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Management and Sales Forecasting of an E-commerce Information System Using Data Mining and Convolutional Neural Networks

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***Abstract* - The exponential development of e-commerce in recent decades has enhanced convenience for individuals. Compared to the conventional business environment, e-commerce is characterized by increased dynamism and complexity, resulting in several obstacles. Data mining assists individuals in effectively addressing these difficulties. Traditional data mining cannot efficiently use big data in the power provider industry. It heavily relies on time-consuming and labor-intensive feature engineering, and the resulting model could be more easily scalable. Convolutional Neural Networks (CNN) can efficiently use vast amounts of data and autonomously extract valuable elements from the original input, resulting in increased effectiveness. This article utilizes a CNN to extract valuable insights from e-commerce information to forecast commodities sales accurately and proposes a CNN-based Sales Forecasting Model (CNN-SFM). The findings indicate that using data mining and CNN yields a high level of precision in forecasting forthcoming people buying capacity data. The correlation variable between actual usage information and projected usage information was 0.98, and the highest mean error was just 1.78%. Data mining can effectively extract hidden relevant information and forecast future consumption habits for e-commerce systems. CNN demonstrates proficiency in accurately predicting forthcoming consumption power and trends.**

***Keywords:* E-commerce, Data Mining, Convolutional Neural Networks, Sales Forecasting**

I. Introduction

The fast advancement of advanced computers, network connectivity, and data mining in recent decades has been extensively utilized in many human tasks (Dogan & Birant, 2021). The practice and academic communities are now significantly emphasizing the digital and intelligent evolution of e-commerce operations. Numerous institutions and enterprises have made substantial advancements in intelligent e-commerce (Escursell et al., 2021). Data mining uses algorithmic strengths to extract the underlying temporal and spatial information using clustering and Bessell methods (Zhao et al., 2020). The content of the e-commerce managing platform exhibits a correlation between duration and spatial characteristics, making it applicable to e-commerce systems.

In the contemporary age of big data and digital data, a vast array of pertinent information exists in every aspect of human existence. Man often needs help locating this information and its significance, but data mining can effectively use it (Oatley, 2022). The present e-commerce area is moving towards efficiently extracting valuable information from complicated and chaotic initial details (Hakkaraki, 2023). This will aid in generating correct judgments and achieving intelligent e-commerce management mechanisms. The key challenges company managers address are accurately identifying and gathering this information and determining the growth path of e-commerce managing system using several sources (Zhang et al., 2022). The organization's data and information from internal and external sources are undergoing significant changes. The conventional business analytic task does not fulfill the company’s need for timely data upgrades. An efficient e-commerce managing model is crucial for the organization. Humans have extensively used e-commerce for various purposes, such as shopping, medical services, and office work. However, the potential of this data has yet to be thoroughly explored. It is logical to investigate the significance and direct future patterns thoroughly. So, the CNN-based Sales Forecasting Model (CNN-SFM) is proposed in this research.

