Figures ix
List of Tables x
List of Abbreviations xi
Chapter 1 1
Introduction 1
1.1 Prolegomena 1
1.2 Aims 1
1.3 Objectives 1
1.3 Background and Motivation 2
1.4 Problem Definition 3
1.5 Approach to skincare product Recommendations 3
1.6 System Requirements 4
1.7 Structure of the thesis 4
1.8 Summary 4
Chapter 2 6
Existing literature on skincare product recommendations 6
2.1 Introduction 6
2.2 Determinants of skin conditions 6
2.3 Determination of skin types 7
2.4 Facial skincare product types 8
2.5 ML based skin condition identification 9
2.6 Rule based skincare products recommendation system 10
2.7 State of the art skincare products recommendation systems 11
2.8 Analysis literature 14

2.9 Problem Definition 15
2.10 Summary 16
Chapter 3 17
Technology adopted 17
3.1 Introduction 17
3.2 Introduction to Ontology 17
3.3 Protégé 19
3.4 Convolutional Neural Network (CNN) 20
3.6 Google Colaboratory 22
3.5 Summary of the technology adopted 23
Chapter 4 24
Ontology-based ML approach for product recommendation 24
4.1 Introduction 24
4.2 Hypothesis 24
4.3 Input to the recommender system 24
4.4 Output 25
4.5 Process 25
4.6 Users 26
4.7 Features 26
4.8 Summary 26
Chapter 5 27
Design of facial skincare recommender system 27
5.1 Introduction 27
5.2 Top Level Architecture 27
5.3 Data collection for Ontology mapping 28
5.4 Data collection for ML engine 29
5.5 ML Engine 29
5.6 Ontology module 30
5.7 Recommendation Engine 32
5.8 User Interaction module 32
5.9 Summary 33
Chapter 6 34

Implemention of skincare recommendation system 34
6.1 Introduction 34
6.2 Developing the skincare recommender system. 34
6.3 ML Engine development 34
6.3.1 Data Acquisition 34
6.3.2 Data Preprocessing 35
6.3.3 Designing and Training Convolution Neural Network Model 36
6.4 Ontology development 37
6.4.1 Data Acquisition Ontology Model 37
6.4.2 Data Preprocessing for Ontology modelling 38
6.4.3 Ontology modelling 39
6.4.4 Skin Information ontology 41
6.4.5 User Profile 42
6.4.5 Skincare product ontology 42
6.5 UI development 46
6.6 Recommendation Engine 50
6.7 Summary 51
Chapter 7 53
Evaluation 53
7.1 Introduction 53
7.2 Experimental Design 53
7.3 Experimental Results 53
7.4 Conclusions of the experiment 56
7.5 CNN model evaluation 56
7.6 Summary 56
Chapter 8 57
Conclusion 57
8.1 Introduction 57
8.2 Conclusions 57
8.3 Limitations and Further Works 58
8.4 Summary 58
References 59

Appendix A 64
Product Information acquisition questionnaire 64
Appendix B 67
System evaluation questionnaire 67
Appendix C 71
Facial skincare recommender system User Interface 71
Appendix D 75
Code: Facial skincare recommender system 75

LIST OF FIGURES

Figure	Description	Page
Figure 3.1	Class hierarchy for the skin information class	18
Figure 3.2	The Protégé OWL plugin interface	20
Figure 3.3	Effect of a convolution operation	21
Figure 3.4	General CNN architecture diagram	22
Figure 5.1	Architecture diagram for product recommender system	28
Figure 5.2	Training CNN model in Google Colab	30
Figure 5.3	Ontology construction	32
Figure 6.1	Preprocessing data for ontology construction	39
Figure 6.2	Document analysis	40
Figure 6.3	Class hierarchy of *SkinInformation* class	41
Figure 6.4	Illustration of the skin information ontology	42
Figure 6.5	Illustration of the person ontology	42
Figure 6.6	Skincare product class hierarchy	43
Figure 6.7	Skincare domain ontologies hierarchy	44
Figure 6.8	Screenshot of SPARQL queries implemented	48
Figure 6.9	Screenshot of main system interface	49
Figure 6.10	Screenshot of product recommendation screen	49
Figure 7.1	Feedback of accuracy of product recommendation	54
Figure 7.2	Feedback of product personalization	54
Figure 7.3	Feedback of product familiarity	55
Figure 7.4	Feedback of product diversity	55
Figure 7.5	Feedback of UI interactivity	55
Figure 7.6	Feedback of overall satisfaction of system	55

LIST OF TABLES

Table	Description	Page
Table 6.1	Object properties	45
Table 6.2	Data type properties	46

LIST OF ABBREVIATIONS

Abbreviation	Description
AHA	Alpha Hydroxy Acid
AI	Artificial Intelligence
BHA	Beta Hydroxy Acid
BSTS	Baumann Skin Typing System
CNN	Convolutional Neural Network
CBF	Content Based Filtering
CF	Collaborative Filtering
ES	Expert System
GPU	Graphics Processing Unit
GUI	Graphical User Interface
IDE	Integrated Development Environment
ML	Machine Learning
OTC	Over The Counter
OWL	Web Ontology Language
PHP	Hypertext Processor
TF-IDF	Term Frequency – Inverse Document Frequency
UI	User Interface
UV	Ultraviolet

CHAPTER 1

INTRODUCTION

1.1 Prolegomena

At present, skincare is a global interest shared by both men and women. The skincare industry has seen an increase in demand and popularity due to the rising investments made in the research and development of novel skin care products. In 2021, the skincare industry was valued at USD 130.50 billion [1]. Additionally, the global market for facial care products, which accounts for 70.0% of the total global skin care industry, has experienced tremendous growth. In 2021, it had a USD 94.2 billion valuation [2]. The increased creation of facial skin care products has been sparked by people's growing knowledge of the value of preserving facial skin health while enhancing its appearance and preventing skin disorders [2]**.** The extensive and dynamic nature of the skincare market has created a dilemma for consumers in selecting skin care products that are suitable for their skin impairments and skin types. As a result, extensive research has been done to personalize and suggest facial care products based on customer feedback and skin diagnosis.

In this study, a hybrid strategy is put forth that combines the advantages of machine learning (ML) and ontology. The system analyzes skin conditions and skin types and makes suggestions for skincare products using methods of ML and ontological modeling.

1.2 Aims

The aim of this project is to design and develop a system for facial skincare products recommendation using machine learning and ontology.

1.3 Objectives

The following are the objectives identified for the ML and Ontology based hybrid solution for facial skin care products recommendation system.

- Critical review of literature in facial skincare domain and skin diagnosis.
- In-depth study of technologies adopted in facial skincare products recommender systems.
- Design an ontology-based machine learning approach for facial skincare products recommendation.

- Develop a prototype for recommending facial skincare products using the design ontology-based machine learning approach.
- Evaluate the prototype of the system.

1.3 Background and Motivation

The largest organ in the body, the skin's main function is to shield the body from environmental hazards such as UV radiation, dirty air, fine dust, and temperature variations [3]. Beyond serving its primary purpose, facial skin also serves as a mood indicator and a means of expressing emotions and feelings [4]. According to observational research, 1.79% of the world's diseases are caused by skin conditions [5]. Over 90% of people around the world experience acne symptoms, making acne vulgaris a major skin problem [6, pp. 2016–2]. According to estimates, 80% of the visible indicators of aging are caused by extrinsic factors, including pollution, UV radiation, and lifestyle decisions like smoking, sleeping postures, nutrition, and regular skincare routines [7]. Even if facial acne and other treatable skin conditions like pigmentation, wrinkles, and dullness are not serious disease conditions, they can have a significant psychological impact and interfere with a person's social life. Consequently, maintaining the appearance of healthy facial skin helps boost a person's self-confidence. For consumers, choosing facial skincare products is not an easy undertaking with the availability of a wide variety of specifications in cosmetics, whether they purchase goods from pharmacies, department stores, or online. They seek out recommendations from friends, doctors, or their favorite bloggers, and frequently buy expensive products that do not deliver the desired results [7].

According to the research [8], [9], [10], [11] AI has demonstrated significant potential for identifying skin type, and skin problems and recommending skin care products. Among the many other AI technologies that have produced skin diagnosis tools and skincare product recommender systems are ML, expert systems (ES), and ontology. Convolutional Neural Networks (CNNs), a type of deep learning framework based on computer vision, are frequently used in ML solutions for skin diagnosis. A model with a classification accuracy of 95.89% has been proposed by AcneNet, a deep CNN-based acne class classification approach [12]. In their study, Ting-Yu Lin et al. categorized the severity of acne using ML technology, determined whether a person had oily, dry, or neutral skin, and offered skincare product suggestions [13]. The capacity to explain product recommendations, not considering the user's input about additional skin problems for personalization and recommending skincare products that are merely kept in the system database are the main shortcomings of ML-based systems. Rules-based ES recommends skincare products mimic the work of human experts who convert human knowledge to computers. The inference engine asks users questions and records their responses. It then examines the user's assessment of their skin's state using forward and backward chaining techniques [10], [14]. However, some dermatologists have had difficulty making a diagnosis with the naked eye because several skin illnesses are identical to one another [8]. Therefore, the users' assessment of inferencing based on skin concerns may not be sufficient for product recommendations. Since ES rules are not continuously updated, the skincare domain creates a lot of dynamic, unstructured information. Recently, ontological systems for making recommendations have gained popularity [15] [16], [17]. Ontologies formalize the relationships between concepts from a variety of fields. Therefore, user profiles and information about the skincare domain are represented in Web Ontology Language (OWL) ontologies in the proposed system, and reasoning is done over the knowledge base for product recommendation. As a result, a hybrid solution for ML and ontology-based skin condition recognition and product recommender is provided.

1.4 Problem Definition

Due to the dynamic and vast nature of the skincare domain with unstructured and unformalized information, diagnosing a user's skin type and skin disorders and building a skin care product recommendation system has been a research challenge. This proposed ML and ontology-based skincare products recommender system is an effective solution for skin diagnosis and skincare product recommendations. Using ML to identify skin conditions and developing a recommender system by ontological mapping of skincare concepts and user information is an efficient and accurate recommendation technique for personalized skincare products.

1.5 Approach to skincare product Recommendations

This system has been developed on the premise that facial skincare product recommendations can be made as an AI solution, using ML to identify skin conditions and ontology to represent the skincare domain and user profiles. The user’s information is taken for product personalization via the User Interface (UI), such as facial image, skin type, skin conditions, and allergy ingredients. The system will predict the acne severity of a person using the facial image input to the system by the constructed CNN model. To predict acne severity, the ACNE04 [18] dataset was customized and trained on CNNs identifying the features and patterns of acne severity classes mild, moderate, and severe. Using the Protégé open-source ontology editor, user profiles and skincare information were mapped as hierarchical classes and defined relationships between them as object and data properties allowing the inferencing of new knowledge which is not capable of traditional databases. Then customized skincare products were recommended using semantic similarity of the user information, facial skincare concepts, and product information.

1.6 System Requirements

For the implementation of this novel approach for user facial skin condition identification and product recommendations by ontological mapping, the following system requirements are identified as hardware and software requirements.

- Personal computer with core i5 processor or above
- Google colaboratory open-source platform
- Protégé open-source ontology editor
- Python language
- PyCharm Integrated Development Environment (IDE)

1.7 Structure of the thesis

The rest of the thesis document is structured as follows. The next chapter critically reviews the skincare domain literature, highlighting the technologies adopted, state-of-the-art solutions, and limitations of skin care product recommender systems. Chapter 3 gives an in-depth analysis of the technology and software adopted in system development. It is focusing mainly on ontology technologies and ML model development using CNNs. Chapter 4 explains in detail the ontology-based ML approach for facial skincare product recommendation in our proposed study. Chapter 5 discusses comprehensively the design and architecture of the technologies that were utilized to build the proposed solution. The central and most important component of the solution, namely its implementation, is explained in depth in Chapter 6. That is the development strategy for a facial skincare recommender system using ontology and ML technologies. The thorough evaluation procedure of the developed solution is described in detail in Chapter 7, which includes getting feedback from experts and users of the system and its analysis. In Chapter 8, conclusions obtained from the research are highlighted, and recommendations for prospective future works are made.

1.8 Summary

This chapter summarizes the research, identifying the skin conditions and skin type and providing facial skincare products recommendation. It describes the aims and objectives that this study hopes to accomplish with the research background and motivation. Also, this chapter provides the structure of the following chapters of the thesis. The next chapter will discuss the existing skincare research and other works related to facial skincare recommender systems.

CHAPTER 2

EXISTING LITERATURE ON SKINCARE PRODUCT RECOMMENDATIONS

2.1 Introduction

The previous chapter provided an overview of the thesis by defining the aims and objectives, background and motivation, problem definition and approach, and identifying the technology to address the topic of study. This chapter critically reviews the skincare domain, including the causes of skin conditions, the determination of skin types, and suggestions for skincare products. The potentials and limitations of technologies used for existing skincare product recommendations are also discussed.

2.2 Determinants of skin conditions

Since ancient times, it has been a highly sought-after human need to have an even-toned, clear, and beautiful complexion. A statement by zoologist Desmond Morris in 1967 [7] highlights the fact that healthy, even-toned, clear, and radiant skin has been sought by both men and women since early times. The skin makes up around 15% of the body's overall weight and serves as the main defense mechanism against external environmental factors such as ultraviolet (UV) rays, polluted air, fine dust, wind, and temperature changes [3], [19].

As the largest organ, the skin is faced with multiple environmental hazards daily, and with chronological aging, skin problems become more evident when compared to well-maintained, younger-looking skin. In contrast to periodic appointments with skincare experts, research has shown that everyday skincare routines may potentially have a significant long-term impact on a person's overall complexion quality [7], [19]. Skin aging can be classified as extrinsic or intrinsic. According to estimations, external factors are responsible for 80% of the apparent indicators of skin aging, such as UV radiation, pollution, and lifestyle decisions like smoking, sleeping positions, diet, and daily skincare practices, while only 20% are caused by intrinsic factors, such as genetics, general health, and stress levels. Some overt signs of intrinsic aging are thinning of the stratum corneum, atrophy, fine wrinkles, and dryness, while some of the visible signs of extrinsic aging are thickening of the epidermal layer, uneven pigmentation, dullness, dryness, creases, and laxity, which are the main reasons people opt for dermatological treatments [7].

Acne vulgaris is a skin condition that affects a person's physiological conditions, self-esteem, and confidence. Acne stigmatizes both adults and teenagers. This skin condition develops when oil and dead skin cells clog hair follicles. It causes whiteheads, blackheads, or pimples, leading to widespread nodulocystic lesions with the potential for scarring. Post-inflammatory hyperpigmentation is more likely to occur in people with darker skin types. It causes much mental anguish for people suffering from acne conditions [7], [20]. Early diagnosis, together with accurate continuous self-tracking, would benefit in controlling and treating this illness. Since the majority of consumers tend to treat their acne on their own, helping them select a successful skincare plan will improve their overall physical appearance and increase their contentment. Acne treatments are based on how severe the condition is. Over the counter (OTC) products can be used to manage mild to moderate acne severity. In order to treat severe to very severe cases, dermatologist treatment is required [7], [21]. Therefore, in our proposed recommender system based on literature as well as dermatologist guidance, users with severe and very severe acne cases are directed to seek dermatologist assistance. As a means to treat mild and moderate acne conditions, OTC products such as gels, soaps, pads, creams, and lotions that consist of ingredients such as salicylic acid, benzoyl peroxide, and sulfur could be applied to the skin [7], [21].

The most prevalent skin condition, acne vulgaris, also known as acne, is most prevalent during adolescence [28, 33]. Acne affects 80% of teenagers [9], and sometimes the symptoms continue into adulthood. [23]. Due to the fact that acne commonly results in scarring and discoloration and causes significant inferior and depressive emotions, there are a lot of acne sufferers who urgently need specific therapy [48]. Dermatologists must consider the severity of the acne in order to decide on an exact and consistent course of treatment [24]. Additionally, young dermatologists require a reference diagnosis that is trustworthy and objective.

2.3 Determination of skin types

In recommending skincare products, another determining factor is the person's skin type. In The Skin Type Solution: The Baumann Skin Typing System (BSTS), a new system for classifying skin types was created. The BSTS score, which is produced from a self-administered questionnaire, was developed on the theory that skin may be assessed based on the key parameters as follows:

- oil versus dry.
- sensitive versus resistant.
- pigmented versus non-pigmented.

- wrinkled versus tight.

There are sixteen possible combinations of skin types. Ingredients in the formulation of skin care products should preferably support a certain skin type (oily, dry, combination, or sensitive) [7], [22]. The BSTS concept was considered when mapping the skin information class and its subclasses in the hierarchical mapping of the proposed recommender system ontology.

2.4 Facial skincare product types

According to research, the most effective skincare routine was modeled as a pyramid. Which is the clinically based guide for selecting skincare products that most skin care professionals seek. According to the pyramid structure, any skin care routine must contain sunscreens, which provide protection and repair [23]. Dermatologists have advised patients to avoid excessive sun exposure because UV radiation is primarily responsible for skin cancer, premature aging, wrinkles, sagging skin, and pigmentation. Therefore, it's crucial to choose a sunscreen that offers UVA and UVB protection and has an SPF of 30 or higher. Using wide-spectrum sun protection is important as well since it assists in guarding against UVA radiation damage, and the SPF factor only protects skin against UVB radiation [24].

Next, the focus of the skincare routine should be hydration, skin exfoliation, and cell renewal, which are the middle layers of the pyramid [23]. Moisturizing products contain two types of ingredients: occlusives and humectants. They function by covering the skin's surface with a water-resistant layer, thereby reducing transepidermal water loss (TEWL). It reduces the fine lines caused by dehydration and repairs the skin barrier, restoring the skin’s natural water balance [22]. Dead skin cells are taken off the surface of the skin during exfoliation. Exfoliation makes the skin look more radiant, increases the effectiveness of topical skin care products, and helps to avoid clogged pores. Alpha-hydroxy acids (AHAs) and beta-hydroxy acids (BHAs) are the two categories of chemical exfoliants used. Glycolic acid, lactic acid, citric acid, and malic acid are the main components of AHAs, which are often produced from sweet fruits. They peel away the skin’s surface and improve skin tone. BHAs are composed of salicylic acid and are oil-soluble. These acids penetrate your hair follicles deeply to clear out clogged pores by drying out extra oils and dead skin cells. As a result, acne and sun damage are the two main conditions that BHAs are used to treat [24]. Retinoids have been used systemically and topically for many years to address dermatologic conditions, most notably acne. Retinoids have been extensively studied for the prevention and therapy of photoaging and premature aging through healthy cell turnover [22]. Then, at the top of the pyramid, we have activation and rejuvenation.

Using peptides activates enzyme release or regulates protein production, which would lead to firmer, younger-looking skin [22].

2.5 ML based skin condition identification

ML-based skin condition analysis has been an active research field. Many research proposals combined deep learning techniques with computer vision technologies for image analysis [18], [25]–[27]. The following paragraphs discuss the existing ML-based skin condition analysis research. In our study, we analyze the acne severity level of a person's facial image as the skin condition for the proposed ML engine development.

Park and Kim presented a method in their study for skin condition analysis using the camera module built into a smartphone [25]. Acne, pigmentation, blemishes, and flush skin diseases were predicted using smartphone snapshots of the face. Here, a cascade classifier based on Haar features was used to detect the facial features and regions. and skin regions were detected using YCbCr and HSV (hue, saturation, value) color models.

A study was done by Wen, Yu, and colleagues [26] with the ACNE04 open-source dataset, which was the same dataset used in our thesis for ML engine development. Contrary to the majority of the earlier works on facial acne analysis, the models explored in this study are object recognition models with a convolutional neural network (CNN) as their foundation and have better interpretability. They thereby produce more reliable results for the detection of acne and the assessment of the severity of facial acne. The highest mean average precision value of the model was 0.536. The inaccuracy associated with counting acne lesions was 0.43, but the actual error could range from -6.22 to 7.08 due to the standard deviation.

