Deep Learning Technique for selecting appropriate Beauty Care Products for different skin Type

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Abstract: This research has been undertaken to ease the challenging task of the beauty industry by using Deep Learning Method. Nowadays, the cosmetic product plays a major role in the appearance of personality. Customers are given a number of items with online shopping and e-commerce websites. It's difficult for us to pick the best product for our skin. Over recent years recommendation systems have been commonly used for providing user recommendations in various commercial platforms. The sparsity of the data and the scalability of the method however limit the performance of the algorithms used for recommendation and it is difficult to further improve the quality of the results of the recommendations. Hence we propose a predictive system that provides a precise idea of which product is best for our skin type using the Deep Learning Technique. The suggestion is based on the types of skin that might be Normal, Combination, Dry, Oily, and Sensitive. We have implemented the Deep Neural Network (DNN) model for cosmetic product composition. Finally, it is validated, by comparing with other recommendation algorithms on our generated dataset, that our model can effectively boost the recommendation performance.

***IndexTerms* – Deep Learning, Deep Neural Network, Cosmetic Product Suggestion.**

I. INTRODUCTION

As the field of Machine Learning (ML) become larger, the products of ML applied in daily life also increases and it provide convenience to people in various aspects. In recent times, Deep Learning is the most popular subfield of ML. Certainly deep learning can perform various tasks that have uses in medical science, computer technology, gaming and the list continues.

The cosmetics industry is becoming increasingly large over the years, and so the product supplied by this industry and the consumers are also rising. Therefore the selection of appropriate cosmetic product becomes very important based on this expansion of products and consumers. Because cosmetic products play an important role in your personal appearance, you need to select the right product according to your personal needs (i.e., skin type).Finding perfect cosmetic for the skin type of user in pretty difficult- since each individual has unique skin texture. Even if we find the customer's product this can lead to skin disorder, which is a very complex issue. To solve this beauty industry problem, we can use the methodology of machine learning - deep learning, as it works fine with unstructured and large quantities of data with promising results.

Furthermore, a customer may wish to choose a beauty product based on a variety of personal factors. Beauty consultants are often very helpful when making product recommendations, a number of modern marketing and beauty product sales techniques are unable to provide such a personal consultant. For example, discount stores, online purchasing agreements, telephone ordering, and mail-in product sales frequently lack any substantial exchange of contact other than that required to consummate a product sale. Therefore you need to recommend the items automatically. This could be provided by selecting product information based on the personal information in a database

1.1 Cosmetic Product Suggestion

Cosmetic product refers to the products one uses to enhance their looks. It can include various types of cosmetic items-Lipsticks, Kajal, Eyeliner, Foundation, Eye shadow, Mascara, Compact, Face wash, Body lotion etc. The design of cosmetic products consists of so many steps and activities to find the compatibility between each of the items it comprises. Since not everyone is so good at choosing the right product for them, this solution surely will assist them.

Fig-1.1: Composition of cosmetic procuts based on dry and normal skin

1.2 Need for Deep Learning

In recent years, Deep Learning has provided many types of research in fields such as computer vision, natural language processing, machine translation, chatbots, and many others. They provide stable performance and deprived the property of learning feature representation from scratch. This influence also applied to the recommendation area, where deep learning methods give significant results in comparison to traditional methods. Deep Neural networks are composite in the manner that multiple neural building blocks composed into a single differentiable function and trained end-to-end. Contrary to linear models, deep neural networks is capable of modeling the non-linearity in data with nonlinear activations such as ReLU, sigmoid, tanh, etc. Enables the identification of complex and complicated interaction patterns of user objects.

Deep learning techniques have a high degree of flexibility, especially with the development of many common deep learning frameworks such as TensorFlow, Keras, and PyTorch. Most of these tools are developed in a flexible way and have active support in the community and professional. The good modularization makes development and engineering a lot more efficient.

