Enhancing e-Commerce Strategies: A Deep Learning Framework for Customer Behavior Prediction

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ABSTRACT

Today, the use of artificial intelligence (AI) to enhance the processes of online shopping is crucial for e-commerce as it uses the past purchasing behavior of customer-automated processes. Nevertheless, predicting or understanding customers' buying behavior remains a major challenge. This research work attempts to put forward a new approach by utilizing Deep Learning (DL) models to identify whether a customer will buy or not depending on his age and salary. By employing lightweight dense layers in the DL architecture, the model is trained with the use of publicly available datasets and has great accuracy and performance metrics. This predictive model offers valuable lessons for e-commerce because the recommendation and marketing personalization methods it deploys can be integrated into the business to yield improved experience and performance for customers and users.

Keywords-artificial intelligence; deep learning; e-commerce applications; customer buying behavior

I. INTRODUCTION

New technologies have simplified online access to a constant stream of instant buying opportunities, which brings both benefits and challenges, involving the temptation and ease of impulse buying [1, 2]. According to [3], impulse buying happens when someone suddenly decides to buy something without planning or considering their long-term goals and priorities. This kind of buying is frequently linked to extreme shopping behavior that could negatively impact a person's welfare and financial status, particularly when shopping online [4]. In digital marketplaces, targeted advertising is a vital marketing strategy, where companies use information from customers' web browsing and search behaviors to show the latter more relevant to their preferences ads and keep them engaged with personalized messages [5-8]. Social media, in particular, can be effective for personalized advertising and can lead to impulse buying. Therefore, it is important to understand how consumers feel about targeted advertising, as a positive attitude towards these ads is linked to their intentions and actual buying behavior. Most businesses are primarily focused on extracting consumer insights explicitly, based on the latter's expressed characteristics, by going through their comments, scores, and others. These techniques, undoubtedly, can deliver useful information but, they are, obviously, time-consuming and even more tedious if one wants to understand people's intentions on purchasing something based on their interactions with the products' review pages. Such a targeting method may waste too much of the resources and could be inaccurate in predicting the potential customers' behavior.

The present study puts forward an innovative means to enable a more accurate forecast of customer buying behavior through the assimilation of personal information (age and salary) at the registration stage. This way companies can quickly filter-out less likely average buyers, saving their marketing funds and effort for more qualified users. This strategy can save resources and time, leading to more precise targeting and sales serving the aim of the market. This paper introduces a DL model reinforced with a Machine Learning (ML) based approach incorporating variable patterns to achieve high predictability through the collected information. It encompasses unsupervised learning for feature extraction and iterative self-training to minimize categorization errors [9, 10]. This incorporation is achieved in an easy-to-use and expandable manner enabling it to be inserted into different online shopping platforms.

The main contributions of the current work are:

- Integration of personal information (age and salary) at the registration stage to enhance the accuracy of customer buying behavior forecast.
- Implementation of a DL model based on dense layers to predict customer purchasing behavior, classifying consumers into binary categories (likely to buy and not likely to buy).
- Proposal of a more efficient marketing strategy by quickly filtering out less likely average buyers.

- Facilitation of more precise targeting and sales through the assimilation of personal information, leading to enhanced market outcomes.
- An easy-to-use and expandable model is proposed, that can be inserted into various online shopping platforms for improved customer behavior prediction.

II. RELATED STUDIES

In the recent years, Artificial Intelligence (AI) gained notable attention across several sectors, with growing interest in Artificial Neural Networks (ANNs) for several tasks, such as prediction, recognition, and big data analytics [11]. AI systems are considerably applied in computer science and numerous other disciplines, providing a competitive edge over conventional statistical models. The core concepts of AI include ANNs, evolutionary computing, fuzzy inference systems, and expert systems [12, 13]. Recently, organizations have faced increasingly dynamic, uncertain, complex, and unclear economic environments, wherein changes in technology, environments, and socio-economic factors continually contest and erode existing competitive advantages, making them fleeting and temporary [14, 15]. ANNs are distributed systems that process information and are composed of numerous simple computational units that interact through weighted connections. In today's hypercompetitive and complex corporate environment, various economic factors compete, collaborate, and sometimes work together to manage and analyze vast amounts of data [16, 17]. Authors in [18] studied the collection of explicit and implicit data from consumers to determine their perceptions based on nutritional information on particular products. In [19], a short-term context is provided to improve consumer product searches, indicating that the performance can be enhanced by employing the implicit user clicks from both long and short-term contexts. Nevertheless, it lacks comprehensiveness in terms of focus on the short-term scenario for individualized product searches. Authors in [20] explore the impact of implicit attributes on the consumer decision making process focusing on several different factors. Several research studies have examined the process of predicting consumer behavior [21, 22], focusing on different applications. In [23, 24], the authors describe predicting consumer behavior using sentiment analysis and analytical approaches, converting categorical inputs into numerical data to forecast consumer scores and ultimately predict behavior. However, these studies do not specifically address buying behavior.

