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A DENSE RECURRENT NEURAL NETWORK WITH ATTENTION MODEL AND PRECISE FEATURE RETRIEVAL FOR CUSTOMER BEHAVIOUR PREDICTION TO ENHANCE MARKETING DECISIONS

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ABSTRACT

Online platforms are essential for consumer interaction in the digital environment. In the current situation, it is critical to comprehend consumer behaviour in order to improve user experience, maximize marketing efforts, and improve company expansion. Nowadays, the majority of consumer behaviour models are constructed by applying machine learning and data mining techniques to real customer data. Forecasting customer behaviour is a difficult and unpredictable task. Therefore, sophisticated techniques and approaches are required to detect the client's behaviour. Thus, a new customer behaviour prediction model is implemented in this work to enhance consumers' experience in digital environments like online shopping. First, the customer behaviour data is collected from benchmark sites. Then, the collected data is utilized by the Restricted Boltzmann Machines (RBM) for retrieving useful features. These features are processed by the proposed Dense Recurrent Neural Network with Attention (DRNN-A) for predicting customer behaviours. This model is helpful for business organizations to increase their profits by showcasing the products that are frequently purchased by customers. Experimental evaluations are performed to check the prediction efficacy of the developed model.

Keywords- *Customer Behaviour Prediction; Marketing Decisions; Restricted Boltzmann Machines; Dense Recurrent Neural Network with Attention*

1. INTRODUCTION

The purchasing behaviour of the consumer has drastically changed with the expansion of the e-commerce markets [1]. The need for precise and understandable prediction models emerges, which can assist companies in making strategic decisions by predicting the behaviour of the customer. Business organizations improve client retention and manage inventory effectively with the help of consumer behaviour analysis. Despite the availability of recent models on consumer behaviour-related topics, a state-of-the-art assessment of consumer behaviour still needs improvement. Marketing strategy planning is made more difficult because of the cultural shifts that affect consumer behaviour. Customers' perceptions of the same products vary from person to person. Consumer behaviour is examined by both internal and external factors [2]. Economic and psychological circumstances are examples of internal causes, while social and cultural issues are examples of external impacts. Consumer behaviour in the market is essential to economics, marketers, etc. Consumers purchase their needs based on their preferences and financial constraints. Consumer behaviour is the subject of numerous theories and models. Consumers may also be impacted by peer pressure, social influence, brand loyalty, and recommendations from friends and family. Some of these components might be less necessary, depending on the customers and circumstances. Customer behaviour and marketing strategy have dynamic interactions. Marketers can develop more tailored ads that better satisfy the needs and expectations of their target audience by using information from consumer behaviour analysis. To influence consumer behaviour, marketers invest in a variety of media platforms. Ads on each media

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platform are composed differently and uniquely engage viewers. Digitalization has altered the media habits of consumers [3].

Over the past few years, the widespread adoption of deep learning tools has improved the quality of life for people. The development of deep learning models has a significant impact on a number of fields, including literature, the arts, and science. The deep learning system can identify patterns in existing data [4]. This technique relies on models such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) for customer behaviour analysis. The development of these models has tremendously benefited from automated content generation to complex problem-solving in research contexts [5]. However, greater focus should be given to the useful applications of deep learning models in market research and consumer insights. Issues, including explainability and robustness, are the common issues faced by the prior models in this field. These gaps are filled by the suggested deep learning-assisted models that successfully perform the consumer behaviour analysis and xsdwe5345xsdwe53456+allow companies to handle the complexities of modern consumer dynamics.

Research design justification: In this research, an effective deep learning model is designed for customer behaviour prediction by leveraging the strengths of RBM-based feature retrieval and DRNN-A-enabled customer behaviour prediction. This model is generally applicable for forecasting the purchasing patterns of customers and to generate reliable customer-centric decisions by examining the large-scale behavioural patterns and highlighting complicated sequential details within the behavioural patterns. Thus, this integration enables the designed model to present a reliable customer behaviour prediction outcome and improve marketing decision-making.

Aim of the research: The core aim of this research is to develop an innovative and robust customer behaviour prediction model for determining the purchasing behaviour and their requirements. Moreover, this model concentrate to enhance customer engagement by providing customized recommendations. To ensure reliable prediction performance, the designed architecture employed an RBM-aided feature extraction procedure for highlighting the significant and hidden patterns within the given input data. Moreover, this employed a DRNN-A model for capturing both the significant temporal and sequential information from the extracted behavioural patterns, resulting in an accurate prediction outcome. Additionally, this research aimed to analyze the purchase behaviour of the customer for improving customer-centric decision-making and personalized recommendations related to marketing.

