Effective Prediction of Online Reviews for Improvement of Customer Recommendation Services by Hybrid Classification Approach

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Abstract

Customers post online product reviews based on their own experience. They may share their thoughts and comments on items on online shopping websites. The sentiment analysis comprises of opinion or idea process and process of sorting high rating reviews according to how well the product satisfies. Opinion mining is a technique for extracting useful data from large amounts of texts in order to use those to enhance or expand a company's operations. According to consumer evaluations, many of the goods aren't as good as they seem. It's common that buyers submit their thoughts on a product but then forget to rate it. The prior data preprocessing is more efficient to extract the features by CNN approach. This proposed methodology breaks down each user's rating prediction model into two parts: one based on the review text and other based on the user rating matrix with the help of CNN feature engineering. The goal of this study is to classify all reviews into ratings by SVM model. This proposed classification model provides good accuracy to predict the online reviews efficiently. For reviews without ratings, a further prediction of feelings is generated using multiple classifiers. The benefits of this proposed model are honed using helpfulness ratings from a small number of evaluations such as accuracy, F1 score, sensitivity, and precision. According to studies using the standard benchmark dataset, the accuracy of customized recommendation services, user happiness, and corporate trust may all be enhanced by including review helpfulness information in the recommender system.

Keywords: Online reviews, SVM classification, feature extraction, CNN, word vectorization, recommendation systems

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1. Introduction

Customers nowadays are increasingly reliant on internet reviews when determining whether to use e-commerce firms' services. These evaluations have a major impact on the success or failure of any product. Because of this, studies are often skewed in favour of good or bad outcomes. Fake reviews, opinion spamming, or unrealistic reviews may also be referred to as "used" or "misleading reviews". In today's digital age, organisations and consumers face the issue of false online reviews. It is difficult to distinguish between true evaluations and those that aren't [1-5]. There have been efforts to model and forecast how beneficial online reviews are, on the search engine results pages. Predicting how useful the research will be, can be done automatically by counting the number of people who vote "helpful". For automated helpfulness prediction, NLP and text mining researchers in the field of review helpfulness have mostly concentrated on finding textual content aspects of useful reviews. Alternatively, academics attempt to get a better understanding of how humans evaluate helpfulness and the elements that impact that judgement process.

More than a decade ago, since its beginning, modelling and predicting how useful reviews are, has been more popular. Customer reviews (e.g., for hotels, restaurants, goods, and movies) have become more important in today's marketplace. A review helpfulness prediction algorithm might save users a significant amount of time by enabling them to concentrate on the most helpful reviews available on the internet. Because of this, a product suggestion system might be as beneficial as a successful review helpfulness prediction system [6-9]. Many people depend on internet reviews to make purchasing choices. Many reviews for a single product have made impossible for buyers to read all the reviews and judge the product's quality. Moreover, the quality and usefulness of each review might vary widely. Consumers have a difficult time sifting through many ideas and their serrated nature to determine which evaluations are worth reading. Public opinion has a significant impact on businesses' capacity to sell their goods, discover new possibilities, and anticipate sales. It is feasible to project opinions and evaluate a significant quantity of data using sentiment analysis algorithms, which benefits both consumers and businesses [10-15].

2. Organization of the Research

This research article comprises of several sections, described as follows: Section 3 provides past research work and research gaps; Section 4 provides the proposed methodology for online review prediction with a high accuracy level. Section 5 delivers the dataset classified by the proposed method and its description. Finally, the research work is concluded with possible future challenges of online review predictions.

3. Preliminaries

Wang et al. noted that even though reviews' content is an absolute measure of sentiment propensity, they found that this could not account for the complete review's score. Even if an item gets a good rating, a critical reviewer may employ cryptic language to describe it. There are extra standards that must be met for different items. It isn't enough to just analyze the review content [16]. The combination type reviewer technique was suggested by Li et al that reviewer and item information should be included in the body of the review. For the regression model to learn its parameters and forecast the review rating, they employ tensor factorization methods to consider the reviewers' personal attributes while mining review material. Only the reviewer's and item's impact on review content are considered in this technique, which utilizes review content to predict review rating [17].

