Sentiment Analysis and Product Review Classification in E-commerce Platform

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***Abstract*—Online shopping is becoming one of the most demanding everyday needs, nowadays. These days people are feeling comfortable shopping online. The number of its customers is increasing day by day as well as raising some problems. The major problem is that the customers can not choose the quality-full product by reading every review of an online product. Besides, the product reviews are helpful to improve the services of an e-commerce site but required huge manpower and time. We have focused on Bangla text and aimed to solve these problems by the application of Deep Neural Network (DNN) and Natural Language Processing (NLP). In this study, we have proposed two deep learning NLP models: one is for sentiment analysis and the other one is for Product Review Classification intended to improve both the quality and services. Significantly, our proposed models result in high accuracy: 0.84 and 0.69 for both Sentiment Analysis and Product Review Classification, respectively. Undoubtedly, these models can help the customers to choose the right product and the service provider to improve their services.**

***Index Terms*—Sentiment Analysis, Online Product Review Classification, E-commerce, Bangla NLP, Deep Learning.**

I. Introduction

Online shopping is very popular nowadays. Around 2 billion people in the world use e-commerce sites to buy daily necessities. Almost 63 percent of shopping is done on e-commerce sites. Day by day the demand for online shopping is rapidly increasing and the market is growing by 25% to 30% every year. People feel comfortable shopping staying at home. Moreover, while it is a must to stay at home in the corona pandemic, people are fulfilling product needs using online shops. This article [1] informs that online sales growth is 76 percent in June 2020 compared with June 2019 due to the corona-virus pandemic. After getting delivery, customers are used to writing reviews or comments to express their sentiment regarding the quality of the products as well as services. However, in online shopping, e-commerce service providers suffer a lot to help customers to select reliable products. Usually, customers look at product reviews to select good products. But sometimes it is very arduous to select a product by looking at a huge amount of reviews manually. Again, online shops are usually third party organizations, who sell merchants' products to customers, composed of different teams to take care of various issues. For example, one team collects complaints from customers to improve their services, in contrast, other team collects customers' recommendations to promote their products. But, for a particular team it is very much time-consuming to read all kinds of reviews and manually separate by category and also needs lots of manpower. That is why they can not provide a fully efficient service to the customers.

If these problems can be solved by an autonomous system many customers, businessmen, and e-commerce service providers will be able to save a huge amount of time. They won't have to read a thousand reviews anymore. It will be beneficial for both consumers, merchants, and service providers. Without reading any review, customers will be able to know if the quality of a product is good or bad and order products with confidence. On the other hand, e-commerce service providers can easily analyze problems with their products as well as customers' needs. Moreover, it will also allow e-commerce sites to promote themselves and solve delivery errors. The improvement team of e-commerce sites will be able to work relatively more efficiently.

We have aimed to solve the aforementioned issues by using Natural Language Processing (NLP) and developed two Deep Neural Network (DNN) based models: one is for sentiment analysis and the other is for product review classification. The sentiment analysis model will help the service providers to show product quality to the customers on customers' point of view. On the other hand, the product review classification model is not only able to help the service providers but also can help customers. Targeting the merchants and e-commerce sites, we have classified the reviews into four categories namely *'Complain'*, *'Recommended'*, *'Wrong delivery'*, and *'Appreciation'*. The *'Recommended'* category can help a customer to buy a product without any hesitation. *'Wrong delivery'* category can help the merchants to improve their service. *'Complain'* category may help the service providers to solve errors and the *'Appreciation'* category may ensure the merchants that they are providing a good service.

In this study, we have intended to work with Bangla text which is spoken by 228 million people all around the world. But in the online platform, Bengali people seem to be more comfortable with Phonetic Bangla and sometimes with English. That is why, we have created our dataset by incorporating the Bangla, Phonetic Bangla, and English texts which makes it a unique dataset as well as more complex.

