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Analysis of E-Commerce User Behavior Data Analysis Model using Fuzzy Neural Network

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Abstract: - E-commerce has become a globally popular and successful strategic approach. Without really having to set foot in a store, consumers may make a request and have their goods delivered to them within days, if not hours. Evaluations are becoming increasingly important since shoppers rely on them when deciding what to buy Internet. The significance of the online platform in the company is only expected to grow, making it all the more vital to learn what motivates people to go online. Predicted immediate and long-lasting effects, prior exposure, and favorable circumstances were postulated to encourage adoption. In this study, we present a fuzzy neural network (FNN) for analyzing online shoppers' habits. Anyone working to spread the word about the Internet's advantages should render it as user-friendly as feasible. Customers using an online store often do four things: browse, bookmark, add to the store, and spend. This article is grounded on its track record across many product classes and times. The real-time analytic work investigated the skew and history of user activity in the aggregate. The study findings revealed that the suggested model has provided an accuracy of 96% and computation time of 69s which shows effective analysis on user behavior in ecommerce.

Keywords: E-commerce, fuzzy neural network (FNN), user behavior, online store, quality of life, and public policy

Research Highlights

- E-commerce's widespread success and widespread adoption make it a viable business strategy. Customers can place an order without ever having to physically visit a business, and their products will be delivered to their doorstep within a matter of days, if not hours.
- Since the Internet will continue to play an increasingly important role in running the business, understanding what draws people to the web is crucial. Adoption was theorized to be facilitated by a combination of factors, including positive context, past experience, and positive reinforcement.
- To better understand how people shop online, we introduce a fuzzy neural network (FNN) here. Promoters of the Internet's virtues should make the network as intuitive to use as they can.
- This article is grounded on its track record across different product classes and timeframes. The real-time analytics looked into the aggregate activity skew and history.
- The study outcomes revealed that the suggested model has offered an accuracy of 96% and calculation time of 69s which exhibits excellent analysis on user behavior in ecommerce.

1. Introduction

The buying and selling of goods and services via the internet is referred to as electronic commerce, or e-commerce. Transactions between businesses and consumers can be included in this category. Since it offers convenience to both consumers and sellers, e-commerce has grown in popularity over the last several seasons.E-commerce having grown in popularity over the last few years because of the efficiency it provides to both customers and companies.E-commerce has completely transformed the way customers purchase and given companies new ways to connect with customers worldwide [1]. The activities, preferences, and patterns of behavior demonstrated consumers on e-commerce platforms are referred to as e-commerce user behavior. E-commerce user behavior may include a broad variety of actions, including product browsing, product searching, product adding to cart, product completion, customer reviews, and products promoting on social media.For e-commerce organizations to better understand their consumers and create strategies to increase customer pleasure, loyalty, and retention, it is essential to understand the behavior of e-commerce users [2]. An artificial neural network that contains fuzzy logic is called a fuzzy neural network (FNN). In employing language phrases to describe variables rather than exact numerical values, fuzzy logic enables the depiction of uncertainty and imprecision in data. Fuzzy logic is used in FNN to specify the input and output variables in addition to the procedures for combining the variables to achieve the desired outcome. The network is made up of numerous layers of linked nodes, each of which processes its input using mathematics to generate an output [3]. FNN, that combine artificial neural networks with fuzzy logic, are often employed in complex systems models and information processing. It may be used to examine and understand information from an array of industries, including as engineering, medical, and finance.There are many different methods and strategies that may be used to evaluate and interpret data sources while working with FNN. Acquiring the data together and pre-processing constitutes the initial stage in a data analysis for FNN. For the data to be appropriate for analysis, that needs cleansing and transformation.FNN data analysis is a multi-step, iterative process that uses a variety of methodologies. It calls for proficiency in fuzzy logic and neural networks, as well

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as in-depth knowledge of the particular area or domain being discovered [4][5]. Fuzzy logic and artificial neural networks are used in an e-commerce user behavior data analysis model based on FNNs to evaluate and model user behavior data in e-commerce systems. The FNN can be employed to evaluate user behavior information as it occurs on e-commerce systems after it has been tuned and verified. E-commerce companies may learn more about customer behavior, preferences, and interests through the application of a model for analyzing user behavior data based on FNN. This may be used to provide individualized product suggestions and marketing efforts, as well as increase consumer involvement, loyalty, and satisfaction [6]. Figure 1 depicts the e-commerce user behavior.