Significance of research contributions: The significance of this research lies in the introduction of an innovative customer behaviour prediction model for resolving the drawbacks faced by the classical customer behaviour prediction techniques and generating customer-centric decisions based on the customer requirements. The designed architecture integrates the strength of the RBM for capturing the latent behaviour patterns from the given customer behaviour data. The RBM concentrates on capturing the important hidden features within the behavioral data by effectively resolving the influence of gradient issues. Additionally, this work integrated a DRNN-A model for predicting the behaviour of each customer based on the extracted behavioral patterns. Here, the DRNN-A is responsible for capturing the temporal patterns and significant purchase behaviour to generate customer-centric decisions for increasing customer satisfaction and customer engagement. Furthermore, this model permits companies to analyze the purchase behaviour patterns and provide personalized recommendations for customers to improve the customer experience.

Contributions: The unique research contributions of the proposed research lie in the following points:

- To put forward a unique deep learning model for predicting customer behaviour, which is more important in the business sector for expanding and attracting their clients by designing effective marketing strategies. The suggested model greatly aided the business organization in determining the needs and wants of the customer to expand the success of the organization. In addition, the proposed model delivers the targeted marketing strategies for increasing sales and revenues in the company, and the designed model provides personalized recommendations to the user for enhancing the overall experience of the customer.
- To suggest RBM for extracting the pertinent features from the customer data collected to reduce the overall dimensionality. The complex data

distribution in the customer data is effectively learned by the RBM because of its higher computational efficiency. In addition, the non-linear patterns and relationship with the input data can be easily learned by the RBM, so it can extract only relevant features from the data, which greatly enhances the customer behaviour prediction capability of the suggested model.

- To recommend DRNN-A for predicting customer behaviour to enhance the marketing strategies of the business sector. The designed DRNN-A is adopted by the companies for enhancing the satisfaction of the customer via the optimization of the marketing efforts, which ultimately results in increased profitability in the business. Here, the proposed model incorporates an attention module with the DRNN that provides deeper insight into the behaviour and preferences of the customer and helps to provide targeted marketing strategies for enhancing the intent of the customer to buy the products and promote customer-centric decision making.

Organization: The overall organizations of the manuscript is given as follows: The reviews of the existing works are given in Section II. The fundamental illustration of the developed customer behaviour prediction model and its data source description is given in Section III. The attention-based deep structure for predicting customer behaviour, with its feature extraction step, is discussed in Section IV. The extensive experiments of the proposed model are given in Section V. The conclusion of the proposed model is given in Section VI.

2. LITERATURE SURVEY

2.1 Related Works

Literature Selection criteria: The literature for this research is selected based on customer behaviour prediction, examination, segmentation, customer engagement, and priority-based decision-making in e-commerce environments. Here, the recent studies between the time range 2019 and 2026 are selected as it offers the recent advancements made in the domain of artificial intelligence for accomplishing customer purchase behaviour prediction. Moreover, experimental reviews and comparative studies are also considered to validate the reliability of the literature.

In 2024, KIM *et al.* [1] have suggested the Recency, Frequency, Monetary, Visits, Durations, Actions (RFMVDA) model for classifying the data that reflects the behaviour of the customer. In the e-commerce environment, the session and behaviour units of the customer were analyzed by this model. Finally, the customer behaviour-based classification results were provided by the Deep Neural Network (DNN).

In 2019, LING *et al.* [2] have presented Fully Connected Long Short-Term Networks (FC-LSTM) for predicting the purchase intent of the customer. The features from the purchase history and demographics were integrated within the suggested model to improve the prediction performance. The extensive results of the proposed model were compared to prior approaches to confirm the overall efficiency of the model.

In 2023, LEE *et al.* [3] have proposed a hybrid model named Buy Till You Die (BTYD) with K-means clustering for the prediction of the behaviour from the customer churn. Then, the behaviour of the customer was divided into four types after observing the customer churn. The suggested model predicted the customer churn for retaining the important customers of the companies.

In 2025, Kasemrat *et al.* [4] have proposed an attention-enhanced Long Short-Term Memory (LSTM) for addressing the interpretability challenges to predict the high value of customers in the e-commerce sector. The outstanding predictive performance of the proposed model was confirmed in the experimentation process.

In 2022, Baratzadeh and Hasheminejad [5] have proposed a convolutional LSTM (C-LSTM) for detecting fraud actions during transactions. These models solve the unequal class distribution problem to provide sensible data that provides accurate results in fraudulent activity detection. In order to measure the results of the suggested model, the experimental validation was conducted with prior models.

