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Research Article

Customer Sentiment Analysis for Online Shopping Platforms Using NLP and Deep Learning Methods

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Abstract

Customer sentiment classification has emerged as an essential part of digital commerce intelligence as online malls to shop in grow exponentially in product and user base. Social media like Flipkart have hundreds of product categories and millions of reviews. But the user feedback is very unstructured and may include HTML objects, URLs, punctuations and colloquialisms, which restrict the capability of contextual learning. In order to solve these difficulties, the structured Natural Language Processing pipeline is used, which involves removing null-texts, removing HTML tags and URLs, filtering by numbers and punctuation, removing stop-words, lexical-similarity stemming, tokenization, sentiment labeling by ratings, label encoding, and TF-IDF weighted features extraction. To be tested, the processed data is separated. It is advised to use a recurrent neural network (RNN) for categorization in order to preserve sequential sentiment and word order. The evaluation's findings show that sentiment is very dependable, with 95.08% accuracy; SVM achieved 81.77% and 90.02% with a feedforward neural network. The rapid loss reduction, constant epoch convergence, and the limited validation deviation of 25 training cycles suggest that it can be easily used to ensure robust generalization when faced with class imbalance to enable scalable sentiment intelligence to be used in automated review interpretation, analytics, and adaptive decision support in e-commerce websites.

Keywords: Sentiment Analysis, Flipkart Reviews, Natural Language Processing, Deep Learning Classification, E-Commerce Analytics.

Introduction

Electronic commerce is shortened to "e-commerce." It describes how goods and services are traded online and through electronic media. Using the internet and information technology, such as Electronic Data Interchange (EDI), to conduct business is known as e-commerce[1][2]. E-commerce refers to an online vendor's website, such as Flipkart, that offers goods or services to clients directly through a portal. Credit card, debit card, and electronic fund transfer (EFT) payments can be made via the website's digital shopping cart or basket system. Additionally, the platforms enable users to publish reviews that express their opinions on any product. By analyzing their sentiments, the traders find out the customer experience through their sentiments. Sentiment analysis is a technique used to examine text-based data[3]. Text data includes customer reviews, complaints, comments, discussions, social media tweets, and more. Every day, a lot of data is produced due to the rise in human interaction[4]. Sentiment analysis may be used to identify if reviews are neutral, favorable, or negative. Businesses may gain insight into how consumers see brand strategy by analyzing this type of data. Natural Language Processing (NLP), it uses machine learning (ML), hybrid, and lexicon-based methods to classify data, including sentiment analysis as a subset.

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Product reviews on e-commerce websites are produced in natural languages like English owing to ML and NLP. This technique is used to ascertain the mood or emotion of the underlying text[5]. Sentimental analysis can be used, for instance, to anger, love, hatred, positivity, negativity, and so on NLP is necessary for opinion mining in order to extract the semantics of opinion words and phrases. However, NLP still faces unresolved issues that are too complicated to be properly addressed[6]. This complicated behavior is represented in sentiment analysis, which heavily relies on natural language processing. Opinion mining and NLP's assumptions for text classification are incompatible because of their differences[7]. To overcome this limitation, deep learning is the best solution for it.

A component of ML, DL was originally suggested by G.E. Hinton in 2006. Neural networks serve as its base[8]. Neural networks, which are composed of many neurons that create an incredible network, are influenced by the human brain[9]. Both supervised and unsupervised categories may be taught by deep learning networks. Deep learning has a significant impact on both supervised and unsupervised learning, and many academics use it for sentiment analysis. It is made up of several well-liked and successful models that are utilized to successfully address a wide range of issues.

