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E-Commerce Information System Using Neural Network Algorithms

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Abstract

Numerous disciplines have experienced quick progress due to artificial intelligence technology's rapid development. The e-commerce management system contains secret data on future development patterns and customer behavior. Data mining technology has the potential to extract valuable information and facilitate the growth of electronic commerce. In addition to analyzing related technologies like data mining and future trend prediction, this study examines the importance and benefits of data mining technology in using e-commerce management systems. The benefits of clustering and naïve Bayesian data mining techniques have been utilized in this study to categorize product details, buying preferences, and other data, and then mine the corresponding data. Next, future purchasing power is predicted using neural networks' advantages in non - linear data processing.

Keywords: E-Commerce, Data Mining, Neural Network.

1. INTRODUCTION:

Artificial intelligence technologies, such as machine learning algorithms, have become widely employed in human daily activities due to the fast growth of high-performance computers, the Internet, and data mining in recent years. Comparably, the area of practice and research is now focusing on the digital and intelligent transformation of e-commerce management, and several organizations and businesses have achieved significant strides in intelligent e-commerce. By using algorithms like clustering and Bessell, data mining technology may fully utilize its algorithmic advantages and extract the link time and spatial information that are implicitly present in the data. This technology may be used in the e-commerce system. The data information of the e-commerce management system is a typical time and space characteristic relationship.

Big data and electronic information are prevalent in today's world, with a wealth of extremely important information available in all spheres of existence. Although it is difficult for a human to locate this information and its relevance, data mining technologies can effectively utilize it.

Realizing the intelligent potential of e-commerce management systems and helping the e-commerce industry make informed decisions by effectively extracting valuable information from complicated and disorganized original data will be the overarching trend in the modern e-commerce industry. Enterprise managers' main challenges are accurately identifying and summarizing these data and determining the development direction of e-commerce management based on multiple facts. The information and data coming from both inside and outside the company are also changing quickly.

The enterprise's need for information updates is beyond what the standard business analysis job can provide. For the business, the intelligent e-commerce management model is vital. Humans today rely heavily on e-commerce for activities like office work, shopping, and medical care, but the data behind these uses is only being uncovered. It makes sense to thoroughly investigate the significance and direct upcoming developments. Research on large data mining and neural networks in e-commerce management systems has been conducted thus far. Zu and co.

It investigated the relationship between customer kinds and shopping types using the matrix theory method, which uses mathematical statistics to categorize and compile data on things like brand preferences and daily consumption patterns. The method's ability to extract precise and useful information from a vast amount of data on customers and their purchasing experiences is demonstrated by the conclusion, which can assist e-commerce businesses in creating practical and effective logistics management strategies.

A data mining and decision management model for online e-commerce management that integrates data collection and cleaning, data mining and analysis, strategy formation, and consumption consideration was proposed by Luo et al. using the enhanced IPA model, support vector machine, and Bayesian machine learning algorithms. the impact of other variables and consumer psychology on purchasing decisions. The benefits of edge computing techniques were incorporated into the e-commerce supply chain assessment framework by Qu et al. This model has the ability to create a fuzzy neural network based on the supply chain simultaneously. The accuracy and viability of this strategy in e-commerce are further demonstrated by the fact that the predicted value of the price plan agrees well with the actual value. Lai and Cai established a China-Japanese cross-border e-commerce management model based on the work's attributes and the preferences of the consumer using FPGA analysis technology and a huge data mining method. A sensitive customer behavior model, or QoS-CBMG, was presented by Ghavamipoor et al. for the purpose of enhancing e-commerce platform service quality and boosting revenue. In an effort to create the relationship between consumers and demands as quickly as possible, Luk et al. thoroughly explored the population of potential customers, gathered behavioral data, and developed an intelligent customer identification model.

To extract future trends in product information, Qi et al. mined online e-commerce product data using the traditional analysis model KANO. Vanderveld created a customer value system based on purchasing behavior and a customer lifetime value system based on the value link between products and customers using the random forest method. The purpose of the system's deployment was to forecast the daily worth of hundreds of millions of users. This approach to managing e-commerce is effective. Mach-Krol and Hadasik investigated the function of big data mining in comprehending consumer behavior using conventional system search techniques as well as sophisticated big data analysis BDA theoretical methodologies.

Customer behavior and the time dimension are strongly correlated, according to the study's findings. It is evident from the literature review above that the majority of studies focus primarily on data classification in the e-commerce industry. They do not further forecast the data in the e-commerce domain; instead, they mostly use decision trees and support vector machines. This article genuinely realizes the intelligent process of e-commerce information by using the clustering approach to classify and predict the results based on the features of the acquired customer behavior data. The swift advancement of big data and e-commerce technologies across many businesses has resulted in a plethora of relevant data that may be extracted and employed. Deep learning and data mining technologies are now applied in e-commerce management systems, which are highly practical and effective for users, thanks to the quick advancement of computer technology and hardware. Additionally, big data collection technology has advanced significantly. By comprehending the customers who have made purchases on the website or the level of interest that customers have in their products, the RFM method can characterize the value of customers. It can also describe the value of customers by analyzing their behaviors, which can be differentiated based on time, frequency, amount, etc. Additionally, it can extract information about the characteristics of their behaviors and can be actively recommended through e-commerce recommendation systems.

