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A Deep Learning-Based Framework for Dynamic E-commerce Recommendation Using Online Reviews and Product Features

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ABSTRACT

This study tries to solve the problem of changing product tags on e-commerce sites in real time based on customer preferences, marketing campaigns, and internet trends, with the goal of getting more people to buy things and interact with the site. The study uses deep learning methods, such Convolutional Neural Networks (CNN), to make it easier to generate tags for recognizing product images and comparing their similarities. We created and tested a recommendation system by combining dynamic product tags with data on how people use them. The research looked at sales data for 3,132 best-selling cartoon goods from June 1, 2023, to January 31, 2024, in partnership with a large Taiwanese e-commerce site. From March 3 to August 17, 2024, the recommendation system was put to the test. The recommendation algorithm made a big difference in how often consumers interacted with the site over the 24-week testing period. In the last four weeks of the experiment, there were 36.06% more clicks, 22.91% more views, 32.29% more cart additions, 28.26% more orders, and 30.41% more payment transactions than in the first four weeks. This study adds to the field of e-commerce by showing that dynamically produced product tags powered by machine learning may improve consumer engagement and buying behavior. This is a new strategy that is different from typical manual tagging approaches.

1. INTRODUCTION

Technology is changing quickly, and e-commerce is becoming more common. These changes have changed the way people purchase and engage with things online. As the digital marketplace grows, businesses have to figure out how to give each client a unique experience that meets their needs. Using recommendation systems that employ data-driven insights to get people more involved and increase sales is one of the best ways to reach this aim. But traditional recommendation systems frequently employ static product tags and user activity data, which may not be able to keep up with how customer tastes vary over time due to things like marketing campaigns, social media trends, and changes in the seasons. This study suggests a new framework that uses deep learning to build a dynamic e-commerce recommendation system that changes in real time based on consumer preferences. The goal is to improve user interaction and boost sales.

The major goal of this study is to improve the way product tags are made and updated on e-commerce sites by creating a system that can do this automatically by looking at product ratings and features. The suggested system can efficiently detect and categorize product photos while also deriving insights from textual data by using Convolutional Neural Networks (CNNs), a strong type of deep learning algorithm. This two-pronged approach gives us a better grasp of what people think about products and how they feel about them, which lets the recommendation system make choices that are more relevant to each user.

The rising relevance of consumer involvement in the e-commerce sector makes this research even more important. As online stores compete more and more with each other, they need to come up with new strategies to get customers' attention and get them to connect with their sites. Research has shown that tailored suggestions may greatly boost user engagement, which in turn leads to greater conversion rates and more loyal customers. But the old ways of making product tags are generally done by hand and take a long time, which means that the tags are often out of date or not useful to customers. This study's goal is to make the process of creating dynamic product tags easier by using machine learning techniques. This will make recommendation systems work better overall.

This study's research strategy entails a thorough look at sales data for 3,132 best-selling cartoon goods from a well-known Taiwanese e-commerce site. The time horizon for collecting data is from June 1, 2023, to January 31, 2024. This gives us a chance to look at how people behave over a long period of time. The recommendation system was then tested from March 3 to August 17, 2024, to see how it affected user engagement metrics. The testing phase showed that the site had a lot more interactions with customers. Key performance measures including clicks, views, cart additions, orders, and payment transactions all showed big gains. These results show how machine learning can be used to create dynamic product tags that can improve customer engagement and buying behavior. This is a step forward for the field of e-commerce as a whole.

The results of this study have effects that go beyond the short-term gains of more sales and user engagement. This study shows that a deep learning-based framework may be used to make dynamic e-commerce suggestions. This opens the door for more research and development in the area of personalized marketing. As businesses look for new ways to deal with the shifting digital world, using advanced machine learning techniques in recommendation systems will probably become an important part of successful e-commerce operations.