In their research on deep learning-based skin cancer detection using Google colaboratory technologies, Kanani and Padole suggested a DL model utilizing the HAM10000 ("Human Against Machine with 10000 Training Images") dataset to recognize seven different forms of skin cancer [27]. They have augmented the dataset using techniques, leading to an artificial increase in the dataset and preventing any overfitting issues. They have constructed a CNN model with the Keras Sequential API. The model architecture consisted of the conv2D layers, 32, 64, 128, and 256 filters, and 1024 filters for the final fully connected layer. Here, MaxPool2D is employed for pooling and used to lessen the amount of computation required and, to some extent, overcome overfitting. The model was trained over 100 iterations and has achieved a test accuracy of 77.98%, validation accuracy of 77.31%, and training accuracy of about 82%.

Research conducted by Patricia, Santiago, and Javier developed an expert system combined with deep learning technology that effectively detected dermatological skin impairments such as melasma, pityriasis, and dermatitis with an average accuracy rate of 90%. This system consisted of two stages where a facial image was analyzed and processed using CNN to extract characteristics and patterns that could be used to create classified models, which were then used to identify a disease. Secondly, a dermatology specialist would give feedback on predicted images, which enables the algorithm to learn automatically [28]. This system could be used for pre diagnosis of skin condition by a user by updating their facial image to the system.

Wu et al. [18] presented a novel approach for acne severity prediction using a unified framework that can simultaneously learn to rate the severity of local lesions and the overall level of acne intensity in facial images. They have used the Hyashi criterion for grading the intensity of pimples as mild, moderate, severe, or very severe. With the use of Label Distribution Learning (LDL), which gives each instance a label distribution containing the extent to which each label defines it, each instance of acne image data was analyzed. Instead of using a single label to describe an acne image, it utilized two acne label distributions to represent the lesion number and acne severity. To assess the effectiveness of the object counting, they used mean absolute error (MAE) and root mean square error (MSE). Their model was based on ResNet-50, whose parameters were pre-trained on the ImageNet dataset. The model achieved dermatologist-level performance in acne severity detection with an accuracy of 84.11%. Other than the proposed model, their work presented the ACNE04 dataset. This is a novel collection of images that offers annotated bounding boxes for lesions and acne severity labeling done by dermatological experts.

2.6 Rule based skincare products recommendation system

Rules-based expert systems that make skincare product recommendations imitate the work of skincare experts who interpret information from humans to computers. Users are questioned by the inference engine, and their answers are recorded for analysis. The user's evaluation of their skin condition is then examined utilizing forward and backward chaining methods, and skin care products are suggested [10], [14].

The study by Pornchai Nopparatkiat and colleagues proposed an expert system-based method for the treatment of skin problems using Thai herbal recipes and Thai herbal cosmetics, adopting Hypertext Processor (PHP) and MySQL database technologies. The created expert system consists of the primary knowledge-based tools that diagnose skin issues such as acne, melasma, freckles, wrinkles, and uneven skin tone. In this recommendation system, the knowledge base was limited to these skin impairments that were in the database and suggested treatments for those issues, including safeguarding and preserving skin health. Also, another major drawback of the system was that the accessibility of Thai herbal medicines and cosmetics was limited to Thai natives and not readily available internationally [10].

Abdullah and Basari developed an ES that provided users with information and consultations to identify skin types [29]. It recommends treatment solutions for the skin type and helps avoid the formation of any serious skin disorders. The database system used for the system's development is MySQL, and the programming language used was PHP. The advantages of the Skincare Routine Expert System were that it enables users to quickly determine the type of skin they have and receive recommendations for the best treatments. One of the major limitations of this ES is the creation of a set of rules given the abundance of information regarding the signs and symptoms of the acquired disease. Due to this, a finite number of rules utilizing database technologies cannot express all information or facts about skincare disorders and treatment solutions.

An ES developed by Ramdan and colleagues had an accuracy of 80% in determining the facial skin type of a person, whether it was dry, oily, normal, combination, or sensitive, using the Certainty Factor (CF) method [30]. It was a web-based application that could be used to assist a beautician or beauty clinic in determining the patient's facial skin type. This system offered information and knowledge about facial skin, including definitions and detailed descriptions, as well as handling and solutions if a person had that skin type and skin indication, which is the skin condition. But the product suggestions were limited for the skincare line Drwskincare where data was collected for system development. The limitation of skincare product accessibility for people who are not familiar with Drwskincare products is a major drawback. The skin conditions for which the products were recommended were limited, and the user’s allergies to the ingredients were not taken into account when recommendations were given.

2.7 State of the art skincare products recommendation systems

Collaborative Filtering gives (CF) recommendation based on rating of the past users. In content-based filtering (CBF), the user’s preferences and item details are considered when giving recommendations for suitable products. They are widely used in product recommendations.

Using the term frequency-inverse document frequency (TF-IDF) algorithm, Lee developed the CBF technique for cosmetic product recommendation [32]. Due to this method's discovery of term relationships, the items are guaranteed to meet the user's requirements. That is the mapping of the user’s skin type and the ingredient composition of products. The user chooses from six product categories (moisturizing cream, facial treatments, cleanser, face mask, eye treatment, and sun protection) and enters one of the five skin types (oily, combination, dry, normal, and sensitive). Then, Sephora data, which contains details on additional products, is given to the content-based recommender system along with the user's skin type and the product's ingredients. All six product categories are considered when recommendations are produced using this method. The method gives recommendations for each of the six product categories after assessing the similarity of constituent composition within items. If the user simply enters their skin type without choosing a product, the system prompts them to choose one of the following skin concerns: anti-aging, moisturizing, oil control, acne treatment, redness control, and smaller pores. Then, it filters products using the same method as CBF by using TF-IDF. The system was tested on a small sample and yielded an accuracy higher than 75%. But this system has major drawbacks, such as not catering to a user’s multiple skin concerns, acne severity level, or allergies to product ingredients when recommending products.

Another content-based filtering approach by Putriany, Jauhari, and Heroza presented a content-based filtering approach with K-means clustering for skincare product recommendations using products of their preference [31]. The system will use the content-based filtering approach to do data clustering using cosine similarity calculations for skin care products. Users would make a selection of one or more products. Then the system will recommend products from the user's preferred product cluster. The system will check to see if the cluster has any of the products the user liked, and if so, the user will be recommended products from the same cluster. The user's preferred products might not be suitable for the user if the user selects a product randomly. Also, a major shortcoming is the user’s skin type; conditions are not considered.

Cross-domain recommendation systems are a novel approach to developing recommendation systems. An innovative technique for developing ontologies for cross-domain recommendations on problems of facial skin and associated cosmetics was described in the study conducted by Moe and Aung [32]. Their work offered a technique for creating ontologies utilizing taxonomic conversational case-based reasoning (TCCBR) to make cross-domain suggestions based on facial skin diseases and associated cosmetics. The Ford-Fulkerson algorithm was used to create a conceptual link between the two domain ontologies for the cross-domain recommendation. Two ontologies were constructed using the Protégé editor, where the target domain was the cosmetics domain, and the source domain was the skincare problems domain. Most recommendation engines only offer suggestions for items from a particular domain. A consumer may occasionally need unified recommendations across several domains. Using cross-domain recommendations, objects from multiple domains can be suggested. Here, TCCBR was utilized to obtain the characteristic of personalization since it enables users to partially define their problems, then, through discussions, more clearly detect the user's issue and provide a suitable solution. The system had a competitive advantage and was more accurate than previous relevant efforts since skincare ideas were mapped using ontology to deliver cross-domain recommendations based on facial skin issues and related cosmetics.

For skincare ingredients, Jeong mostly employed Natural Language Processing (NLP) to match them with different skin types and to tackle the information overloading problem caused because of the existing large number of skincare products suitable for varying skin concerns and skin types [33]. She preprocessed 1472 products from Sephora after scraping information about their brand, cost, rating, ingredients, and suitable skin types. She separated the different products into six product categories as well as five skin types. To compare ingredients with products, data were preprocessed, and the ingredients list was tokenized. In the next step, the document-term matrix was built, where the cosmetic product corresponds to a document and each chemical composition correlates to a term. The ingredients were then one hot encoded. Since the dimensions of the existing matrix were high, T-distributed Stochastic Neighbor Embedding (t-SNE) was used for dimensionality reduction. While preserving similarities between the items, it provides the ability to vectorize or visualize cosmetic items in two-dimensional coordinates, and the distances between points indicate the similarities of items to one another. Then, using cosine similarity, suggested the top five items with similar properties. This approach gives an insight into skincare products with ingredient lists suitable for each skin type. But customization based on the various skincare needs of the user cannot be achieved.

As discussed in the previous section, with the advent of computer vision and image analysis technologies used in ML-based skin condition identification, ML and DL based approaches are new trends in skincare product recommendation. AcneNet, a deep CNN-based acne class classification approach has proposed a model with a classification accuracy of 95.89% [12].

A study done by Li et al. [34] proposed the development of an ML and DL-based algorithm for skin condition identification and product recommendations. In order to recognize important aspects in facial images, regions of interest sub-images are used as input data for multi-label models and the object detection algorithm YOLOv4. Each sub-image uses the YOLOv4 identifier of the second layer to pinpoint the affected region of the skin image and calculates the local block's pixel area in relation to the main body to evaluate the correlation between feature parts and degrees and establish a starting point for the multi-label model optimization that follows. The skin condition classification employs an image processing technique to automatically remove, reduce noise, enhance, normalize, and extract features from the sub-images in order to provide the feature vectors of the sub-images required to train the multi-label classification model. Based on the skin condition identified, products were recommended. The major drawback here is the explainability of the product recommendations. Additionally, the products are unable to be customized based on all users' skincare needs, such as skin type and allergy ingredients, and product recommendations are limited to certain skin concerns that the model is able to identify.

The study conducted by Ting-Yu Lin et al. [13] identified if the person's skin type was oily, dry, or neutral, classified the severity of acne using ML classification technology and provided recommendations for skincare products. Here, the facial image of the user was captured using Logitech's C310 camera, and then the Open CV facial detection model was used to find the image's facial areas. Using the regions of interest captured, which are the cheeks, forehead, and chin, to classify the skin type and detect acne. The skincare products that are stored in the database were recommended through the UI based on the predicted skin type and acne severity level (mild, moderate, and severe). The overall work provides a novel business model consisting of an electronic payment system, a system for identifying finger veins, and a system for recommending skincare products. The same drawbacks faced in earlier ML-based product recommendation systems can be observed. Here, the products were also limited to the ones stored in the database, resulting in less customization and not considering additional skin concerns. A major improvement is that the user's skin type and acne severity level was considered in product recommendations. Similarly, Hsia et al. [35] presented a study to identify skin type and acne conditions using facial images as input. Products stored in the database were recommended based on the user's skin type and acne severity.

2.8 Analysis literature

The existing skincare product recommender systems based on AI solutions such as expert systems, ML solutions, NLP systems, and data mining techniques have identified the following potentials and limitations.

The main drawbacks of ML-based systems are their inability to provide explanations for the recommendation of skincare products, their failure to take into account the user's input regarding additional skin concerns when personalizing recommendations, and their tendency to only recommend products that are kept in the system database. The potential of ML systems is that users can conveniently identify their skin concerns and skin types by uploading a facial image to the system and getting product recommendations [13], [34], [35].

Rules-based expert systems that recommend skincare products mimic the work of human experts who convert human knowledge to computers. The inference engine asks the user questions and records their responses. It then examines the user's assessment of their skin's state using the forward and backward chaining techniques [10], [29], [30]. However, some dermatologists have had difficulty making a diagnosis with the naked eye because several skin illnesses are identical to one another [8]. Also, in some scenarios, only a limited number of products stored in the system's database are recommended, and due to the dynamic and extensive nature of the skincare domain, a limited number of ES rules cannot recommend skincare products for all skin concerns and ES rules are not updated regularly. The main advantage is that ES provides explanations for the product suggestions so that users are aware of the concerns and recommendations.

CBF and CF algorithms are used mostly in recommender systems, as per the literature [31], [36]. Based on the closeness of the users' prior ratings, collaborative filtering makes recommendations. Collaborative filtering is a widely used technique. The drawback of collaborative-based filtering is the cold start problem. Making recommendations is challenging when the users or the items are new. Also, another drawback is that it is susceptible to fraud user attacks, in which several fictitious user profiles are entered into the system to affect the user recommendarions, potentially having a significant negative impact on the systems. With more people and items, collaborative filtering performance suffers. As a result, the collaborative filtering algorithm needs to be modified frequently over time [31]. Based on item descriptions and user preferences, content-based filtering recommends suitable items to users. Active users can supply reliable information even if they are not logged in, so content-based filtering benefits them. The limitation of content-based filtering is that it cannot recommend suitable products when the content analyzed for an item does not contain adequate information.

2.9 Problem Definition

In the present day, making recommendations on the Internet is a common occurrence. There has been an increase in the number of works published in several recommendation systems-related fields. Our literature review has revealed many limitations in the area of skin care product recommendations. More importantly, many researchers have recognized the need for skincare product recommendations online with the rate of arrival of new skincare products to the market. Therefore, we define our research problem as the fact that the current approaches to skincare product recommendations are rather inefficient and inaccurate when the skin care domain is changing rapidly, and consumers find it difficult to select a suitable facial care product that suits their skin condition and skin type. Prospective buyers seek help from the counter or require dermatological guidance to buy the product suitable for them, but not all counters can provide appropriate recommendations to buy the products, and dermatologist consultations are not accessible for most people. Numerous skincare products on the market demonstrate the significance of skincare to both men's and women's lifestyles. Given that each person has a unique skin profile, a recommendation system is necessary to assist and provide personalized product suggestions based on user preferences. Also, provide suggestions that effectively reduce the number of options available, guiding consumers to the products that are best for their skin.

2.10 Summary

This chapter discussed the literature on the determination of skin conditions and skin types, types of facial care products, and ML-based facial condition identification. Also, the rule-based and current state of the art skincare product recommendation systems were critically analyzed. Based on the review, we have summarized the advantages, limitations, and technology used in major research in facial skincare recommender systems. More importantly, we define our research problem as the need for more accurate and efficient skin care product recommendation systems, which have been a research challenge. In Chapter 3, we give an in-depth study of the technologies adopted for solving the research problem.

CHAPTER 3

TECHNOLOGY ADOPTED

3.1 Introduction

Chapter 2 discussed the rule-based and state-of-the-art skincare recommendation systems and, hence, identified the limitations and issues present in these systems. In this chapter, we present the major tools and technologies that have been used to address our problem domain. With the information overload on the internet, many sources of information about novel skin care products are available. These information sources are sometimes not reliable and mislead many prospective buyers. Using this novel system, facial skincare products customized for the user's skin requirements can be recommended. The details of the user's skin type and conditions are input into the system via the system user interface developed by the Python Tkinter module. Then the information was preprocessed, and using the Protégé ontology editor, ontology modeling was done. To assess the user's acne severity, an ML model was developed using CNNs.

3.2 Introduction to Ontology

The concept of ontology has existed since the earliest days, which date back to the times of Aristotle. It is a discipline of philosophy, which means existence. Ontology can explain what kinds of items exist in a system's domain, their meanings, and how they are interrelated [37].

The latest AI developments tend to represent knowledge as ontologies, which allow for knowledge sharing and reuse among different software entities. An ontology can be used to record knowledge and make it accessible to both machines and humans. The objective is to establish a shared vocabulary and semantic framework for exchanging knowledge in that field [38].

A formally represented body of knowledge is called conceptualization: concepts, objects, and entities that exist in a domain of interest and the relationships that prevail among them [39]. As in our research interests, the created skincare domain knowledge base, or skincare domain and user profile knowledge-based system, is focused on conceptualization. Thus, according to Thomas Gruber's definition, "An ontology is an explicit specification of a conceptualization". Ontology describes a domain of interest by defining a finite set of representational terms and the relationships between those terms [39]. These defined terms are:

- Classes (concepts) are a series of ideas or topics within a domain of interest. Skin type, concern, acne severity, user, and key ingredients are a few concepts or classes used in our constructed facial skincare recommender system ontology.
- Attributes (relationships) are the relationships between those concepts in hierarchies of classes [40]. As per our constructed skincare ontology, an example of a class hierarchy is that skin type and concern are subclasses of the skin information class. That is, all objects in the skin type and skin concern classes are also included in the skin information class. Figure 3.1 depicts the class hierarchy for the skin information class.
- Individuals (instances) are specific objects or instances that fall within the defined classes [40]. For example, dry skin, normal skin, oily skin, and sensitive skin are some instances that belong to the skin type class.

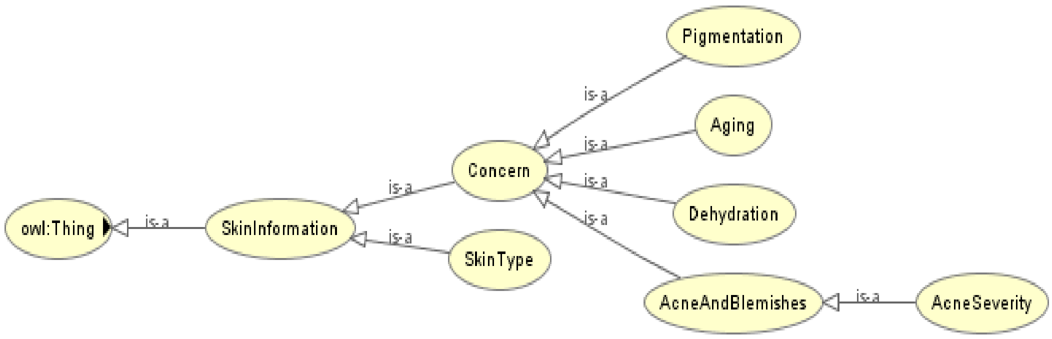


Figure 3.1: Class hierarchy for the skin information class.

Representing the skincare knowledge as ontologies is more suitable since the skincare domain is dynamic, having an extensive amount of data with different skin types, skin conditions, skincare brands, and abundant product information rather than using traditional databases, which are limited to structuring data, storing it as tables, and querying it, unable to expand easily when additional information needs to be integrated. Ontologies also allow for inferring new knowledge over pre-existing knowledge across relationships defined among the key data concepts [38].

Thus, ontology is ideal for modeling the knowledge base of the vast and complex skincare domain by defining concepts, individuals, and the properties that define the relationships among them.

3.3 Protégé

The Protégé open-source ontology editor was selected as the ontology editor for this project. In many sectors of application domains, it is the most commonly used open-source, cross-platform, cross-domain technology for building and managing terminologies, ontologies, and knowledge bases. It is a versatile, robust, and well-supported programming environment where the user community routinely contributes updates that improve the software [41]. Developers and researchers can create efficient knowledge-based systems using Protégé. Protégé offers an easy-to-use graphical user interface in creating ontologies by enabling various design panes for hierarchical design, property design, restriction building, comment and definition creation, and disjoint function construction. OWL is one of the ontology languages that Protégé supports [42], [43]. Through its use of the syntax and rules of the OWL language as well as reasoning assistance, the Protégé OWL plugin enables the assisted building of OWL ontologies.

Corresponding to the OWL ontology classes, Properties, and Individuals (instances), Protégé comprises Classes, properties (or slots) and individuals (also known instances). Classes are the terms or concepts of the domain of discourse. Properties or attributes between classes and individuals are also known as slots. Instances denote the specific object or instances of classes [41].

Figure 3.2 shows the ontology interface, which has tabs for OWL classes, properties, individuals, OWL Viz etc.