Intelligent e-commerce management will undoubtedly become a historical development trend and an inevitable outcome of strong market demand due to the rapid advancement of science and technology. Future trends can be predicted with great advantage by neural networks, and e-commerce management benefits from the abundance of prospective information in this field.

1.1 THE IMPORTANCE OF DATA MINING AND E-COMMERCE INFORMATION SYSTEMS:

Data mining technology allows an e-commerce system to fully extract the relationship between different features and, at the same time, extract data that is not possible for humans to collect. It is very unfortunate for e-commerce practitioners that it is difficult for humans to directly establish some connections with these scattered variables, making it difficult to find the connections and relevance among them. For example, e-commerce managers can obtain customers' purchase amount, purchase quantity, purchase frequency, and other information through their website system. If you can fully utilize these data, identify the connections between them, and direct the enterprise's or company's future development trend and business model. It can help e-commerce managers not only create more suitable business plans, but it can also foretell future customers' purchasing patterns in advance, allowing them to raise the competitiveness of their offerings. Additionally, it can give salespeople access to vital customer resources and additional data assistance, both of which are significant for increasing sales. Generally speaking, using the connection between big data to inform future development and marketing plans in the big data era is a significant and competitive business. Enterprise-class e-commerce involves a large number of clients and many data kinds. It is hard to count these heavy data, and it is extremely hard to locate the rules. However, it can be much harder to find these laws by hand-calculating statistics for some e-commerce products if they are tied to the progression of the seasons or weather. Data mining technology and algorithms have advanced quickly thanks to the persistent efforts of computer staff members. A wide range of clustering or data mining algorithms based on probability prediction have emerged, and these methods have varying applicability. Additionally, it offers additional options for neural network prediction and data mining for e-commerce. Data mining technology is an effective way to increase e-commerce practitioners' productivity and the company's capacity to forecast future trends. As a result, in the age of big data and autonomous technology development, determining which data mining techniques and neural network prediction models are best for businesses and consumers is a difficult but worthwhile task. These tools can help sales staff by increasing their workspace, but they can also have a significant positive impact on the enterprise as a whole. Data mining technology has also benefited a greater number of customers and huge businesses, which is a development that cannot be overlooked.

1.2 THE PREPARATION OF DATASETS AND DATA CLEANING:

Neural networks and data mining techniques both have stringent requirements for datasets, and poor datasets will significantly impair prediction accuracy. Even though data preparation is the foundational task of learning, it's a crucial stage. Data selection and data pretreatment are the two steps that make up the data preparation process. Finding the related data for tasks related to discovery, including client buy frequency and purchase value, is the aim of data selection. Operators in the e-commerce space are primarily focused on the business's profit and loss position. Sales of goods, customer buy frequency, and quantity are the primary characteristics that have a stronger association with the profit and loss situation.

Consequently, the frequency, preference, and amount of clients' purchases are chosen in this article. These datasets provide a more intuitive representation of e-commerce performance. Data type conversion, missing value calculations, and noisy data removal are often steps in the data prediction process. In practice, it can be challenging to ensure the data set's integrity and there's a chance that some data points are absent. This calls for further work to fill in any gaps in the data based on the circumstances after it reaches the format needed by the machine learning technique. Similar distributions must characterize the data that are gathered, and extreme values must not arise as this will result in high prediction errors.

The dataset, which forms the neural network's input layer, is mostly made up of the customer's consumption amount, frequency, and kind of products purchased. The neural network's output layer represents the value of its customers. Figure 1 illustrates the data set processing procedure used in the neural network prediction and data mining processes. It is evident that the collected data undergo preprocessing procedures including data cleaning, after which the data's accuracy and availability are investigated, and lastly the collected data are fed into the model.

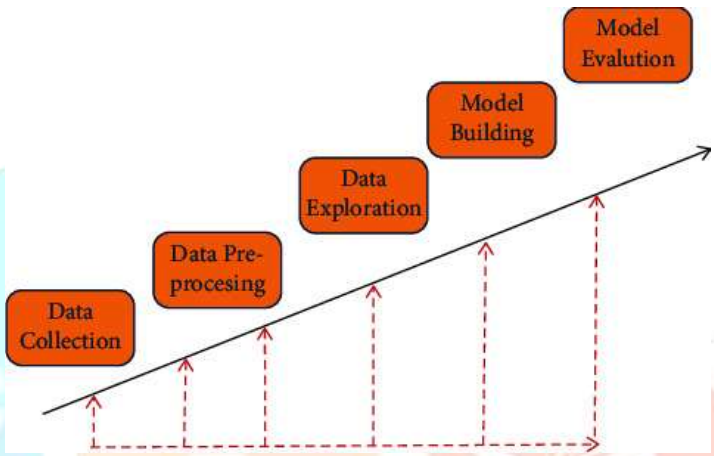

Figure 1: The way datasets are processed for data mining and neural network prediction.

