CURETO: Skin Diseases Detection Using Image Processing And CNN

R.K.M.S.K Karunanayake ¹, W.G Malaka Dananjaya ², M.S.Y Peiris ³, B.R.I.S. Gunatileka ⁴, Shashika Lokuliyana ⁵, Anuththara Kuruppu ⁶

Department of Information Technology Sri Lanka Institute of Information Technology Malabe, Sri Lanka

 $\frac{shamalkarunanayake@gmail.com^1, malaka0779402015@gmail.com^2, saranipeiris17@gmail.com^3,}{isurugunatileka.ig@gmail.com^4, shashika.l@sliit.lk}^5, \underbrace{thilmi.k@sliit.lk}^6$

Abstract—Busy lifestyles these days have led people to forget to drink water regularly which results in inadequate hydration and oily skin, oily skin has become one of the main factors for Acne vulgaris. Acne vulgaris, particularly on the face, greatly affects a person's social, mental wellbeing and personal satisfaction for teens. Besides the fact that acne is well known as an inflammatory disorder, it was reported to have caused serious long-term consequences such as depression, scarring, mental illness, including pain and suicide. In this research work, a smartphone-based expert system namely "Cureto" is implemented using a hybrid approach i.e. using deep convolutional neural network (CNN) and natural language processing (NLP). The proposed work is designed, implemented and tested to classify Acne density, skin sensitivity and to identify the specific acne subtypes namely whiteheads, blackheads, papules, pustules, nodules and cysts. The proposed work not only classifies Acne Vulgaris but also recommends appropriate treatments based on their classification, severity and other demographic factors such as age, gender, etc. The results obtained show that for Acne type classification the accuracy ranges from 90%-95% and for Skin Sensitivity and Acne density the accuracy ranges from 93%-96%.

Keywords— Acne Vulgaris, Convolutional Neural Networks (CNN), Natural Language Processing (NLP), Recommendation, Sensitivity

I. INTRODUCTION

Skin being the biggest organ in the human body it is imperative to keep up a sound skin. It is said that most regular skin diseases in 2013 were acne vulgaris, dermatitis, urticaria and psoriasis and it is a fact that skin illnesses have become regular around the world [1].

Acne vulgaris, particularly on the face, greatly affects a patient's passionate, social, and mental wellbeing, and personal satisfaction for youths and youthful grown-ups. Even though acne is well known as an inflammatory disease for a long time, severe outcomes of the disease such as distress, scarring, mental unsettling influences including despondency and suicide have been identified quite recently [1]. It can be demonstrated that treating acne can give a huge impact on diminishing the psychological and social pain of patients [2]. It is very important to identify the exact severity stage of acne to treat acne properly [3]. 9.4% of the global population have acne [4], but if we take it another way roughly 85% of the population in the age range from 11 years to 30 years of old have had acne at some point in their life [5]. If we take an aggregate of all the acne treatment costs in the world, each year it exceeds one billion US dollars [6] [7].

Acne wounds can be categorized into several types [8]. They are mainly blackheads, whiteheads, papules, pustules, nodules and cysts [9]. If not treated properly, the

density level of acne can increase. The higher the acne density level, then it becomes more difficult to treat. When it becomes worse the drugs that usually doctors prescribe to treat the disease have numerous side effects [10]. When it comes to Acne Severity one of the ways to measure it is the Global Assessment of acne severity along with analyzing the number of lesions on the infected skin area. The four identified stages are clear skin without any inflammations, clear almost skin with a small number dispersed comedones and very few papules, skin with mild acne which includes a small number of comedones, papules, pustules and even a nodule and skin covered with a considerable number of comedones, papules, pustules and multiple nodules [11]. Not only these factor skin sensitivities should also be considered when acne treatments are given. According to [12], skin sensitivity also can be categorized as follows subjective symptoms such as stinging, itching, burning and/or visible skin changes such as redness, dryness, scaling, peeling, bumps, hives. If irrelevant treatment is given without considering the acne subtype, an increase in acne density and skin sensitivity in acne vulgaris could be seen.