Significance and Contribution

This study is motivated by the increasing use of customer feedback as a strategic asset by the e-commerce platforms. Millions of reviews published on these sites, such as Flipkart, determine the perception of the product, price setting, level of trust in the services, and the net brand value, and sentiment insights are vital in business. Nevertheless, such feedback is very unstructured, may include informal language, noise, repetitive wording, and class imbalances and restricts the efficacy of traditional sentiment analysis methods. The traditional lexicon-based or ML methods find it hard to describe sequential interdependencies, conditional clauses, and subtle contextual changes in tone, which diminishes the quality of artificial intelligence. To overcome them, this paper offers a Recurrent Neural Network (RNN)-based sentiment classification framework. Key contributions include:

- Collection of a Flipkart product review dataset of large scale and undergoing variety of categories within the Kaggle.
- Using a standard NLP preparation pipeline that consists of TF-IDF-based feature extraction, label encoding, stemming, stop word removal, normalization, tokenization, and noise reduction.
- Using an RNN model to learn successive sentiment patterns and preserve word sequence.
- The model's performance is assessed using the F1-score, recall, accuracy, and precision.
- Provided a practical sentiment-analysis pipeline to be used in a real e-commerce system to enhance customer feedback interpretation and automate it.

Justification and Novelty

This paper is novel in the sense that it uses a complete NLP preprocessing pipeline and deploys a deep recurrent learning model to learn word-order dependencies on a large-scale set of real reviews about a product. The work also adds value through its empirical investigations of sentiment-class imbalance, the provision of comparative benchmarks, and the justification of deep learning as a required extension of rule-based opinion mining to scalable and generalizable e-commerce sentiment intelligence that can be deployed in the real world. Also, the paper includes the visual and quantitative analysis, showing how the sequential models can be used better than the classical methods in the real world in sentiment classification.

Structure of the paper

The study is structured as follows: Section II demonstrates current research on ML and DL techniques for consumer sentiment analysis. Section III details the methods and supplies utilized. Section IV presents the results of the suggested system's experiments. Section V concludes the paper and discusses the future directions.

Literature Review

This section reviews recent studies on Product review sentiment analysis using ML and DL methods. The recent studies are given below:

Juanatas et al. (2019) focusses on creating a platform that can gather information in the form of comments or evaluations. Based on the evaluations and comments, the software was able to produce textual and quantitative data. The Scrum Agile technique was employed by the researchers. This study tested the acceptance of the system's application using a questionnaire and the descriptive research approach. One hundred respondents assessed it. To determine whether there was a significant difference, the mean value was computed and compared using analysis of variance. The crucial value of the null hypothesis was also assessed using ANOVA. The F-value of 6.48972% suggests that there is a large variance in the judgements of the four groups of respondents based on the data[10].

Alrehili and Albalawi (2019) Analyse a set of Amazon customer reviews using an emotional analysis method. As intended, classify each review into the positive or negative review class using the ensemble machine learning technique. Five classifiers were integrated in this work using voting, an ensemble machine learning technique: Naive Bayes, Support Vector Machines (SVMs), Random Forest, Bagging, and Boosting. The proposed model was compared against the five classifiers

in six different scenarios using Weka. These examples involve the usage of trigram, bigram, and unigram (with or without stop of word removal). The random forest strategy produces the highest accuracy of 89.87% when unigram and halting word removal are used, although the voting approach performs well in the other situations[11].

Porntrakoon and Moemeng (2018) offer a method that automatically analyses the sentiment of Thai customers' product, pricing, and delivery assessments using a multi-dimensional vocabulary and sentiment compensation system. A Thai-language customer review is tokenized using the longest matching approach. Its mood is then ascertained by examination. The sentiment compensation technique automatically modifies a sentiment in a customer's review that lacks a dimension. With an overall accuracy of 93.60%, the data reveal that the suggested strategy outperforms the dimension to sentiment (D2S) and sentiment to dimension (S2D) approaches[12].

Polsawat et al. (2018) An proper assessment becomes difficult when attempting to study and comprehend the wide range of client ideas and attitudes. When evaluating both positive and negative words in certain phrases, the SentiWordNet algorithm makes mistakes and many research investigations come across semantic conflicts of words or synonymous terms. In order to help customers make judgements about what to buy, the present study aims to use DBpedia to address the aforementioned problems, account for word meaning variations, and provide a user interface for retrieving items using keywords. In this study, sentiment analysis was measured at 94%[13].

