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Sentiment Analysis Using Natural Language Processing on Text Messages

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Abstract:- In this digitalized age, e-commerce is rising popularity since it gives products to consumers' doorsteps without them having to leave their residences. The value of reviews has increased as buyers rely on them to make educated purchases. Machine learning may assist the task of sorting through hundreds of reviews by categorising and learning from them. Sentiment analysis, which focuses on understanding emotions and attitudes, is a key application of Natural Language Processing (NLP). This study focuses on analyzation on sentiments of Amazon product ratings utilising methods for supervised learning. The dataset utilised contains thousands of reviews across different categories. Various NLP models, including Recurrent Neural Networks (RNNs), are experimented with for categorising reviews into good, negative, or neutral attitudes. The way in which the models is tested utilising recall, accuracy, and precision. The ramifications of sentiment analysis results for businesses and customers on the Amazon platform are being investigated. This research delivers insights into sentiment analysis on Amazon's dataset and its practical applications. E-commerce is become increasingly popular, and sentiment analysis applying machine learning may aid analyse vast amounts of data to recognise emotions efficiently. Various machine learning methods, including K-Means Clustering, Decision Trees (DTs), Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Bayesian Networks (BNs), have been employed for emotion categorization. This research contains a comparison of earlier studies and provides a real-time sentiment analysis system to track everyday sentiments and give acceptable suggestions to users. Sentiment analysis is a crucial aspect of Natural Language Processing (NLP) that focuses on categorising sentiment polarity. This research seeks to solve issues in sentiment analysis and presents a general approach for categorising sentiment in online product reviews from Amazon.com. Sentence-level and review-level classification investigations are done, providing positive results. Future sentiment analysis work is also mentioned.

Keywords: *Sentiment analysis, NLP, feature extraction, text categorization, machine learning.*

1. Introduction

Sentiment analysis, sometimes known as opinion mining, is the process of analysing and identifying people's opinions or emotions expressed in text data. It has gained considerable interest, particularly Considering the growth of user-generated material on social networking sites. Platforms like Twitter provide APIs for researchers and developers to collect and analyse data for sentiment analysis.

E-commerce companies like Amazon have grown crucial in the digital era, giving a broad range of things and gathering numerous client reviews. Sentiment analysis applied to these ratings can extract important data regarding customer contentment, product quality, and industry trends. By automatically assessing sentiment in the text, businesses may analyse consumer comments and make intelligent conclusions to enhance their products or services[1].

Social media platforms like Instagram, Twitter, and WhatsApp have aided to addressing mental health challenges, creating awareness, and delivering support for those in need. Sentiment analysis may be used to study social media material, recognising indicators of stress and anxiety for early intervention and access to mental health care.

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To develop a full sentiment analysis platform, several approaches may be utilised, including examining audio and video content in addition to text. OpenCV, a computer vision library, can recognise face expressions using facial recognition algorithms, capturing emotions beyond words.

Sentiment analysis techniques span several methodologies, such as lexicon-based, graph-based, network-based, machine learning, deep learning, ensemble-based, rule-based, and hybrid approaches. The Natural Language Toolkit (NLTK) is a key resource for processing natural language and accomplishing tasks like spell checking, machine translation, and text classification.

Customer evaluations are vital in influencing buy selections, with more than 88% of online shoppers see reviews as being just as real as personal suggestions. Ground truth data, including ratings offered by customers, helps train supervised learning models for sentiment analysis.

In conclusion, sentiment analysis is a robust method in Natural Language Processing (NLP) for categorising sentiments or emotions in text data. It finds practical uses in e-commerce, mental health, and social media analysis. Leveraging machine learning and deep learning methodologies, sentiment analysis gives important insights supporting decision-making process[1].

Star Level	General Meaning
☆	I hate it.
☆☆	I don't like it.
☆☆☆	It's okay.
☆☆☆☆	I like it.
☆☆☆☆☆	I love it.

