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Product Classification With the Motivation of Target Consumers by Deep Learning

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ABSTRACT Due to the dynamic and competitive market environment, it is widely recognized that the development of new products and processes has become the critical point of attention for many companies. The first step in the product development process is to define the nature and function of the product, which is to classify the new product. The traditional product classification process only focuses on the product and market, which is developed by designers on the basis of the products of past dynasties. This way is labor-consuming, inefficient, and has become a bottleneck or constraint for these enterprises to improve their productivities and regulate production. In recent years, Artificial Intelligence has been applied in a wide range of fields including product classification. How to apply machine learning technologies to solve the classification problem of product classification has been widely concerned by researchers. In this paper, a fast and effective product classification, called MdmNet, is proposed, which is based on a novel attempt that embeds the innovation idea of human in machine learning technologies. MdmNet includes three modules: a target customer modeling method based on the deep learning technologies a consumer information deduction method based on the MDM that builds a consumer feature closed loop and output the classification result of the consumers' perspective, and a weighted fusion module. Experiments conducted on benchmark datasets Cars demonstrate the impressive performance of the proposed MdmNet. This paper first attempts to add consumer motivation analysis to traditional machine learning method, which has a strong application prospect.

INDEX TERMS New product development, motivation design model, product classification, deep learning.

I. INTRODUCTION

In the background of fierce competition, the time it takes for a new product to go from design and production to final launch often determines the final sales and profitability.

In order to speed up the product design process, after getting the idea of the new products, the designers will first categorize the new products and then choose a general design outline according to the category based on which the details will be continually designed. Therefore, product classification plays a very important role in the design process.

In traditional design fields, it is the designer who defines new product categories independently. However, this way is labor-consuming, inefficient, and has become a bottleneck or constraint for these enterprises to improve their productivities and regulate production. Moreover, the results obtained by this method are not accurate. Because the design process is dominated by the designer, there is no customer participation, which will lead to mismatches between the new product and the needs of consumers. Specifically, for companies that lack experience in past generations of products, it is struggle for them to find efficient and effective processes and management activities for product classification [1].

Therefore, it is needed to explore a new approach to help designers make decisions. With the rise of artificial intelligence in the last two years, the development of technology progress, in many areas of industry, there are more and more artificial intelligence products slowly appear in the field of design. With the help of machine learning, designers are able to build the connection between the product and its target consumers.

Among the ML methods that are used in the design field, the most commonly used is the image classification model. A computer learns from input data how to perform classification tasks. However, the deep learning models need high-definition images as the input and extract complex

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features, which is very time-consuming. For example, the training process of a common network structure ResNet 18 with the 3-channels color input image that has a resolution of (224,224) occupies a lot of memory and time resources.

In addition, since the training data is defined by the designer and there is no consumers' participation, only the classification results from the designer's perspective can be obtained. In practical applications, designers and users may focus on different characteristics. For the same product, they may have different definitions. When this happens, designers will design products that do not meet user expectations and thus lose the target market.

If the designer can predict the consumers' definition of the product and improve the product design method from the consumers' point of view, the separation between the product and the market can be avoided, so as to improve the economic benefit. One of the schemes to improve the classification results is to integrate consumer-defined data into the model training. However, due to privacy concerns, the information of target consumers is hard to collect, and the data quality obtained through the questionnaire is difficult to guarantee. To solve the above challenges, this paper proposes a framework that can model the mental activities of target customers, thus simulating customer data and enhancing the performance of classification models.

There are many ways to model the target user. Previous studies have shown that there is a close relationship between customers behavior and their cognitive orientation. However, it is difficult to understand consumer cognitive orientations through traditional market surveys, and the best way to do so is through interaction. Therefore, effectively handling observations and interviews collected in the field is necessary to understand consumer cognition, as they can help explain the meaning behind the relevant phenomena.

To meet this requirement, Luh [2] proposed Empathic Design Model (EDM) which would be able to determine consumer cognitive orientation. Empathic design is a new market research technique that aims to meet the needs of consumers through analysis of detailed observations. The EDM model includes observing related phenomena, laddering the cognition, connecting the elements of the Associations Matrix, producing the hierarchy of the following four items, attributes, functional consequences, psychosocial consequences and values, and then producing a prototype to help designers and consumers reach a consensus on the cognitive structure of products [3]–[7].

The case study of the design of an "electronic tour guide" proofed that the EDM is able to analyze customer's requirements and then improve the method of industrial product design, and this may lead to widespread future use of this model. Moreover, EDM is easy to handle and very useful, each step of EDM can be executed easily and is closely connected to the next step, and this can shorten the design time, which is especially important for the NIA [8]–[10].