II. DEEP LEARNING (DL)

Deep Learning is a field of Machine Learning that allows computational models that are composed of multiple processing layers of representation and abstraction that help to make sense of data such as images, sound, and text.

Deep learning is a part of a wider machine learning family, based on ANN-inspired algorithms[1]. Deep learning algorithms such as Deep Neural Networks (DNN), Deep Belief Networks (DBN) were applied to fields like computer vision, speech recognition, natural language processing, audio-video recognition, bio-informatics, medical image analysis, where they provided comparable and, in some cases, better outcomes for human experts.

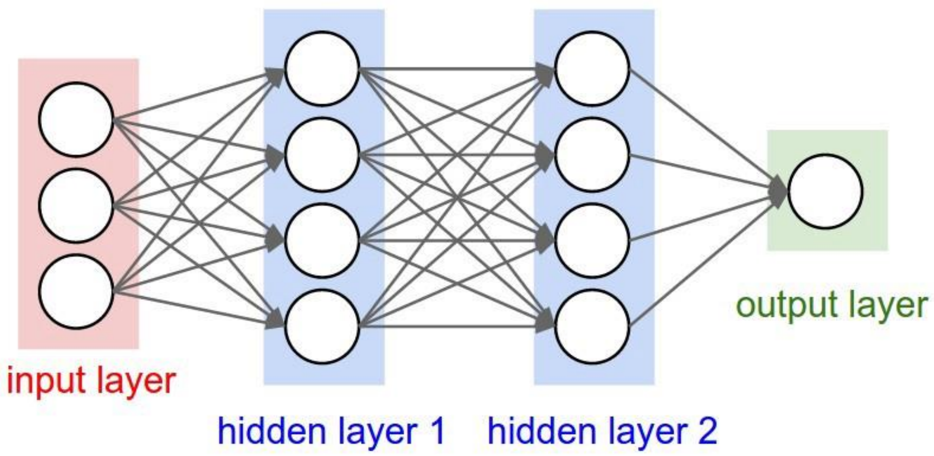

Fig-2.1: Deep Learning Architecture with Two hidden layers

Basically Deep Neural Network is composed of a number of hidden layers it can be any number. The input layer takes the inputs. The input cell is known as neuron and each neuron is connected with some weight. The weight decides which input is more important. Then the inputs are passed to the hidden layer. Each neuron has activation function, which transfers non-linear relationships between inputs of each cell before the finalized output.

2.1 Deep Learning for Cosmetic Item Composition

The composition of cosmetic products is a task process that harmonizes the decision on which product is best for the skin types given. Since not everyone is good enough to decide what to choose, the cosmetic product composition problem arises. Deep Learning Technique will provide the solution to this problem as it provides better accuracy. Deep Neural Network (DNN), Recurrent

Neural Network (RNN), Convolution Neural Network (CNN), and the Deep Belief Network (DBN) are the deep learning techniques. These methods provide better recommendation performance with regard to traditional methods of recommendation. There is an advantage of better outcomes for new problems when working with Deep Learning.

Various Deep Learning Techniques:
DNN: Deep Neural Network (DNN) is an Artificial Neural Network (ANN) with multiple layers between the input and output layers. The DNN identifies the right mathematical manipulation between input and output, whether the relationship is linear or non-linear[3].
CNN: Convolutional Neural Network (CNN) is a special kind of feed forward neural network with convolution layers and pooling operations. It can capture the global and local features and significantly enhancing the efficiency and accuracy. It performs well with grid-like topology in the processing of data[2].
RNN: Recurrent Neural Network (RNN) is suitable for modeling sequential data. For remembering the former computation there are loops and memories[2].
DBN: In machine learning, a Deep Belief Network (DBN) is a generative graphic model, or alternatively a category of a deep neural network, consisting of multiple layers of latent variables ("hidden units"), with connections between layers but not between units within each layer[4].
AE: Autoencoder (AE) is an unsupervised model attempting to reconstruct its input data in the output layer. In general, the bottleneck layer (the middle-most layer) is used to represent the input data as the salient feature. Variants of autoencoders such as denoising autoencoder marginalized denoising autoencoder, sparse autoencoder, contractive autoencoder, and variational autoencoder (VAE)[2].

