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Research Article

Predictions Of Consumer Behaviour And Their Impact On Visual Merchandising Using Combined Machine Learning Concept

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ABSTRACT

Visual merchandising (VM) has grown in popularity recently as a quick and economical technique to renovate retail businesses. The strategy that will enhance sales and profits while also directly influencing customer traffic and their experiences is the best visual merchandising technique. The number of customers that visit your store is greatly influenced by your extensive and dynamic visual merchandising. Due to the intense rivalry in today's supermarkets, the study's goal is to acquire insight into the pertinent theoretical knowledge on visual merchandising and into current information on customer behaviour identification using the deep machine learning algorithm with precise references. Conclusions on the relationship between VM and brand image, customer purchasing behaviour, and competitive advantage of a certain brand will be drawn using this insight. This study aims to investigate the connection between visual merchandising and customer impulse buying habits using Artificial intelligence (AI) namely the Machine Learning concept. Due to the shortcomings of the conventional K-means approach, consumer segmentation theory, a new adaptive GA+K-means-ANN algorithm based on Genetic algorithm (GA) deep artificial neural network (ANN) combined along with classic K-means algorithm is projected, which can be applicable to e-commerce customers' segmentation for visual management techniques. Additionally, efforts have been made to comprehend the visual merchandising strategy that has the greatest influence on consumers. This study also aims to shed light on the reasons why visual merchandising should be regarded as a crucial element of a strategic marketing plan in order to boost sales and enhance the reputation of a business.

Keywords— Customer experience; visual merchandising, machine learning, adaptation models, ANN

I. INTRODUCTION

In the retail market sector, visual merchandising is the process of displaying and promoting goods in order to increase sales. You must use the best visual merchandising strategy for your store and products if you want visitors to find their ideal purchase with ease. The term "silent salesman" can be applied to visual merchandising without any qualifiers. The necessity of the hour is to properly utilize all resources because they are scarce and real estate prices areskyrocketing. To do this, retail managers will work to make sure that all available space in the store is used. Researchers also discovered that sense of smell by the customer and what they smell are directly related, and when the fragrance is particularly nice, this further influences their mood by 40%.
A retail store's product display can be created to be intriguing, appealing, and appealing to the customer using visual merchandising (VM), which will be referred to as VM from now on. This serves to both urge customers to enter the store and to imprint a particular mental image on them (Dash M., Akshaya L., 2016).

The phrase "e-commerce," also named as "electronic commerce" or "online commerce," refers tothe exchange of funds and data required to accomplish transactions comprising the selling and buying of goods/services via the internet (Shopify).

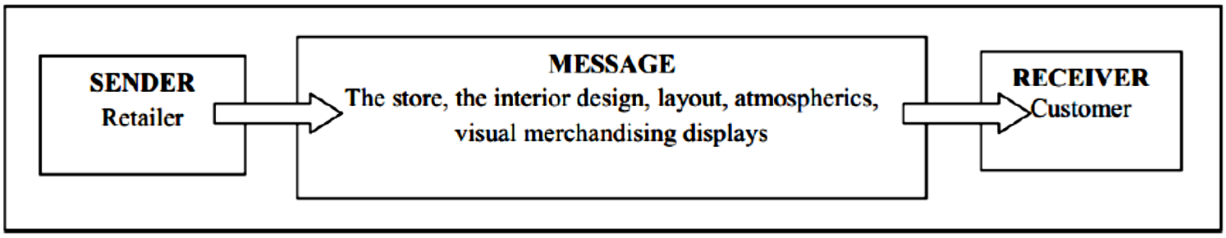

Figure 1. Communication Practice involved in Visual Merchandising

Figure 1 (Bell, J., and Ternus, K. 2006) above illustrates the fundamental idea of the VM technique. Customer behavior, according to Kardes (2002), is the study of consumer reactions to goods and services as well as to the marketing of goods and services. Consumer activities is the study of how individuals or groups choose, purchase, use, or discard services, ideas, products, or experiences to satiate their necessities and requests, with respect to Solomon and Rabolt (2004).

1.1 *Visual merchandising components*

The four primary components of visual merchandising, which are:

- Store layout
- Store exterior
- Interior displays
- Store interior

Three elements make up a store's exterior: marquees, entrances, and window displays. An architectural awning called The Marquees extends through the entrance. Customer convenience and store security are the two most crucial purposes of a store entrance. There are several sorts of entrances that can be employed nowadays, including revolving, push-pull, and computerized doors. The most crucial component should be a window display because it shapes the consumer's first impression of the store. Even before the customer enters the store, it starts the selling process [26]. Window displays come in a variety of styles, including closed, open-back, angled, arcade, and cornered.

Four components make up the store's layout: the selling area, the merchandising area, thecustomer area, and the staff area. A feature in VM termed as focal points states to eminently lovely display vignettes. They can be made up of any combination of items. High focal points, which are situated at the endpoints of store traffic patterns, lure customers within a store by giving them somewhere to go.

Designing the interior of the store with a comfortable environment in mind for consumers to feel at ease is vital since it encourages them to spend more time there and make more purchases. It should be planned such that visitors won't get lost, overwhelmed, or stuck in long lines. The interior of the store includes fixtures, lighting, and other design elements, including floor and wall coverings. The product in the store is displayed inside to show it off.

Customers can make their own selections with the aid of well-lit items and without assistance from staff. Displays might be architectural, closed, open, point-of-purchase, or retail decorating. Fixtures and accessories are used in interior displays to hold the item.

Visual merchandising makes use of a variety of materials and colors while relying on fundamental design principles. Themes, forms, colors, fixtures, mannequins, hangings, platforms, paintings and wall art, tablecloths, fabrics, and banners, furniture, and tables, poles or stands, accessories, lighting effect, and pops, and music are therefore used to create an effective visual show (Dash M., Akshaya L., 2016).

Although the fundamental VM tools are addressed, it is significant to emphasize that technology is now an integral part of every industry, including retail fashion. A shop manager can employ a variety of software alternatives to keep VM strategy and execution organized and current.

Contribution of our work

This research survey will be very important for both academics and business. The key rewards ofthis study include designers who may use it to quickly develop designs as a creative tool and fashion consumers who can discover fresh, untried fashion. Additionally, this survey benefits academics, professionals, and students with an interest in deep learning-based fashion image generating as well as creative design and garment industry picture analysis.