DL has made significant strides across various domains, including the natural language processing [25], medical field [26-28], agriculture [29-31], smart transportation [32, 33], and e-commerce [34-36]. In the market, a substantial portion of tasks has been automated and computerized. However, despite these advancements, recent literature reveals a notable gap: there is still a lack of research focused on understanding customer purchasing behavior in relation to age and salary.

III. PROPOSED METHODOLOGY

The architecture of the proposed DL model is illustrated in Figure 1. The model consists of multiple dense layers designed to process the input data, including the age and salary information of customers. Each layer in the model plays a specific role in transforming the input data into a binary output indicating the likelihood of a purchase (Yes or No). The structure of the input layer, hidden layers, and the output layer is outlined demonstrating how the data flow through the network and how the various parameters are adjusted during training to optimize the model's performance, thus, providing a clearer understanding of the latter's intricate design and functioning.

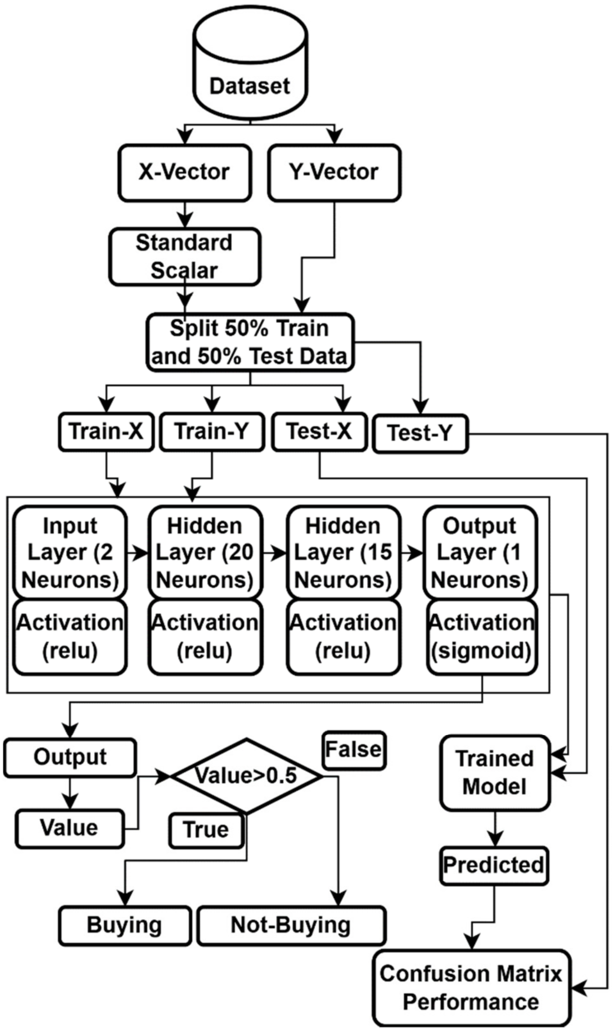


Fig. 1. The proposed. DL model for buying behavior prediction.

A. Hyper Parameters

The hyperparameters used in the provided code are: Adamax optimizer and binary_crossentropy loss function, which is suitable for binary classification tasks, while the model's performance is evaluated with the accuracy metric. The model is trained with a validation split of 25%, meaning that 25% of the training data are reserved for validation purposes. The batch size is set to 1, indicating that the model weights are updated after each training sample. Finally, the model is trained for 50 epochs.

B. Dataset Collection

The dataset was taken from [37], and provides an incredible opportunity to investigate the correlation between age, estimated salary, and consumer response to advert campaigns. On the other hand, knowing these relationships can lead to the development of predictive models, which will be deployed for forecasting future buying behaviors based on demography and financial factors. Figure 2 displays that the maximum age in the dataset is 60 years and the minimum age is 20 years, with the highest estimated salary being 140,000.