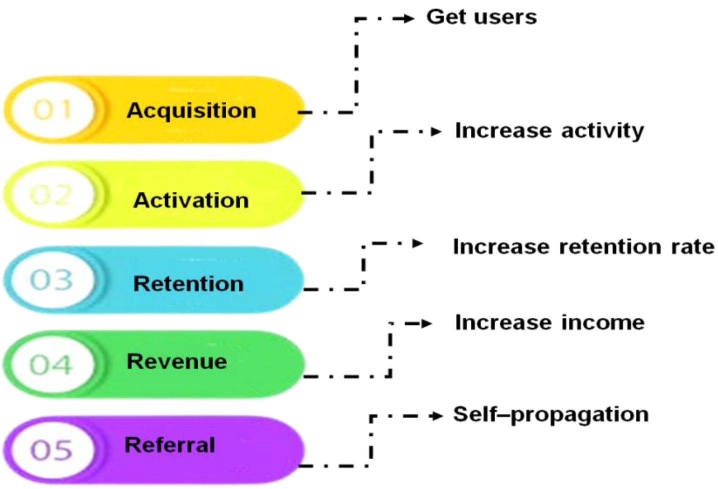

Figure 1: E-commerce user behavior

E-commerce organizations have benefited from big data analysis to enhance their workflows and sustain and grow their income.The practice of analyzing large amounts of data to offer a viewpoint for business choices is known as big data analytics (BDA).BDA has a significant impact on e-commerce in many aspects, including understanding Gianmaria Silvello, an assistant editor, oversaw the examination of this article and gave her approval for publishing. It is responsible for determining customer pleasure, analyzing user behavior, and boosting profitability [7]. The creation of new e-commerce platforms has a big impact on the expansion of the whole industry. Therefore, in order to direct the development of e-commerce systems and e-commerce platforms, it is essential to apply scientific forecasting methodologies to anticipate and analyze the purchasing patterns of users of e-commerce platforms [8]. E-commerce behavior refers to the attitudes, preferences, and behavioral patterns that businesses and consumers exhibit on e-commerce platforms. The success of e-commerce platforms may be significantly influenced by how firms and customers behave. Businesses may obtain insights into how their consumers are engaging with their platform, pinpoint areas for development, and create focused plans to boost engagement and revenue by comprehending these aspects and evaluating e-commerce behavior data [9] [10]. FNN-based data analysis models are an effective tool for understanding and modeling complicated data. In this research, the technology acceptance model is modified to represent user behavior. The proposed a fuzzy neural network (FNN) technique for classifies an e-commerce user behavior data analysis.