According to Xing et al. research based on Amazon product, evaluations might reveal negation expressions [18]. Therefore, the data acquired between February and April 2014 was classified at the sentence and review levels. Recommendations were made by Aashutosh Bhatt and his colleagues using product feature sentiment analysis taken from Amazon evaluations of the iPhone 5. Data from the POS approach was provided in graphs at every sentence level [19].

Online product reviews were mined by Ahmad Kamal [20] with the use of supervised and rule-based approaches. Bhumika [21] and colleagues examined several machine learning models and evaluated the performance of the models using Twitter data.

4. Proposed Hybrid Classification Approach

4.1 Construction of CNN framework with Data pre-processing

The preprocessing of this proposed algorithm comprises of data cleaning and vectorization to create the user profile through recommendation discriminators for constructing CNN model. The review's usefulness is classified in the first step. Generally, the helpfulness reviews are categorized as positive and negative through SVM classifier. Besides, it makes use of a "hybrid model," a mix of SVM and CNN. In the second stage, a user profile is created that includes interactions between the user and the item that are directly related to the user's helpful reviews. It was necessary to predict users' preferences based on their interactions during the final stage using the most widely used categorization methods [22 – 26]. Each step of the process is described below.

4.2 Textual Feature Extraction (TFE)

The CNN-based hybrid models are constructed in the initial phase to categorize review helpfulness information. Figure 1 depicts the CNN-based hybrid model's overall architecture. Natural Language Processing (NLP) experiments have shown that a suggested hybrid model has outstanding classification performance for classifying review helpfulness. For prediction, CNN may lower the input characteristics, and the features are extracted for the better prediction by strongly correlating each word through the final classification model across all given inputs. Each review's helpfulness information is categorized when a review-level semantic representation is generated. This proposed research builds a hybrid CNN and SVM approach that is used to minimize the predicted error from the correlated output for the given input and propagate the score. It is then used to forecast the useful comments of immediate reviews in a user-friendly manner [26]. Three layers make up the CNN hybrid model. The helpfulness data is used to create word embedding. It is clear from the reviewer's writing that the product has been extensively reviewed by an honest user. One-hot encoding is often used in current text-mining frameworks to encode each word as a vector [27].

4.3 Feature Mapping

Long-distance word dependencies may be encoded using the feature mapping approach [28, 29]. There have been a number of hybrid CNNs that integrate SVM approach models because of their benefits. As a regression model, it predicts numerical values, and as a classification model, it is utilized for numerous categorization issues. As described in this proposed approach, the convolution filters for convolution operation between the kernels and max-pooling layers are employed to lower the dimension of the space in order to extract the emotional analysis of the input provided text from the review of the input text [30, 31].

4.3.1 User Item Interaction (UII)

This proposed hybrid approach focuses to eliminate the over fitting and data sparsity issues. Moreover, this huge matrix dimensions are reduced by max pooling layers to turn the vector values that are zero. The proposed research work uses a word embedding layer to handle the review comments of the word by converting to another vector type. A multi-channel convolutional layer is used in the second layer. Several sized filters are used to extract the bad words through vectorization from the online review text [32 - 34]. Generally, the convolution process is done by CNN in the filter operation by sliding window technique.

