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Age, Gender, and Sentiments: Navigating the Landscape of Review Interpretation

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ABSTRACT:
Sentiment analysis serves as a powerful lens through which businesses gain invaluable insights into customer feedback, enabling them to enhance products and services, thereby boosting sales. The intricate web of sentiments expressed by diverse customers necessitates a nuanced approach. Within this landscape, age and gender emerge as pivotal demographic factors influencing the accuracy of sentiment analysis in text reviews. The interplay between age and sentiment is fascinating. Younger individuals often weave informal language into their reviews, punctuating their expressions with extremes of emotion. In contrast, their older counterparts tend towards formality and a more measured emotional spectrum. Moreover, the gender dimension adds another layer to this intricate tapestry, with women and men showcasing unique ways of expressing emotions and distinct focal points in their textual reviews. Recognizing the impact of these demographic factors on sentiment analysis, our study takes a comprehensive approach. Leveraging Natural Language Processing (NLP) features, we delve into reviews encompassing a broad spectrum of age and gender demographics. By doing so, we aim to refine sentiment analysis models, ensuring a nuanced understanding of customer sentiments. In our proposed study, we meticulously analyze user reviews, constructing models that unravel the intricate dance between age, gender, and sentimental values. Employing a repertoire of machine learning algorithms, we scrutinize three distinct sets of attributes: all features, age features, and gender features. The results unveiled a compelling narrative, affirming the profound influence of age and gender on the nuanced landscape of sentimental values. Our journey into sentiment analysis, entwined with machine learning prowess and enriched by NLP insights, yields a deeper understanding of customer sentiments.

Keywords: - Sentiment analysis, machine learning, textual features, Natural Language Processing, Reviews.

INTRODUCTION:

Sentiment analysis:

This NLP technique analyses text input to determine emotional tone or sentiment. It can detect whether the message is good, negative, neutral, or more complex emotions like joy, sadness, wrath, etc. Sentiment analysis aims to automatically classify text sentiment. This has many uses: Business insights: Sentiment analysis helps assess customer feedback on products and services. This data can inform their product, marketing, and customer service decisions. attitude analysis is widely used to monitor social media for public attitude towards brands, events, political leaders, and more. This helps businesses and individuals learn public opinion and alter their plans.

Market research: Product evaluations, forum conversations, and online comments can reveal market trends, client preferences, and emerging difficulties. Sentiment analysis in online reviews, news stories, and other references helps organizations manage their online reputation. This lets them address negative and capitalize on favorable sentiment.

Financial analysis: Financial analysts utilize sentiment analysis to assess market sentiment and predict market moves using news, social media, and other text sources.

Political analysis: attitude analysis can assist political campaigns modify their messaging and plans by analyzing popular attitude towards politicians, policies, and issues.

Customer feedback analysis: Businesses can analyse customer feedback to assess satisfaction and enhance products and services.

Content creation: Sentiment analysis helps content providers understand audience reception. It can help them create more engaging and relevant content. Machine learning algorithms and NLP are used to classify text into sentiment categories in sentiment analysis. These systems learn from labelled text datasets using sentiment labels. The model learns to identify text patterns and verbal clues that indicate emotions. Sentiment analysis can struggle to understand sarcasm, irony, context, and cultural nuances. Researchers and developers constantly increase sentiment analysis accuracy and flexibility. New applications for sentiment analysis are being developed constantly. Sentiment analysis accuracy is improving, but it can be better. Knowing the limits of sentiment analysis is crucial. Sentiment analysis can help businesses, organizations, and individuals make decisions, but it should not be the main reason.

Sentiment Analysis Types:

Polarity-oriented sentiment analysis classifies text as positive, negative, or neutral. This popular sentiment analysis tool is used for customer feedback and social media monitoring.

Emotion recognition: goes beyond polarity to identify emotions like joy, sorrow, fury, and fear. This method is more complicated than polarity-based analysis but useful for understanding customer satisfaction and identifying potential issues.

Aspect-focused sentiment analysis: examines product or service qualities including cost, quality, or customer service. This sentiment analysis has finer granularity than polarity-based or emotion recognition. It's useful for product refinement and client satisfaction surveys.