In the study [11], used of smartphone applications in e-commerce are viewed as data processing operations. To measure the comfort of using smartphone applications to more about the services, the distance of information-state transition concept is created. To improve system design and boost the effectiveness of online buying, it is important to unbiased assess and contrast different mobile e-commerce retailing applications. In light of consumer internet purchasing patterns of behavior, a distinct DIT-based assessment strategy for mobile applications usefulness in e-commerce selling is consequently, provided. The research [12] is to analyze gen-adoption Z's patterns for e-commerce utilizing 1047 reliable data observations. Self-efficacy, perceived usefulness, attitude, intention, and e-commerce adoption are all strongly correlated, according to the Smart Partial Least Square analysis. In the article [13], they investigate the behaviors that can influence brand purchases in order to examine brand buy prediction. Humans advance in three ways. They examine real-world e-commerce data from several perspectives. In concentrating on consumer brand purchases, they can observe whether habits interact and change over time. The study [14] discussed the studies on government financing platforms in the field, examines its risk factors, and attempts to develop a suitable early alert assessment index method of economic risk. In beginning with the FNN model of artificial intelligence, it differs from the conventional model for logistic assessment of regression based on analysis on historical information when choosing risk assessment techniques. The study [15] determined the main characteristics pushing businesses to develop cloud-based information analytics. The paper [16] examined real-world company information data, created an innovative cross-border e-commerce customer support model, optimized customer care details, met client demands, and raised business profitability. The research [17] provided an easy-to-use but effective customized recommendation system for cross-border e-commerce that addresses complexity by integrating fuzzy association principle with complex preference. The study [18] investigated a cross-border logistics risk assessment model for e-commerce that is built on an enhanced neural network to address the issues. The technique may assist cross-border e-commerce businesses in choosing the best third-party settlement platforms, hence lowering their capital settlement costs. Insufficient risk, bottleneck, and logistics risk assessment evaluation are issues the enhanced neural network-based electronic commerce logistics cross-border hazard evaluation model addresses [19]. The enhanced neural network-based model for e-commerce cross-border logistical risk analysis may be used to rate risk prior to company growth in order to apply various risk management strategies for varying individual risk.

2. Materials and Method

People's shopping behaviors have evolved in history's highly interconnected society. Increasing numbers of consumers opt to purchase online rather than visit physical stores. E-commerce enables consumers to look through many product listings, compare prices, stay abreast of breaking news, make wish lists, and get individualized service according to their preferences. This expanding online industry is very aggressive because of the convenience with which customers may switch to another online store if their immediate needs are not met. Hence, e-commerce business managers need to recognize and comprehend how customers use the service, how they decide what to buy, and why they make those decisions. The steps involved in the proposed technique are shown in figure 2.

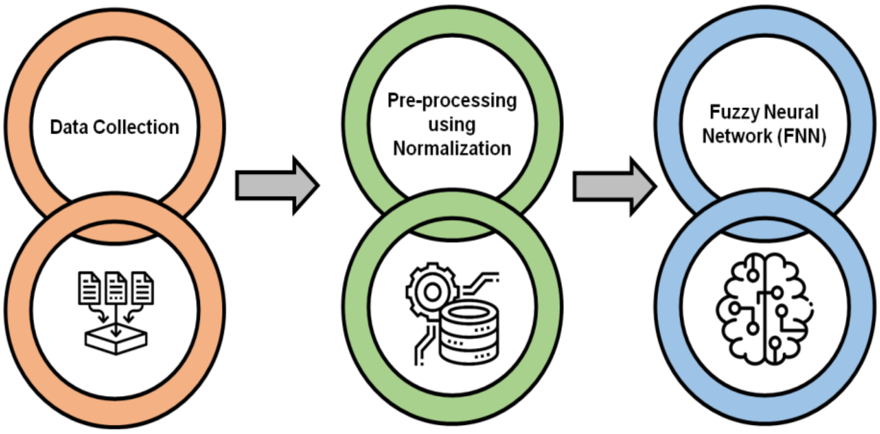

Figure 2: The workflow of the suggested method

A. Data collection

Given the absence of massive data for brochure creation, we developed a novel dataset called TaoDescribe to fill the void. It involves product titles, aspects, customer categories, and descriptions. Taobao is World's leading e-commerce platform, and that's where they got our information from. From November 2013 until December 2018, the platform's vendors and internet companies wrote all the marketing material and data. An automated annotation of each information instance's feature and customer group is performed utilizing the techniques. Information from the CN-DBpedia database is also correlated to every data point. This allows such data to be used in producing product descriptions for customization and the inclusion of prior learning. After normalization, the total number of occurrences in the database is 2,129,187 (x, y, a, w). The accompanying sections will provide more information on the database.