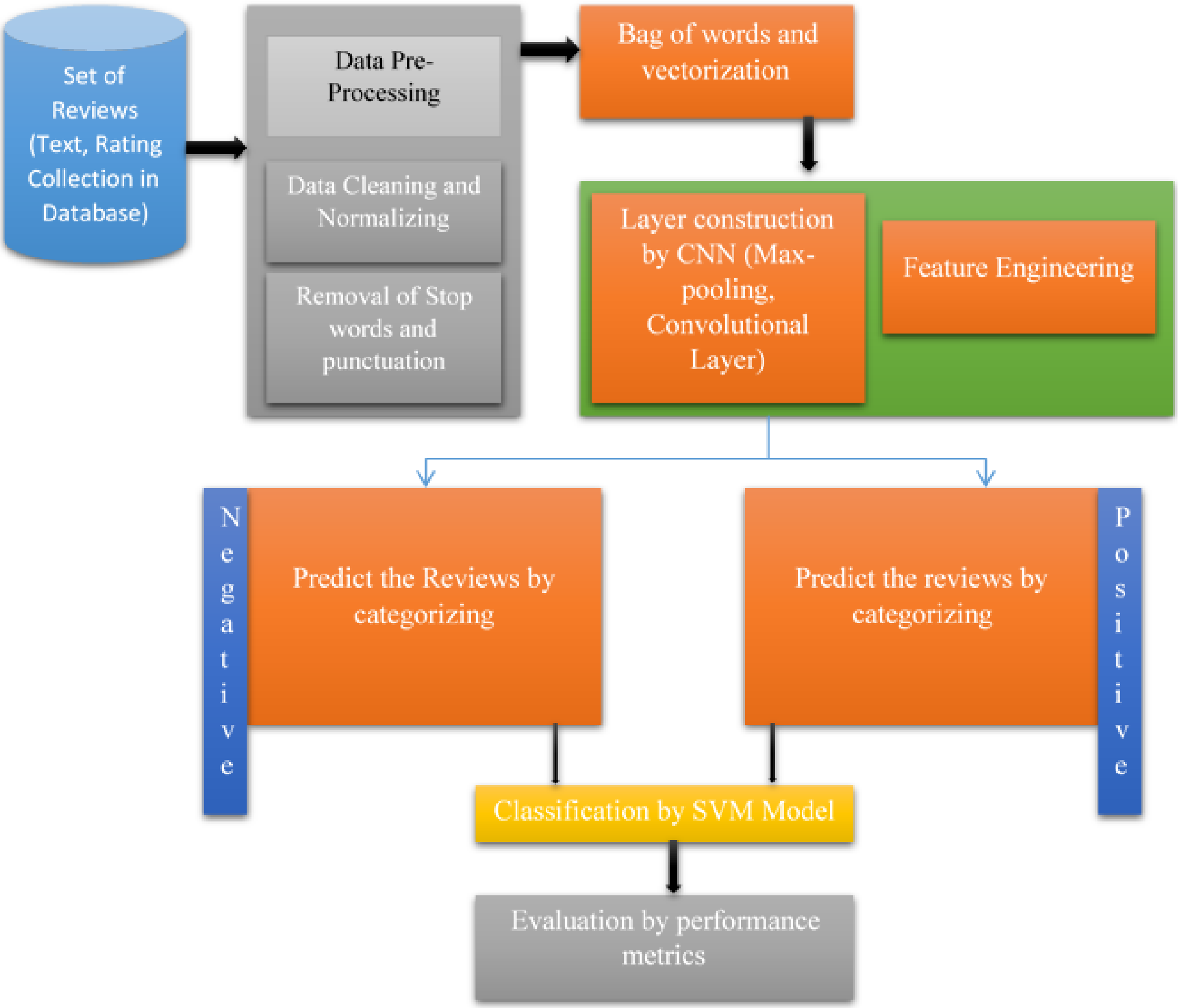

Figure 1. Proposed framework for online reviews prediction

4.3.2 Third layer construction

Another layer of attention is used to forecast the characteristics mapped by numerous vectors in the third layer of the network. The suggested model's time step is represented by a vector in the convolution layer output. In a neural network, there are two parts: forward and backward networks. Review semantics are captured by the forward network, which runs left to right, while sequence features are captured by the back network, which runs right to left. The classification findings of the helpfulness information are posted in the authorized buyer or seller profiles by positive or negative comments. Finally, it is used to categorize and review the usefulness of information in this proposed hybrid CNN-based model.