III. RELATED WORK

Deep Learning is successful in Natural Language Processing (NLP), computer vision, Speech recognition and other fields. Notable recent application areas are music recommendations, news recommendations and recommendations based on a session[13]. Tingting Li, Ruihe Qian et al, proposed a Deep Generative adversarial network for make-up image transfer to non-make-up image[16].

Rio Iwabuchi, Yoko Nakajima, et al., proposed the Recommender system based on User Evaluation and Cosmetic Ingredients. Their work focuses on recommending the cosmetic product, in which the ingredients use user ratings to have a high cosmetic effect. So they have effectively specified user categories with similar skin and extract the user attributes (i.e. skin quality and age) that users set at the time of registration. They derive a skin lotion with a high ratio of cosmetic effect tag for each cosmetic product. They have employed a natural classification method to determine this threshold. They have applied the concept of TF-IDF for ingredient extraction, which is used to find a word that characterizes a sentence. They estimated and sorted IF-IPF values. The recommendation will be based on the top ingredient of the IF-IPF value that has been sorted[5].Deep Generative adversarial network for make-up image transfer to non-makeup image[16].

In 2017, Yuki Matsunami et al. introduced a method of recommending Cosmetic Review by Tag in the recommender scheme. The aim of this research is to add a tag to review text. They have used an automatic scoring method to evaluate the review text. System reads a text and judges the sentences, then extracts the k unit from that review text and finally sums up all the factors by examining the sentence and measuring the target review score. Then the framework suggests a tag with a high score for evaluation expression[6].

Asami Okuda et al. have introduced identifying similar users based on their preferences toward clusters of cosmetic products. They proposed a method for creating clusters of related cosmetic products based on measuring the average score for each element and making the cluster depending on the scores similarity. The system then recommends appropriate review based on similar users discovered by the clustering method[7].

Christopher J. Holder et al. defined a Visual Siamese clustering for recommendation on cosmetic products in 2019. This work focuses on creating a model capable of matching images of new subjects based on visual similarity. The approach is based on the consumer feature 's visual similarity and a selection of people whose preference is already known. Siamese network learns to cluster together images of eyes belonging to the same person based on visual similarity[8].

Yuncheng Li et al. proposed the composition of the mining fashion outfit, using an end-to-end deep learning approach to set data. With the support of the Outfit Scoring Function, the authors proposed a generic algorithm for automated outfit creation. The outfit scoring method operates with four functions, Fusion Model, Pooling Model and Classification Model followed by Feature Extraction[9].

IV. RESEARCH METHODOLOGY

The research work is followed by dataset gathering, data preprocessing, implementing model and finally get the result.

4.1 Data Gathering and data preprocessing

As for training the deep learning model we need data related to cosmetic products, so we have gathered about 6778 product information from the @sephora website. Each product contains suitable skin type (i.e., normal, dry, normal, sensitive, and oily), ingredients of the product, price and the category (i.e., moisturizer, sunscreen lotion, cleanser, concealer, eye cream and face mask etc).Machine cannot understand textual data directly so we have to convert them into machine understandable format. For this we are applying data preprocessing step, which involves missing values removals, cleaning of data and encoding of data. We only consider that feature into training which have more impact in the recommendation of the cosmetic product.

4.2 Implementation Environment

For this research work implementation we have used 4 GB RAM, Windows 10 Intel® Core i5-4200 CPU. The programming environment we have used is python langauage with version python 3.6.4. For Deep Learning Runtime we have used Tensorflow v2.0.0 CPU, Keras v2.3.1, and other python liabries which are needed.