B. Data preprocessing using normalization

Data normalization improves security by reducing the amount of data stored by removing duplicates and guaranteeing that each resource group has exactly one record. Every step of this process uses the same set of parameter adjustments to keep the spacing from changing. Min-Max While there are alternative standardized processes, normalizing is still used. The resulting normalizing expression looks like

$$n = \left(\left(\frac{(a-a_{min})}{(a_{max}-a_{min})}\right) * (1-0) + 0\right) \quad (1)$$

The normalized data ranges from zero to 1, with a_{max} and a_{min} representing the upper and lower bounds. The measured and calculated quantities of the characters stand for their mean and median. Spectral dispersion is typically employed to describe the non-normal distribution, while the lowest variance implies familiar data sources. Mean, median, and variance may be calculated using equations (2), (3), and (4), respectively.

$$M = \frac{\sum_{i-1}^{n} y_1}{n}$$

(2)

$$M_d = \begin{cases} y\frac{n}{2}, & ifniseven \\ \frac{\left(y\left[\frac{n-1}{2}\right] + y\left[\frac{n+1}{2}\right]\right)}{2}, & ifnisodd \end{cases} \quad (3)$$

$$S_k = \frac{n\sum_{i=1}^{n}(y_i-\overline{y})^3}{(n-1)(n-2)\sigma^3} \quad (4)$$

Here$n$ is the weighted sum of records in the database, y represents the database variables, $\bar{y}$ represents the mean, and the variance isσ. The objective of privacy normalized is to collect and classify all relevant information on the subject. Some anomaly detection strategies rely heavily on normalizing characteristics.

C. Fuzzy neural network (FNN)

Fuzzy neural networks (FNNs) are built on the principle of fuzzy sets and are taught using neural network-inspired training methods. With the classification qualities of fuzzification and the expansion of variables made possible by artificial neural networks, FNN was capable of solving issues of varying types, facilitating the ability to discover answers for an upgrade to the sophisticated modeling' attributes. Using the customer's issue databases as input, they detect behavior methods that build a collection of fuzzier rules for translating quantitative information into verbal settings understandable by those unfamiliar with the primary concepts of artificial intelligence. Adding fuzzification to a neural network may make it more cost-effective, reliable, and easily comprehended than the individual techniques alone. The basic equation for fuzzification can be represented as follows equation (5):

$$\mu A(x) = f(x) \quad (5)$$

Where $\mu A(x)$ is the input value x level of membership in the fuzzy set A. $f(x)$ is a membership function that establishes x fuzzy set A membership.

The neural network training process can be represented as equation (6):

$$\theta^* = \text{argmin}(\text{L}(y, f(x;\, \theta))) \quad (6)$$

Where: θ^* shows the network parameters that have been optimized. $\text{L}(y, \text{f}(x;\, \theta))$ is The loss function calculates the error between the target (y) and the predicted output $(f(x;\, \theta))$.

The system suggests using FNN and training them using the databases that establish anomaly tendencies. With these parameters, the design can pick up on database tendencies and traits, giving rise to trend categorization and developing a fuzzy-rules-based expert system. Based on the data structure used to make anomaly occurrences, the framework would contain four aspects: function, time, bytes collected, and bytes transmitted. Symmetrical model parameters will be used to integrate these four characteristics. FNNs implemented in a hybrid paradigm for accurately predicting are focused on the necessary conditions for neural networks using fuzzy inference methods. The program's outcome has been the quadratic sum of the outputs of the fuzzy system in the predecessor networks multiplied by the activating intensity of their normalizing fuzzy system in the following method.

The study suggests a user-behavior-based FNN, incorporating a participatory e-commerce approach and an analytical tool for FNN parameters to boost efficiency. The FNN's framework modification is coordinated with the development of its parameters due to the self-organizing mechanism's usage of a particular evaluation technique and a structure adjustment technique. The FNN is evaluated using input from both interneurons and interlayers. It then tweaks itself using the architecture optimization framework to add and remove fuzzy sets as needed to achieve architectural self-organization of user activity. While doing a self-organizing study of action, FNN doesn't require a predefined level before reaching certain conclusions. This quality makes it suitable for use in real-world situations.