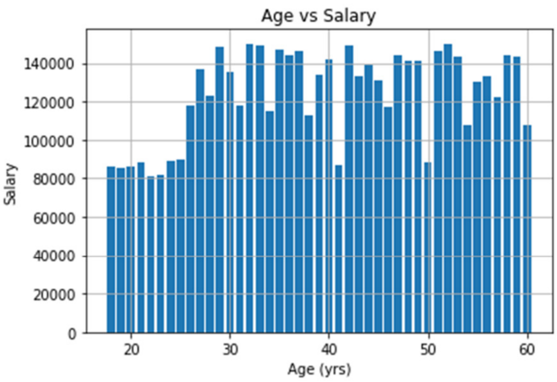


Fig. 2. Age vs salary of people in the dataset.

(a)
(b)

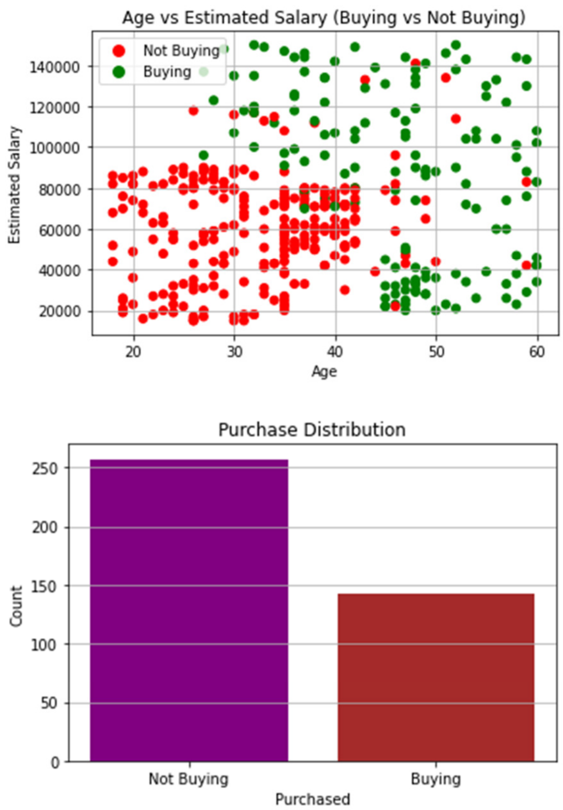


Fig. 3. (a) Scattered plot and (b) bar plot of purchased and not-purchased behavior of the people of the dataset.

Figure 3 presents a scatter plot disclosing the relationship between salary and age and highlighting the buying behavior of individuals. The plot differentiates between those who have made purchases and those who have not. It reveals that individuals aged 20 to 40 with an estimated salary ranging from 20,000 to 80,000 tend to have limited purchasing power, as indicated by the higher concentration of non-purchasers within this demographic group of the bar plot. This insight suggests that within this age and salary bracket, there is a noticeable trend of lower buying activity. In the entire dataset, both the age and estimated salary columns exhibit a normal distribution, as illustrated in Figure 4, which resembles a bell curve. The bell-shaped curve indicates that the majority of observations cluster around the mean, with fewer instances occurring at the extremes.

(a)
(b)

Fig. 4. The normal distribution of the independent dariables.

C. Standard Scalar and Splitting of the Dataset

The dataset consists of three columns. The first two columns, Age and EstimatedSalary, are independent variables and are referred to as the X-Vector. The third column, Purchased, is the dependent variable, representing a person's buying behavior, and is referred to as the Y-Vector. A sample can be seen in Table I.

The X-Vector is passed through a standard scaler to ensure that the set of data being fed to the machine is standard. The main function of this scaler is to scale each value to be within the range of 0 and 1. Standardizing features includes the mean and variance being zero and one respectively. If mean and/or standard deviation is set to true, the standard score of a sample x is defined as: z=x-μ/σ, where μ is the mean of the training samples and σ is their standard deviation. In the case of centering and scaling, the statistics are computed for each feature on the training set. These mean and standard deviation values are later used for transformation of the new data into the known distribution [38]. The proposed model splits the standardized vectors into 50% training data and 20% test data, with samples depicted in Tables II and III, respectively.

