iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: XII Month of publication: December 2025

DOI: https://doi.org/10.22214/ijraset.2025.76657

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

RAG-Enhanced Sentiment Analysis System Using Transformer Models and FAISS for Customer Review Analysis

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Abstract: With the rapidgrowthof e-commerceplatformsanddigitalservices,customerreviewshavebecomeavaluable source of informationforunderstandingusersentimentandimprovingproductquality.Traditionalsentimentanalysisapproachesprimarilyfocus onclassifyingreviewsintosentimentcategoriesbutoftenfailtoprovide contextual insightsor relatedcustomer experiences. To overcomethislimitation,thispaperproposesaRetrieval- Augmented Generation (RAG) enhancedsentimentanalysis system thatcombinesTransformer-basedsentiment classification with semantic similarity retrieval.

The proposedsystem utilizes a fine-tunedTransformer model for sentiment predictionandHugging Face sentence embeddings to convert customer reviewsinto vector representations.Theseembeddings areindexedusingFacebook AISimilarity Search (FAISS)to enable efficientretrievalofsemantically similarreviews. Additionally, a Streamlit- based interactive webapplicationis developedto visualizesentiment predictions, confidence scores,similar review retrieval, andwordcloudrepresentations.

Experimental results demonstrate that the integration of sentiment classification with retrieval-based techniques enhances contextual understanding and interpretability of customer opinions. The proposed system is scalable, efficient, and suitable forreal-world applications such as customer feedback analysis, business intelligence, and decision support systems.

Keywords: Sentiment Analysis, Retrieval-Augmented Generation (RAG), Transformer Models, FAISS, Natural Language Processing, Streamlit

I. INTRODUCTION

Customer reviews and user-generated textual content have become an essential source of information for businesses operating ine-commerce platforms, digital services, and online marketplaces. These reviews reflect customer opinions, satisfactionlevels, andexpectations,thereby playinga significant role in influencingpurchasing decisionsandbusinessstrategies. However,themassivevolumeoftextualdatagenerateddailymakesmanualanalysisinfeasible,necessitatingtheuseofautomatedsentimentanalysistechniques.SentimentanalysisisaprominentresearchareawithinNaturalLanguageProcessing(NLP)thatfocusesonidentifyingandclassifyingemotionsoropinionsexpressedintextintopredefinedcategoriessuchaspositive, negative, or neutral.Early sentiment analysismethods relied on traditional machinelearning algorithms,including NaïveBayes ,Support VectorMachines, andLogistic Regression. Whilethesemethodsprovidedbaselineperformance, theywerelimitedinhandlingcomplexlanguagepatterns, contextual dependencies, andsemantic relationships.

Recent advancements in deeplearning, particularly Transformer-basedarchitectures suchas BERT, RoBERTa,and DistilBERT, have significantlyimprovedsentiment classificationperformance.Thesemodels leverageself-attention mechanisms to capture contextual information across entire sentences, enabling more accurate understanding of sentiment in complexandambiguoustext. Despite their effectiveness, most sentiment analysissystems aredesigned solelytooutputsentimentlabelsorconfidencescores, offeringlimitedinterpretabilityandcontextualinsights.

In practical applications, understandingsentiment alone is ofteninsufficient. Business analysts and decision-makers require additional context, suchas similar customer experiences and relatedfeedback,to makeinformeddecisions. Traditional sentiment analysis models lackthe capabilityto retrieve orreference semantically relatedreviews,which restrictstheirapplicabilityinreal-worldcustomerfeedbackanalysis.

To overcome these limitations, Retrieval-Augmented Generation(RAG) has emerged as a powerful paradigm that combinespredictive models with information retrieval techniques. RAG enhances model outputs by retrieving relevant informationfromlarge datasets usingvector-based similarity search. When applied to sentiment analysis, this approach enablesnot onlysentiment predictionbut also the retrieval ofsemantically similar reviews, thereby enriching contextual understanding.

