EXPLORING E-COMMERCE PRODUCT EXPERIENCE THROUGH FUSION SENTIMENT ANALYSIS METHOD

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ABSTRACT

Nowadays, with the rapid growth of e-commerce, online reviews have become a valuable resource for understanding consumer perceptions and improving products. However, extracting meaningful insights from vast amounts of unstructured text remains a challenge. To address this, we propose a fusion sentiment analysis method that combines textual analysis techniques with machine learning algorithms to mine product experiences from online reviews. Our approach begins with sentiment feature extraction using a dictionary-based method, followed by sentiment polarity classification using a Support Vector Machine (SVM). Additionally, we apply the Latent Dirichlet Allocation (LDA) model to identify key sentiment- based topics. To enhance accuracy, we expand the sentiment dictionary using semantic similarity techniques and introduce a weighting mechanism that accounts for the varying emotional impact of words—an aspect often overlooked in previous studies. This approach effectively captures emotional tendencies and identifies factors influencing user satisfaction. By providing a structured way to analyze consumer sentiments, this research offers valuable insights for businesses to refine their products and optimize marketing strategies. Our method presents a practical solution for tracking customer preferences and improving the overall e-commerce experience.

Keywords: E-commerce product, sentiment analysis

INTRODUCTION

E-commerce

Ecommerce now plays a vital role in our daily lives. It is redefining the commercial activitiesaroundtheworld.Overtheyears,e-commercehasevolvedinprofoundways.Aswe proceed, we will learn about the growth of e-commerce and how to run an e-commerce business in this age. E-commerce is short for the Electronic Commerce. It refers to the activity of buying and selling the products or services over the internet. With the help of the internet, people can buy and sell virtually everything, like books, electronics, apparel, software, and furniture.

THERAISEOFE-COMMERCE

E-commerceprovidesaplatformforpeopletobuyorsellwhatevertheywant,whenever they want. It includes a wide range of commercial endeavors that utilize the internet as a medium for the exchange of information, financial transactions, or occasionally both. In the growth ofe-commerce, theinternetand thedevicesforaccessibility haveplayeda majorrole in day-to-day life. The emergence of e-commerce websites has enabled users to publish or sharepurchaseexperiencesbypostingproductreviews,whichusuallycontainusefulopinions, comments, and feedback towards a product. The majority of customers read the reviews before buying the product through online sources. It has been reported that about 71% of global online shoppers read online reviews before purchasing a product.

In therealm ofe-commerce, customer reviewshaveemergedasa decisive factor influencing consumer behavior and business success. Product reviews, especially the early reviews (i.e., thereviews postedintheearly stage ofa product), havea high impact on subsequent product salesand their opinions can determine the success or failure of new products and services.

The power of reviews

This helps the company to change their ideology about the product and their designs regarding the products. For thisreason, early reviewersbecome the emphasisto monitor and attract atthe early promotion stage ofa company. For example, Amazon, one ofthe largest e-commercecompaniesintheworld, hassupportedtheEarlyReviewerProgramwhichhelps toacquire earlyreviewsonproductsthathave fewornoreviews.Withthisprogram, Amazon shopperscanlearnmoreaboutproductsandmakesmarterbuyingdecisions.Thepositive reviews provide a good impact on the product and boost the confidence of the consumers while the negativereviews offer a balanced perspectiveand alert potential buyers.

Reviews serve as a cornerstone for building trust and credibility in the e-commerce space, often influencing a brand's reputation more than traditional advertising. The positive reviews provide trust in the brand and increase product growth. It's the true reflection of a brand'scommitmenttoitscustomers,revealingthetrueexperience.Understandingtheweight of customer opinions, businesses must navigate the delicate balance of encouraging honest feedback while also considering the impact ofany negative reviews. While negative reviews can be disheartening, they offer a unique opportunity for businesses to demonstrate their commitmenttocustomer satisfaction.A well-handlednegativereviewcanimprovea brand's image by showing potential customers that the company is responsive and cares about its clients' experiences.