Sentiment analysis examples:

Here are some sentiment-labeled reviews.

Table 1.0 *for review sentiment.*

Review Type	Review Text
Positive Review	I absolutely loved this product! It's incredibly versatile and well-designed. The quality is top-notch, and it exceeded my expectations. I can't wait to recommend it to my friends!
Negative Review	This service was a complete disappointment. The customer support was unresponsive, and the product didn't work as advertised. I wasted my money and time on this, and I won't be using it again.
Neutral Review	The hotel stay was average. The room was clean, but the amenities were lacking. The location was convenient, but the noise from the nearby construction was bothersome.
Positive Movie Review	Wow, what an amazing film! The storyline was captivating, the acting was top-notch, and the visuals were breathtaking. I was on the edge of my seat the entire time.
Negative Movie Review	I was really disappointed by this movie. The plot was confusing, the characters felt one-dimensional, and the pacing was off. I expected more from such a hyped film.
Positive Restaurant Review	Had an incredible dining experience at this restaurant! The food was exquisite, the service was impeccable, and the ambiance was perfect for a special evening out.
Positive Product Review	I'm so glad I bought this gadget. It's made my life so much easier. The setup was a breeze, and the performance is outstanding. Highly recommend!
Negative Product Review	This product is a total waste of money. It broke within a week of using it, and the company's customer service was unhelpful. I regret making this purchase.
Neutral Tech Product Review	The new software update has some interesting features, but it also introduced a few bugs. It's a mixed bag, and I hope they address the issues soon.

Motivations:

- To study the sentiment analysis can effect on the age and gender or not.
- To study to find the what kind of age are effect.
- To study what kind of gender are affected.
- To study with and without these factors the sentiment analysis with machine learning an effect on the classification.

PROBLEM STATEMENT:

Sentiment analysis of the reviews is most important source of the decisions makers. The sentiment analysis helps the organization to improve sales quality and helps them for the next polices making. But the target marketing is the need of today organization what to know how to get the women and men reviews but they have different products which are based on the age and gender some products for male and some for female and some for child, elder, young, men women girls. In the sentiment analysis we can find emotions of the product user but organization want to know the multiple gender and multiple age people reviews on the same product so they can make global business strategy for future plan and improve businesses growth.

LITERATURE REVIEW:

The field of behavioral finance lacks a coherent and well-structured theoretical framework. The purpose of this article is to contribute to the continuous process of systematization in the sector by investigating the influences of education, gender, and age on investor behavior and mood. Based on responses from 106 professional investors who were engaged in Spain's market in February 2017[1], this study presents conclusions. There are also seven questions about investor mood that will be used to calculate a confidence index, and a total of twenty questions about the practitioner's thoughts on behavioral finance. We begin by drawing attention to the discrepancy between the importance of behavioral finance and the level of training in this area[2].

This chasm exists because there is insufficient training for the job. The confidence levels of investors and those of their consumers are very different, as is the makeup of each group. Because of its efficacy in mitigating the effects of self-perception bias [3], the usage of the institutional investor confidence index is a crucial step in determining investors' true profiles. Younger investors are more impacted by cognitive and emotional biases, while female investors view themselves as being more driven by logical analysis and are less risk averse than male investors. This agrees with what has been found in other investigations. By creating a model to analyses investors' emotions, we add significantly to the literature[4]. Our findings show that investors with more professional experience and women tend to be more optimistic and confident.

The prerequisites for becoming a teacher can be met in large part through online or distance learning. Within these bounds, teachers must make use of all available data to adapt and enhance their methods all during the duration of instruction. Sentiment analysis (SA) can aid training by providing real-time feed-back on the expressed sentiments. SA can provide fast feedback on the emotions that were conveyed, despite its limited application in educational contexts, sluggish assessment, and vulnerability to interpretive concerns like gender bias[5]. The goal of this study was to create and analyses a SA gender-sensitive technique as a proxy for characterization of the emotional climate of teacher trainees participating in an online course. An exploratory case study (N = 48) employing multiple research methods was conducted with students enrolled in an Interuniversity Master of Educational Technology course [6]. The system's efficacy was confirmed by a qualitative examination of participants' satisfaction with their Master's degrees and through a quantitative analysis of participants' learning attainment shown by their comments.