2. METHODOLOGY:

2.1 Data Mining:

The automatic classification technology known as "data mining" is used to extract more pertinent categories from vast amounts of acquired data. Simultaneously, there are significant differences in the features of the acquired data, which is also the preprocessing step of the data mining process. Using techniques like clustering, decision trees, and self-defined model hyperparameters, determine the best classification procedure. After that, it may be completely employed to identify the relationships between the data and serve as the foundational information needed to forecast future consumer behavior. Multidimensional data, often known as non-dependent data, is comparatively easy. The term "dependent data" refers to a relationship with a certain correlation change between data components. The link between these two terms is particularly separated into implicit and explicit reliance on data mining.

Data mining is a particularly appropriate use in e-commerce. The connection between attributes, including the association between client buy product data, consumption amount, and personal consumption frequency or season, is not the only thing found in e-commerce information. In addition, a plethora of open-source algorithm libraries and guidance techniques have been made available by the computer science community for use in e-commerce management data mining tactics. You may apply several algorithmic principles to data from various sources, and in the end, you can choose an algorithm that best fits the unique features of your data.

2.2 CLUSTERING THEORY:

In machine learning, clustering is a frequently utilized unsupervised learning category. It can categorize several groups based on how relevant the data is. The technique of grouping a dataset based on a certain criterion (such as density and distance) is called clustering. Strong similarities exist between data within a category, whereas maximum differences exist between categories. Increasing the disparities between classes and continuously estimating the similarity between the same classes are other processes included in the clustering optimization process. It may be separated into partition clustering methods, density-based clustering methods, hierarchical clustering methods, and so forth based on the various clustering techniques. The partition clustering approach is the data mining technique chosen in this article based on the feature connection between the datasets. The density-based clustering approach is depicted in Figure 3, whereas the K-means method is shown in Figure 2. In this study, e-commerce was investigated using the K-means approach. While clustering is a well-established classification technique, decision trees and support vector machines are used for the majority of e-commerce classification issues, and only a small number of research have used clustering techniques, which may be due to the e-commerce dataset that was chosen. This paper examines the use in e-commerce using the clustering approach based on the distance method, which is quite novel.

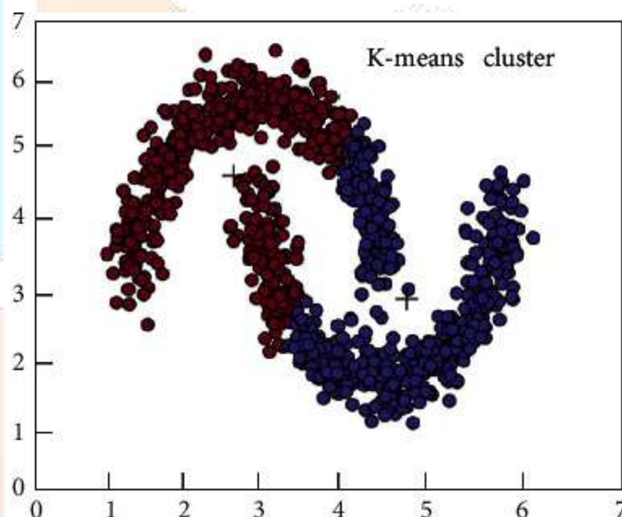

Figure 2: K-means technique.

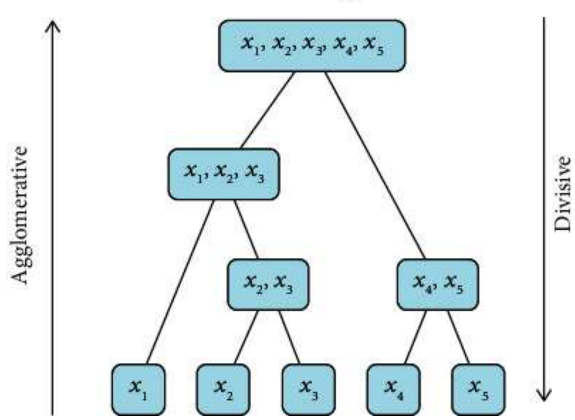

Figure 3: The density-based technique.