3. Result and discussion

Evaluating the proposed methodology in relation to established techniques like PTM (Powerful Transformer Model) [20] and DL (deep learning) [21]. Metrics including accuracy, precision, recall, computation time, and implementation cost are used in our analysis.

Accuracy

It represents the proportion of correctly classified samples. It calculates how similar the final outcomes and the input data are to each other. As demonstrated by the graph, the new method is more accurate than the previous one.

$$Accuracy = \frac{t_p+t_n}{t_p+t_n+f_p+f_n} \quad (7)$$

Insufficient accuracy results in a difference between the actual number and the outcome. The proportion of real results shows the overall balance of the data. To evaluate accuracy, use equation (7).

The equivalent values for the accuracy measures are displayed in Figure 3. The suggested method's FNN value is 97% when compared to other methods already in use, such as PTM, which has an accuracy rate of 68.4%, and DL, which has an accuracy rating of 87%. The proposed FNN outperforms other approaches in terms of accuracy and e-commerce user behavior. Table 1 shows the recommended method's accuracy compares to the current methods.

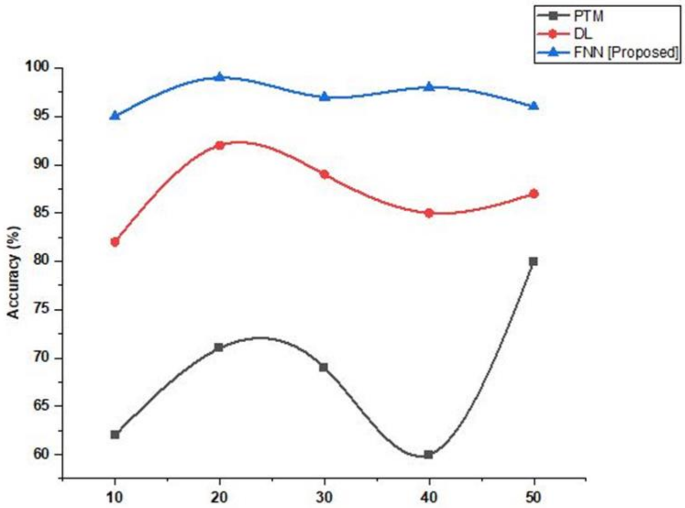

Figure 3: Accuracy comparisons of proposed and existing methods.

Table 1: Value of Accuracy

Accuracy (%)			
	PTM	**DL**	**FNN [Proposed]**
10	**62**	**82**	**95**
20	**71**	**92**	**99**
30	**69**	**89**	**97**
40	**60**	**85**	**98**
50	**80**	**87**	**96**

Precision

Precision, which can be simply defined as the proportion of correctly classified cases in all cases of predictively positive data, is the primary requirement for accuracy. To calculate the precision, use equation (8).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (8)$$

The precision measurements' comparable values are displayed in Figure 4. The proposed approach has a FNN value of 97%, which is higher than that of existing methods such PTM, which has a precision rate of 89%, and DL, which has a precision rating of 80%. Compared to existing approaches, the proposed FNN has better Precision and performs well in e-commerce user behavior. Table 2 shows the recommended method's precision compares to the current approaches.

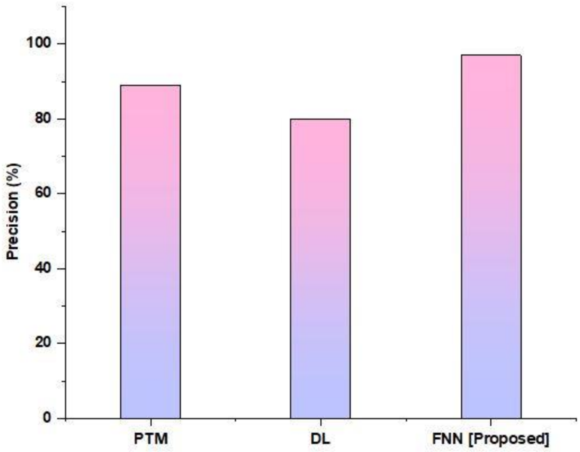

Figure 4: Precision comparisons of proposed and existing methods.