The success of EDM inspired us that there must be a close relationship between customer's behavior and the way they define products, since the customers' behaviors and the way they define products are both influenced by cognitive orientation. However, it is difficult to understand the target consumer through traditional market surveys, and the best way to do so is through interaction. Therefore, effectively handling observations and interviews collected in the field is necessary to understand target consumers, as they can help explain the meaning behind the relevant phenomena.

On the basis of EDM, we propose a Motivation Design Model (MDM). The major task of MDM is to understand the target consumers and gain insight into the cognitive structure of consumers' impressions of the product. By deeply mining the relationship between consumers' interests and their expectations, MDM is able to derive other consumers related information, includes incentive, desirability and willingness. Therefore, a consumer feature closed loop including expectation, incentive, desirability and willingness is constructed, which is able to output the classification results of consumers' perspective [11], [12].

In this paper, a fast and effective framework of product classification, called MdmNet, is proposed, which is based on a novel attempt that embeds the innovation idea of human in machine learning technologies. MdmNet is a learning framework that combines a psychological model MDM and a deep learning model CNN. It is built on the basic assumption that customer information can be extended by some facts and the accuracy of product classification will be improved if more information is provided.

MdmNet includes three modules: a target customer modeling method based on the deep learning technologies, a consumer information deduction method based on the MDM that builds a consumers' feature closed loop and output the classification result of the consumer's perspective [13]–[18], and a weighted fusion module. By using a range of machine learning techniques to infer customer psychological activities, the final output of Memento incorporates the classification results from both the designer's perspective and the consumer's perspective without the need for time-consuming and costly market research.

Experiments conducted on benchmark datasets Cars demonstrate the impressive performance of the proposed MdmNet. This paper is the first time to add consumer motivation analysis to traditional machine learning method, which has a strong application prospect.

II. RELATED WORK

The first step in the product development process is to define the nature and function of the product, which is to classify the new product [19], [38], [39]. The concept of "product classification" consists of dividing products according to specific characteristics so that they form a structured category. In order to meet various purposes, many researches and organizations have put forward the method and theory of product classification. In general, besides of a standardized product classification system, there are also many informal methods of product classification devised by various industry organizations. In the initial stage, product classification lets a firm know what kind of product it will design. Second, the product classification embodies the design and clarifies production feasibility. Third, the product classification can represent the methods and materials associated with a successful design. Lastly, product classification proves that the whole manufacturing process is effective [36], [37].

In this study, product classification is defined as a proof-of-concept prototype, referring to nuclear design concepts and features which can then be extended. The main aims with this kind of prototype are to clarify product functions and configurations, as well as its practical uses, thereby helping to indicate a correct direction for product development. A good prototype is designed within clear limitations, helping development personnel to more easily understand the desired features of the product and thus engage in meaningful group discussions, leading to the development of improved products and shortening the time to market.

In the field of computer vision, image classification is arguably the most basic and common problem, from the previous manual feature extraction combined with traditional classification models. To today's deep learning, although the recognition rate of each database in the field of classification and recognition is constantly being refreshed, from common object recognition, to fine-grained object recognition, to face recognition, each segment of the image recognition field is making continuous progress.

The success of CNN on ImageNet has enabled many people to see the breakthrough of AI in the field of image classification recognition, but, finally, a bottleneck has been encountered, and the current research on classification recognition has indeed made great progress compared with a decade or two ago, but the difficulties are still numerous.

There are many factors that affect image classification and recognition, the most common ones are illumination, deformation and scale; there are also occlusion and blur, which are all general factors.

There is also a large category of factors that are different in form for the same category, which can be attributed to too much variation within the category.

Finally, there is the more common fine-grained classification, that is, they may all belong to one big category, but subdivided down, there are subtle differences, fine-grained classification is also a branch of image classification recognition, more common classification is the classification of dogs, birds, and various types of aircraft, this kind of problem is too small differences between classes.

In addition to the above challenges, in the field of product design, traditional image classification models are no longer appropriate because the classification results are influenced by the mental activities of the target customers.

MdmNet adopts the human centered design idea, which belongs to the category of ergonomics. Ergonomics is a subject that studies the interaction between human, machinery and their working environment [20]–[22]. It originated in Europe and formed in the United States. At present, people's understanding of man-machine relationship has changed from ‘‘suitable for human and machine’’ to a new stage of ‘‘pleasant for machine’’.

A large number of different definitions of ergonomics and of human factors exist recently. Most definitions stress the view of ergonomics as both a science which provides fundamental understanding and also a technology: applying that understanding to problems of design in their widest sense. Within this view, the ergonomics problem space contains all elements of the total human-environment system, comprising people's interactions with hardware, software, firmware (including space), and other people (liveware) both individually and as social groups.

Different countries, fields and institutions have different definitions of ergonomics [23]–[26]. In this paper, ergonomics is the theoretical and fundamental understanding of human behavior and performance in purposeful interacting sociotechnical systems, and the application of that understanding to design of interactions in the context of real settings.