In 2025, Kim *et al.* [21] have designed an effective behaviour prediction model named RFMVDA by leveraging the significance of deep learning. The core objective of this model was to highlight the customer information and behaviour details for improving e-commerce marketing. Further, the behaviour prediction process was carried out by the DNN model.

In 2025, Hooshmand *et al.* [22] have implemented an advanced LSTM model named DLSTM-GA by embedding the strength of Genetic

Algorithm (GA). This model aimed to predict the requirements of the customer by analyzing the behaviour patterns. Moreover, the GA was employed to boost the prediction performance of the model by fine-tuning LSTM parameters.

In 2026, Manikandan *et al.* [23] have designed an advanced machine learning model with a feature selection approach for performing robust customer segmentation by analyzing the purchase behaviour patterns. This model employed the Fuzzy-C-Means (FCM) clustering technique for accomplishing the segmentation procedure, while the Multilayer Perceptron (MLP) was employed for classification tasks. Finally, the effectiveness of the designed model was further improved through Enhanced Dung Beetle Optimization (EDBO)-based parameter optimization.

Need for proposed research: Thus, various research works have been implemented for predicting customer behavior. Though these works provide better results, they also have some problems. According to the discussed literature review, the DNN [1] [21] often depends on a handcrafted feature extraction technique for capturing the important behavioral indicators and lacks the ability to understand the sequential consumer actions or thoughts. The FC-LSTM [2] have offered precise prediction performance. Yet, it struggles to determine the most influential behavioral characteristic. Moreover, the clustering-aided model [3] [23] is less effective in capturing the complicated non-linear and temporal patterns while handling huge datasets. In addition, the attention-aided LSTM [4], Conventional-LSTM [5], and DLSTM-GA [22] are ineffective in capturing varying behaviour patterns of the customer, which is significant for generating personalized recommendations in dynamic e-commerce surroundings. These limitations indicate that effective feature extraction, temporal data modelling and comprehensive behavioural pattern analysis are essential for creating appropriate decisions regarding marketing strategies. Considering these drawbacks, this work designed an intelligent customer behaviour prediction model for enhancing marketing decisions by embedding an effective feature extraction mechanism.

2.2 Problem statement

In any type of industry, customer relationship management is considered a very important issue. The stable revenue for the company in the markets is provided by the stable consumer. The e-commerce sector uses the past purchase behaviour of users to enhance the production of the company. However, predicting the behaviour of the customer in a dynamic marketing environment is a challenging task because of the dynamic nature of customer contacts and purchase patterns. The challenges involved in the customer behaviour prediction by the prior models are listed in Table I.

- Understanding the customer buying behaviour via the existing models [1] [4] is a challenging task, and they do not provide the greatest accuracy in the task of behaviour prediction, so those models are not suited for providing the marketing personalization to enhance the yield of the company. In this work, feature extraction with a deep learning-based model is proposed that analyzes the behaviour of the customer for adopting the marketing personalization, which helps to increase the yield of the company.
- The influential behaviour features of the consumer are not analyzed by the existing models [2] [5], so they are not effective for providing targeted marketing strategies for the user. Here, the RBM is used for extracting the features from the data that seek to suggest marketing strategies for enhancing the growth of the markets and business organizations.
- The behaviour of the customer evolved over time, so an understanding of this data is required, but it is not possible with existing works [3] [22]. So, this research adopted a DRNN-A, which can effectively handle the growing complexity of the customer data for determining the actions of the different customers.

Table 1.Features And Challenges Of The Prior Customer Behaviour Prediction Models

Author [citation]	Methodology	Features	Challenges
KIM *et al.* [1]	DNN	• The high volume of data in the e-commerce platform can be easily handled through this model.	• The relationship between revenue growth and the retention rate is not analyzed by this model.
LING *et al.* [2]	FC-LSTM	• The interaction between the promotion model and the customer is	• The suggested model only focuses on the entertainment

		precisely modelled by this approach.	service products, and it does not have the capability to handle heterogeneous data.
LEE *et al.* [3]	BTYD and K-Means clustering algorithm,	• The change in the dynamic movement of the customer within the specified time is determined by this model.	• The repetitive behaviour of the customer is not determined by this model.
Kasemrat *et al.* [4]	LSTM	• The high-value customer in the e-commerce sector is determined by this model. The transparency of the influential behaviour of the customer is enhanced by this model.	• The robustness of the model is very low, and it has very low scalability.
Baratzadeh and Hasheminejad [5]	C-LSTM	• The dynamic behaviour of the fraudster is determined by this model.	• The occurrence of fraud in the banking sector is not determined by this model.