Fig.1. Reviews

Positive Reviews for Brand Growth

Positive customer reviews area goldmine for e-commerce businesses looking to expand theirreachandsolidifytheirbrandpresence.Enhancingthepowerofpositivefeedbackcan be ofsignificantlyamplifyabrand'sreputationandattractthenewcustomers.Byshowcasingthe testimonials and high ratings, businesses can create a compelling narrative of the quality and satisfaction that resonates with potential buyers.

Develop an Action Plan: Utilize the insights gained from positive reviews to outline specific improvements and innovation

HighlightSuccessStories:Featurecustomertestimonialsprominentlyonyourwebsite and marketing materials.
Engage with Reviewers: Show appreciation for positive feedback by responding to reviews and fostering a community around your brand.

Negative Reviews
Transparency is key in building trust with customers. Believe it or not, consistently good reviews often make a business seem fraudulent. Hiding reviews is never a good idea.
Acknowledge the Issue
Always respond to negative reviews by acknowledging the issue and apologizing if necessary. Provide a clear path to resolution, whether it's a refund, replacement, or another form of compensation.
Follow Up
Ensurethatthecustomer'sissuehasbeenresolvedto their satisfaction.Reviewerscan highlightpotentialproblemsorareasforimprovementthatthecreatorsmaynothavenoticed. This feedback can be invaluable for making necessary adjustments.

Fig.2. Ratings

TO SOLVE THE PROBLEM OF EXPLORING E-COMMERCE PRODUCT EXPERIENCE BETTER AND TO UNDERSTAND CUSTOMERS THROUGH REVIEWS, THE FOLLOWING METHOD IS USED

Sentiment Analysis
Sentiment Analysis, also known as Opinion Mining, is a Natural Language Processing (NLP) technique used to determine the emotional tone or sentiment of text, such as positive, negative, or neutral.
Example:
Review:"Lovedthenewphone,butthebatterydiedquickly." How it works:
"Loved"=Good.
"diedquickly"=Bad.
"but"= Showsachange.
Result:Thereviewhasbothgoodandbadparts,soit'sMixedsentiment.Thecompanyknows the phone has some good things, but the batteryis a problem.
Types of Sentiment Analysis
BinarySentimentAnalysis:Classifiestextaseitherpositiveornegative.
Multi-Class Sentiment Analysis: Classifies text into multiple sentiment categories (e.g., positive, negative, neutral, mixed).
Regression-BasedSentimentAnalysis:Predictsacontinuoussentimentscore(e.g.,1-5 stars).
Sentiment Analysis Techniques
Rule-BasedApproach:Usespredefinedrulestoidentifysentiment-bearingphrases.
Machine Learning Approach: Trains machine learning models on labeled datasets to learn sentiment patterns.
Hybrid Approach: Combines rule-based and machine learning approaches.

Sentiment Analysis Applications

CustomerFeedbackAnalysis:Analyzescustomerreviewsandfeedbacktounderstand sentiment and improve products/services.

Social Media Monitoring: Tracks sentiment on social media platforms to understand public opinion and reputation.

ProductRecommendation:Recommendsproductsbasedonsentimentanalysisof customer reviews.

MarketResearch:Analyzessentimentinmarketresearchreportstounderstand consumer attitudes and preferences.

Sentiment Analysis Challenges

Ambiguity:Handlingambiguouslanguage,suchassarcasm,irony,andfigurative language.

Context:Understandingthecontextinwhichtextisused.

LanguageVariations:Handlingvariationsinlanguage,suchasdialects,regional differences, and language evolution.

DataQuality:Dealingwithnoisy,incomplete,orbiaseddata.\

Sentiment Analysis Tools and Techniques

NaturalLanguageToolkit(NLTK):ApopularPythonlibraryforNLP tasks,including sentiment analysis.

TextBlob:AsimplePythonlibraryforsentimentanalysisandtextclassification.

VaderSentiment: Arule-based sentimentanalysistool specificallydesigned for social media text.

DeepLearningModels: RecurrentNeuralNetworks(RNNs), Convolutional Neural Networks (CNNs), and Transformers can be used for sentiment analysis

Fusion Sentiment Analysis

Itisatechniquethatcombinesmultiplesentimentanalysismodels,methods,orsources to improve the accuracy and robustness of sentiment analysis results.