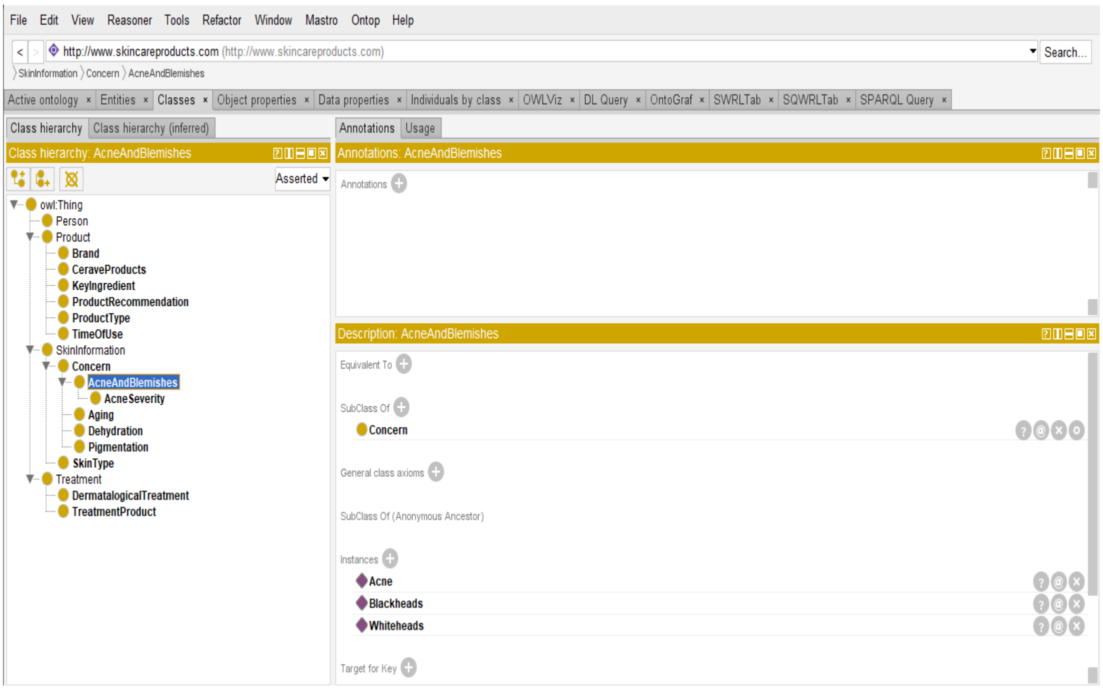
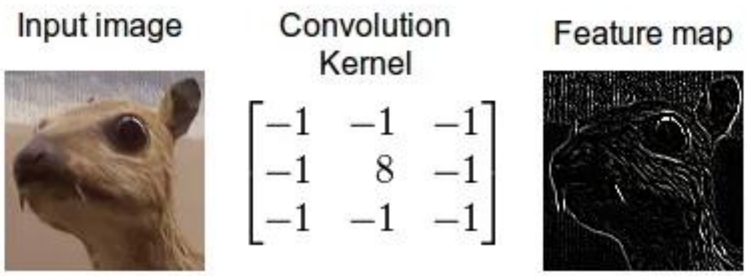


Figure 3.2: The Protégé OWL plugin interface.

3.4 Convolutional Neural Network (CNN)

(ConvNets, or CNNs) are, when compared with neural networks, more often utilized for classification and computer vision tasks. Ordinary neural networks struggle to scale for high-resolution images, whereas convolutional neural networks do. Prior to CNNs, extremely tedious approaches for acquiring features were needed for object identification in images. In contrast, convolutional neural networks at present provide a more scalable technique for categorizing images and identifying objects by utilizing matrix multiplication and principles from linear algebra to discover patterns in images. Nevertheless, modeling them may require the use of graphics processing units (GPUs) because they can be computationally expensive.

A stack of many layers is used to create a CNN architecture, that makes use of a distinct purpose that is by extracting relevant features to turn the input volume into the output volume. Several distinct types of layers are used in building CNN models as discussed below [44]–[46].



$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Figure 3.3: Effect of a convolution operation. Source [46].

- Convolutional Layers: This is the core functional layer of the CNN architecture. The convolutional layer consists of a feature detector, often referred to as a filter, input data, and a feature map. Convolution is the process by which, to assess whether the feature is there, the filter scans the image's receptive fields. A filter is a matrix whose values for its elements specify the type of alteration made to the original image. The convolution operation functions by applying the filter to an image segment and then computing the dot product between the input pixels and the filter. A feature map is generated as a result of the input and filter's subsequent dot products. Thereby, features are learned automatically through these layers. So, convolutions serve the purpose of isolating various visual features in image inputs. These features are later used by dense layers. Figure 3.3 shows the effect of the convolution operation [44]–[46].
- Pooling Layers: Compressing the input images with a pooling layer helps the network run more efficiently and consume less memory. Reducing the number of parameters entails reducing the image dimensions. Using a kernel, pooling layers combine a portion of the input image into a single value. Max pooling and average pooling are the two primary types of pooling layers. When the filter moves by scanning through the image in max pooling, it chooses the pixel with the highest value to send to the output array. A 2x2 max pooling kernel, as an example, pulls away 4 pixels from the input and outputs just the pixel with the highest value. In average pooling, the average value is transmitted to the output. CNN suffers significant information loss at the pooling layer, yet there are still several advantages. They lessen complexity, increase effectiveness, and reduce the possibility of overfitting in CNN model development [44]–[46].
- Fully Connected Layer: When the network is fully connected, as the name suggests, every node in the first layer is linked to every other node in the second

layer. Utilizing the attributes that the prior layers had extracted categorization is carried out. All of the neurons in one layer communicate with all of the neurons in the other layer. The features that were collected from the previous layers and their corresponding filters are used in this layer to carry out the classification process. Fully linked layers usually use a softmax activation function, which produces a probability ranging from 0 to 1 when categorizing inputs [44]–[46].

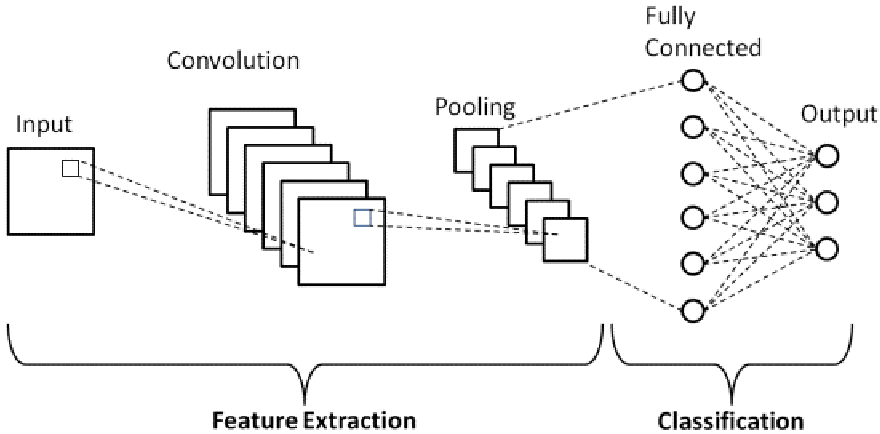


Figure 3.4: General CNN architecture diagram for image classification. Source [47].

3.6 Google Colaboratory

Colaboratory, also known as "Colab", is a product introduced by Google Research. Colab is used in areas such as machine learning, data analysis, and education. Anyone with a Gmail account can use the browser to build and execute any Python programs. Colab is a hosted Jupyter Notebook service that offers no-installation access to computational capabilities, including GPUs. To execute the CNN model, Colab enables the configuration of a virtual machine as a runtime by connecting to Google GPUs or utilizing the cloud platform capabilities offered by Google. The majority of the ML libraries are already installed, so there is no configuration required. This allows deep learning models to be trained in Colab with a minimum amount of coding. Through Google Drive, information can be downloaded to the local computer's hard drive and uploaded from the local computer. Users can connect Google Colab to their Google Drives and use datasets stored in their Google Drive. Thus, the ACNE04 dataset used in this study was stored in Google Drive and accessed through Colab for training [27], [48], [49].

3.5 Summary of the technology adopted

In this chapter, we discussed the theoretical foundation for our study, an ontology-based ML skincare recommender system. The next chapter discusses the approach to system development.

CHAPTER 4

ONTOLOGY-BASED ML APPROACH FOR PRODUCT RECOMMENDATION

4.1 Introduction

In Chapter 3, we presented an in-depth study of the technologies adopted for our skincare product recommendation system. This chapter elaborates on our approach to skincare product recommendations. In the ML module, the system accepts a facial image for skin condition identification. For personalization of the product recommendation, the user's skin type, other skin impairments, and any allergy ingredients are input to the system via the user interface. By ontologically mapping skin care domain concepts with user profiles, products are recommended for the user to utilize under the supervision of a dermatologist. Here we have structured the chapter with the following subheadings: hypothesis, input, output, process, users, and features of our recommender system.

4.2 Hypothesis

Facial skincare product recommendations can be implemented as an AI solution using ML for skin condition identification, an ontology for modeling the skincare domain, and user profile information for the personalization of products.

4.3 Input to the recommender system

The inputs taken into the recommender system through the user interface are the client’s personal data, which are username, gender, and age. Skin-related information, such as the facial image for acne severity prediction (the acne severity of the facial skin can be selected manually if the prediction is uncertain), skin type (normal skin, dry skin, oily skin, combination skin, sensitive skin), required product type (cleanser, exfoliant, eye cream, moisturizer, sunscreen, toner), skin concerns (acne, blackheads, whiteheads, eye puffiness, fine lines, wrinkles, dullness, dark spots, enlarged pores, dark eye circles, crow’s feet wrinkles, hydration, skin barrier restoration, acne scarring, brightening). Any allergy-causing ingredients for the user’s skin (ex: glycolic acid, benzoyl peroxide, lactic acid, salicylic acid, etc.). The system excludes these products with allergy-causing ingredients. The system then customizes the facial care products based on the input. Also, the system takes in a rating for recommended products as feedback to make the system more relevant to users.

4.4 Output

Our facial skincare product recommender has been designed to generate two kinds of outputs: the acne severity prediction of the user's facial skin, which was selected as the skin condition for the ML module, and personalized skincare product recommendations. The products recommended consist of the following information: product name, brand name of the product, time of using the product (AM/ PM), and product rating. The acne severity prediction is used as an input for the product recommendation system. Also, the system provides user guidance to seek dermatological assistance based on the severity of the skin conditions. Because OTC products, for example, will not be suitable for treating severe acne conditions.

4.5 Process

Based on the premise that facial skincare product recommendations can be developed as an AI solution using ML to identify skin conditions and ontology mapping to represent the skincare domain and user profiles, skincare-related domain data were gathered to properly define the knowledge base of the ontology. Since the skincare domain is vast and dynamic, expert knowledge was required to properly define the key concepts and their relationships. So, experts such as dermatologists were consulted, and their responses were noted down. Then skincare websites and dermatology textbooks were referred to get information about skincare products and how product recommendations are made. Then skincare domain key terms are represented in the OWL ontology using the Protégé ontology editor. That is, information about key concepts in skincare, such as skin types and skin conditions, was mapped as hierarchical classes and subclasses with object and data properties defined among them.

An ML solution was developed to identify the acne severity of the facial skin as mild, moderate, or severe. The CNN model was constructed by training on the ACNE04 dataset and customizing it using images from other skin care-related websites, such as the dermanetz.org website, to overcome the class imbalances in the existing ACNE04 dataset. These datasets are freely available for research purposes. Based on dermatologist advice, users with severe acne cases are directed by the system for dermatological assistance. Since dermatologists are well-versed in this subject, they can provide appropriate information about treatment regimens.

The user interface is the component that links our system together. From the UI, skin type, concern, user facial image, etc. were taken as inputs. For accurate and most effective personalization of skincare products, the user interface takes user input through different queries. OWL ontology querying was done by using RDFLib packages to display the OWL ontology data on the Python Tkinter graphical user interface. The user's facial image was used for ML prediction, and the other information was used for ontology mapping and further personalization based on the user’s needs. Finally, the recommendation engine, which is the main critical feature, was developed by manipulating the object and data properties between the ontology classes using the Python Owlready2 package to provide recommendations.

4.6 Users

The recommendation of our system's skin care products is targeted at young adults and adults in the age range of 15 to 60. Considering the skin sensitivity of children, it is not suitable to use cosmetics and pharmaceutical products without the supervision of dermatologists. Both youth and adults can use the system-recommended facial skincare products as directed by a dermatologist.

4.7 Features

The following features were identified in the recommendation system:

- ML module for acne severity prediction using facial image.
- Skincare domain and user profile ontologies were mapped with hierarchical relationships for filtering skincare products.
- Easy-to-use UI that can select skin care products based on skin type, concern, and acne conditions, and product type while filtering out any allergy ingredients.
- Allow users to rate products and low rated products are excluded from future recommendations.
- Alerts users based on concern and acne severity if dermatological assistance is required.

4.8 Summary

This chapter critically reviews the approach adapted for the skincare product recommender system under hypothesis, input, output, users, and the features of the developed system.

CHAPTER 5

DESIGN OF FACIAL SKINCARE RECOMMENDER SYSTEM

5.1 Introduction

The previous chapter described the approach for the hybrid ML and ontology-based skincare product recommender system, outlining the hypothesis, input, output, process, users, and features. This chapter focuses on the system functionalities and how they are designed for system development. The design of the proposed recommender system and solution to the problem statement will be described in detail, elaborating on the main system modules in this chapter.

5.2 Top Level Architecture

The proposed ontology-based ML framework for facial care product recommendation uses a hybrid filtering strategy that includes both ML and ontology-based technologies for filtering, with the objective of recommending skincare cosmetics and cosmeceutical items for users. As shown in Figure 5.1, a hybrid recommender system consists of three main layers. The data gathering layer is the first layer, which includes the data collection module and all the information resources. This is used to accumulate all the facial skin-related important concepts and skincare product-related information needed for precise, customized product recommendations. The second layer consists of the primary functional components of the system. They are the ML engine for acne severity prediction, the ontological data model, and the recommendation engine. The detailed functionality and design characteristics of the components will be explained in the upcoming sections. The user application layer enables user interaction with the framework and is the third and last layer. It allows users to make selections, enter their skin details for personalization, and provide feedback on the recommended products. The layers and modules of the framework interact with one another's inputs and outputs based on each layer's and module's input and output.

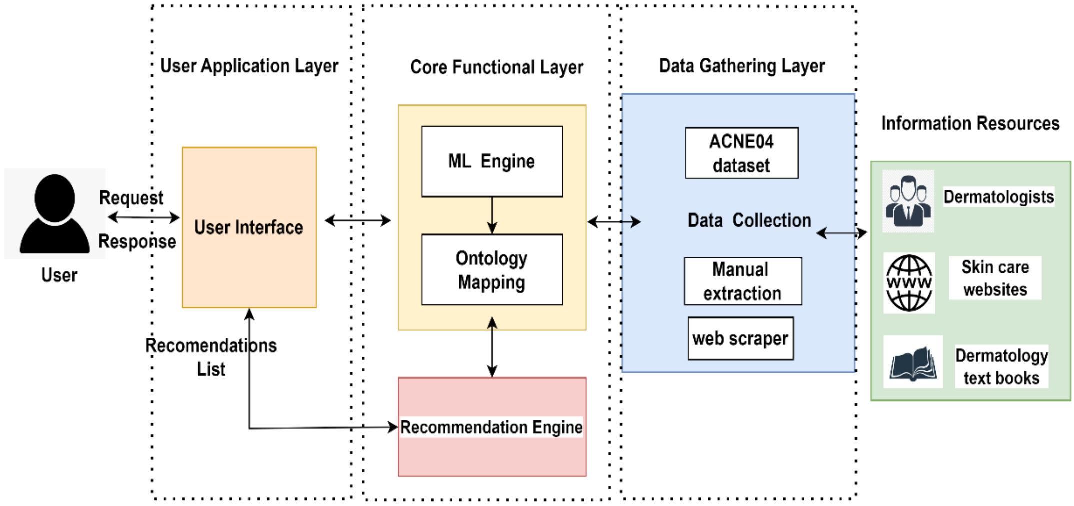


Figure 5.1: System architecture for skincare product recommender system.

5.3 Data collection for Ontology mapping

Since our main system architecture depends on the conceptualization of the skincare domain and the ontological mapping of skincare concepts, product information, and user profiles, it is necessary to collect all the necessary information for a precise and personalized recommendation of cosmetics to each individual. The skincare domain concepts are dynamic and vast, and to build the vocabulary of terms that are most appropriate for a skincare product recommendation, expert support and guidance are sought. The target of our system is to assist users in selecting the best skincare products for them. So, to build up the representational terms to map for our otology, dermatologists were interviewed on the basis of how OTC skincare products can be recommended. That is the identification of features and parameters that need to be considered when recommending facial care cosmetics or cosmeceuticals. Then, based on the dermatologist's suggestion and guidance, dermatology textbooks were further referred to improve knowledge of skincare concepts and the means by which skincare product recommendations are made. The criteria for recommending skincare products were further analyzed by researching cosmetics and cosmeceutical websites. Skincare product information from six brand websites was collected manually and also using a web scraper and noted down in an Excel sheet.

5.4 Data collection for ML engine

The dataset for the ML engine was freely obtained from the internet. It was the ACNE04 dataset built by Xiaoping Wu and his colleagues [18] in their research to address the problem of acne image analysis by joint methods of lesion counting of the facial image and global acne severity assessment. The acne dataset consists of facial images that were labeled as belonging to four acne severity classes: mild, moderate, severe, and very severe by skincare professionals. The global assessment of acne severity classification was considered for our feature training in the ML model. Since the data was imbalanced between the classes. The severe and very severe classes were merged to form one prediction class as severe. Also, to improve accuracy and avoid overfitting, the dataset was customized with images selected from the skincare website DermNet (dermanetz.org), and newly labeled images were put into each class. The customized data was used to train and construct the CNN model.

5.5 ML Engine

Dermatologists must consider the severity of the acne in order to decide on an exact and consistent course of treatment. Additionally, young dermatologists require a reference diagnosis that is trustworthy and objective [19]. Also, when discussed with a dermatological expert, acne severity level was identified as a key parameter that was considered when making facial skincare product recommendations. Therefore, acne severity prediction was considered for skin condition identification in our ML module.

The main aim of the ML Engine is to develop a CNN model for automatic acne severity assessment of a user’s facial image using the Google Colab environment. Here, the input taken was the ACNE04 dataset, which was customized as per the requirement for acne severity prediction in three classes: mild, moderate, and severe. The dataset was customized due to the class imbalances in the existing dataset as well as our ML modules need to identify the severity cases for these conditions only in product recommendations. Severe and very severe cases were merged since the acne images were overlapping with one another, and both severe and very severe cases will be redirected for dermatological assistance as they require prescription medication to treat the conditions.

The system uses image processing algorithms to extract characteristics from the patient-provided facial image, which feeds the convolutional neural network. The network can classify images by dividing them into layers, making it simpler to extract patterns through the use of various filters. The CNN model developed was loaded into the UI and allowed the user to input the facial image. The output of the ML engine, that is, the acne severity level of a user's facial image, is further enhanced by querying against the ontology knowledge base in product recommendations. The ontology module will be discussed in the next section. The architecture diagram of CNN model trained in Colab environment is shown in Figure 5.2 below.