3. FUNDAMENTAL ILLUSTRATION OF THE DEVELOPED CUSTOMER BEHAVIOUR REDICTION MODEL AND ITS DATA SOURCE DESCRIPTION

3.1 Structural Illustration of Proposed Model

The development of e-commerce is promoted by the rapid development of internet technology. E-commerce has broad development prospects, as shown by the forecast of e-commerce transactions. The consumer behaviour-mining framework is used by most of the business sectors to serve their clients. These models are used in most of the sales, marketing and forecasting trends for increasing the yield by designing effective marketing strategies. The behaviour of the customer is predicted via the conventional machine learning models. The existing works do not accurately predict the actions of the user, and they also require a longer time for implementation. The pattern of the user behaviour is not analyzed by the prior models, so they are not effective for making promotional schemes for enhancing the services and products of the company. These critical issues of the prior models are solved by the new approach proposed in this research work. The overview of the proposed model is given in Fig. 1.

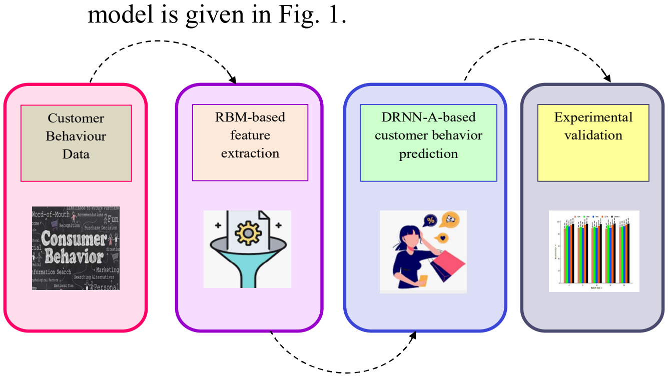

Fig 1. The overview of the proposed model

This research introduced a deep learning model for predicting customer behaviour to adopt marketing strategies for enhancing the growth of the company. The proposed deep learning paradigm analyzes the behavioural pattern of the user for designing promotional schemes for enhancing the reach of the product. The behaviour of the user with respect to the purchasing item is determined by the recommended model to increase the growth of the business and its earnings. The prediction of customer behaviour is more important for enterprises to better create their own product, which greatly enhances the profitability of the company. The suggested model provided accurate results in forecasting customer behaviour by finding the hidden patterns of the data, which facilitates the new product based on the preferences of the customer. This model enhances customer loyalty and increases the growth of the business, particularly in the sales sector, by predicting the behaviour patterns of the customers. This research collects the customer's behaviour data from two open resources. The collected customer data are passed to the RBM model for extracting the features from the high-dimensional data. In the prediction of customer behaviour, the useful features from the data retrieved by the RBM help to highlight the relevant aspects of the customer's behaviour in the collected data. The analysis of the data is simpler and easier with the feature extraction because it reduces the overall dimensionality of the data. The RBM model retains the important information in the collected data. The RBM has the capability to represent the high-dimensional data in a lower-dimensional space for eliminating the irrelevant features in the data, and underlying features in the data are learned for extracting the relevant features from the input data. Once the features are retrieved using the RBM, the DRNN-A performs the customer behaviour prediction task from the extracted features. The DRNN-A model attained higher predictive accuracy in the customer's behaviour prediction task since it incorporates the advantages of the attention module, which ensures the interpretability of the DRNN-A model. The influential behaviour patterns of the customer are effectively determined by the DRNN-A model and enable the prediction of the key customer behaviour. The suggested model is a more effective tool that aligns with the target marketing strategies to enhance the yield from the particular product or company. The recommended model enables the business to make effective decisions and marketing strategies to enhance the revenues of the company. The proposed model detects the purchasing behaviour (purchased or not purchased) of the consumer. The convenient outcome attained from the prior models is validated with the prior model to prove the effectiveness of the proposed approach.

3.2 Customer Behaviour Dataset Description

This research uses the two public resources for collecting the required customer behaviour data. The descriptions of the two open-source datasets are given as follows:

Dataset 1 (Online Shoppers Intention UCI Machine Learning): Dataset 1 is loaded from the link of https://www.kaggle.com/datasets/henrysue/online-shoppers-intention with access date: 2025-04-28. The feature vectors belonging to 12330 sessions are available in this dataset. The summary of the dataset has 1 file with 18 columns.