The following can be used to characterize the training, testing, and anticipated values: (1)–(3). Three distance assessment indicators are added to the study to more accurately assess the correctness of the datasets that have been split up by clusters. The distance technique is typically used to measure the clustering measurement standard, and there are likely three methods to determine distance. The output value is denoted by y, the anticipated value by yˆ, and the input dataset by x.

$$\text{Train}=\{(x1,y1)(x2,y2),\ldots,(xn,yn),\ldots(xN,yN)\},$$

(1)

$$\text{Test}=\{(x1,y1),(x2,y2),\ldots,(xm,ym),\ldots(xM,yM)\},$$

(2)

$$\hat{y}=\{\hat{y}1,\hat{y}2,\ldots,\hat{y}m,\ldots,\hat{y}M\}.$$

(3)

Where x represents the input vector, y is the output vector, and p the number of clustered categories, is the distance of the Minkowski technique. The purpose of this study, p = 4 or p = 5, is to confirm how the number of categories affects the clustering effect to determine the optimal categorization standard based on consumer behavior. Y is the actual value, while x is the input dataset.

$$d(X,Y)=|x1-y1|p+|x2-y2|p+|x3-y3|p+\ldots+||xq-yq||p\surd \quad (4)$$

When p = 2, the Euclidean method's distance is the Minkowski method's special case. This form is comparable to the average error evaluation index, another widely used evaluation index.

$$d(X,Y)=|x1-y1|2+|x2-y2|2+|x3-y3|2+\ldots+|xm-ym|2\surd.(5)$$

When p = 1, the Manhattan method's distance is the Minkowski method's special case.

$$d(X,Y)=|x1-y1|+|x2-y2|+|x3-y3|+\ldots+|xn-yn|.$$

(6)

2.3 CNN Neural Networks:

In the sphere of e-commerce, the dataset is enormous and laborious. A fully connected neural network will need a significant amount of processing time and resources, which is undesirable for real-world e-commerce applications. CNN offers the benefit of weight sharing, which may significantly lower computational complexity and improve feature extraction. Additionally, it is simple to use on the TensorFlow framework. This article sets a higher learning rate and more filters, which minimizes the computational complexity. CNN is extensively utilized in image identification, target detection, and other domains and has clear benefits when it comes to extracting data characteristics. This algorithm is rather advanced.

The e-commerce management system has a wealth of consumer attributes, including purchase type and quantity, that are critical to estimating customer value. The CNN can efficiently extract characteristics, execute nonlinear operations to derive a specific mapping connection, and then forecast future purchasing patterns. This technique works well for e-commerce feature extraction and prediction. Figure 4 depicts the CNN procedure. Using the pooling layer and activation function layer, the CNN may execute convolution operations based on the number of filters and sliding steps specified by the model. Afterward, it can perform the model prediction output and compare it with the actual one. In order to anticipate the future trend, the gradient is simultaneously reduced using the backpropagation method and the loss function. Ultimately, the ideal weight parameter for the customer data in the e-commerce management system is discovered. The model's weights, biases, and hyperparameters are established after it has been trained. A significant amount of time is saved in actual operation as this model no longer needs to be trained. In real-world prediction, some e-commerce data is gathered, and the corresponding mapping value may be produced directly through this model, which is compatible with the output in the simulation. Numerous disciplines have demonstrated the effectiveness of CNN in extracting data characteristics. This article also makes use of the Tensor Flow Framework

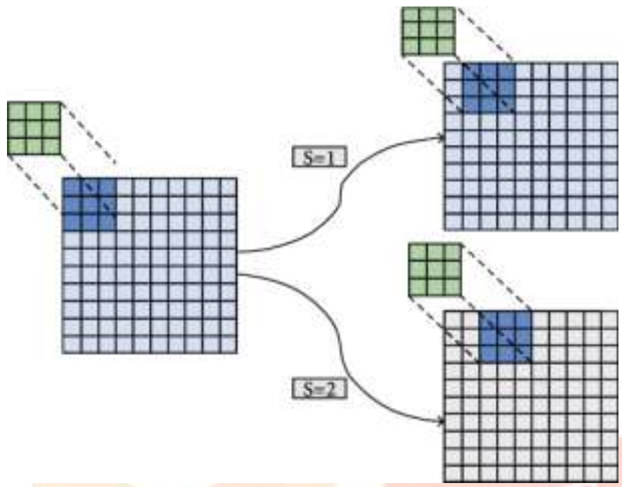

Figure 4: The processing of CNN

Equations (7) through (12) depict the CNN's forward and backpropagation procedures. According to (7), this is how the convolutional layer performs the convolution operation; the convolution operation process is represented by the ∗ symbol. The following is a description of this process: The convolution process is initially carried out by the convolution kernel kijν and the feature xíY−1. The bias parameter bjζ is then added, and the convolution layer's output parameter is the activation function's excitation value. The mapping function is denoted by f, and the output value is xj.

xj=f ∑i∈Mjxζ−1i∗kζij+bζj (7)

This is the feature's residual calculating procedure. The purpose of the function up(x) is to enable the convolution process by reshaping δj\+1 into the same form as δj̈Y.