Hegde and Padma (2017) Sentiment analysis (SA) of Kannada documents has been studied. The goal of the research is to improve the Kannada language sentiment analyzer's performance over the previous study. This study proposes an ensemble of classifiers using the random forest approach to determine the sentiment's polarity and evaluate its performance. It also supports multi-class labels and recognizes the sentiment polarity of conditional and comparative statements. The Random Forest technique-based approach appears to be more successful for SA in Kannada, as the total accuracy rose from 65% to 72%[14].

Qin and Petrounias (2017) suggests a fresh paradigm for fine-grained sentiment analysis that is based on semantics. To provide accurate sentiment categorization, it also provides a helpful application of the framework for analysing the emotions conveyed in customer reviews. The validity and reliability of the suggested framework were assessed using datasets from two domains (phone goods and hotel services). With a sentiment classification accuracy of 91.3%, the suggested method significantly outperformed the baseline (SentiWordNet), which had a result of 71.0%[15].

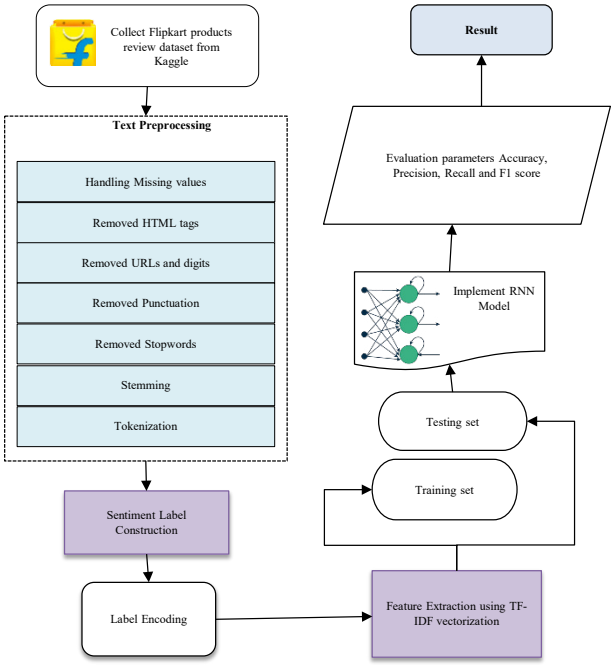

Figure 1: Flowchart for Product review Sentiment Analysis using the Flipkart Products Review Dataset

Table I shows that lexicon, semantic, and classical ML methods prevail among product review sentiment analysis, future research on this topic is geared towards multilingual expansion, improved sensitivity to sophisticated expressions of sentiment into actual e-commerce systems.

Methodology

In the proposed methodology of analyze customer sentiment of online shopping platforms using advanced techniques. the Flipkart products review dataset is collected and undergoes preprocessing using techniques such as Handling missing values, removing HTML tags, removing URLs and digits, removing punctuation, removing stop-words, stemming, Tokenization, Sentiment label construction, label encoding and feature extraction (TF-IDF) vectorization. The data is then split into two sets: 20% for testing and 80% for training. After that, use the RNN DL model that was trained using the processed data. Model performance is evaluated using metrics such as accuracy, precision, recall, F1 score, and ROC AUC. The results are then analyzed to determine efficacy. Figure 1 illustrates this process.