To validate the performance of our proposed models, we have applied several evaluation matrices such as accuracy, precision, recall, and f1-score. Both of our models, sentiment analysis, and product review classification, have provided high accuracy. In the case of sentiment analysis the training, validation, and testing accuracies are 0.84, 0.83, and 0.84 respectively. While the training, validation, and testing accuracy for the product review classification model are 0.70, 0.69, and 0.69 respectively.

The rest of this paper is represented as follows. Section II represents the related work in the e-commerce field followed by the data described in section III. One of the essential tasks, data prepossessing, has been described in section IV. The methodology and the result and analysis are shown in sections V and VI respectively. And finally, we have concluded our work in section VII.

II. Related Work

In recent years, Researchers are applying deep learning in various fields [2]. There has been an increasing amount of literature on NLP and some Bangladeshi researchers have been emphasized on solving the problems related to Bangla text. But a few work has been conducted those are concerned with the e-commerce business. Some of the state-of-the-art works related to Bangla NLP have been described below.

In [3], the prominent authors classified two types of Bangla language: 'shadhu' and 'cholito'. They applied Multinomial Naive Bayes classification and obtained very promising results with 99% accuracy and 97% f1-score. Contribution in [4], authors took several approaches to classify fake and real news. They applied three machine learning algorithms and built a DNN model which provided the best accuracy score. The contribution on [5] highlighted an approach to classify Bangla and phonetic Bangla reviews using vectorizers and traditional machine learning algorithms. This proposed methodology achieved the best performance on SVM with a 75.5% accuracy score. In another research [6], author highlighted a methodology to establish an autonomous system. They performed their model on restaurant reviews. The suggested model is the Multinomial Naive Bays algorithm that provided a much more improved accuracy score. The author in [7] represents a Deep Learning approach to classify sentiment for Bangla sentences. The author performed a Binary Classification and Multiclass Classification. They implemented Convolution Neural Network(CNN) and Long-Short Term Memory(LSTM) on their dataset which is collected from online news portal articles. The result showed 49% and 75% accuracy respectively on multiclass and binary classification. The paper [8] encompasses some of the contributions in this field. This work proposed a CNN model that is applied to Bangla comments collected from different sources and showed tremendous improvement as a result.

There are relatively few historical studies in the area of detecting abusive comments in social media. One of these works [9] experimented with a model on the toxic comment dataset from Kaggle. Their LSTM and CNN model performed in a way that ensures a 97 percent accuracy score. There is another work in this field [10]. This work highlighted some approaches to classify multiple emotions. They applied CNN and LSTM to data that are collected from youtube comments. 65% accuracy has been found out from this method. In an analysis of [11], Another sentiment analysis approach was performed in this work. The author proposed a method that classifies sentiments from Google Play Store Bangla Comments. The proposed Method highlights the Support Vector Machine(SVM) algorithm to classify sentiments. This experiment accomplished 76.48% accuracy. In [12] , the author came up with an ideal approach that achieves a 0.865 F1 score.

There are a few numbers of works on Sentiment analysis in the E-commerce site. In [13], the author proposed the SVM algorithm to classify comments from various e-commerce sites. Using this approach, researchers were able to achieve an 82.92% accuracy score. We know about [14], established their model to categorize online marketing reviews from amazon. They categorized their data into five sentiments. In a follow-up study, another research has been done on customer perception. The author proposed a Deep Learning method that shows improvement as a result. In an investigation into [15], the Author suggested a model that classified product reviews. SVM and Naive Bayes algorithms are adopted and SVM shows better performance.

III. Dataset Description

In this research, we have worked with a real world dataset. We have collected product reviews from various e-commerce sites namely Daraz, BDshop, and Evally which are the topmost online shops in Bangladesh. The uniqueness of this dataset is, it contains Bangla, Phonetic Bangla, and English text. We have put Phonetic Bangla text in the dataset because 80 percent of internet users express their opinion in Phonetic Bangla on the online platform. The purpose of including three types of Bangla text in the dataset is to make the model more generalized.