While the results show that SA cannot be used to accurately predict how well students will perform on a learning task, it can help teachers anticipate how students will behave in the context of the task and, as a result, use SA results to fine-tune and improve the quality of guidance provided during the course. Our data shows that there are differences between the sexes in terms of emotional climate, with female participants expressing more pessimism. This supports previously observed discrimination based on gender [7]. As a final item to think about, the formation of a positive atmosphere in an online learning environment may be aided by the development of well-adjusted teaching-learning sequences that include suitable scaffolding [8].

Internal processing, such as mental imagery, is critically important in many facets of human existence, including cognition, pathology, and daily functioning. The neural network that facilitates mental imagery is modulated from the bottom up by the content of mental imagery [9]. In this work, we looked at how gender and age interact with the neural circuits that power our capacity for emotional visualization[10]. We employed functional magnetic resonance imaging (fMRI) to explore the brain circuits that are active during emotion mental imagery as opposed to action mental imagery. In order to prevent participants from daydreaming and increase their focus on the job at hand, we had them do a letter detection task on the same stimuli. The ages of the participants ranged from 14 to 65. Female participants showed significantly higher activation within the right putamen, which is involved in the processing of emotional information, when compared to male participants. Activation associated with mental imagery in the left insula and cingulate cortex, areas implicated in self-awareness, decreased significantly with age[11], [12]. The limbic system region known as the left putamen showed significantly less activation in relation to emotion verbs as age increased. This finding hints at a top-down approach by which gender and age can influence the brain circuits involved for mental imagery, either in conjunction with the bottom-up influence of the type of stimuli or directly. Emotion recognition apps use these aspects of the speaker's speech to help them classify data[13]. Numerous studies have looked into the feasibility of determining a speaker's age and gender based on the topics they frequently discuss in their talks. Voice emotion detection has experienced substantial breakthroughs in recent years [14].

We looked into whether or not there was a correlation between age and the efficacy of facial expression recognition software's. As part of our study, we built hierarchical classification models to see how crucial it is to know a subject's age and gender before assigning an emotion label [15]. In this study, we compared the efficacy of four different models and showed how age and gender affect the precision with which they identify emotions. Our research showed that employing separate emotion models based on variables like age, gender, and demography led to more precise emotion identification. The results show that, compared to using a single classifier for all individuals, using specialized emotion models for each gender and age group improves accuracy.

METHODOLOGY:

The diagram shows the processes of the proposed method in this section we study dataset and views the values of the dataset and Data cleaning helps us to preprocesses dataset and extract the important columns and extract the features from the reviews columns and then prepare the training and test and labels and use the diverse algorithms with and without age and gender factor and get the final results.

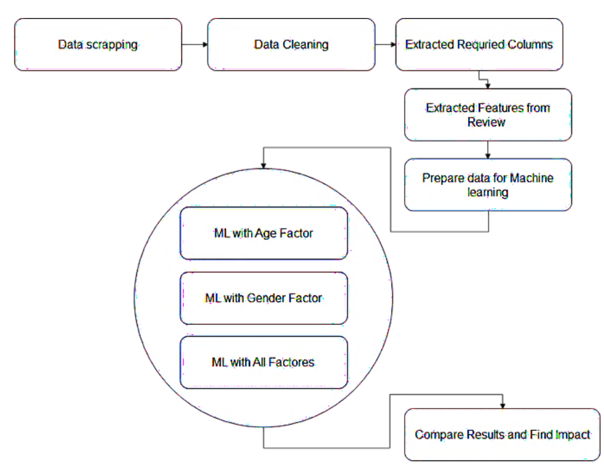

Figure 1.0 *Processes Model Diagram.*

Data collection:

The dataset is collected from the online medicine selling e-commerce website where customer buy the same product for different age and gender so downloaded the dataset from[16].

