Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766412

CLUSTERING CUSTOMER PREDICTIVE ANALYTICS TOWARDS MANAGING THE CUSTOMER RATING COMPLAINTS IN CUSTOMER MANAGEMENT SYSTEM

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Abstract

Data analytics is a major consideration to build efficient and automated prediction system to the various business needs. Especially many technologies based industries focusing to increase the business growth on offering the right product to right customer at right time. However, despite of various advantageous of data analytics models, clustering customer complaints to online product of the e commerce platform is becoming a vital research in the ecommerce industry. E- commerce is a platform for marketing and promoting the product to online customer. In order to evaluate the opinion of the customers to products purchased using e commerce system is extracted with respect to various challenges and advantages. Extracted opinion of the customer is processed to obtain the intension and behavioural patterns on the statements which express the agreement and disagreement of the product. To reveal the negative or positive feelings of the customer rating, advancement in the information technology is employed with sentiment analysis. Deep Attention Network with long short term memory architecture is proposed in this work to obtain the latent factors of the user to enhance the customer retention. Model is adaptable to temporal and time varying data along its existence of long term dependences between the users. Initially data preprocessing is employed to extract the user profile on analysis of behavioural and psychographic information's. Preprocessed data is employed for Latent Dirichlet Allocation feature to extract the opinion of the latent user intention on the parsed data and store long dependency of the data in latent representations on the LTSM Model. Latent user intention is projected to the long short term memory for efficient data organizing on indexing as network. Organized data is employed to deep attention network composed of various layer is considered as learning representative which provides valuable forecasting as suggestion and recommendation to products to enhance the customer retention. We evaluate the performance of the proposed deep learning approach on Amazon dataset which considers the reviews of the customer complaints to various products. It has been proved to be outperforming against state-of-the-art methods against precision, recall and F Measure respectively.

Keywords: E commerce, Customer Complaint, Long short term memory, Deep Attention Network, Latent Dirichlet Allocation, Sentiment Analysis

1. Introduction

Opinion analysis is carried out using natural language processing technique in order to identify and extracts the behavioural and psychographic information of the user. Natural language processing technique is implemented to various domains to gather the data involvement on the different contexts. In particular, sentiment analysis aid to predict and recommends the appropriate solutions to clustered customer on their product of different businesses [1]. In specific, sentiment analysis determines its importance in the predicting the solutions to customer complaints in commerce application. E commerce application has become a necessary online shopping platform for the customer to the purchase product with more sophistication [2]. Especially implementation of the lockdown due covid -19, educational institution and manufacturing organization has adapted to work from home and study from home model to minimize peoples on outdoor activities. Further e commerce application has increased peoples conveniences to purchase the necessary items in the pandemic situations. In order to evaluate the opinion of the peoples to e commerce with respect to various challenges and advantages, sentiment analysis has been employed to gain valuable insight on basis of user ratings.

Customer Management Systems interfaces social networks are largely employed to gather product and customer information, purchase transaction and their feedback with their multiple emotional dispositions on the product [3]. This opinion information is highly sourced with the data providing the feelings of the customer on the product with the statements that expresses agreement or disagreement in the comment sections to reveal the negative or positive feelings of the customer on their product experience or purchasing intentions. Those opinions have been analysed using sentiment learning for performing the sentiment clustering [4]. With present technology enhancement in the software technology, it is becomes necessary for the business to cluster the customer and predict the product adoption rate in future. Therefore, a new optimized dense attention network with long short term memory architecture is projected in this work to provide prediction of the customer adoption rate to the product on clustering the customer complaints.

Model is resilient to temporal and time changing customer options along its existence of long term dependences among the customers. Initially data preprocessing is carried out using customer profiling with stop removal and stemming process. Preprocessed data is employed for Latent Dirichlet Allocation [5] approach to extract the opinion of the customer on their latent intention to context and those extracted features is managed in the latent representations on the LTSM Model to structure the long dependency of the customer[6]. Latent customer intention vector is projected to the long short term memory towards clustering the customer into various clusters. Cluster customer sentiment information is implemented to Deep Attention Network which composed of numerous layers to represent as learning structures to yield predict the customer complaints and adoption rate to particular product.