For two different applications, we have manually annotated each review in two-stages. For our first experiment, we have labeled the reviews *'good'* and *'bad'* based on the quality of products on customers' points of view. In contrast, for the second experiment, the reviews have been categorized based on the expression of customers' comments. In this case, the reviews have been labeled with *'Complain'*, *'Recommended'*, *'Wrong delivery'*, and *'Appreciation'*. The distributions of the different target classes in our prepared dataset have been shown in Table I and II.

TABLE I
CLASS DISTRIBUTION FOR SENTIMENT ANALYSIS

Class Labels	Counts
good	2830
bad	2279

From Table I, we can observed that our dataset is properly balanced for the Sentiment Analysis. But Table II shows, for

TABLE II
CLASS DISTRIBUTION FOR PRODUCT REVIEW CLASSIFICATION

Class Labels	Counts
Complain	1908
Recommended	1562
Appreciation	1185
Wrong delivery	454

Product Review Classification, the dataset is slightly imbalanced that has made the model more complex to gain the best performance.

IV. DATA PREPROCESSING

Usually, raw data contains a big number of unwanted elements that directly affect the performance of the machine learning or deep learning models. That is why, we have removed those elements such as stop-words, punctuations, and unwanted characters from our dataset.

A. Removing Stop-words

Stop-words are the words that do not contains any significant information, even sometimes decrease the performance of the model. So, we have suppressed all of the stop-words from our dataset.

B. Removing Punctuation

Punctuations do not carry any informative meaning for the classification tasks. That is why, to reduce the complexity, we have removed the puntuations from the data as well.

C. Removing Unnecessary Characters

As we have scraped the product reviews from online, the dataset contains many unnecessary characters like '@', '=', '&', and so on. These characters have zero impact and likely to mislead the learning of our models. To improve the model performance, we have normalized our dataset by removing these characters.

D. Data Partitioning

Data partitioning is an important task since the ratio of the partitions has an impact on the evaluation of the performance of a deep learning model. We have split our dataset into train, validation, and test dataset. In the case of sentiment analysis, our training, validation, and test dataset contain 4085 (=80%), 715(=14%), and 307 (=6%) instances, respectively. On the other hand, the training, validation, and test dataset for Product Review Classification contain 3574 (=70%), 1073 (=21%), and 460 (=9%) instances, respectively.

E. Feature Extraction

Feature extraction is an indispensable task to train up any DNN model. In order to extract the feature vectors, in this study, we have applied the fastText pre-trained model for Bangla language. FastText, developed by Facebook's AI Research (FAIR) lab, provides word embeddings of shape (1, 300) against each of the word. Thus, for each of the sample text, we have obtained a feature vector of shape (1, 300) by aggregating the individual vectors of the words contained by the text.

V. METHODOLOGY

We can divide this phase into two: designing the architecture of our proposed DNN models and validating the performance of the models.

A. DNN Model Architecture

Each of the DNN model contains some common artifacts such as the input and output layers, hiddern layers, activation functions, and optimizers. Proper selection of the number of hidden layers and the number of neurons in the hidden layers have the utmost impact on the performance of the desinged DNN model. In [16], the author extensively describes the way to select parameters for an efficient DNN model and its significance. However, the architectures of our proposed Sentiment Analysis and Product Review Classification models have been shown in Figure 1 and 2, respectively.