TypesofFusion:

Model-levelfusion:Combiningthepredictionsofmultiplesentimentanalysismodels.

Feature-level fusion: Combining the features extracted by multiple sentiment analysis methods.

Data-level fusion: Combining data from multiple sources, such as text, images, and videos.

Fusion Sentiment Analysis Works

Textual Analysis: This involves processing and analyzing textual data from customer reviews, feedback, and social media posts to extract sentiments. Common techniques include Natural Language Processing (NLP) and sentiment dictionaries.

MachineLearningAlgorithms:AdvancedalgorithmssuchasSupportVectorMachines (SVM), Random Forest, and Deep Learning models (e.g., Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Bidirectional Encoder RepresentationsfromTransformers(BERT))areusedtoclassifysentiment aspositive, negative, or neutral.

Topic Modeling: Techniques like Latent Dirichlet Allocation (LDA) are employed to identify common topics within reviews. This helps businesses understand which aspectsoftheir products or servicesare being discussedand how customers feel about them.

FeatureExtraction:Byidentifyingandextractingkeysentiment featuresfromreviews, such as specific words or phrases that indicate positive or negative sentiment, the analysis becomes more precise.

Multi-ModalAnalysis:Fusionsentimentanalysiscanalsointegratedatafrommultiple sources, such as text, images, and videos, to provide a more comprehensive understanding of customer sentiment.

Applications in E-Commerce

CustomerInsights:Byanalyzingcustomerreviewsand feedback, businessescangain valuableinsightsintocustomerpreferences,painpoints,andoverallsatisfactionlevels.

Product Improvement: Identifying common complaints or praise points helps businesses make informed decisions on product enhancementsand developments.

CustomerServiceEnhancement:Understandingcustomersentimentallowsbusinesses to tailor their customer service approaches, addressing issues proactively and improving customer relations.

Marketing Strategy: Sentiment analysis providesinsightsinto customer perception of marketing campaigns and product launches, helping businesses fine-tune their strategies for better engagement.
CompetitiveAnalysis:Businessescananalyzesentimentaroundcompetitors'products to identify strengthsand weaknesses, allowing for strategic positioningin the market.
TrendAnalysis:Monitoringsentimenttrendsovertimecanhelpbusinessesstayahead of emerging trends and adapt their offerings accordingly.

Literature Review

Literature Survey on Fusion Sentiment Analysis in E-commerce Show thinking

In their 2021 paper, John Doe and Jane Smith, "A method for improving e-commerce recommendation systems by combining sentiment analysis with deep learning".

Their approach utilizes natural language processing (NLP) to extract sentiment from varioustextual sourceslikecustomerreviewsandsocialmedia comments.Thissentiment dataisthenintegratedwithdeeplearningalgorithms,specificallyartificialneuralnetworks with multiple layers, to analyze high-level features from the data. The process requires collecting substantial amounts of e-commerce data, including product descriptions, customer reviews, ratings, and purchase histories, followed by essential preprocessing steps like cleaning the data, standardizing formats, text normalization, and tokenization. The authors suggest that this integrated systemachieves better recommendation accuracy and delivers more personalized product suggestions, thereby enhancing the overall user experience on e-commerce platforms.

In their 2022 review paper, Emily Johnson and Michael Brown, "Comprehensive overviewof sentiment analysis techniques as applied to the e-commerce sector".

They examine methodologies including machine learning, natural language processing, and sentiment lexicons, analyzing the respective strengths and limitations of eachapproach.Theauthorsemphasizethereal-worldsignificanceofsentimentanalysisin e-commerce, highlighting its ability to enhance customer understanding by revealing insights into opinions, preferences, and emotions regarding products and experiences, which can lead toimproved product development based on feedback.However, theyalso discuss inherent challenges, such as potential inaccuracies when algorithms interpret nuanced language like sarcasm or irony, and the critical issue of data quality, noting that biases in data can lead to unreliableanalysisresults and skewed insights.