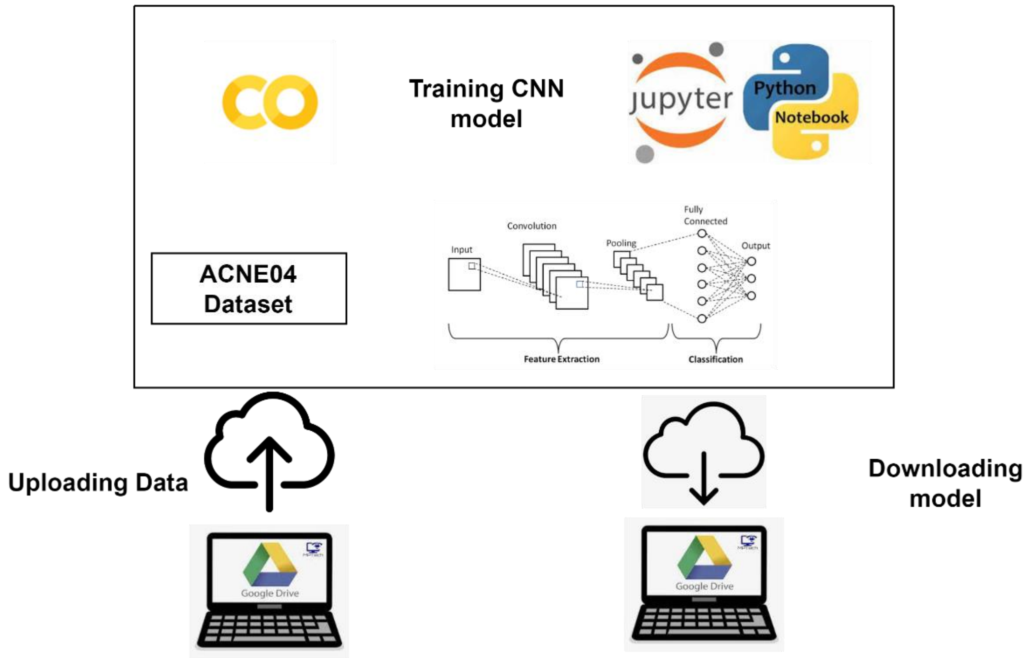


Figure 5.2: Training CNN model in Google Colab.

5.6 Ontology module

There has been an increasing demand for an appropriate construction approach for ontology due to the growing need for ontology to be used more effectively in a variety of different fields. A potential method to overcome the constraints of traditional recommender systems is to incorporate ontology and domain knowledge into the suggestion-generation process. Applications that employ ontologies to structure knowledge regarding the objects and users in a domain of interest when generating recommendations are known as ontology-based (OB) recommender systems. Ontology-based recommender systems for skincare make use of ontological knowledge about skincare concepts, cosmetics, cosmeceuticals, and users to map relevant products that can solve an individual user's skincare needs. These systems make use of ontologies, which are important for knowledge representation and information sharing. The accuracy and quality of suggestions are improved by combining ontology domain knowledge about skincare, facial care products, and user profiles; this also helps to overcome issues faced with traditional recommendation approaches, such as information overloading and the cold start problem.

The creation of ontologies for the user profile, essential skincare concepts, and details about skincare products, as well as the mapping between these ontologies, are all included in the ontology model in order to fully understand the product recommendations. The developed ontology knowledge base will be utilized as input in the recommender engine after the ontologies are built and mapped. The information about ontology mapping will be stored in an OWL file, which will be queried and used as a knowledge base for the recommendation generation process. As per the suggested method, ontology concepts are utilized to structure domain expertise (the domain's taxonomy that is being studied), user information (the consumer profile), information about the facial skin concepts for product selection (the skincare concepts), and information about each product (the product profile).

The term "ontology" in the context of the domain of knowledge implies both concrete and clear explanations of the domain concepts. The ontologies created for the facial skincare recommender system allow applications to interpret and understand the context of consumer profiles, facial skin-related information, and product details based on their semantics. That is, ontology enables different users and applications to understand the knowledge structure to share information and communicate in a standardized way. Additionally, the ontologies' hierarchical structure enables the re-utilization of the application’s ontology developed (that is, in the same way, software engineering develops reusable common code) to outline the study fields and construct a new system or application based on existing ontologies without having to start from scratch.

Three ontologies were built as part of the current work. First, there is the skincare information ontology, then there is the user ontology, and finally, there is the product information ontology. The ontologies that use the hierarchical mapping between ontology classes to determine how similar they are to one another have been evaluated using the protégé tool. These three ontologies that model knowledge of different concepts have finally been integrated into a single ontology. Thusly produced, the ontology model considerably lessens information overload.

Also, the ML engine discussed in the previous chapter provides users with acne severity-related skin information that will be taken as input for product recommendation. The output of the ML engine is further enhanced by querying against the ontology knowledge base. By querying against the ontology knowledge base, the system can identify additional skincare concepts and product-related information that can further personalize product recommendations. The ontological mapping of skincare domains improves the accuracy of product recommendations. Therefore, rather than using ML or ontology alone for skincare product recommendation, it is more effective to use both technologies together.

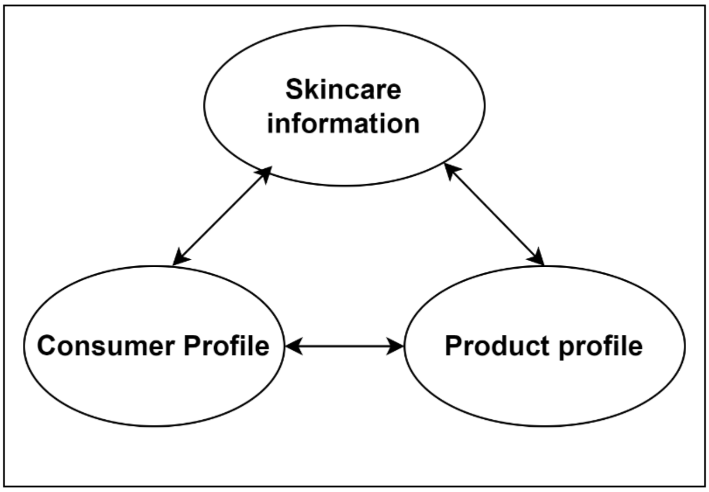


Figure 5.3: Ontology construction.

5.7 Recommendation Engine

The output from the ML engine and the inputs obtained from the user interface relating to the user's skin-related information are queried against the developed ontology knowledge base. The recommendation engine is used to query the ontology knowledge base to identify the relevant skincare concepts and the relationships that exist between these skincare concepts and the skincare products to generate recommendations based on user profile information. Thus, semantic similarity between the skincare concepts, product information, and user skin type details was mapped using the Protégé ontology editor and the Python OWLReady2 package. The implementation of this engine will be discussed in the next chapter.

5.8 User Interaction module

The user interface (UI) component makes it easier for users to communicate and interact with the proposed recommender system. As discussed earlier, ontology provides a structured representation of domain knowledge. The output of the ML engine is further enhanced by querying against the ontology knowledge base. But the ontology module may not be easy for a user to understand, interact with, or communicate with directly. By providing an intuitive and simple-to-use interface, users can easily navigate through the system, enter their preferences and skincare requirements to get the customized skincare product list, and also get feedback from the system based on their skin concerns and skin type to take the next best action. The UI provides the interconnection between the ML module, the ontology module, and the user. The UI also allows the users to give feedback and ratings for the products recommended, which leads to further improvement of the system's functionality and also updates the ontology knowledge base regarding the user’s profile, which leads to more accurate and customized product recommendations.

The user interacts with the system by entering user information and facial skin-related details into the system and providing feedback and ratings for the recommended products. The system UI provides the recommended products and feedback based on the user’s input. The Python Tkinter graphical user interface (GUI) module was used for UI development. It was appropriate to use the Python Tkinter module since, for our ML engine development, we have used Python, and connecting to an OWL ontology file can be easily done through the Python libraries available, such as RDfLib and OwlReady2. So, Python Tkinter library was selected as the technology for GUI development.

5.9 Summary

The novel architecture put forward for the ontology-based ML approach for skincare recommendation framework's design specifications was discussed in this chapter.
The creation of a facial skincare recommendation system is supported by the proposed framework. Based on the semantic similarity of ontology ideas between the skincare product information and the user's facial skincare information, the facial care product recommender system is constructed to provide cosmetic and cosmeceutical recommendations to consumers. In the proposed ontology module, data was combined from different sources and mapped all the information into a single, integrated module to obtain thorough information about users' facial skin concerns and respond to users' inquiries.

Furthermore, a facial image recognition algorithm for acne severity prediction was designed to make the system more effortless for the user. The user interface is also engaging and helpful in collecting facial skin-related information from the user to make the system more personalized.

CHAPTER 6

IMPLEMENTION OF SKINCARE RECOMMENDATION SYSTEM

6.1 Introduction

This chapter lays out a detailed description of the development of the facial skincare recommender system. The implementation details of each module stated in the previous chapter will be elaborated on, emphasizing the tools, technologies, and algorithms used to construct the proposed recommendation system.

In the previous chapter, we have mainly divided the design of the application into three main layers: the data gathering layer, the core functional layer, and the user application layer. This chapter will describe how each layer that was specified during the design phase will be implemented.

6.2 Developing the skincare recommender system.

As seen in the previous chapter, there are three main layers in the design of the facial skincare product recommendation system. The data gathering layer consisted of the design details of data collection methods for the two main components of the core functional layer: ontology mapping and ML module development. The UI acts as the bridge between the ML engine and the ontology. In the implementation chapter, we will discuss each of the implementation details, dividing them into three main system components: ML module development, ontology development, and user interface development and their subparts.

6.3 ML Engine development

A CNN model to identify three different types of acne severity classes using the custom-built ACNE04 dataset has been proposed in this study. The implementation details of the proposed model will be discussed in the following sections.

6.3.1 Data Acquisition

The first stage of the model implementation was to find acne severity-labeled images. Since it was difficult to manually gather acne image datasets from users, freely available online datasets were studied. Based on the literature, the ACNE04 dataset by

Wu et al. includes bounding box annotations, the number of lesions, and the severity of acne for each facial image. The severity of acne was graded into four classes: mild (0), moderate (1), severe (2), and very severe (3). Experts had annotated the facial photos that were taken from the front of the patients at a 70-degree angle [18]. This dataset was freely available for use. Our study was tremendously aided by this, and this dataset was used as the foundation for creating and evaluating models.

There were class imbalances, which led to customizing the data set as per the system requirements. The classes 0, 1, 2, and 3 had 532, 642, 190, and 145 images, respectively. Severe and very severe classes were merged as one to avoid this class imbalance and overfitting problems. The initial ACNE04 dataset contained 1,457 images. After customizing it, it contained 1469 images. Acne images were selected from the publicly available Dermnet website (https://dermnetnz.org/), which had facial acne images of severe cases. Derment is a website that provides free dermatology resources. After customization, dataset classes 0, 1, and 2 had 532, 642, and 341 images, respectively.

For our research purposes severe and very severe cases also need to be directed to dermatological assistance. So, users with severe and very severe acne conditions were considered as one class and given a system generated message to seek dermatological support. Appendix C shows attached relevant screenshot of the system UI.

6.3.2 Data Preprocessing

To prevent any problems from occurring when training the CNN model, images with invalid extensions were removed during data preprocessing. Scaling and data augmentation were the next steps taken in the data preparation process. All of the images were scaled to fall within the same scale range. The image pixel values were scaled to be between 0 and 1. It helps with the CNN model’s convergence and optimization. Appendix D contains the code segment that shows how to scale the images and verify that the scaling process is applied, that is pixel values are within the range of 0 and 1.

Data augmentation techniques help increase the size of the training dataset by applying various random transformations to the original images. It helps prevent overfitting of the model and helps improve the performance and further generalization of the model by making the training dataset more diverse. A few of the augmentation techniques used in model development were horizontal and vertical flips, rotations, color jitters, translations, and so on. Appendix D shows the full code for applied augmentation techniques. These applied preprocessing techniques helped improve the performance of the CNN model.

6.3.3 Designing and Training Convolution Neural Network Model

The next stage is to design and train the CNN model. Keras Sequential API is used in creating the model by adding layers sequentially in the model architecture. The data augmentation layer is first applied to the model. As explained in the previous data preprocessing section.

The first layer is a convolution layer (Conv2D) with 16 filters and a stride of one to extract local features from the input images. The model is built of two more layers of Conv2D with filters of 32 and 16, respectively. Following the Conv2D layer, Max Pooling Layers are applied to minimize the feature maps' spatial dimensions and capture key features. This layer down-samples by choosing the highest value from a pool of values in a local region. It also helps in preventing overfitting issues.

A flatten layer (Flatten) was inserted after the convolutional and max pooling layers to transform the 3D feature maps into a 1D feature vector that can afterwards be utilized as input to fully connected layers.

The next addition is a fully connected dense layer (Dense) with 512 units with the ReLU activation function. This layer uses a matrix multiplication operation and element-wise activation to extract global patterns and representations from the feature vector that has been flattened.

After the dense layer, a dropout layer (Dropout) having a rate of 0.5 is inserted to avoid overfitting. Dropout assists in regularizing the model and preventing an over depending on certain neurons by setting a random percentage of input units to 0 during training.

Since this model is developed for 3-class classification, the output layer is a dense layer of 3 units with a softmax activation function. When classifying images, each class's distribution probability is output by the neural network.

In training, the categorical cross-entropy loss function is used since this model is a multi-class classification problem. The Adam optimizer, a popular stochastic gradient descent algorithm, is used, which adapts the learning rate during training. Initially, the model was trained for 15 epochs, but due to overfitting issues, an early stopping regularization technique was used, which means the CNN model will be stopped from training if validation loss does not improve for three consecutive epochs. The code in Appendix D shows how the CNN model was developed.

6.4 Ontology development

The following sections provide a thorough explanation of the development of the ontology model. In the proposed facial skincare recommender system, three types of ontologies are generated. The developed OWL ontology will be used by the recommender engine for querying facial care products. Also, the output of the ML engine will be improved by querying against the ontology knowledge base.

6.4.1 Data Acquisition Ontology Model

There are a large number of sources of skincare-related information that can be accessed through the internet. Novel products are also being developed regularly to meet the skincare needs of consumers. Consequently, it is not easy to find specific details regarding facial skincare concerns and product information. Therefore, it is essential to adopt a method that is efficient and effective and aims to organize and retrieve relevant details in the skincare domain. To gather all relevant data necessary for system development, proper guidance is required in relation to the recommendation of facial care products.

Skincare experts were consulted to identify the parameters that are essential in facial care OTC product selection. The key criteria that users need to look into when selecting skincare products were noted down when carrying out the dermatologist's interviews. They were the main guidelines that were followed when collecting further information for the recommender system from the dermatology textbooks and facial care product websites. The main guidelines that need to be followed in skincare product recommendations are the user’s skin type, skin concerns, age range, gender, the possibility of acne on the user’s face, the severity of acne present with acne types, and if users are allergic to any ingredients that are present in skincare products and need to avoid using them. Based on these benchmarks, skincare textbooks, articles, cosmetics, and cosmeceutical websites were referenced, and all the necessary information about the skincare domain and product information was gathered. Data were gathered manually as well as using a web scraper tool such as Scrapestorm. To understanding and map skincare concepts in ontology development, BSTS was followed. It helps to identify skin types such as oily, dry, pigmented, non-pigmented, etc. A person can take the BSTS questionnaire and identify their skin type as mentioned in the literature.

A survey was conducted to understand the existing skincare habits of consumers. Eleven male and ten female participants filled out the survey. Most participants were between the age range of 21–30, and the rest were in the age range of 31–40. The participants were asked about the skincare routine details they follow, how they tend to purchase skincare products, and the popular skincare brands that they use. Appendix A shows the attached survey form.

Based on the survey results, the most important data that is needed for our recommender system development was analyzed. A significant number of responses were recorded for the option that skincare products were purchased by browsing websites and identifying skin type, skin condition, and suitable ingredients. A similar number of responses were recorded for selecting skincare products based on recommendations by dermatologists or experts, recommendations by friends, and purchasing because of social media advertising. Here, purchasing products because of friends' recommendations or social media advertisements is not suitable. They might not cater to a person's individual skin type and concerns. So, the development of the recommender system is demanding.

Also, the most popular skincare brands that were used were Janet, The Ordinary, Paula's Choice, and Cerave, based on survey outcomes. Taking this into account, these brands were selected for product recommendation. The product information was collected from these skincare brands: Janet, The Ordinary, Paula's Choice, Cerave, and Nature's Secret. Skincare product related information was extracted from these websites by identifying the features of the products. Eight identified product features were used in system development: product name, skin concerns that the product treats, suitable skin types, time of use, key ingredients included, product type, if the product treats acne, the acne severity it can address, and the brand name of the product. Information was collected from the above-mentioned skincare brand websites relating to these key features of facial skincare products.

6.4.2 Data Preprocessing for Ontology modelling

The preprocessing data component prepares and preprocesses the data from both the facial skin related information and product details into a format suitable for ontology mapping. Identifying different attributes related to products is needed to create product profiles. In the development of product information ontology and skin information ontology, the key constituents affecting a user when selecting cosmetics or cosmeceutical products needed to be identified. These identified factors subsequently created the ontology's primary classes. As stated in the data collection section, the information gathered regarding various key features of facial skincare products was organized in an Excel sheet for easy creation of the relevant ontology classes, subclasses, and instances. Fig. 6.1 shows a snippet of the Excel sheet organized with the facial care products and key features with values relating to the Nature's Secret cosmetics brand.

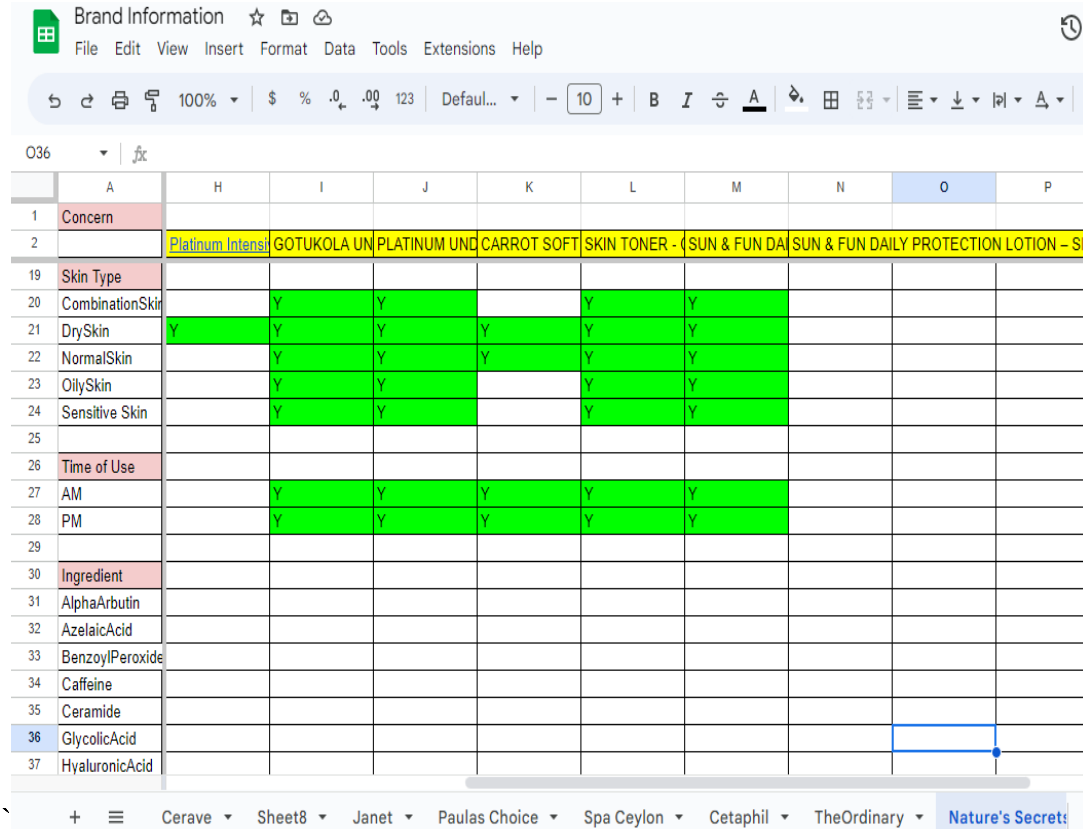


Figure 6.1: Preprocessing data for ontology construction

6.4.3 Ontology modelling

Ontologies aim to describe the objects and ideas that exist within a domain and share a common vocabulary with defined attributes and relationships. Protégé is an open-source software that is used for construction and managing ontologies. Among wide number of application disciplines, Protégé is the most frequently used tool for creating and maintaining ontologies, and knowledge bases. [41]. So, we have selected Protégé as our primary development environment to create the proposed recommender system ontology.

