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Cosmetics Recommendation Using Decision Tree Classification Machine Learning Model

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Abstract:- The interest for beauty care products has developed as of late, particularly in the space of skincare, all over the planet. Customers have generally depended on top selling things or ideas from the counter while shopping available. These is an inquiry that on the off chance that an item will work with a specific client since everybody has a particular skin condition. The primary objective of this proposition is to foster a framework for suggesting skincare items in view of the client's skin type and the cosmetics of the item.

Keywords:- *Decision Trees, Personalized Beauty, Skin Type Classification, Feature Extraction for Beauty Products, Beauty Product Recommendation Systems, User Preferences in Cosmetics, Skin Undertone Analysis, Cosmetics Dataset, Beauty Product Reviews.*

I. INTRODUCTION

As a title state itself the procedure is used to recommend the restorative thing. As extra people began visiting the excellence care items counter to get thing thoughts, there was a looking at extension in the need for state of the art developments. In any case, this technique is drawn-out and a significant part of the time incapable. Clients have found it attempting to go with the most ideal decisions as a result of the staggering proportion of information that is open on the web.

To determine the issue of information over-weight and smooth out the decision cycle, researchers have proposed a couple recommender systems. Decision tree is used the most frequently. we can cross survey the outcome proposition to our clients.

As a title state itself the system is used to recommend the remedial thing. As extra people began visiting the excellence care items counter to get thing thoughts, there was a relating extension in the essential for state of the art developments. Regardless, this strategy is dreary and occasionally unproductive. Clients have found it attempting to seek after the ideal decisions in view of the staggering proportion of information that is available on the web.

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II. LITERATURE REVIEW

In "Characterization In view of Choice Tree Calculation for AI" Behzad TahazJijol*, Adnan Mohsina Abdulazeez proposed the essential objective of the Choice tree calculation which is connected with the directed getting to know calculation family, is building a training model that can be utilized to foresee the class or cost of objective factors by utilizing

Both Matsunami and Okuda utilized the technique for deciding client similitude to inspect audits of restorative Items. They removed positioning as well as genuine audits with individual inclinations and Conclusions utilizing algorithmic evaluating and k-implies group examination Ye likewise utilized cooperative Separating, however she focused on tending to the deficiencies of the ordinary methodology. Evaluations are Utilized to affirm the outcomes despite the fact that it doesn't channel things in view of them.

To adjust skincare item suggestions very however much as could be expected, Putriany utilized content-in view of their review. The framework was planned around the specific client. She focused on the client Record yet in addition considered viewpoints like complexion, use, evaluating, portrayal, and photos for Better idea .To settle this issue, Jeong made a recommender framework that depends on the parts of beauty care products.

III. METHODOLOGY

This study aims to create a regression algorithm model using the Google Collaboratory tool and Jupyter Notebook. The steps of the modelling process are shown in Figure . The first step is to obtain the datasets from the Kaggle website; Then, the data is pre-processed, which involves Data Cleaning and Feature Engineering; Next, the Exploratory Data Analysis (EDA) is performed; To apply machine learning with the Decision Tree and for some sample data is required. The table below shows some data about different cosmetics products. The data is sourced from Kaggle.com .