This paper proposes a RAG-enhanced sentiment analysis framework that integrates Transformer-based sentiment classificationwith FAISS-basedsemantic similarity retrieval. Customerreviews are firstanalyzed usinga fine-tuned Transformer model to predict sentiment polarity. Subsequently, Hugging Face sentence embeddings are used to convert textual data into dense vector representations, which are indexed using Facebook AI Similarity Search (FAISS)forefficientandscalableretrievalofsimilarreviews.

Furthermore, the proposedsystem is deployedas an interactiveStreamlitwebapplication, allowingusersto perform real-time sentiment analysis,retrieve similar reviews, visualize confidence scores, and explore textual trends using word clouds. This end-to-end system bridges the gap between sentiment classification and contextual analysis, providingapracticalandscalable solutionforintelligentcustomerreviewinterpretation.

II. LITERATURE REVIEW

Sentimentanalysishasbeenextensivelystudiedinthefieldof NaturalLanguageProcessing duetoitswide applicabilityin analyzingcustomer feedback, social mediacontent, and online reviews.Earlyresearchfocusedon lexicon-basedandtraditionalmachine learningapproaches, wheresentimentpolaritywasdeterminedusingpredefinedsentimentdictionariesorhandcraftedfeatures.TechniquessuchasNaïveBayes,SupportVector Machines, andLogistic Regression werecommonlyemployedfortextclassificationtasks.Whilethesemethods achieved reasonable performanceon small datasets, theystruggledwith complexlinguisticstructures, sarcasm, and contextual dependencies.

Withtheadvancementofdeeplearning,neuralnetwork-basedmodelssuchasConvolutionalNeuralNetworks (CNNs)andLongShort-TermMemory(LSTM)networkswereintroducedforsentimentclassification.These models demonstratedimprovedperformance bylearningdistributedrepresentations of text andcapturingsequential dependencies. However,theywerestilllimited bytheirinability toeffectivelymodellongrangecontextualrelationshipsandoftenrequiredextensivefeatureengineeringandlargelabeleddatasets.

TheintroductionofTransformerbasedarchitecturesmarkedasignificantbreakthroughinsentimentanalysisresearch.ModelssuchasBERT, RoBERTa,andDistilBERTleverageself-attentionmechanismstocapture contextual information acrossentiresentences and documents. Several studieshave demonstrated that Transformer- basedmodelsoutperformtraditiona landrecurrentneura networkapproachesinsentimentclassificationtasks. Despitetheirhighaccuracy,mostexistingTransformer-basedsentimentanalysissystems focussolelyon classificationoutputs,providinglimitedinterpretabilityandcontextualinsightsforendusers.

Recentresearchhasexploredinformationretrievaltechniquestoenhancetextanalysissystems.Vector-based similarity searchmethods,suchas Facebook AI SimilaritySearch (FAISS), enable efficientretrievalof semantically similar documents fromlarge-scaledatasets. However,the integration of sentiment analysismodelswithretrieval- basedsystemsremainsrelatively underexplored.Mostexistingapproachestreatsentimentclassificationand informationretrieval as separatetasks, thereby limitingtheir effectiveness in real-world decision-making scenarios.

To address these limitations, Retrieval-Augmented Generation (RAG) has emerged as a promising framework that combinespredictive models with semantic retrieval mechanisms. By integrating sentiment analysis with FAISS- based similaritysearch, RAG enables systems to not only predict sentiment but also retrieve relevant contextual informationin the formof similar reviews. This approach enhances interpretability and provides richer insights for business intelligence and customer feedback analysis. The proposed work builds upon these advancements by developingaunifiedRAG-basedsentimentanalysisframeworkwithreal-timedeploymentcapabilities.

III. METHODOLOGY

A. System Architecture

The proposed system follows amodulararchitecturethatintegratessentimentclassificationwithretrieval-based contextualanalysis. Thearchitectureconsistsoffivemajorcomponents:dataingestion,textpreprocessing, sentiment classification, semanticretrievalusing FAISS,anduserinterfacedeployment.Userinputreviewsare processedthrough a trained Transformer-basedsentimentanalysis model, followed bysemantic similaritysearchto retrieve relevant reviews froma vector database. Theoverall workflowensures accuratesentiment predictionwhile providing contextualinsightsthroughsimilarreviewretrieval.