The rest of the article is partitioned as follows, review of literatures work are illustrated in section 2, the design of proposed architecture of the long short term dense attention network is mentioned in section 3 and implementation results and performance effectiveness of the proposed architecture is described in section 4 using amazon dataset along performance evaluation against conventional approaches on numerous metric has been explained. Finally article will be concluded in section 5.

2. Related works

In this section, sentiment analysis employing machine learning approaches has been assessed in detail on basis of techniques of feature extraction and opinion classification is described along prediction. Each machine learning architectures produces optimal performance with respect to accuracy and effectiveness has been represented in detail and few techniques which performs nearly similar to the proposed architecture is analysed as follows

2.1. Sentiment Analysis for E-Commerce Product Rating and Reviews

In this model, sentiment lexicon is implemented to extract and increase the sentiment features on the numerous contexts in the customer rating [7]. Extracted lexicon is classified on basis of polarity employing machine learning architectures. Feature vector contain the Sentiment feature as word embedding model and those feature is classified on basis of the Feature weighting through Support Vector Machine or KNN classifier.

2.2. Semi-supervised multitask learning

In this method, aspect based sentiment analysis is implemented to extract the work describing the aspect of the entity. Those extracted work will be analysed with sentiments on processing it in vector form. Vector is analysed on dependencies structures and exploit the indirect association on the opinion words. Opinion words are allocated with sentiments employing decision tree classifier such as Naive bayes or c4.5 algorithm [8].

3. Proposed model

This section provides a detailed design specification of the proposed architecture entitled as Dense Attention Network [9] with long short term recurrent neural network as deep learning architecture implemented for predicting the adaption rate of the customer to the products of e- commerce system on inclusion of parametric tuning of the layers using error function to gather the effective prediction to the customer opinions.

3.1. Data Preprocessing –Customer profiling

E commerce system composed of product information and customer information on basis of the transaction and rating to the product. Further profile of the customer from customer management system of e commerce is extracted [10]. Profile of the customer is processed as follows

$C = \{c_1, c2, c3....C_n\}$ Eq.1

- **Customer Profiling**

The Customer profiling from e- commerce system is obtained to gather their opinion and intention of each customer in the content management system including various contexts on their feedback to the product with respect to time on various product category. Those customer intentions are dynamically maintained, and it is employed to the sentiment analysis model [11] to determine the customer sentiment to the product experience and their adoption rate of the customer for future purchases. Moreover, the customer profiling contains the information of the customer with specified product constraints.

$P_c = \{P_{c1}, P_{c2}, P_{c3....} P_{cn}\}$...Eq.2

- **Product Adoption Estimation**

In order to eliminate the intrinsic error rate, weighted voting based approach has been employed on the opinion to customer experience to the product on intention aggregation of the customer on basis of learning customer context. Especially, it is to compute large no of classes to the customer opinion with respect to sentiment to the various product context with respect to customer behaviour and customer experience [12] to the context.

Furthermore Latent Dirichlet Allocation has been implemented to compute the latent information of customer on their product experience. Customer profile has been illustrated in the matrix form as complete customer information matrix. The Complete customer information matrix composed of column mentioning the demographic, behavioural and physiographic factors of the customer characteristics and row mentioning the customer product experience. It further projected to minimize over fitting challenges on estimating the customer projection matrix [13].