The steps of the suggested technique are briefly discussed below:

Data Collection

The study used the Flipkart products review dataset[1], that

1 https://www.kaggle.com/datasets/mansithummar67/flipkart-product-review-dataset/data

Table 1: Summary of Background Study for Machine Learning and Lexicon-Based Approaches in Product Review Sentiment Analysis

Author	*Methods*	*Dataset*	*Key Findings*	*Limitations & Future Work*
Juanatas et al. (2019)	Scrum Agile methodology; descriptive research; quantitative + text data extraction	User-generated comments and reviews collected via custom-built platform; evaluated by 100 respondents	Developed a platform capable of capturing reviews and generating both numeric and text-based insights; ANOVA results showed significant differences among the 4 respondent groups (F = 6.48972)	Does not apply machine learning sentiment models; future work could integrate automated sentiment classification or expand user testing for system validation
Alrehili & Albalawi (2019)	Ensemble Voting classifier combining NB, SVM, Random Forest, Bagging, Boosting; unigram, bigram, trigram features with/ without stopword removal	Amazon customer reviews	Random Forest achieved highest accuracy (89.87%) using unigram + stopword removal; Voting ensemble showed best performance in several scenarios when compared with individual classifiers	Experiments limited to Amazon data and classical ML models; future work could include deep learning, transformer-based models, or cross-domain validation
Porntrakoon & Moemeng (2018)	Multi-dimensional lexicon; sentiment-compensation technique; longest matching algorithm for Thai tokenization	Thai-language consumer reviews (product, price, shipping)	Proposed method outperformed S2D and D2S approaches with overall accuracy of 93.60%; effectively handled implicit sentiments within dimensions	Focused only on Thai language; future studies should expand to multilingual datasets and incorporate machine learning models for improved generalization
Polsawat et al. (2018)	DBpedia-based semantic correction; SentiWordNet improvement; keyword-based UI for product retrieval	Consumer product review corpus with ambiguous word meanings	Achieved 94% sentiment-analysis accuracy; semantic conflict (synonyms, ambiguous terms) successfully mitigated using DBpedia knowledge base	Limited to lexicon-based techniques; future work should integrate machine learning or neural networks to handle more complex sentiment patterns
Hegde & Padma (2017)	Naïve Bayes and Random Forest (ensemble approach) for Kannada text sentiment	Kannada-language sentiment dataset	Accuracy improved from 65% to 72% using Random Forest; addressed issues in multi-class labels and comparative/ conditional sentiment expressions	Dataset size limited; classification approaches could be expanded using deep learning architectures tailored for low-resource languages
Qin & Petrounias (2017)	Semantic lexicon; multi-word expression handling; fine-grained sentiment framework	Phone product reviews & hotel service reviews	Proposed semantic-based framework achieved 91.3% accuracy vs. 71% baseline (SentiWordNet); effectively handled contextual and mixed-opinion statements	Framework needs testing on larger and newer domains; integration with machine learning or neural embeddings could further enhance accuracy

was available on Kaggle, to support research in product review sentiment analysis. This dataset includes 104 distinct product categories from flipkart.com. There are five columns and 1,94,276 rows in this dataset. The dataset contains product reviews and customer's sentiment. It is available in the flipkart_product.csv file format. This dataset includes product names, costs, ratings, reviews, and sentiment analysis summaries. It contains negative positive and neutral sentiments; these sentiments are showcased in the word clouds below:

In Figure 2, the word cloud produced by the positive evaluations is shown, highlighting the most prevalent and notable terms utilized in the positive sentiment. The most used and the most influential words are good, product, nice, excellent, great, love, best, amazing, awesome, and quality, which is a clear indication of a high level of customer satisfaction. The other commonly used words including price, value, happy, perfect, easy, fast, and thank also highlight that people are appreciative of the performance of the product and its affordability, as well as shopping experience on the platform.

Figure 3 shows the word cloud created from negative evaluations, which highlights the most important terms associated with a negative attitude. The most frequent words and the biggest and dominating ones are bad, poor, quality, product, don't buy, waste, problem, and money, which are a clear indication that the customers are highly dissatisfied. Further recurring complaints on product flaws, flawed quality of building, misleading, false expectations, and disappointing delivery or performance



Figure 2: Word Cloud for Positive reviews of the dataset



Figure 3: Word Cloud for Negative Reviews of the Dataset



Figure 4: Word Cloud for Neutral Reviews

are also witnessed through other terms like worst, return, damaged, bad quality, not good, fake, issue, and packing, small and defected.