- In addition to this, the survey's main contribution is summarised as follows:
- Encourage companies to apply artificial intelligence for designing process in their product, act as a first step in the development of a design tool to create prototypes quickly, and support design procedures and innovation in the manufacturing sector.
- We give a synopsis of the most recent study and list its benefits and drawbacks. The models for a particular problem or unsolved problems can be found by experts with ease.
- We implemented Deep learning concept to visually analyze the customer's activities. This approach will improve the retail industries profit and can reduce the error rate, when comparing to previous visual merchandising concepts.
- We recommend a retail planogram for fashion retail stores based on video analytics software by creating heat maps to show which parts of the store generate the most foot traffic.
- We exploit customer analytics software to learn about customer behavior.
- We ensure fashion retailers to make data-driven decisions in arranging the fashion accessories across the store layout.

II. RELATED WORK

2.1 Theory related to customer segmentation

Numerous specialists and academics have been drawn to research "segmentation" since it was initially put forth by American marketer Wendell r. Smith. Customer segmentation, anothername for the practice of breaking a market into groups of buyers with distinct needs, preferences,and behaviors [15], is referred to as segmentation (Hoegele et al. 2016). The researchers offered two separate market segmentation concepts: product and customer-oriented segmentation, depending on various times, markets, and sectors. Customer segmentation is a method of separating consumer groups based on various traits. It is a crucial component of customerrelationship management and has gradually grown in importance as a requirement for businesses applying CRM.

Theoretically, various market segments will choose whether to buy a particular kind of goods in the market given their current circumstances in a clear tactical business model and a particular market. Various customer groups will have different consuming intentions as a result of the desire for appearance, the focus on service quality, or the inconsistent method the product realizes value [16]. In order to achieve the objectives of reasonable resource allocation and the furthermost profitable design of consumer marketing programmes, this type of theory recommends revising and predicting the future consumption trend of consumers through segmentation of consumer information and consumption behavior along with the profit market scheduling of businesses (Huang et al. 2014). It is impossible to separate the support of consumer segmentation technology from the ongoing development and enhancement of Internet consumption techniques. An important factor in the competition among market positioning, marketing strategies, and competitors is the company's cognition and trend investigation of customers' consumption patterns.

Finding recurring elements in the attribute embedding of images has been done in the past using clustering models like the Gaussian mixture model (GMM) [17, 18]. Any (produced) image's embedding can be projected onto a GMM to see how well it fits into the styles that have been identified after styles have been identified. So, we may assess how closely an image resembles a specific aesthetic.

2.2 Theory related to Neural Network

Earlier layers of the model additionally capture significant themes in images as opposed to employing an attribute prediction model's prediction scores as the embedding. When photos are projected onto the eventual feature space in model, Matzen et al [22] used technique to identify styles as Gaussian mixture components. More particular learnt features are captured in thesecond-to-last layer compared to the output of the last fully-connected layer. In addition to attribute ratings, it acts as a useful embedding for identifying high-level themes [19]. The methoddeveloped by Matzen et al. [17] is modified to detect styles in the dataset FashionGen and utilise them to direct the generation toward a certain style.

In conclusion, style refers to a broader sense of visual motifs in clothing and is the focus of fashion study. The concept has not yet been taken into account in generation, beyond theattributes related to the various layers of the Generative Adversarial Networks (GANs), particular items, or textures. A system is offered that allows for the creation of designs based on fashion trends identified by a GMM in an unsupervised way [13]. The GMM directs the creation of designs while being integrated into an evolutionary search.

Customer happiness in online retailers is assessed using a multivariate linear regression machine learning model [27]. The particular goals are to: Produce academic questionnaires for the gathering of information regarding aspects that affect customer satisfaction; create a model for multiple linear regressions using the data; utilize the model's desktop application implementation in Python to evaluate it using known linear regression model evaluation measures.

III. PRELIMINARIES

This study aims to investigate the connection among visual merchandising and customer impulse buying habits. Additionally, efforts have been made to comprehend the visual merchandising strategy that has the greatest influence on consumers. This study also aims to shed light on the reasons why visual merchandising should be regarded as a crucial element of a strategic marketing plan in order to boost sales and enhance the reputation of a business. The results of the current study show that there is a very substantial correlation between two categories of visual merchandising strategies and consumer impulse buying habits.

3.1 Fundamentals of Artificial Intelligence

From the point of view of purchase and merchandising, AI used in predictive analysis by pattern predicting and automatic product labeling, visual merchandising platforms, personal styling platforms, and performance measurement. Online product and visual resemblance recommendations whole the look recommendations, and customized recommendations per country, per individual customer and per user section, are all illustrations of AI in e-commerce [6]. AI can be used in automated product tagging, visual search, natural language search, and chat-bot support for customer care, branding strategies, and marketing strategy.

A wide range of activities are covered by the topic of AI. It is possible to deploy artificial intelligence for intellectual pursuits. We occasionally co-exist alongside AI in our daily lives without even realizing it. Even so, it has demonstrated over time that it is a developing region with great potential to advance humankind. Given that it is so vast and has so many definitions and related subfields, it is challenging to characterize.

Understanding knowledge is just as important as creating it, and although some definitions of artificial intelligence tend to emphasize perception and comprehension of knowledge, others emphasize its application in more practical contexts [7].

3.2 Several types of Machine Learning (ML) algorithms

It is a branch of computing that aims to improve machine performance through experience with a given activity. This topic crosses several disciplines, including computer science, analytics, algebra, and engineering, all of which have overlapping elements. Machine learning techniques have been applied to diagnostics, management, robotics, and predictive modeling over the past 20 years. Figure 1 illustrates how ML is a collection of AI and how deep learning could be a set of machines learning.

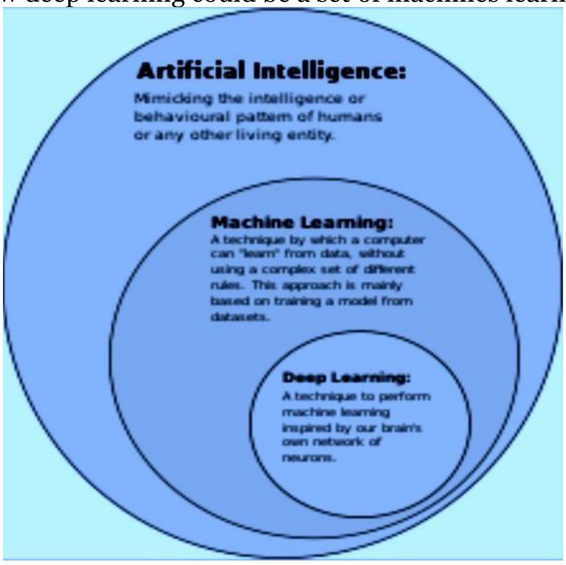

Fig. 1. A set of machines learning concepts

There are various machine learning approaches, depending on the goal, such as supervised, Unsupervised, and reinforcement learning concept.