II. BACKGROUND AND SURVEY

Due to the increasing popularity of e-commerce, several approaches have been suggested and used to predict commodity sales. Logistic regression is an extended linear regression model that uses logical functions to provide predictions for classification issues. It is built on the principles of linear regression. Utilized Logistic Regression (LR) to assess the stability level of telecom clients since this approach is proficient at elucidating dichotomous difficulties and accurately modeling the link between the dependent and independent variables (Zennaro et al., 2022). Bandyopadhyay et al. utilized the Principal Component Analysis (PCA) to investigate client categorization issues in the telecommunications sector to mitigate customer attrition (Bandyopadhyay et al., 2021). The fundamental concept of a Decision Tree (DT) is that the rules for categorizing the depiction are derived from a set of random and unordered examples based on specific criteria using a top-down recursive approach (Kim & Lee, 2022). Used a DT algorithm to forecast the purchasing patterns of clients (Esmeli et al., 2022). It can demonstrate logical categorization compared to other prediction systems. In utilized DT to predict consumers' shopping lists (Matuszelański & Kopczewska, 2022). Random Forest [RF] is a technique that involves creating a forest of DT that is unconnected and randomly selected (Xu & Sang, 2022). Once the forest is constructed, upon receiving another sample, all the Dts within the forest are consulted to determine the grouping of the sample. The projected outcome is determined by selecting the category most often chosen by DT (Yin & Tao, 2021) In utilized the RF to retain existing consumers in the insurance sector (Rosário & Raimundo, 2021). In used a fusion model of perceptron vector machine, LR, and RF to forecast consumers' repeated buy behaviors on the e-commerce platform (Zaghloul et al., 2024). This approach yielded favorable outcomes. Like RF, Gradient Boosting Decision Tree (GBDT) is a combinatorial framework that relies on DT (Feng, 2022). The concept involves constructing a DT iteratively, with each iteration focusing on the path that minimizes the loss function of the current model. Chen et al. utilized GBDT to provide tailored recommendations for customers (Chen, 2022). They obtained favorable outcomes in the construction of the feature project (Rika et al., 2023).

A Convolutional Neural Network (CNN) is a sophisticated technique for processing data that imitates the information-processing mechanism of the human brain (Liu, 2022). It has the attributes of self-organization, adaptation, and learning. Yin et al. utilized a CNN to construct a predictive model for determining the likelihood of consumers making repeated purchases (Jelena & Srđan, 2023). They discovered that CNN has robust learning capabilities when dealing with complicated non-linear relationships among characteristic factors. Wang et al. used a CNN to encode the image of each commodity as real number vectors (Wang & Qiu, 2021). They then solved nonlinear optimization issues based on these variables to create commodity prediction data. In used a CNN to develop an end-to-end model that directly produced commodity price predictions (Li et al., 2023). In utilized semantic analysis to extract topic content and entity type from user-generated content (Alzahrani et al., 2022). They then gathered additional topic-related content from other sites to improve their semantic understanding of user behavior (Arora, 2024). They developed a model to provide tailored suggestions to users. Alzahrani et al. introduced a novel clustering element to assess user behavior and forecast the popularity of recently introduced items (Alzahrani et al., 2022).

Based on the examination of relevant citations, it is evident that the data mining technique depends on artificial feature design. This process is time-consuming and labor-intensive and requires specialized skills in specific domains (Varshavardhini & Rajesh, 2023). The scalability and accessibility of the model obtained from standard data mining approaches are constrained, making it impractical to efficiently utilize the vast quantity of data accessible to power providers (Camgözlü & Kutlu, 2023). Due to its capacity for extracting efficient features from enormous amounts of unprocessed information, CNN yields a model with enhanced usability. The CNN model is very expressive and can efficiently use a substantial volume of training information to acquire a more extensive range of pattern data. This research presents an approach using CNN to forecast sales volume, aiming to address the limitations of standard data mining techniques. The technique utilizes a CNN to separate impactful elements from the initial structured information. It applies this strategy to predict commodities sales accurately. Empirical tests conducted on extensive datasets demonstrate that the suggested method enhances the precision of predicting commodity sales.

III. PROPOSED CNN-BASED SALES FORECASTING MODEL

Data mining technology is an automated categorization technique that identifies groups from a vast quantity of acquired data. The acquired data exhibit significant feature variations, necessitating preprocessing as part of the data mining procedure. Discover the most efficient categorization procedure using techniques like clustering, DT, and self-defined modeling hyperparameters. It is maximally utilized to establish the correlation between the information and to serve as the fundamental data for forecasting future client behavior. Non-dependent information, often known as data with multiple dimensions, is relatively straightforward. Dependent information, often known as dependence, refers to the connection between information components that undergo a specific correlation modification. Data mining categorizes this connection into implicit dependency and explicit reliance.