4.4 SVM classifier

A common benefit of using CNN and SVM together is that they are successful in high-dimensional areas, which leads to excellent outcomes. Furthermore, during the decision function, a subset of training points known as support vectors are employed to refine the choice further. Finally, the kernel function is supplied for use in various versatile applications.

It is possible to use Support Vector Classification (SVC) to address regression issues utilizing this approach. Support Vector Regression is the name given to this technique. To develop a SVC model, the cost function does not care about the training points beyond the model's margin of error, as mentioned above. Support Vector Regression produces a model that relies only on a small part of the training data, since the cost function excludes samples whose prediction is near the goal.

5. Results and Discussion

This proposed hybrid model is tested with two datasets that included user reviews and rating information. Besides, this proposed recommendation framework's performance is evaluated using a dataset that includes 0.6Million evaluations of moderate goods from huge number of consumers gathered between January 2012 to July 2020. This section summarises the descriptive statistics for the two datasets. Figure 2 shows the prediction during training and testing statistical population from the dataset where the x axis is number of epochs and y axis shows accuracy and loss values by this proposed hybrid model.

Figure 2. Performance of Training and Testing

It uses DS1 and the metrics of performance for the proposed model. Besides, it helps to identify the accurate model's classification performance. Then, DS2 dataset is analyzed and experimented and use Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) measurements to find the efficient prediction model. The proposed framework should train on at least 80% of each dataset. Furthermore, the performance should be assessed using the remaining 20% of each dataset.

Table 1. Computed performance metrics

Deep Learning Model	Accuracy	MAE	RMSE	Precision	Overall Predicted Error
CNN model	83.12%	0.88 ± 8.2%	0.92 ± 2%	88.14%	0.345
Pre trained SVM	82.89%	0.79 ± 7%	0.82 ± 5%	89.99%	0.295
Fusion of CNN and SVM approach	94.58%	0.58 ± 3%	0.748 ± 1%	95.42%	0.112

The table clearly shows that the percentages of variation in the errors are very less by using the proposed CNN and SVM approach. This training dataset includes only assessments that received at least 10 helpful or unhelpful votes in DS1. The usefulness score is computed by dividing the received number of rating votes by the number of useful rating votes. When the helpfulness score is evaluated, the obtained graph displays its dispersion. To acquire the most accurate results, it is preferable to use only constructive evaluations ($q1 > 0.9$) (MAE) and ($q2 < 0.2$) (overall predicted error) as the training and testing dataset. Here the q1 is maximum MAE point and q2 is minimum predicted error value that are noted. The table values are plotted in figure 3 & 4.

For evaluating the suggested hybrid model's classification performance, the study determined ideal word count and review duration. Figure 4 depicts the accuracy and precision of the categorization performance after five trials. CNN and SVM are used in a hybrid model that outperforms existing baseline models by 94.58 percent accuracy and has a precision of 95.42 percent. The other deep learning models outperform CNN, despite the fact that the CNN single model has a good classification impact. It is clear that the suggested hybrid model outperforms the existing single classifier methods such as the pre trained CNN and Support Vector Machine (SVM).

