IMDB movie review sentiment analysis using machine learning

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***Abstract*—Sentiment analysis is the current popular method to know the business value in the market by analyzing the user feedback. Sentiment analysis helps the business to know the pulse of the customer and where to improve factors. Using Natural Language Processing (NLP) we can analyze the sentiments underlying the sentences whether positive or negative. Now a days, a lot of businesses are looking towards customer satisfaction factors and their opinions. Movie industry is one of them. In our project, we have collected the reviews from the Internet Movie Database (IMDB) dataset from Kaggle to analyze the sentiments of the reviews. For text processing and modelling BoW(Bag of Words) and TFIDF vectorizer models are implemented and compared the results of both the methods. In our project, BoW(Bag of Words) and TFIDF vectorizer models are being implemented and to classify the given inputs we have used two classification algorithms SGD(Stochastic Gradient Descent) and Multinomial Naive Bayes compared the results of both the methods. The project's goal is to categorize the provided review as either positive or negative using Multinomial Naive Bayes and Stochastic Gradient Descent algorithms. The algorithms are implemented using sklearn library and the whole project is implemented using Python programming language. Both the algorithms achieved 80 percent accuracy and BoW model outperformed the TF-IDF model. Dataset is collected from Kaggle open-source repository. It contains 50k movie reviews each review is classified into positive or negative. IMDB is a most popular website for movie or celebrity content. And the project is deployed into the web application Python Flask framework, HTML and CSS.**

***Index Terms*—BoW(Bag of Words), Internet Movie Database(IMDB), Natural Language Processing(NLP), Stochastic Gradient Descent(SGD), Term Frequency-Inverse Document Frequency(TF-IDF),**

I. Introduction

One of the qualities that makes humans stand out from other animal clans is emotions. Humans show different emotions in different situations, happy, sad and understanding emotions is a complex task. This customer behavior also applies to shopping when purchasing a product or expressing the thoughts on the purchased product. Sentiment analysis is finding the emotional tone in a piece of text. This is also known as opinion mining. In general, the main types of the tones are categorized into positive, negative and neutral. Natural language process (NLP) which is a branch in machine learning deals with this task. This task is often performed on textual data. Sentiment analysis is mainly performed to solve the business problems as understanding the brand values through reviews and ratings. For example, an e-commerce business can be improved by analyzing the reviews of the various customers. There are different kinds of sentiments but the most common one is the polarity of reviews that include positive, negative, and neutral. The second type of the sentiment is the intentions of the customer interested and not interested, the third type of the sentiment is specific emotion of the customers like happy, sad and the last category is urgency. Every day, different kind of data is generated from different entities. In that text data is generated from several industries and majority of the text data is generated from the following industries e-commerce sites movie databases. This datum is used mainly for sentiment analysis putting NLP (Natural Language Processing) to work. Using NLP drawing, meaningful insights make the businesses understand the brand value in the market [1]. The two top text classification models, Multinomial Naive Bayes and Stochastic Gradient Descent are used to categorize the text. SGD, which employs convex loss functions like (Linear) Support Vector Machines and Logistic Regression, is an effective method for classification applications. Large-scale and sparse machine learning issues that can arise in text classification and natural language processing can be effectively addressed by SGD. [2]. In addition to SGD, Multinomial Naive Bayes algorithms also outperform the traditional algorithms in text classification. Natural Language Processing uses the Multinomial Naive Bayes algorithm as a probabilistic learning technique most frequently (NLP). The method, which guesses the tag of a text such as an email or newspaper article, is based on the Bayes theorem. On the small text dataset for the news classifier, the Multinomial Naive Bayes classifier had an accuracy of 73% whereas the Bernoulli Naive Bayes classifier had an accuracy of 69%.

The sentiment analysis is crucial to the businesses to understand the customer behavior and to improve business brand values. There are different kinds of approaches to analyze the sentiments because the reviews of the product or business come in various forms. If the goal of the business is to analyze the overall emotion of the review rating like happy, very happy, sad and very sad, then we can use fine grain technique to solve the problem. If the rating's scale is 1-5. Ratings of 1-2 are considered as very sad and sad and the ratings 3-5 are neutral happy and very happy. We must determine the emotion of the text from the key words if the business objective is to categorize the review's emotion based on aspects as if no direct emotion is indicated in the review. A negative category would be "This product is not safe for children," for instance. If the company wants to classify customer reviews based on intent, it will examine the buyer's motivations for making a purchase. The corporation will market the product by tracking the user with the resources if the customer falls under the "going to buy in the future" group. The business will save time and money by not advertising the product if a customer falls under the "already buy" category.