Figure 1: Rating on reviews from Amazon.com

Sentiment analysis is an effective approach for analysing the sentiments and intentions communicated in a piece of work, such as an essay or labour. Language serves as a vehicle for transmitting thoughts and feelings, and sentiment analysis enables us to uncover these sentiments, whether they are good, bad, or neutral.

Let's consider a restaurant chain that provides a range of culinary goods, including milkshakes, burgers, sandwiches, and pizza. Customers get the ability to purchase and leave reviews on the company's website. Positive ratings demonstrate user pleasure, while negative assessments suggest opportunities for growth. Neutral reviews, on the other hand, lack a defined attitude.

These assessments play a crucial role in helping the company enhance food quality and value, create brand awareness, and increase sales. However, personally analysing a big number of evaluations might be time-consuming and unfeasible. This is where sentiment analytics comes into play.

Sentiment analytics combines natural language processing and machine learning to assess enormous volumes of data, such as consumer ratings. This empowers the company to make data-driven decisions based on real-world realities rather than relying on a limited sample size.

In today's digital era, e-commerce platforms have become the main means of international goods exchange. As a result, it has become normal practice for purchasers to research product evaluations before making a purchase. Therefore, employing sentiment analytics to measure user feedback and get insights regarding product attractiveness has become vital.

Instead of manually analysing a large number of remarks, sentiment analytics allows for the classification and polarization of opinions based on essential aspects, delivering a full picture of the product's attractiveness to consumers globally. By employing machine learning algorithms, sentiment analytics streamlines the process, allowing for speedier and more relevant insights.

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Sentiment analytics is a powerful tool that aids in understanding the emotions and intentions expressed in a piece of work. By examining consumer reviews and comments, businesses may make intelligent decisions to enhance their products and services. In the digital era, sentiment analytics plays a crucial role in discovering client preferences and enriching the complete customer experience.

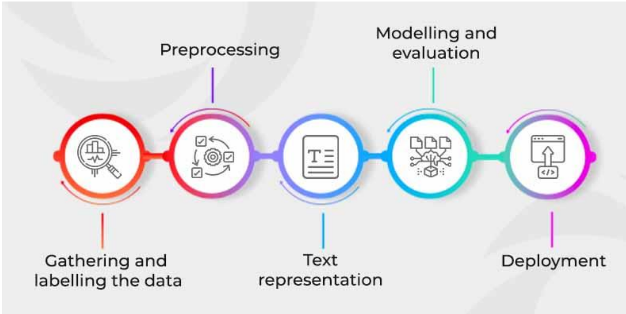

Figure-2: Steps employed in Sentiment Analysis

2. Literature Review

Sentiment analysis plays a significant role in classifying written language into positive, negative, or neutral feelings at many levels, including document, phrase, and entity/aspect levels. The concentration on entity and aspect levels enables a more detailed understanding of attitudes. In today's multilingual world, with about 6500 languages, language goes beyond communication, interweaving with emotions, identities, and cultures, providing obstacles for accurate robot evaluations. Natural Language Processing (NLP), a subset of language technology, involves sentiment analysis to extract meaningful information from data.

Python is extensively used in sentiment analysis research, with Multinomial Naive Bayesian (MNB) and Support Vector Machine (SVM) are crucial classifiers. Supervised learning algorithms like SVM and MNB are utilised to predict review ratings using text on a numerical scale, applying varied approaches such as hold-out cross-validation to measure classifier accuracy and recall values.

In e-commerce sentiment analysis, particularly on sites like Amazon, collecting relevant information from varied consumer assessments is a primary focus. Challenges related with Amazon reviews, such as unstructured material and varied review durations, are emphasised, highlighting the necessity to discriminate between real user feedback and possibly biased or erroneous information.

Various NLP models, including Neural networks that are recurrent (RNNs), convolutional (CNNs), and models based on transformers, such as BERT and GPT, are applied for sentiment analysis on Amazon reviews. Comparative evaluations give information regarding their efficacy[2].

Assessing sentiment analysis models comprises parameters such as area under the curve, F1 score, recall, accuracy, and precision the ROC curve, with the necessity of adopting suitable assessment techniques depending on research aims stressed.