4.3 Prposed Methodology

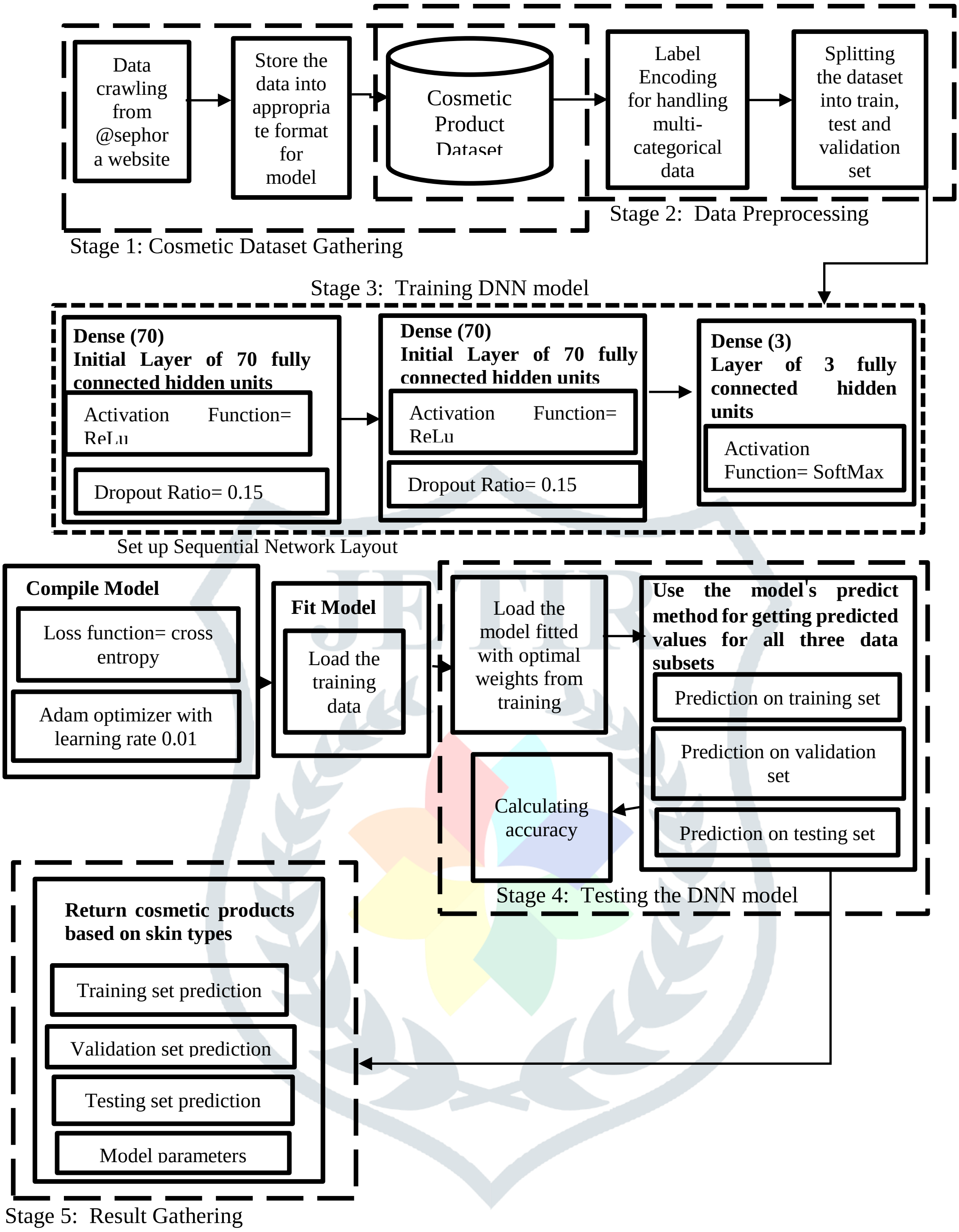

Fig-4.1: Block diagram of proposed method

As shown above the proposed model is divided in to five stages:

Stage 1: Gathering of Cosmetic Dataset.
The cosmetic data from various websites @cosme and @Nykaa gathered for this model evaluation.