Data mining techniques are ideal for use in e-commerce. E-commerce data not only encompasses the connection among many variables, like the connection among client buying information, usage quantity, personal consumption rate, and seasonal patterns. The discipline has furnished several open-source algorithmic libraries and guiding methodologies for mining information tactics in e-commerce administration. To handle data from various sources, one applies multiple algorithmic rules and eventually identifies a method that aligns with the specific properties of the data.

3.1. Data Mining Approach in e-commerce

Data mining is separated into various processes, including identifying business objectives, collecting and extracting data, preprocessing the information, constructing mining models, performing data mining, analyzing the outcomes, and using the findings, as seen in Figure 1.

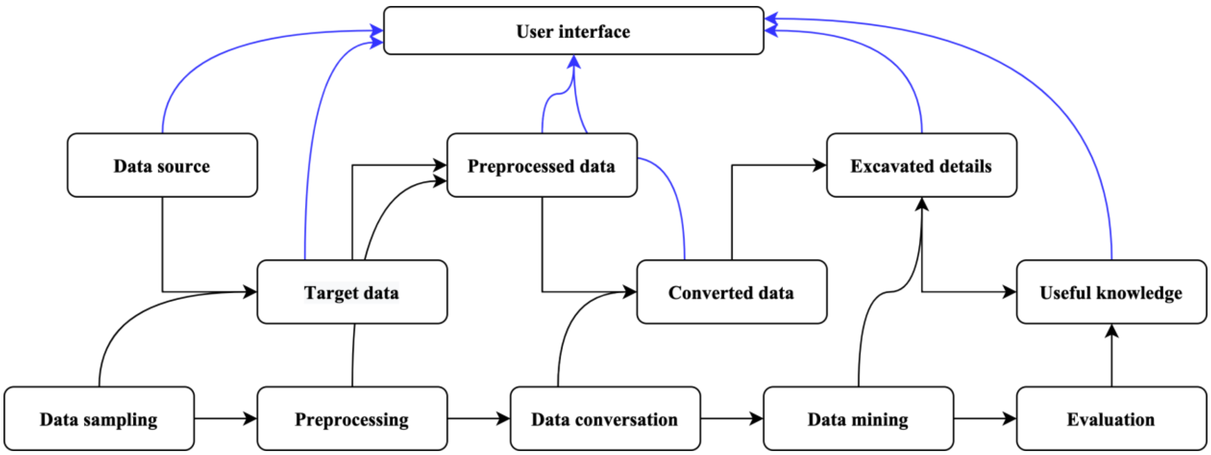

Fig. 1 Data Mining Procedure in E-commerce

1. Determine the specific problems or challenges faced by the firm. Data mining in typical applications yields unanticipated outcomes, but the issues that need attention are specific and foreseeable. Data mining without careful analysis might be resource-intensive and provide unsatisfying outcomes.
2. Data acquisition and curation. To precisely define the exact data mining goals, it must be done to gather all the relevant data for the organization. Data selection aims to extract pertinent details from the acquired data to enhance the accuracy of data mining.
3. Pre-processing the information. Data pre-processing involves many vital phases, including integration, purification, definition, and conversion. Data pre-processing aims to ready the data for data mining. It serves as the foundation for constructing a model. The quality of the information impacts the efficiency of data mining. The most challenging task is to minimize the variance.
4. Create a data mining strategy. Utilize data mining methods to construct suitable mining models tailored to address the specific challenges.
5. Data mining. Utilize the model to extract valuable, potentially practical, and easily understandable knowledge and details from processed information.
6. Examination and assessment of findings.

3.2. CNN Model

The dataset in the area of e-commerce could be more extensive and attractive. Utilizing a fully connected CNN in e-commerce applications is impractical due to its high computational resource and time demand. The CNN has the benefit of weight sharing, significantly reducing computational complexity. It excels in extracting crucial characteristics. It is efficiently executed using the TensorFlow framework. This research decreases complexity by increasing the filtering process and the training ratio. CNN has evident benefits in extracting information characteristics and is utilized in object identification, target identification, and other domains. The algorithm is advanced and well-developed. The e-commerce management system encompasses several consumer attributes, including the buying model and quantity, crucial in predicting consumer worth. The CNN efficiently extracts data, conducts non-linear processes to establish a specific mapping connection, and predicts future purchasing pattern. This strategy is appropriate for the process of extracting features and making predictions in the field of e-commerce.