Practical ramifications of sentiment analysis findings on Amazon are investigated, spanning corporate operations, product development, marketing methods, and their influence on consumer choice and satisfaction. Ethical considerations linked to privacy, bias in sentiment analysis, and potential implications of automated decision-making are discussed.

Sentiment analysis of Amazon product evaluations has become a thriving research topic, proving its usefulness on large-scale, real-world datasets and its practical value for businesses and customers. Ongoing problems include resolving data quality, ethical issues, and building more accurate and interpretable sentiment analysis systems.

It's noteworthy that sentiment analysis study encompasses numerous areas including sentiment categorization, emotion detection, and product ratings prediction. The usage of algorithms such as the perceptron method, naive bayes, and support vector machines has been investigated, with Multinomial Naive Bayesian commonly emphasised for its efficacy in research publications[3].

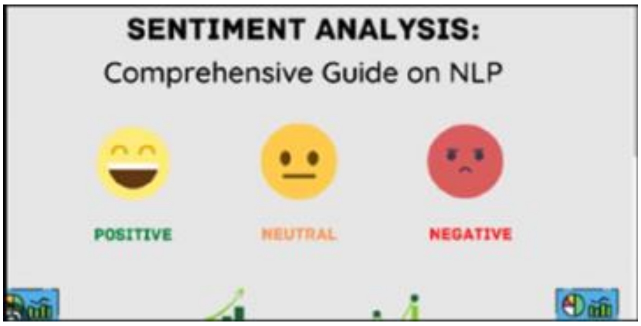

Figure-3: NLP Guide

3. Methodology

Dataset description:

Since one of the most popular e-commerce websites worldwide is Amazon Store. a substantial number of reviews may be gathered there. We made advantage of research from that was supplied in the format of product information on Amazon. The dataset was unlabelled, hence we had to label it before utilising it in a supervised learning model[5].

We need to supply our active learning process some pre-labelled training and testing datasets, as well as some unlabelled ones. We must give some manually marked reviews as training and testing sets in order to use active learning. The learning technique will then ask an Oracle or a user to identify a little sample of data from a pool of unlabelled dataset. And to determine the accuracy, many classifiers will be run. Accuracy determines if the border of the decision is separating the majority of the data in two groups. The tagging of the data rises with precision. We integrate those data with data that has already been pre-labelled if the accuracy is higher than or equal to 90% to obtain our labelled dataset[6].

This study piece gathers secondary data accessible on the internet and their investigation effort. Sentiment analysis became an essential component of many organisations such as biometrics, lustral analytics, and evaluation of the review and any material procedures. It is also used for assessments, survey responses, online e-commerce businesses, and speech analysis of any person and social media accounts and services for digital marketing for any business, current or prospective [7]. Eventually, it helps with market size and exponential growth research as well as competitive analysis of competitors' businesses and provide solutions for constructive industry-related issues and prospects for expansion. Its drawbacks include ambiguous terminology, snarky, and sarcastic negotiation techniques.

The Sentiment Analysis Architecture involves: Data Collection (diverse dataset), Preprocessing (cleaning, tokenization, numerical conversion), Feature Extraction (TF-IDF, word embeddings, BERT for context), Model Selection (RNNs, CNNs, transformers), Evaluation (metrics assessment), and Deployment (real-time analysis, updates). This approach enables accurate sentiment comprehension across domains.

We tagged our datasets for our model using both a manual and an active learning strategy. Various classifiers are employed in the active learning procedure to give accuracy up to an acceptable level. After achieving good findings, we examined the tagged datasets. We found features from the processed dataset that many classifiers later utilised to categorise. In order to extract features with higher accuracy, we utilised two alternative approaches: the bag of words technique and the tf-idf & Chi square strategy.

Key Characteristics:

Data Source: The dataset is taken from publicly available Amazon product reviews. The evaluations are gathered to reflect a random and unbiased selection of user-generated material from the platform.

Textual Content: Each entry in the dataset consists of the following important elements:

Review Text: The core textual substance of the user's review. This text is the major focus of sentiment analysis.