3.2.1 Artificial neural network

It is possible to think of artificial neural networks (ANNs) as algorithms that separate out various representational layers from input data as depicted in below Figure 2. A complicated algorithmor network is created by combining a number of basic computations, which are the building blocks of an algorithm. Layers are used to organise ANNs, including input layers, output levels, and hidden layers in between. A hidden layer only serves to highlight incomplete input or output. If the network has more than one clock layer, it is referred to be a deep neural network (DNN) [8].

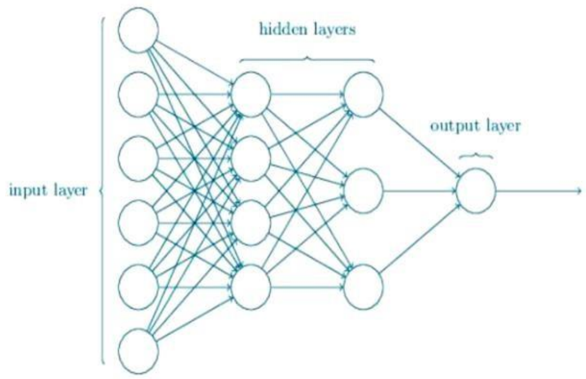

Fig. 2. Architecture of Artificial Neural Network

3.2.2 Deep learning

Recently, networks with "deep" structures—meaning they have many more hidden layers than conventional neural networks—have been referred to as "deep learning" (Figure 4). A few examples include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) [9], Long Short-Term Memory (LSTMs), and Variational Auto-encoders (VAEs).

For example, picture recognition, self-captioning, speech synthesis, natural language processing, and other tasks, deep learning uses deep (artificial) neural networks with more than one hidden layer to enable machines to understand more abstract data patterns and concepts [9].

A deep learning technique gradually extracts higher-level functionality from the input using many layers (as demonstrated in Figure 3). For instance, lower layers in image processing may detect boundaries, whereas higher levels may recognize concepts that have meaning for people, such figures or characters [10]. Additionally, computational models made up of numerous processing layers can be used to learn data demonstrations at innumerable abstraction levels.This is how deep learning is defined.

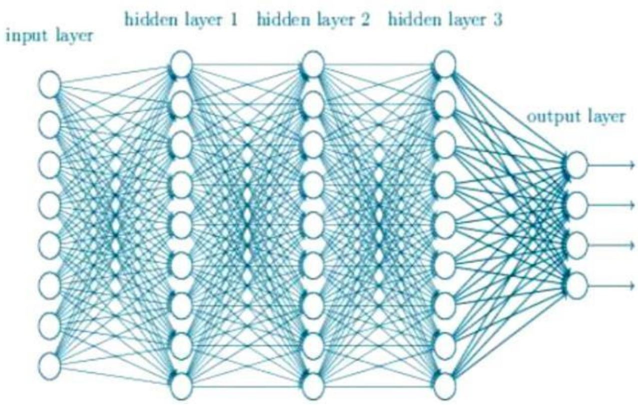

Fig. 3. Architecture in Deep Learning concept

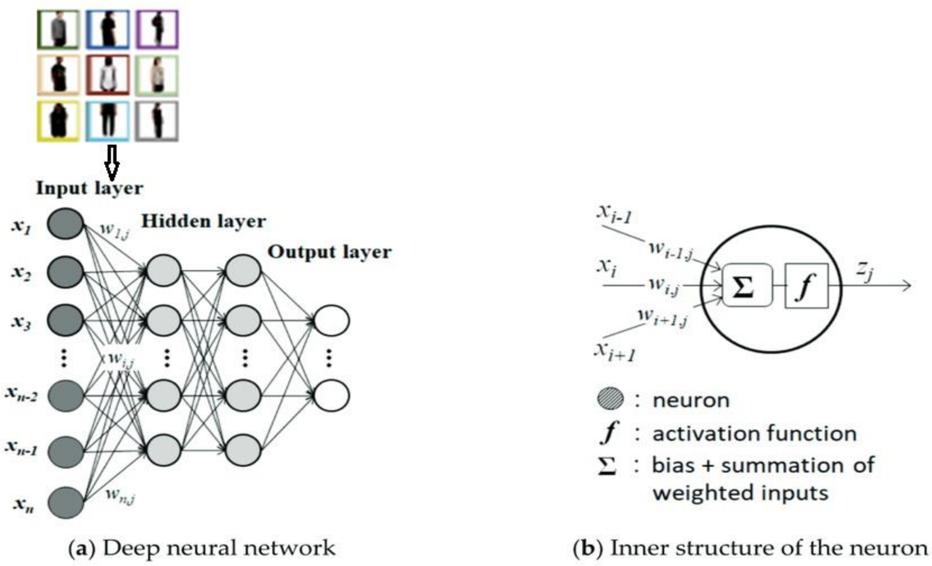

Fig. 4. The architecture of a Deep ANN that performs classification of Customers

The above mentioned concepts are utilized mostly in fashion designing approaches, and some other techniques. Since, they are not specifically utilized for concerning the customer's actions; we tried to introduce the new concepts to detect their activities as depicted in Figure 4.

3.3 K-means clustering process

One of the division-based clustering algorithms is K-means clustering. It uses an iterativeheuristic technique to partition data objects again and update cluster hubs. The algorithm's fundamental principle is as follows: Assume a set of element objects and the desired number of clusters. In the first round, a randomly chosen sample element serves as the initial cluster centre. The distances among other sample elements and the centre point are then calculated, and the clusters are then sorted into groups based on the calculated distances. The above stages are continuously iterated upon in each of the rounds that follow, and until the requirement that the clustering centre point no longer changes during the iteration process is met, the average value ofthe element objects achieved this time is used as the centre point of the subsequent round of clustering [20].

The initial clustering centre can be modified using either the batch modification approach or the individual modification method. After all data objects have been classified, the batch modification approach alters the clustering centre; the individual modification method modifies the clustering centre every time a data object's classification changes and begins calculating the mean of the two classes involved. It is clear from the preceding description that the batch change method requires few calculations and clusters quickly. However, the clustering outcome greatly depends on the initial cluster centre; the individual modification method's clustering outcomes are correlated with the classification order of the data objects, thus it is essential to choose representative objects as the clustering centre. To create multiple clustering and enhance the clustering impact when utilising the individual modification approach, the number of clusters, the minimum distance among classes, as well as the maximum distance within classes should all be often modified.

IV. PROPOSED CONCEPT

One of the various strategies that businesses may use to distinguish themselves and assist in establishing their brand in the chosen market segment is visual merchandising. These approaches consider the significance of visual merchandising and, among other things, how it may help and maintain a company's visual consistency, draw in new clients, and differentiate a brand from rivals (add competitive advantage).