δζj=βζ+1j(f′(u)ζl∘up(δζ+1j)).

(8)

The gradient computation process is depicted in the following equation, where W is the weight, δj} is the weight parameter, and bi is the bias:

∂W∂bj=∑u,vδζjuv.

(9)

The derivative of the bias parameter, kijν, a matrix-like parameter, is displayed in the following equation:

∂E∂kζij=∑u,v(δζj)uv(pζ−1i)uv. (10)

Equation (11) illustrates how the pooling layer's sampling procedure works, using both average and maximum pooling techniques. The total of the eigenvalues is the function down(xjζ−1). The output is then biased in accordance with the activation function.

$$xj=f(\sum u,v\beta\zeta j down(x\zeta-1i)+b\zeta j). \quad (11)$$

The pooling layer calculates the parameters using the following equation, where f′ is the derivative of the pooling layer function (11) mentioned above:

$$\delta\zeta j=f'(u\zeta j)\circ conv2(\delta\zeta+1j,rot180(k\zeta+1j). \quad (12)$$

2.4 DATA NORMALIZATION PROCESSING AND UNCERTAINTY ANALYSIS:

E-commerce client data collection involves a lot of attributes, which is bad for the dataset as a whole. Simultaneously, there exist discernible disparities in the attributes of the consumer's purchase quantity, product category, and frequency as gathered from diverse sources. Neural networks and clustering algorithms cannot operate well with this. Normalizing the datasets is necessary since the neural network's function involves continuously determining the weights between the datasets that may best reflect the correlation. Improving the distribution features and correlation of the input data by normalization can hasten convergence and raise prediction accuracy. Simultaneously, a great deal of uncertainty arises when an unknown consumer behavior is employed as an input layer to forecast future patterns in purchasing behavior. This article requires to quantitatively assess the prediction process's uncertainty in order to prevent the neural network's overconfident prediction process. The variational Bayesian approach is used to uncertainty analysis in the following equation, where the process of minimizing the variational posterior distribution q(ψ) and the actual posterior distribution p(ψ) is denoted by KL(q(ψ))‖(p(ψ):

$$VB=\sum l=1L\int q(\psi)\ln\ p(YN|Xn,(\psi)d\psi-KL(q(\psi)\|\ p(\psi). \quad (13)$$

3. RESULT ANALYSIS AND DISCUSSION:

The method of clustering client purchase behavior is calculated, as seen in Figure 5. The foundation for classification is the product kind, frequency, and quantity of purchases made by the consumer. First, adjust the number and distance between clustering groups as indicated in Figure 5. The clustering method selects the best cluster class path by iteratively adjusting the distances and gaps between various categories. The clustering findings of client purchase behavior under nonuncertainty analysis and uncertainty analysis settings are displayed in Figures 6 and 7, respectively. It is evident that data on consumer behavior is better grouped in uncertain environments. Figure 6 illustrates that there is little variation across the four distinct customer behaviors, indicating that the clustering effect has not yet materialized to the extent that there is a significant difference among the categories. Nonetheless, this method's clustering effect performs better inside the same category. The neural network is no longer predictably overconfident when faced with ambiguous analysis. Figure 7 illustrates how the clustering impact on consumer behavior is superior to Figure 6's. In addition to grouping similar categories together, this clustering technique aims to maximize the difference between any two categories. This clustering technique is superior.

By comparing Figures 7 and 8, it is evident from the comparison that the optimized algorithm performs better in terms of classification and can segment the consumption value in e-commerce with a high degree of correlation, as opposed to Figure 7's mutual intersection scenario.

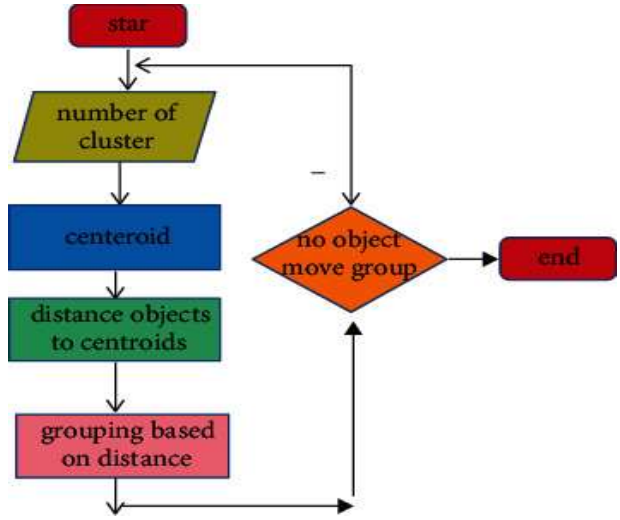

Figure 5: The procedure for grouping consumer purchase behavior by computation.