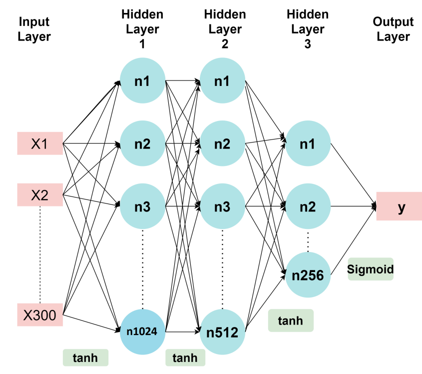

Fig. 1. DNN Model for Sentiment Analysis

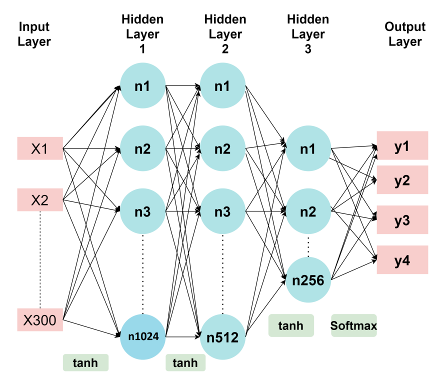

Fig. 2. DNN Model for Product Review Classification

1) Neurons in the Input and Output Layers: The input layers of a neural network depends on the shape of the training data. As the number of the input features for both of our models is identical, which is 300, we have specified 300 neurons in the input layer. On the other hand, for classification, the number of the neurons in the output layer depends on the number of unique classes. For our Sentiment analysis model, basically, we have performed a binary classification and thus we have specified 1 neuron in the output layer. While we have specified 4 neurons in the output layer of our Product Review Classification model architecture based on the unique classes.

2) Hidden Layers and Neurons: It's an important factor determining the number of hidden layers to design a neural network structure. It defines the complexity and efficiency of DNN architecture. A study in [17], Jeff Heaton explained, what should be the number of hidden layers for a DNN architecture. We set three hidden layers for our model according to Jeff's idea. As we don't have huge data we don't need more than three hidden layers. More than 3 hidden layers will make the model more complex, inefficient and it also may cause overfitting. In [18], Moolayi explained a thumb rule for determining the number of neurons in hidden layers. According to Moolayi, if x is the number of input dimensions, the number of neurons in the first hidden layers should be the closest number of 2x in the power of 2. However, in both of the sentiment analysis and product review classification models, we have specified the number of neurons 1024, 512, and 256 for the first, second, and third hidden layer, respectively.

3) Activation Functions: Activation functions play a very important role in any neural network [19]. The activation function triggers a neuron or node and determines whether the data from this node will be sent to the next node. We have used these three activation functions briefly explained as follow:

tanh: Tanh, stands for tangent hytperbolic function, is a sigmoid shaped function ranges from -1 to 1. As we have negative values and positive values in the vectorized form of our training dataset in the range of -1 to 1, that is why, we have used tanh activation function in the input and hidden layers. The mathematical form of this function can be written as follows:

$$f(x) = tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{1}$$

Sigmoid: Sigmoid is a popular non-linear activation function and the output range is [0,1]. Since the target columns of out preprocessed sentiment analysis dataset contains either 0 or 1, we have applied the sigmoid activation function in the output layer of the model. The sigmoid function can be expressed mathematically by:

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

Softmax: The Softmax is a generalization of the sigmoid function that is used to manage multiple classes (multi-class taxonomy). We have applied this function at the output layer of the Product Review Classification model to obtain the probability of occurrence for each of the four classes. The Softmax function can take any type of score (an array or vector) and return the appropriate probabilities, the larger the scores the larger the return value. The mathematical formula for the Softmax function is:

$$S(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{i} e^{y_j}}. \tag{3}$$

4) Optimization Algorithm: The optimization algorithm has a vital role in neural networks that converges the model into the most suitable form by adjusting weights. There are several optimization algorithms such as Adam, RMSprop, SGD and so on. In our experiment, we have applied the Adam optimization algorithm for both of the models with a learning rate 0.001. The significance of this function is that it has relatively low memory requirements and performs well with a minimal hyper-parameter tuning. The mathematical expressions for Adam are as follows:

$$v_t = \beta_1 v_{t-1} - (1-\beta_1) g_t, \tag{4}$$

$$s_t = \beta_2 s_{t-1} - (1-\beta_2) g_t, \tag{5}$$

$$\Delta w_t = -\eta \frac{v_t}{\sqrt{s_t + \epsilon}} g_t, \tag{6}$$

$$w_{t+1} = w_t + \Delta w_t. \tag{7}$$

where
η = Initial learning rate
g_t = Gradient at time t along w_j
v_t = Exponential average of gradients along w_j
s_t = Exponential average of squares of gradients along w_j
$\beta_1; \beta_2$= Hyperparameters