	A	B	C	D	E	F	G	H	I	J	K
1	Label	Brand	Name	Price	Rank	Ingredients	Combinati	Dry	Normal	Oily	Sensitive
2	Moisturizer	LA MER	Crème de la Mer	175	4.1	Algae (Seaweed) Extract, Mineral Oil, Petrolatum, Glycerin, Isohexa	1	1	1	1	1
3	Moisturizer	SK-II	Facial Treatment Essence	179	4.1	Galactomyces Ferment Filtrate (Pitera), Butylene Glycol, Pentylene	1	1	1	1	1
4	Moisturizer	DRUNK ELEPHANT	Protini™ Polypeptide Cream	68	4.4	Water, Dicaprylyl Carbonate, Glycerin, Cetearyl Alcohol, Cetearyl (	1	1	1	1	0
5	Moisturizer	LA MER	The Moisturizing Soft Cream	175	3.8	Algae (Seaweed) Extract, Cyclopentasiloxane, Petrolatum, Glyceryl	1	1	1	1	1
6	Moisturizer	IT COSMETICS	Your Skin But Better™ CC+™ Cream with SPF 50+	38	4.1	Water, Snail Secretion Filtrate, Phenyl Trimethicone, Dimethicone,	1	1	1	1	1
7	Moisturizer	TATCHA	The Water Cream	68	4.2	Water, Saccharomyces/Camellia Sinensis Leaf/Cladosiphon Okam	1	0	1	1	1
8	Moisturizer	DRUNK ELEPHANT	Lala Retro™ Whipped Cream	60	4.2	Water, Glycerin, Caprylic/ Capric Triglyceride, Isopropyl Isostearat	1	1	1	1	0
9	Moisturizer	DRUNK ELEPHANT	Virgin Marula Luxury Facial Oil	72	4.4	100% Unrefined Sclerocraya Birrea (Marula) Kernel Oil.	1	1	1	1	0
10	Moisturizer	KIEHL'S SINCE 1851	Ultra Facial Cream	29	4.4	Water, Glycerin, Cyclohexasiloxane, Squalane, Bis-Peg-18 Methyl E	1	1	1	1	1
11	Moisturizer	LA MER	Little Miss Miracle Limited-Edition Crème de la Mer	325	5	Algae (Seaweed) Extract, Mineral Oil, Petrolatum, Glycerin, Isohexa	0	0	0	0	0
12	Moisturizer	FRESH	Lotus Youth Preserve Moisturizer	45	4.3	Water, Glycerin, Propylene Glycol Dicaprylate/Dicaprate, Pentylen	0	0	0	0	0
13	Moisturizer	KIEHL'S SINCE 1851	Midnight Recovery Concentrate	47	4.4	Caprylic/Capric Triglyceride Dicaprylyl Carbonate Squalane Rosa C	1	1	1	1	1
14	Moisturizer	BELIF	The True Cream Aqua Bomb	38	4.5	Water, Dipropylene Glycol, Glycerin, Methl Trimethicone, Alcohol I	1	0	1	1	0
15	Moisturizer	SUNDAY RILEY	Luna Sleeping Night Oil	105	4.1	Persea Gratissima (Extra Virgin, Cold Pressed Avocado) Oil, Vitis Vi	1	1	1	1	1
16	Moisturizer	FARMACY	Honeymoon Glow AHA Resurfacing Night Serum wi	58	4.6	Water, Lactic Acid, Propanediol, Jojoba Esters, Glycolic Acid, Potas	1	1	1	1	1
17	Moisturizer	DRUNK ELEPHANT	The Littles™	90	4.4	Beste™ No.9 Jelly Cleanser: Water, Sodium Lauroyl Methyl Isethio	1	1	1	1	0
18	Moisturizer	FIRST AID BEAUTY	Ultra Repair® Cream Intense Hydration	30	4.6	Water, Stearic Acid, Glycerin, C12-15 Alkyl Benzoate, Caprylic/Cap	1	1	1	1	1
19	Moisturizer	CLINIQUE	Moisture Surge 72-Hour Auto-Replenishing Hydratc	39	4.4	Water , Dimethicone , Butylene Glycol , Glycerin , Trisiloxane , Treh	1	1	1	1	1
20	Moisturizer	FRESH	Rose Deep Hydration Moisturizer	40	4.4	Water, Glycerin, EthylhexylIsononanoate, Butylene Glycol, Pentyle	0	0	0	0	0
21	Moisturizer	SK-II	R.N.A. POWER Face Cream	230	4.3	Water, Glycerin, Galactomyces Ferment Filtrate*, Isohexadecane,	0	1	1	0	1
22	Moisturizer	LA MER	Crème de la Mer Mini	85	4.1	Algae (Seaweed) Extract, Mineral Oil, Petrolatum, Glycerin, Isohexa	1	1	1	1	1
23	Moisturizer	BAREMINERALS	COMPLEXION RESCUE™ Tinted Moisturizer Broad S	30	3.9	Water, Coconut Alkanes, Propanediol, Squalane, Trehalose, Isoste	0	0	0	0	0
24	Moisturizer	SHISEIDO	Bio-Performance Advanced Super Revitalizing Crea	78	4.6	Water, Glycerin, Cyclomethicone, Butylene Glycol, Dimethicone, C	0	0	0	0	0
25	Moisturizer	FRESH	Black Tea Firming Overnight Mask	92	4.1	Water, Glycerin, Butylene Glycol, Jojoba Esters, Isohexadecane, Ar	1	1	1	0	0
26	Moisturizer	BELIF	The True Cream Moisturizing Bomb	38	4.6	Water, Glycerin, Cyclohexasiloxane, Hydrogenated Polydecene, Di	0	1	1	0	0
27	Moisturizer	CHARLOTTE TILBURY	Charlotte's Magic Cream	100	4.4	Water, Homosalate , Glyceryl Stearate SE, Ethylhexyl Salicylate, Bu	0	0	0	0	0
28	Moisturizer	DRUNK ELEPHANT	Virgin Marula Luxury Facial Oil Mini	40	4.5	100% Unrefined Sclerocraya Birrea (Marula) Kernel Oil.	1	1	1	1	0
29	Moisturizer	ORIGINS	Dr. Andrew Weil For Origins™ Mega-Mushroom Rel	34	4.4	Water, Butylene Glycol, PEG-4, Citrus Aurantium Dulcis (Orange) O	1	1	1	1	1
30	Moisturizer	CLINIQUE	Dramatically Different Moisturizing Lotion+	28	3.9	Water , Mineral Oil/Paraffinum Liquidum/Huile Minerale , Glycerin	1	1	0	0	0