Dataset Description:

The dataset consists on the 11 factors or attributes her are the dataset attributes with description.

Table 2.0 *Dataset attributes and descriptions*

Factors	Attributes Descriptions
Age:	The Age of the customer
Condition:	What the customer have issue for which they want to buy product
Date:	What is the date of the transaction
Drug ID:	The product Database ID
Ease of Use:	Score rating the how much it's easy to use
Effectiveness:	How much the effectiveness of the medicine after using
Reviews:	The feedback written by customer after using the product
Satisfaction:	Score of the satisfaction in between 0 to 5
Sex:	Gender of the customer
Sides:	What they face issues after using the product
User full count:	If the review is useful then status 1 if not than 0 The useful

Since the classes are involved Positive, Negative, Neutral sentiment. The distribution of the classes is visualized in the Figure 2.0 in which positive and negative classes are having difference almost 1500 but the neutral values are so at low in number this may affect on our machine

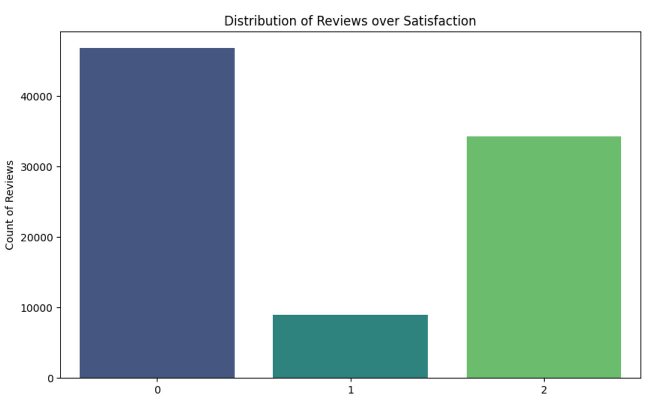

Figure 2.0 *Sentiment classes distribution.*

The provided data plot reveals a detailed breakdown of customer distribution based on age groups, offering valuable insights into the composition of the customer base. The largest cohorts are observed within the 45-54 and 55-64 age brackets, comprising 52,405 and 48,480 customers, respectively, indicating a substantial presence of middle-aged and older adult consumers. Additionally, the 35-44 and 25-34 age groups exhibit significant representation with 37,005 and 34,077 customers, highlighting diversity in the customer base across different life stages. The 65-74 age group, while slightly lower in count at 25,971 customers, still represents a noteworthy market segment with potential unique preferences or requirements. It's important to note the category labeled as "Other values," encompassing 31,299 customers, which requires further exploration to understand and categorize additional age groups not specified in the provided breakdown. Businesses can leverage these insights to tailor marketing strategies, product offerings, and customer experiences to align with the preferences and needs of the predominant age groups, ultimately optimizing their approach to engage a diverse customer base effectively.

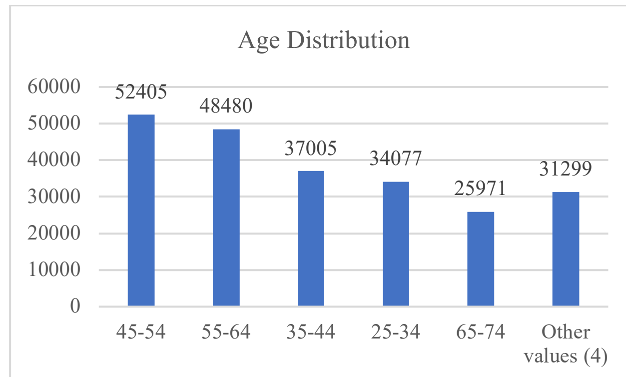

Figure 3.0 *Distribution of Age.*

The dataset also contains on the rating of satisfaction in the **Figure 4.0** its actually the rating processes of each product given by each customer the values are range in between 0 to 5 it means o is the low satisfaction and 5 is the maximum satisfaction in the data the 1(Satisfactory) rating persons are approximately 28-thousand and the 5-rating(Amazing) is near about 25 thousand so it means the maximum satisfaction and satisfactory is almost same in the **Figure 5.0** its shows the females customers are more then males customers.