The word cloud based on neutral evaluations is displayed in Figure 4, with the most prevalent terms suggesting moderate or mixed opinions. Key words were product, good, quality, working, small, size, average, money, buy, expected, use, nymc, osm, price, work, don't buy and item, which point to a balanced opinion. Other often used words like normal, little, much, need, installation, look, received and month imply factual, descriptive, and neither greatly positive nor negative reviews oriented

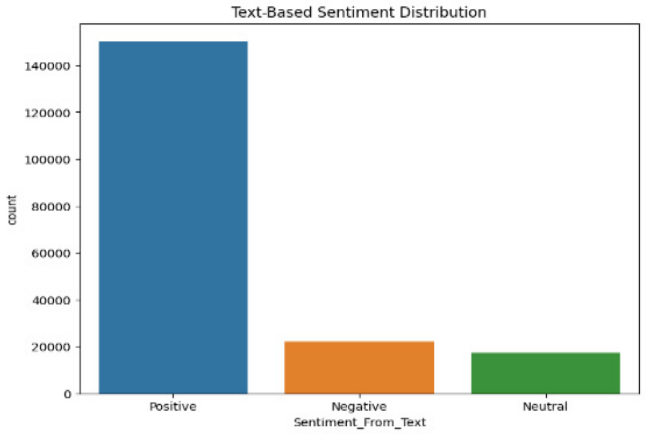

Figure 5: Text-Based Sentiment Distribution

towards functionality, size, price justification and overall expectations being met without extraordinary satisfaction or disillusionment.

Figure 5 presents the bar chart of sentiment label distributions in the dataset, and it is evident that Negative, Neutral, and Positive sentiment categories occur most of the time. The y-axis shows the number of feelings, while the x-axis shows the labels of the emotions. The chart indicates that there is a drastic imbalance of the classes as Positive sentiment is the highest with 1, 50, 377 instances, then Negative sentiment comes with 22, 023 instances, and lastly, Neutral sentiment has the lowest with 17, 456 instances. Such a skewed distribution, and especially the underrepresentation of the Neutral and Negative classes, can be a major factor that affects the sentiment analysis models' generalization and performance.

Text Preprocessing

Cleaning and converting raw text into a machine-readable format require text pre-processing, organized version. This step improves the overall quality of writing and helps models understand the information in a better way. Pre-processing steps they are as follows:

Handling missing values

The column with the Review values was changed to a string type to maintain the same regulation of handling texts and the null values in that column were set to empty strings to prevent error during the text preprocessing[16].

Removed HTML tags

The markup elements presented in the reviews were removed to leave the text.

Eliminated URLs and numbers

Hyperlinks that start with common web prefixes have been removed to prevent the extraneous information. To avoid irrelevant noise, the numerical characters were removed.

Removed Punctuation

All punctuation marks were eliminated on the text to make it look cleaner in lexical representation.

Stopword Removal

A predefined stopword list was used to remove those non-informative stopwords in English. The removal of such common yet weak semantically meaning tokens enhanced the relevance of the remaining words.

Stemming

Stemming process was used to simplify words to base or root. The action contributed to normalizing various versions of words and reduced sparsity of vocabulary as words with similar semantic meaning were combined.

Tokenization

A processing of the normalized text was done using tokenization that was based on the unit words. The tokenization was done to make sure that every review was a structured order of lexical elements that could be further used to extract features.

Sentiment Label Construction

The rating scores were converted into categories of sentiment in order to make target labels to be used in classification. Ratings less than three were designated Negative, equal to three were designated Neutral and more than three were designated Positive. The result of this mapping was a three-class sentiment distribution that can be used in multi-class classification.

Label Encoding

Sentiment labels were encoded as numeric values using the standard label-encoding methods in a bid to fit in models of ML. This change assigns every sentiment type a unique numeric code, thus making sure the algorithm can process and interpret the categorical information effectively.