B. Evaluation Metrics

In order to validate the classification performance of our models, we have applied several evaluation matrices namely Accuracy, Precision, Recall, and F1 Score. We have generated the confusion matrix for both of the models and calculates the value of the matrices by using the following equations.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}, \tag{8}$$

$$\text{Precision} = \frac{TP}{TP+FP}, \tag{9}$$

$$\text{Recall} = \frac{TP}{TP+FN}, \tag{10}$$

$$\text{F1-Score} = 2 * \frac{Recall * Precision}{Recall + Precision}. \tag{11}$$

Where,
TP= True Positive
TN= True Negative
FP= False Positive
FN= False Negative

VI. Result and Analysis

In this phase, we have analyzed the results to figure out the performance of our proposed models. We have recorded the numeric value of our result in 2 decimal places. Analyzation has been performed in three steps. Firstly, we have generated the learning curves to analyze training and validation performance which has helped us to determine if there is any underfitting or overfitting issue. And then, we have performed a prediction on test dataset to analyze the performance of the model in reality. And finally, to understand the individual class performance, we have generated a classification report and confusion matrix.

A. Sentiment Analysis

To obtain the learning graph, We have plotted the loss function with respect to the epochs. Figure 3 represents the loss vs epochs for the sentiment analysis model. From Figure 3, we can observe that the training and validation loss have been converged consistently and has been intercepted at 13^{th} iteration. It is a obvious sign that our model has been well-learned.

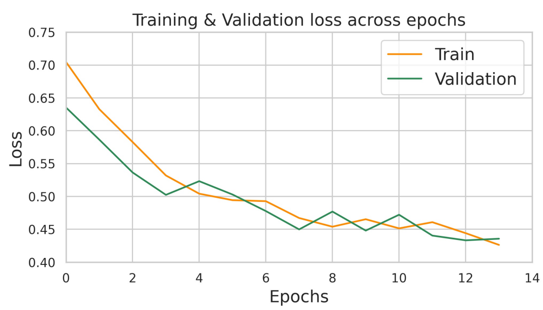

Fig. 3. Loss vs Epoch Curve for Sentiment Analysis

The training, validation, and testing accuracies for the sentiment analysis model have been shown in Table III. From this table, it is appear that the validation accuracy (=0.83) is slightly lower than the training accuracy that indicates the our sentiment analysis model has not been over-fitted or under-fitted during the training phase. Again, the precision, recall, and f1-score have also been calculated and shown in Table IV. From this we can see that out model have resulted in a good f1-score for both of the classes: good (=0.85) and bad (=0.83).

TABLE III
Performance of the Sentiment Analysis

Dataset	Accuracy
Training	0.84
Validation	0.83
Test	0.84

For understanding the true and false classification behavior of our sentiment analysis model, we have generated the confusion matrix as well which is presented in Table V. From the confusion matrix we can observe that, out of 307 test samples, the number of misclassification for the 'good' and 'bad classes are 28 and 21, respectively.

TABLE IV
Classification Report of the Sentiment Analysis

	Precision	Recall	F1-Score
Bad	0.81	0.85	0.83
Good	0.87	0.84	0.85

TABLE V
Confusion Matrix for Sentiment Analysis

		Predicted	
		Bad	*Good*
Actual	*Bad*	116	21
	Good	28	142

Based on the above analysis, we can say that the performance of our sentiment analysis model is really good.