Different types analyzing tools track different contexts of the text. Choosing the techniques depend on the business problems. There is a huge gap between what people feel and what they express. This issue is the main challenge in analyzing the emotion of the texts. And the other reasons are inaccurate training also leads to inaccurate results of the sentiments. If the review is "the color of the product is green" the actual intention of the customer is: the purchased product has a different color since that is not reflecting in the review it may be categorized as neutral instead of negative. Another example of misclassification of emotion includes lexicons like everything and anything can add to type of the emotion. Another challenge in sentiment analysis is the presence of contradictory statements in a review like " I was very sad yesterday but I am happy now."

Text classification or sentiment analysis has various applications. In some scenarios, this classification or analysis is done behind the scenes and in some scenarios, it is done in the face. Few applications of this task are:

- Automating the processes
- Finding and solving the issues on the basis of urgency
- Creating the VoC(Voice of Customers) and working on it

One of the businesses whose work is measured by reviews is cinema. Film criticism is divided into two categories one is Journalism and the other one is public talk. Film reviews are written in different formats as narrating the short plot of the movie and the other type is polarity of the movie positive or negative. Positive reviews are written with an intent that a reader can go and watch the movie. These reviews save time and give a brief overview of the movie. IMDB is a popular online database where these reviews are saved. Initially, this idea was started as a fan operated unofficial group to comment on video games, movies, TV series. In 1993, this was evolved as a website to help the audience to get a sense of the content before watching it. There are advantages and disadvantages to a reader with the movie reviews. The advantages are:

- A nice summary of the plot of the negative review of the movie saves the reader time of reader
- The review can save the reader spending the amount on it

Disadvantages are:

- A reader cannot purely depend on the review to make a choice since these reviews are purely individual opinions
- Sometimes, these can be biased
- The reader and the writer interests may differ for example the reader is in interested in the technical points in the movie where as the writer's review is about humor in the movie

In addition to machine learning, deep learning also proved to be the most efficient method to solve text classification problems. With its wide range of applications, it is selected as State of the Art algorithm(SOTA). It showed the most efficient results when applied to text classification problems.

II. Motivation

- With evolution of internet and ecommerce business everything has come to our fingertips, either it can be buying the product or reviewing the product.
- According to the survey in 2017, a buyer read average of 7 reviews of the product before purchasing. The statistics of the previous year shows the number is 6.
- Nowadays, a lot of businesses are looking towards customer satisfaction factors and their opinions. Movie industry is one of them. In our project, we have collected the reviews from the Internet Movie Database(IMDB) dataset from Kaggle to analyze the sentiments of the reviews.
- Generally, text data is messy, but the machine learning models expect well defined fixed length data. BoW is a feature extraction technique like machine learning models. BoW forms the vocabulary of the text and counts the frequency of the words. Bag means the models ignore the order it only considers the presence of the word.
- The disadvantages of BoW model is with the introduction of new words, the size of the matrix increases Resulting in more sparsity. Use of the TF-IDF vectorizer is an alternate strategy. transforms a group of raw text into a TF-IDF feature matrix. Tf-IDF is the same as Count Vectorizer but includes the inverse transform capability. Simply put, it computes the relative count of each word in a document.

III. Objectives

Main objectives of the project are:

- Our project's primary goal is to categorize the given sentence or review as either positive or negative.
- Applying feature extraction methods from scikit-learn BoW and TFIDF Vectorizer to extract the tokens
- Implementing Multinomial Naive Bayes and Stochastic Gradient Descent(SGD) classification algorithms

- Conducting a comparative analysis of the classification algorithms
- Concluding the project with observations