Cumulative Customer Vector for specified product characteristics is $C_i = \frac{1}{n} \int \boldsymbol{c}(\frac{cy}{cx})^{-2} \sum_{x \varepsilon C}^{n} U$...Eq.3

Resultant Customer Vector for entire product Characteristics $R_i = \int \boldsymbol{C}(\frac{cy}{cx})^{-2}$ U….Eq.4

Customer vectors on the Customer experience and behaviours to the product have been determined as subspace on multiple factors. Optimal Latent feature for the sentiment analysis is computed on utilizing customer scatter matrix [14] is provided by

Customer Scatter Matrix on dynamic behavior $S_i = \int \boldsymbol{C}(\frac{cy}{cx})^{2}$ Ri ….Eq.5

Customer Projection Matrix composed of customer profile has been processed employing transformation matrix for matrix normalization [15] on the selected customer pool with similar characteristics [9]. The linear association on product-adapted parameters of the customer feature learning is established on pair wise similarities of the behaviour aspects. Latent Feature vector of the customer has been gathered for customer pool.

3.2.Long Short Term Memory Dense Attention Network

LTSM is aggregated with Dense Attention Network (DAN) to predict or recommend the customer adoption rate to the new product of e commerce. In this work, customer adoption rate to the product in e commerce system is processed along customer profiles associated with it[16]. LTSM is employed to cluster the customer on their sequence of intention with respect to behaviour, demographic and physiographic information. LTSM network is stacked vertically

LSTM architecture contains as integration of multiple states termed as cell state, input layer, input gate, forget gate and output gate. Processed information in the LTSM network produces the result as directed acylic graph[17]. Directed Acylic Graph represents the Customer latent information in graph structure. On back propagation of the DAC produces the association of the customers and it produces the clustering of customer with same intention to the products. Table 1 depicts the parameter of LTSM-DAN model

Table 1: Hyper Parameter of LTSM -DAN

Hyper Parameter	Values
Learning Rate	0.03
Epoch Value	40
Word Embedding Vector Size	500
Sequence length	500
Error function	Cross entropy

- **Abstraction layer**

In this layer, high level features of the customer profile are extracted in the network abstraction layer[18]. It utilizes the activation function to illustatrates the feature extracted in the vector form. Word embedding Vector is managed as gradient decent on sequence of the customer behaviour, demographics and physiographic. Abstraction layer determines the next state of the customer on analysing the current state of the word embedding vector of the customer by processing with product specific parameters. Adoption rate of the customer to the product is achieved on aggregating the work embedding vectors of each customer intention[19]. Further biased customer embedding vector is illustrated as next state or adoption rate. It is represented as

Product Adaptation Rate = (tanh) $\sum_{C=0}^{n} R^k A^{n-k}[C_i]$ Eq.6

Where tanh is considered as activation function to determine the customer adaption to the current product specification and its adoption value is inserted in the cell state of the LTSM Model

- **Hidden Layer**

In this layer, hidden content embedding vectors of the customer is represented as customer states. Further state illustrates the sentiment feature of the customer opinion of the customer product experience extracted from the abstract layer and it is associated with the forget gate[20]. The forget gate of LTSM architecture determines the state information stored in the cell state with respect to other available latent customer feature extracted from the demographic and psychographic information and those characteristics has to be hidden and eliminated[21].

The forget gate of LTSM implements the sigmoid function as its activation function to determine the sentiment or opinion to be the gathered latent information[22]. Figure 1 illustrates the architecture of the proposed cluster prediction analytics of the customer complaint towards product adoption rate.

Each customer state in the hidden layer has been forgotten in LTSM.

It is given by

The hidden information of the customer data in the forget gate as

$$H_c(t) = \sigma(W(H_c(t)+C(R) \int_i^n s(t)] + \text{bias})...\text{Eq.7}$$

Hidden Clustered Customer Vector is provided by

$$C_h(C) = \tanh(H_c \int_i^n s(t)) \;....\text{Eq.8}$$

The forgotten information of the customer data in the LSTM layer is managed in the forget layer of LTSM as it is vital for the analysis of the sentiment of the customer on computing the behavioural changes and dynamic intention variation of the clustered customers[23].