cosmetics data

Fig 1: Dataset

This data can cleaned and explorated using machine learning techniques and that mostly sutable for Decision tree and Random forest algorithms .

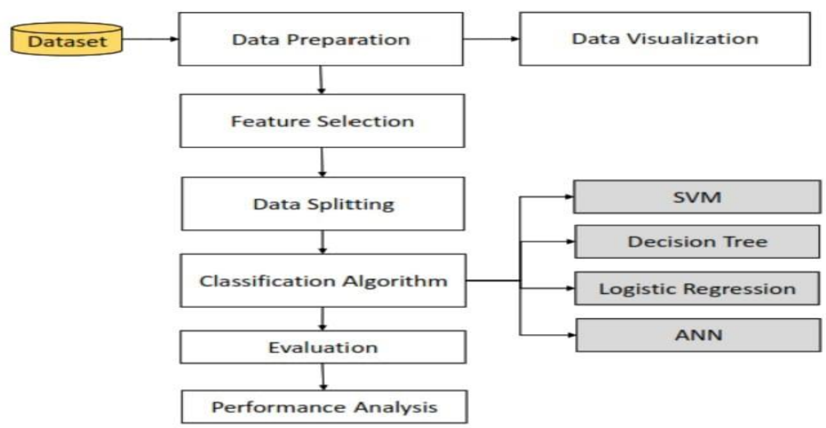

Fig. 2. Research Methodology

➢ *Entropy*

Entropy is the estimation of confusion or contaminations in the data handled in AI. It decides how a choice tree decides to divide information.