IV. Related work

With the revolution of data in every industry there is a huge demand for NLP techniques. Traditional methods in machine learning algorithms, i.e., classification algorithms are not suitable for the analysis of sentiments hidden in the text. These algorithms lack feedback blocks in their architecture[3]. Primary task in sentimental analysis is computing the feedback. LSTM networks are an improved version of RNNs. LSTM network contains an extra embedding layer which is helpful to compute the feedback. Common task in any Natural Language Processing technique is creating sparse vectors from the preprocessed data to feed the model. Creating a sparse vector from the data is called Bag of words. Bag of words process creates unnecessary memory to store the vector data. This issue can be overcome using a word embedding method One of the challenging task in Natural Language Process is to classify or identify various language texts. Language translation and identification task has the applications and use cases in various fields. For example, Chinese language is has the one of the difficult structured language in the world [10]. We have implemented classification algorithms on this language but the results were not satisfactory. But to overcome the difficulties at the language level we need to go to the roots of the process that is on which context we are solving the problem. There aspects to the languages this aspect based approach solves the issues in language and context categorization [19].Though we consider the aspect based reviews the results are not fruitful in some cases because of the presence of lexicons in the language. If we deal with the lexicons easily, we can eliminate the text classification problems efficiently [8]. Another step forward from lexicon analysis, bag of words' methods have their own drawbacks that do not capture the order and semantics of the text.TF-IDF vectorizer too has limitations. To overcome these two problems, we have used word embeddings that have come to the rescue. They capture the context or meaning of the words and ordering [11]. Sentiment analysis or opinion mining can be done in different ways the most common way is to find the emotion of the review and the other approach is to finding the score of the aspect in a given review [16].

Now a days, e-commerce websites are largely dependent on the customer satisfaction to improve the performance of the brand values. But the bottlenecks in this process are complexity of the text. This cannot be solved in single step procedures. In three step procedures like removal of stop words, SAP (Sentiment Analysis and Prediction) and KNN classification model com- binned efforts improved the classification results [15]. Other than e-commerce industry sentiment analysis applications are reached to medical domain as well. With the pandemic of COVID-19, this is applied to know the sentiments of the Covid-19 tweets in the twitter. The analysis became popular and give the best results on the machine learning algorithms [12]. New approaches are spread to two level sentimental analysis that is not limited to only review of the customer it is linked to other factors as well price and shipping as well. Reviews related to price, shipping are collected from Thai dataset. These reviews are tokenized and its polarity is analyzed. This is a novel approach, and it has numerous advantages [14]. New experiments on hotel review dataset and beer review dataset proved that SAAM(Sentence Attribute Aspect Model) can outperform the neural network models like CNN and RNN. In SAAM sentence level word embeddings and document level scorings are used to classify the polarity of the review [20]. Choosing the algorithms is a task in machine learning. In addition to social media sentiment analysis, sentiment analysis was used in presidential elections of Indonesia that was conducted in 2019. Naive Bayes classifier proved to be the best algorithm that gives the best results on this dataset. In Naive Bayes, we have several algorithms to classify the text. Multinomial Naive Bayes classifier is also proved to be the best algorithm in sentiment or text analysis [17]. This can be applied to other industries also like designing where choosing the automatic color palette [13]. Study on IBM Watson's Natural Language set proved that scores of the sentimentality are directly related to the attitude scores of the population [**?**]. For marketing, social media is a best option to with the Word of Mouth the marketing of any business is spread easily. But the words used in non-social media are different from the vocabulary used in the social media. We have conducted an experimental analysis of the words and then created as dataset from it for future analysis of the sentiments of the text [2] [5]. The popularity of the reviews of online business much more active now a days but these reviews can be deceptive sometimes. Conducting analysis on finding fake business reviews helps the organizations in many ways [7]. Most of the communication now is happening online and through calls. This communication is happening majorly in the English language but the considerable amount of communications is happening in Hindi language as well. Deep neural networks are proven to be performed well on the Hindi dataset [4]. The point of sentiment analysis here is the project is related to movie review sentiment analysis. Instead of analyzing the sentiments of the reviews directly. In this we have collected sentiments of the movie in the form of plot, actors, director and music. Sentiments of the reviews of these categories analyzed with most impact. After the analysis, we have found that plot category has the most reliable review section which leads to the success of the movie [17]. For image analysis we have popular algorithms CNN, which gives the accurate results while analyzing the image data. Likewise, for text classification algorithms in deep learning LSTM is the most popular algorithm. LSTM contains the gates for memory which helps to find the contexts of the sentences. But in a novel approach is to build a hybrid model with CNN and LSTM that eliminates the drawbacks in each method [6]. Sentiment analysis(SA) is not limited to the text, this can be done with images also. With facial images, we can detect the emotions in the image. Deep Neural Networks perform well on sentiment analysis through images [18]. As per the recent studies, multi modal sentiment analysis gained popularity than the unimodal sentiment analysis. Considering different modal sentiments gives the better understanding of the data [9]. Like Chinese language, Arabic also has noisy content to analyze the data. Though the language has noisy content, Discriminative Multinomial Naive Bayes eliminated the disadvantages of the time consumption of processing the data by this algorithm compared to the existing algorithms [1]. Text classification dataset is not balanced in nature but these can be made balanced using sampling techniques like over sampling and under sampling [3].