The problem will also be approached in this work from the standpoint of consistent consumer behavior. This viewpoint is intriguing because there are currently an incredible number ofproduct brands available, giving consumers the greatest selection ever. As a result, it is crucial for brands to distinguish themselves from the competition and identify their essence—which must undoubtedly be distinctive. This essay will also discuss the value of the physical store experience in the era of e-commerce in addition to the previously discussed components of this approach.

Deep ANN classifier is modeled with deliberation for the constrictions mentioned above. Thereafter, a genetic algorithm is established and their computational experimentations are performed on different problem sizes. The efficient clustering of the relevant data can be modeled using adaptive K-means clustering analysis approach. The basic flow chart of the proposed customer activity analysis is shown in Fig. 5.

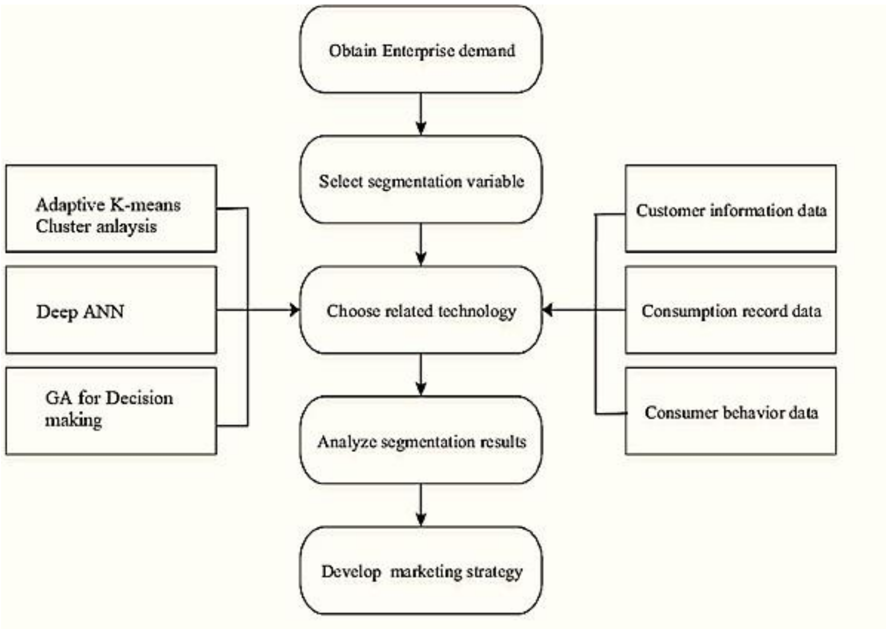

Fig. 5 Blocks of the proposed customer activity analysis

4.1 Adaptive K-means clustering concept

K-means is one of the traditional clustering algorithms used in the partitioning approach, as we previously said. This approach is highly efficient, but because it requires knowing how many clusters there are, K, it poses some challenges for automated calculations. The K values for the K-means segmentation method are determined using a combination of the maximum connected domain algorithm and K-means [22]. Extensive testing has revealed that K typically has a value between 2 and 10. To determine an accurate K value, we restore the image to only contain the target item using the maximum connected domain algorithm, record the result, and then compareit to the K value.

Algorithm 1: Steps followed in Adaptive K-means concept

Initialize K from 2 to 10
Randomly initialize K cluster centroids $\mu_1, \mu_2, \cdots, \mu_k \in \mathbb{R}^n$
if $K \leq 10$, repeat{
for each pixel $x^{(i)}$
$c^{(i)}$:= index (*from* 1 *to* K) of cluster centroid closest to $x^{(i)}$
for k = 1 to K
μ_k := average (*mean*) *of points assigned to cluster k*
Compare the maximum connected domain results
if right, print results, break;
else K=K+1;
}

his adaptive K-means pseudo code demonstrates, when selecting the K value, it starts at 2 and gradually rises to 10. Our extensive sets of experimental findings show that cluster K is often chosen between 2 and 10. The K-means method's success depends on choosing the right K value.We begin by choosing K = 2, meaning that picture segmentation begin with two clusters, and aresubsequently segmented as shown in the above stages (Algorithm 1).

The number of segmentation results is finally calculated using the maximum connected domain algorithm. The K value has been chosen successfully if the final segmentation result's image number matches it [22]. If the K value is different, it will be increased until the two numbers mentioned above agree. Following the segmentation of all target items using the adaptive K- means method and clustering, we received the segmentation results with little background influence.

4.2 Deep ANN classifier

As a computational approach, Artificial Neural Network (ANN) uses a directed network of linked neurons to map inputs to outputs [23, 24]. Deep NN is expanded as a deep neural network, made up of many layers. It can be a plain multilayer perceptron.

The am artificial neural network was trained using the information gathered. The dataset'sattributes served as the artificial neural network's inputs, and its output was the degree ofcustomer happiness. Training sets (80% of the data) and testing sets (20% of the data) are created from the total dataset. Tenfold cross-validation is the validation technique utilised [25].

Finding repeating themes in the embedding space are done through clustering, which depends on the embedding. We only used photographs that display the majority of full-body images when building the style model in order to accurately represent the distribution of all clothes and make the grouping computationally effective. As a result, an embedding for each image of an outfit in the dataset is retrieved. The suggested genetic algorithm modifies a population of latent vectors that were first created from the distribution as the latent variables throughout a number of generations. The algorithm determines which latent vectors from the current generation are most likely to belong to the specified style cluster. The objective is to produce a set of latent vectors that represent the desired style of designs. The equations are assessed similarly to how a neural network algorithm computes [14]. We recommend adaptive K-means clustering and GA for decision making progress in place of clustering and an optimizer.

An ANN is used to create a nonlinear function from the inputs, and the weights learned during the network's learning phase are used to govern the ANN's outputs. The learning process and methodology primarily use Back Propagation and Supervised Learning (BP). The efficient functioning of BP training requires a bounded differentiable activation function. The most well- known of all functions, the sigmoid function, has been used. It is limited to the interval between0 and 1, not including zero (1). The aggregate output of the neurons is scaled by a sigmoid function before being transmitted to the next layer of neurons. For error propagation network learning, a network's capacity to change its weights in response to faults is crucial. We show a schematic representation of the deep learning algorithm used in the paper in Fig.6.