Review Rating: The numerical rating supplied by the reviewer (e.g., a star rating out of 5). This works as a reference for the ground truth sentiment (e.g., a 5-star rating indicating a good sentiment).

Product Information: Details about the product being evaluated, including its category, brand, and product name.

Review Date: The date when the review was posted, which may be applied for time-based analysis.

Sentiment Labels: The reviews are labelled based on the rating supplied by the reviewer. those with high ratings (e.g., 4 or 5 stars) are labelled as positive, and those with low ratings (e.g., 1 or 2 stars) are labelled as negative. Reviews with moderate ratings (e.g., 3 stars) are generally seen as impartial.

Data Volume:

Total Records: The dataset comprises a considerable quantity of records, with thousands or even millions of reviews, depending on the dataset's size and breadth.

Data Split: It may be divided into test, validation, and training sets to aid in the evaluation and training of models.

Data Preprocessing:

Text cleaning may be done to minimise extraneous letters, punctuation, and special symbols.

Tokenization and stemming/lemmatization can be used to preprocess the text data.

Data balancing techniques may be done to give an equal representation of positive and negative opinions.

Language: The reviews are normally in the language of the individual Amazon platform (e.g., English, Spanish, etc.). The dataset may focus on a single language or encompass numerous languages[8].

Potential Uses:

Training and testing sentiment analysis models using machine learning and NLP approaches.

Assessing consumer pleasure and evaluating market changes on Amazon.

Analysing the influence of product characteristics, brands, or categories on sentiment.

Investigating temporal patterns in emotion throughout time.

Ethical Considerations:

Data protection and consent: Ensure that data is obtained in conformity with privacy rules and with the approval of reviewers.

Avoiding prejudice: Address any potential bias in the dataset, such as bias in review ratings or sentiment tagging.

The Amazon Product Review Sentiment Dataset is a significant resource for scholars and data scientists interested in researching sentiment analysis within the context of one of the world's largest e-commerce platforms. It supplies the essential text samples and sentiment labels to create and test machine learning models for sentiment analysis[9].

Model components:

Tokenization: It is the procedure for separating a series of letters into tokens, which are sentences or words, terms, icons, or other objects. Tokens might be single words, phrases, or even whole sentences. Special characters such as punctuation are omitted from the procedure of tokenization. Tokens are the foundation for all other operations, such as text mining and processing.

Removing Stop Words: Those are the terms that portions of a phrase they are useless for any kind of text mining. In order to maximise the study's accuracy, we often remove key phrases. Different combinations of Various stop words are used based on the nation, language, and other elements. Many stop words are present used in English.

POS tagging: This method is usually called POS tagging. Adjectives, pronouns, verbs, adverbs, conjunctions, and their subclasses are all regarded as components of speech. A programme dubbed This goal is accomplished by Parts of Speech tagger, or POS tagger. Parts of Speech tagging is the process of giving the given word a part of speech assignment.

Quantifying emotions: An elaborate dataset comprising a huge number of words and the emotions linked with them was developed. Following the extraction of relevant phrases The text is compared with ours. to the text in the database, which enables us to identify the feeling lurking behind the language. Following the successful extraction of the words and their emotions, the text was given to a Counter, which helps us evaluate the feelings expressed in the text. The number of emotions found in a sample video that was fed into the classifier is shown in Figure.