Here, ontologies are used to model information regarding the skincare products (the product profile), knowledge about the user (the user profile), and skincare concepts (the skincare profile). Ontologies allow the representation of domain knowledge in a structured and formal way. By sharing a common understanding of the knowledge structure, different applications and systems can reuse ontologies and share data in a standardized way, which improves systems' interoperability and reduces data inconsistencies.

In system development, three ontologies were modeled: the skincare concepts ontology, the skincare product information ontology, and the user profile ontology. These three ontologies were later merged and formed a single skincare domain ontology. An ontology data model describes information about a collection of classes or concepts and the relationships among them. The following figure 6.2 shows the proposed recommender system document analysis design diagram for ontology creation.

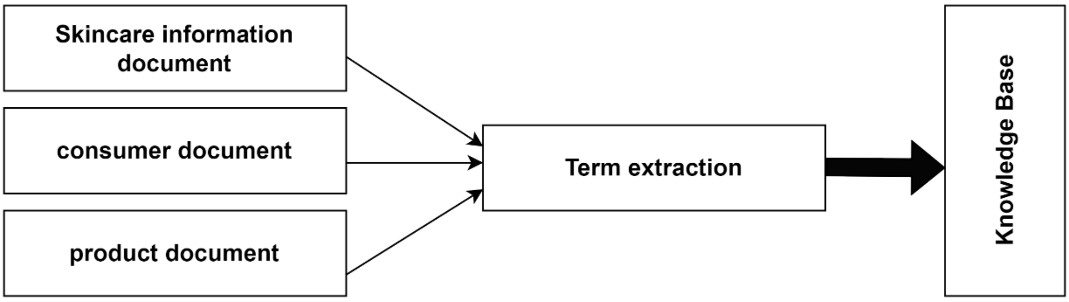


Figure 6.2: Skincare domain document analysis.

The key steps that were followed when ontology construction was based on the guidelines in "Ontology Development 101" by Noy and McGuinness [43] were:

1. The recommender system ontology domain was determined as the skincare domain, and facial skincare products and facial skincare information were determined as the scope of development.
2. There were not many existing ontologies that were feasible to use and matched our specific criteria for recommender system development. The concepts of the new system ontology were modeled by referring to and getting guidance from the accessible existing ontologies.
3. Ontology was defined as a set of terminologies that aid in classifying and describing domain concepts such as the person, facial skin information, and product information.
4. The next step is to define the class hierarchies. Taxonomy is used to define the hierarchical organization of classes. Hierarchies are used by inference engines to represent inheritance relationships [50]. The main methods available for defining class hierarchies are top-down processes, bottom-up processes, and combination processes. Here, we have followed the top-down method, where we first define the general skin care concepts and, moving down the class

hierarchy, specialized concepts are defined. As in figure 6.3, the skin information class is defined first, then concern and skin type, are subclasses of it. The concern class further has more specific subclasses such as *AcneAndBlemishes*, *Aging*, *Dehydration* and *Pigmentation*.

5. The next step is to define the properties. The relationship between members of a class is known as the properties in an ontology. Data properties and object properties are the two basic types of properties. The object properties serve as a representation of the binary relationships that exist between members of the classes. For example, the *suitableFor* object property is defined between the *TreatmentProduct* (domain) class and the *SkinType* (range) class. It shows the relationship or feature in skin care products that is suitable for certain skin types. Another example is the *Treats* object relationship defined between *TreatmentProduct* (domain) class and *Concern* (range) class. It shows the relationship that skincare products (*TreatmentProduct*) can be used to treat certain skin conditions. An individual is linked to a data literal via a data property, such as defined for Person *hasAge*, *hasGender*. Table 6.1 and 6.2 provides a detailed description of the defined object and data type properties.

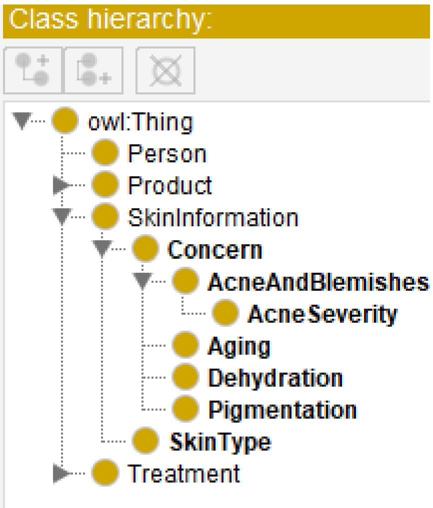


Figure 6.3: Snapshot of class hierarchy of *SkinInformation* class as seen in Protégé editor.

6.4.4 Skin Information ontology

Identifying different attributes or features of the facial skincare domain that are necessary and affect facial skincare product recommendations is vital. These key concepts then form the classes of ontology. Based on Baumann Skin Typing Systems

(BSTS) and the expert knowledge obtained through interviews, the facial skin factors that were most important for determining the best choice for facial skincare products were skin type and skin concern, where skin concern further breaks down into subclasses such as *AcneAndBlemishes*, *Aging*, *Dehydration*, *Pigmentation*. Based on expert input, *AcneAndBlemishes* class is further divided into *AcneSeverity* subclass based on acne severity. Figure 6.4 shows the class hierarchy of the skin information ontology, with main classes and subclasses.

The corresponding classes in the user profile, product profile, and skin information profile are determined using an ontology reference. The ontology model was created and evaluated using the protégé tool.

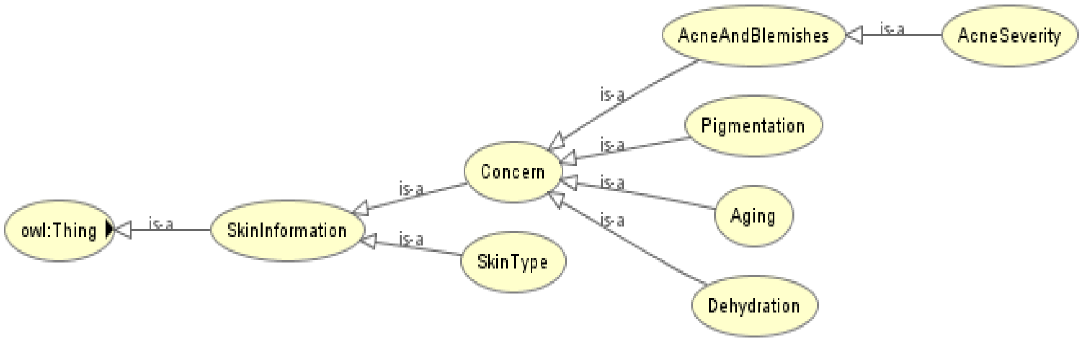


Figure 6.4: Illustration of the skin information ontology

6.4.5 User Profile

The user profile needs to be mapped before recommending skincare products. The user profile is kept simple with the user's personal details. The most critical factors are included in the facial skin information class hierarchies that will be mapped to recommend products for the user. Here, we record the user’s personal details only with the data type properties *hasAge* and *hasGender*. Figure 6.5 shows the OWLviz representation of the person class hierarchy.

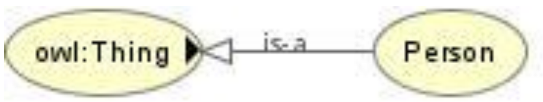


Figure 6.5: Illustration of the person ontology

6.4.5 Skincare product ontology

The skincare product ontology class hierarchy represents the details of the skincare products in our recommender system. It consists of all the product information that was previously extracted under key features in order to recommend products to the user. These product details help to map the semantic similarity between the skincare concepts and the product information. Also, when the products are recommended, this product information is shared with the user. For example, the *TimeOfUse*, *Brand* classes consist of the time the product can be applied to the facial skin and the brand of the cosmetics product. Then, the user can assign ratings to the products. If the user needs to give feedback by rating the recommended product it is recorded as an instance of the *ProductRecommendation* subclass. In the class hierarchy *Treatment* and the subclass *TreatmentProduct* as in Figure 6.8 shows the named products, while *DermatologicalTreatment* specifies other than the cosmetics or cosmeceuticals products recommended user would need to seek dermatological assistance based on the concern as well as the severity. For example, if a person has concerns about acne and its severe the system recommends seeking dermatological assistance. Figure 6.6 shows the OWLviz representation of the skincare product class hierarchy.

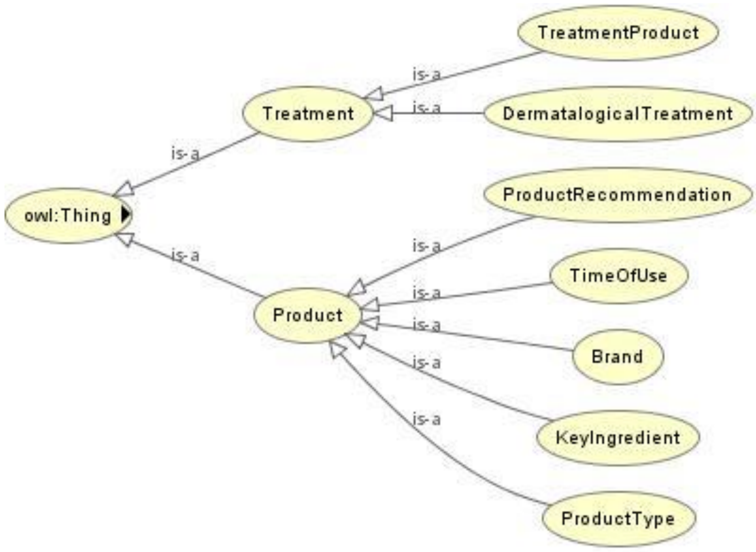


Figure 6.6: OWLViz representation of the skincare product class hierarchy

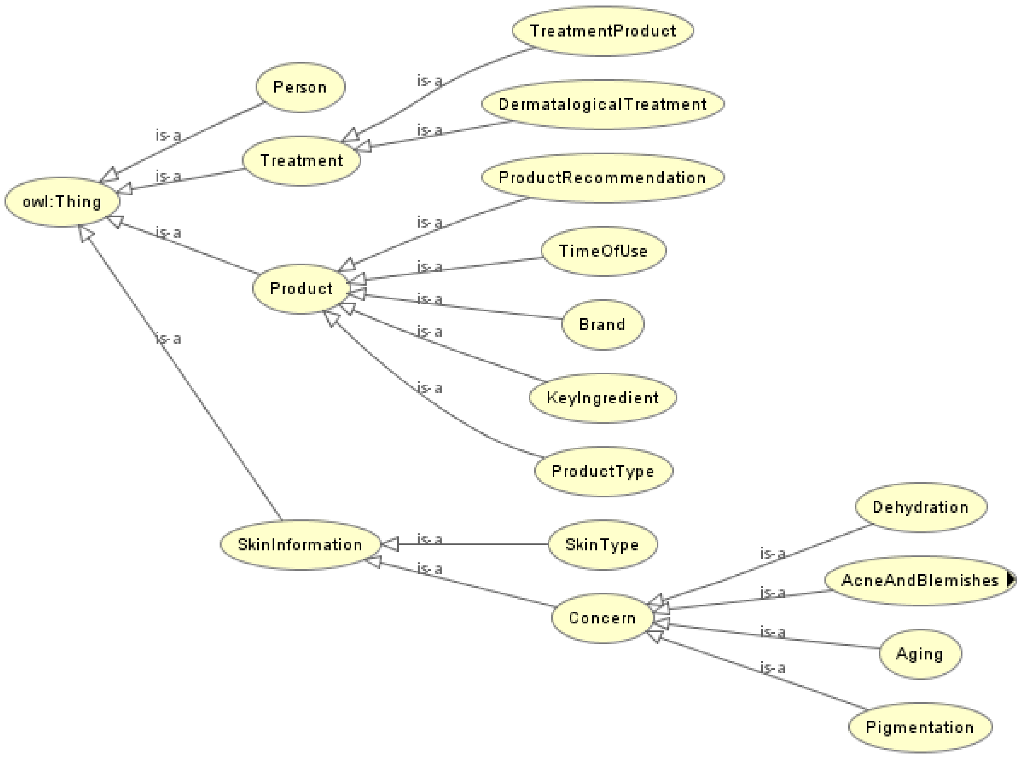


Figure 6.7: OWLViz representation of skin information, person and product information ontologies (skincare domain ontologies class hierarchy).

Table 6.1 shows all the object properties with their domain and range with their explanations.

Table 6.2 shows all the data type properties with their explanations.

Object Property	Domain	Range	Description
hasBrand	TreatmentProduct	Brand	Brand name of product
hasKeyIngredient	TreatmentProduct	KeyIngredient	Key Ingredient of product
hasProductRecommendation	TreatmentProduct	ProductRecommendation	Rating and recommendation given as feedback by user

Treats	TreatmentProdtuct	Concerns	Product treats which concern
suitableFor	TreatmentProduct	SkinType	Product suits which skin types
requireDermatologicalTreatment	Concern	DermatologicalTreatment	If concern require dermatologist assistance
TreatsAcneSeverity	TreatmentProduct	AcneSeverity	Product treats which severity level of acne
TypeofProduct	TreatmentProduct	ProductType	Product type
UsedAt	TreatmentProduct	TimeOfUse	Used time of product
userRecommendation	ProductRecommendation	Person	The rating and feedback given by user

Table 6.1: Object properties defined in the ontology.

Data Property	Domain	Range	Description
hasAge	Person	xsd:int	Age of user
hasGender	Person	xsd:string	Gender of the user

hasRating	ProductRecommendation	xsd:int	Rating given for a product by user

Table 6.2: Data type properties defined in the ontology.

After creating and mapping the ontologies, the skincare domain ontology modeled will be utilized as input in the recommender engine.

6.5 UI development

The Python Tkinter standard library was used to develop the GUI of the recommender system. Since it is lightweight and cross-platform, the built desktop application can be used across multiple operating systems, such as Windows and MacOS. The client can interact via the built-in UI and enter personal details as well as skin-related information. The data captured, therefore, by the UI is the username, age, gender, facial image, acne severity, skin type, product type, skin concern, and any allergy ingredients.

The UI is constructed by loading various frames and widgets into the Tkinter window. All the other elements are contained within the window, which is the foundational element. The following code snippet shows how the Tkinter window is initialized.

```
window = tk.Tk()

window.configure(width=500, height=300)

app= prepareGUI(window)

app.mainloop()
```

Then frames and widgets were added to make the UI more attractive and easier to use. Input by the user, personal information, and skincare-related information were structured under different frames. Frames are created using the "Frame" and "LabelFrame" classes from the Tkinter Library. Frames can be used to organize other GUI widgets (such as buttons, labels, etc.) within a window.

Using the GUI, the user can obtain a prediction of the acne severity level of their facial skin by uploading a photo. Then the pre-trained CNN model analyzes the facial image and gives a prediction if the user has mild, moderate, or severe levels of acne severity.

If the predicted acne severity is uncertain for the user and the CNN model developed is not 100% accurate, the system provides the option to manually select the acne severity. The user can select the drop-down that provides the best method for them to enter acne severity.

Figure 6.9 shows the system UI with acne severity prediction.

Next, the most important factor for product recommendation is the user’s skin type selection. Skin type and product type selections are displayed in the UI as drop-down or option menu widgets. The different skin types are combination skin, dry skin, oily skin, etc. The product types shown in the drop-down are cleanser, exfoliant, eye cream, moisturizer, serum, etc. Here, users can get recommendations from all available products by inserting the "All" dropdown selection.

The skin type and product data that are appearing in the UI are queried from the "FacialSkincareRecommendationSystem.owl" OWL file. It comprises the RDF/XML code describing the skincare domain ontology that was modeled earlier using the Protégé ontology editor.

The Rdflib Python library, which can read RDF/XML OWL ontologies directly and has comprehensive SPARQL querying capability, was used for the data retrieval from the OWL file. Using the function defineQueries(), SPARQL queries were defined as string variables. Using these queries, information was retrieved from the RDF graph. The data to display on the UI was queried as shown in Figure 6.8, a snapshot of SPARQL queries that was implemented in code. Based on Figure 6.8, the strings declared as SPARQL queries, "querySkinTypes", "queryProductTypes", "queryKeyIngredients", and “querySkinConcerns” as seen in code are explained below.

The "querySkinTypes" string, retrieves all the instances of the "SkinType" class in ontology. Similarly, "queryProductTypes" retrieves instances of product types from the "ProductType" class; "querySkinConcerns" retrieves instances from the "SkinConcern" class; and "queryKeyIngredients" retrieves instances from the "KeyIngredient" class.

```
def defineQueries(self):
    self.querySkinConcerns = """
            SELECT ?x
            WHERE { ?x rdf:type/rdfs:subClassOf* sko:Concern.
              FILTER NOT EXISTS {
?x rdf:type/rdfs:subClassOf* [rdfs:subClassOf* sko:AcneSeverity].
              }
            }
        """
    self.querySkinTypes = """
                    SELECT ?x
                    WHERE { ?x rdf:type/rdfs:subClassOf* sko:SkinType.
                    }
                """
    self.queryProductTypes = """
                    SELECT ?x
                    WHERE { ?x rdf:type/rdfs:subClassOf* sko:ProductType.
                    }
                """
    self.queryKeyIngredients = """
                            SELECT ?x
                            WHERE { ?x rdf:type/rdfs:subClassOf* sko:KeyIngredient.
                            }
                        """
```

Figure 6.8: Screenshot of code snippet implementing SPARQL queries using Python.

The skin concerns and allergy ingredients are implemented using the CheckButton widget in Tkinter. They appear as on/off selections. So, the selected concerns and allergy ingredients are passed in an array to the recommendation engine.

Once the user has made all the selections, by pressing the "Query Products" button in the UI as shown in Figure 6.9, they can proceed to view the recommended skincare products. Here, the user is given the information in a new window. The personal details of the user are shown in one frame with the recommendation if dermatological assistance is required, and in the other frame, the recommended product details are shown in tabular form. The product details, such as the product name, brand, usage time, and rating, are displayed. Figure 6.12 shows the screen with the product recommendation list and the details of the recommended products with the user's personal information.

Users can provide feedback by rating the products recommended. A rating from one to five can be assigned to a product, with five being the maximum rating and the recommended product that best suits the user's skincare needs.

Additionally, a button widget was added to the UI that provides information about the different skin types. When the "Skin Type Details" button is pressed, it opens up in a new window and helps identify the client's skin type by sharing skin details. A screenshot of the skin type details screen is attached in Appendix C.

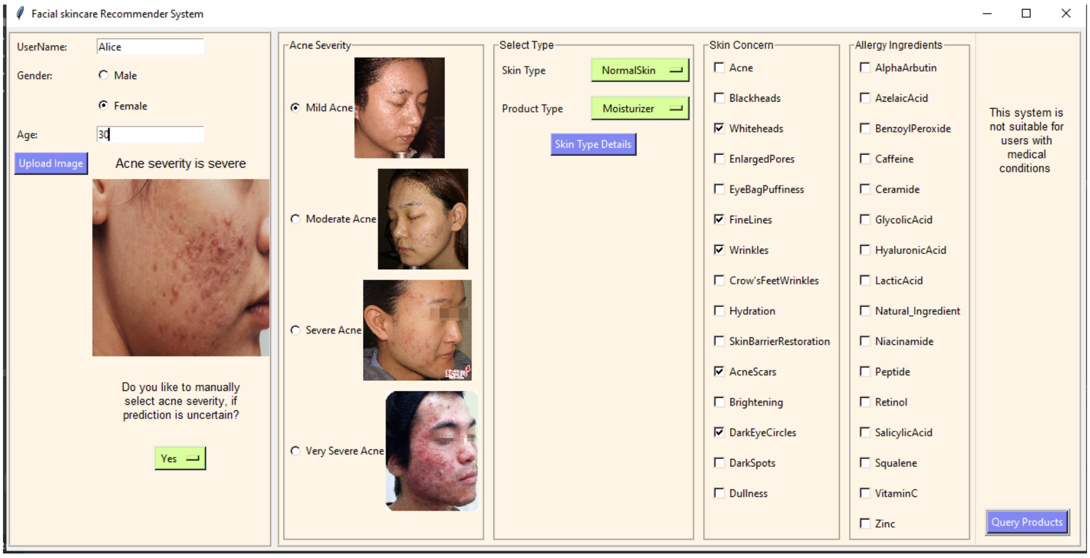


Figure 6.9: Screenshot of the main screen of facial skincare recommender system.