V. Data Description

Dataset is collected from Kaggle open source repository link. It contains 50k movie reviews each review is classified into positive or negative. IMDB is a most popular website for movie or celebrity content. In this dataset movie reviews are randomly scrapped and converted into the csv file. The dataset contains an equal distribution of training and testing reviews i.e., 25,000 training and 25,000 testing. In our project, we have customized the training and testing ratio to 80-20 ration with that we have training data of 40000 samples and remaining samples are used for testing. The size of the dataset is 27MB. After performing the statistical analysis, we have found that there are 418 duplicate reviews in the dataset and 49582 unique reviews. With this dataset, we can perform the binary classification of reviews.

VI. Proposed Framework

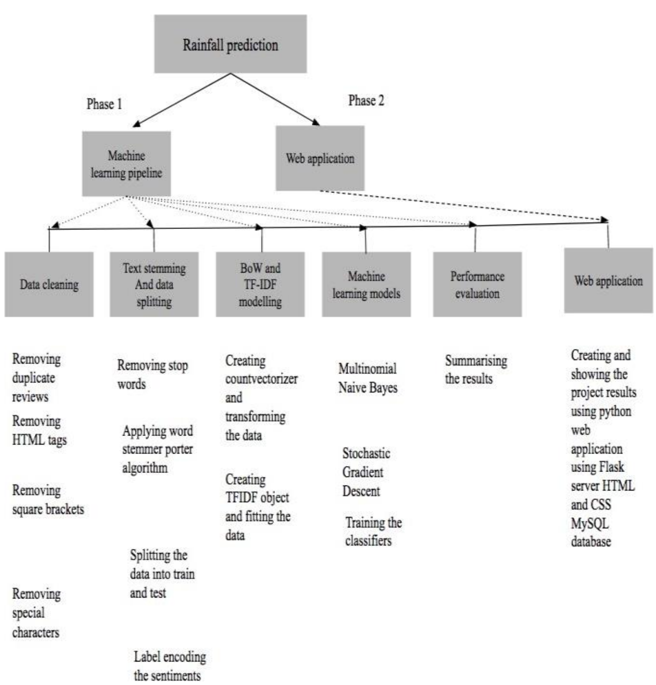

Figure 1. Workflow

The first step in our project flow is to cleanse the raw data. In all the datum cleaning steps identifying the null values is an important step. Removal of null values improves the model performance since they do not add any value to the models. In the second stage of data cleaning in text classification involves removal special characters, square brackets, back or forward slashes and stop words. Removing all these makes the data clean and easy to use for the next steps.

Removing null values and text stemming of the data. Categorical target variables are label encoded using scikit-learn label encoding. The following stage involves applying the 80/20 rule to divide the data into train and test sets. To transform the text into vectors, split data is sent to the BoW and TF-IDF models. To classify text into good or negative reviews, converted vectors are once more fed into machine learning models.

A. Tools and technologies:

Programming language is used to develop the project. For model creation scikit-learn Python library is used. After reaching the classification, which is the last phase of the project, we have deployed the project into the web application using HTML, CSS and Bootstrap for front end development and Python programming language for back-end development.

B. Text preprocessing:

We have utilized a regular expression module to carry out text preparation activities. Additionally, text stemming is done to reduce a word's inflectional forms and occasionally derivationally related forms to a single base form. Porter's algorithm is the most popular and successful approach for stemming English. Porter's approach uses five word reduction steps in succession. There are several accepted conventions for choosing rules in each phrase, such as choosing the rule from each rule group that applies to the longest suffix.