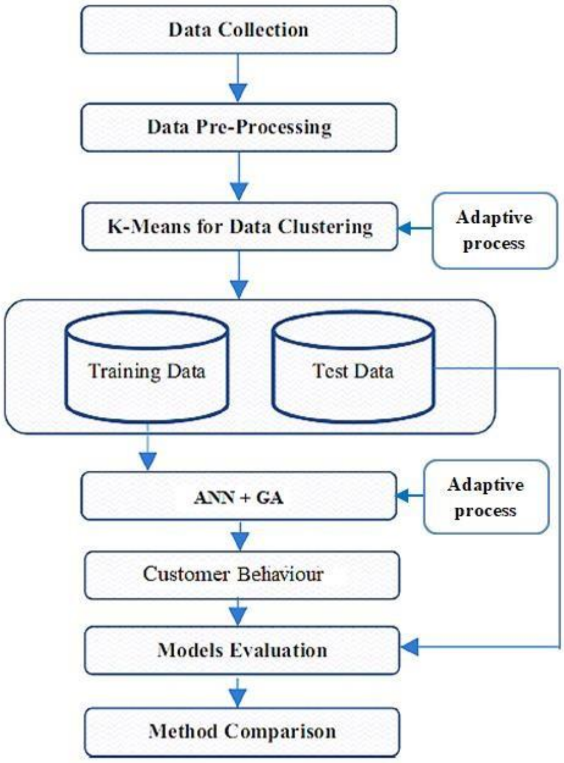

Fig. 6 Proposed flow diagram

4.3 Decision maker GA

GA was used in this study since it is a practical and efficient method for solving optimization issues. It is frequently used to solve issues in business, science, and engineering. The GA idea is simple to grasp and put into practise. The GA-ANN used in this study provides multi-constrained optimization and supports a very high number of parameters. Additionally, GA develops a solution depend on the population of individuals rather than from a single individual and operates on a broad and massive solution search space that can handle different solution representations. Additionally, with each iteration, the answer gets better (or stays the same) over time.

Unfortunately, GA takes a long time because it takes a lot of computation power to create a multi-constrained solution for each iteration. Next, after performing each normal GA procedure, several limitations must be checked and corrected (selection, crossover, and mutation). A target style's latent vector y* must be obtained by maximizing the fitness function in order for the generated images to fit into a style cluster. The specified parameters match the GA progress that is involved in [13].

4.4 Adaptation in Crossover process

We presented the Adaptive Gaussian (AG) model to improve the parameters of projected and experimental customer satisfaction levels for the i^{th} instance in the dataset. This AG can solve quickly by adjusting particular features of the position that is engaged in the optimization process by including the parameters results. This may result in the algorithm converging more quickly while maintaining the properties of the traditional approach.

$$A(y) = (G_{\sigma}(y^{*}) - G_{\sigma}(y_i)) \quad (1)$$

$$G_{\sigma}(y) = \frac{}{\sigma\sqrt{2\pi}} e^{\frac{-1}{2}\left(\frac{x-}{\sigma}\right)^{2}} \quad (2)$$

Where c, σ, $G(y)$ and θ are expected value, variance, Gaussian function of a variable y, and the function must be alternated in a specific direction correspondingly.

The equation below gives the final progeny along with the AG. The selected progeny mayfly has an AG distribution random number added to it for mutation in order to make contract with the likely premature convergence, in which the consideration of ideal value may be taken as the local optimal could be slightly better than the global optimal. The final mutation equation is as follows.

In order to handle the possibility of premature convergence, when the optimal value is thought to be the local ideal fairly better than selecting the global value, the distributed random number AG is added to the mutation process. The formula for adaptive mutation is as follows.

$$y_i = y_i + \text{Ⓠ}\{AG\} \qquad (3)$$

$$\text{where, } \varphi = \begin{cases} 1 & if\ (y_i^* - y_{i-1}) = 0 \\ 0 & else \end{cases} \qquad (4)$$

In the aforementioned equations, the probability factor Ⓠ is given. The likelihood factor is 1 if the features of this vector position obtained in iteration I using local or global best positions are identical to the features obtained in iteration (i-1) using local or global best positions. If not, the probability factor is zero and the answer remains the same. Last but not least, only careful selection of GA parameters, namely rate of mutation, crossover, and selection criteria, or population size, might lead to a useful outcome.
This study presents the estimation of GA in relation to the multi-constrained GA-ANN with many parameters, by considering the merits and demerits of GA that have already been presented. The following contributions are made to the GA by this work.
An enhancement process carried out after the crossover and before the mutation has enhanced the general GA. There have been three suggested techniques for improving adaptable solutions. Identifying less profitable products for the current customer and allocating them to other customers where they could create more profit is the primary objective of each strategy, on the one hand. However, the process identifies products on other customers that, if allocated to the current client, would be more profitable. The process of improvement carries out appropriate product movements. Additionally, GA was integrated with the precise solution approach, locating the product numbers on the customer's pallet.
Mutation use non-uniform process with the goal of getting closer to a target cluster. [2]. With a probability of 0.5, a variable of a latent vector y is mutated by adding some noise drawn from theoriginal distribution.

$$Y_i = Y_i + \text{noise} \sim N(\varphi) \qquad (5)$$

The likelihood that a population member will change is determined by the mutation rate. Although a genetic algorithm's mutation rate is often set to a few percent [11], we take into account both low (0.2) and high (0.5) mutation rates because preliminary runs revealed little diversity in the population. Despite the system's ability to produce images with the highest level of fitness, the designs may not always match the target fashions exactly as one may anticipate. A machine-specific awareness of fashion style is seen in the generations. Although some of the generated images show visual similarities to the target cluster, some generated outputs offer the possibility that the algorithm may interpret styles differently, highlighting the need to enhancethe fitness metric.

$$Final\_Fitness = \begin{cases} \frac{1}{1+Y_i}, & i(Y_i \geq 0) \\ 1 + \text{abs}(Y_i), & if(Y_i < 0) \end{cases} \qquad (6)$$

Before use, GA and clustering theory adjusted the Deep ANN's MSE-based design using thefollowing equation:

$$\text{MSE} = \frac{1}{N}\sum_{1}(y_i^* - y_i)^2 \qquad (7)$$

where N denotes the total number of instances, and y^* and Y_i stand for the anticipated and actual customer satisfaction levels for the ith instance in the collection, respectively. When evaluating visual merchandising, these clusters offer useful insights into customers' preferences. Additionally, we have genuine data for our method that we have gathered for this study. Business managers today can benefit from the study of social data utilising sophisticated learningtechniques used by fashion retailers to better identify client categories. This will thus increase their market competitive advantages.