Dataset 2 (Customer-Behaviour): The Customer Behaviour source is the 2nd dataset taken from the link of https://www.kaggle.com/datasets/denisadutca/customer-behaviour with access date: 2025-04-28. The gender, unique ID, and salary of the customer and the salary of the 400 clients are included in this dataset. Whether the customer decided to buy the specific product or not is also collected from this dataset.

The term d_q is the collected customer behaviour data, and $q = 1,2.....Q$ here the total quantity of the collected data is represented as Q.

4. ATTENTION-BASED DEEP STRUCTURE FOR PREDICTING CUSTOMER BEHAVIOUR WITH ITS FEATURE EXTRACTION STEP

4.1 RBM for Feature Extraction

The RBM [16] is used for extracting the features from the data in the unsupervised setting. Here, the use of latent variables is used for modelling the independent structure between the variables of the network. This model extracts meaningful features from the data by analyzing its temporal and spatial structure. It requires only a single set of parameters for changing the entire topology. The o visible units are used for developing the RBM where $w \in \{0,1\}^o$, $i \in \{0,1\}^o$ and this model consists of n hidden units. Eq. (1) represents the joint probability of these units.

$$q(w,i) = \frac{1}{A} e^{-F(w,i)} \tag{1}$$

The energy function $F(w,i)$ is determined using Eq. (2).

$$F(w,i) = -b^T w - c^T i - w^T Xi \tag{2}$$

The interaction between the hidden and the visible units is expressed by the matrix $X \in \mathrm{M}^{o \times n}$, the visible and the hidden unit's biases are denoted as $b \in \mathrm{M}^o$ and $c \in \mathrm{M}^n$, the expression for the partition function is denoted in Eq. (3).

$$A(b,c.X) = \sum_{w,i} e^{-F(w,i)} \tag{3}$$

The visible units of the RBM are conditionally independent because of the bipartite structure of the network. In addition, the statistical dependencies between the visible units are also captured by the RBM. The expression for the update rule for the term X is denoted in Eq. (4).

$$\Delta X = \left\langle wi^T \right\rangle_{DATA} - \left\langle wi^T \right\rangle_{MODEL} \tag{4}$$

The expected value with respect to the data and model is represented as $\left\langle wi^T \right\rangle_{DATA}, \left\langle wi^T \right\rangle_{MODEL}$. The features attained from the RBM are demoted as g_o^{rbm}.

4.2 Recurrent Neural Networks

The RNN [18] model does not require extensive feature engineering for accurate customer behaviour prediction. The higher prediction accuracy is attained when applying the RNN model to the sequence of customer actions. With each action, the latent state is maintained by the RNN model. The sequence of the data $Y = y_1, y_2, y_3$ with varying length U is adopted by the RNN. The connected sequences of the computational cells are used for constructing the RNN. The hidden state $i_u \in \beta_e$ is maintained at the step u while handing the input y_u. The cell state at the previous time step i_{u-1} and the input y_u is used for computing the hidden state and it is given in Eq. (5).

$$i_u = \kappa\left(X_y y_u + X_i i_{u-1} + c\right) \tag{5}$$

Here, the learned weight is expressed as X, the sigmoid function is denoted as κ and the bias vector is expressed as c. From the input sequence, the information is captured through the hidden state i_u.

4.3 Dense RNN with Attention Model for Customer Behaviour Prediction

The extracted features g_o^{rbm} from the collected data are passed to the DRNN-A to predict the behaviour of the customers. The DRNN-A model attained higher prediction accuracy while ensuring the interpretability of the customer's behaviour prediction. Since complex relationships and patterns in the data can be easily captured through the dense RNN. The behaviour of the customer is better understood by the incorporation of the attention mechanism because it selectively focuses on the important parts of the features. Focusing on the most relevant parts of the input region helps to enhance the interpretability of the dense RNN. This enhanced interpretability highlights the important features of the prediction to get a reliable outcome. The dense RNN model provides robust performance in the analysis of the time series data, but the interpretation capability of the model is poor. These issues are solved by the attention model because it enhances transparency and interpretability in customer behaviour prediction. The extracted features are given to the DRNN-A model, where each layer of the model operates independently and remembers the past events. Further, the complex patterns of the features are learned through the dense connections within the model. When making the prediction, the most important parts of the input data are focused on by the attention model. Finally, the trends and patterns in customer behaviour are captured by the DRNN-A for accurate customer behaviour prediction. The marketing strategies are personalized based on the prediction results from the DRNN-A, where ad targeting is optimized for improving the product recommendations.