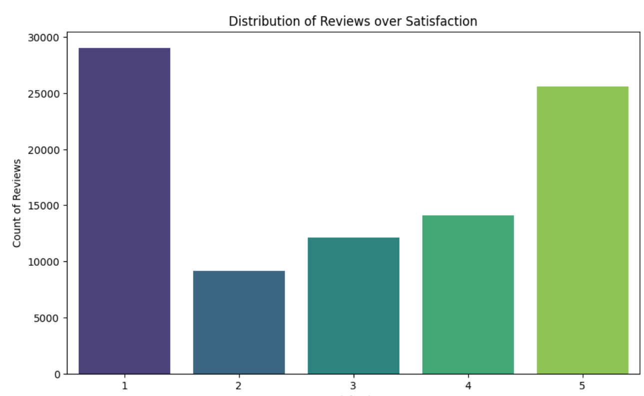

Figure 4.0 *Rating of Satisfaction*

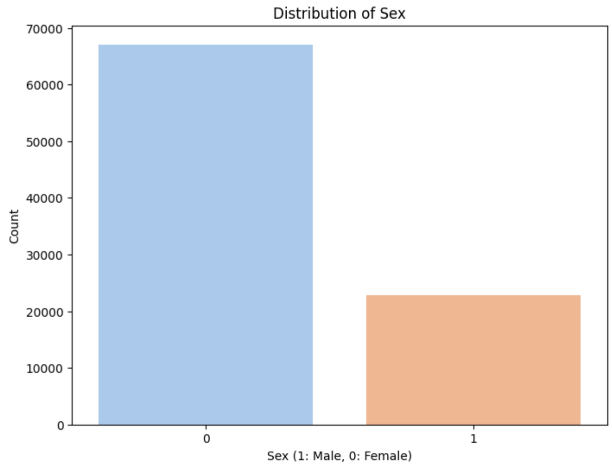

Figure 5.0 *Gender Customer ratio.*

Feature Extraction:
Data set consisting on the different features and we extracted the features for classification we arrange this in the three sections. The main strategy of the experiments is containing on the following steps.

- All features included Age, Gender, Polarity, Reviews.
- Features with Age, Polarity, Reviews.
- Features with Gender & polarity.

The features are extracted using vectorization in which we use count vectorization and generate the results are based on the classification report and confusion matrix with visualization in the next sections. In the **Figure 6.0** shows features division.

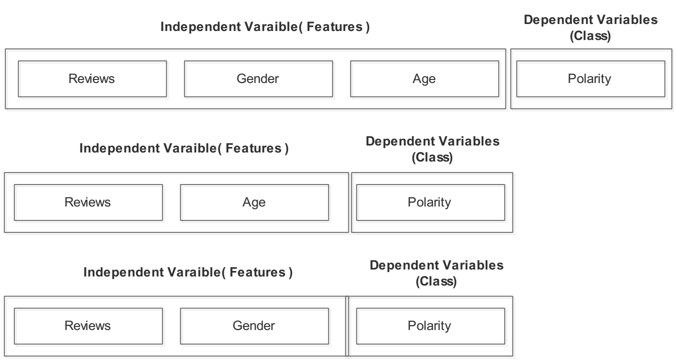

Figure 6.0 *Features division.*

RESULTS & DISCUSSION:

After the features extraction we use two models Multinomial Naïve bayes and logistic regression and use the all-feature extraction techniques here is we use remove the gender form features and train and test the model after the training the model.

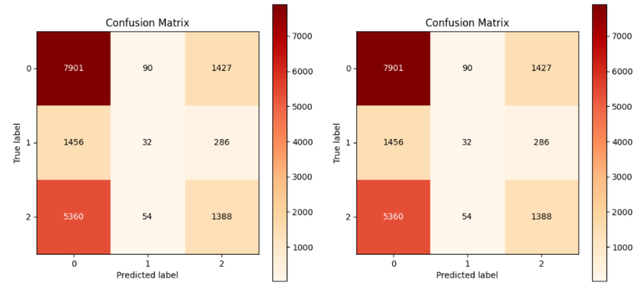

Figure 7.0 *With Age feature Multinomial naïve bayes & Logistic regression.*

we get the results with model accuracy for Multinomial Naïve Bayes is 53 percent and logistic regression is 49 percent. In the next phase we use gander as feature with sentiment and polarity and train and test the model to see the effect of the model performance. In the figure 7.0and Table 3.0 shows the results with age factor.