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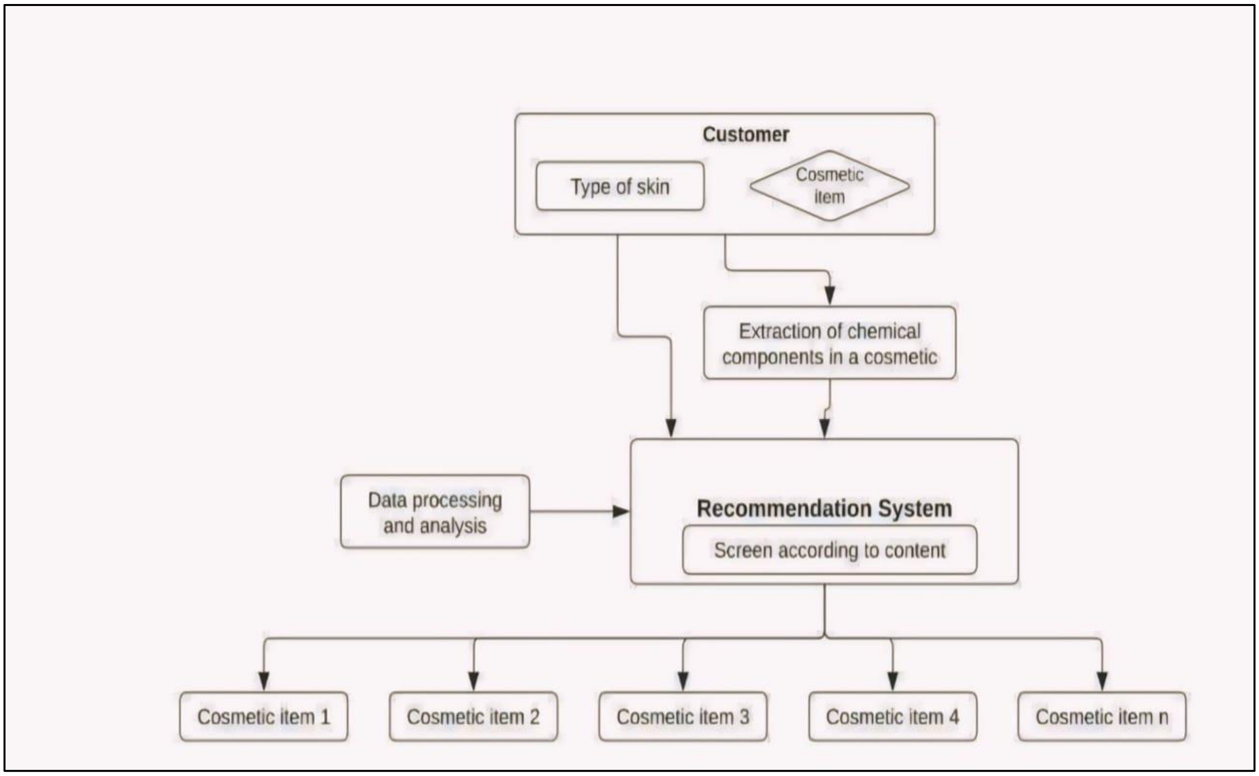

Fig 3: General Architecture

Applying decision tree on the code:

```
moisturizers = df[df["Label"]=="Moisturizer"]
moisturizers_dry = moisturizers[moisturizers["Dry"]==1]
moisturizers_dry =moisturizers_dry.reset_index(drop=True)
moisturizers
selected_label = "Moisturizer"
skin_types = ["Combination", "Dry", "Normal", "Oily", "Sensitive"]
def analyze_label(df, label):
    filtered_df = df[df['Label'] == label]
    fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(20, 12))
    fig.suptitle(f'Price vs. Rank for {label}s', fontsize=16)
    fig.delaxes(axes[1, 2])
    for i, skin_type in enumerate(skin_types):
        filtered_skin_df = filtered_df[filtered_df[skin_type] == 1]
        rank_color = filtered_skin_df['Rank'] / filtered_skin_df['Rank'].max()  # Adjust for color scaling
        top_3_indices = filtered_skin_df['Rank'].nlargest(3).index
        scatter = sns.scatterplot(
            data=filtered_skin_df, x='Price', y='Rank',
            hue=rank_color, palette='viridis', ax=axes[i // 3, i % 3]
        )
        scatter.get_legend().remove()  # Remove the legend
        mean_price = filtered_skin_df['Price'].mean()
        median_price = filtered_skin_df['Price'].median()
        mean_rank = filtered_skin_df['Rank'].mean()
        median_rank = filtered_skin_df['Rank'].median()
        axes[i // 3, i % 3].axvline(x=mean_price, color='red', linestyle='--', label='Mean Price')
        axes[i // 3, i % 3].axvline(x=median_price, color='green', linestyle='--', label='Median Price')
        axes[i // 3, i % 3].axhline(y=mean_rank, color='blue', linestyle='--', label='Mean Rank')
        axes[i // 3, i % 3].axhline(y=median_rank, color='purple', linestyle='--', label='Median Rank')
        axes[i // 3, i % 3].scatter(
            filtered_skin_df.loc[top_3_indices, 'Price'],
            filtered_skin_df.loc[top_3_indices, 'Rank'],
            color='orange', marker='^', s=100, label='Top 3 Ranks')
        axes[i // 3, i % 3].set_title(f'Price vs. Rank ({skin_type} Skin)')
        axes[i // 3, i % 3].legend()
    plt.tight_layout()
    plt.subplots_adjust(top=0.9)  # Adjust title position
    plt.show()
    summary_stats = filtered_df[['Price', 'Rank']].describe()
    print(f'Summary Statistics for {label}s:\n{summary_stats}')
    analyze_label(df, "Moisturizer")
```