Table 2: Value of Precision

Techniques	Precision (%)

PTM	89
DL	80
FNN [Proposed]	97

Recall

Recall refers to a model's ability to recognize each significant sample in a set of collected data. From a statistical perspective, the definition of it is the ratio of True Positives to the total of True Positives and False Negatives. Equation (9) is utilized to compute the recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (9)$$

A comparison of the recall measures' data is displayed in Figure 5. There were 73.2% recall rates for PTM and 82.8% for DL. Recall of 95.8% was achieved by the suggested strategy, which outperformed the present findings. Table 3 compares the proposed method's recall to the current approaches.

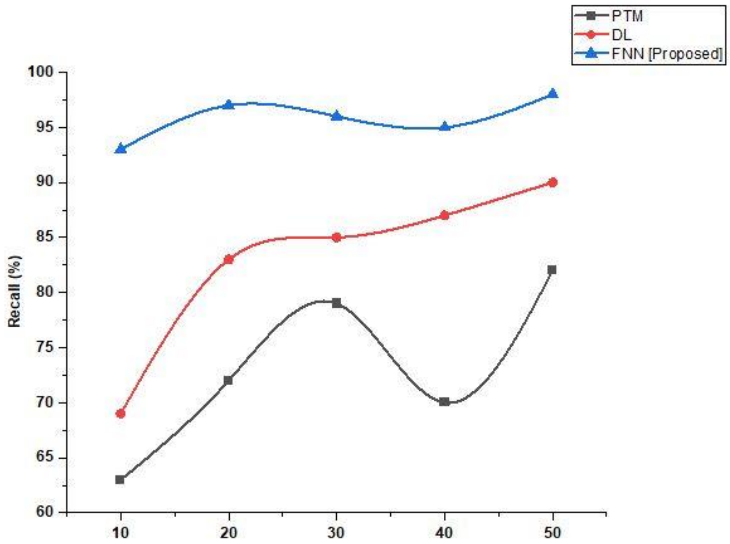

Figure 5: Recall comparisons of proposed and existing methods.

Table 3: Value of Recall

Recall (%)			
	PTM	DL	FNN [Proposed]
10	63	69	93
20	72	83	97
30	79	85	96
40	70	87	95
50	82	90	98

Computation time

Computation time is the amount of time needed to carry out a calculation.The term computation time describes how long it takes a computer or other system to perform a certain activity or action. Depending on the size of the work, it might be expressed in seconds, moments, hours, or even days.The complexity of the algorithm, the volume of the input data, the speed and effectiveness of the hardware and software being utilized, and the accessibility of computational power are just a few of the possible variables that might affect the long a work takes to compute.Computation time is a significant factor in several domains, including scientific computing, machine learning, and computer graphics, where large-scale calculations are frequent. In the proposed method the computation time is low compare to existing approach. The computation time of the suggested method is displayed in Figure 6. Table 4 presents the outcome of the proposed method.