C. Bag of Words(BoW):

Bag of Words modeling uses the count vectorizer. The flow of this model is: The first step in the BoW modeling is inputting the preprocessed text. From the preprocessed input text, unique words are extracted and created vocabulary of the input text. With the vocabulary binary vector is created for each sentence using codes 0 and 1. Here, 0 means absence of the word and 1 means the presence of the unique word in the sentence. Fig 7 is the life cycle of the BoW model. This model starts at the input text and ends with vectors of the sentences. Countvectorizer is used to perform the operation. To implement this Countvectorizer function is imported from scikit-learn library.

The limitations of the BoW model are:

- Vocabulary: If the new words add to the sentence then the vocabulary of the model would also increase.
- Sparsity: With the increase of vocabulary representation of zeros in the matrix also increases thereby increasing the sparsity of the matrix.
- Ordering and grammar: BoW model is not focusing on the ordering of the words and grammar of the sentence.

D. TF-IDF Vectorizer:

TF-IDF means Term Frequency Inverse Document Frequency. In the first stage, this method focuses on the frequency of the words means how frequently the words appear in the corpus. One problem with calculating the frequency is most frequent words dominate the corpus. To avoid this, inverse frequency is used unlike the calculation of frequency. Inverse frequency calculates the how rarely the word appears in the corpus.

E. Multinomial Naive Bayes:

Multinomial Naive Bayes is a collection of many algorithms which uses probabilistic learning for the prediction of text output tags. Naive Bayes algorithms' principle is the prediction of the one feature does not depend on the other. It works on the mathematical concept of conditional probability.

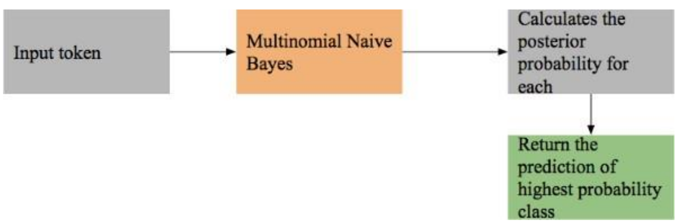

Figure 2. Working of Multinomial Naive Bayes

F. Stochastic Gradient Descent:

Stochastic Gradient is an iterative process to optimize the loss function or objective function. This is also called as Stochastic approximation. This algorithm is implemented using scikit-learn. The below table describes the attribute information of the algorithm.

S.No.	ATTRIBUTE	DESCRIPTION
1.	coef	Weights
2.	n_iter	Number of iterations
3.	loss_function	Loss Function
4.	t	Number of weight updates

Table I
ATTRIBUTE INFO

VII. RESULTS ANALYSIS

- **Model1:** For result analysis, we have trained and tested with the both the models Multinomial Naive Bayes and Stochastic Gradient Descent.
- Multinomial model is trained and tested with BoW model and TF-IDF feature extractor model.
- For both the methods' model gave the same results on the test set, i.e., 75 percent accuracy.
- We created a confusion matrix and classification report to better understand performance. The classification report displays performance indicators besides accuracy. BoW model enabled Multinomial Naive Bayes to obtain high precision for the category of negative reviews and high recall and F1-score for the category of positive reviews.

classification report of BoW model:

	precision	recall	f1-score	support
0	0.74	0.76	0.75	4756
1	0.76	0.74	0.75	4826
accuracy			0.75	9582
macro avg	0.75	0.75	0.75	9582
weighted avg	0.75	0.75	0.75	9582

Figure 3. Multinomial classification report

The purpose of the confusion matrix is to breakdown the miss classification categories. Out of 9582 test samples, 7178 samples are correctly classified. Other samples are misclassified. This misclassification rate is high for positive that means positive reviews are misclassified as negative.

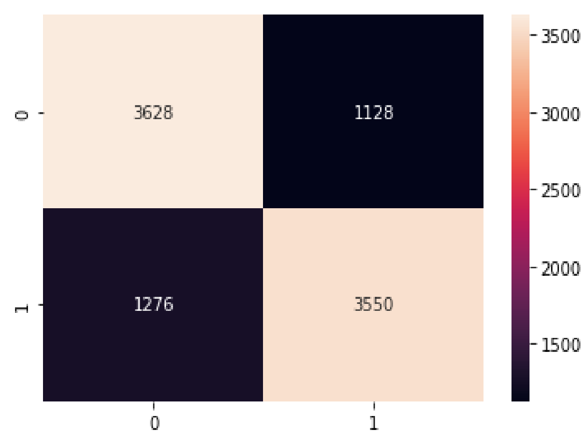

Figure 4. Multinomial confusion matrix

- **Model2:** In the second step, Multinomial Naive Bayes is trained with TF-IDF vectorizer. It also achieved 75 percent on the test set. For this model also, we have constructed the classification report and confusion matrix.
- from the classification report we can see that precision of the positive review class is high and recall and F1 score is high for negative review class.
- Confusion matrix is constructed to check the misscalssification rate for each category. Correctly categorized or predicated samples are 7176 and miss classification rate is high for negative class.
- **Model3:** In the third step, we have implemented SGD classifier with Bow model.
- Classification report is constructed to know the true positives and false positives
- Confusion matrix is constructed to know the rate of classification.