Feature Extraction

The reviews of the texts were summarized as numerical features obtained through Term Frequency-Inverse Document Frequency is referred to as TF-IDF. The text was converted into weighted unigram features using the vectorizer, which the cleaned text was then transformed through, and all input features were automatically lowercased and standard English stop words were removed. The vocabulary size was unconstrained, and all terms relevant to the feature space were permitted to enter it. The vectorizer was trained on the training corpus and then applied to both the training and test data to produce a sparse, high-dimensional feature matrix. The vocabulary was also extracted to facilitate interpretability and analysis.

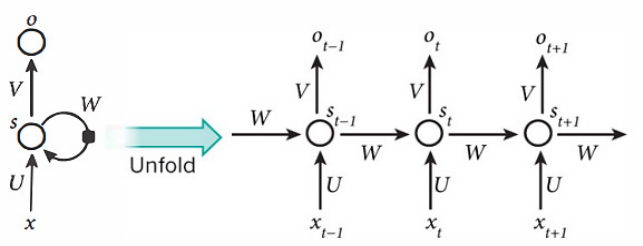

Figure 6: RNN Unfold Framework[19]

Data splitting

In the Product review sentiment dataset is splitting into two subsets: 20% of the dataset is used for testing, while the other 80% is used for training.

Classification of Proposed Recurrent Neural Network (RNN) Model

The RNN's objective is to utilize sequential information, and its output is predicated on earlier calculations. Because RNNs have a concealed state that repeats itself and is activated based on the previous time, they can manage a variable-length sequence input, unlike feedforward neural networks[17][18]. However, because new words are more important than older terms, recurrent networks are biased models. As seen in Figure. 6, RNN has a memory that can store data in arbitrarily lengthy sequences.

The following formulae control how an RNN is calculated:

At time step t, x_t is the input. For instance, x_i may be a one-hot vector or word embedding that matches the i-th word in a sentence.

h_t is the network's hidden state and "memory" at time step t. It is computed using Equation (1)'s input at the current step and the prior hidden state:

$$h_t = \sigma\left(Ux_t + Wh_{t-1}\right) \tag{1}$$

Here, the first hidden state is usually calculated by initializing h0 to a zero vector.

The output at time step t is denoted by o_t. A vector of probabilities for each sentiment category would be used for sentiment categorization of short texts. Equation (2) calculates it as follows:

$$o_t = softmax\left(Vh_t\right) \tag{2}$$

The ability to obtain better-suited statistics may be useful for capturing long-text semantics in recurrent networks.

Evaluation Metrics

To assess the categorization algorithms' effectiveness

using the sentiment dataset from product reviews, a confusion matrix is utilized, capturing the outcomes of predicted versus actual classifications. The matrix includes four key components. The confusion matrix is listed in below:

- **True positives (TP):** Positive points that are in fact positive[20].
- **False positives (FP):** The positive-labelled locations that are True negative.
- **True negatives (TN):** The negative points that are true negative.
- **False negatives (FN):** The negative-labelled locations that are true positive. Following performance measures are as follows:

Accuracy

The percentage of samples that the model correctly classifies relative to all samples is known as the accuracy rate; generally speaking, the greater the accuracy rate, the better[21]. It is described in Equation. (3).

$$Accuracy = \frac{TP + TN}{TP + Fp + TN + FN} \tag{3}$$

Precision

The accuracy rate is the proportion of samples where the real label is positive and the forecast result is positive. It is defined in Equation. (4).

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

Recall

The ratio of instances where the prediction is accurate and the real emotion is positive to Recall is the total number of samples[22]. It is defined in the Equation. (5).