We had proposed the original version of framework in [27], [44]–[48], and the idea was also to combine CNN with MDM network to improve the classification effect by modeling the target users and predicting their mental activities. However, the framework has some shortcomings.

Firstly, the input images are not resized and grayed out. Although in general, the higher the resolution, the more information the image presents and the richer the features the CNN can extract. However, as we mentioned in the Introduction Section, in the field of product design, high-resolution images are not only difficult to obtain, but the larger the image is, the more computationally intensive it is, and the longer the training time will be. In addition, it also takes up more computational time and resources in practical applications.

In addition, the original framework is composed of two modules: a target costumer modeling module and a customer information deduction module. Whereas the MdmNet proposed in this paper contains three modules: a target customer modeling method, a consumer information deduction method based on the MDM, and a weighted fusion module.

The target costumer modeling modules in both frameworks are used to expand the user's region of interest and this process is simulated by using an image retrieval model. The improvement of the MdmNet proposed in this paper over the previous version lies in the following two points:

First, MdmNet proposes a computer simulation approach for MDM. In [27], we mentioned that the MDM is applied on the costumers' information to continue to dig customer characteristics, but this part of the work is still done manually.

The MDM module is simulated by image processing and similarity calculation. In MDM module, the image is described by its histogram. The customer's expectation is a series of standard product images, which are randomly selected for each class. Then, we evaluate the similarity between interest and expectation of target consumers. The MDM module then outputs a probability ranking, which is described as a classification result output from the target customer's perspective.

Second, after the target costumer modeling module, MdmNet adds a weighted fusion module for comprehensively considering classification results from designers and consumers. After getting the retrieval sequence, original framework will score the result of image retrieval and use the score to indicate the user's interest and complaint, and fuse the score information into the visual information of the input image to form multi-level information that contains not only visual information but also implies the user's mental activity. The data structure is {Extracted products features, Scores}.

However, in the new product development stage, due to the lack of real feedback data, the user ratings are predicted by the model deviate from the actual situation. Moreover, in the model training stage, the rating data will be used as training data input, and the inaccuracy of the rating will cause inaccurate classification results.

To solve the above problem, the MdmNet proposed in this paper does not include user information in the input features, but quantifies the user's mental activity by scoring, and inputs this result into the weighted fusion module together with the output result of the traditional CNN. Then, the weight coefficients $\mathbf{W}_a$ and $\mathbf{W}_b$ are used to define the significance of $\mathbf{S}_{designer}$ and $\mathbf{S}_{customer}$ to the final score respectively.

III. METHEDOLOGY

A. NETWORK STRUCTURE

As aforementioned, the product classification framework MdmNet proposed in this paper is a novel attempt that embeds the innovation idea of human in machine learning technologies and has not been validated in marketing cases yet. In MdmNet, we simulate the process using a range of computer technologies. The target customer's modeling process is simulated by using a pretrained image retrieval model, and its able to obtain consumers' interests, then give the interests information to the subsequent MDM. The main purpose of consumer modeling is to expand information based on the limited facts, so as to make up for the lack of consumer information.

Then, the MDM is applied on the customers' interests and expectations. MDM can build a consumers' feature closed loop including expectation, incentive, desirability and willingness. The output of MDM is the classification result of the consumers' perspective.

In MdmNet, we use the following steps to implement MDM. First, we randomly select a standard image from each class of products to simulate consumer expectations. Then, when classifying new products, we will evaluate the similarity between new products and the expectations. The ranking of similarity is the order of which class the new product belongs from the consumers' point of view. In MDM, we use histogram to describe product features, and use Pearson correlation coefficient to evaluate the similarity.

Color feature extraction has become an important means of almost all content-based image classification technologies. Because the same kind of objects generally have similar color characteristics, so people use color distribution to distinguish the image content according to this point. However, due to the particularity of product classification: the same product often has multiple colors, and the training time cannot be long. Therefore, in MdmNet, we reshape it to single channel gray image. The gray level histogram can reflect the relationship between the frequency of each gray level pixel in an image and the gray level. It is widely used in various fields of image processing because of its low computational cost and many advantages, such as image translation, rotation, and scaling invariance.

Through the first two modules, we get the classification result of the consumers' perspective. Meanwhile, by using a ResNet-based approach for classification, we can get classification result of the designer perspective. Both results are expressed by sorted sequences, that is, the most likely class of the new product is at the top of the sequence. The later the class is, the less likely the new product is to belong to this class. In fusion module, we perform weighted fusion of the two sequences. By adjusting the weight coefficient, we can adjust the proportion of result of the consumers' perspective and the result of the designer perspective in the final result. The details are given in the next chapter.