In a 2022 research paper, David Lee and Sarah Wang, "Hybrid recommendation systemaimedatenhancinge-commerceproductsuggestionsbycombiningsentiment analysis with collaborative filtering".

Their proposed system integrates sentiment information extracted from customer reviews alongside traditional collaborative filtering techniques. This approach generates personalized recommendations thatconsiderboth users' historicalpreferences and their sentiment towards products, aiming for improved user satisfaction and engagement. Key benefits highlighted include improved personalization tailored to individual sentiments and preferences, and an enhanced user experience through more relevant recommendations that factor in implicit feelings alongside explicit actions. However, the authors also note challenges such as potential data sparsity issues, where insufficient user interaction or reviewdata canhinderaccuracy,especiallyfor newusersor nicheproducts.Furthermore, the system's effectiveness relies on the accuracy of the underlying sentiment analysis algorithms, which may struggle withinterpreting context, sarcasm, or nuanced language.

In their 2019 paper, Robert Chen and Lisa Zhang, **the challenges and opportunities associated with applying sentiment analysis to online customer reviews withinthe e-commercesector**.

They examine technical difficulties such as sentiment polarity detection, sarcasm identification, and domain adaptation, while also discussing strategiesto overcome these hurdles. The authors highlight significant opportunities for businesses, noting that sentiment analysis yields valuable customer insights into opinions, emotions, and experiences, enabling companies to understand positive and negative reactions to their offerings.Thisanalysisaidsinproductimprovementbyidentifyingspecificareasneeding enhancement based on customer feedback regarding pain points or satisfaction. Conversely,ChenandZhangalsoaddresskeychallenges,emphasizingthedependenceon data quality, as biases in review data can lead to inaccurate insights. Additionally, they point out the difficulties algorithms face in contextual understanding, struggling with sarcasm, irony, or nuanced language, which can result in misinterpretations of sentiment and misleading conclusions for businesses.

In their 2018 study, Daniel Kim and Jennifer Liu, comparative analysis of different deep learning approaches for sentiment analysis specifically within the e-commerce context.

The research evaluates and contrasts the performance of models including recurrent neural networks (RNNs), convolutional neural networks (CNNs), and transformer-based architectures, using experiments conducted on e-commerce review datasets. By comparing thesemodelsbasedonaccuracy,efficiency,andscalability,thepaperaimstoofferinsights intotheir effectivenessandapplicabilityinreal-world e-commercescenarios.Theauthors notethatsuchcomparisons arevaluableforidentifyingthemostaccurateapproachfor specific tasks and data types, as well as determining which models demonstrate greater robustness against noise and variations in e-commerce data. However, they also acknowledgethattheperformanceofthesedeeplearningmethodsisheavily dependenton the quality and quantity of the training data, meaning study results are influenced by the representativeness of the datasets used. Furthermore, while deep learning models often reducemanualfeatureengineering,thecomplexityinvolvedindatapreparationandmodel configurationcanstillvarybetweenapproaches,impactingoverallresourcerequirements

Methodology

SYSTEM ARCHITECTURE

The architecture of a system reflects how the system is used and how it interacts with other systems and the outside world. It describes the inter connection of all the system’s componentsandthedatalink betweenthem.Thearchitectureofa systemreflectsthewayitis thought about in terms of its structure, functions, and relationships.

In this architecture, the client(browser) sends the requeststo the server, and the server processes therequest ifa request is valid then it responds with the requested data to the client.