Table 3.0 *With Age feature Model classification accuracy results.*

SR. NO	ALGORITHM	FEATURES	ACC
1	Multinomial Naïve Bayes	Reviews, Age, rating	53%
2	Logistic Regression	Reviews, Age, rating	49%

Here are the results of models with including Gander feature and remove the age feature and the **Figure 8.0** and **Tabe 4.0** shows the results.

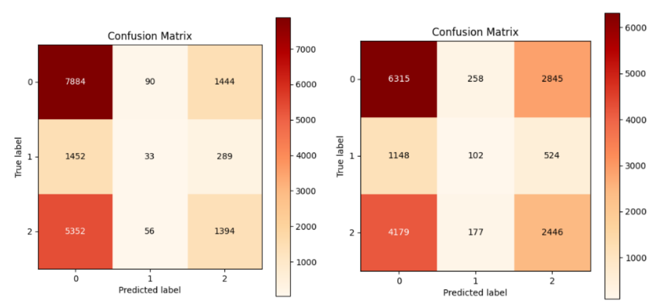

Figure 8.0 *Gender features the models results.*

Table 4.0 *Model classification accuracy with Gender features.*

SR. NO	ALGORITHM	FEATURES	ACC
1	Multinomial Naïve Bayes	Reviews, Gender, rating	52%
2	Logistic Regression	Reviews, Gender, rating	56%

We evaluated the performance of two classification algorithms, Multinomial Naïve Bayes and Logistic Regression, in the context of a predictive task. The models were trained and tested on a dataset that included the features of Reviews, Gender, and Rating. Notably, Logistic Regression demonstrated superior accuracy, achieving a 56% accuracy rate compared to

Multinomial Naïve Bayes, which yielded a 52% accuracy. The inclusion of gender as a feature underscores its relevance in contributing to the models' predictive capabilities. To provide a more comprehensive assessment.

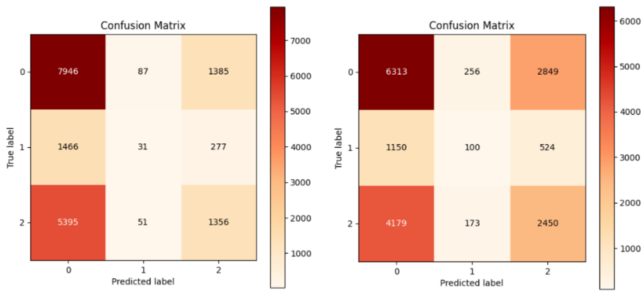

Figure 9.0 *All features confusion matrix.*

Table 5.0 *With All Features models classification report.*

SR. NO	ALGORITHM	FEATURES	PERFORMANCE
1	Multinomial Naïve Bayes	All Features	52%
2	Logistic Regression	All Features	49%

The presented results outline the performance of three distinct classification algorithms—Multinomial Naïve Bayes, Logistic Regression, and Support Vector Machine—utilizing the entirety of available features. The accuracy rates for each algorithm are reported as 52%, 49%, and 47%, respectively. Multinomial Naïve Bayes emerges as the top-performing algorithm in this comparison, achieving the highest accuracy at 52%. Logistic Regression follows closely with a 49% accuracy, while Support Vector Machine trails with a 47% accuracy. These results shed light on the relative effectiveness of each algorithm in the given predictive task, where Multinomial Naïve Bayes demonstrates the highest predictive capability.

The use of all available features in the models suggests that these features collectively contribute to the predictive performance of the algorithms. However, despite their inclusive feature sets, the variations in accuracy highlight the importance of algorithm selection in the context of the specific dataset and task.