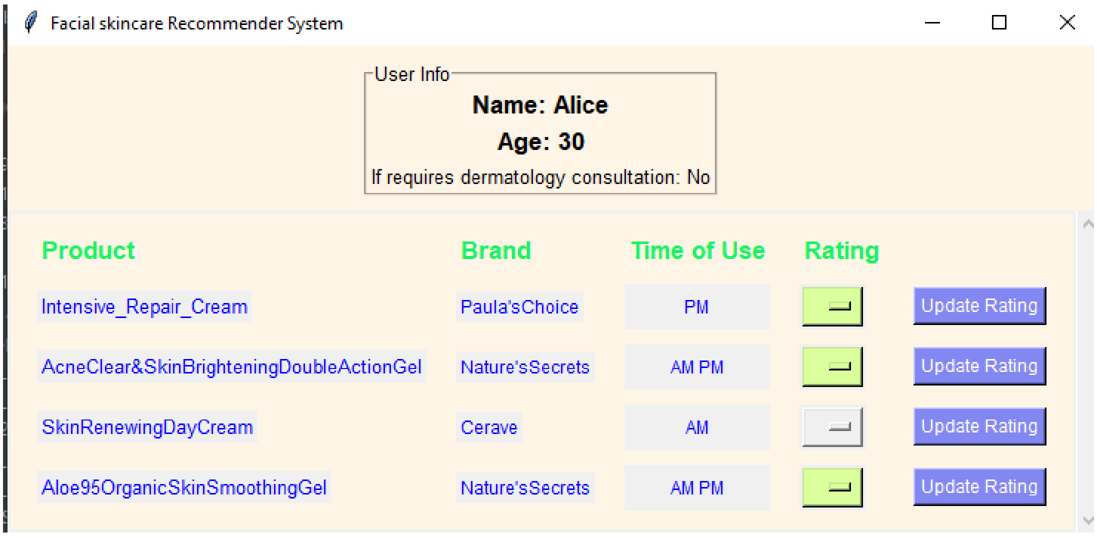


Figure 6.10: Screenshot of the product recommendation screen.

In order to maintain the consistency of the system, we have added several verifications that will provide warnings via the system UI if triggered. These will be checked when the user enters data into the system. For example:

- If username is empty

- If the user's age is not between 16 and 60.

Thus, UI builds the bridge between the ML engine, the modeled ontology, and the user for providing facial skincare recommendations.

6.6 Recommendation Engine

This is the most critical component of the recommendation system. The main inputs from the user are queried against the skincare domain knowledge base. The output from the ML engine is also further enhanced by querying against the skincare domain knowledge base when recommending products using the recommender engine.

The Owlready2 Python library has been used, which provides a convenient way to manipulate ontology classes, instances, and properties similar to handling regular Python objects [51]. This library was used to query the inputs taken via the UI with the OWL ontology.

The function named "defineQueries", recommends products based on the user-selected criteria, such as skin concerns, skin type, and acne severity, and searches for ontology instances in the OWL file for products using the object properties defined among OWL classes. For example, when the function searches for products that treat acne, as shown in the following code snippet, it iterates through the ontology searching for instances that have object property assertions that "Treat" "Acne" in the "TreatmentProduct" class. Further, it looks for instances that cure acne with a certain severity level (acneSeverity) using the "TreatsAcneSeverity" object property and are suitable for the user’s skin type (skinType) using the "suitableFor" object property.

Here, object properties are used to define relationships among classes or individuals in the OWL ontology. Therefore, utilizing this relationship between ontology instances helps personalize skincare products by searching for products that meet specific user criteria.

```
products = []
products_with_brand = []
allergy_products = []
if len(skinConcern) != 0:
    for concern in skinConcern:
        if concern == "Acne":
            products += self.onto.search(
```

```
            Treats=self.sko["Acne"],
      TreatsAcneSeverity=self.sko[acneSeverity],suitableFor=self.sko[skinType])
        if concern != "Acne":
          products += self.onto.search(
            Treats=self.sko[concern], suitableFor=self.sko[skinType])
          products = list(set(products))
```

In the same manner, products that contain allergy-causing ingredients are filtered out using the "hasKeyIngredient" property of the product list. Also, products are filtered based on the specified product type by checking if the product's "TypeofProduct" property matches the specified product type.

Additional information for the queried products was further added, such as brand using the "hasBrand" property, time of use using the "UsedAt" property, and rating using the "hasProductRecommendation" property.

Finally, the product list includes the products that have been filtered based on the user-specified criteria, such as skin concerns, allergy ingredients, skin type, acne severity, product name, and product type, as well as additional details of products to display in the UI, such as the brand of the product, time of use, and rating. Appendix D shows the code implemented for product recommendations.

When displaying product lists, the client is informed if dermatological treatment is required for a given combination of skin conditions and acne severity level. For the concerns and acne severity level instances selected by the user, if the "requireDermatologicalTreatment" property value is set to yes, it indicates that the skin concern needs to be examined by a skincare professional. If the attribute value is set to no, it does not require examination. For example, severe and very severe cases of acne need to be assessed by a dermatologist.

6.7 Summary

In this chapter, we describe the data acquisition and preprocessing methods for ontology modeling and ML model development. Then, implementation details of the ML model with CNN in the Google Colab runtime environment were discussed. Also discussed were the implementation details of ontology modeling in the skincare domain using the Protégé open-source ontology editor and the development of the facial skincare recommender system's UI, where the user interacts with the system and gets feedback. Finally, the implementation details of the recommendation engine, which is the core system component, take into account the user’s facial skin concerns, skin type, and other criteria for further personalization of products. In the next chapter, we will discuss the evaluation of the developed recommender system.

CHAPTER 7

EVALUATION

7.1 Introduction

The previous chapter shared a vivid description of the implementation of the recommender system. The system components were described separately, elaborating on their functionality and the development methods using the tools, technologies, and algorithms that have been used. In this chapter, an elaborate description of the experimental setup and evaluation of the developed recommender system will be provided. Also, this chapter will discuss whether the objectives defined in earlier chapters were met by the implemented facial skincare recommender system and to what extent.

7.2 Experimental Design

This study used 24 test subjects (12 males and 12 females). A questionnaire was prepared to determine consumer satisfaction and the quality of the suggested skincare products for the users. Five-point Likert-scale survey questions were asked. Likert scales have become an essential survey tool to get feedback on a person’s opinion or attitude regarding a product. It ranges from polar opposites to complete satisfaction to complete dissatisfaction [51]. Questions were structured to be asked under the categories of accuracy, familiarity, novelty of the product recommendations, and interactivity of the system. An optional question was asked if the user wanted to give any suggestions or feedback for further improving the system. This questionnaire determines whether the developed system has met the objectives and met the user's requirements and needs. Appendix B shows the attached questionnaire.

7.3 Experimental Results

The objectives of this study were to design and develop an ontology-based machine learning approach for facial skincare product recommendation and evaluate the prototype of the system. Experimental results were collected based on the survey conducted. Also, this system was evaluated by the dermatology specialist, who provided all the specifications for the system's development in order to ensure reliable functionality. The following figures show the analysis of the user-based testing questionnaire from 24 users.

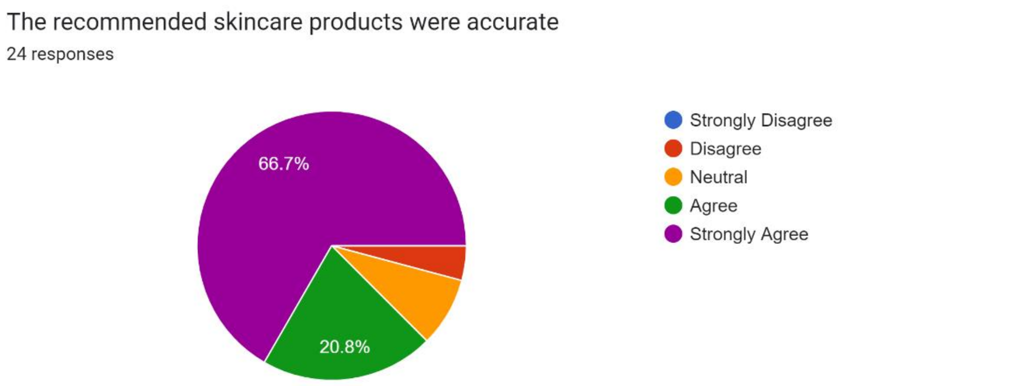


Figure 7.1: Percentage of feedback for the accuracy of the recommended products.

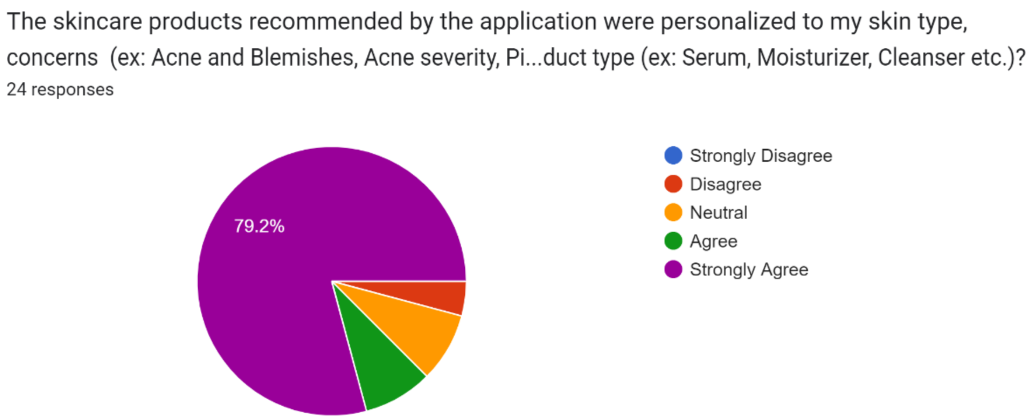


Figure 7.2: Percentage of feedback for how personalized the products are.

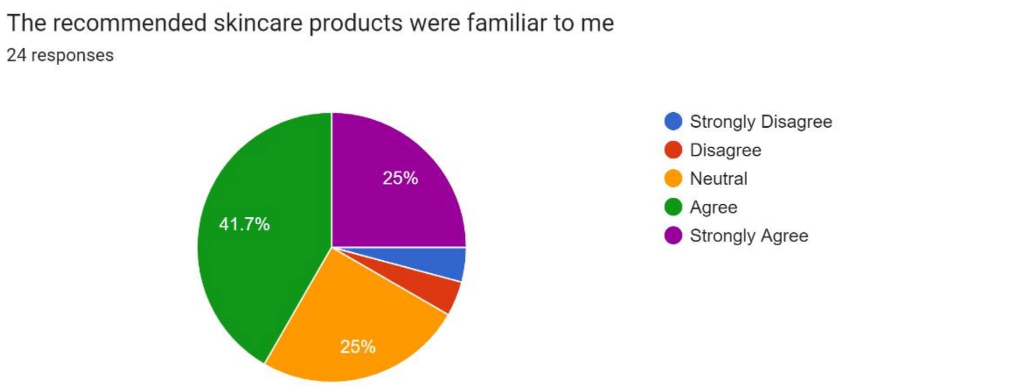


Figure 7.3: Percentage of feedback for how familiar the products are.

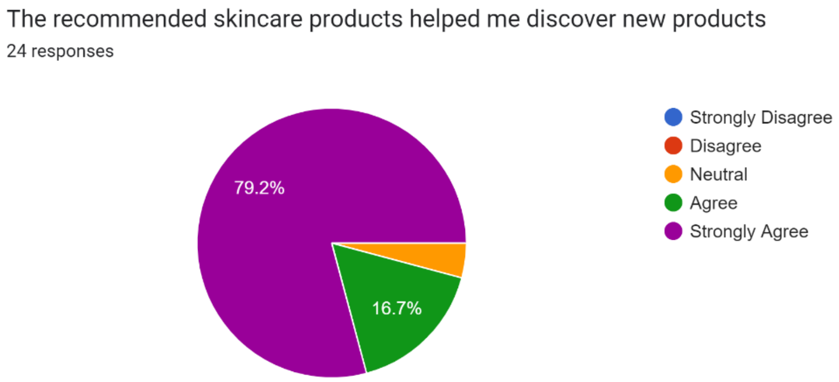


Figure 7.4: Percentage from feedback for how diverse the products are.

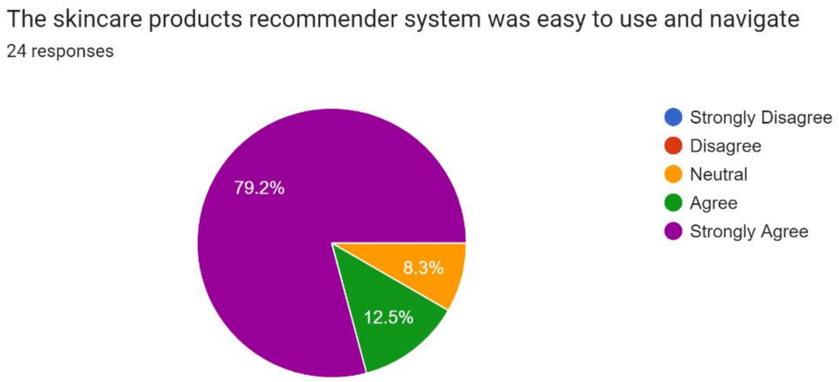


Figure 7.5: Percentage of feedback for how interactive and user-friendly the system's user interface is.

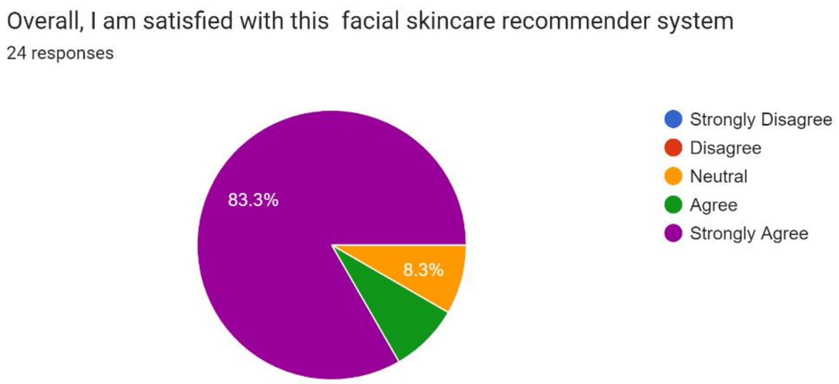


Figure 7.6: Percentage from feedback for overall satisfaction with using the system.

7.4 Conclusions of the experiment

From the results of the survey conducted, as shown in Figures 7.1 and 7.2, 87.5% of the participants said that the products were accurate, suitable for their skin type and skin concerns, and personalized according to their skincare needs. Also, 91.7% of the users stated that the user interface was easy to use and not complicated. Moreover, 91.6% of the users were satisfied with the overall functionality and user-friendliness of the facial skincare recommender system. As new facial care products were introduced to the users by the system, depending on the results in Figures 7.3 and 7.4, 66.7% of participants stated that they were familiar with the products recommended, and 95.9% affirmed that recommended products helped them discover new products.

7.5 CNN model evaluation

Even though the acne severity prediction of the user's facial image input is not the main objective achieved in this research, it was crucial that the CNN model's performance be evaluated since it provides an output from the system to the user. Standard ML evaluation techniques were used in model performance evaluations. Thus, the model had a precision, recall, and accuracy score of 78.2%, 75.1%, and 77.5%, respectively.

7.6 Summary

In this chapter, the experimental design and performance evaluation of the facial skincare recommender system based on the experimental results have been described. The Likert-scale survey questionnaire prepared addresses the criteria for testing system accuracy, usability, user-friendliness, and diversity of recommended products. Other than user testing, an expert dermatologist evaluated the system and ensured its reliable functionality. In the next chapter, conclusions and future work on this project are discussed.

CHAPTER 8

CONCLUSION

8.1 Introduction

The previous chapter described the system evaluation and the analysis of the results obtained. This chapter discusses the conclusions attained by the study of this thesis. Also, stating the achievement of each research objective. The final sections outline possible future works that can be accomplished.

8.2 Conclusions

With the dynamic and constantly expanding skincare industry, users are presented with a myriad of available facial care products. Selecting the skin care products that best suit the skin type and conditions is vital; otherwise, allergic reactions might occur with products that contain ingredients that are incompatible with the user's skin type. The existing skincare product recommendation systems fail to impart thorough knowledge about skincare product details and are not personalized to address individual users' skincare needs. This study presented a novel hybrid approach to providing recommendations based on ML and ontology. An ML model was utilized to identify the acne severity of the user's facial image. Acne severity was selected as the skin condition because, based on the literature, the majority of people suffer from acne vulgaris. The acne severity level is a key parameter when dermatologists recommend facial care products. This ontology-based recommender system is knowledge-based and employs ontologies to map knowledge about skincare concepts, facial care products, and user profiles in the recommendation process. The Protégé open-source ontology editor was used in ontology construction. In addition, ontology mapping of the user profile, skincare product information, and facial skin information utilizes the semantic similarity between these concepts in product recommendation. Since more than 87.5% of participants approved of the suggested skincare products and the results matched their particular skincare requirements, the evaluation results show that this machine learning and ontology-based facial skincare recommender system is effective and accurate for skincare product recommendations. Thus, the aim of this research is successfully accomplished.

The following objectives were identified in reaching the aim of this project.

- Critical review of literature in facial skincare domain and skin diagnosis.

- In-depth study of technologies adopted in facial skincare products recommender systems.
- Design an ontology-based machine learning approach for facial skincare products recommendation.
- Develop a prototype for recommending facial skincare products using the design ontology-based machine learning approach.
- Evaluate the prototype of the system.

During project implementation, all objectives are met to a greater extent.

8.3 Limitations and Further Works

The developed facial skincare recommender system can be further improved by implementing and employing a ML model to predict the user's skin type. It would improve the user experience of the system. Since skin type is a critical factor in personalizing skincare products.

We have also identified that we can improve the ML module to give predictions for skin conditions using the user's facial image. Other than the prediction of acne severity level, the ML model can enhance the ability to identify different acne types such as whiteheads, blackheads, papules, pustules, nodules, and cysts. Based on the literature, dermatologists also sometimes face difficulty accurately identifying acne types due to their overlapping features.

This application is developed as a desktop application; for further work, this system can be implemented into an accessible web-based application. Also, create user roles such as admin user and client user. An admin user would be able to update the knowledge base of the ontology since the skincare domain is constantly changing and updating.

8.4 Summary

In this chapter, we have discussed the conclusions reached by carrying out the research ontology-based ML approach for facial skincare products recommendation. The system design, implementation, and evaluation are taken into account in drawing the conclusions. Further, problems encountered, and the limitations of the skincare product recommender system are discussed, along with future developments that can additionally improve the performance of the system.

REFERENCES

[1] "Skin Care Products Market Size Report, 2022-2030." https://www.grandviewresearch.com/industry-analysis/skin-care-products-market (accessed Jul. 21, 2022).

[2] "Global Facial Care Market Size & Share | Industry Report, 2019-2025." https://www.grandviewresearch.com/industry-analysis/facial-care-market (accessed Jul. 19, 2022).