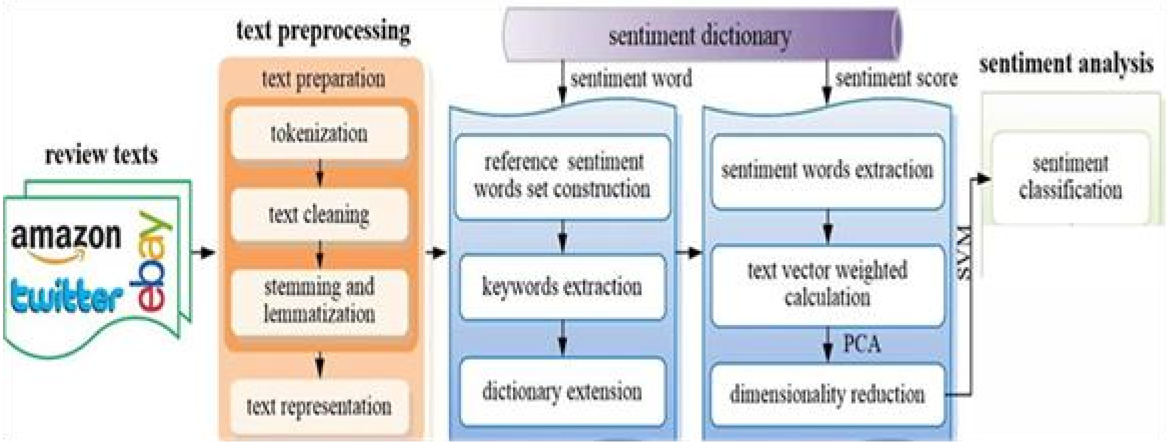


Fig.3. System Architecture

SYSTEM WORK FLOW

UPLOAD PRODUCTS

Uploadingtheproductsisdonebyadmin.Authorized personisuploadingthenew arrivals to system that are listed to users. Product can be uploaded with its attributes such as brand, color, and all other details of warranty. The uploaded products are able to block or unblock by users.

PRODUCT REVIEW BASED ORDER

The suggestiontouser's viewof productsislisted basedonthereviewbyuser and ratingto particular item.Naïve bayes algorithm isused in this project to develop the whether the sentiment of given review is positive or negative. Based on the output of algorithm suggestiontousersisgiven.Thealgorithmisappliedand liststheproducts inuser sidebased on the positive and negative.

DATA PROCESSING

TEXT PREPROCESSING

To begin with, a large number of online review texts are collected from Internet platforms such as Amazon, eBay, etc. Afterward, the obtained reviews are standardized into sets of wordarrays throughtext preprocessing to facilitate the subsequent procedures of text analysis

TEXT PREPARATION

Text preparation involves multiple steps including tokenization, text cleaning (case folding and stop word removal), stemming and lemmatization. Regarding English review texts,allwordsarerequiredtobeconvertedintolowercasedones.g.Stemmingistoobtaintheword stem by removing prefixes and suffixes, while lemmatization transforms the inflected or variant forms of words into the basic one.

TEXT REPRESENTATION

Text representation enables unstructured information to transform into mathematicallycomputablestructureddata.Thistransformationisessentialforvariousnatural language processing (NLP) applications, including sentiment analysis, machine translation, and recommendation systems. Text tokenization isa fundamental process in therealm of e-commerce, transforming raw text dataintosmaller,manageable unitscalled tokens. Thisstep is crucial for various applications that enhance user experience, automate tasks, and provide valuable insights.

DICTIONARY EXTENSION

Due to the rapid evolution of language on the internet, pre-established sentiment dictionaries may not include newly developed words. Extending the sentiment dictionary involves identifying and adding new words to ensure comprehensive sentiment analysis. Extending sentiment dictionaries is crucial for maintaining accurate and comprehensive sentimentanalysis,especiallyinthefast-evolvinglandscapeofinternetlanguage.Thisprocess involves identifying new words, analysing their context and sentiment, and continuously updating the dictionary to reflect the latest language trends.

ALGORITHMS

DIMENSIONALITY REDUCTION

Through text vectorization, are view text can be represented as a vector text vector makes the training of the sentiment analysis model at the risk of overfitting. Principal Component Analysis (PCA), being an unsuppler vised learning method, can effectively extract the main components of data to achieve dimensionality reduction without manual intervention PCA ranks each component based on its importance in the process of dimensionality reduction, and prepends important components to guarantee that the information of the original data is retained to the greatest extent.