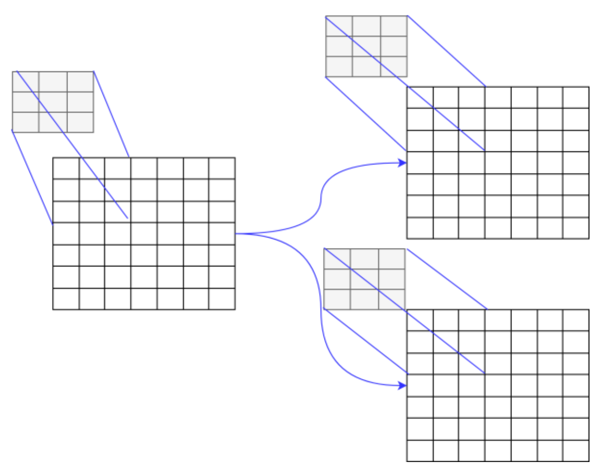

Fig. 2 CNN Procedure

Figure 2 depicts the CNN procedure. The CNN executes a convolving function based on the amount of filtering and sliding stages specified by the system. It generates model predictions by passing the result via the pooling and activating layers and comparing them with the actual values. The gradient is reduced using the losing value and the backpropagating technique, identifying the ideal weighting factor for predicting future trends in the consumer information of the e-commerce management. After the model has been trained, the values for the weights, presumptions, and hyper-variables are established. In practical forecasting scenarios, information from e-commerce is gathered, and this model provides the correct mapping value. The output from this model aligns with the simulation results. Training this framework in real-world operations is unnecessary, resulting in significant time savings.

CNN has shown strong performance in extracting information features across several domains. This work employs TensorFlow and Keras for training and testing. This article utilizes 128 filters and employs a learning rate of 0.001. The backpropagation procedure is executed using the optimization approach of gradient descent. This article employs five CNN layers.

The convolutional layer performs convolution functions, where the $*$ sign denotes the procedure for convolution. The convolution process is performed by the convolution kernel k_{xy}^{l} and the feature i_x^{l-1}. The bias variable b_y^l is subsequently included, and the convolution stage's output variable is the activation work's exciting value. The result value is denoted as i_y and is determined by the mapping operator f.

$$i_y = f\left(\sum_{x=0}^{M_y} i_x^{l-1} * k_{xy}^{l} + b_y^l\right) \quad (1)$$

This is the procedure of calculating the residual of the features. The function $up(i)$ is to transform the shape of δ_y^{l+1} to match the shape of δ_y^l, to simplify the convolution procedure.

$$\delta_y^l = \beta_y^{l+1}\left(f'(i)_d^l \circ up\left(\delta_y^{l+1}\right)\right) \quad (2)$$

Equation (3) illustrates the computation of the gradient. b_x represents the biasing value, δ_y^l denotes the scaling variable, W represents the weighting factor, and b_x represents the biasing value:

$$\frac{dW}{db_y} = \sum_{x=0}^{N}\sum_{y=0}^{N}\left(\delta_y^l\right)_{x,y}(p_x^{l-1})_{x,y} \quad (3)$$

Equation (4) illustrates the sampling procedure in the pooling layer, which encompasses both maximal and mean pooling approaches. The operation down(i_x^{l-1}) is to calculate the sum of the eigenvalues. It introduces a bias to the result based on the activation value.

$$i_y = f\left(\sum_{x=0}^{M_y} \beta_x^l * \mathrm{down}(i_x^{l-1}) + b_y^l\right) \quad (4)$$