Therefore, to minimize the above-mentioned problems there is indeed a clear need for knowledgeable, expert systems to classify acne vulgaris and also identify facial skin conditions such as acne density and skin sensitivity in the early stages itself. In previous research works the authors have tried many approaches to classify acne using traditional machine learning algorithms. Hence the target of this research is to propose a mobile application to identify skin sensitivity, Acne density and to classify the Acne type using an image or based on symptoms while recommending a home remedy. In this research work concepts related to Machine Learning, Deep Learning, Image Processing and Natural Language Processing are used.

The rest of the paper is organized as follows. In section II, a critical analysis of the literature review is presented. The methodology is explained in section III. In section IV, the results are discussed. Conclusions and future work are presented in section V.

II. LITERATURE REVIEW

Under this section, the authors reviewed several research papers to recognize existing research areas building a mobile application with the possibilities of acne subtype, skin sensitivity, and acne density identification together with recommending homeopathic treatments. Further, it is subdivided into areas of convolutional neural network for image classification, Natural language processing for text classification and recommendation algorithm.

In 2016, the authors have built a mobile application to detect and classify acne. The main objective of this research was to find a proper solution to identify and classify acne severity from photos taken by a cellphone. Here three different segmentation methods have been used in which two-level k-means clustering outperformed the others and also when it comes to classification part two machine learning methods were used. Here FCM (fuzzy c-means) method outperformed the Support Vector Machine (SVM). The authors have mentioned that the texture method they used is insufficient and needs further improvement. Also, they have mentioned that color tones and hair in the pictures affect accuracy. Therefore, Cureto focuses on tropical skin and to eliminate inaccuracy areas with heavy facial air will be ignored [13].

In research done by Sunyani technical university in 2019, they have used a Web-based approach to diagnose Skin Diseases. Researchers concluded that CNN is enough to extract features from the images. Also, they have successfully managed to reduce the computational time (0.0001 seconds) together with an increase in accuracy. However, the study did not specifically focus on acne subtype classification and also this is mainly a web-based application [14] therefore Cureto will address the issue of portability and subtype classification.

Recent research done in 2018 focused on identifying acne using smartphone images [11]. However, they mainly classify Acne into only two subtypes namely papules and pustules. They have used a facial recognition algorithm to separately identify features in the face and to classify acne accordingly. One of the main limitations the authors have presented is that the presence of more than one face and also bad lighting will affect the classification. However, the main disadvantage seen in this study is even though the accuracy is high they have classified acne only to two types but dermatologists and also websites have specifically stated that Acne can be of mainly six types as mentioned above.

In the classification of images based on convolutional neural networks, the authors have found many researches on the diagnosis of a medical condition based on deep learning techniques. In another study, researchers jointly train a CNN-RNN model and achieve multilabel classification and common thorax disease analysis. Their experimental results demonstrate the excellent capability of deep networks for medical images to reflect features [15].

Going further, in a study done by Cardiff university [15] they have developed a grading of acne visual and Counting Via Label Distribution learning. Authors conclude that Deep Feature outperforms both the other method, they have clearly stated that deep features represent acne via information of a high semantic level and better performance. Accordingly, it is also said that ResNet50 [16] reaches the best performance in basic CNN models. Therefore, in the proposed research component CNN model will be used to classify acne subtype, acne density and skin sensitivity.

Under the classification using Natural Language Processing the most relevant research to Acne identification is a study to apply natural language processing to Reddit comments about dermatology topics to assess for feasibility and potential for insights and engagement [17]which was done in 2019 using Latent Dirichlet Allocation (LDA). The biggest limitation in this as confirmed by the research team

itself is the use of LDA where in which it is an unsupervised model, which means that there is no ground-based truth comparable to the model performance. However, during this research, the authors have decided to use a supervised learning model. In our study, the authors decided to use Naïve Bayes. Support Vector Machine and also adding a novelty by using a deep learning classifier namely [18] convolutional neural networks and finally selecting the most appropriate classifier according to the dataset.