TABLE I. SAMPLE OF X- AND Y-VECTORS

X-Vector		Y-Vector
Age	EstimatedSalary	Buying behavior
26	80000	0
26	52000	0
20	86000	0
32	18000	0
18	82000	0
29	80000	0
47	25000	1
45	26000	1
46	28000	1
48	29000	1
45	22000	1

TABLE II. SAMPLE FROM TRAIN DATA

S.No	Age	EstimatedSalary
1	0.216134	-0.27906
2	2.065931	2.257809
3	1.871216	-1.19351
4	1.384427	-0.83953
5	0.897638	1.372856
6	1.481785	2.257809
7	-0.27065	-1.16401
8	1.968574	1.018875
9	0.702923	-0.63304
10	-1.43895	0.458405

TABLE III. SAMPLE FROM TEST DATA

S.No	Age	EstimatedSalary
1	0.044078	-0.67938
2	-0.23727	0.058274
3	-0.70618	0.176299
4	-0.23727	-0.67938
5	-0.98753	-1.56456
6	-0.6124	-1.71209
7	-0.14349	2.094192
8	-1.83157	-0.14827
9	0.88812	-0.88592
10	-0.70618	-0.70888

D. Deep Learning Model Construction

The DL model consists of 4 layers: input, output, and two hidden layers. The input layer contains two neurons as the shape of the input data contains 2 columns in the input vector. The output layer contains one neuron and the output has binary the form of 'Yes' (1) or 'No' (0) buying behavior. After some trials, the optimized values were 20 neurons at the first hidden layer and 15 neurons at the second hidden layer. ReLu function is applied at each layer to convert the product of input with weight and the addition of biases to obtain a single output. Figure 5 portrays the complete description of the proposed DL model with the parameters of each layer.

```
Layer (type)            Output Shape          Param
#
=====================================================
dense_16 (Dense)         (None, 2)             6
-----------------------------------------------------
dense_17 (Dense)         (None, 20)            60
-----------------------------------------------------
dense_18 (Dense)         (None, 15)            315
-----------------------------------------------------
dense_19 (Dense)         (None, 1)             16
=====================================================
Total params: 397
Trainable params: 397
```

Fig. 5. Summary of the DL model.

E. Prediction at the Output Layer

By deploying a sigmoid function in the output layer, the model calculates the probability of predicting the target labels (i.e. the buying behavior as 'Yes' (1) or 'No' (0)). The net input is determined utilizing (1), where the weight vector is denoted as w, the input vector as x, and the bias as b. The sigmoid function is then computed employing (2).

$$f(z) = \frac{1}{1-e^{-(z)}} \tag{1}$$

where:

$$z= \left(\sum_{i=1}^{n} xi\ wi + bi\right)$$

$$\text{Output} = \begin{cases} 1, & f(z) > 0.5 \\ 0, & f(z) < 0.5 \end{cases} \tag{2}$$

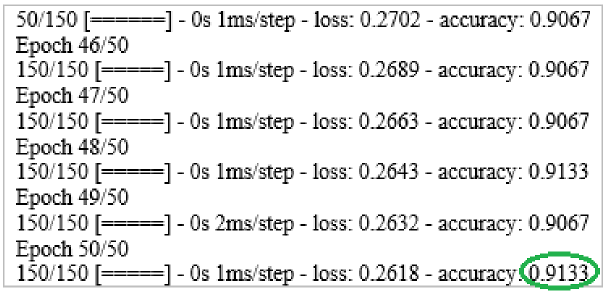
If the resultant value at the output layer is greater than 0.5, it indicates that the customer is likely to exhibit a buying behavior, categorized as 'Yes'. Conversely, if the resultant value is 0.5 or lower, it suggests that the customer is unlikely to exhibit a buying behavior, categorized as 'No'.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

After implementing the proposed model in Python using Keras and TensorFlow, the former was trained on the training data depicted in Table II. Following numerous attempts to optimize the model, the final set of hyperparameters was determined. The model implements the Adamax optimizer and binary_crossentropy loss function, with a validation split of 0.25 and a total of 50 epochs. Figure 6 illustrates the training progress over the last five epochs, where the model achieved 91% accuracy at the final layer.