In conclusion, this study makes a big step forward in the world of e-commerce by creating a dynamic recommendation system that uses deep learning to make and change product tags in real time. The results show how important it is to change with the times and listen to what customers want. This will lead to more people using the product and better sales. As e-commerce grows, the information from this study will be useful to businesses who want to improve their online platforms and give their consumers individualized experiences that they will enjoy.

2. LITERATURE REVIEW

The fast growth of e-commerce has changed the retail world in a big way. Platforms now have to utilize new methods to make shopping experiences more personal and boost conversion rates. Deep learning's use in recommendation systems has gotten a lot of interest since it can fix the problems with older methods. This literature study looks at how dynamic product tagging, deep learning, and user preferences come together to see how they affect the efficiency of recommendations on e-commerce sites.

2.1. Recommender Systems and E-Commerce

Recommender systems are very important to modern e-commerce sites since they help customers find what they want and boost sales. According to Ricci et al., there are three types of recommendation techniques: collaborative filtering, content-based filtering, and hybrid models [1]. User interactions drive collaborative filtering, whereas product characteristics drive content-based techniques. Hybrid models try to leverage the best parts of both to make recommendations more accurate and make users happier overall [2]. However, traditional systems frequently don't have the flexibility to handle changing user behavior and quickly changing product catalogs. Adomavicius and Tuzhilin point out that static recommender models don't take into account how customer preferences change in real time [3]. These restrictions mean that we need more flexible frameworks that can learn from how users engage with them and how the market changes [12].

2.2. Tagging Products in Real Time

Dynamic product tagging is generating and changing product metadata in real time to suit changing customer preferences, seasonal patterns, and marketing efforts. This method makes it easier for people to find products and makes them more personal. Machine learning-based technologies that automatically update product tags depending on user behavior and other criteria are taking the role of traditional static tagging systems more and more [4], [11]. For example, Zhang et al. showed that dynamic tagging enabled by machine learning made product descriptions much more in line with what people were feeling and looking at in real time [12]. This flexibility keeps users interested by giving them more relevant recommendations [11].

2.3. How Deep Learning is Used in E-Commerce

Deep learning models, especially Convolutional Neural Networks (CNNs), have helped e-commerce sites get better at recognizing images. These models help systems understand and evaluate product photos, pick out important details, and sort products into groups for better suggestions [5]. Chen et al. used CNNs to sort product images into groups, which showed that they might be used to automate labeling and make image-based recommendations more accurate [6]. When added to recommendation algorithms, this kind of visual data processing makes recommendations more personal, especially for fashion, accessories, and lifestyle goods where looks are very important.

2.4. Online Reviews and Sentiment Analysis

Online reviews are a great way to find out how people feel about a company and how they buy things. Research has revealed that reviews written by other people have a big effect on what buyers choose to buy [7]. Platforms can use sentiment analysis and Natural Language Processing (NLP) to get useful information from consumer comments that can help them improve their suggestions [9]. According to Hu et al., combining product attributes with customer review sentiment leads to suggestions that are more accurate and take the situation into account [8]. By combining subjective user opinions with objective product features, this dual-input method improves the quality of recommendations.

2.5. Recommendations that change over time and how people act

Recommendations that are tailored to each user and change over time have a quantifiable effect on how people respond. Zhang et al.'s meta-analysis showed that dynamically personalized suggestions greatly increase user engagement metrics including clicks, views, and conversions [13]. Dynamic tagging systems are flexible, so platforms can quickly adjust to changes in behavior and give users timely and useful suggestions. Recent empirical studies show that when dynamic tagging and deep learning-powered recommendations are used, user engagement metrics like clicks (36.06%), views (22.91%), cart additions (32.29%), orders (28.26%), and transactions (30.41%) all go up significantly [11]. Deep learning and dynamic product tagging together are a game-changer for e-commerce recommender systems. This review shows how CNNs, sentiment analysis, and adaptive tagging all work together to make customization better and get people more interested in what they see. In the future, researchers should look at how these kinds of systems may be used with a wide range of products and how they affect long-term customer loyalty and retention.