B. Dataset Preprocessing

The datasetused in this studyconsistsof customer reviews collected from ane-commerce platform.The raw dataset contains attributes such as reviewtext, ratings, and metadata. Duringpreprocessing, missing values were removed, and non-textual elements suchas HTML tags andspecial characters were cleaned. All reviews were converted to stringformat to ensurecompatibilitywith Natural Language Processingpipelines. Tokenization,stopword removal, andnormalizationwereapplied toimprovethe qualityoftextual datafordownstreamtasks.

C. Sentiment Analysis Model

ATransformerbasedsentimentanalysismodelwasemployedtoclassifycustomerreviewsintosentimentcategories.Themodelleveragesapretrainedlanguagerepresentationfinetunedonlabeledsentimentdatatocapturecontextualdependencieswithintext.Unliketraditionalmachinelearningmodels,theTransformer architectureutilizesself-attentionmechanisms,enablingeffectivehandlingoflong-rangedependencies and semanticnuances.Thetrainedmodeloutputssentimentpolarityalongwithaconfidencescore,whichislater presented to the user.

D. Retrieval-AugmentedGenerationUsingFAISS

To enhance interpretability and contextual relevance,Retrieval-AugmentedGeneration(RAG)wasimplemented using FAISS. Review texts were convertedintodensevectorembeddingsusingaSentenceTransformermodel. These embeddingswereindexedusing FAISS for efficientsimilaritysearch.Whenausersubmitsareview,its embeddingis generatedandcompared againstthe indexed vectors to retrievethe top-k semanticallysimilar reviews. Thisapproachallowsthesystemtoprovidesupporting evidencealong sidesentimentpredictions,improving analyticaldepthanddecision-making capabilities.

E. System Deployment Using Streamlit

The completesystem was deployed as aninteractive web application usingStreamlit. The interface enables users to inputreviews,viewpredictedsentimentresults,confidencelevels,andretrievesimilarreviewsinrealtime.
Additionalvisualizationcomponents,suchassentimentconfidenceindicatorsandwordclouds,wereintegratedtoimprove usability. The deployed application demonstratesthepractical applicabilityoftheproposedapproachin real-world sentiment analysis scenarios.

IV. DATASET DESCRIPTION AND EXPERIMENTAL SETUP

A. Dataset Description

The dataset usedinthis researchconsistsofcustomerreviewdatacollectedfromanonlineretailplatform.The datasetincludestextual reviewsrepresentinguseropinionsonvariousproducts.Afterinitialcleaningandpreprocessing,thefinalizeddatasetwasstoredinastructuredcomma-separatedvalues(CSV)formatnamed *Reviews.csv*.Thedatasetcontainsauthenticuser-generatedcontent,makingitsuitableforreal-worldsentiment analysis applications.

B. Data Preparation

Prior tomodel training and retrieval operations,thedatasetunderwentmultiplepreprocessingsteps.Thesesteps included removalof duplicate entries, handlingof missingvalues, andnormalizationof textualcontent. The cleaned review texts were converted intonumericalembeddingsusingasentenceembeddingmodel.TheseembeddingswerestoredandindexedusingFAISStoenableefficientsimilarity-basedretrieval.Thispreparationensured consistencybetweenthesentimentpredictionandretrievalmodules.

C. Experimental Environment

Allexperiments wereconductedusingPythonprogramminglanguage. Theimplementationutilized popular libraries including HuggingFace Transformers for sentiment classification, FAISSfor vector similaritysearch,andStreamlit for applicationdeployment. Model trainingand testingwere performedin a controlleddevelopment environment to ensure reproducibility. Theexperimental setup was designed to evaluate both sentiment prediction accuracy and retrievalefficiencyunderrealisticusageconditions.