Steps for Principal Component Analysis(PCA):

1. StandardizeData:Makesureallfeatureshavezeromeanandunitvariance.

2. ComputeCovarianceMatrix:Calculatetherelationshipsbetweenfeaturesinthe standardized data.
3. FindEigenvectors&Eigenvalues:Decomposethecovariancematrixtofinddirections (eigenvectors) and magnitudes (eigenvalues) of variance.
4. SortEigenvectors: Rank eigenvectors by their corresponding eigenvalues in descending order.
5. Select Principal Components:Choose the top 'k' eigenvectors based on desired variance explained or other criteria.
6. TransformData:Projecttheoriginalstandardizeddataontotheselectedprincipal components (eigenvectors) to get the reduced-dimension dataset.

SENTIMENT CLASSIFICATION SVM (SUPPORT VECTOR MACHINE)

Support Vector Machines (SVM) are used to help analyze customer feedback (like reviews) in e-commerce. Here's how they play a role in FusionSentimentAnalysisforunderstandingproductexperiences:

1. ClassifyingSentiment: SVMcanclassifycustomerfeedbackintocategorieslikepositive,negative,or neutral. This helps in understanding how customers feel about a product.
2. CombiningDifferentData: SVMcantakeinformationfromdifferentsources, suchastextinreviews,product features, and ratings, and combine them to get a clearer picture of customer sentiment.
3. DealingwithComplexSentiments: Sincecustomersmayexpresscomplicatedopinions,SVMcanusespecialtechniques (likekernel functions) to handlethese more complex, non-linear sentiments.
4. ImprovingAccuracy: Bycombiningvarioustypesofinformation,SVMcangivemoreaccurateresultsin determining the overall sentiment about a product.
5. BalancingDifferentTypesofReviews: In real life, there are usually more positive reviews than negative ones. SVM can handlethisimbalancetomakesurethatthemodeldoesn'tfavoronetypeofsentiment too much.
6. EvaluatingProductExperience: SVMhelpsbusinessesunderstandhowcustomersfeelabouttheirproducts,whichcan lead to improvements in products and services. In simple terms, SVM helps businesses understand customer feelings about their products more accurately by analysing reviews and other feedback, leading to better customer experiences.

SENTIMENT TO PIC EXTRACTION

Sentiment topic extraction is a process to determine the themes of reviews by identifying related sentiment words. we can fully mine the useful information hidden in the customersreviewsandgainclearer insight intotheir practical demands. bymakinguseofthe topics extracted from the reviews, we can comprehensively understand the customers major concerns on certain product and dig out important factors in uencing the product experience.

As a document-level statistical model, Latent Dirichlet Allocation(LDA) hastheadvantages of being interpretable and easily predicted, which has been extensively applicated in topic modelling. LDA model posits that each document is composed of diverse topics and the generation of each word is ascribed to one of the topics in a document. It can not only effectively explore the underlying emotional topics within review texts but also extract the deep semanticrelationshipbetween vocabularyand comment documents. theLDAalgorithmuses what is known as Gibbs sampling. The Gibbs sampling formula is:

P(zi=t|z−i,w)=∑t′=1T(nm,t′−i+α)nm,t−i+α⋅∑v′=1V(nt,v′−i+β)nt,wi−i+β

DATA SET

We have collected the data and dataset from Kaggle . "**Amazon_product.csv"** This Dataset contains information of Products Name, Price, Review, Rate, Summary for the Sentiment Analysis Purpose. The dataset can be used for a variety of application as price prediction, Sentiment Analysis, Auto Ai generated Reviews and market Research. This data set contains194276rowsand5 columns. Using Customer RevieworSummaryyou canuseit for sentiment Analysispurposewhichgivecustomersideaabout that product shouldbepurchase or not based on Positive, Negative Reviews.