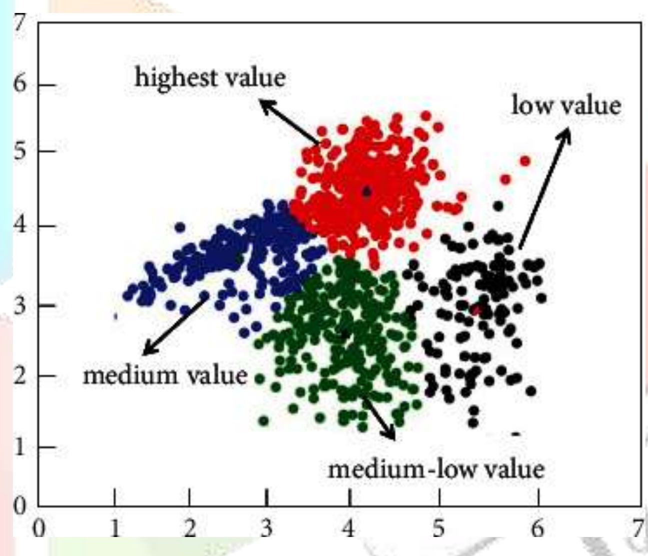

Figure 6: The clustering of client purchase behavior in the computation results.

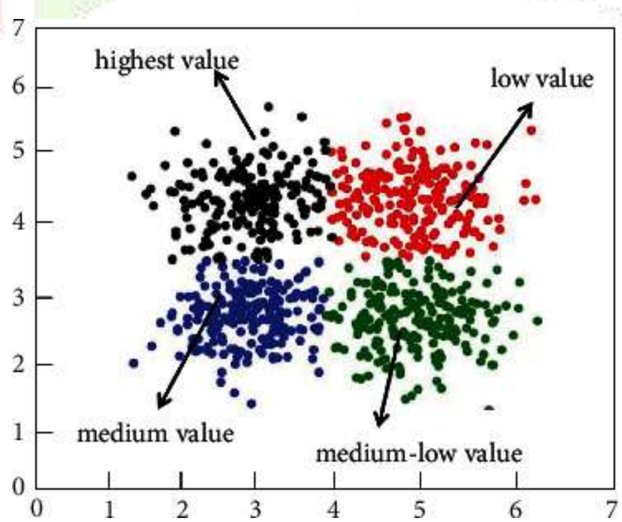

Figure 7: The clustering of client purchase behavior calculations under ideal circumstances.

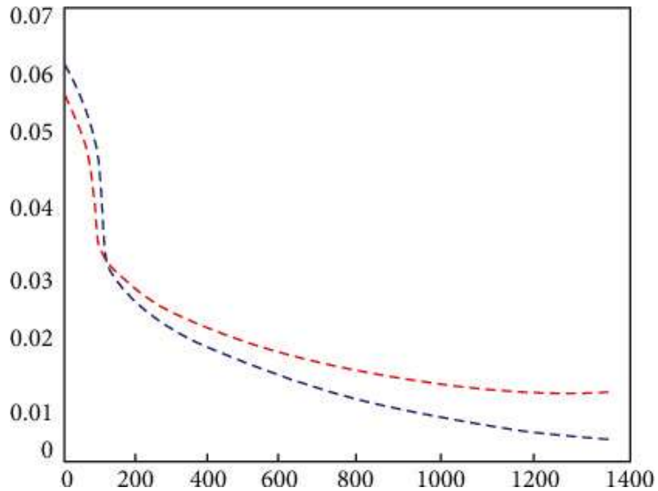

Figure 8: The loss function is trained and tested.

The training and test sets' iterative loss function approach is depicted in Figure 8. Figures 9 and 10 respectively, demonstrate the projected value heat map and the error heat map for various periods and customer groups to more intuitively check the viability and accuracy of the neural network in forecasting the e-commerce management system. Figure 9 shows that, generally speaking, CNN predicts the data following the clustering process, and the customer value forecast is rather accurate. Furthermore, it forecasts not just the value of a single customer's purchasing behavior throughout many months, but also the variations among various consumer groups. This tendency of developments is also accurately anticipated at the same time. The e-commerce management system's neural network model forecasts the trend problem with excellent feasibility, as demonstrated by the description above. The error heat cloud diagram is displayed in Figure 10 all of the predictions are within an acceptable range, and the error of the customer value forecast result is comparatively minimal. The forecast errors from March to July are often somewhat high, which can be because summertime client buying behavior is complicated and unpredictable. This result aligns with the features of real-world purchasing behavior, which is an activity that has seasonal traits. The neural network model may be enhanced with additional sample attributes in the summer, when seasonal behavior is strongest, to increase prediction accuracy; this will allow it to learn more complicated behavior traits. The genuine and forecasted values of customer value are displayed in Figure 11.