4.5 Steps for Optimizing our Merchandising using AI & Machine Learning

The market isn't what it once was, but when a company understands how to appeal to its target consumer, it isn't necessarily a bad thing. The once-fairly direct route down the commercial thoroughfare is now littered with potholes, detours, and abrupt twists and turns. If a company doesn't take enough care to avoid these problems, its path to conversions can easily turn clumsy, convoluted, and inaccurate.
However, businesses are not powerless in their attempts to identify and engage their target client segments, regardless of how complicated or unpredictable the modern marketplace gets. When fuelled by the forward-looking and in-depth insights offered by AI and machine learning, merchandise optimization in the large digital ecosystem has evolved into a crucial component of achieving sustainable success.
By utilising AI and machine learning in their merchandise optimization methods, namely six essential

elements to improve engagement and conversions, we specifically offer brand insights and innovation. Brands can gain the competitive advantage necessary in a harsh environment by paying close attention to and emphasising these elements.

- ❖ Visual Merchandising: Visual marketing is rapidly establishing itself in the digital sphere as well. By applying such ideas to increase engagement and conversions when combined with other aspects of merchandise optimization, it enables a brand to create an identity and a story. For e.g. 67% of customers reveals that the image of the product plays a pivotal role in their decision making of the purchase.
- ❖ Personalization: By promoting a distinctive buying experience that responds to a person's particular tastes, expectations, requirements, and preferences, personalization is a wideyet potent idea that can counteract that destructive dynamic. For e.g. with the knowledge and computational power of modern technology, brands can now determine a client's preferences and shape the customer journey with messaging that speaks to them specifically.
- ❖ Recommendations: When a retailer makes recommendations to a specific customer based on that customer's preferences and buying habits, the retailer exposes the customer to goods and concepts that the customer would otherwise hardly ever consider or come across on their own. For e.g. it can scrutinize the customer data and then process with the introduced algorithms to classify their relevant data in real time progress.
- ❖ Product Assortment: Used to sell as much merchandise as possible while also appealingto customers. For e.g. those conventional methods used unsophisticated procedures to make decisions about future product inventory based on historical sales data.
- ❖ Product pricing: In the digital market, the usual customer will look for a product across a number of different retailers to discover the best option for their budget, along with comments and reviews from other customers. For e.g. there are now machine learning tools available that build price optimization models that determine the best mix ofproduct pricing, consumer demand, and profit margins.
- ❖ Promotions: Since, the goal of promotion is to increase revenue and profitability; brands must always balance the advantages that promotions offer to consumers with theseeffects. This idea is rarely easy or simple to implement in a sales environment that is as dynamic as this one. For e.g. a smart strategy for developing successful promos that benefit all parties is one that makes use of AI's capacity for data collection and machinelearning's capacity for data analysis.

Finally, AI, customer data, new algorithms, and processing power work together to create a sort of crystal ball that gives businesses the ability to accurately predict the best product assortments rather than just responding to shifting consumer wants after the fact. AI also gives merchants a far more precise way to group things according to various characteristics, occasions of use, styles, or themes — nuanced correlations that improve the dependability and ability of a digital store's search function to meet the needs of its customers.

V. Dataset

The generative model and the style model are trained using the dataset from FashionGen's [23] clothing division, which has a resolution of 256x256 pixels. The subset consists of almost 200,000 photos of clothes worn by a model, with each outfit appearing in four different poses. The majority of the dataset consists of whole-body outfit images that were captured in uniform lighting conditions against white backgrounds, which created the perfect environment for generation and clustering to concentrate only on fashion attributes and identify styles across a variety of artifacts.
On a Linkert scale of 0 to 10, the questions were designed to gauge the degree of users'satisfaction with online retailers [27]. 1500 replies were sent in total, but only 1220 of them wereused because 280 of them were either incompletely filled out or unusable. Categorical and continuous scales were used to set responses in two stages. The level of client satisfaction with each of the elements was covered in the questions.

VI. Results

To create designs for five various styles; we tested our model with each parameter combination. The size range of the posterior probability distribution for each target style cluster for the images is 228 to 367. Table 4 compares the mean maximum fitness attained throughout each of the five runs. The outcomes that we present are averages for the entire system's five runs, or "style clusters," which we performed. Remember that the posterior probability of an image belonging to a resultant component defines the fitness to be maximized. Consequently, it might range froma lowest of 0 to a highest of 1. The images provide a mean value among 0.92 and 0.98. Thus, Table 1 & 2 is evaluated for the adaptive GA fitness across all five runs per parameter combination for mutation of 0.2 & 0.5.

Table 1. Maximum Average fitness values for Pmut=0.2

		P_{mut}=0.5			
		Nts=3		Nts=6	
		GAN+GA [13]	Proposed	GAN+GA [13]	Proposed
pcx=0.7	Npop=100	0.5826	0.6784	0.214	0.34
	Npop=200	0.431	0.5741	0.5791	0.6647
pcx=0.9	Npop=100	0.438	0.6487	0.3955	0.4578
	Npop=200	0.8373	0.9145	0.2742	0.6587

Table 2. Maximum Average fitness values for Pmut=0.5

		P_{mut}=0.5			
		Nts=3		Nts=6	
		GAN+GA [13]	Proposed	GAN+GA [13]	Proposed
pcx=0.7	Npop=100	0.6121	0.684	0.214	0.384
	Npop=200	0.6241	0.771	0.5791	0.667
pcx=0.9	Npop=100	0.75	0.8747	0.3955	0.478
	Npop=200	0.743	0.8945	0.2742	0.57

The fitness measure and the visual coherency to the intended style are in alignment for some of the studied designs. After around half of the generations, the population reached a local maximum, which made it possible to only optimise a small feature in the succeeding generations. Despite the fact that convergence to a local maximum is a goal for genetic algorithms, it presentsa challenge in this case. The ensuing evolution that underlies the dominant appearance was brought on by the population's predominance of weak style matches. When fitness plateaus, one way to increase diversity in the population is to increase mutation rates or the birth rate.

Our style model may not have the sensitivity of human shapes/models, because it is based on the representation of an attribute model trained to identify garment aspects. However, having considerations of backgrounds in physiology and clothing, these ideas influence to perceive the designs.

Therefore, the recommended system may uncover some entirely distinct features hidden below to be defining characteristics of a style. The designs produced by the evolutionary searchdemonstrate a particular machine conception of fashion style. To further examine that assertion, we must find out whether our model is adequate to capture styles. The disparity in perception might also be caused by the fact that computational networks cannot detect minute variances in style.

Using the same dataset, the simulation outcomes of PSO-ANN with ANN and clustering models are assessed and contrasted. Table 3 presents the findings of the comparisons. The averagevalues of the MSE and R2 coefficients of determination for the three distinct models are shown in the table below [14]. The simulation of results amply prove that among the numerous techniques, such as ANN, *k*-means-PSO-ANN, *k*-means-ANN, the newly developed adaptive GA with K-means-ANN can provide some better resultant values. The respective values aredepicted in separate Figures 7-8.