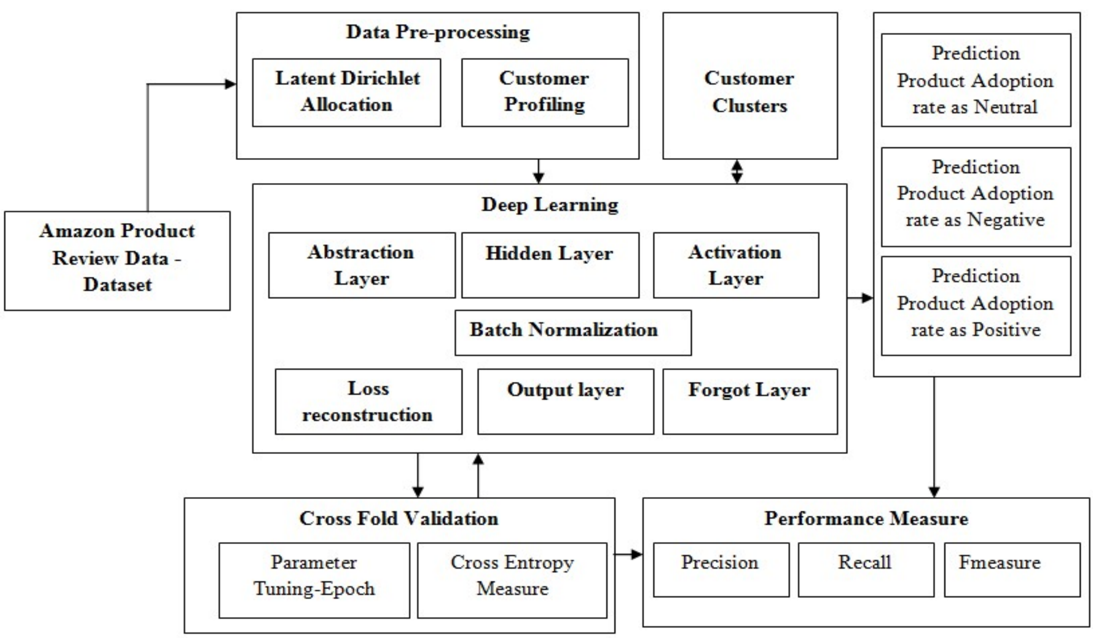

Figure 1: Architecture of proposed predictive customer clustering for product adoption

The input gate of LTSM is essential to the model as it estimates the adoption rate of the customer on the various states and to identify the future adaptation of the user to the product[24]. In

Particular, prediction of the future customer intension to product characteristics is evaluated using the information of current, previous and forget states of the customer containing the intention I(t). The current state intension is given as $C_i(t)$ and the previous user intention $P_i\ (t-1)$
Future Intention of the Customer for product characteristics

$$F_i(t) = \tanh(c_{i(t)+p_i(t)} \int_i^n u(t)) + bi \ldots Eq.9$$

Where $f_i(t)$ is the prediction output of the future customer intention, W_i and b_i are weight matrix and bias vector of the input gate illustrating the customer intention on various state respectively, and tanh is the sigmoid activation function to enable processing of forget gate on the inputs from the input gate[25]. The sigmoid activation function of the input gate provides the assurance that the output of the input gate $g_i(t)$ will been constrained in the range of sentiment (positive, Neutral, Negative) . However, $f_i(t)$ near to the sentiment range allows the customer product information to the dynamic context is to be stored in the output state of LTSM layer.

- **Activation function**

Thus, the learning rate of the proposed architecture is to evaluate and adjusts the weights of the sequence of customer intention on incorporating the sigmoid activation function. The activation function of proposed deep attention network is represented in multiple to single structure for cluster customer intentions. The activation function is constituted with bias to generate the desired prediction output. It is represented as follows

$$\tanh = \frac{1}{1+e^{-z}}(C(t)) \ldots\ldots Eq.10$$

It is implemented for analysing the customer intention to determine adaptation rate to enhanced product and further it is analysing to provides the group adaption rate to the product characteristics for clustered customers.