classification report of tfidf model:

	precision	recall	f1-score	support
0	0.76	0.73	0.74	4756
1	0.74	0.77	0.76	4826
accuracy			0.75	9582
macro avg	0.75	0.75	0.75	9582
weighted avg	0.75	0.75	0.75	9582

Figure 5. Classification report TF-IDF Multinomial

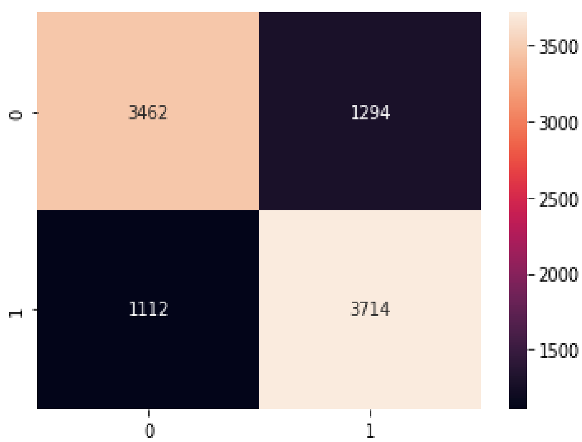

Figure 6. Confusion matrix multinomial TF-IDF

- To understand performance better, we have constructed classification report and confusion matrix
- Stochastic Gradient Descent achieved 51 percent accuracy on test data.
- High precision is 95 for the positive category, high recall for negative category and High F1score for negative category
- Correct classification samples are 4844 out of 9000 samples only 50 percent of the samples are correctly classified other 50 percent is misclassified. The misclassification rate is high for the negative category that is 4737 negative reviews are incorrectly classified as positive reviews.

classification report of BoW model:

	precision	recall	f1-score	support
0	0.95	0.00	0.01	4756
1	0.50	1.00	0.67	4826
accuracy			0.51	9582
macro avg	0.73	0.50	0.34	9582
weighted avg	0.73	0.51	0.34	9582

Figure 7. Classification report SGD BoW

- **Model4:** In the fourth step, we have implemented SGD classifier with TF-IDF vectorizer model.

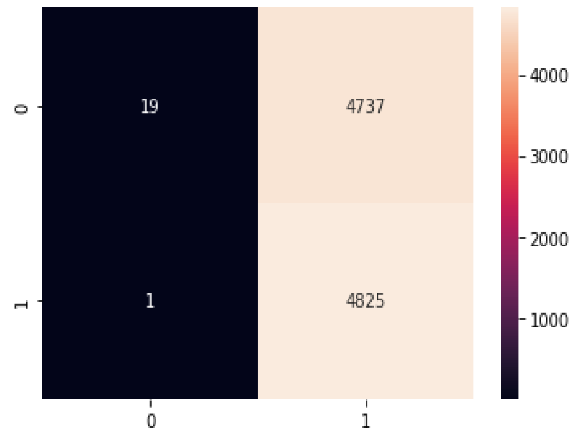

Figure 8. Confusion matrix SGD BoW

- Classification report is constructed to know the true positives and false positives
- Confusion matrix is constructed to know the rate of classification.
- To understand performance better, we have constructed classification report and confusion matrix
- Stochastic Gradient Descent achieved 50 percent accuracy on test data
- High precision is 50 percent for the negative category, high recall for negative category and High F1score for negative category
- Correct classification samples are 4826 out of 9000 samples only 50 percent of the samples are correctly classified other 50 percent is misclassified. The misclassification rate is high for the negative category that is 4756 negative reviews are incorrectly classified as positive reviews.

classification report of tfidf model:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	4756
1	0.50	1.00	0.67	4826
accuracy			0.50	9582
macro avg	0.25	0.50	0.33	9582
weighted avg	0.25	0.50	0.34	9582

Figure 9. Classification report SGD TF-IDF

In the end, we have visualized the word cloud for both positive and negative reviews. Word cloud gives the frequency of the words in a particular context.