Table 3 Comparisons results of MSE and R^2 values for several methods

Techniques	MSE	Coefficient ofDetermination(R^2)
ANN [14]	0.173	0.921
k-Means-ANN [14]	0.158	0.8238
k-means-PSO-ANN [14]	0.094	0.977
Proposed method (adaptive GA K-means+ANN)	`	0.986

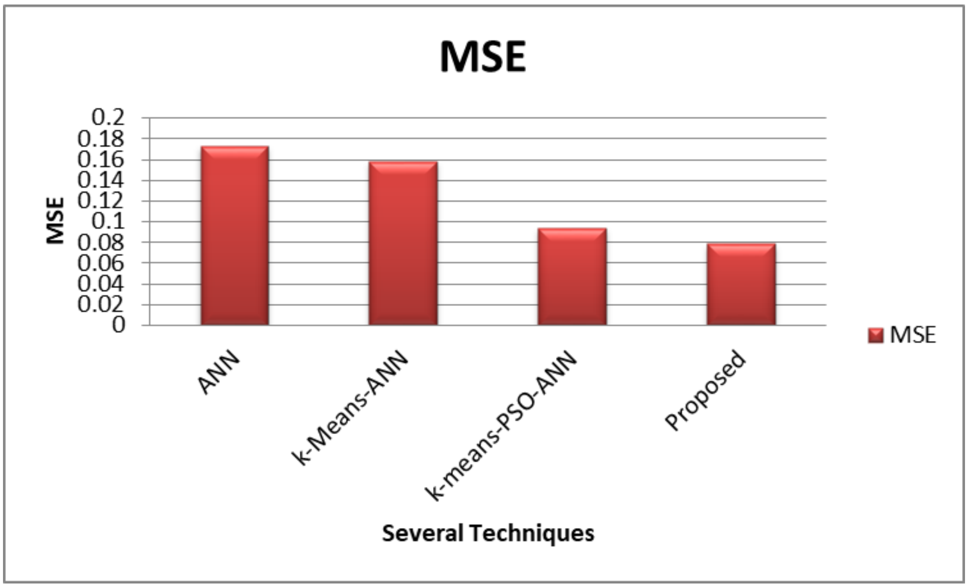

Fig. 7. Comparisons results of MSE values for several techniques

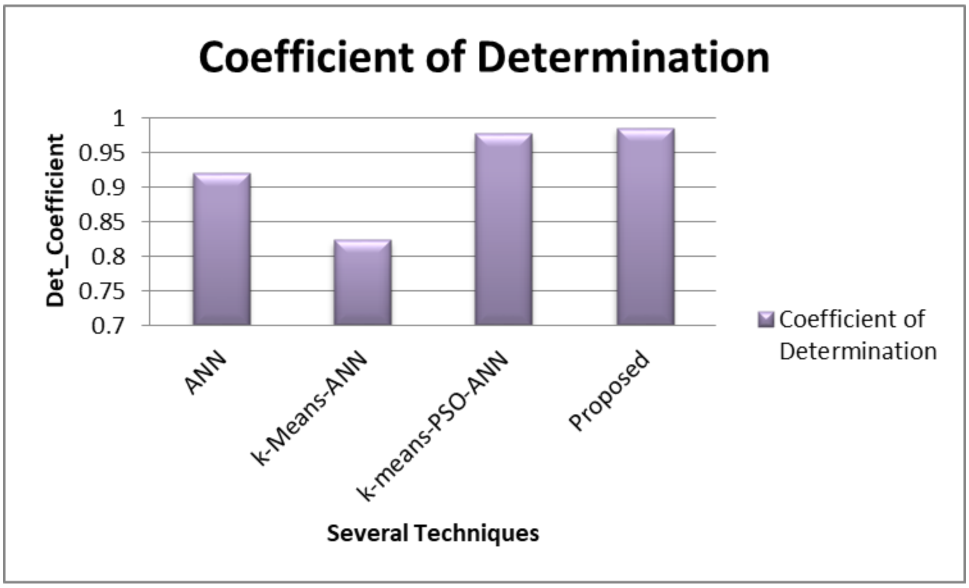

Fig. 8. Comparisons results of R^2 values for several techniques

With the aid of this new system, these combined approaches offer useful information regarding customer preferences. Additionally, we have gathered actual data for our method evaluation in this study. Nowadays, the analysis of social data using sophisticated learning approaches can aid business managers in better detecting the customers' segments for the analysis of their behaviour. As a result, their competitive advantages in the fashion sector will increase.

As previously mentioned, standardized academic surveys provided the dataset for this study [27]. To better comprehend the complete set, we perform summary statistics and some visualisations below. Correlation analysis is specifically used to determine the relationship between each predictor variable and the predicted variable as consumer contentment. The most closely connected variables to the goal variable, customer satisfaction, were identified using a Pearson correlation analysis.

This new study offers a solid framework for managers and business owners to use as they continuously look for ways to increase customer satisfaction by altering various business-related elements. It might be a good idea for vendors and business owners to investigate how improving website aesthetics affects client happiness. By altering the values for the website design quality, this is accomplished. The introduction of this evidence revealed a significant improvement in customer satisfaction levels. The simulation results indicate that an increase in post-order service and hedonic factors had the largest positive impact on customer satisfaction levels. This testing was also applied to the other variables.

With inputs of 7 for site design quality, 6 for post order support, 8 for product quality, 5 for online stores' facilities, 8 on hedonic aspects, and 9 for online store image, the system predicts a satisfaction level of 9.186 in the [27] linear regression model. Given that it is scaled from 1 to 10, the predicted satisfaction level of 9.816 implies high satisfaction. For the same dataset, we obtain the customer satisfaction level of about

9.884 with the better satisfaction level than the previous methodology as tabulated in Table 4.

Table 4 Comparisons results of customer satisfaction level

Techniques	MSE	Coefficient of Determination (R^2)	MAE	Predictionlevel
Regression model [27]	0.463	0.7511	0.478	9.186
Proposed model	0.358	0.8238	0.347	9.297

VII. Conclusion and Future Work

The goal of this study was to broaden the traditional generative deep learning approach in order to make it easier to generate designs that are responsive to applications of fashion trends. We looked into using an adaptive evolutionary algorithm in conjunction with K-means and ANN to direct the creation of images based on previously discovered style clusters. Our suggested framework makes it easier to find photos that respond to particular style clusters. To create the hybrid methodology, the modified clustering and ANN are both taken into consideration. Adaptive GA was used to enhance the ANN technique's performance. The experimental findings show that, compared to the previous approaches, the suggested procedure offers a promising direction for directing the search for style-coherent designs. The familiar artificial neural network techniques employed in market segmentation may be better understood by organisation strategists as a result of these publications. MSE, MAE, Customer Prediction level and coefficient of determination measurements were used to gauge the method's efficacy. Additionally, we contrasted the final fitness outcomes with the earlier approach. Since consumer diversity necessitates market segmentation, it is necessary to find appropriate methods for targeting, planning, marketing, and revenue management. Regarding the research findings, we advise conducting additional research in the area of market segmentation. Strategists must segment the market and subsequently boost an organization's profitability in order to maximise earnings through segmentation.