Stage 2: Data Preprocessing
In Deep Learning models if you feed the garbage data, then you should expect garbage result with high probability. So data preprocessing step is necessary for cleansing of data which is required for the given model. Data preprocessing can be done by normalization, dealing with the missing data.

Stage 3: Training of Deep Neural Network for Cosmetic products composition

In this stage the training data will feed to the input layer of DNN and then using the input layer cells it then forwarded to the hidden layer, which process some steps for cosmetic product composition and the output of that will forwarded to the output layer, where we get the cosmetic product composition.

Stage 4: Testing of Model
After training the model it is required to test the model for whether the output given by it is accurate or not

Stage 5: Result
The cosmetic product composition will be given based on skin types; dry, natural or oily.
The proposed model will use Deep Learning Technique for cosmetic product composition for various skin types, which will improve the composition quality. Deep Neural Network will help in better performance in composition task. This will lead to better and reliable cosmetic product composition.

V. RESULTS

5.1 Results of DNN model

We have implemented a DNN model with two hidden layer with 70 nodes dense layer, activation function ReLU and 0.15 dropout ratio. Finally we have output layer with SOFTMAX function with 3 nodes for multiclass classification. We have trained the DNN model with 100 epoch and batch size 10, we can test the result of the model which is measured by accuracy matrix. We have trained our model on 2665 and test on 1143 instances.
Here is the performance matrix of the DNN model.

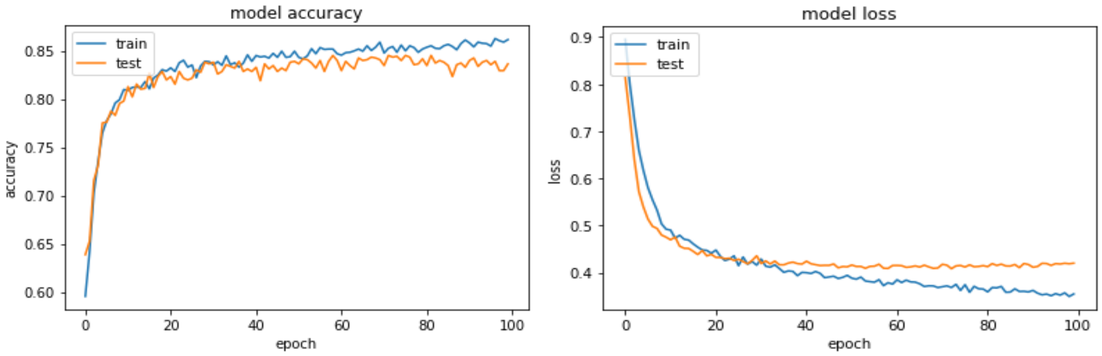

Fig-5.1: Performance Matrix of DNN model

5.2 Comparison of proposed model with ML algorithm

The next step of the research is to compare these performance of model to validate the outcome. We have applied Machine Learning algorithms like Support Vector Machine(SVM), k-Nearest Neighbour(kNN), Logistic Regression to our dataset. The proposed model gives better result than ML algotithms.

Table 5.1: Comparision of DNN model with Machine Learning Algorithms

Method	Dataset Used	Accuracy
SVM	@sephora	76.85
kNN	@sephora	75.40
Logistic Regression	@sephora	76.40
DNN(Our Proposed Model)	@sephora	85.40

With this statistics we can say that our proposed model gives more reliable performance than the machine learning algorithms.

VI. CONCLUSION

Decision making in today's world is more complex than the past, as for consumers who are now confronted by various kind of choice for each type of products and brands. This DNN approach provides the composition based on skin types (i.e. dry, oily or natural).Our main goal is to provide cosmetic products with a better composition. By using Deep Neural Network the proposed system suggest the products with 85.60% accuracy. For future work, we will look forward to apply other Deep Learning technique with large dataset.

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