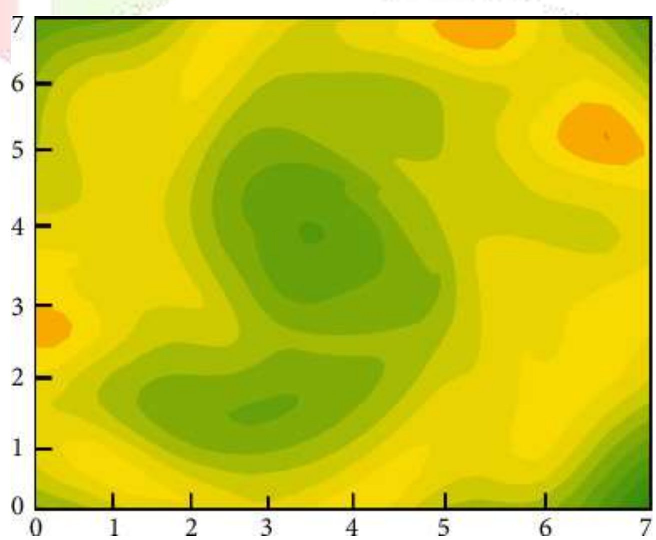

Figure 9: The value forecast heatmap for consumer activity in various months.

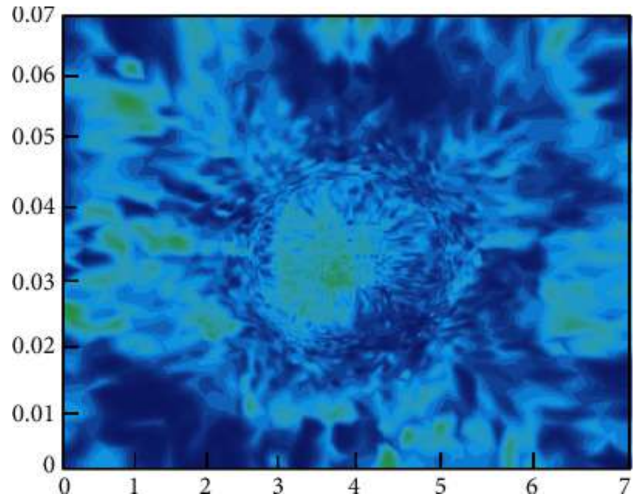

Figure 10: Heatmap showing the expected value inaccuracy for various customer groups and months

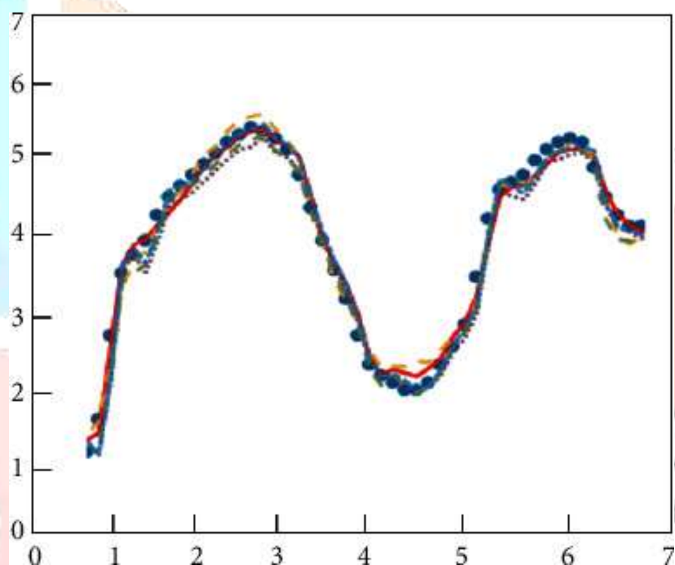

Figure 11: Real value as well as predicted value.

The scatter plot of linear correlation coefficients and the error histogram, respectively, are displayed in Figures 12 and 13 to further graphically demonstrate the prediction power of neural networks in the e-commerce management system. The relationship between the real value and the expected value is represented by the linear correlation coefficient. The prediction impact is better the closer its value is near 1. Figure 10 makes it abundantly evident that there is a significant correlation between the real and anticipated values of consumer behavior value; this correlation has already achieved a good value of 0.9785. Simultaneously, the linear correlation coefficient graph provides insight into the error's distribution range.

The projected value significantly deviates from the linear straight line from March to July, as seen in Figure 10 above, but it has a stronger linear association in other months. Every one of them is dispersed over the two sides of a straight line. The average value of the error, which might represent the prediction mistake in a macroscopic view, is shown in the error histogram. Figure 13 makes it immediately clear that the errors are within a reasonable range, with the largest error being just 2.32%. In the e-commerce industry, this error number is already considered good. Simultaneously, the error histogram makes it evident how the prediction error and the month changed over time.

The neural network model is more accurate at predicting the shift trend in customer value over the course of a month than it is at predicting the value of a particular group or month. Figure 12 makes it evident that there is a rather excellent linear correlation—basically surpassing 0.95—between the expected and actual values of e-commerce, suggesting that the predictions are generally in agreement with the reality. These e-commerce data points are also very close in distance and equally distributed on both sides of the linear function.