[3] Y. Lee, J. Choi, and S. Shin, "A Study on the Direction of Evaluation Indicators for Personalized Beauty Self-care," *J. Fash. Bus.*, vol. 24, no. 6, pp. 120–134, 2020, doi: 10.12940/jfb.2020.24.6.120.

[4] A. Alagić *et al.*, "Application of artificial intelligence in the analysis of the facial skin health condition," *IFAC-Pap.*, vol. 55, no. 4, pp. 31–37, Jan. 2022, doi: 10.1016/j.ifacol.2022.06.005.

[5] C. Karimkhani *et al.*, "Global Skin Disease Morbidity and Mortality," *JAMA Dermatol.*, vol. 153, no. 5, pp. 406–412, May 2017, doi: 10.1001/jamadermatol.2016.5538.

[6] Reportlinker, "Global Acne Market Report for 2016-2026." https://www.prnewswire.com/news-releases/global-acne-market-report-for-2016-2026-300576931.html (accessed Jul. 23, 2022).

[7] K. Rodan, K. Fields, G. Majewski, and T. Falla, "Skincare Bootcamp: The Evolving Role of Skincare," *Plast. Reconstr. Surg. Glob. Open*, vol. 4, no. 12 Suppl, p. e1152, Dec. 2016, doi: 10.1097/GOX.0000000000001152.

[8] A. Quattrini, C. Boër, T. Leidi, and R. Paydar, "A Deep Learning-Based Facial Acne Classification System," *Clin. Cosmet. Investig. Dermatol.*, vol. 15, pp. 851–857, May 2022, doi: 10.2147/CCID.S360450.

[9] H.-T. Chan, T.-Y. Lin, S.-C. Deng, C.-H. Hsia, and C.-F. Lai, "Smart Facial Skincare Products Using Computer Vision Technologies," in *2021 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, Dec. 2021, pp. 1674–1677.

[10] P. Nopparatkiat, B. na Nagara, and C. Chansa-ngavej, "Expert System for Skin Problem Consultation in Thai Traditional Medicine," *Afr. J. Tradit. Complement. Altern. Med.*, vol. 11, no. 1, pp. 103–108, Nov. 2013.

[11] "SkinSmart: A Recommendation System for Skincare Products," *Data Science Blog*. https://nycdatascience.com/blog/student-works/skinsmart-recommendation-system-skincare-products/ (accessed Jul. 30, 2022).

[12] M. S. Junayed *et al.*, *AcneNet - A Deep CNN Based Classification Approach for Acne Classes*. 2019, p. 208. doi: 10.1109/ICTS.2019.8850935.

[13] T.-Y. Lin, H.-T. Chan, C.-H. Hsia, and C.-F. Lai, “Facial Skincare Products’ Recommendation with Computer Vision Technologies,” *Electronics*, vol. 11, no. 1, Art. no. 1, Jan. 2022, doi: 10.3390/electronics11010143.

[14] C. P. C. Munaiseche, J. P. Amel, V. P. Rantung, G. C. Rorimpandey, F. I. Sangkop, and P. T. D. Rompas, “Expert System Implementation for the Diagnosis of Skin Diseases using Forward Chaining Method:,” in *Proceedings of the 7th Engineering International Conference on Education, Concept and Application on Green Technology*, Semarang, Indonesia: SCITEPRESS - Science and Technology Publications, 2018, pp. 287–291. doi: 10.5220/0009009902870291.

[15] M. E. Ibrahim, Y. Yang, D. Ndzi, G. Yang, and M. Almaliki, “Ontology-based Personalised Course Recommendation Framework,” p. 21.

[16] R. Alaa, M. Gawich, and M. Fernandez-Veiga, *Personalized Recommendation for Online Retail Applications Based on Ontology Evolution*. 2020, p. 16. doi: 10.1145/3397125.3397134.

[17] “Nutrition for Elder Care: a nutritional semantic recommender system for the elderly - Espín - 2016 - Expert Systems - Wiley Online Library.” https://onlinelibrary.wiley.com/doi/epdf/10.1111/exsy.12143 (accessed Jul. 29, 2022).

[18] X. Wu *et al.*, “Joint Acne Image Grading and Counting via Label Distribution Learning,” in *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*, Seoul, Korea (South): IEEE, Oct. 2019, pp. 10641–10650. doi: 10.1109/ICCV.2019.01074.

[19] “A Review of Skin and the Effects of Aging on Skin Structure and Function,” *Wound Manag. Prev.*, vol. 52, no. 9, Sep. 2006, Accessed: Mar. 28, 2023. [Online]. Available: https://www.hmpgloballearningnetwork.com/site/wmp/content/a-review-skin-and-effects-aging-skin-structure-and-function

[20] “Acne - Symptoms and causes,” *Mayo Clinic*. https://www.mayoclinic.org/diseases-conditions/acne/symptoms-causes/syc-20368047 (accessed Apr. 07, 2023).

[21] “Acne: Causes, treatment, and tips,” Nov. 27, 2017. https://www.medicalnewstoday.com/articles/107146 (accessed Apr. 07, 2023).

[22] L. Baumann and L. Baumann, *Cosmetic dermatology and medicine: principles and practice*, 2nd ed. New York: McGraw-Hill, 2009.

[23] Z. D. Draelos, “Revisiting the Skin Health and Beauty Pyramid: A Clinically Based Guide to Selecting Topical Skincare Products,” vol. 20, no. 6, 2021.

[24] “Meaning of Exfoliating: What Is It, Why You Should, and How to Start,” *Healthline*, Sep. 26, 2018. https://www.healthline.com/health/beauty-skin-care/meaning-of-exfoliating (accessed Apr. 09, 2023).

[25] K.-H. Park and Y.-H. Kim, “Skin Condition Analysis of Facial Image using Smart Device: Based on Acne, Pigmentation, Flush and Blemish,” *J. Adv. Inf. Technol. Converg.*, vol. 8, no. 2, pp. 47–58, Dec. 2018, doi: 10.14801/JAITC.2018.8.2.47.

[26] H. Wen *et al.*, “Acne detection and severity evaluation with interpretable convolutional neural network models,” *Technol. Health Care*, vol. 30, no. S1, pp. 143–153, Jan. 2022, doi: 10.3233/THC-228014.

[27] P. Kanani, “Deep Learning to Detect Skin Cancer using Google Colab,” *Int. J. Eng. Adv. Technol.*, vol. 8, pp. 2176–2183, Aug. 2019, doi: 10.35940/ijeat.F8587.088619.

[28] M. Patricia, E. Santiago, and M. Javier, “Expert System for the Pre-diagnosis of Skin Diseases,” *Int. J. Mach. Learn. Comput.*, vol. 10, pp. 81–86, Jan. 2020, doi: 10.18178/ijmlc.2020.10.1.902.

[29] N. Abdullah and A. S. H. Basari, “The Development of a Skincare Routine Expert System,” *Appl. Inf. Technol. Comput. Sci.*, vol. 3, no. 2, Art. no. 2, Nov. 2022.

[30] D. S. Ramdan, C. A. Sugianto, and R. D. Monica, “Expert System of Facial Skin Type Diagnosis and Skincare Recommendation Based on Certainty Factor,” *J. Appl. Intell. Syst.*, vol. 7, no. 3, Art. no. 3, Dec. 2022, doi: 10.33633/jais.v7i3.7150.

[31] V. Putriany, J. Jauhari, and R. Izwan Heroza, “Item Clustering as An Input for Skin Care Product Recommended System using Content Based Filtering,” *J. Phys. Conf. Ser.*, vol. 1196, p. 012004, Mar. 2019, doi: 10.1088/1742-6596/1196/1/012004.

[32] H. H. Moe and W. T. Aung, “Building Ontologies for Cross-domain Recommendation on Facial Skin Problem and Related Cosmetics,” *Int. J. Inf. Technol. Comput. Sci.*, vol. 6, no. 6, pp. 33–39, May 2014, doi: 10.5815/ijitcs.2014.06.05.

[33] “For Your Skin Beauty: Mapping Cosmetic Items with Bokeh | by Jiwon Jeong | Towards Data Science.” https://towardsdatascience.com/for-your-skin-beauty-mapping-cosmetic-items-with-bokeh-af7523ca68e5 (accessed Aug. 13, 2022).

[34] H.-H. Li, Y.-H. Liao, Y.-N. Huang, and P.-J. Cheng, “Based on machine learning for personalized skin care products recommendation engine,” in *2020 International Symposium on Computer, Consumer and Control (IS3C)*, Nov. 2020, pp. 460–462. doi: 10.1109/IS3C50286.2020.00125.

[35] C.-H. Hsia, T.-Y. Lin, J.-L. Lin, H. Prasetyo, S.-L. Chen, and H.-W. Tseng, “System for Recommending Facial Skincare Products,” *Sens. Mater.*, vol. 32, no. 10, p. 3235, Oct. 2020, doi: 10.18494/SAM.2020.2862.

[36] G. Lee, “A Content-based Skincare Product Recommendation System,” p. 5, 2020.

[37] C. Welty, "Ontology Research," *AI Mag.*, vol. 24, no. 3, Art. no. 3, Sep. 2003, doi: 10.1609/aimag.v24i3.1714.

[38] R. Stevens, C. A. Goble, and S. Bechhofer, "Ontology-based knowledge representation for bioinformatics," *Brief. Bioinform.*, vol. 1, no. 4, pp. 398–414, Nov. 2000, doi: 10.1093/bib/1.4.398.

[39] T. R. Gruber, "Toward principles for the design of ontologies used for knowledge sharing?," *Int. J. Hum.-Comput. Stud.*, vol. 43, no. 5, pp. 907–928, Nov. 1995, doi: 10.1006/ijhc.1995.1081.

[40] G. Antoniou and G. Antoniou, Eds., *A Semantic Web primer*, 3rd ed. in Cooperative information systems. Cambridge, Mass: MIT Press, 2012.

[41] D. Rubin, N. Noy, and M. Musen, "Protégé: A Tool for Managing and Using Terminology in Radiology Applications," *J. Digit. Imaging Off. J. Soc. Comput. Appl. Radiol.*, vol. 20 Suppl 1, pp. 34–46, Dec. 2007, doi: 10.1007/s10278-007-9065-0.

[42] "protégé." https://protege.stanford.edu/ (accessed Aug. 13, 2022).

[43] N. F. Noy and D. L. McGuinness, "Ontology Development 101: A Guide to Creating Your First Ontology," p. 25.

[44] "What are Convolutional Neural Networks? | IBM." https://www.ibm.com/topics/convolutional-neural-networks (accessed Apr. 14, 2023).

[45] R. Andreoni, "Building a Convolutional Neural Network from Scratch using Numpy," *Medium*, Oct. 13, 2022. https://towardsdatascience.com/building-a-convolutional-neural-network-from-scratch-using-numpy-a22808a00a40 (accessed Apr. 21, 2023).

[46] T. A. Team, "Beginners Guide to Convolutional Neural Network from… – Towards AI." https://towardsai.net/p/machine-learning/beginner-guides-to-convolutional-neural-network-from-scratch-kuzushiji-mnist-75f42c175b21, https://towardsai.net/p/machine-learning/beginner-guides-to-convolutional-neural-network-from-scratch-kuzushiji-mnist-75f42c175b21 (accessed Apr. 21, 2023).

[47] S. Balaji, "Binary Image classifier CNN using TensorFlow," *Techiepedia*, Aug. 29, 2020. https://medium.com/techiepedia/binary-image-classifier-cnn-using-tensorflow-a3f5d6746697 (accessed Apr. 22, 2023).

[48] "Google Colab." https://research.google.com/colaboratory/faq.html (accessed Apr. 14, 2023).

[49] B. Ekanayake, "A DEEP LEARNING-BASED BUILDING DEFECTS DETECTION TOOL FOR SUSTAINABILITY MONITORING," p. 12, 2022.

[50] M. E. Ibrahim, "An Ontology-based Hybrid Approach to Course Recommendation in Higher Education".

[51] P. Page, "Likert scale survey questions and examples," *The Jotform Blog*, Jan. 24, 2023. https://www.jotform.com/blog/likert-scale-survey-example/ (accessed Apr. 05, 2023).

APPENDIX A

PRODUCT INFORMATION ACQUISITION QUESTIONNAIRE

To collect information regarding the existing popular skincare brands and the skincare routines that the users currently follow, a survey was shared among eleven males and ten females. The participants were asked about the skincare routine details they follow, how they tend to purchase skincare products, and the popular skincare brands that they use. This section includes the questionnaire shared among participants via Google Forms.

Popular Skincare Brands in SL

For the partial completion of Masters Degree Program in AI from UOM this questionnaire will be carried out in strict confidentiality of your privacy

* Indicates required question

1. Gender *

   Mark only one oval.

   - Male
   - Female

2. Age Ranges *

   Mark only one oval.

   - 15-20
   - 21-30
   - 31-40
   - 41-50
   - Above 51

3. The skincare brands that you use? *

Check all that apply.

- [ ] Cerave
- [ ] Cetaphil
- [ ] Cosrx
- [ ] Farmacy
- [ ] Nutrogena
- [ ] PaulasChoice
- [ ] The Inkey List
- [ ] Simple
- [ ] Janet
- [ ] The Ordinary
- [ ] Versed
- [ ] Mesoestetic
- [ ] Glow Recipe
- [ ] Other:

4. If you do have a skin care routine and the details about it?

5. How do you purchase skincare products *

Check all that apply.

- [ ] Recommendation by Dermatologist or expert
- [ ] Purchasing by browsing website and identifying skin type and condition and suitable ingredients
- [ ] Social Media Ads
- [ ] Recommendation by friends
- [ ] Other: ______________

APPENDIX B

SYSTEM EVALUATION QUESTIONNAIRE

To get user feedback and evaluate the overall system based on accuracy as well as user satisfaction with the facial care recommendation system, the following questionnaire was shared among users:

4/22/23, 9:08 PM Facial Skincare Recommender system assessment

Facial Skincare Recommender system assessment

For the partial completion of Masters Degree Program in AI from UOM this questionnaire will be carried out in strict confidentiality of your privacy to evaluate the developed facial skincare recommender system

* Indicates required question

1. Gender *

Mark only one oval.

- Male
- Female

2. Age Ranges *

Mark only one oval.

- 15-20
- 21-30
- 31-40
- 41-50
- Above 51

3. The recommended skincare products were accurate *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

4. The skincare products recommended by the application were personalized to my skin type, concerns (ex: Acne and Blemishes, Acne severity, Pigmentation, Dehydration, Aging) and required product type (ex: Serum, Moisturizer, Cleanser etc.)? *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

5. The recommended skincare products were familiar to me *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

6. The recommended skincare products helped me discover new products *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

7. The system recommended to seek assistance from dermatologist for severe acne cases and skin diseases *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

8. The skincare products recommender system was easy to use and navigate *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

9. Overall, I am satisfied with this facial skincare recommender system *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

10. I would recommend this skincare recommender system application to others *

Mark only one oval.

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

11. Do you have any suggestions or feedback? If yes, please leave them below

APPENDIX C

FACIAL SKINCARE RECOMMENDER SYSTEM USER INTERFACE

In this section, various screenshots of the user interface of the prototype facial skincare recommender system will be shared. Also, different test scenarios where user information is entered, and product recommendations given will be demonstrated here. Screenshots denoting key features of the developed system will also be shared here.

- Skincare products recommended for user Alice with
- Acne Severity: Mild
- Gender: Female
- Age: 30
- Skin Type: Normal Skin
- Product Type: Cleanser
- Skin Concern: Acne, Blackheads, Hydration, Acne Scars
- Skin Allergy Ingredients: Caffeine, Lactic Acid

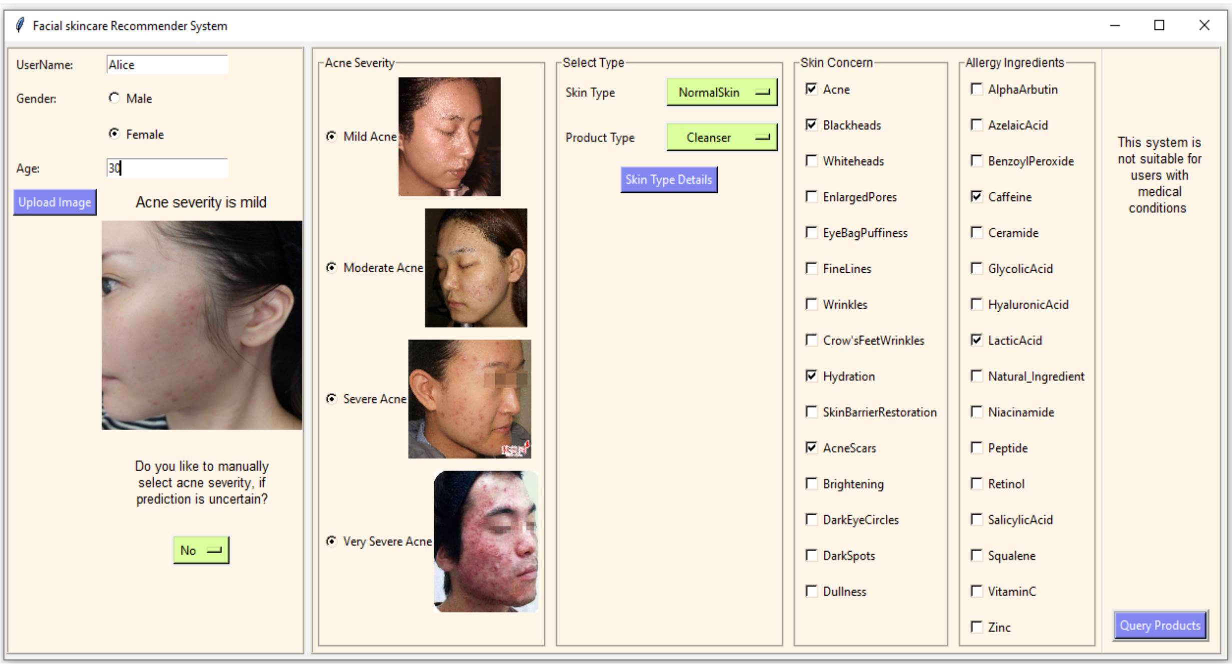


Figure C.1: Facial skincare recommender main selections window.

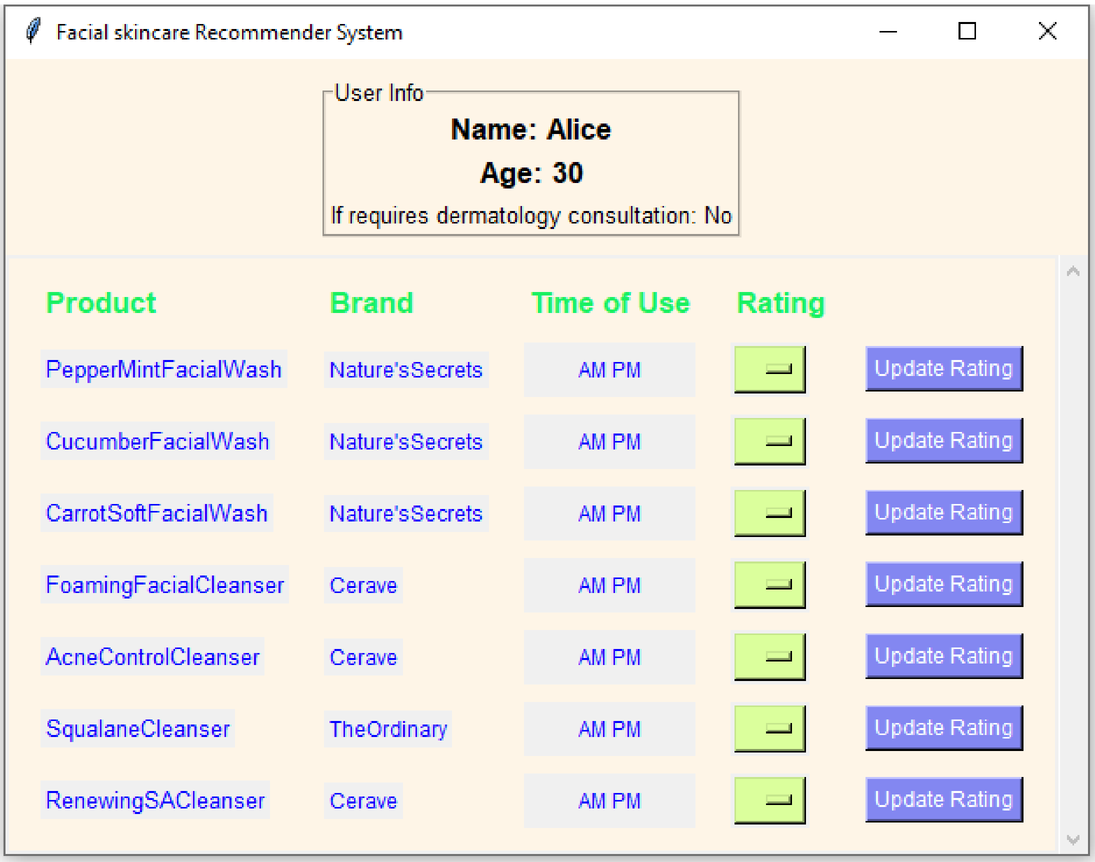


Figure C.2: Recommended product list screen.