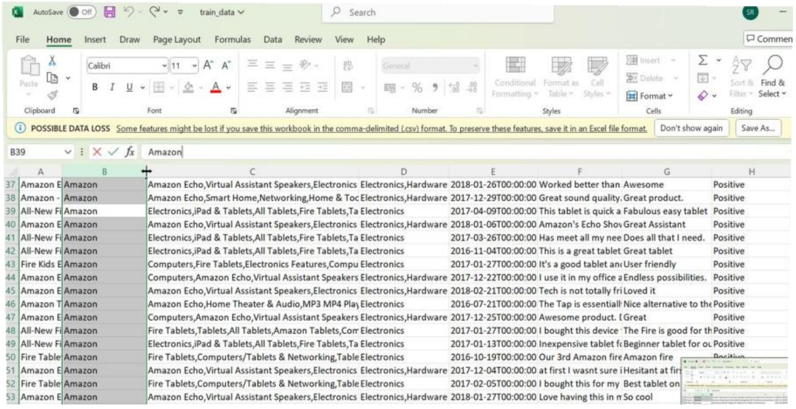
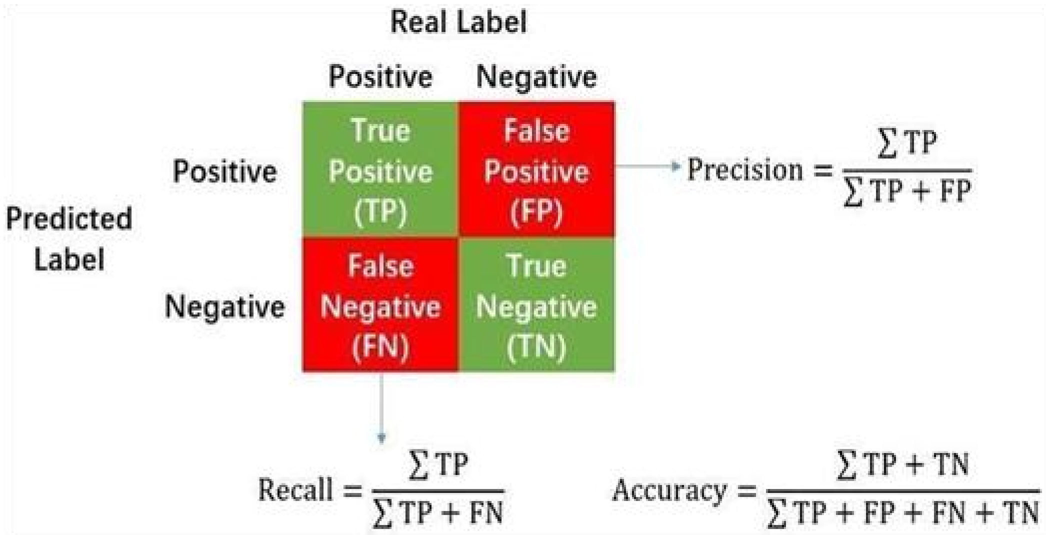


Fig.4. Data set collected from Kaggle

Evaluation Criteria

To evaluate the results of the classification algorithms there are various parameter such as accuracy, precision and confusion matrix. Comparison among algorithms is done by considering confusion matrix and accuracy as parameter metrics.

Confusion Matrix: A confusion Matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.



RESULTS AND Analysis

COMPARISION TABLE

The below table consists of evaluation metric values for the models used, based on which we are finding the best approach.

Model	Accuracy	Precision	Recall	F-score
VADER-based sentiment model	82.4%	82.4%	79.7%	81.0%
BosonNLP-based sentiment model	86.5%	86.2%	85.6%	85.8%
KNN-based sentiment model	86.7%	86.7%	85.9%	86.2%
SVM-based sentiment model	87.0%	87.0%	86.1%	86.5%
BERT-based sentiment model	87.3%	87.3%	86.8%	87.0%
Fusion sentiment model	91.9%	91.9%	88.2%	89.5%