MdmNet can output the classification results from the consumers' perspective and integrate them with the classification results from the designer's perspective, so as to obtain more comprehensive classification results. MdmNet is composed of a target customer modeling module and a consumer information deduction module MDM, and a weighted fusion module, which can be seen from Fig. 1.

B. TARGET CUSTOMER MODELING

As mentioned earlier, the purpose of MdmNet is to predict the definition of new product by target consumers. However, it is difficult for us to get consumers ' views on the new product. Since consumers ' historical purchase records are relatively easy to obtain, we use the past purchase library to expand new product information. The specific approach is to find products that similar to new product in the history database. In this paper, we defined these similar products as the interests of the target consumers.

According to EDM, we know that consumers' behavior is positively correlated with their cognitive orientation. The cognition is related to personal experience and it will not change in a short time, so does the behavior. Therefore, there is a correlation between the target consumers' past and future purchase. We can predict their definition of the new product by analyzing their definitions of related products.

The purpose of consumers modeling is to find the interests of the target consumers. In order to accurately describe the image features, we need a model with a large learning capacity. Convolutional neural networks (CNNs) constitute one such class of models [28]–[31]. Their capacity can be

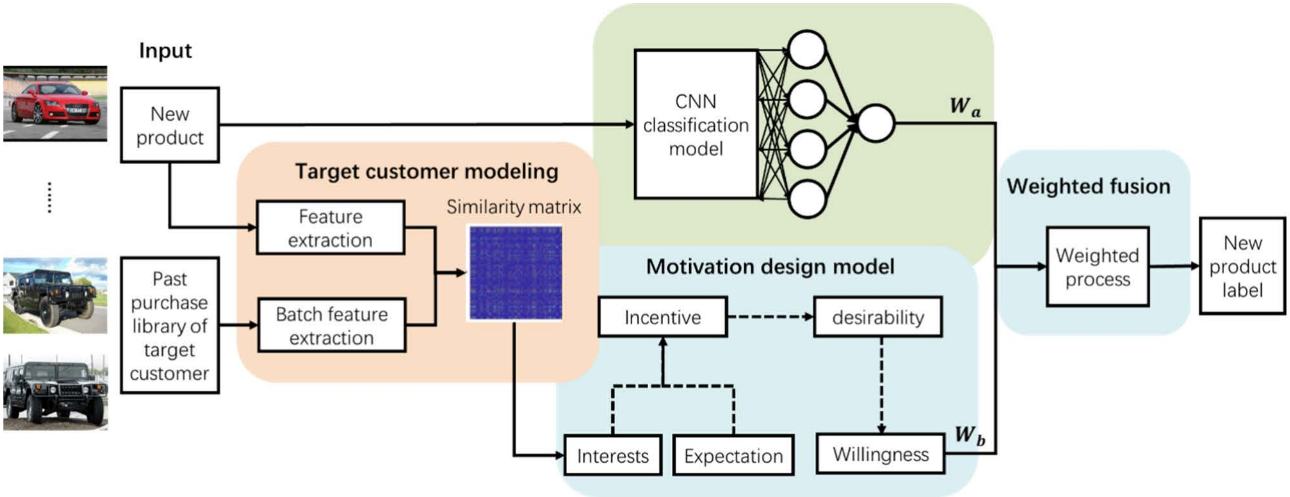

FIGURE 1. An overview of the proposed MdmNet. The main network consisting of a target customer modeling method based on the deep learning technologies a consumer information deduction method based on the MDM that builds a customer feature closed loop and output the classification result of the customers perspective, and a weighted fusion module.

controlled by varying their depth and breadth, and they also make strong and mostly correct assumptions about the nature of products. Thus, compared to standard feedforward neural networks with similarly-sized layers, CNNs have much fewer connections and parameters and so they are easier to train, while their theoretically-best performance is likely to be only slightly worse.

Inspiring from the advancement of CNNs, we utilize the image retrieval technology to expand the information of target consumers. We introduce a simple yet effective supervised learning framework for rapid image retrieval [31], [32]. The inputs of the image retrieval model are the image of new product and the past purchase of target customers. The output is a series of similar images, which are described as customers' interests in MdmNet. Specifically, this module extracts features from the new product and the products in the past purchase library. Then, the distance between the new product's vector and the vectors of the library is calculated to find the similar pairs, and the corresponding similar products are the searching results.

C. MOTIVATION DESIGN MODEL

In the Target Customer Modeling step, we utilize the image retrieval technology to achieve the interests of target consumers. Then, the MDM is applied on the customers' interests and expectations to continue to output the classification result of the consumers' perspective.