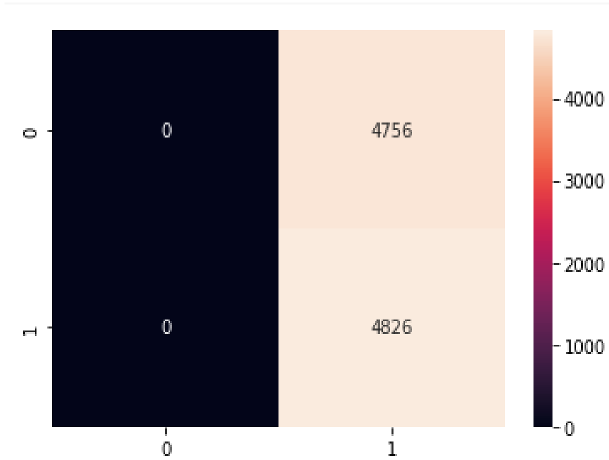

Figure 10. Confusion matrix SGD TF-IDF

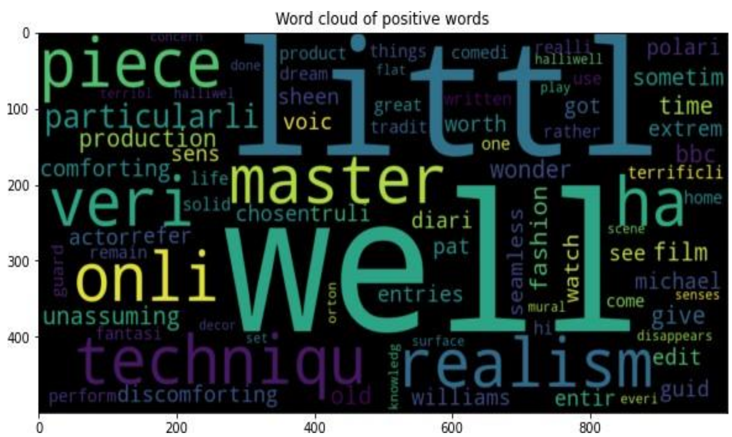

Figure 11. Word cloud visualization for positive words

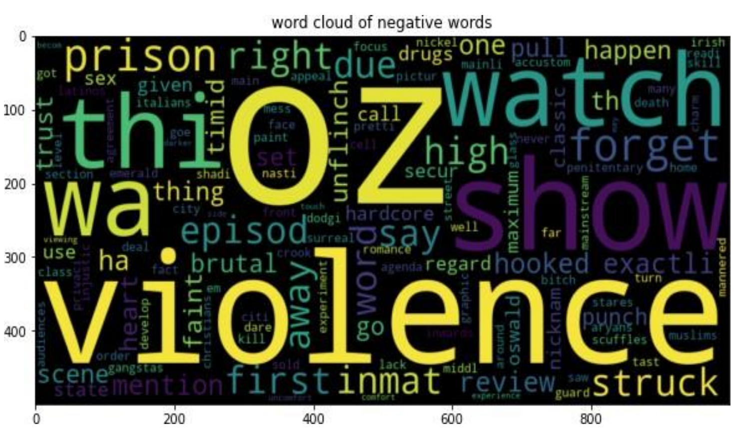

Figure 12. Word cloud visualization for negative words

VIII. Results summary

Upon conducting the experimental analysis with Bag of Words and TF IDF methods with machine learning models SGD and Multinomial Naive Bayes. Multinomial Naive bayes algorithm performed well compared to the SGD. If we analyze the performance, BoW and TF IDF methods, both the methods gave similar results.

References

[1] Hussain Al Salman. An enhanced method for Twitter social media sentiment analysis of Arabic tweets. 2020, pages 1-4, Third International Conference on Computer Applications & Information Security (ICCAIS). IEEE, 2020.

[2] Li-Chen Cheng and Song-Lin Tsai. Deep learning for automated sentiment analysis of social media. In *Proceedings of the 2019 IEEE/ACM international conference on advances in social networks analysis and mining*, pages 1001–1004, 2019.