A. Prediction of Test Data

The test data from Table III were applied to the trained model. The model then predicted the output for each row of the test data. These predictions are presented as a sample in Table IV, demonstrating the model's ability to forecast the target labels based on the test input.



```
50/150 [======] - 0s 1ms/step - loss: 0.2702 - accuracy: 0.9067
Epoch 46/50
150/150 [=====] - 0s 1ms/step - loss: 0.2689 - accuracy: 0.9067
Epoch 47/50
150/150 [=====] - 0s 1ms/step - loss: 0.2663 - accuracy: 0.9067
Epoch 48/50
150/150 [=====] - 0s 1ms/step - loss: 0.2643 - accuracy: 0.9133
Epoch 49/50
150/150 [=====] - 0s 2ms/step - loss: 0.2632 - accuracy: 0.9067
Epoch 50/50
150/150 [=====] - 0s 1ms/step - loss: 0.2618 - accuracy: 0.9133
```

Fig. 6. Training of the proposed model.

TABLE IV. SAMPLE OF THE PREDICTION ON THE TEST DATA

S.No	Age	Estimated salary	Actual behavior	Sigmoid predicted behavior
1	-0.70618	0.412347	0	0
2	0.044078	-0.67938	0	0
3	-0.23727	0.058274	0	0
4	-0.70618	0.176299	0	0
5	-0.23727	-0.67938	0	0
6	-0.98753	-1.56456	0	0
7	-0.6124	-1.71209	0	0
8	-0.14349	2.094192	1	1
9	-1.83157	-0.14827	0	0
10	0.88812	-0.88592	0	1

During both the training and testing stages of the proposed model, there is a noticeable trend of decreasing loss and increasing accuracy, as displayed in Figure 7. This pattern suggests that as the model learns from the data and iteratively adjusts its parameters, it becomes more proficient at making predictions with reduced error and improved precision. This observed decline in loss signifies that the model is converging towards better performance, while the simultaneous increase in accuracy indicates its growing ability to correctly classify instances within the dataset.

B. Statistical Analysis

The proposed model correctly predicts most of the classes, though there are some incorrect predictions. To evaluate the model's performance, the count of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) is used. A true positive (true(1)) is when the model correctly predicts a value of 1, which was actually 1. A false positive (false(1)) is when the model predicts a value of 1, but the actual value is 0. A true negative (true(0)) is when the model correctly predicts a value of 0, which was actually 0. A false negative (false(0)) is when the model predicts a value of 0, but the actual value is 1. The confusion matrix parameters [39, 40] derived from the predictions evidenced in Table IV are presented in Table V. This table includes the counts of TP, FP, TN, and FN, providing a detailed breakdown of the model's performance in predicting the target labels. Accuracy, recall, and F1-score are determined by [41, 42]:

$$\text{Presicion}=\frac{TP}{TP+FP} \tag{3}$$

$$\text{Recall}=\frac{TP}{TP+FN} \tag{4}$$

$$\text{F1}=\frac{2(\text{Precision}*\text{Recall})}{\text{Precision}+\text{Recall}} \tag{5}$$

$$\text{Accuracy}=\frac{TP+TN}{TP+FP+TN+FN} \tag{6}$$

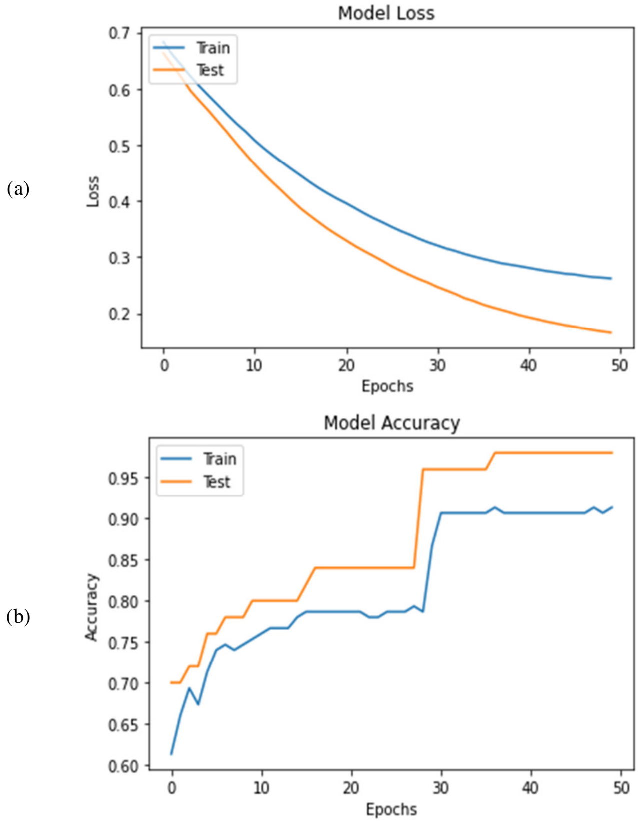


Fig. 7. (a) Loss and (b) accuracy during training.