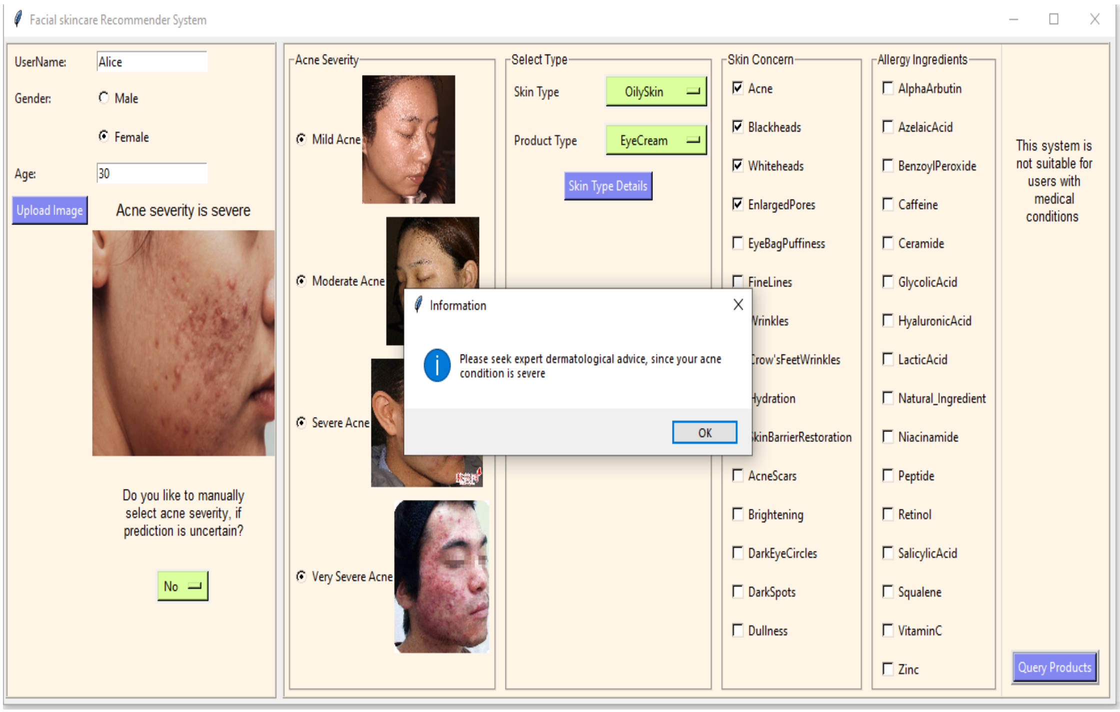


Figure C.3: Screenshot prompting user to seek dermatological assistance.

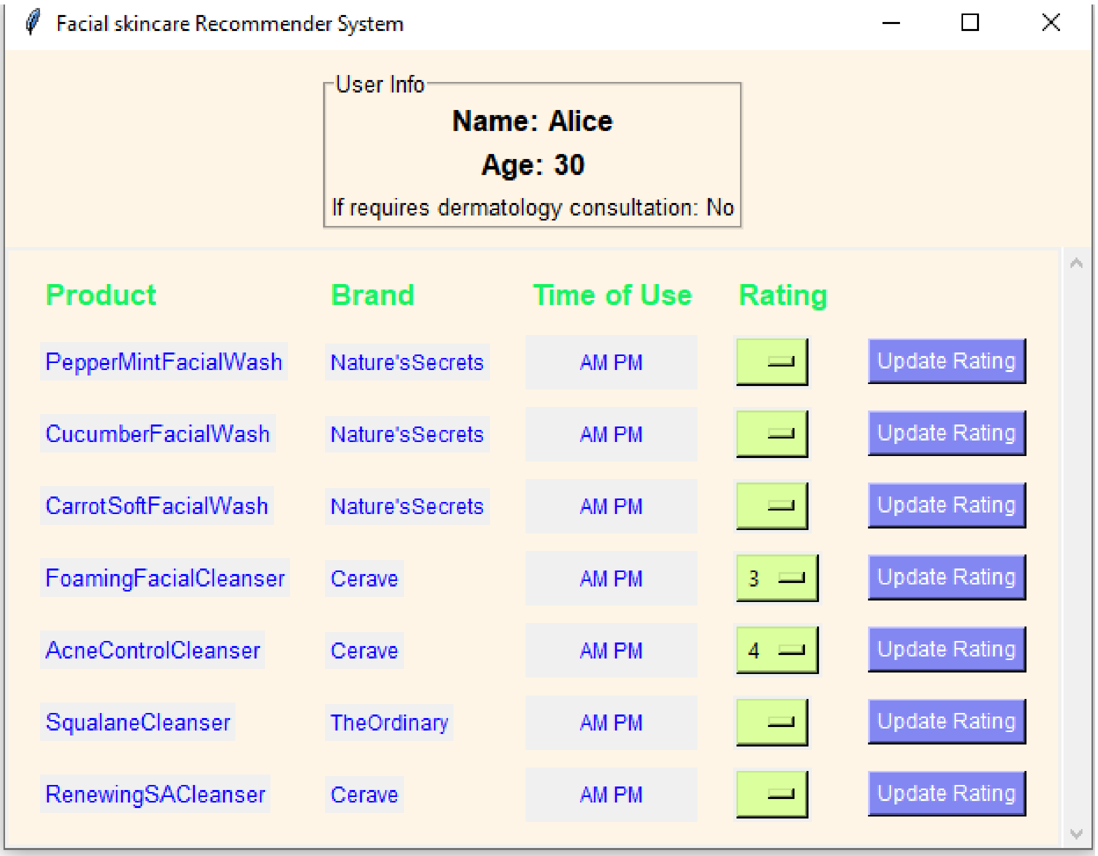


Figure C.4: Update product rating.

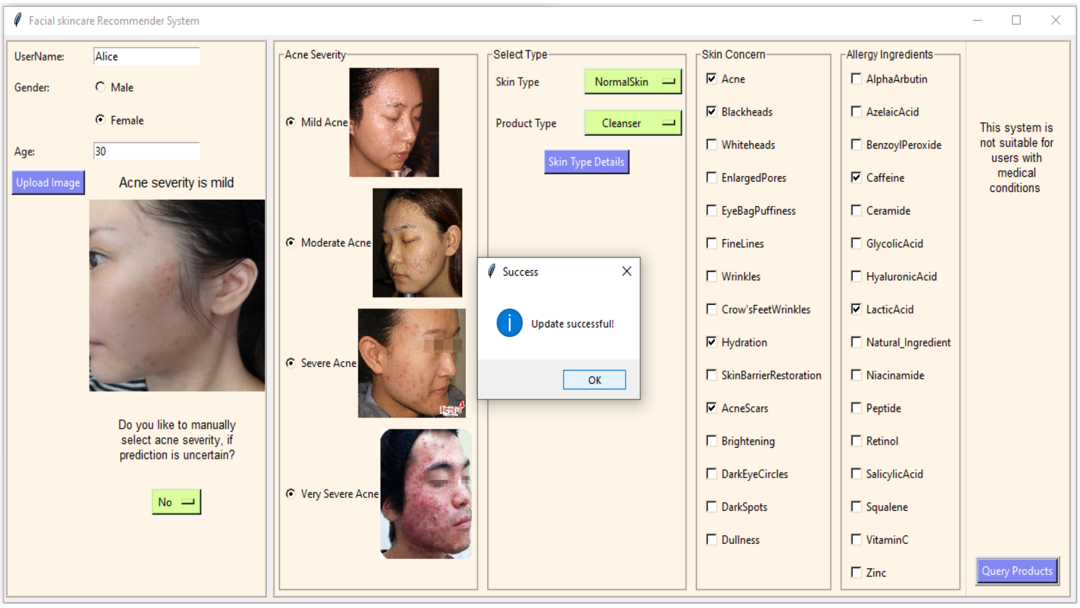


Figure C.5: Update product rating success message.

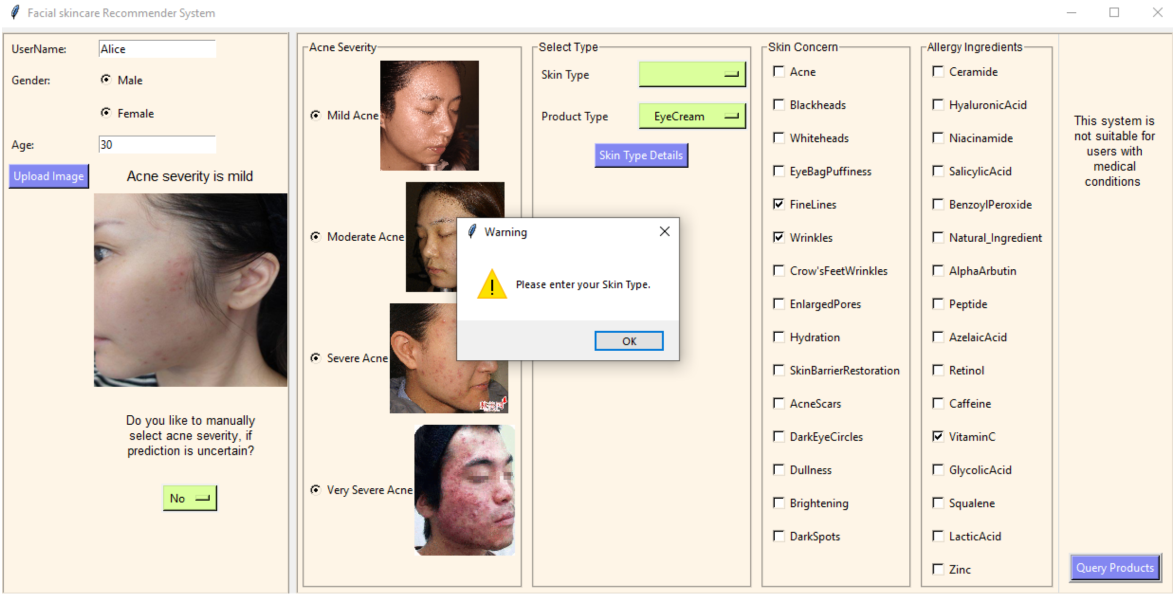


Figure C.6: System Validation.

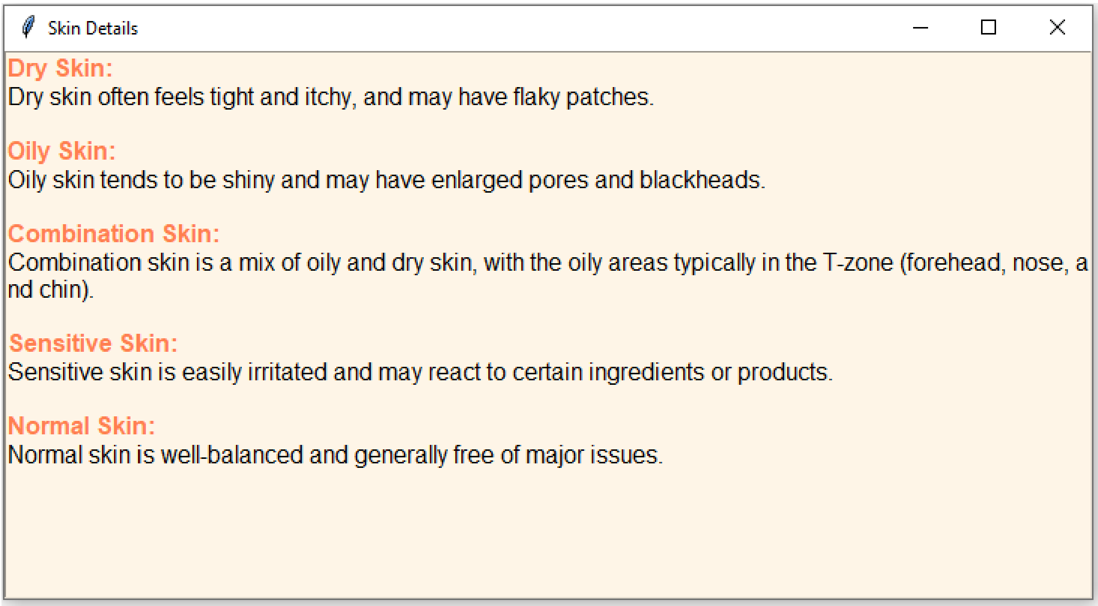


Figure C.7: Skin type details screen.

APPENDIX D

CODE: FACIAL SKINCARE RECOMMENDER SYSTEM

This section will include the code used to develop the system.

<u>CNN Model development: data preprocessing</u>

<u>Data Scaling</u>

```
scaled_data = data.map(lambda x, y: (x/255, y))
scaled_iterator = scaled_data.as_numpy_iterator()
scaled_batch = scaled_iterator.next()
scaled_batch[0].max()
```

<u>Data Augmentation</u>

```
data_augmentation = tf.keras.Sequential([
  layers.RandomFlip("horizontal_and_vertical"),
  layers.RandomRotation(0.4),
  layers.RandomContrast(0.3),
  layers.RandomTranslation(
    0.2,
    0.35,
    fill_mode='reflect',
    interpolation='bilinear',
    seed=None,
    fill_value=0.2),
  layers.LayerNormalization(
  axis=-1,
  epsilon=0.001,
  center=True,
  scale=True,
  beta_initializer="zeros",
```

```
    gamma_initializer="ones",
    beta_regularizer=None,
    gamma_regularizer=None,
    beta_constraint=None,
    gamma_constraint=None
)
])
```

<u>CNN Model Architecture development:</u>

```
model = Sequential(name="Acne_3_Class_Classification")
data_augmentation,
model.add(Conv2D(16, (3,3), 1, activation='relu', input_shape=(256,256,3)))
model.add(MaxPooling2D())
model.add(Conv2D(32, (3,3), 1, activation='relu'))
model.add(MaxPooling2D())
model.add(Conv2D(16, (3,3), 1, activation='relu'))
model.add(MaxPooling2D())
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(3, activation='softmax'))
```

<u>User personal details captured in system UI:</u>

```
self.label_name = tk.Label( self.frame1, text="UserName:", fg=self.textColor, bg=self.textboxcolor )
 self.entry_name = tk.Entry(self.frame1)
 self.label_gender = tk.Label(
 self.frame1, text="Gender:", fg=self.textColor, bg=self.textboxcolor )
 self.var_gender = tk.StringVar()
 self.radio_male = tk.Radiobutton(
```

```
self.frame1,
text="Male",
variable=self.var_gender,
value="male",
bg=self.bgcolor,
)
self.radio_female = tk.Radiobutton(
self.frame1,text="Female",variable=self.var_gender,value="female",bg=self.bgcolor)
self.label_age = tk.Label(
self.frame1, text="Age:", fg=self.textColor, bg=self.textboxcolor)
self.entry_age = tk.Entry(
self.frame1,
validate="key",
validatecommand=(window.register(self.validate), "%P"),)
```

<u>Handle acne severity prediction</u>

```
    def predict(self):
        try:
            filepath = filedialog.askopenfilename()
            img = cv2.imread(filepath)
            opn_img = Image.open(filepath)
            opn_img = opn_img.resize((255, 255), resample=Image.BICUBIC)
            temp_img = tf.image.resize(img, (256, 256))
            opn_img = ImageTk.PhotoImage(opn_img)
            self.opn_img = opn_img
            resize_img = temp_img.numpy().astype(int)
            model = load_model("./acneSeverityModel_FEB_12_3Classes.h5")
            yhat_testing = model.predict(np.expand_dims(resize_img / 255.0, 0))
            predicted_class_index = np.argmax(yhat_testing)
```

```
        print("class: ", yhat_testing)
        label_display_image = tk.Label(
            self.frame1, image=opn_img, width=200, height=200, padx=self.padx
        )
        acne_prediction = self.selectAcneSeverity(str(predicted_class_index))
        print(acne_prediction)
```

Filtering skincare products for recommendations

```
def defineQueries(
    self, skinConcern, allergyIngredients, skinType, acneSeverity, name, productType
):
    products = []
    products_with_brand = []
    allergy_products = []
    if len(skinConcern) != 0:
        for concern in skinConcern:
            if concern == "Acne":
                products += self.onto.search(
                    Treats=self.sko["Acne"],
                    TreatsAcneSeverity=self.sko[acneSeverity],)
            if concern != "Acne":
                products += self.onto.search(
                    Treats=self.sko[concern], suitableFor=self.sko[skinType]
                )
                products = list(set(products))
    else:
        products += self.onto.search(suitableFor=self.sko[skinType])
    for ingredient in allergyIngredients:
```

```
            allergy_products += self.onto.search(hasKeyIngredient=self.sko[ingredient])
        for element in allergy_products:
            if element in products:
                products.remove(element)
        results = []
        for product in products:
            if productType != "All" and productType != "":
                if (
                    not product.TypeofProduct
                    or self.sko[productType] not in product.TypeofProduct
                ):
                    continue
            brand = product.hasBrand[0] if product.hasBrand else None
            time_of_use = ()
            if len(product.UsedAt) > 0:
                time_of_use = (product.UsedAt[0],)
            if len(product.UsedAt) > 1:
                time_of_use += (product.UsedAt[1],)
            rating = self.getRating(name, product.name)
            if rating is not None and rating >= 2:
                products_with_brand.append((product, brand, time_of_use, rating))
            elif rating is None:
                products_with_brand.append((product, brand, time_of_use, rating))
        return products_with_brand
```

<u>Check if concern requires dermatological assistance.</u>

```
    def check_dermatological_treatment(self, skinConcern, acne_severity):
        requireDermatologicalAssistance = "No"
        try:
```

```
    acne_severity_iri = self.sko[acne_severity].iri
    acne_severity_individual = self.onto.search_one(iri=acne_severity_iri)
    acne_severity_dermatalogical_treatment_value = str(
        acne_severity_individual.requireDermatologicalTreatment[0]
    ).split(".")[-1]
    if acne_severity_dermatalogical_treatment_value == "Yes":
        print(f"Dermatological treatment is required for {acne_severity}")
        requireDermatologicalAssistance = "Yes"
    if requireDermatologicalAssistance == "No":
        for concern in skinConcern:
            concern_individual = self.onto.get_individual(self.sko[concern])
            if concern_individual is None:
                continue
            if hasattr(concern_individual, "requireDermatologicalTreatment"):
                concern_individual_dermatalogical_treatment_value = str(
                    concern_individual.requireDermatologicalTreatment[0]
                ).split(".")[-1]
                if concern_individual_dermatalogical_treatment_value == "Yes":
                    requireDermatologicalAssistance = "Yes"
                    break
    return requireDermatologicalAssistance
except Exception as e:
    print(e)
    return requireDermatologicalAssistance
```