New design opportunities arise when fashion style analysis and fashion generation are integrated, such as expanding trend forecasts to create trending designs. To develop a solid and trustworthy exploration technique, more study is necessary. Future research could look into how generative models' potential as tools for creative design is increased by their capacity to respond to stylistic advancements via unsupervised learning. It is also advised to use a variety of data sources while comparing alternative approaches.

VIII. REFERENCES

1. Dash, M., and Akshaya, L. 2016. A study on the impact of visual merchandising on impulse purchase in apparel retail stores. International Journal of Marketing & Business Communication, 5(2) Accessed 14.03.2019. https://search-proquest-com.ezproxy.puv.fi/docview/1839179382?accountid=27304.
2. Bell, J. and Ternus, K. 2006. Silent selling. 3rd ed., New York: Fairchild Publications, p. 21.
3. Kardes, F. R. 2002. Consumer Behavior and Managerial Decision Making, 2nd Edition, Prentice Hall, Upper Saddle River, NJ.
4. Solomon, M. R. and Rabolt, N. J. 2006. Consumer Behavior in Fashion, Pearson Education.
5. Kavitha, A. and Sahithi P. (University College of Technology at Osmania University, Hyderabad). Essential Elements of Visual Merchandising. Fibre2fashion.com. Accessed 23.02.2019 https://static.fibre2fashion.com/ArticleResources/PdfFiles/69/6841.pdf
6. "How to Use Artificial Intelligence (Ai) in Online Fashion Retail in 2021," Exponea, 12 January 2021. [Online]. Available: https://exponea.com/blog/impact-artificial-intelligence-online-fashion- retail/. [Accessed 04 April 2021].
7. N. P. a. R. S., "Artificial Intelligence: A Modern Approach (3)," in Artificial Intelligence, Prentice Hall, 2010, p. 77.
8. L. D. a. D. Yu, "Deep Learning: Methods and Applications," in Foundations and Trends in Signal Processing, vol. 7, oct-2014, p. 428–434
9. Alexander NILSSON, Martin THÖNNERS, "A Framework for Generative Product Design Powered by Deep Learning and Artificial Intelligence," June 14, 2018.
10. Wikipedia, "Deep learning," 12 September 2021. [Online]. Available: https://en.wikipedia.org/wiki/Deep_learning. [Accessed 16 September 2021].
11. L. B. Y. B. a. P. H. Y. LeCun, "Gradient-Based Learning Applied to Document Recognition," in in Proceedings of IEEE, California, USA, November 1998.
12. D. H. a. T. Wiesel, "Receptive Fields, Binocular Interaction and Functional Architecture in the Cat's Visual Cortex," Journal of Physiology, vol. 160, pp. 106-154, 1962.
13. Grabe, I., Zhu, J. and Agirrezabal, M., 2022. Fashion Style Generation: Evolutionary Search with Gaussian Mixture Models in the Latent Space. In *International Conference on Computational*

Intelligence in Music, Sound, Art and Design (Part of EvoStar) (pp. 84-100). Springer, Cham.
14. Alghamdi, A., 2022. A Hybrid Method for Customer Segmentation in Saudi Arabia Restaurants Using Clustering, Neural Networks and Optimization Learning Techniques. Arabian Journal for Science and Engineering, pp.1-19.
15. Hoegele, D., Schmidt, S.L. and Torgler, B., 2016. The importance of key celebrity characteristics for customer segmentation by age and gender: Does beauty matter in professional football? Review of Managerial Science, 10(3), pp.601-627.
16. Chiu, C.M., Wang, E.T., Fang, Y.H. and Huang, H.Y., 2014. Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk. Information Systems Journal, 24(1), pp.85-114.
17. Matzen, K., Bala, K., Snavely, N.: StreetStyle: Exploring world-wide clothing styles from millions of photos (2017).
18. Al-Halah, Z., Grauman, K.: Modeling Fashion Influence from Photos. IEEE Transactions on Multimedia (2020). https://doi.org/10.1109/TMM.2020.3037459.
19. Mahmood, A., Ospina, A.G., Bennamoun, M., An, S., Sohel, F., Boussaid, F., Hovey, R., Fisher, R.B., Kendrick, G.A.: Automatic hierarchical classification of kelps using deep residual features. Sensors 20(2), 447 (2020).
20. Punhani, R., Arora, V.P.S., Sabitha, A.S. and Shukla, V.K., 2021. Segmenting e-Commerce Customer through Data Mining Techniques. In Journal of Physics: Conference Series (Vol. 1714, No. 1, p. 012026). IOP Publishing.
21. Zheng, X., Lei, Q., Yao, R., Gong, Y. and Yin, Q., 2018. Image segmentation based on adaptive K-means algorithm. *EURASIP Journal on Image and Video Processing*, *2018*(1), pp.1-10.
22. Li, Y., Chu, X., Tian, D., Feng, J. and Mu, W., 2021. Customer segmentation using K-means clustering and the adaptive particle swarm optimization algorithm. *Applied Soft Computing*, *113*, p.107924.
23. Zhang, W.; Li, H.; Li, Y.; Liu, H.; Chen, Y.; Ding, X.: Application of deep learning algorithms in geotechnical engineering: a short critical review. Artif. Intell. Rev. **54**(8), 5633–5673 (2021).
24. Zhang, W.; Zhang, R.; Wu, C.; Goh, A.T.C.; Lacasse, S.; Liu, Z.; Liu, H.: State-of-the-art review of soft computing applications in underground excavations. Geosci. Front. **11**(4), 1095–1106 (2020).
25. Zhang,W.;Wu, C.; Li, Y.;Wang, L.; Samui, P.: Assessment of pile drivability using random forest regression and multivariate adaptive regression splines. Georisk Assess. Manag. Risk Eng. Syst. Geohazards **15**(1), 27–40 (2021).
26. Sukhodoeva, I., 2019. The Effect of Visual Merchandising on Customers' Purchasing Decisions.
27. Acheme, I.D., Osemengbe, U., Makinde, A.S. and Vincent, O.R., Online Stores: Analysis of user Experience with Multiple Linear Regression Model (2021).