TABLE V. CONFUSION MATRIX PARAMETERS

S.No	Actual behavior	Sigmoid predicted behavior	Confusion matrix parameters
1	0	0	True(0)
2	0	0	True(0)
3	0	0	True(0)
4	0	0	True(0)
5	0	0	True(0)
6	0	0	True(0)
7	0	0	True(0)
8	1	1	True(1)
9	0	0	True(0)
10	0	1	False(1)
11	1	0	False(0)

By applying (3)-(6), the proposed model demonstrated the excellent precision, recall, and F1 score, as detailed in Table VI. In particular, for the class 'No' (0), the model achieved a precision of 0.91, meaning that 91% of the predictions for this class were correct. The recall for this class is 0.88, indicating that the model correctly identified 88% of all actual 'No' cases. The F1 score, which is the harmonic mean of precision and recall, is 0.90 for this class. For the class 'Yes' (1), the precision is 0.81, indicating that 81% of the predictions for this class were accurate. The recall is 0.85, meaning the model correctly identified 85% of all actual 'Yes' cases. The F1 score for this class is 0.83. On average, the model has a precision and recall of 0.87, with an overall F1 score of 0.87. The accuracy of the model, which measures the proportion of all correct predictions, is also 0.87. Figure 8 visually represents the performance metrics.

TABLE VI. CONFUSION MATRIX MEASURES OF THE PROPOSED MODEL

Class	Precision	Recall	F1 score
Buying Behavior 'No' (0)	0.91	0.88	0.90
Buying Behavior 'Yes' (1)	0.81	0.85	0.83
Average	0.87	0.87	0.87
Accuracy	0.87		

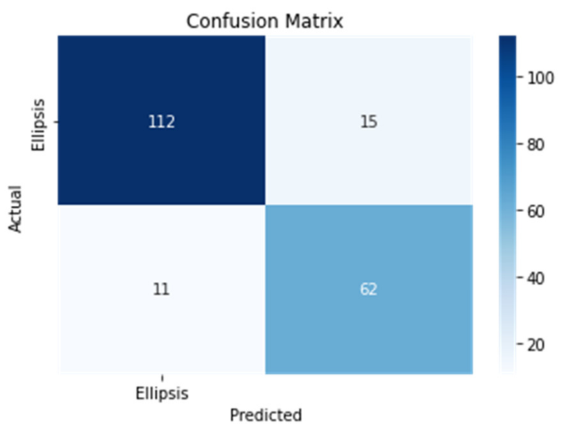


Fig. 8. The confusion matrix.

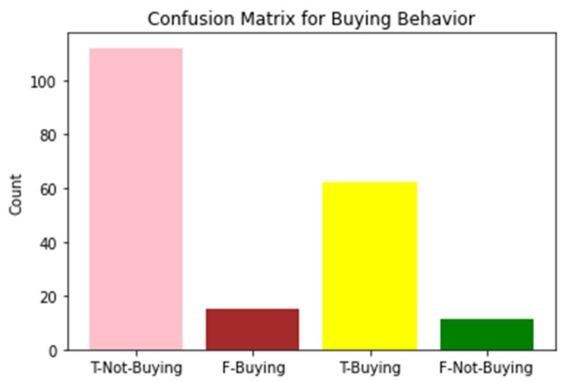


Fig. 9. Comparison of true and false classification.

In Figure 9, the comparison between true and false classifications reveals a notable trend: true values outweigh false values, suggesting a commendable accuracy in the model's predictive capabilities. This distinction is pivotal, as it underscores the model's ability to accurately identify instances where a customer's purchasing behavior aligns with the predictions made by the model. True values, representing instances where the model correctly predicts a purchase or non-purchase decision, dominate the comparison, signifying the efficacy of the proposed model in discerning genuine buying behavior patterns. Conversely, false values, though present, are comparatively lower. In Figures 10-12, the precision, recall, and F1-score metrics pertaining to different categories of buying behavior—namely, buying behavior categorized as "Yes," buying behavior categorized as "No," and the collective buying behavior encompassing both "Yes" and "No"—show remarkable levels of performance.