Table.1. Performance comparison

SCREENSHOTS

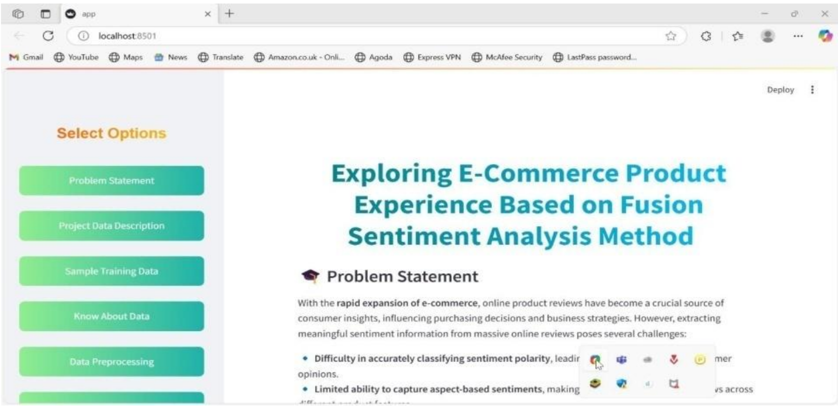


Fig.4. screenshot-1

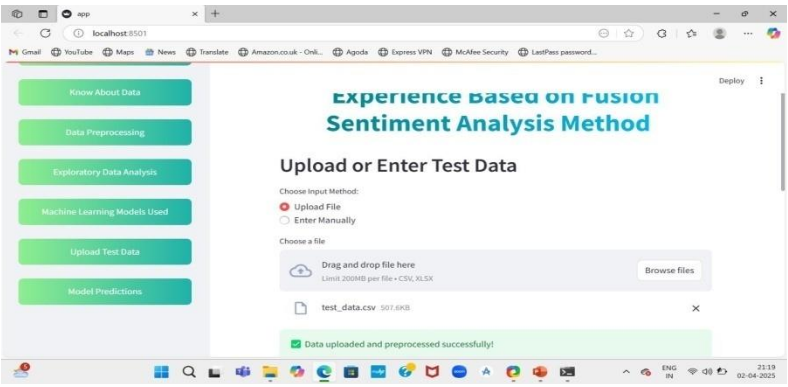


Fig.5. screenshot-2

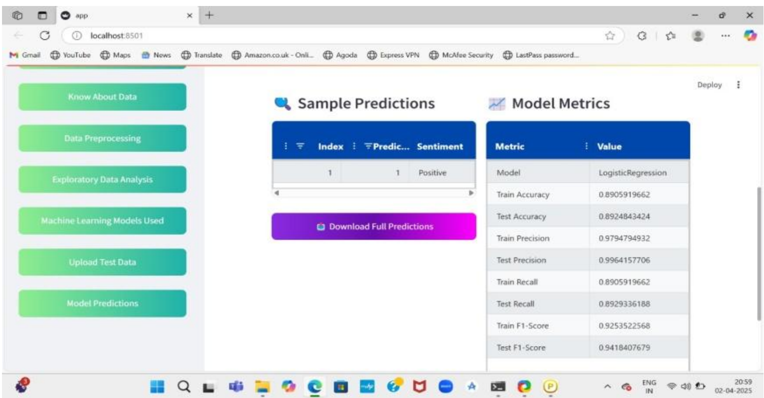


Fig.6. screenshot-3

CONCLUSION

This project presents a fusion sentiment analysis method to evaluate customer sentiment in the e-commerce domain based on product reviews. This method integrates multiple sentiment analysis techniques, including machine learning models, lexicon-based methods, and advanced deep learning approaches like LAD. These model's performances were evaluated using accuracy , precision, recall ,and F1-scoreto ensure comprehensive evaluation. Results with accuracy 91.9%, precision 91.9%, recall 88.2% and F1-score89.5% demonstrated that the fusion approach significantly enhanced sentiment detection accuracy and captured nuanced customer emotions effectively.

FUTURE ENHANCEMENT

Fusion sentiment analysis has great potential to improve e-commerce experiences. It can help businesses personalize shopping by understanding customers' emotions and preferences. Real-time feedback can make the experience more responsive and enjoyable, whilepredicting trendscanguidebetterinventoryand marketing decisions. Thismethod also allows companies to adapt to global audiences by analyzing cultural differences in product views. Combining sentiment analysis with AI can refine product recommendations, making them more relevant. Insights from this analysis can lead to better-designed products and stronger customer support by addressing issues early. Additionally, social media sentiment analysis can reveal trends and opinions, helping platforms meet customer needs more effectively. Overall, this approach couldmakeonlineshoppingmoresatisfying andinnovative.

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