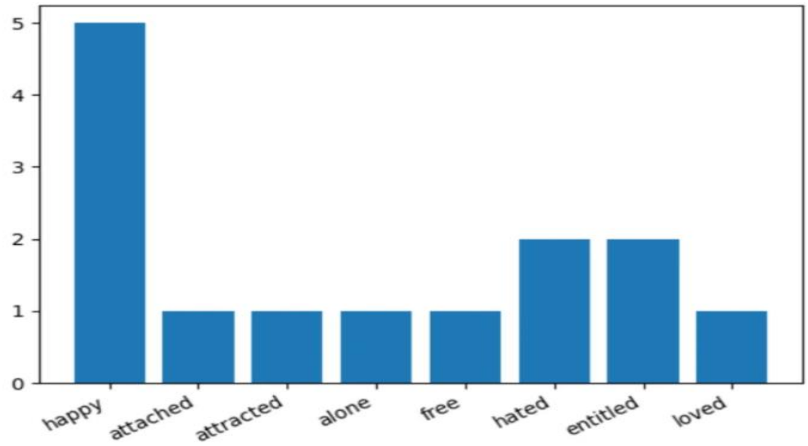

Figure 4 : Emotions based on data a Bar chart depiction

TF-IDF: A method for retrieving strategy known as TF-IDF weights both the inverse document frequency (IDF) and the a word's frequency (TF). Each term has a distinct IDF and TF score. The total of the terms' TF*IDF weights is the definition of the product ratings for the keyword in TF and IDF. Simply put, we may say that a term is less common& vice versa based on the weighted average of the TF*IDF score. Word frequency is represented by its TF[10].

A word's IDF denotes how common that phrase is across the corpus

♣ True Positive (TP) denotes the quantity of data. successfully classified.

♣ False positives, or FPs, are numbers. of rectify incorrectly categorised data.

♣ False Negative, or FN, denotes quantities of erroneous data labelled as correct.

♣ TN (True Negative) is the quantity of erroneous data classified

Precision: accuracy evaluates a classifier's accuracy, the number of return documents that are accurate. A better accuracy implies fewer false positives, while a lower accuracy corresponds to a higher false positive rate. Precision (P) is the proportion of correctly classified instances to total instances. It is characterised as

$$Precision = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Positive(FP)}$$

Recall: A classifier's sensitivity is determined by recall; how many positive results it yields. Greater memory equals fewer misleading negative results. The number of recalls divided by the suitable categorised according to the total anticipated occurrence count. This could be portrayed as

$$Recall = \frac{True\ Positive(TP)}{True\ Positive(TP) + False\ Negative(FN)}$$

F-Measure: When recall and precision are combined, a single statistic called as F-measure, and It is the precision and recall weighted harmonic mean. It may be described as

$$F\text{-}measure = \frac{2*Recall*Precision}{Recall + Precision}$$

Accuracy: The classifier's accuracy indicates how often it makes the right guess. The ratio of accurate predictions to correct forecasts is called accuracy as well as the overall count of forecasts.

$$Accuracy = \frac{TrueNegatives + TruePositive}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

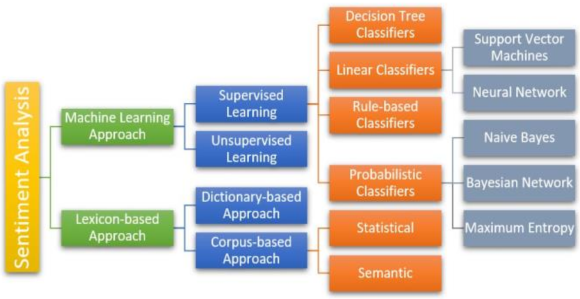

Figure 5: Sentiment Analysis Architecture

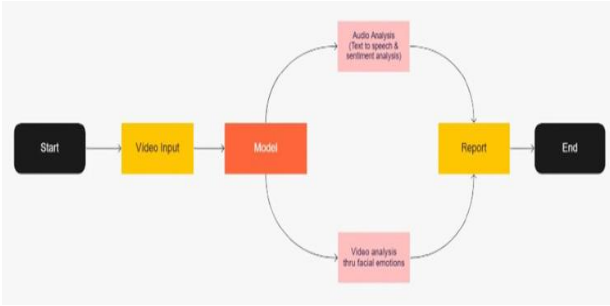

Figure 6: Pictorial illustration of video input processing for sentiment analysis

4. Results and Discussion

Count of Reviews by Stars:

Figure 7: Bar Chart showing Count of Reviews

Compound Score via Amazon Star Review

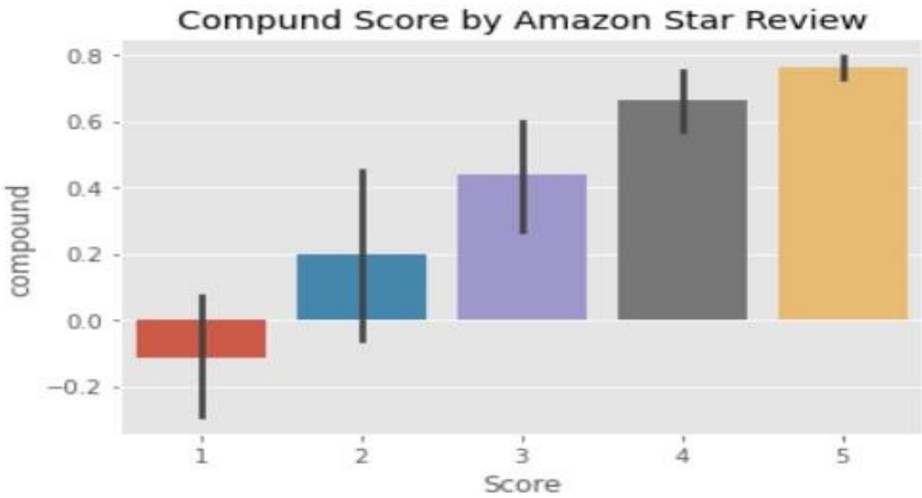

Figure 8: Compound Score by Amazon Star

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Result of Scores:

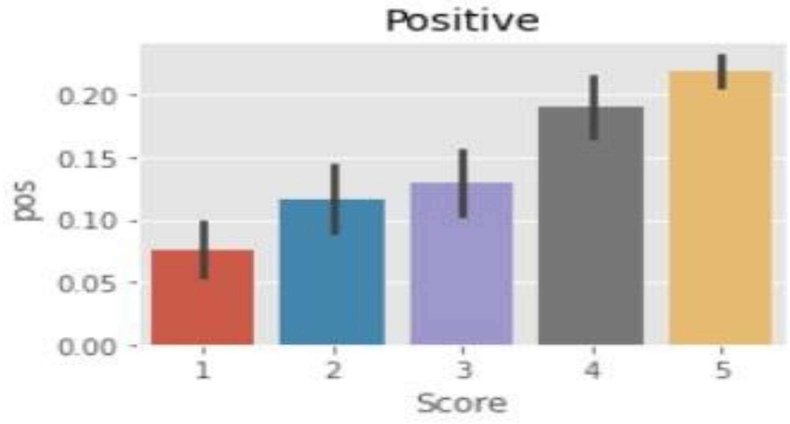

Figure-9: Positive Score

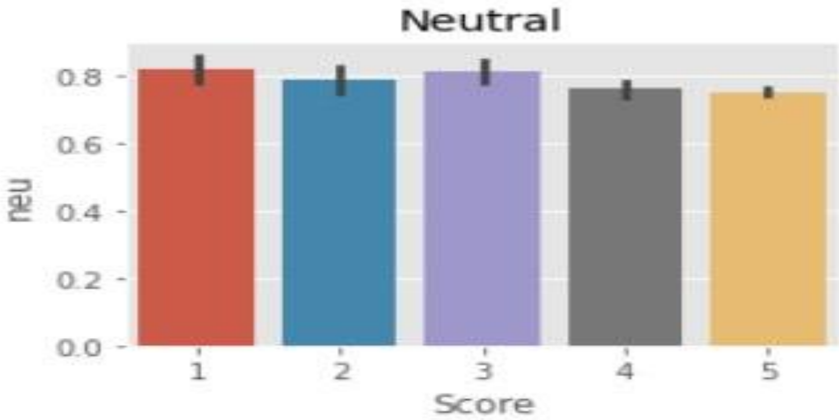

Figure 10 :Neutral Score

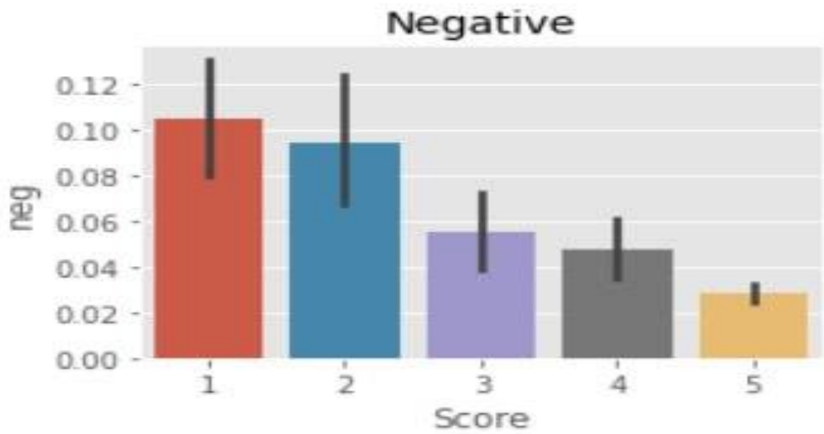

Figure-11: Negative Score

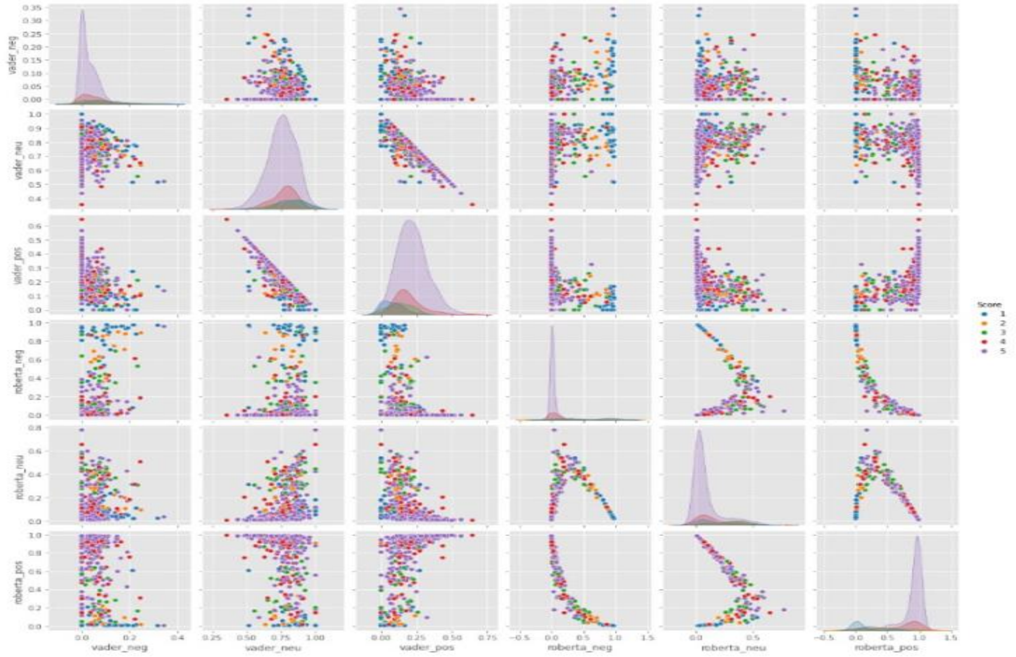

Figure-12: Comparing the Scores

5. Conclusions and Future Work

In this research, we introduced a supervised learning technique to polarize a considerable quantity of unlabelled product review data. We exhibited our approach, which combines two separate types of feature extractor techniques and uses supervised learning. We described the underlying theory driving the model, the technique we followed in our study, and the performance indicator for the experiment that was carried out across a considerable quantity of data.

We also contrasted our findings with numerous other similar product assessment surveys. We also investigated a number of academic articles on sentiment analysis employing text-based datasets.