Several types of research have been done related to the recommendation, but none has been found up to now personalized homeopathic specifically for acne recommendation. A study which has already done a literature review on existing medicinal recommendation systems, have described the various features those recommendation systems have used [9]. This study shows that CADRE [19] has used a Collaborative Filtering algorithm to develop recommendation system for online pharmacies recommend drugs. Collaborative Filtering is best suited for recommending based on how other users had responded to a certain item. The features of the item are not considered here, only user preferences are considered. The content-based Algorithm is best suited for recommending based on the features of said item that are more related to a single user [19].

In 2016, students at Thammasat University has researched to make an acne detection system to track medical treatment progress. This system was mainly a desktop-based application developed using .NET C#. The Open CV library was used in image processing and also for patient face detection Haar Cascade classifier was used. The drawback of this system is it does not validate the BLOB results with an acne feature set and they have planned on doing it as a future work using a confusion matrix [20].

A study done by conducted by Fuji et al. displayed the possibility of classifying forms of acne lesion by applying a combination of several linear discriminating functions (LDF). By using a multispectral image (MSI) they were able to distinguish many types of skin lesions such as comedo, reddish papule, pustule and scar [21]. It is stated that misclassifications have been found in some photos that have segmented scar areas represented by a yellow color (skin colors) and the author itself has stated that it is a limitation in the classifier. Hence, in the proposed research work, the classification will be considered regardless of the skin color but mainly focusing on tropical facial features.

Based on the literature study, the authors have figured out that there hasn't been any single system built mainly based on a mobile application with the four components that will be developed in this study up to date.

III. METHODOLOGY

This research proposes a mobile application that will take the user input image or user symptoms description or sometimes both and give output on Acne Density, Skin Sensitivity, Acne subtype and appropriate treatment recommendation as shown in Figure 1.

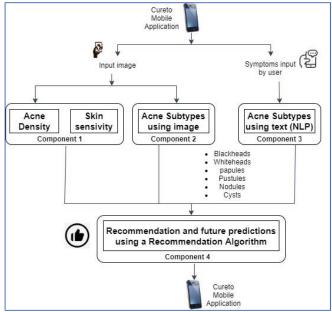


Fig.1. System Architecture

The mobile application as shown in Fig. 2 is build using the Flutter framework, dart programming language and firebase database and the backend server is implemented using the Python language in which are all the processing related to machine learning are done and produces the user inputs and outputs through the Restful API endpoints within a time frame of 30 seconds for an image based on the image size and less than 5 seconds for text input.



Fig 2: Results interface in Cureto

A. Acne Density and Skin Sensitivity Identification

Acne Density identification is based on the percentage of acne on the face compared to other facial skin conditions like warts, blister, skin cancer, redness, bumps, hives, rosacea, eczema, psoriasis, cellulitis, melanoma, lupus, vitiligo, etc.

When it comes to skin sensitivity there are various methods to identify skin sensitivity such as [13] subjective symptoms such as stinging, itching, burning and or visible skin changes such as redness, dryness, scaling, peeling, bumps, hives. Hence, our research is only based on visible

skin changes as we are getting the diagnosis using images. The outputs will be of 3 levels as mild-moderate and severe which is based on the percentages of results obtained by the two models acne density and skin sensitivity.

Since the Input is an image, classification using Image Processing was used. As the first step, the images were preprocessed and afterward Image Processing algorithms were used. Based on the background researches it could be found that several similar approaches have been conducted using machine learning algorithms like KNN, SVM, logistic regression. However, in this research, classification is based on CNN because no transfer learning does happen in machine learning algorithms, Deep learning there is transfer learning happens. Therefore, we used a transfer learning CNN model with 100 epochs with Resnext features for the classifications.

Data distribution consists of training data with the percentages of 80% and validation data with the percentage of 20%. After pre-processing, features are extracted using Resnext architecture. Out of the many trained CNNs available, we used a Transfer learning CNN model with 100 epochs with Resnext features for the classification and after observing the different accuracies in the literature survey. Instead of sticking to a one CNN model, we have tested few architectures to enhance our results. When considering the dataset it was taken from different angles to increase the accuracy. Data augmentation techniques were also used to improve the dataset functionalities.