Equation (4) depicts the pooling layer's computation procedure to determine the variables. f' denotes the pooling layer variable derivative mentioned in Equation (5).

$$\delta_y^l = f'(i)_d^l \circ cnv\left(\delta_y^{l+1}, i_x^{l+1}\right) \quad (5)$$

3.3 Data Normalization and Uncertainty Evaluation

Collecting e-commerce client information has several aspects that are detrimental to the dataset. There are evident disparities in the attributes of the consumer’s purchase value, product category, and buying frequency obtained from different channels. This has a detrimental effect on the functioning of CNN and clustering methods. The CNN operation aims to continuously determine the optimal weights among the datasets that can accurately reflect the correlation. It is necessary to normalize the databases. Applying data normalization techniques that increase dispersion features and correlation accelerates convergence speed and enhances the precision of predictions.

Significant ambiguity exists when unfamiliar consumer pattern is utilized as an inputting stage and forecasts future purchasing patterns. To mitigate the issue of the CNN excessively confident forecasting procedure, this research needs to quantitatively determine the uncertainty associated with the prediction procedure.

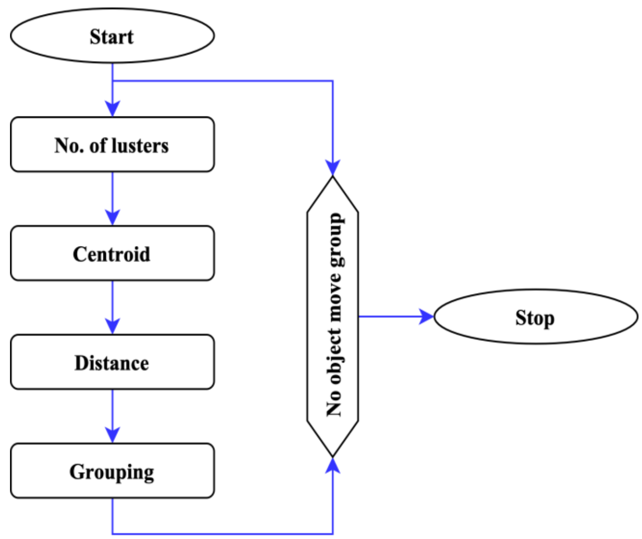

Fig. 3 Customer Purchase Behavior Prediction Flow

Figure 3 depicts the process of grouping client purchasing behavior. The categorization is based on the kind of items purchased, the frequency of buying, and the amount the consumer spends. Begin by customizing the quantity and proximity of clustering groups. The clustering method iteratively optimizes the gap and ranges between different groups to get the ideal cluster classification.

IV. Simulation Analysis and Outcomes

The dataset from the Alibaba group consists of 18 million entries. The research chose recordings for five of these regions. The selected records include the period from September to December 2023. Each log data captures 25-dimensional metrics, such as sales volume, number of views, queries, total transactional amount, and pricing. This research aims to employ an information frame encompassing the period from September to December 2023 to forecast the sales volume of every item in Region (R). These specific data specimens will serve as the test set for the predictions. The final range of the sample data box used in the training model was from January to April 2024. After acquiring training data specimens using the sliding timing window, these specimens were split randomly into two groups: a training set and an evaluation set, with a ratio of 4:1.