We achieved over 90% accuracy, over 90% precision, and over 90% recall using the F1 measure. To compare different volumes of data, we performed multiple simulations utilising cross validation, training-testing ratios, and other feature extraction approaches. The findings were good. In the majority of instances, 10-fold increased accuracy while Support Vector Machine (SVM) gave the best classification outputs. It is tricky to collect a big gold standard dataset for this reason as e-commerce sites have constraints on revealing data publicly. Additionally, scraping data gives complications as it is tricky to collect adequate information to employ it as actual public reviews of distinct things.

Sentiment analysis on the Amazon dataset has demonstrated to be a valuable tool for understanding the perspectives and sentiments of consumers. Through our studies with several NLP models, we have got outstanding accuracy rates in sentiment classification, demonstrating the possibilities for automating the process of evaluating customer sentiment in product evaluations. The insights gathered from this analysis have substantial repercussions for both Amazon as a platform and businesses selling their things on it. Amazon may utilise sentiment analysis to uncover areas for development, assess consumer contentment, and make data-driven choices to optimise the user experience. Businesses, on the other hand, may receive insights about the strengths and weaknesses of their items, helping them adapt their marketing and development activities to fit client expectations.

In conclusion, this study underlines the usefulness of sentiment analysis in the context of e-commerce, particularly notably on Amazon. The vast number of textual data available on the platform is a fantastic resource for businesses, marketers, and Amazon itself to optimise the customer experience and drive changes in product offers.

Sentiment analysis is a strong approach for obtaining useful insights from this data, and its potential applications are diverse, ranging from recommendation systems to quality control. As technology continues to improve, sentiment research on Amazon's dataset will remain an important resource for businesses and scholars looking to obtain a better knowledge of customer sentiment in the digital marketplace.

Future research things might be included in the model to improve it and increase its practicality.

Our next project will use Principal Component Analysis (PCA) in conjunction with active learning to fully automate data categorization and eliminate the need for Oracle assistance. Applications that interact with customers to get a product score may be connected with the model. We may adjust the algorithm to Since we used a large-scale dataset, we improved accuracy and usefulness by using local market sites. Ultimately, we will continue to work on this project until this paradigm is used to all other sorts of text-based assessments and comments.

References

[1] Abdul-Mageed, M., M.T. Diab, and M. Korayem. Subjectivity and sentiment analysis of modern standard Arabic. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics:shortpapers, 2011.

[2] Akkaya, C., J. Wiebe, and R. Mihalcea. Subjectivity word sense disambiguation. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing (EMNLP-2009), 2009.

[3] Alm, C.O. Subjective natural language problems: motivations, applications, characterizations, and implications. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics:shortpapers (ACL-2011), 2011.

[4] Andreevskaia, A. and S. Bergler. Mining WordNet for fuzzy sentiment: Sentiment tag extraction from WordNet glosses. In Proceedings of Conference of the European Chapter of the Association for Computational Linguistics (EACL-06), 2006.

[5] Archak, N., A. Ghose, and P.G. Ipeirotis. Show me the money!: deriving the pricing power of product features by mining consumer reviews. In Proceedings of the ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD-2007), 2007.

[6] Aue, A. and M. Gamon. Customizing sentiment classifiers to new domains: a case study. In Proceedings of Recent Advances in Natural Language Processing (RANLP-2005), 2005.

[7] Beineke, P., T. Hastie, C. Manning, and S. Vaithyanathan. An exploration of sentiment summarization. In Proceedings of AAAI Spring Symposium on Exploring Attitude and Affect in Text: Theories and Applications, 2003.

[8] Bethard, S., H. Yu, A. Thornton, V. Hatzivassiloglou, and D. Jurafsky. Automatic extraction of opinion propositions and their holders. In Proceedings of the AAAI Spring Symposium on Exploring Attitude and Affect in Text, 2004.

[9] Bickerstaffe, A. and I. Zukerman. A hierarchical classifier applied to multi-way sentiment detection. In Proceedings of the 23rd International Conference on Computational Linguistics (Coling 2010), 2010.

[10] Blei, D., A. Ng, and M. Jordan. Latent dirichlet allocation. The Journal of Machine Learning Research, 2003, 3: p. 993-1022.