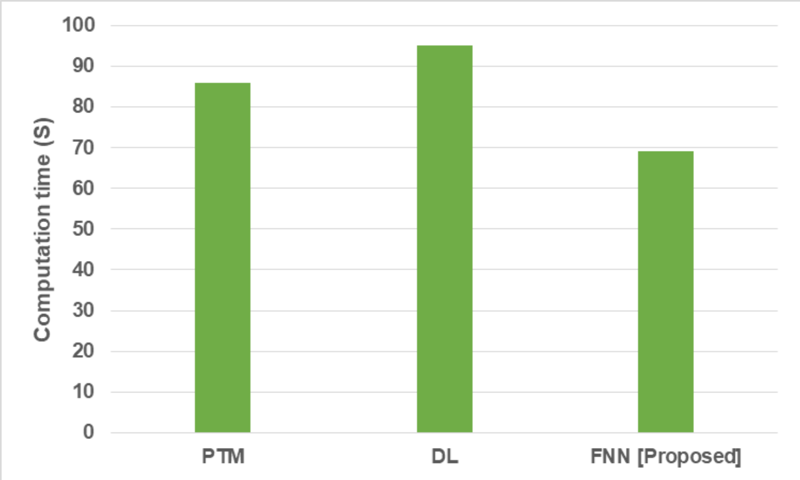

Figure 6: Computation time comparisons of proposed and existing methods

Table 4: Results of Implementation cost

Techniques	Computation time (s)
PTM	86
DL	95
FNN [Proposed]	69

Implementation costs

The losses incurred in developing and implementing a plan to implement one or more particular concrete proof treatments are known as implementation costs. While designing an implementation, it is important for businesses to take their budget and needs into thorough consideration in order to make the project effective and long-lasting. Compared to a conventional e-commerce implementation, using a data-driven approach to user behavior analysis provides additional costs (AC). The cost of implementation includes indirect costs (IC) like overhead and administrative charges as well as direct costs (DC) like materials, labor, and equipment. Figure 7 illustrates the cost of implementing the suggested strategy. Table 5 displays the recommended technique's implementation cost results. It demonstrates that the recommended strategy requires a lower expenditure. An expression for a general illustration of implementation costs is as follows equation (10):

$$\text{implementation costs} = DC + IC + AC \tag{10}$$

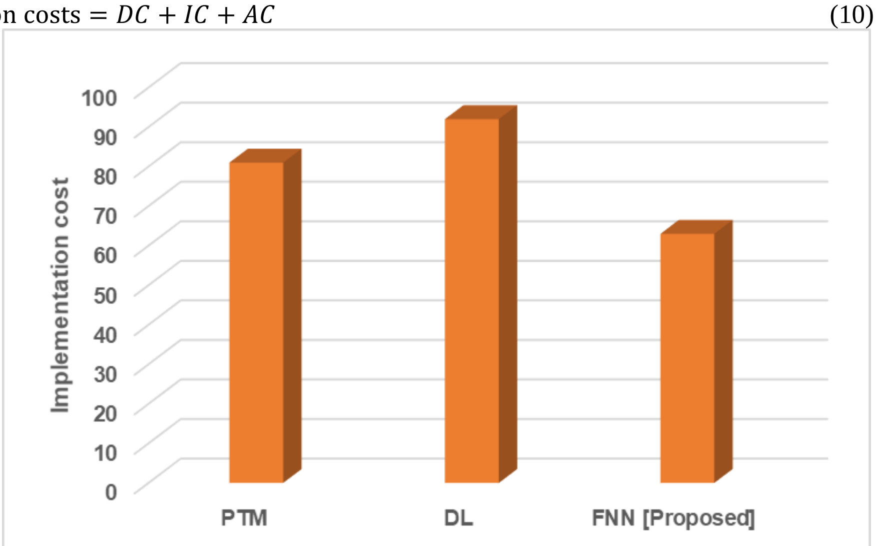

Figure 7: Implementation cost of proposed and existing methods

Table 5: Value of Implementation cost

Techniques	Implementation cost
PTM	**81**
DL	**92**
FNN [Proposed]	**63**

4. Conclusion

This study's findings suggest that anticipated short-term utility, projected long-term utility, previous history and favorable factors are all highly linked to online activity for commercial purposes. Although internal variables have a role in online use, it is essential to emphasize that external ones have a significant additional effect. One of the critical takeaways from this research is that respondents' level of Internet-use competence is a crucial motivator. Thus, favorable circumstances will play an essential part in assisting producers in accomplishing this aim. It may prove fascinating to look into what influences consumers to purchase online. Additional investigation on online shoppers' demographics is needed to understand their biases for specific product categories better. Much of this work might be done with a customer initiative inside the sector. With our suggested FNN approach, we were able to achieve a precision of 98%. Future research might focus on expanding current methods of user behavior training and exploring alternative brain architectures to enhance model precision.

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