- **Output Layer**

The output layer works as output gate to generate the prediction output using the various state processing and layer processing in the LTSM model. The output gate of LTSM model determines which suitable state of the customer state information. The activation function of the output gate $g_o(t)$ is implemented to filter the output containing the future prediction of the adaptation rate of the customer on basis of the sentiment value such as positive, neural and negative. Particular outcome is termed as resulting final output z(t).In present architecture, output layer predict the adoption rate on basis of the customer sentiment attached in feedback or opinion representing the user intention , behaviours and perception..

$$A_iC(t) = (g_i(t)f_i(t)) \ldots Eq.11$$

The sigmoid activation function of the LTSM output layer process effectively in customer management database to determine the adoption rate of customer to e commerce system by producing the output of the LSTM block in the range of sentiment (positive, Neutral , Negative), which also guarantees the network on providing desired output for long range of the customer information on processing using LTSM model.

- **Loss Layer**

This layer is to ensure the accuracy on resultant prediction of customer adaption on fine tuning the hyperparameter of multiple layers of deep attention network to produce the minimum reconstruction error among forget layer hidden layer and sigmoid activation layer.

$$l_t = SoftMax\ (U_w * U_t) \ldots Eq.12$$

Further cross entropy loss function has been implemented to manage the interclasses variation of customer cluster and interclass and intraclass variation of prediction rate. Model parameter of neural network is updated to predict the future adaption to the product of the particular business. Soft max and cross entropy mechanism will produce the effective results to various business domains and different languages.

Algorithm 1: Prediction of clustered customer adaption rate to the product recommendation

Input: Amazon Dataset
Output: Clustered customer Adaption rate of product with respect to sentiment analysis
Process
Information Preprocessing ()
Customer Profiling ()
$C_t(t)$ = Intention {behavioural, Physiographical, Demographic}
$P_i(t)$ = Preference {behavioural, Physiographical, Demographic}
Embedding vector = $E(C_t(t)+ P_i(t))$
Sentiment lexicon computation using LDA()
$S_i(t)$ = Word Embedding Vector W_t
LTSM -DAN()
Customer Clustering ()
Cluster CC= {C1,C2….Cn)
Abstract learning ()
Compute High Level Feature
Hidden Layer ()
Extract the latent customer intention () and Customer preference() as states
Forget Layer ()
Compute hidden customer intention and store it in hidden state
Compute eliminated intention ()
Activation Layer ()
Use Sigmoid Function Tanh () for prediction of customer for product adaption
Cross Entropy Layer ()
Minimize Inter-cluster variance ()
Output Layer ()
Prediction of Clustered Group = {Positive, Neutral, Negative }
Softmax ()

4. Experimental Results

Experimental analysis of DAN-LTSM architecture using hyperparameter tuning on amazon product review dataset towards customer clustering and prediction of adoption rate to new developed or updated product characteristics. Data contains opinion of the customer to their existing and current product experience. Prediction model is established with sentiment analysis framework. The performance analysis of the proposed architecture has been evaluated with precision, recall and Fmeasure metrics. The proposed architecture is experimented and evaluated on cross fold validation. The training parameter of the deep learning has been illustrated in the table 2

Table 2: Training parameters

Parameter	Value
Attention Network	Bi directional

Learning rate	10^{-6}
Loss Function	cross entropy
Word embedding Vector batch size	30
Epoch	50

4.1. Dataset Description

We have carried out extensive experiments on Amazon Product review datasets composed of 15000 reviews in order to measure the outcome of the product using feedback system of e commerce application. In this model, dataset is segmented into equal parts for training and testing. In this experiment, training of model uses 60% of dataset, Validation model uses 20% of dataset and testing utilizes 20% of dataset.

4.2. Evaluation

Model is evaluated on the prediction outcome as it containing the adoption rate of the customer to purchased product. It has been evaluated with respect to following performance measures against conventional machine learning approaches. In this work, proposed architecture is validated using 10-fold validation to estimate the prediction performance on various time frames of the dataset. The performance evaluation of the proposed multilayer DAN_LTSM model with on the process of activation function, forget layer, Hidden layer, loss function and Output layer with SoftMax processing is depicted.