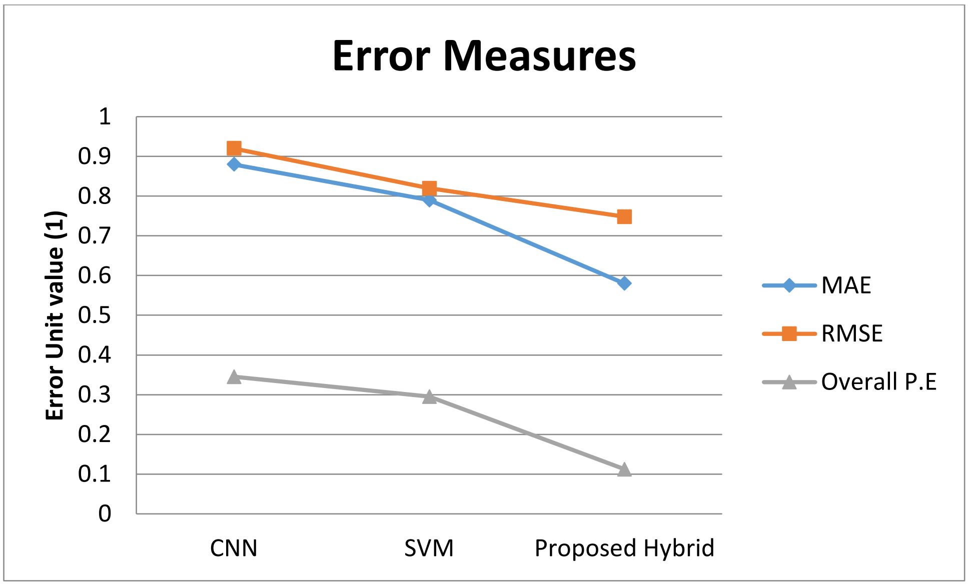

Figure 3. Error measurements for the proposed model

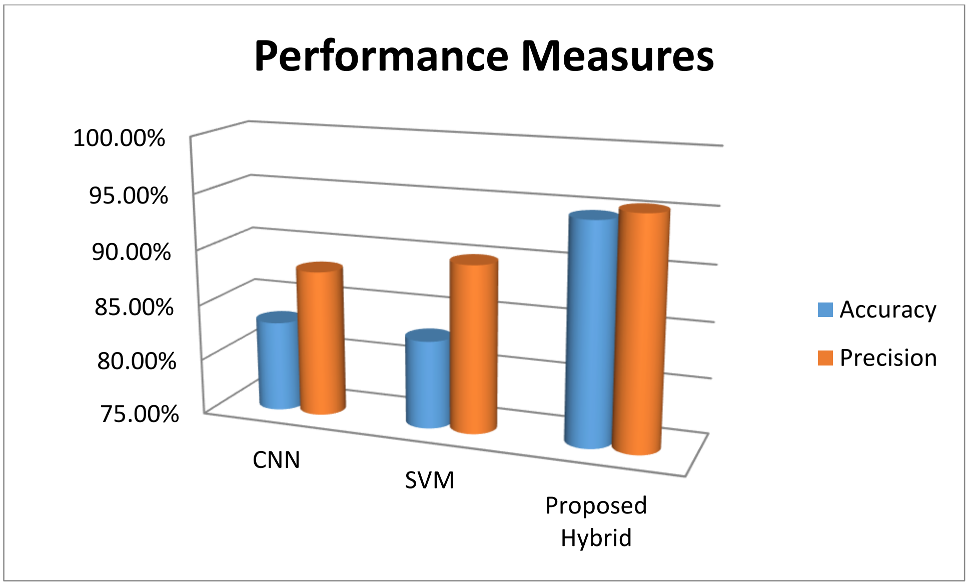

Figure 4. Performance chart of the proposed model

Combining the techniques for the improvement of overall classification performance by this proposed work is ultimate and is proved by the processing of CNN feature mapping and classification by SVM approach, for the word vectors prediction. This proposed workflow mechanism proves that learning crucial traits in online review prediction through varying the weights assigned to them, identifies the difference between the various single-type classifier models, tabulated in Table 1.

6. Conclusion

A combination of CNN and SVM is proposed as a framework for filtering useful reviews and incorporating them into the customized recommendation service. The suggested work is based on a hybrid model that have shown great classification performance in research on natural language processing approaches to filter helpful reviews in order to meet the goal of the proposed work. The detection and removal of bogus reviews using machine learning algorithms is an important and noteworthy feature. Fake reviews are identified and eliminated using this module so that new users or visitors are not deceived, making it a more trustworthy and feasible app for the users. It would be better if the item characteristics, purchasing history, and other information were considered when making recommendations. As future research, the dates of the written review need to be considered since this might lead to a sequential bias issue. In the future, deep neural network approaches may be applied to further model the users' personality and sentiment expressions.

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