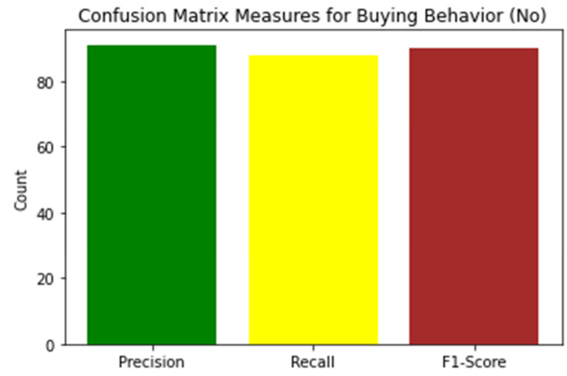


Fig. 10. Confusion matrix measures for Buying Behavior (No).

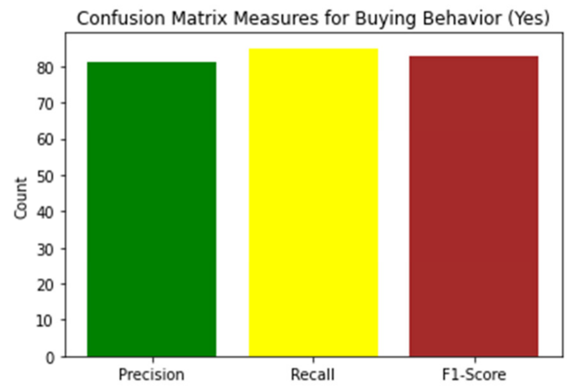


Fig. 11. Confusion matrix measures for Buying Behavior (Yes).

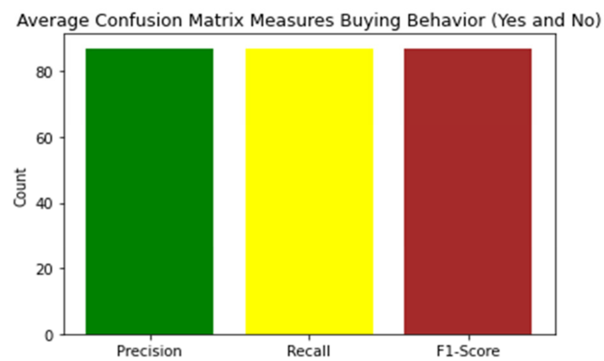


Fig. 12. Average confusion matrix measures for Buying Behavior.

Receiver Operating Characteristic (ROC) curves [43], are used to manifest how well a test or combination of tests balance between sensitivity (the ability to correctly identify positives) and specificity (the ability to correctly identify negatives) at different cutoff points. The area under the ROC curve gives an overall measure of how well the tests perform within a model. A larger area under the curve suggests a more effective test. This helps in comparing different tests. In Figure 13, the ROC curve for the proposed model on test data is exhibited.

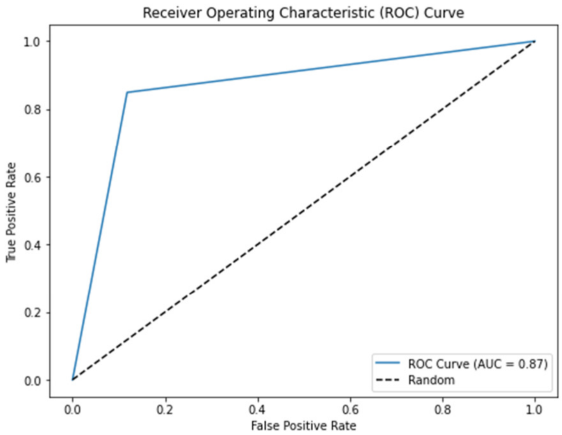


Fig. 13. ROC curve of the proposed model.