- **Precision**

Precision is a mentioned as Positive predictive value of the sentiment class. It is further mentioned as the fraction of similar instances among each cluster generated using the model. Figure 2 illustrate the performance evaluation of the proposed architecture in terms of precision on dataset. Performance measures are suitable for determining the feasibility of proposed architecture on adaption rate prediction. Effectiveness is achieved due to hyper parameter tuning

$$\text{Precision} = \frac{\text{True positive}}{True\ positive + Fals\ \ Positive} \quad .....\text{Eq.13}$$

True positive is a number of similar customers in the cluster and false positive is number of dissimilar customers in the cluster extracted

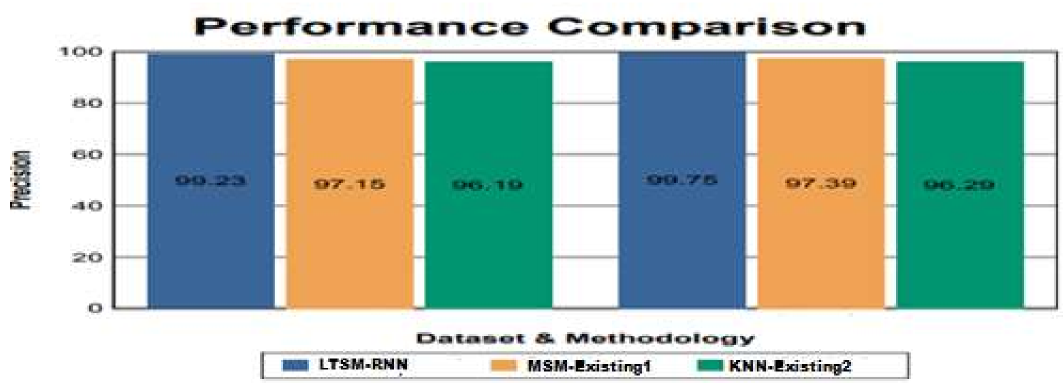

Figure 2: Performance analysis of the methodology on aspect of Precision.

- **Recall**

Recall is considered as ratio of similar customer in the cluster to total amount of relevant customers of the dataset [17]. The recall is the part of the similar customer they are successfully classified into the exact classes.

Recall = $\frac{\text{True positive}}{True\ positive+Fals\ \ negative}$ ...Eq.14

True positive is a number of similar customers in the cluster and false negative is number of similar customers in the cluster extracted. Figure 3 represents the performance evaluation of the proposed architecture on recall measure along conventional approaches.

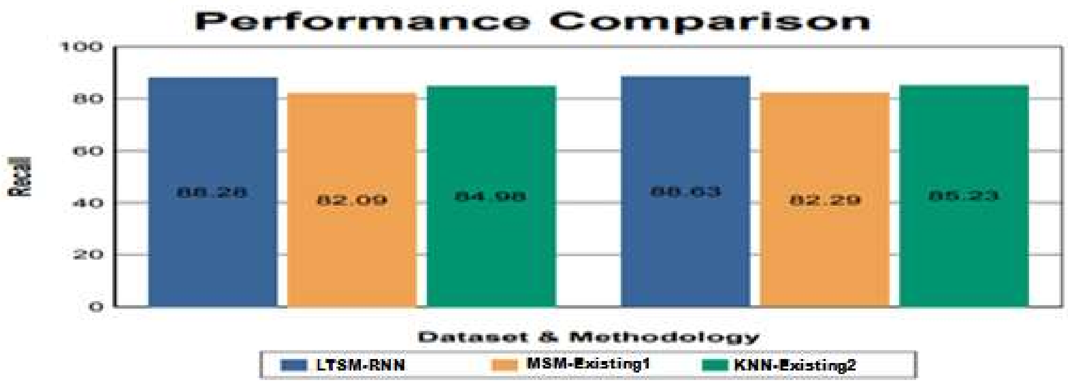

Figure 3: Performance analysis of the methodology on aspect of Recall

Prediction quality of the model depends on activation functions in every layer to process the dataset with respect to dataset. Forget layer generates the feature map to represent the cluster containing customer characteristics. F measure is an accuracy measure for computing the quality of the prediction on clustered data.