The dense RNN [17] can be used for analyzing the sequential data. The recurrent and feedforward paths are the major components of the dense RNN. The relationship between the recurrent and feedback reduces the complexity involved in customer behaviour prediction. Here, the gradient flow is greatly improved via the number of paths because of the increase in density of the connections. The vanishing gradient problem in time is prevented because of the increase in the magnitude of the gradients. Towards the residual connections, the skip connections are applied in the dense RNN. The skip connection through time is equal to the hidden state at the time u, which is obtained through the shortcut path from the prior multiple hidden states. The feedback connection between the different layers is available within the shortcut path of the network. The dense RNN is expressed in Eq. (6).

$$i_u^k = \kappa\left(X^k i_u^{k-1} + \sum_{l=1}^{L}\sum_{j=1}^{M} h^{(l,j)\to k} V^{(l,j)\to k} i_{u-l}^{j}\right) \quad (6)$$

The attention module is represented as $h^{(l,j)\to k}$, and it is given in Eq. (7).

$$h^{(l,j)\to k} = \varepsilon\left(x_h^j i_u^{k-1} + v_h^{(l,j)\to k} i_{u-l}^{j}\right) \quad (7)$$

The above expression indicates the prior hidden state, the vector is denoted as $v_h^{(l,j)\to k}$ and i_u^{k-1}, the sigmoid activation is denoted as ε, and the weight matrix is represented as $V^{(l,j)\to k}$. The pictorial illustration of the proposed DRNN-A-based Customer Behaviour Prediction is given in Fig. 2.

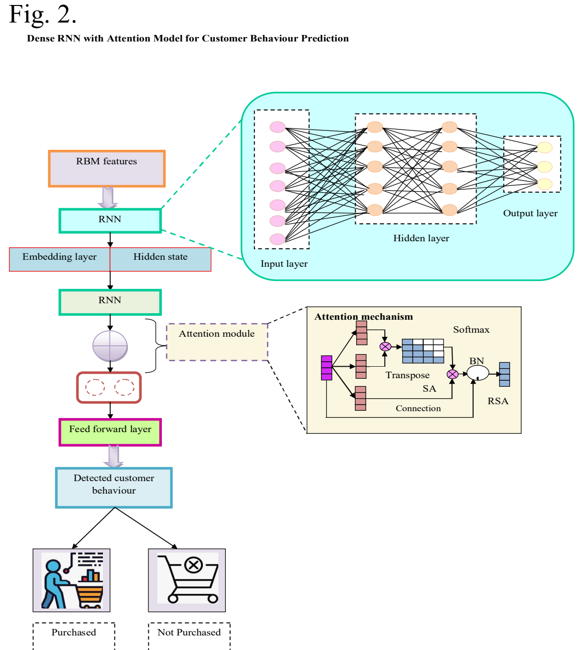

Figure 2. A pictorial illustration of the proposed DRNN-A-based Customer Behaviour Prediction

5. RESULTS AND EXPERIMENTS

5.1 Experimental Criteria

Python software was used for conducting the experiments on the proposed customer behaviour prediction model. The prediction performance of the proposed model was understood by comparing the results with the prior models, such as SVM [20], DNN [1], RNN [19], and LSTM [2]. In order to reduce the influence of uneven

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variations and guarantee an unbiased outcome, the simulation procedures were executed under specific circumstances by considering a definite hardware setup, evaluation measures, identical databases, data pre-processing procedures, hyperparameter configuration, epochs, train-test split ratio and batch sizes values. Here, the designed DRNN-A-aided customer behavior prediction model and existing prediction techniques like SVM, DNN, RNN, and LSTM were trained and validated by employing these experimental setups to ensure accurate and reliable performance.

5.2 Batch size-based analysis

Fig. 3 shows the experiment conducted on the proposed DRNN-A by varying the batch size to examine the performance of the customer behaviour prediction model. It is found from the graph that the suggested DRNN-A model gained significant advantages over the prior models, such as SVM, DNN, RNN and LSTM in the customer behaviour prediction, as the presented DRNN-A models reached an accuracy of 96.69%. The FNR of the proposed DRNN-A is used to further prove the efficiency of the suggested DRNN-A in the behaviour prediction. Here, the suggested DRNN-A model reaches the FNR of 0.71 to 0.63 while raising the batch size from 4 to 64. Thus, the results of the proposed DRNN-A supported the performance of the designed model in customer behaviour prediction, and this model can empathize with the behaviour of the customer to provide strong marketing strategies for enhancing the revenue of the organization.