Firstly, we randomly select the standard product images of each class as the consumers' expectation. Next, we will calculate the similarity between expectations and interests for subsequent output of classification results from consumers perspectives. Before calculating the similarity, a pre-process method is applied to the image. As mentioned earlier, in order to recover the real situation of product classification, we resize the original color image to (56, 56) and only retain a single channel, which can greatly improve the response speed of the framework.

In addition, we use histogram equalization technology in preprocessing stage. Histogram equalization is a method to enhance image contrast. Its main idea is to change the histogram distribution of an image into an approximately uniform distribution, so as to enhance the image contrast.

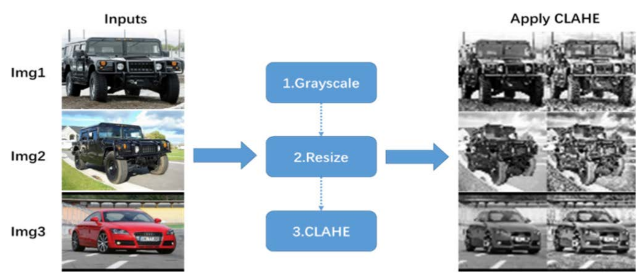

FIGURE 2. The preprocessing of input images.

Figure 2 shows an example before and after image preprocessing. In Fig. 2, $\boldsymbol{Img_1}$ and $\boldsymbol{Img_2}$ belong to one class, and $\boldsymbol{Img_3}$ is different from them. As described earlier, we first apply the resizing and gray-scaling processes. However, in the experiment, we found that the image contrast decreased after turning into gray image. Therefore, we use Contrast Limited Adaptive Histogram Equalization (CLAHE) to highlight the characteristics of the product. As shown in the Fig. 2, after the CLAHE process, the details of the car became more obvious.

In MDM, the product image is described by its histogram. Then, we need to evaluate the similarity between interest and expectation of target consumers. In this paper, Bhattacharyya coefficient and Pearson correlation coefficient are used to calculate the correlation.

Pearson correlation coefficient is a linear correlation coefficient, which reflects the degree of linear correlation between two quantities. The Pearson coefficient ranges from −1 to 1. The closer the absolute value is to 1, the stronger the correlation (negative correlation / positive correlation). As shown in Table 1, for $\boldsymbol{Img_1}$ and $\boldsymbol{Img_2}$ that belonging to the same class, the Pearson coefficient between them is significantly higher than that between different class, while the Bhattacharyya coefficient has no significant difference. Therefore, in this paper, we select Pearson correlation coefficient to evaluate the correlation between interest and expectation of target consumers.

TABLE 1. Comparison of two similarity measurements for MDM.

Methods	Img1 & Img2	Img1 & Img3	Img2 & Img3
Bhattacharyya	-7.9895	-7.9791	-7.9811
Pearson	0.1715	0.0588	-0.0115

For the traditional machine learning model, the output of the model is consistent every time without adding new training data. However, people are different from machines, when consumers classify products, the decision may be affected by a variety of psychological and environmental factors, including the individual, time, place, event, thing, or situation, which will lead to personalized results.

As the theory proposed by Luh [13], it is the need that guides human behavior. Some needs are extravert, which are concerned with physiological levels; some arc introvert, which are concerned with psychological ones. Moreover, these needs can be categorized as individual needs, family needs, and social needs. Although there are all kinds of human needs, after considerable research only a handful of basic needs have emerged. Abundant evidence collected by cultural anthropologists indicates that although there are tremendous differences between cultures in the means used to fulfill these needs, the fundamental needs of all human beings are quite alike, whereas psychological needs vary according to the qualities of the environment.

MDM is proposed based on the concept of human needs [14], [33], [34]. In this step, the MDM starts with the target consumer interests and expectations, then extend the information of target consumers from four aspects including expectation, incentive, desirability, and willingness. There are 11 main steps in MDM, including (a) personal building: subject behavior analysis; (b) subject motivation analysis: initial motivation (IM); (c) subject complaint journey analysis: complaint set (ΣCM); (d) mirroring for wishful journey: solution set; (e) selection of desirable solution (DS) as activity design guideline; (f) major stakeholder analysis: key participants (KP); (g) KP behavioral analyses: ΣCMs of each KP; (h) mirroring for solution set of each KP: work demand for each KP; (i) mission statement and activity design (AD): Planned Scenario (PS); (j) AD matching with PS for all KPs; (k) subject motivation formation in PS: designed motivation (DM). Finally, MDM will output the classification results from the consumers' perspective.

D. WEIGHTED FUSION

Previously, we obtained the classification results from the perspective of consumers and designers, and both results are expressed in an ordered sequence (abbreviated as consumer's rank and designer's rank). Taking the classification results from the designer's perspective as an example, the greater the probability of which category new product belongs to, the higher the position of the category in the sequence.

The traditional product classification framework only considers the designer's point of view, so it directly outputs the classification results from the designer's point of view. However, the MdmNet proposed in this paper will comprehensively consider designers and consumers, and the fusion occurs in the weighted fusion module.