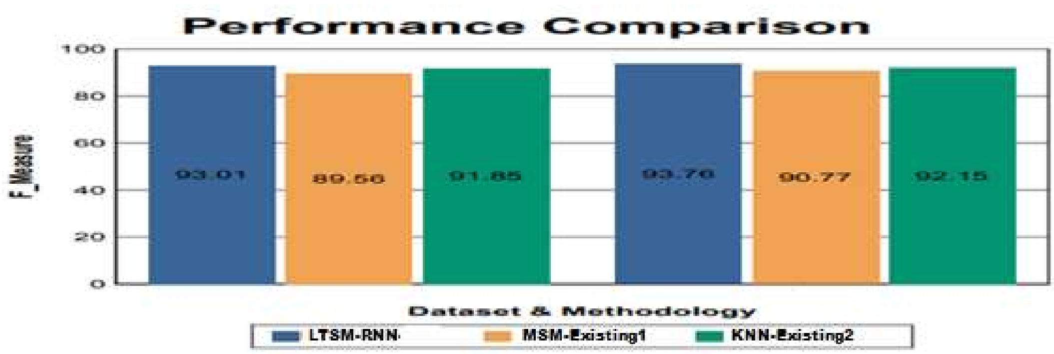

Figure 4: Performance analysis of the methodology on aspect of F- Measure

- **F measure**

It is the number of correct predictions to the customer data among total number of predictions to whole category of data[18].

Accuracy is given by

$$\frac{\text{True positive+Tru}\ \ \text{Negative}}{True\ positive+Tru\ \ Negative+fal\ \ positive+False\ negative}...\text{Eq.15}$$

The multiple user intention generated may have multiple adaption rate. Figure 4 represents the performance of the proposed architecture in terms of f measure against conventional approaches on adaption rate prediction with respect to sentiments [19]. Table 2 presents the performance value of the model using sentiment analysis.

Table 2: Performance Analysis of Proposed architecture against state of art approaches to Amazon review dataset – Category 1

Technique	Precision	Recall	F measure
DAN-LTSM Learning- Proposed	0.9923	0.8828	0.9301
Multiscale Matching based Classification Learning –Existing 1	0.9715	0.8209	0.8956
KNN Based Learning - Existing 2	0.9619	0.84.98	0.9185

The prediction of the customer adaption to the product of the ecommerce application is analysed using sentiment analysis as it is made effective with LTSM optimization. The model is capable of detecting the underlying structure of the data distribution in general. Hyper-parameter tuning [20] is a very important component of the proposed models. In addition, the cross-validation has been employed to dataset alone to determine the high effective value to the hyper-parameters in opinion processing using sentiment analysis.

Conclusion

Particular article has been designed and implemented using DAN-LTSM architecture for opinion mining on the customer reviews to online products in e commerce applications. Sentiment analysis is incorporated with proposed architecture to cluster the customer and predict the adoption rate of the customer to the product. Proposed model utilizes the LTSM-DAN based parameterized and loss function to the amazon product review dataset for enhanced prediction results containing the adaption rate of the customer to the product and its enhancement in future using behavioural factors, physiographical factor and demographic factors as their intension. Deep learning architecture utilizes the features in forget and Hidden layer to represent latent feature on the Sigmoid activation function to obtain the desired results. Further softmax layer and loss layer has been embedded to produce the highly discriminative prediction patterns. Finally generated prediction outcomes have been optimized using LTSM technique to generate optimal sentiment to their adaption rate.

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