[3] Kushankur Ghosh, Arghasree Banerjee, Sankhadeep Chatterjee, and Soumya Sen. Imbalanced twitter sentiment analysis using minority oversampling. In *2019 IEEE 10th International Conference on Awareness Science and Technology (iCAST)*, pages 1–5. IEEE, 2019.

[4] Amit Kumar Goel and Kalpana Batra. A deep learning classification approach for short messages sentiment analysis. In *2020 International Conference on System, Computation, Automation and Networking (ICSCAN)*, pages 1–3. IEEE, 2020.

[5] Kai-xu Han, Chien-Ching Chiu, and Wei Chien. The application of support vector machine (svm) on the sentiment analysis of internet posts. In *2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE)*, pages 154–155. IEEE, 2019.

[6] Md Rakibul Haque, Salma Akter Lima, and Sadia Zaman Mishu. Performance analysis of different neural networks for sentiment analysis on imdb movie reviews. In *2019 3rd International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE)*, pages 161–164. IEEE, 2019.

[7] Rakibul Hassan and Md Rabiul Islam. Impact of sentiment analysis in fake online review detection. In *2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*, pages 21–24. IEEE, 2021.

[8] Victoria Ikoro, Maria Sharmina, Khaleel Malik, and Riza Batista-Navarro. Analyzing sentiments expressed on twitter by uk energy company consumers. In *2018 Fifth international conference on social networks analysis, management and security (SNAMS)*, pages 95–98. IEEE, 2018.

[9] Ayush Kumar and Jithendra Vepa. Gated mechanism for attention based multi modal sentiment analysis. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 4477–4481. IEEE, 2020.

[10] Gen Li, QiuSheng Zheng, Long Zhang, SuZhou Guo, and LiYue Niu. Sentiment infomation based model for chinese text sentiment analysis. In *2020 IEEE 3rd International Conference on Automation, Electronics and Electrical Engineering (AUTEEE)*, pages 366–371. IEEE, 2020.

[11] Jianyan Li and Yongquan Liang. Refining word embeddings based on improved genetic algorithm for sentiment analysis. In *2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC)*, volume 9, pages 213–216. IEEE, 2020.

[12] Anu J Nair, G Veena, and Aadithya Vinayak. Comparative study of twitter sentiment on covid-19 tweets. In *2021 5th International Conference on Computing Methodologies and Communication (ICCMC)*, pages 1773–1778. IEEE, 2021.

[13] Ya-Fang Peng and Tzren-Ru Chou. Automatic color palette design using color image and sentiment analysis. In *2019 IEEE 4th International Conference on Cloud Computing and Big Data Analysis (ICCCBDA)*, pages 389–392. IEEE, 2019.

[14] Paitoon Porntrakoon and Chayapol Moemeng. Thai sentiment analysis for consumer's review in multiple dimensions using sentiment compensation technique (sensecomp). In *2018 15th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, pages 25–28. IEEE, 2018.

[15] Abdul Razzaq, Muhammad Asim, Zulqrnain Ali, Salman Qadri, Imran Mumtaz, Dost Muhammad Khan, and Qasim Niaz. Text sentiment analysis using frequency-based vigorous features. *China Communications*, 16(12):145–153, 2019.

[16] Satuluri Vanaja and Meena Belwal. Aspect-level sentiment analysis on e-commerce data. In *2018 International Conference on Inventive Research in Computing Applications (ICIRCA)*, pages 1275–1279. IEEE, 2018.

[17] Meylan Wongkar and Apriandy Angdresey. Sentiment analysis using naive bayes algorithm of the data crawler: Twitter. In *2019 Fourth International Conference on Informatics and Computing (ICIC)*, pages 1–5. IEEE, 2019.

[18] Yatharth Yadav, Vikas Kumar, Vipin Ranga, and Ram Murti Rawat. Analysis of facial sentiments: a deep-learning way. In *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, pages 541–545. IEEE, 2020.

[19] Jian Yang and Juan Yang. Aspect based sentiment analysis with self-attention and gated convolutional networks. In *2020 IEEE 11th International Conference on Software Engineering and Service Science (ICSESS)*, pages 146–149. IEEE, 2020.

[20] Yifan Zhang, Fan Yang, Marjan Hosseinia, and Arjun Mukherjee. Multi-aspect sentiment analysis with latent sentiment-aspect attribution. In *2020 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, pages 532–539. IEEE, 2020.