When the fusion occurs, a scoring strategy is adopted. We take the position of one class label in the ranks as the score. For a label, because it has different positions in designer's rank and consumer's rank, we will get two scores, which are recorded as $\mathbf{S}_{\boldsymbol{designer}}$ and $\mathbf{S}_{\boldsymbol{customer}}$. In MdmNet, we use the weight coefficients $\boldsymbol{W_a}$ and $\boldsymbol{W_b}$ to define the significance of $\mathbf{S}_{\boldsymbol{designer}}$ and $\mathbf{S}_{\boldsymbol{customer}}$ to the final score respectively. The final score of a label is calculated as follow:

$$\text{Score} = W_a * S_{designer} + W_b^* S_{customer} \tag{1}$$

where $\boldsymbol{W_a + W_b = 1}$.

After that, MdmNet will sort the labels according to the final score, and output the label with the highest score as the classification result.

IV. EXPERIMENT

In this section, we demonstrate the benefits of our approach. We start with introducing the datasets and then present our experimental results of each module.

FIGURE 3. Samples images of the Stanford Cars dataset.

A. DATASET

The Stanford Cars dataset [35] contains 16,185 images of 196 classes of cars. The data is split into 8,144 training images and 8,041 testing images, where each class has been split

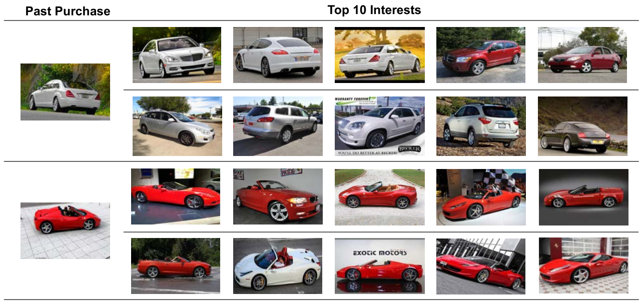

FIGURE 4. **The expanded interests of the target consumer.**

FIGURE 5. **The MdmNet can output a more comprehensive product classification result.**

roughly into 50% for training and 50% for testing. Classes are typically at the level of Make, Model, Year, e.g., 2012 Tesla Model S or 2012 BMW M3 coupe. Three kinds of data needed in our experiment come from the dataset. Specifically, new product is one of the images in test set; last purchase library of target consumer contains all images of training test; and the expectation of the target consumer are randomly selected from each class of test set.

B. CUSTOMER INTEREST

The target consumer modeling in MdmNet obtains customer interests through image retrieval technology. Figure 3 shows the output of target consumer modeling. It is the 10 products most similar to new product in the past purchase library. As can be seen, similar products found by the consumer modeling from the past purchase library are similar to new products, which indicates that the consumer modeling module is able to expand the information of target consumers.

C. CLASSIFICATION RESULTS

In order to see the classification results more intuitively, we use the product itself, instead of the class label, to represent the results.

Take the new product in Figure 5 as an example. By comparing the similarity with the expectations of the target consumers, the classification results of the consumers' perspective can be obtained, as shown in consumer's rank. The classification results from the designer's perspective can be obtained by learning from the data of the past library. The top 10 classification results with the highest probability are shown in designer's rank. The output of MdmNet combines both results from designer and consumers.

We use a CNN-based model to simulate designers to make classification judgment, and use the data in past purchase library for training. In this paper, we use ResNet 18 as the backbone network, the learning rate is set to 0.001, and the loss function uses the cross-entropy loss function.

Figure 6 shows the experimental results from the consumer's perspective and the designer's perspective. The solid line represents the classification result of the consumer's output by MDM, and the dotted line represents the classification result of the designer. Different colors represent the evaluation criteria of rank-1, rank-5, rank-10, rank-20, rank-30, rank-40 and rank-50 respectively.

From the experimental results in Figure 6, it can be seen that the classification result from the consumer's perspective is better than that from the designer's perspective. The reason for this phenomenon is that there are few training data, and CNN model is difficult to give full play to its prediction ability. Just as the real application scenario of product classification problem. When only a few data are available, designers often have bias and make wrong judgments about the target consumers.

In the following experiments, we set the parameters W_a and W_b in MdmNet to the following combinations: (0.9, 0.1), (0.8, 0.2), (0.7, 0.3, (0.6, 0.4), (0.5, 0.5), (0.4, 0.6), (0.3, 0.7), (0.2, 0.8), (0.1, 0.9) and (1, 0) respectively, to study the effects of parameter.