Significant training configurations and the model parameters were batch size=64, drop rate=0.5, epochs=100, validation percentage=20%, testing percentage=80% and learning rate=0.001. Since there were few training images, increased the training batch size from the default value of 100 to 64. Batch size defines how many images were used per one iteration. We include all our validation data set into the validation batch size since it will eventually lead to more stable results through various training iterations.

When considering the selected architectures, Resnext has gained the 3.03% top-5 error rate in previous classification studies. Resnext is a homogenous, multi-branch architecture that has only a few hyper-parameters to set and it has exposed a new dimension called cardinality which represents the size of a set of transformations. The newly exposed dimension is an essential factor when compared to dimensions of depth and width. Here we used 2 versions of the model which contains 50 and 101 layers with Resnext. And in Seresnext, include a squeeze-and-excitation (SE) block that recalibrates channel feature responses adaptively. Here also the authors have used two versions of the model which contain 50 and 101 layers with Seresnext.

B. Acne Subtype Identification using Image

In this section, it could be seen how the dataset is divided into testing and training datasets according to a given ratio namely 80:20. In the image processing phase mainly three subcategories are identified namely image preprocessing, image segmentation and feature extraction. In the image processing phase, the image is first segmented and then resized into 224x224. After pre-processing, features are extracted using Senet transfer learning.

The dataset was pre-processed to eliminate any null values or unwanted values. The key features of items are then

selected to create the model. After the model was created 80% of the pre-processed dataset was used to train the model. After training, the remaining 20% was used to test if the model was working properly and accurately.

TABLE I. DATA DIVISION

Class	Training Images	Evaluation Images	Validation Images
Whiteheads	320	40	40
Blackheads	320	40	40
Cysts	320	40	40
Nodules	320	40	40
Pustules	320	40	40
Pastules	320	40	40
Normal Skin	320	40	40

In the research, the main focus was to classify Acne type most accurately. To ease the result comparison process, we have implemented 3 different CNN based models to classify images into different classes and we used 15 different CNN architectures by making it easy to select the best performing model at the final android application implementation.

- 1. Custom CNN sequential model with 10 epochs
- 2. Transfer learning CNN with SeNet152 features
- 3. Transfer learning logistic regression with SeNet152 features

Instead of sticking to one CNN model, we build our classifier with different options that can be obtained and analyzed how the accuracy will be differing from model to another depending on the model.

Most of the training configurations were set to default values but the exceptions were: batch size, drop rate, epochs, validation percentage, testing percentage and learning rate. Since there were few training images, we increased the training batch size from default 100 to 32. Batch size defines how many images were used per one iteration. We include all our validation data set into the validation batch size since it will eventually lead to more stable results through various training iterations.

Detailed training configurations are shown in below Table II.

TABLE II: TRAINING CONFIGURATIONS

Training Batch Size	32
Drop Rate	0.5
Epochs	100
Validation Percentage	20%
Training Percentage	80%
Learning Rate	0.001
Beta_1	0.9
Beta_2	0.999
Validation Batch Size	100%

Training the CNN model was performed on a virtual machine provided by the Google Colab platform with the specs of Intel(R) Xeon(R) CPU @ 2.00GHz, 1xTesla K80, compute 3.7, having 2496 CUDA cores, 12GB GDDR5 VRAM.

C. Acne Subtype Identification using Symptoms

This proposed component mainly covers the part of identifying the specific Acne type once the user inputs his/her disease symptoms. Since this is a text recognition part mainly Text classification using Natural language Processing was used. Based on the background researches it could be found that several similar approaches have been used however mainly in these three algorithms specifically Naïve Bayes', Support vector machine and Convolutional Neural network were tested and out of the three, the most accurate model is selected to be used.

As the initial step, an algorithm was developed to read the data, preprocess it by removing stop words, removing non-English words, tokenizing, and turning sentences into lowercase. Next, the whole dataset which resides on the .csv file was split as train and test data randomly and accordingly. It was fed to all three algorithms Naïve Bayes', Support vector machine and Convolutional Neural network to find the best fit. The classification is mainly done based on keywords that are relevant to each disease.