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

F1-score

The ideal value cannot be reached simultaneously due to the reciprocal interaction between the accuracy rate and recall rate evaluation index values. The new evaluation index *F*1 measure is calculated by taking to raise the overall rating of the model, the arithmetic average of the recall and accuracy rates, it is defined in Equation. (6):

$$F1 - Score = \frac{2(Precision * Recall)}{\text{Precision} + \text{Recall}} \tag{6}$$

AUC-ROC

The area under the ROC curve, or AUC value, is a single figure used to evaluate the model's classification performance. The closer the AUC value is to 1, the better the model performs [23]. Model performance is frequently assessed using the ROC curve and AUC, particularly in unbalanced classification issues. A high area under the model is more effective at categorising data, according to the curve.

These criteria are used to analyze the sentiment analysis DL models.

Table 2: RNN model performance for Product Review Sentiment Analysis

Performance Measures	*RNN*
Accuracy	95.08
Precision	95.06
Recall	95.08
F1-score	95.09

Table 3: Ml Model's Comparison On The Flipkart Products Review Dataset For Product Review Sentiment Analysis

Models	*Accuracy*
RNN	95.08
SVM [24]	81.77
Neural Network [25]	90.02

Result Analysis and Discussion

The section utilized the Flipkart product reviews dataset to test the DL model's sentiment analysis. The experiments were run on a computing system with an Intel(R) Xeon(R) 2.3 GHz CPU, NVIDIA P100 GPUs and 16GB of RAM and facilitated effective training and assessment. The RNN model was chosen because it can identify sequential patterns in textual data, and Table II shows its performance metrics. The results indicate that the RNN performed exceptionally well, with an accuracy of 95.08%, precision of 95.06%, recall of 95.08%, and F1-score of 95.09%. These findings show how well the model is at classifying attitudes.

A confusion matrix showing the performance of a classification model with three classes (0, 1, and 2) is