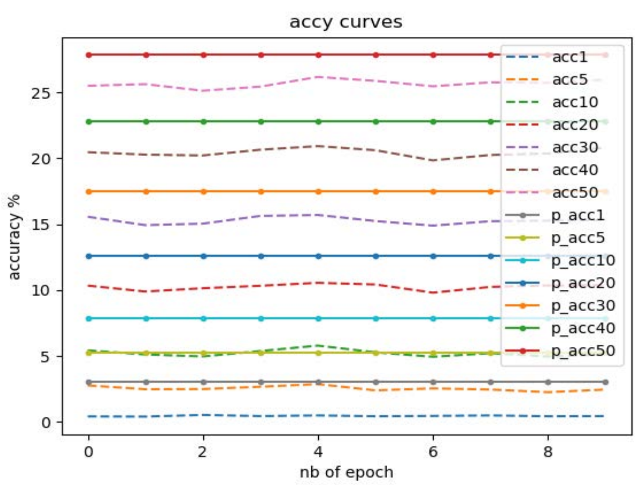

FIGURE 6. **The experimental results from the consumer's and the designer's perspective.**

As shown in Fig. 7, the solid line is the output accuracy curve of MdmNet, and the dotted line is the classification accuracy curve from the designer's perspective of CNN only. It can be seen that MdmNet has improved in accuracy, which means MdmNet is suitable for such kinds of system objects with few data, short time.

As mentioned above, MdmNet can comprehensively consider consumer's rank and designer's rank, so it can produce

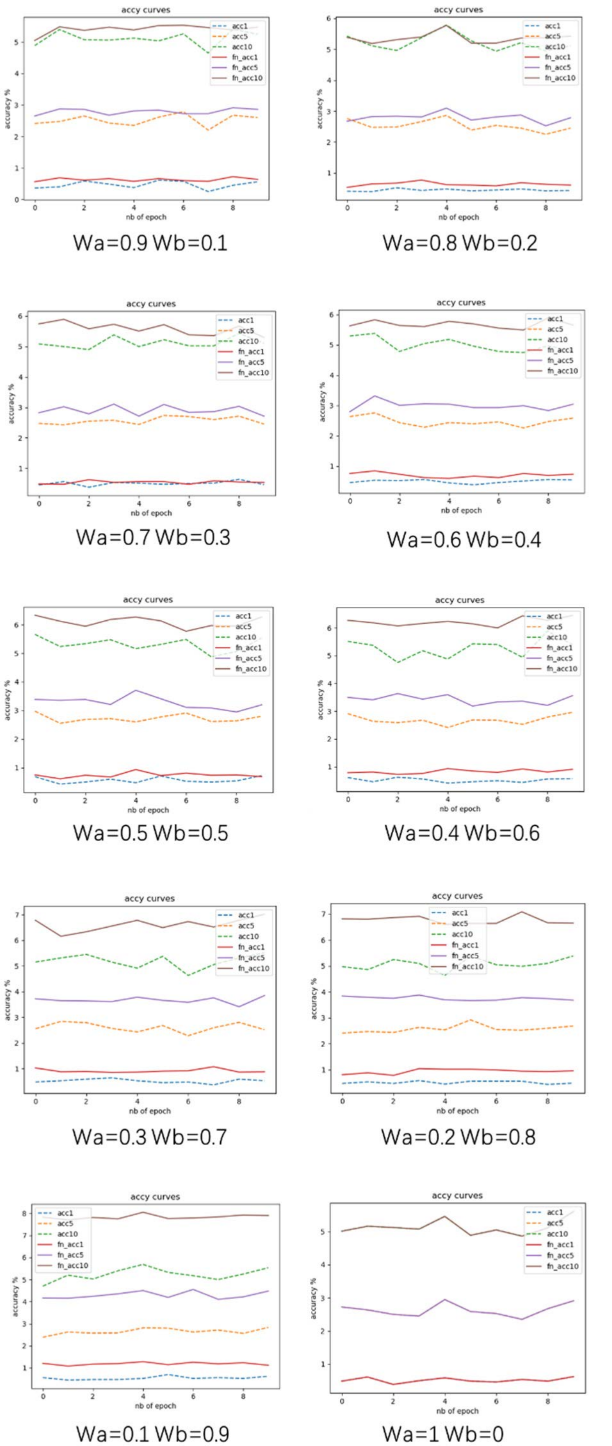

FIGURE 7. The accuracy curve of MdmNet.

more comprehensive classification results. When $W_a > W_b$, the designer's judgment has a great impact on the results, otherwise, the consumer's judgment will play a great impact on the results. Through the experimental results, we can get the following conclusions: when the training data and training time cannot meet the training requirements of the deep learning model, we can get more accurate judgment by increasing the weight coefficient corresponding to target consumers.

The proposed MdmNet is a consumer-centered forecasting framework, which is obviously different from other classification methods. Other classification methods focus on the classification object itself, such as focusing on visual factors such as composition and color on the page, or product modeling and physical product functions. However, the classification results are often different from the cognition and feeling of consumers during usage.