For the initial release of the product Naïve Bayes' was used and a separate REST API namely "AcneTypeBasedOnSymptoms" was implemented to check if the routes are working as expected. The dataset was continuously enhanced to find the most accurate algorithm even though Naïve Bayes' was used for routing testing purposes.

D. Recommendations based on Acne Density, Skin Sensitivity and Acne Sub-type

This component recommends homeopathic remedies and advice based on Acne Type, Acne Severity, and Skin Sensitivity. A Content-based Recommendation Algorithm is used for implementing the recommendation system. The outputs from the previous three components are taken as inputs for recommending the advice and remedies.

When implementing the recommender system, a dataset of .csv file format was created with the features/columns Homeopathic Remedy, Acne Type, Acne Severity, Skin Sensitivity, Advice and Directions. This dataset was then taken into a data frame which was then preprocessed to replace any null values and convert any integers to a string. After the data frame was pre-processed it was then converted into a matrix then the cosine similarities are found within the matrix and the features to base the recommendations (Acne Type, Acne Severity, Skin Sensitivity) are selected. Finally, the inputs (outputs of the previous three components) are fed into the recommender system. The similarity scores are then ordered in descending order, which will give out the highest similarity scores for the most suitable remedies and advice, depending on the given inputs.

After the remedies and advice are recommended, a representation of the skin condition progression, when those remedies and advice are used is shown.

IV. RESULTS AND DISCUSSION

The research work was tested under different conditions to find the strengths and weaknesses in different components.

A. Acne Density and Skin Sensitivity Identification

Once the dataset is split as training and testing datasets and fed to the models the following accuracies were found using 4 Resnext based architectures. As mentioned in the methodology results obtained for the transfer learning model are mentioned in Table III as it was the best model that depicted the realistic results.

TABLE III. ACCURACY COMPARISON

Architecture	Acne Density	Skin sensitivity
resnext101	61.73%	42.37%
resnext50	58.25%	80.51%
seresnext101	85.11%	95.74%
seresnext50	84.79%	95.76%

These accuracies were taken after training the models with more than 4000 image data. However, the accuracy can be enhanced by adding more images. Out of the following, it could be seen that transfer learned seresnext50 architecture performed best with an accuracy of 95.76% for the skin sensitivity model and transfer learned seresnext101 architecture performed best with an accuracy of 85.11% for the acne density model.

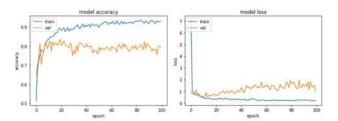
B. Acne Subtype Identification using Image Results & model layers that we obtained from SEResNet152 are illustrated in fig.3.

Layer (type)	Output	Shape	Param #
flatten (Flatten)	(None,	100352)	0
dense (Dense)	(None,	256)	25690368
dropout (Dropout)	(None,	256)	0
dense_1 (Dense)	(None,	7)	1799

Total params: 25,692,167 Trainable params: 25,692,167 Non-trainable params: 0

7/7 [========] - 0s 6ms/step - loss: 0.9696 - accuracy: 0.7955 [INFO] accuracy: 79.55% [INFO] Loss: 0.9695905447006226

Fig.3. Final Accuracy Results



While comparing with the past researches it could be seen that the proposed system classifies Acne into more subtypes than before but most of all the accuracy is important. Therefore, the best accuracy was identified with the transfer learned Sequential CNN model with SeResNet152 features. Performing a multi-class facial image classification of 6 different acne types using deep learning algorithms has been presented in this paper. The system proposed will be able to classify Normal Skin, blackheads, whiteheads, cysts, nodules, pustules, & papules. The authors were able to get the best accuracy result with extracted features using the SeResNet152 pre-trained CNN model. A custom sequential CNN model was applied to those extracted features and finally got an accuracy of 79.55% on the validation data set.