C. Implications to Research Community

It is particularly relevant in the increasingly connected arena of virtual commerce where determining and forecasting consumer behavior has become crucial owing to the many instant purchasing options made available by new devices. One of the issues that is noticed in the digital world setting is that there is a lot of impulse buying. Online advertisement is one of the main forms of digital marketing which relies on consumers' personal information to target them with adverts effectively to increase consumer interest. Social media sites are particularly more effective than most other media in providing personalized ads that will create further impulse to their users to buy. To overcome these issues and increase the predictive power of the model, this research develops a new strategy that combines age and salary information right on the point of a registration to increase the power of prediction regarding potential consumer behavior. The integration of the above stated demographics and financials as well as their analysis should allow to better focus sales effort and resource allocation towards qualified potential customers and increase the overall efficacy of selling. The proposed DL model presents consumers as two binary groups: those who are potentially willing to make a purchase (Yes) and those who are not (No). The model was able to demonstrate high predictability through constant testing and improvements during the model optimization thus signifying high performance. Specific analysis of the performance of the model showed promising accuracy, recall, and F1 measure in both product purchase types. Interestingly, the model achieved an average accuracy rate of 87%, indicating that it is efficient in capturing the consumer choice decision.

The proposed model was tested with the data and proved to be effective by means of the ROC curve. Overall, it is possible to regard the proposed research as a valuable contribution to the literature on consumer buying behavior and the potential to apply DL and demographics in various business scenarios to predict buying behavior. With this approach, companies will be able to strengthen their marketing initiatives, increase the use of such resources bailing on greater customer experience and satisfaction in the digital sphere.

V. COMPARISON WITH SIMILAR STUDIES

The work in [5] focuses on predicting consumer behavior by analyzing implicit product properties through DL techniques. It emphasizes the consumer's journey from viewing a product to purchasing it, considering key variables based on consumer perspectives and product properties. This approach extracts insights from implicit properties, such as customer preferences, product quality perception, and purchasing actions, generating valuable data for accurate behavior prediction. In contrast, the proposed work introduces a new approach that utilizes DL models to predict whether a customer will buy a product based on age and salary at the registration stage. By incorporating lightweight dense layers in the DL architecture, the model is trained on a publicly available dataset, achieving high accuracy and performance. This predictive model offers valuable insights for e-commerce, thereby improving customer experience and business performance. The proposed work achieves the highest scores in accuracy, precision, recall, and F1 score, as noticed in Table VII.

TABLE VII. COMPARISON WITH SIMILAR STUDIES

Model	Accuracy	Precision	Recall	F1-Score
Decision Tree	62%	-	75%	79%
Random Forest	65%	-	72%	73%
Support Vector Machine	62%	-	71%	77%
Artificial Neural Network	69%	-	76	80%
Recurrent Neural Network	71%	-	79%	81%
Proposed	**87%**	**87%**	**87%**	**87%**

VI. CONCLUSION

This paper has effectively outlined a new workflow for predicting consumer buying behavior through the use of Deep Learning (DL) and demographic data. The proposed model shows excellent potential for categorizing consumers as potential purchasers based on its high precision and recall rates and high F1 scores. The research also emphasizes the need to use the age and salary variables in predictive models to expand their potential in the dynamic environment of the online marketplace. There are several lines of research for future work that present opportunities to further develop and apply the above proposed framework. Firstly, it would be possible to extend the model to include other demographic factors and behavioral data in order to create a more thorough explanation of consumer behavior. Furthermore, incorporating live feeds and big data analysis algorithms can improve the model's potential to make dynamic forecasts and learn from changes in the market. This study provides a solid groundwork for the future research on the subject of consumer behavior prediction in the digital age and can be useful for businesses in terms of developing the best approach and strategy for their effective marketing. Through constant improvement and broadening of this framework, researchers and practitioners will be able to identify new ways of using data based on insights to further innovation and growth in the highly dynamic realm of e-commerce.

While the obtained results are commendable, it is imperative to recognize certain limitations for future investigations. Firstly, this research is confined to understanding buying behavior solely based on age and estimated salary. While these factors are undoubtedly influential, future studies may benefit from incorporating additional variables to create a more comprehensive understanding of consumer behavior. Additionally, the proposed model utilizes a data split of 50% for testing and 50% for training, with a validation split of 25% refined over 50 epochs. Although this setup has yielded promising results, exploring different ratios and durations based on varying hyperparameters could provide deeper insights into the model's performance and enhance accuracy. Moreover, the proposed model employs standard scaling techniques, yet there is a potential for improvement by exploring alternative hyperparameters and vector techniques, such as max scaling or mini scaling. Investigating these variations could lead to further enhancements in accuracy and provide a more robust framework for predicting consumer behavior in online shopping environments.

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