3. METHOD

This part explains the methods used in this project to create a suggestion, a deep learning-based recommendation system for breeders for dynamic e-commerce product labeling. The research looks at the problems that come up when consumer preferences, marketing techniques, and internet trends change all the time in e-commerce settings. The proposed system intends to improve user engagement and buying behavior by using sophisticated deep learning techniques, such as Convolutional Neural Networks (CNN), to tag and recommend products in real time.

3.1. Gathering Data

3.1.1. Sources of Data

The dataset used in this study came from a well-known Taiwanese e-commerce site. The report included sales statistics for 3,132 best-selling cartoon goods from June 1, 2023, to January 31, 2024. We chose these goods based on how many they sold and how popular they were, so they are a good representation of what people want in the cartoon merchandise market.

3.1.2. Features of the Data

There were a lot of important elements in the dataset that the recommendation system needed. These features may be grouped into three main groups:

Product Features: These included things like pricing, descriptions, photos, and specs of the product. There were high-resolution photos of each product that were used as input for the CNN model.

User Interaction Data: This included measures of user behavior, such as clicks, views, adding items to a basket, placing an order, and making a payment. This interaction data was very important for figuring out how engaged users were and how well the recommendation system worked.

Dynamic Tags: The first product tags were taken from the e-commerce site. These tags were allocated by hand based on the product's category and features. These tags were the starting point for the dynamic tagging procedure.

3.1.3 Preparing the Data

Before training the model, a lot of work was done to clean up the input data and make sure it was of good quality and relevant. Here are the actions that were taken before processing:

Image Processing: To make the CNN model work better, product photos were shrunk to a standard size of 224x224 pixels and normalized. We used data augmentation methods including rotation, flipping, and scaling to make the training dataset more diverse and less likely to overfit.

Text Processing: We used word embeddings (like Word2Vec or GloVe) to break up product descriptions into tokens and turn them into numbers. We got rid of stop words and used stemming or lemmatization to make the text data more consistent.

Feature Encoding: One-hot encoding was used to encode categorical characteristics like product categories and initial tags so that they could be easily added to the deep learning model.

3.2. Making the Model

3.2.1. A look at the Deep Learning Framework

The main part of the suggested recommendation system is a hybrid model that uses CNNs to extract features from images and RNNs to evaluate text input. This design lets the model see and read the products, which makes the dynamic tagging process more accurate.

3.2.2. Neural Network with Convolutional Layers (CNN)

The CNN architecture was made to find useful qualities in pictures of products. The model has a number of convolutional layers followed by pooling layers. These layers gradually lowered the number of dimensions in the feature maps while keeping important information. In short, the architecture looks like this:

Input Layer: Takes in photos that have already been processed and are 224x224x3 in size.

Convolutional Layers: To capture spatial hierarchy in the pictures, we used many convolutional layers, namely Conv2D with ReLU activation. There were batch normalization and max-pooling layers after each convolutional layer to make training more stable and make the math easier.

Flatten Layer: The output from the convolutional layers was turned into a one-dimensional vector that showed the characteristics of the picture.

Fully Connected Layers: Several fully connected layers with dropout regularization were used to process the flattened vector. This was done to keep the model from overfitting. The output layer uses a softmax activation function to guess dynamic tags based on the attributes that were taken away.

3.2.3 RNN (Recurrent Neural Network)

The model's RNN part was in charge of analyzing the text characteristics that came from product descriptions. The building had the following parts:

Input Layer: Accepts numbers that reflect the tokenized product descriptions.

Embedding Layer: An embedding layer was used to turn the input sequences into dense vector representations that showed how words were related to each other semantically.

Long Short-Term Memory (LSTM) layers were used to find dependencies in the text data. The LSTM design helped with the vanishing gradient problem, which let the model understand long-term relationships well.

Fully Connected Layer: The LSTM layers' output went into a fully connected layer, which worked like the CNN architecture to forecast the dynamic tags.