C. Acne Subtype Identification using Symptoms

As shown in Table IV it could be seen that the CNN algorithm outperforms Naïve Bayes' and SVM. Once the dataset is split as training and testing datasets and fed to the models the following accuracies were found, Naïve Bayes' is 77%(figure 5), SVM is 81%(figure 6) and CNN is 84%.

TABLE IV: NLP ACCURACY COMPARISON

Architecture	Model Accuracy	
Naive Bayes' Accuracy	77.55	
SVM Accuracy	81.73	
CNN Accuracy	84.79	

These accuracies were taken after training the models with 800 plus text data records. However, accuracy can be changed if the number of text records increases. Out of the following, it could be seen CNN performs best.

D. Recommendations based on Acne Density, Skin Sensitivity and Acne Sub-type

Delivering accurate results was the main goal of this research. Accuracy of the recommendation system depends on the number of features; the recommendations are based and the size of the dataset. Initially, three features were selected to base the recommendations, which were Acne Type, Acne Severity, Skin Sensitivity, and with the size of the dataset used, the recommendation system came to produce accurate results. The following figure shows the similarity scores with one feature and with three features. When having one feature the accuracy of the recommendation system was 50% and when three features were used the accuracy was 87% which is shown in Table V.

TABLE V: ACCURACY COMPARISON (RECOMMENDATION)

Accuracy with 1 feature	Accuracy with 2 features	Accuracy with 3 features
50%	69%	87%

To the overall Software Development phase, certain strategies were followed to support future enhancements and changes. When it comes to machine learning codes all are implemented in google cloud which is a cloud platform that supports heavy CPU and GPU processing. Also, all the processing is done in the backend so that the mobile application does not consume system resources massively.

V. CONCLUSION AND FUTURE WORK

This Skin Diseases Detection Using Image Processing And Convolutional Neural networks is a mobile application which enables the user to capture or select an existing image of facial Acne or input the symptoms or both and get an output of Acne density, Skin sensitivity, Acne Subtype and recommendations on the most appropriate Acne homeopathic remedies. The mobile application supports both Android (Version 4.4 or above) and IOS users. By combining all 4 components into a single system we were able to achieve 75-85% accuracy. The summary of the accuracy of the 4 components is shown in Table VI.

TABLE VI. ACCURACY COMPARISON (SYSTEM)

Component		Accuracy	Best Fit Model
Acne	subtype	79.55%	Seresnet152
classification	1		
model(Using	g Images)		

Acne subtype classification model (Using Symptoms)	84%	CNN
Acne density	85.11%	Seresnext101
skin sensitivity model	95.76%	Seresnext50
Recommendation	87%	Content-based
model		algorithm

As future works of our research, we will be focusing on expanding the existing system to classify more facial skin diseases type more accurately using the application of both image and text inputs. When it comes to the recommendation part, the authors are focusing on engaging cosmetic entrepreneurs and dermatologists to recommend their products also in the future.

ACKNOWLEDGMENT

This research work is supported by the Sri Lanka Institute of Information Technology(SLIIT).

REFERENCES

- [1] M. E., J. Newton, S.-B. S., S.-B. S., R. T. and F. A., "The quality of life in acne: a comparison with general medical conditions using generic questionnaires.," *British Journal of Dermatology*, pp. 672-676, 1999.
- [2] H. J., S. R., D. F., T. M., B. E. and L. L., "Suicidal ideation, mental health problems, and social impairment are increased in adolescents with acne: a population-based study.," *Journal of Investigative Dermatology*, pp. 363-370, 2011.
- [3] R. E. and K. A., "New photographic techniques for clinical evaluation of acne.," *Journal of the European Academy of Dermatology and Venereology*, pp. 13-18, 2001.
- [4] D. B. and P. F, "Epidemiology of acne," *Dermatology*, pp. 7-10.
- [5] J. Tan, "Current measures for the evaluation of acne severity," *Expert Review of Dermatology*, pp. 595-603, 2008
- [6] C. L., L. S., H. M., H. K. and E. S., "Acne vulgaris: a disease of Western civilization," *Archives of dermatology*, pp. 1584-1590, 2002.
- [7] G. H., "From new findings in acne pathogenesis to new approaches in treatment," *J Eur Acad Dermatol Venereol*, pp. 1-7, 2015.
- [8] J. Huizen, "Acne types in pictures: Explanations and treatments," Medical News Today, 29 June 2018. [Online]. Available: https://www.medicalnewstoday.com/articles/322322.php# causes. [Accessed 1 Feb 2020].
- [9] C. K. and .. M. A. K. E. B. Stark, "A Literature Review on Medicine Recommender Systems," (IJACSA) International Journal of Advanced Computer Science and Applications, vol. 10, no. 8, 2019.
- [10] Brito, M. d., Anna, I. P., Galindo, J. C., Rosendo, L. H. and &. Santos, "Evaluation of clinical adverse effects and laboratory alterations in patients with acne vulgaris treated