B. Product Review Classification

To validate the learning behavior in the training phase, like sentiment analysis, we have plotted the loss vs epochs that has been presented in Figure 4. Figure 4 appears that the losses for both the training and validation has been remaining quite closer to each other with respect to epochs. It is the sign of a well-fitted model.

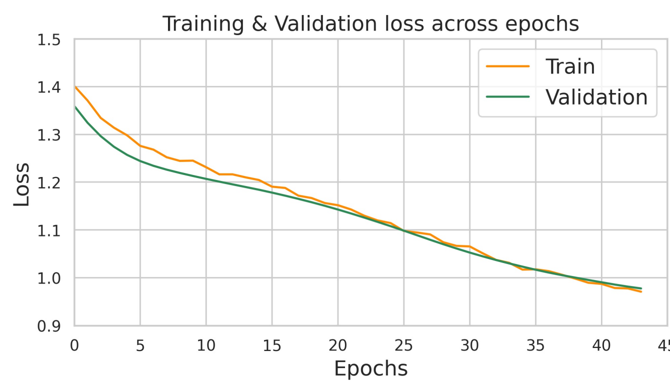

Fig. 4. Loss vs Epoch Curve for Product Review Classification

The training, validation, and testing accuracies of our Product review Classification model have been shown in Table VI. Like sentiment analysis, here the validation accuracy (=0.69) is also quite closer and slightly lower than the training accuracy (=0.70) that indicates this model has been learned from the training data without over-fitting or under-fitting. For imbalanced classes, sometimes the accuracy is not a good measure and thus we have also calculated the precision, recall, and f1-score with the accuracy present in Table VII. From Table VII, we can see that our model have performed well for each of the 4 different classes with a high f1-score.

During the testing phase, we have also generated a confusion matrix to analyze the class-wise performance represents in

TABLE VI
PERMORMANCE OF THE PRODUCT REVIEW ANALYSIS

Dataset	Accuracy
Training	0.70
Validation	0.69
Test	0.69

TABLE VII
CLASSIFICATION REPORT FOR MULTICLASS CLASSIFICATION

	Precision	Recall	F1-Score
Appreciation	0.72	0.55	0.62
Complain	0.7	0.86	0.77
Recommended	0.66	0.63	0.64
Wrong delivery	0.67	0.54	0.59

Table VIII. Where 'A', 'C', 'R' and, 'W' is stands for 'Appreciation', 'Complain', 'Recommended' and, 'Wrong Delivery'.

TABLE VIII
CONFUSION MATRIX FOR MULTICLASS CLASSIFICATION

		Predicted			
		A	*C*	*R*	*W*
Actual	*A*	59	17	30	1
	C	2	148	14	8
	R	21	29	88	2
	W	0	17	2	22

From Table VIII, it can be observed that, despite of being a multi-classification problem, our model has promisingly performed very well for each of the 4 classes except 'Wrong Delivery'.

Overall, we can conclude that our proposed models have learned efficiently from the data. Indisputably, it is able to predict the quality of the online products and classify the product reviews into the given categories, accurately.

VII. CONCLUSION

In this study, We have aimed to propose a Deep Neural Network(DNN) model for predicting online product quality ('good' and 'bad') and classifying them into four categories based on product reviews of the customers. We have used a dataset that has been collected from the biggest online marketplaces in Bangladesh. We have performed some data preprocessing tasks to clean and prepare the data and performed feature extraction to extract numeric features from text data. To vectorize our text, we have applied the FastText word embeddings. We have followed some proven methods from a few organized research studies to design our proposed DNN model. In both of the models, we have defined the hidden layers, number of neurons, optimization algorithms, and tuned the hyperparameters for obtaining the best result. We have used the accuracy matrix, precision, recall and f1-score as the evaluation parameters. To validate the traing phase, we have created a loss vs epochs curve that showed a consistent performance for both models. The testing performance that has been found for sentiment analysis is 0.84, and 0.69 for product review classification those are very much promising. In future, we aim to incorporate more data and compare with different state-of-the-art NLP techniques.

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