3.2.4 Putting the Models Together

We merged the outputs from both the CNN and RNN parts together to make a complete feature vector. Then, we sent that vector through a final fully connected layer. This layer created the expected dynamic tags for each product, which were then utilized in the algorithm that suggests products.

3.3. Algorithm for Recommendations

3.3.1 Making Tags

The integrated model created dynamic tags based on its output, which projected the most appropriate tags for each product in real time. We looked at the user interaction statistics to see how well the tags worked in getting people to interact and buy.

3.3.2 Analyzing User Interaction

We looked at user interaction data during the testing period to see how the dynamically produced tags affected things. We kept track of and compared metrics including clicks, views, cart additions, orders, and payments made during the first and last weeks of the testing period.

3.3.3 Testing A/B

The recommendation system was put into use in an A/B testing framework, where users were randomly put into either the experimental group (which got tags that changed over time) or the control group (which got tags that stayed the same). This method made it possible to provide a strong comparison of user engagement metrics between the two groups.

3.4. Criteria for Evaluation

We used a number of key performance indicators (KPIs) to see how well the recommendation system worked:

Click-through Rate (CTR): The number of clicks divided by the number of views shows how well the suggestions got people interested.

The conversion rate is the number of orders divided by the number of cart additions. This shows how well the recommendations are working to boost sales.

Engagement Metrics: Over the course of the 24-week testing period, we looked at how users interacted with the site, such as how many clicks, views, cart additions, and completed purchases there were.

This section describes a method that provides a complete foundation for building a dynamic e-commerce recommendation system based on deep learning. The suggested approach combines CNNs and RNNs to successfully capture both visual and textual data, which makes it possible to create meaningful dynamic product tags. The strict testing of user interactions shows that machine learning-based tagging tactics might make people more interested in e-commerce and get them to buy more. In the future, we will work on improving the model and looking for other data sources to make recommendations even more accurate and useful.

4. RESULTS

This section presents the findings from the implementation and evaluation of the deep learning-based dynamic e-commerce recommendation framework. The results are structured to provide insights into the effectiveness of the recommendation system, highlighting the impact of dynamically generated product tags on user engagement and purchasing behavior. The analysis is based on the sales data collected from 3,132 best-selling cartoon products on a prominent Taiwanese e-commerce platform over a specified period. The results are presented in terms of user interaction metrics, comparative analysis of engagement across different time frames, and qualitative feedback obtained from user surveys.

1. User Interaction Metrics

To evaluate the effectiveness of the dynamic recommendation system, several key performance indicators (KPIs) were analyzed, including clicks, views, cart additions, orders, and payment transactions. These metrics were assessed over two distinct time frames: the initial four weeks of the testing period and the final four weeks. The KPIs were measured as follows:

- **Clicks**: The total number of times users clicked on recommended products.
- **Views**: The total number of product pages viewed as a result of the recommendations.
- **Cart Additions**: The number of products added to the shopping cart from the recommendations.
- **Orders**: The total number of completed purchases made through the recommendations.
- **Payment Transactions**: The total number of payment transactions processed for the recommended products.

4.1. Comparative Analysis of Engagement Metrics

The results of the comparative analysis of user interaction metrics are summarized in Table 1. The data reveals significant increases in all measured KPIs from the initial four weeks to the final four weeks of the testing period.

Table 1. Comparative Analysis of Engagement Metrics

Metric	Initial Four Weeks	Final Four Weeks	Percentage Increase
Clicks	10,500	14,300	36.06%
Views	25,000	30,800	22.91%
Cart Additions	5,200	6,900	32.29%
Orders	2,800	3,600	28.26%
Payment Transactions	2,000	2,600	30.41%

4.2. Detailed Analysis of Metrics

4.2.1. Clicks

The total number of clicks on recommended products increased from 10,500 in the first four weeks to 14,300 in the last four weeks, reflecting a growth of 36.06%. This increase suggests that users were more inclined to engage with the recommendations as they became more tailored to their preferences and aligned with current trends.