- with oral isotretinoin.," An Bras Dermatol, pp. 331-336, 2010.
- [11] A. M., V. f., V. M., H. K., Z. H., K. W. and M. N., "Automated facial acne assessment from smartphone images," San Francisco, California, United States, 2018.
- [12] DermNet NZ, "Sensitive skin | DermNet NZ," [Online]. Available: https://dermnetnz.org/topics/sensitive-skin/. [Accessed 1 Feb 2020].
- [13] N. Alamdari, K. Tavakolian, M. Alhashim and R. Fazel-Rezai, "Detection and classification of acne lesions in acne patients: A mobile application," in 2016 IEEE International Conference on Electro Information Technology (EIT), 2016.
- [14] S. Akyeramfo-Sam, A. A. Philip, D. Yeboah, N. C. Nartey and I. K. Nti, ""A WebBased Skin Disease Diagnosis Using Convolutional Neural Networks," *International Journal of Information Technology and Computer Science*, 2019.
- [15] X. Wu, N. Wen, J. Liang, Y.-K. Lai, D. She, M.-M. Cheng and J. Yang, "Joint Acne Image Grading and Counting via Label Distribution Learning," in *International Conference* on Computer Vision (ICCV), IEEE Xplore, 2019.
- [16] K. He, X. Zhang, S. Ren and j. Sun, "Deep residual learning for image recognition," *CVPR*, 2016.
- [17] E. Okon, V. Rachakonda, H. J. Hong, C. Callison-Burch and J. B. Lipoff, "Natural language processing of Reddit data to evaluate dermatology patient experiences and therapeutics," *Journal of the American Academy of Dermatology*, 2019.
- [18] S. Reddy, S. Nalluri, S. Kunisetti, S. Ashok and V. B, "Content-Based Movie Recommendation System Using Genre Correlation," Smart Innovation, Systems and Technologies, 2018.
- [19] Y. Z. D. H. M. M. A. A. a. P. L. Zhang, "CADRE. Cloud-Assisted Drug REcommendation Service for Online Pharmacies," *Mobile Networks and Applications*, vol. 20, 2014.
- [20] N. Kittigul and B. Uyyanonvara, " Automatic acne detection system for medical treatment progress report," 2016 7th International Conference of Information and Communication Technology for Embedded Systems (IC-ICTES), 2016.
- [21] T. Y. M. M. Y. M. M. Y. O. N. a. Y. K. H. Fujii, "Extraction of acne lesion in acne patients from multospectral images,," in 30th Annual international conference of the IEEE Engineering in Medicine and Biology Society, no. doi:10.1109/iembs.2008, 2008.
- [22] Karimkhani, "Analysis regarding acne by Karimkhani," 2017.
- [23] B. D, "What Causes Acne," healthline, 2019.
- [24] "Preprocessing and Feature Extraction," [Online]. Available: https://pdfs.semanticscholar.org/535e/dcf62cf7ae0f2cc777 1662a01bcb661bc29a.pdf. [Accessed 2020 Februaury 1].
- [25] "Healthline," [Online]. Available: https://www.healthline.com/health/beauty-skin-care/how-to-get-rid-of-blackheads.