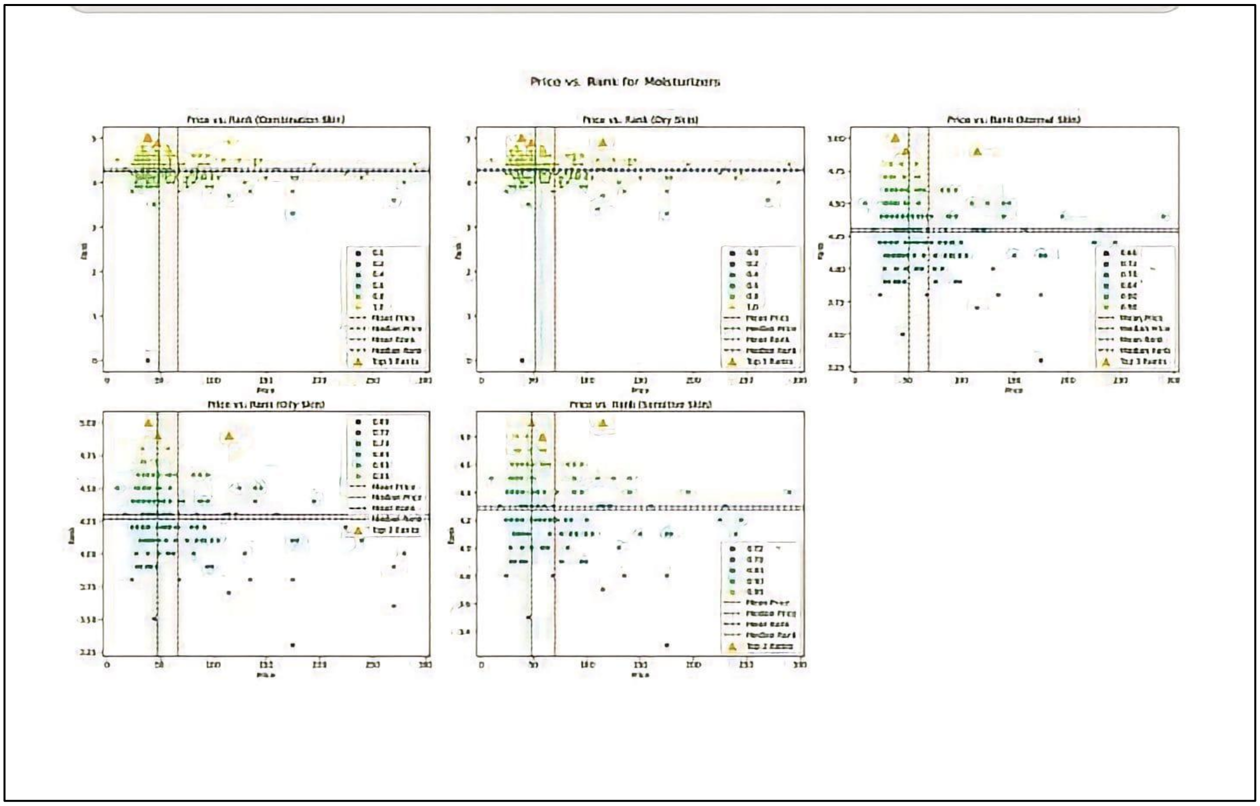

Fig 4: Graphs for Different Skin Types

For this dataset we got the accuracy up to 84% by using Decision making algorithm.

IV. CONCLUSION

By leveraging algorithms such as decision tree, the system aims to enhance the user experience by offering relevant and tailored product recommendations. Continuous monitoring, user feedback loops, and model updates are crucial for maintaining the system's accuracy and relevance over time. As the beauty industry evolves, incorporating emerging trends and staying attuned to user preferences are key considerations for ensuring the ongoing success of the recommendation system. Ultimately, a well-designed and maintained cosmetics recommendation system has the potential to not only improve customer satisfaction but also contribute to the growth and competitiveness of cosmetic brands in the market.

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