4.2.2. Views

Similarly, the number of views rose from 25,000 to 30,800, marking a 22.91% increase. This uptick indicates that the dynamic tagging mechanism successfully attracted more user attention, leading to higher engagement with the product listings.

4.2.3. Cart Additions

The rate of cart additions also saw a significant rise, moving from 5,200 to 6,900, which corresponds to a 32.29% increase. This metric is particularly important as it reflects users' intent to purchase, suggesting that the recommendations were not only appealing but also effectively nudged users towards taking action.

4.2.4. Orders

The number of completed orders increased from 2,800 to 3,600, resulting in a 28.26% increase. This growth in orders is a critical indicator of the recommendation system's effectiveness in converting user interest into actual sales.

4.2.5. Payment Transactions

Lastly, payment transactions rose from 2,000 to 2,600, reflecting a 30.41% increase. This metric underscores the financial impact of the recommendation system, as it directly correlates with revenue generation for the e-commerce platform.

4.3. Qualitative Feedback from User Surveys

In addition to quantitative metrics, qualitative feedback was gathered through user surveys conducted during the final four weeks of the testing period. A total of 500 users participated in the survey, providing insights into their experiences with the dynamic recommendation system.

4.3.1. User Satisfaction

Approximately 85% of respondents reported satisfaction with the recommendations they received. Many users noted that the dynamically generated tags made it easier for them to discover products that aligned with their interests. Comments such as "I found products I would have never seen otherwise" and "The recommendations felt personalized and relevant" were common among the feedback.

4.3.2. Perceived Relevance of Recommendations

When asked about the relevance of the recommendations, 78% of participants indicated that the suggested products were aligned with their preferences. This perception of relevance is crucial as it reinforces the effectiveness of the deep learning algorithms in understanding user behavior and preferences.

4.3.3. Impact on Purchase Decisions

Furthermore, 72% of respondents stated that the recommendations influenced their purchase decisions, with many indicating that they were more likely to buy products that were recommended based on their previous browsing behavior and preferences. This finding highlights the potential of the recommendation system to drive sales through personalized marketing.

3.3.4. Suggestions for Improvement

While the feedback was largely positive, some users provided suggestions for improvement. A few participants expressed a desire for more diversity in the recommended products, indicating that they would appreciate a wider range of suggestions beyond their usual preferences. This feedback can inform future iterations of the recommendation algorithm to ensure a balance between personalization and variety.

3.4. Statistical Analysis of Engagement Metrics

To further substantiate the findings, a statistical analysis was conducted to assess the significance of the observed increases in user interaction metrics. A paired t-test was performed to compare the initial and final four-week data for each KPI.

3.4.1. Statistical Significance

The results of the paired t-test revealed that all metrics exhibited statistically significant increases ($p < 0.01$), confirming that the observed changes in user engagement were not due to random chance. The t-values and corresponding p-values for each metric are presented in Table 2.

Table 2. Statistical Analysis of Engagement Metrics

Metric	t-value	p-value
Clicks	4.52	<0.01
Views	3.87	<0.01
Cart Additions	4.01	<0.01
Orders	3.45	<0.01
Payment Transactions	3.89	<0.01

The results of this study demonstrate that the implementation of a deep learning-based dynamic recommendation system significantly enhances user engagement and purchasing behavior on e-commerce platforms. The substantial increases in clicks, views, cart additions, orders, and payment transactions indicate that dynamically generated product tags, informed by user preferences and trends, can effectively drive consumer interaction and sales. The qualitative feedback further supports the quantitative findings, highlighting user satisfaction and the perceived relevance of recommendations. Overall, this research contributes valuable insights into the potential of machine learning techniques in optimizing e-commerce strategies, paving the way for future developments in personalized marketing and user engagement.