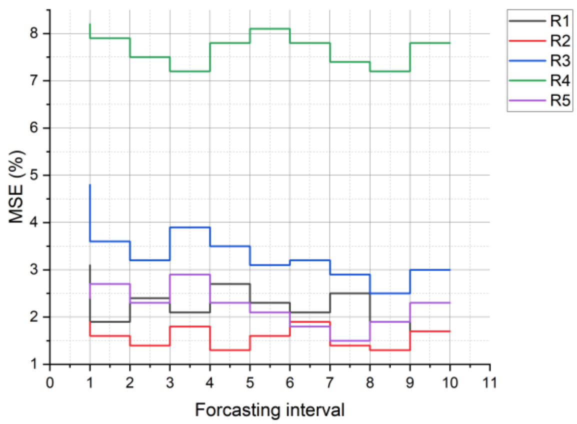

Fig. 4 Mean Square Error Analysis of Different Forecasting Interval

Figure 4 illustrates the Mean square error of average revenue as the duration of the projected interval increases in a dataset of five areas. It is evident that when the initial prediction length is one, the average variation of sales information in the five regions is relatively high, showing a lack of predictive capability in the algorithm. As the prediction period lengthens, the average square deviation of the sales information in the five areas remains relatively stable and gradually reaches a steady state. When the forecast period is eight, the Mean Square Error (MSE) achieves its minimal value, suggesting that the mean sale volume over this interval is more constant. When the duration of the projected interval exceeds 8, the MSE increases at a gradual rate. The forecasting interval is set to eight to enhance the algorithm's prediction accuracy.

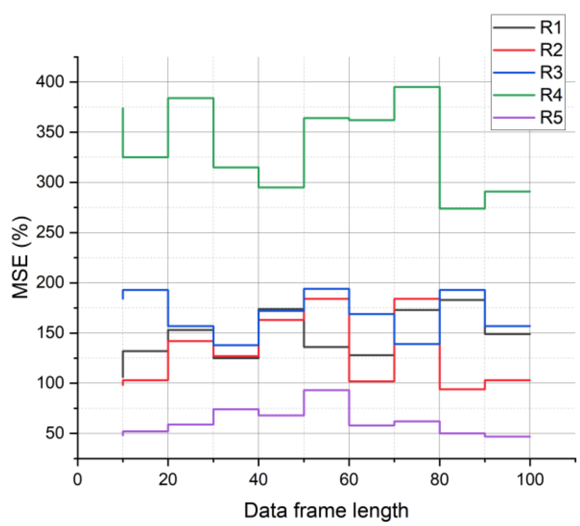

Fig. 5 MSE Analysis of Different Frame Length

The MSE analysis of different frame lengths is shown in Figure 5. The data frame size utilized by the model is a crucial key element that defines the amount of past data employed to forecast future sales. While the model is somewhat resistant to this variable, its information is only adequate if the data box is brief, resulting in a weak prediction impact. If the data box is short, it will include relevant information, resulting in a subpar forecast. Data frames of greater length need increased computational resources. Choosing the data box with the most petite length in practical applications is essential while ensuring correctness. Figure 5 demonstrates that the MSE score first lowers and then climbs as the size of the data box changes. The MSE score indicates the algorithm's reliability. A lower MSE score indicates higher algorithmic stability. Although R3 and R5 did not exhibit the lowest MSE, the remaining three areas had the lowest MSE. This paper selects a data box length 40 to assess the method's resilience.

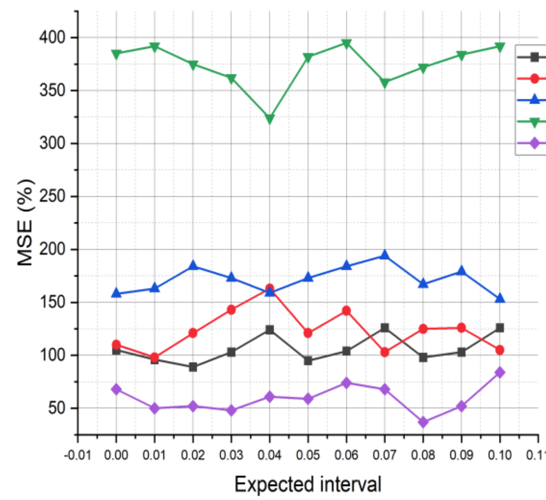

Fig. 6 MSE Analysis of Different Expected Intervals

The MSE analysis of different expected intervals is shown in Figure 6. The point that is closest to the predicted interval has more significance. The variable is employed to modify the pace at which the weight of the specimen decreases. When the magnitude of values is high, the model tends to favour the pattern shown by the most recent specimens, which needs an accurate representation. When the magnitude of the value is low, the model distributes equal importance to all specimens, resulting in a highly representative method. The frequency of days with internet use remains constant, whereas the MSE first declines and then gradually rises. When the value of the variables is 0.02, the MSE generated from the dataset of five locations is the lowest. It indicates that the information has a low level of variance, and the method's stability is more effectively proven. By considering the presence of all specimens, the system ensures that the findings produced are more informative.