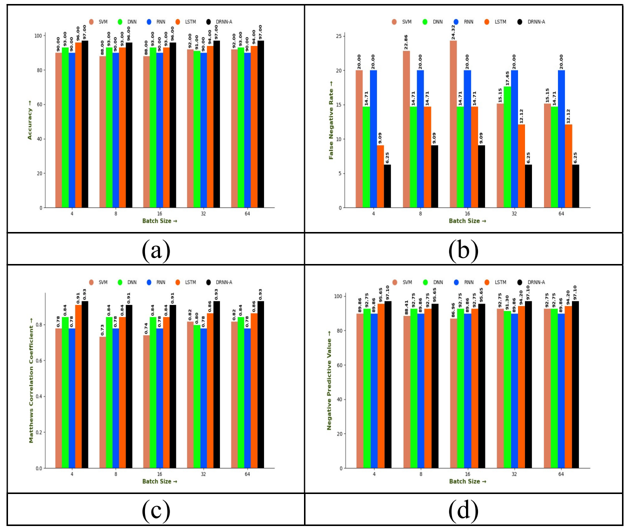
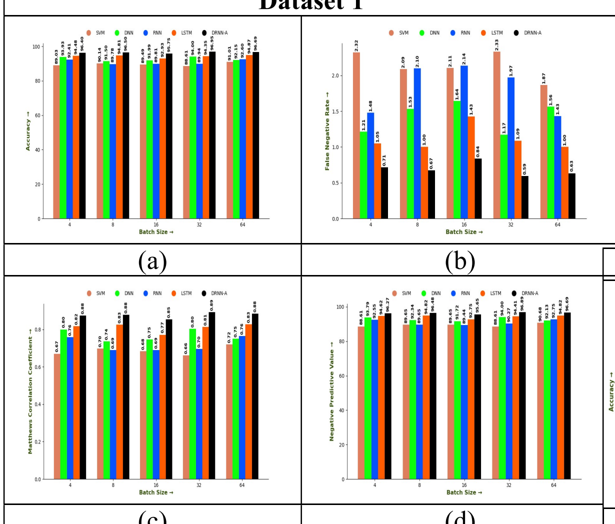


Figure 3. Batch size-based analysis of the proposed customer behaviour prediction model for (a) Accuracy, (b) FNR, (c) MCC, (d) NPV

Dataset 1

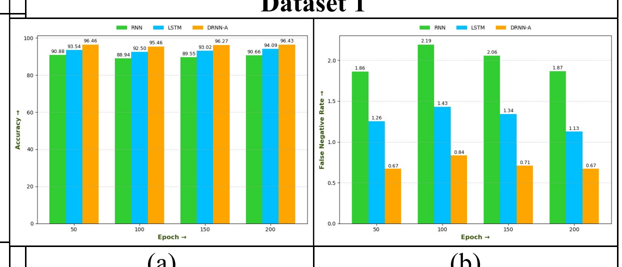


Dataset 2

5.3 Epoch-based analysis

The results of the proposed DRNN-A are also tracked in Fig. 4 by varying the epochs to clearly emphasize the performance of the proposed DRNN-A in customer behaviour prediction. Here, the suggested DRNN-A model's accuracy steadily increased from 90.88% to 96.43% when increasing the epoch from 50 to 200. In addition, the MCC of the suggested DRNN-A is 0.88% in the 50th epoch count, but in the same epoch count, the RNN and LSTM reach the MCC of 0.71 and 0.79, which underscores the predictive effectiveness of the proposed DRNN-A. The previous approaches, including SVM, DNN, RNN and LSTM, do not incorporate attention in their structure, so they provide poor results in customer behaviour prediction. The findings aligned with the prior models showed that the proposed DRNN-A model incorporates the attention model that improves the interpretability of the model, so it attained higher accuracy and prediction in the customer behaviour prediction.

Dataset 1



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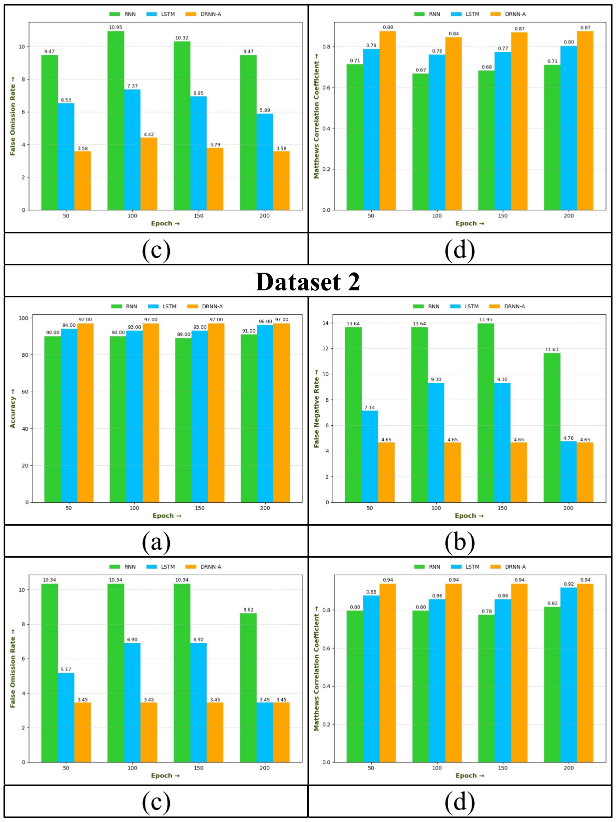