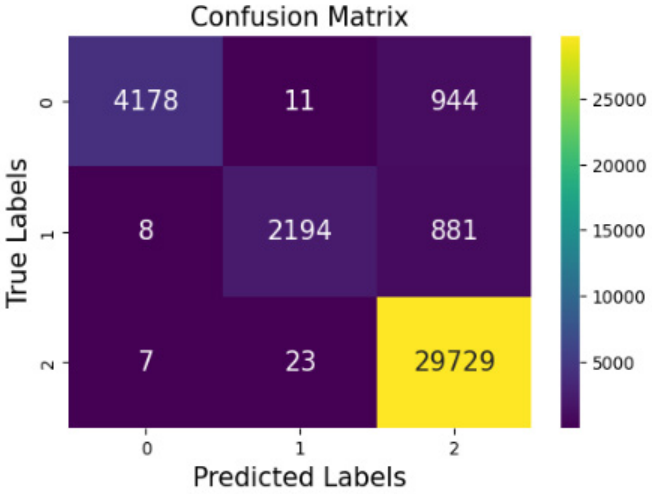

Figure 7: Confusion matrices of RNN Model

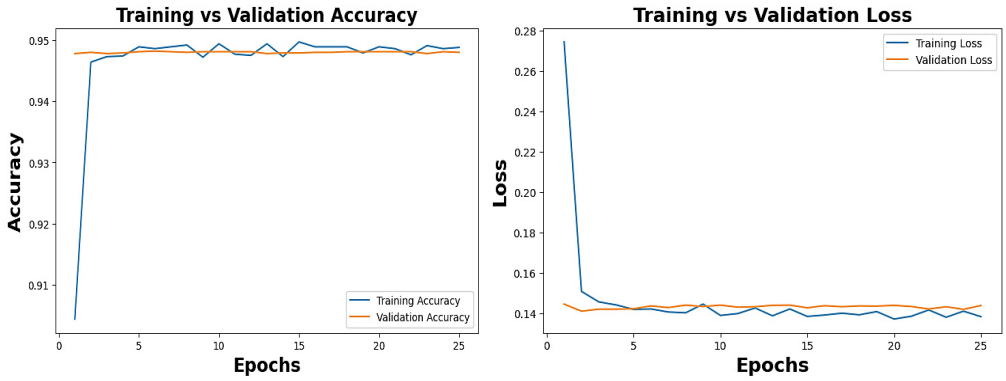

Figure 8: Training vs Validation Accuracy and Loss Plots for RNN Model

presented in Figure 7. The actual labels are shown on the vertical axis, while the expected labels are shown on the horizontal axis. The heatmap scale of color has a dark purple color of low frequencies to a bright yellow of high frequencies. Diagonal values show the correct predictions, 4,178 in Class 0, 2,194 in Class 1 and 29,729 in Class 2, which are the predominant ones and are in bright yellow. The values off-diagonal indicate misclassifications, with the biggest part of them being the cases of Class 0 (944) and Class 1 (881) wrongly classified as Class 2.

Figure 8 indicates that accuracy rises at once to a high and stable 95% threshold, and the training and validation curves converge rapidly and stay close to one another throughout all 25 epochs. This proves to be a great deal of generalization and strength without much overfitting. Likewise, to ensure the success, the right chart supports that the training loss decreases significantly in the initial few epochs to reach low and steady validation loss of about 0.14. In the case of a product review, these metrics mean that it has an efficient production-ready model that gives high and consistent performance in all data, which reduces the chances of performance degradation in practical conditions.

Comparative Analysis and Discussion

The comparative analysis for Product review sentiment analysis on this section contains the sentiment dataset for Flipkart product reviews. Table III offers a comparative assessment of Three models—RNN, SVM, and Neural Network—on the Flipkart product review dataset for sentiment analysis of product evaluations employing F1-score, Accuracy, Precision, and Recall. With an accuracy of 95.08%, the RNN surpassed every other model that was tested. The SVM had the lowest accuracy, at 81.77%. The Neural Network is also reported for comparison, demonstrating moderate performance achieving an accuracy of 90.02%. Overall, the RNN model is demonstrate the highest performance among all models.

These findings prove that the RNN-based classification can enhance sentiment prediction on flipkart review data on the large scale massively. The model was very stable and converged quickly with little deviation between the training and the validation trends, which is good generalization. RNN performed better on sequential context and semantic dependencies than SVM and feedforward neural networks, achieving higher accuracy and equal precision-recall. The confusion matrix indicated that there was predominant representation of positive classes, but the misclassification rates were lower, which confirmed the ability of the model to withstand imbalance. The findings validate deep recurrent learning's efficacy as an e-commerce sentiment analysis tool.

Conclusion and Future Work

Sequential models based on deep learning offer a significant power in understanding the opinions of customers in large-scale e-commerce. In the given work, the Recurrent Neural Network (RNN) was presented as the suggested sentiment-classification model, based on its recurrent memory state to extract the concept of sentiment evolution through word sequences, as opposed to using only solitary text characteristics. The suggested RNN was highly flexible towards informal writing, ungrammatical phrases, nested comparisons, conditional opinion, and sarcastic intonation, negation induced inversion and implicit sentiment cue. The proposed RNN showed resilience to majority-class bias, robust generalization on training cycles, and a stable learning behavior (despite highly imbalanced data with significant positive sentiment) despite a sharp reduction in performance, which indicates the proposed architecture is resilient to majority-class bias. The comparative analysis also confirmed that the proposed RNN is superior to SVM and neural networks, and learning linguistic sequences as sequential semantic representations is more beneficial in sentiment modeling. The above strengths affirm that the suggested model can be used in scalable and

review-based sentiment intelligence, which is a useful tool in interpreting the customer experience accurately to gain an understanding of the product perception and strategic seller feedback. Possible future enhancements will involve incorporating multilingual transformer-based embeddings, lightweight attention-fusion systems and better (more explicit) distinction between aspect-level sentiment indicators. The system may also include explain ability dashboards where the model decisions can be more transparent and employ smarter methods to augment minority-classes. It can also be optimized to high throughput, real-time review scoring to aid adaptive recommendations, validate review-quality, learn dynamic trends and scalable e-commerce analytics.

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