Consumer-centered product classification pays more attention to the study of consumers' cognition and understanding of products. The design idea of ''consumer-centered'' needs to integrate the relevant theoretical knowledge of design art, human factor engineering and cognitive psychology to study the new product from the perspective of ''man-machine-environment''.

Since the consumers' definition of new product is the overall reflection of product attributes and relationships on the basis of specific parameters such as appearance and performance, which is restricted by target consumers' knowledge, experience and understanding ability. Because people have subjective initiative, people can grasp and observe things as a whole and intuitively, and reorganize the structure of things. This subjectivity has considerable fuzziness and primitiveness, which are closely related to human needs.

By analyzing the target consumers, MdmNet studies and analyzes the products or design process from the consumers' perspective, so as to form a more comprehensive product classification system. MdmNet is a learning framework that combines psychological model MDM and deep learning model. It is an attempt to enhance the effect of the model from the perspective of psychology. From the perspective of consumer psychology and needs, MdmNet expounds the important position and role of consumers in product definition, and deeply analyzes how to integrate consumers' emotion into product design, which can solve the problem that designers' product definition is too subjective.

The MdmNet proposed in this paper is a framework that combines deep learning with design science, which has not been validated in marketing cases yet. Therefore, in MdmNet, we simulate the process using a range of computer technologies.

In our experiments, we use ResNet 18, ResNet 50, AlexNet simulate the designer process. The designer's results are inputting to MdmNet framework, and MdmNet will merge the results of the designer and the results from the consumers' perspective. The percentage of the results from the user's perspective is adjusted in the final result, depending on different parameters $\boldsymbol{W_b}$. Table 2 shows that MdmNet proves the classification accuracy under most settings.

V. DISCUSSION AND LIMITATIONS

When developing a new product that is both large and complex, designers tend to collect a huge amount of target consumer data, thinking that in this way consumer demand can

TABLE 2. The performance of ResNet 18, ResNet 50, and AlexNet models is enhanced by applying MdmNet.

Model and Framework		***rank@1***	***rank@5***	***rank@10***
ResNet 18		0.6053	2.8189	5.5259
ResNet 50		0.7338	2.8687	5.4968
AlexNet		0.5057	2.5743	5.248
W_b = **0.9**	**MdmNet +ResNet 18**	**1.3307**	**4.7382**	**7.9343**
	MdmNet +ResNet 50	**1.2436**	**4.3651**	**7.4866**
	MdmNet +AlexNet	**0.721**	**2.624**	**5.248**
W_b = 0.8	MdmNet +ResNet 18	1.2063	3.7682	6.7778
	MdmNet +ResNet 50	1.0073	3.9796	6.8648
	MdmNet +AlexNet	0.547	3.097	6.032
W_b = 0.7	MdmNet +ResNet 18	0.8830	3.5568	6.5788
	MdmNet +ResNet 50	0.8084	3.6438	6.7902
	MdmNet +AlexNet	0.572	2.724	5.360

be known. However, such data is not easy to obtained and can only reveal superficial information and has various other limits, such as the privacy concerns, the best way to do so is through interaction. When processing data of target consumers, more attention should be paid to the nature of their needs.

Many techniques have emerged to elicit these, but these mostly deal with decisions with regard to the product's functions and interface features. Understanding consumers' cognitive structures and related factors and drawing out the concept of a product's classification based on these has received relatively little attention.

This study thus combined deep learning technologies and other image processing techniques to obtain pertinent information on consumers and output the classification results from consumers respective.

The contribution of this study has been to demonstrate that using MDM to elicit consumers' interests and expectations can help designers better understand consumers' behavioral intentions when facing certain products.

The MdmNet proposed in this paper is a framework that can analyze the target consumers through a number of machine learning techniques that are more meaningful in terms of interpersonal relations. Moreover, the framework is able to operate without consumers detailed information, which makes the analysis process safer as well as more convenient and enjoyable. However, we cannot evaluate whether this product classification method can bring economic benefits in the real market environment. In the future, more case studies are needed.

VI. CONCLUSION

In the past, in order to deal with the target consumers demands, businesses had to manufacture products in large quantities and maintain sufficient inventory, to ensure there was no shortage of supply. However, for today's businesses, higher flexibility is needed in both design and production processes in order to cope with dynamic market reactions.

In this paper, a fast and effective product classification, called MdmNet, is proposed, which is based on a novel attempt that embeds the innovation idea of human in machine learning technologies. It is composed of a target customer modeling module based on the deep learning technologies, and a consumer information deduction module MDM, and a weighted fusion module, Experiments conducted on benchmark Cars Dataset demonstrate the impressive performance of the proposed MdmNet.

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