Figure 4 Epoch-based analysis of the proposed customer behaviour prediction model for (a) Accuracy, (b) FNR, (c) FOR, (d) MCC

5.4 Discussion

The criteria used to attain the conclusion are described in the above subsections. In this research, the efficiency of the designed customer behaviour prediction model is evaluated by performing diverse comparative analyses using standard performance metrics, which aims to estimate the accuracy, reliability and overall performance of the designed model throughout the implementation phase. Moreover, the effectiveness of the designed architecture is validated using multiple parameters, including epoch and batch size values. Furthermore, the performance of the designed model is compared with classical behaviour prediction techniques like SVM, DNN, RNN and LSTM. In addition, the conclusion of this research is achieved by monitoring the constant performance offered by the designed model over diverse datasets and performance measures. While considering the batch size value, the designed DRNN-A has attained greater prediction accuracy of 7.05%, 5.46%, 7.48% and 1.78% respectively in dataset 1, which is greater than conventional methods like SVM, DNN, RNN and LSTM. This finding indicates that the incorporation of an attention mechanism with DRNN enabled the model to accurately examine the purchasing behaviour of the customer, which is essential for creating reliable decisions related to marketing. Moreover, the NPV value of the designed model is 6.32%, 3.12%, 6.44% and 3.14%, higher than traditional methods like SVM, DNN, RNN and LSTM, for batch size 16. Thus, the finding denoted that performing RBM-based behavioral pattern extraction assists in presenting precise prediction performance, when compared to conventional methods. Based on the comparative results, it is clear that the designed model has attained better predictive accuracy with minimum FNR values, which indicate the proposed DRNN-A has the ability to accurately determine the purchasing behaviour of the customer and promote reliable marketing decision-making by capturing the informative behavioural patterns and processing sequential details related to customer interactions. Additionally, the designed DRNN-A have outperformed the predictive performance of the existing models like SVM, DNN, RNN and LSTM.

5.5 Comparison Over Existing Models

The designed consumer behaviour prediction model has shown greater effectiveness than conventional technologies due to better feature extraction ability and interpretability. The existing prediction models [1] [2] often depend on behavioral indicators for classifying the purchasing behaviour of the customers, which limits their ability to capture hidden behavioral patterns. Moreover, the traditional clustering techniques [3] [4] are less effective in highlighting the complicated and non-linear temporal patterns between the customer's actions. In specific cases, these models lack the ability to offer poor decision-making and personalized recommendation performance due to the occurrence of gradient issues. Additionally, the scalability and robustness of the models [19] [20] are low due to their inefficiency in processing a vast quantity of behavioral data collected from multiple databases. When compared to existing methods, the designed architecture employed RBM for behavioral feature retrieval and DRNN-A for customer behaviour prediction. Thus, the incorporation of the RBM-aided feature retrieval process assists the model in identifying the high-dimensional patterns from the given behaviour data. Furthermore, the designed DRNN-A model is designed by integrating an attention layer; this incorporation allows the designed model to selectively capture the significant temporal and spatial patterns from the

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input data, which results in precise prediction performance when compared to existing models.

6. CONCLUSION

This research examined the innovative deep learning model for the prediction of customer behaviour to adopt marketing strategies for enhancing profitability. From the collected data, the features were extracted using the RBM. Then, these features were passed to the DRNN-A to predict customer behaviour. To prove the efficiency of the proposed model, validation was conducted. Here, the suggested DRNN-A model's accuracy steadily increased from 90.88% to 96.43% when increasing the epoch from 50 to 200. The evaluation results showed that the proposed DRNN-A has higher performance compared to the usual approaches. The additional data sources, such as clickstream data, demographic interaction and social media interaction, will be incorporated in future for the holistic understanding of customer value.

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