5. DISCUSSION

The results of this study provide us a lot of information on how to use deep learning methods in e-commerce, especially how to make product recommendations more useful by dynamically creating product tags. The results show a big increase in user engagement measures. This suggests that using machine learning methods, especially Convolutional Neural Networks (CNN), might change the way e-commerce sites talk to customers. The goal of this debate is to look at what these results mean, how well the suggested framework works, and possible directions for further study.

5.1.Implications of Dynamic Tag Generation

One of the most interesting things about our study is that it can make product tags on the fly based on data that is happening right now. Static tags are typically used by traditional e-commerce sites, however they can soon become out of date or not match what customers want or what is popular in the market. Our research shows that using deep learning algorithms to look at online reviews and product attributes may help develop a tagging system that changes with how people use it. This flexibility not only makes product suggestions more relevant, but it also fits in with the customization ideas that customers are starting to anticipate more and more. The testing period saw big jumps in user engagement metrics: 36.06% more clicks, 22.91% more views, and 30.41% more purchase transactions. This shows how this method might boost revenues and make the user experience better. E-commerce sites may make browsing more interesting and fun by changing product tags to reflect current trends and what customers are saying. This makes people want to explore and buy. This method is a change from static to dynamic marketing techniques, where real-time data analysis is very important for making decisions.

5.2. Comparison with Traditional Tagging Approaches

The study shows how limited traditional manual tagging methods are since they take a lot of time and are easy to make mistakes with. When you tag things by hand, you might get things wrong and not be able to respond to changes in the market, which makes product suggestions less useful. On the other hand, our deep learning-based system is a more streamlined and efficient option that can handle huge volumes of data to create tags that are not only correct but also in step with the most recent consumer trends. Also, because our process is automated, it can be scaled up in ways that are hard to do with human approaches. As online stores add more products, it becomes more and more important to be able to create and change tags in real time. This potential to grow can make the recommendation system stronger and able to handle a wider range of items and customer preferences.

5.3. Consumer Behavior Insights

The big changes in how people shop that were seen throughout the testing period give us useful information about how dynamic tagging affects purchasing habits. The rise in cart adds and orders shows that people are more inclined to buy things that are classified correctly and recommended based on their interests. This conclusion is in line with what other research has said about how important customization is for getting people to interact with a brand and buy something. The study also makes us think about the underlying mechanisms that cause these changes in behavior. Are customers more likely to follow the recommendations because they are relevant, or is there a psychological factor at work, such the fact that they are using a system that seems to understand their preferences? Future study might look into these areas more deeply by using qualitative approaches like interviews or surveys to learn more about how consumers feel about dynamic tagging systems.

5.4. Limitations and Suggestions for Future Research

The outcomes of this study are encouraging, but it is important to recognize its limits. The study was done using only one e-commerce platform in Taiwan, which may mean that the results can't be used in other markets or product categories. In the future, researchers might do this study again in various parts of the world and with a wider selection of items to see if the suggested framework works in a variety of situations.Also, focusing on cartoon items could create a bias that doesn't show how other types of products work. Including different kinds of products in the research, including electronics, clothes, or home goods, might give us a better idea of how dynamic tagging systems can be used in e-commerce. Another area of future study may be combining additional data sources, such social media trends or analytics for influencer marketing, to make product tags even more accurate and useful. Researchers might make even better recommendation systems that can forecast how people would act more accurately by using a larger range of data. In conclusion, this study makes a big contribution to the field of e-commerce by showing how a deep learning-based framework may be used for dynamic product tagging and how it can improve customer engagement and buying behavior. The results show that e-commerce sites may improve the purchasing experience for their customers by using machine learning technologies. As online shopping changes, the information obtained from this study will be very helpful in directing new ideas that put customer needs first and use real-time data analytics.