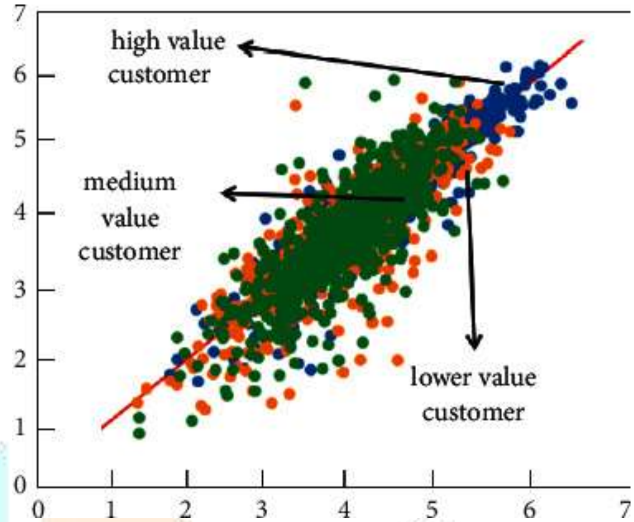

Figure 12: The coefficient of linear correlation.

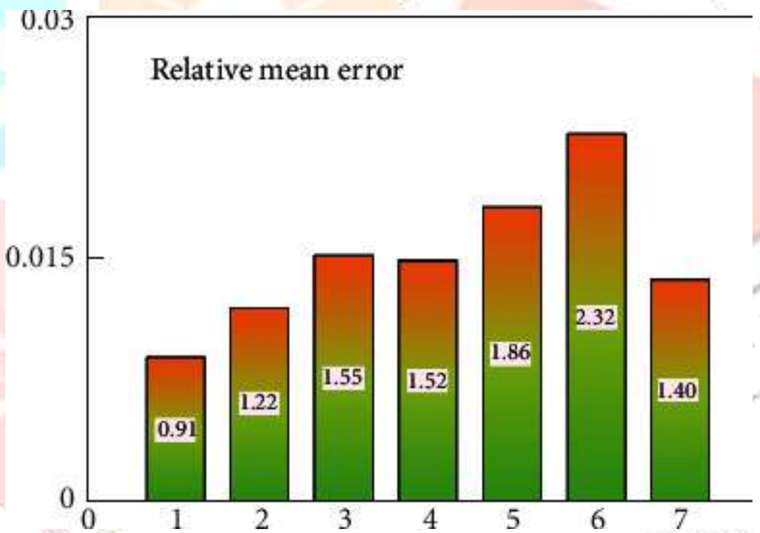

Figure 13: The relative average inaccuracy of the prediction histogram.

CONCLUSION OF THE RESEARCH:

E-commerce technology has advanced quickly in tandem with big data and information technology growth. The e-commerce management system benefits from utilizing the predictive powers of neural networks and data mining technologies to their maximum potential. It may uncover customer preferences, purchasing power, and other relevant information. Based on this prospective knowledge, it can also forecast future trends, which is highly significant and helpful for the growth of businesses and even corporations. E-commerce involves a lot of tiresome tasks, such as classification and prediction. There is currently little study on the prediction of classification outcomes, and the majority of e-commerce classification and prediction employ related machine learning methods like decision trees and support vector machines. In the field of e-commerce, this article uses

CNN to predict the classification results and distance-based clustering to classify. The characteristics of the collected datasets, such as customer purchase frequency, customer purchase amount, and purchase preferences, are combined with these methods, making the article useful for both e-commerce and classification. There is some usefulness to the forecast in real life.

FUTURE ENHANCEMENT:

In this study, significant information is extracted through the classification of customer purchase data using data mining techniques like clustering and naive Bayes. Neural networks are then used to forecast the future spending power of the consumers, yielding an accurate result. In terms of forecast performance, the clustering method with uncertainty analysis will reflect a better classification effect, even though the two clustering methods both show better clustering results when considering the relevance of similar categories and the effects of categories with larger differences. For creating an e-commerce management system, the clustering technique chosen in this article and the beginning value setting have a good reference value. The effect of grouping four distinct customer values together is seen. In a similar vein, the CNN used for this study has a strong predictive capacity and is utilized to extract and forecast the value of consumer behavior. It can show the seasonal aspects of consumer behavior in addition to the patterns in buying behavior for various customer groups and months. A great degree of accuracy has also been attained in the linear correlation between the anticipated and real values of the customer value standard; its value has even reached 0.9785. The e-commerce management system can operate within an acceptable range if the forecasted value error is less than 5%. This article generally makes predictions about the value of consumers based on their actions. It demonstrates strong prediction and classification skills based on the chosen clustering approach and neural network model, which is also a solid benchmark for other e-commerce management domains.

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