Table 6.0 *All models result.*

Sr. No	Algorithm	Features	Performance
1	Multinomial Naïve Bayes	All Features	53%
2	Logistic Regression	All Features	49%
3	Support Vector machine	All Features	56%
4	Multinomial Naïve Bayes	Reviews, Age, rating	53%
5	Logistic Regression	Reviews, Age, rating	49%
6	Support Vector machine	Reviews, Age, rating	52%
7	Multinomial Naïve Bayes	Reviews, Gender, rating	52%
8	Logistic Regression	Reviews, Gender, rating	54%
9	Support Vector machine	Reviews, Gender, rating	52%

All Features Analysis:
Support Vector Machine (SVM) outperforms both Multinomial Naïve Bayes and Logistic Regression when utilizing all available features, achieving the highest accuracy at 56%. This suggests that SVM is well-suited for the complexity inherent in the entire feature set, demonstrating robust predictive capabilities. Multinomial Naïve Bayes follows closely with 53% accuracy, while Logistic Regression lags behind at 49%. The performance disparities highlight the importance of algorithm selection in leveraging the full potential of diverse feature sets.

Reviews, Age, and Rating Analysis:
Multinomial Naïve Bayes and Support Vector Machine exhibit similar accuracy (53%) when considering Reviews, Age, and Rating collectively. Logistic Regression, however, shows a slightly lower accuracy at 49%. This implies that, while all three algorithms can leverage the information contained in Reviews, Age, and Rating, there are subtle differences in their ability to interpret and utilize these features for accurate predictions.

Reviews, Gender, and Rating Analysis:
Logistic Regression stands out in this comparison, achieving the highest accuracy at 54% when using Reviews, Gender, and Rating. Multinomial Naïve Bayes and Support Vector Machine both exhibit a slightly lower accuracy at 52%. This suggests that, for this specific feature combination, Logistic Regression is better suited to capture patterns in the data related to gender, leading to improved predictive performance.

In conclusion, the comparative analysis underscores the nuanced relationship between algorithm choice and feature selection. The superior performance of Support Vector Machine with all features showcases its adaptability to complex datasets, while the algorithmic nuances become more apparent when focusing on specific feature combinations. The findings highlight the importance of a tailored approach to algorithm and feature selection, emphasizing the need to consider both the nature of the data and the specific task objectives for optimal model performance.

CONCLUSION:
Sentiment analysis extracts feedback from customers or users about products or services. Businesses leverage this to enhance sales and address concerns. Due to diverse customers, understanding sentiments from various angles is crucial. Age and gender, influential demographic factors, affect sentiment accuracy. Younger individuals tend to use informal language

with extreme emotions, while older ones express moderately. Gender influences expression and focus in reviews. To enhance accuracy, sentiment models should consider these factors, training on datasets reflecting age and gender diversity.

Our study employs user reviews, employing multiple algorithms on three attribute sets: all features, age-added, and gender-added. Results confirm age and gender impact sentimental values. The findings of the comprehensive psychological study indicate that age and gender are factors that influence sentimental values, and that different classifications can be obtained using the various models. Attitudes are influenced by both age and gender. Age and gender affect feelings. Different persons of different ages and genders can have very diverse responses to the same set of circumstances due to differences in their life experiences, attitudes, and beliefs.

Women are more likely than males to report experiencing negative emotions such as anxiety and despair, and they also express their feelings more frequently and forcefully than men do. Males report feeling happier and prouder. People of a younger age tend to have more intense emotions and are more likely to take risks, whereas persons of an older age tend to have better emotional control and are more cautious. Those of a younger age may experience more anger and dissatisfaction, whilst those of a more senior age may experience higher pleasure and happiness. Although age and gender are not the only factors that influence feelings, the effects they have on people can be significant.

FUTURE WORK:

This is the analysis of the age and gender having on the impact of the sentiment analysis the next work will be on the age, education, gender, and country associated and try to find the impact on the sentiment analysis. There should also can work on the frequency of the sentiment or feedback on the social media with these factors.

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