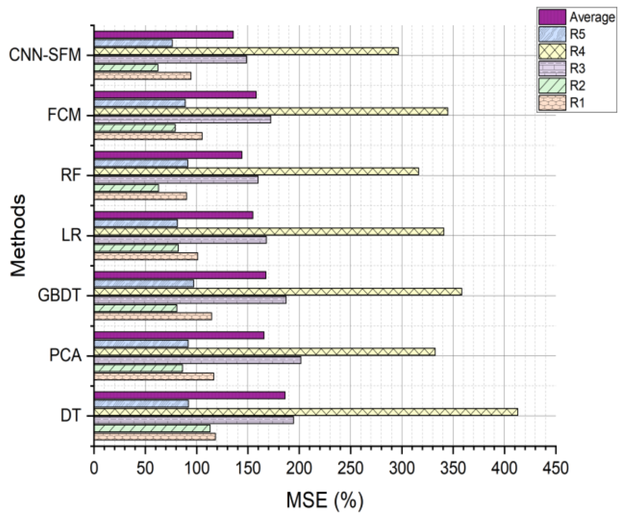

Fig. 7 MSE Analysis of Different Methods

Figure 7 displays empirical findings on examination datasets across five areas. Compared to the time series data analysis method DT, Principal Component Analysis (PCA) can incorporate more information and achieve a superior prediction outcome. While the GBDT is considered the most basic neural network structure, it can extract characteristics automatically. Features obtained by GBDT demonstrate superior effectiveness compared to manually derived features. The predictive performance of CNN-SFM in areas labeled R2, R3, and R5 as LR surpasses the technique presented in RF. CNN-SFM employs the previous knowledge of the temporal locality of the information to extract characteristics more efficiently, resulting in a significant improvement in predicting accuracy. The efficiency of CNN-SFM on the data frame surpasses Fuzzy C-Means (FCM). Applying weights to the training samples makes decreasing the average weighted variance possible. The CNN-SFM method needs advanced techniques such as solid attenuation and transfer learning, resulting in suboptimal performance. The incorporation of sample weight attenuation technologies and learning transfer technology has resulted in a significant improvement. After integrating all these technologies, the overall prediction performance is very competitive. The CNN-SFM has the potential to enhance the precision of sales forecasting significantly.

V. Conclusion and Discussion

This paper utilizes a CNN to extract efficient features from structured timing information. This CNN-SFM approach eliminates the need for manual feature extraction, a time-consuming and labor-intensive process requiring specialized knowledge. CNN-SFM employs a technique to forecast the sales volume of goods by using commodity characteristic details and pertinent original log information as input and predicting the overall volume of sales of goods in an upcoming time frame as outputs. The CNN-SFM minimizes the need for user intervention. CNN-SFM transforms the initial log data associated with the commodity into a distinct "data box" structure by amalgamating the attribute data of the commodities. The CNN extracts impactful characteristics from the data box. The last stage of the CNN-SFM employs linear regression, using these specific attributes as input to forecast the sales volume of items. The linear correlating value among the projected and the actual factor of the consumer standard has achieved a higher level of precision, with a correlation coefficient of 0.98. The margin of error for the forecasted value falls within 5%, a suitable range for the e-commerce managing tool. The research forecasts the worth of consumers by analyzing their activities. The chosen clustering algorithm and CNN model provide strong predictive and classifying skills, making them valuable references for other areas of e-commerce administration.

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