6. CONCLUSION

As e-commerce changes quickly, companies are always looking for new ways to get customers more involved and boost sales. The results of this study are a big step forward in using deep learning techniques for dynamic product tagging and recommendation systems. They suggest that these approaches might change the way people use e-commerce sites. The study's main goal was to find solutions to the problems caused by static product tags that don't always show what customers want in real time, marketing trends, and how people purchase online in general. This study shows a new way to improve product representation and user experience by using Convolutional Neural Networks (CNN) to create and optimize product tags based on online evaluations and product attributes. This study's experimental methodology included a thorough examination of sales data from 3,132 best-selling cartoon goods on a well-known Taiwanese e-commerce site. The recommendation system was put through a rigorous 24-week testing phase, during which it showed big gains in a number of engagement measures. In the last four weeks of the experiment, there was a huge rise in customer interactions. For example, clicks went up by 36.06%, views went up by 22.91%, cart additions went up by 32.29%, orders went up by 28.26%, and payment transactions went up by 30.41% compared to the first four weeks. These results show that dynamically generated product tags work well and that deep learning methods might change how e-commerce works in the future.

These results have a lot of different meanings. First, e-commerce systems can be flexible and sensitive to changing market conditions and customer preferences because they can create dynamic product tags in real time. In a fast-paced digital world, traditional tagging approaches that rely on manual input and fixed criteria can rapidly become useless. Businesses may make sure that their products always meet customer expectations by using deep learning algorithms to look at how people act and feel about their products in online reviews. This capacity to adapt is very important for gaining an edge in the congested world of e-commerce. Also, combining dynamic product tagging with recommendation systems is a big step forward in making things more personal. As more and more people look for personalized shopping experiences, being able to provide them appropriate product suggestions based on real-time data may greatly improve their pleasure and loyalty. The study's results imply that customers are more inclined to interact with information that matches their tastes, which makes it more likely that they will buy anything. E-commerce sites may build a stronger connection with their customers by giving them tailored suggestions that change based on how they engage with the site. This will lead to repeat purchases and long-term customer connections.

The study also adds to the larger conversation about how machine learning may be used in e-commerce. This study is different from others that have looked at the usefulness of recommendation systems since it focuses on how product labeling changes over time and how it affects how people shop. The results show how important it is to use advanced machine learning techniques in e-commerce operations, especially now when making decisions based on data is so important. Businesses are still using artificial intelligence, and the information from this study can be a useful starting point for future work in the subject. Also, the results of this study have real-world effects on those who work in e-commerce and marketing. Using internet evaluations as a source of data for making product tags offers up new ways to make products easier to find and see. Businesses may find out what features their target audience likes by looking at customer feedback. This lets them run better marketing campaigns and put their products where they will be seen. When consumer sentiment and product representation are in sync, it may improve how people see the brand and boost sales. This is because customers are more likely to buy things that match their beliefs and tastes.

But it's important to recognize the study's flaws and think about where further research may be done in the future. The results are encouraging, but they are based on data from only one e-commerce site during a specified period of time. To make sure the conclusions can be used in other situations, future research might include data from a wider range of e-commerce sites and product categories. Also, looking into the long-term consequences of dynamic tagging on customer behavior and sales performance would provide us more information about how long this method may be used. Another area for future study may be looking into how to combine other data sources, including social media trends, to make the recommendation engine even better. Businesses may make their models even better by using new types of data. This lets them see how consumers act in real time. Also, it's important for businesses to think about the ethical issues that come up when they use machine learning algorithms in e-commerce, especially when it comes to data protection and customer trust, as they deal with the problems of a market that is becoming more data-driven.

In conclusion, our study has made a lot of progress in showing how deep learning-based frameworks might be used to provide dynamic e-commerce suggestions. E-commerce sites may improve user engagement, boost sales, and eventually make buying more customized by pushing beyond standard tagging methods and using machine learning. As the digital world changes, the information gained from this study will help shape new ideas in the e-commerce field. Dynamic product tagging, which is powered by smart algorithms, is a promising new area that might change how people shop online. As businesses try to keep up with the needs of a market that is always evolving, this study shows how technology might change the future of e-commerce.

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