V. RESULTS AND PERFORMANCE EVALUATION

The proposed sentiment analysis system enhanced with Retrieval-Augmented Generation (RAG) was evaluated usingreal-world customer review inputs. Thesystem successfullyclassifieduser reviews intopositive,neutral,and negative sentiment categories while simultaneouslyretrieving semantically similar reviews from the dataset using FAISS-based similarity search. For each inputreview, the sentimentclassificationmodelproduceda sentimentlabelalongwith a confidencescore, enablingclear interpretationof the predictionreliability.The integrationof semantic retrievalallowed the systemto presentcontextuallyrelevant pastreviews,improvingexplainabilityandusertrustinthepredictions. The Streamlit-based interface displayed sentiment results in a user-friendly manner, including visual confidence indicatorsandsentimentdistributioncharts. Additionally, thewordcloudvisualizationprovidedinsightsintofrequentlyoccurringtermswithinthedataset,supportingqualitativeanalysisofcustomeropinions. Overall, the system demonstratedeffectiveperformancein bothsentiment predictionandcontextual retrieval.The combineduseof deeplearning–basedsentimentanalysis andvector similarity search ensuredaccurate classification, fastretrieval, andimprovedinterpretability, makingthesystemsuitable forpracticalbusiness intelligence and customer feedbackanalysisapplications.

System Architecture Figure+Caption

SystemArchitectureoftheProposedSentimentAnalysiswithRAGFramework

UserReviewInput

↓

TextPreprocessing

↓

SentimentAnalysisModel(Transformer)

↓

ConfidenceScore&SentimentLabel

↓

SentenceEmbeddingModel

↓

FAISSVectorIndex

↓

Top-KSimilarReviews

↓

StreamlitUserInterface

READY-TO-PASTEFIGURECAPTION

Figure 1 illustrates the architecture of theproposed sentimentanalysissystem integratedwith Retrieval-Augmented Generation (RAG). User reviews are processed through a Transformer-based sentiment classification model to predict sentiment polarity and confidence scores. Simultaneously,semantic embeddings are generated and queried against a FAISS-basedvector database toretrieve contextuallysimilar reviews. The entire pipeline is deployed usingStreamlit, enablingreal-time sentiment analysis and contextual review retrieval through an interactive web interface.

VI. CONCLUSION AND FUTURE WORK

This paper presented an intelligent sentiment analysis system integrated with Retrieval-Augmented Generation (RAG) to enhance the interpretation of user reviews. By combining a Transformer-basedsentiment classification model with FAISS-powered semantic similarity search, the system not only predicts sentiment polarity but also providescontextual supportthrough relevanthistoricalrememberfutureset.

Thedeploymentoftheproposedapproachusinga Streamlit-basedwebinterfacedemonstratesitspractical applicabilityforreal-timecustomer feedback analysis.Theinclusionofvisualanalyticssuchasconfidence indicators and word cloud representationsfurther improves interpretabilityanduser engagement.Inthefuture,the system can beenhancedby incorporatinglarger multilingualdatasets, advanced transformer architectures, andreal- time data streaming from social media platforms. Additionally, integratingexplainableAI(XAI)techniquesand fine-grainedaspect-basedsentimentanalysiscouldfurther improvetransparency andanalyticaldepth.Table Captions

FINAL POLISHED ABSTRACT ABSTRACT

Therapidgrowthofusergeneratedcontentacrossdigitalplatformshasmadesentimentanalysisacriticaltaskforunderstandingcustomeropinionsandfeedback.Traditionalsentimentclassificationapproachesoftenlack contextual awareness,limiting theirabilityto providemeaningfulinsights.Toaddressthislimitation,thispaperproposesanintelligentsentimentanalysissystemenhancedwithRetrievalAugmentedGeneration(RAG)to improveinterpretabilityandcontextualrelevance.

The proposed system employs a Transformer-based deep learning model to classify user reviews into positive, neutral, and negative sentiment categories, along with confidence scores.

In parallel, semantic embeddings are generated usinga sentence embedding model andindexed through FAISS to retrieve contextually similar reviews from a historical dataset. This dual approachenables both accuratesentiment predictionand contextualexplanation of results. The system is deployedas an interactivewebapplicationusingStreamlit, allowingreal-time analysis,visualization of sentiment confidence, and retrievalofsimilarreviews.Experimentalobservations demonstratethatthe integration of sentiment classificationwith semantic retrieval enhances transparency, user trust, and practical applicability in customerfeedback analysisandbusiness intelligencesystems.

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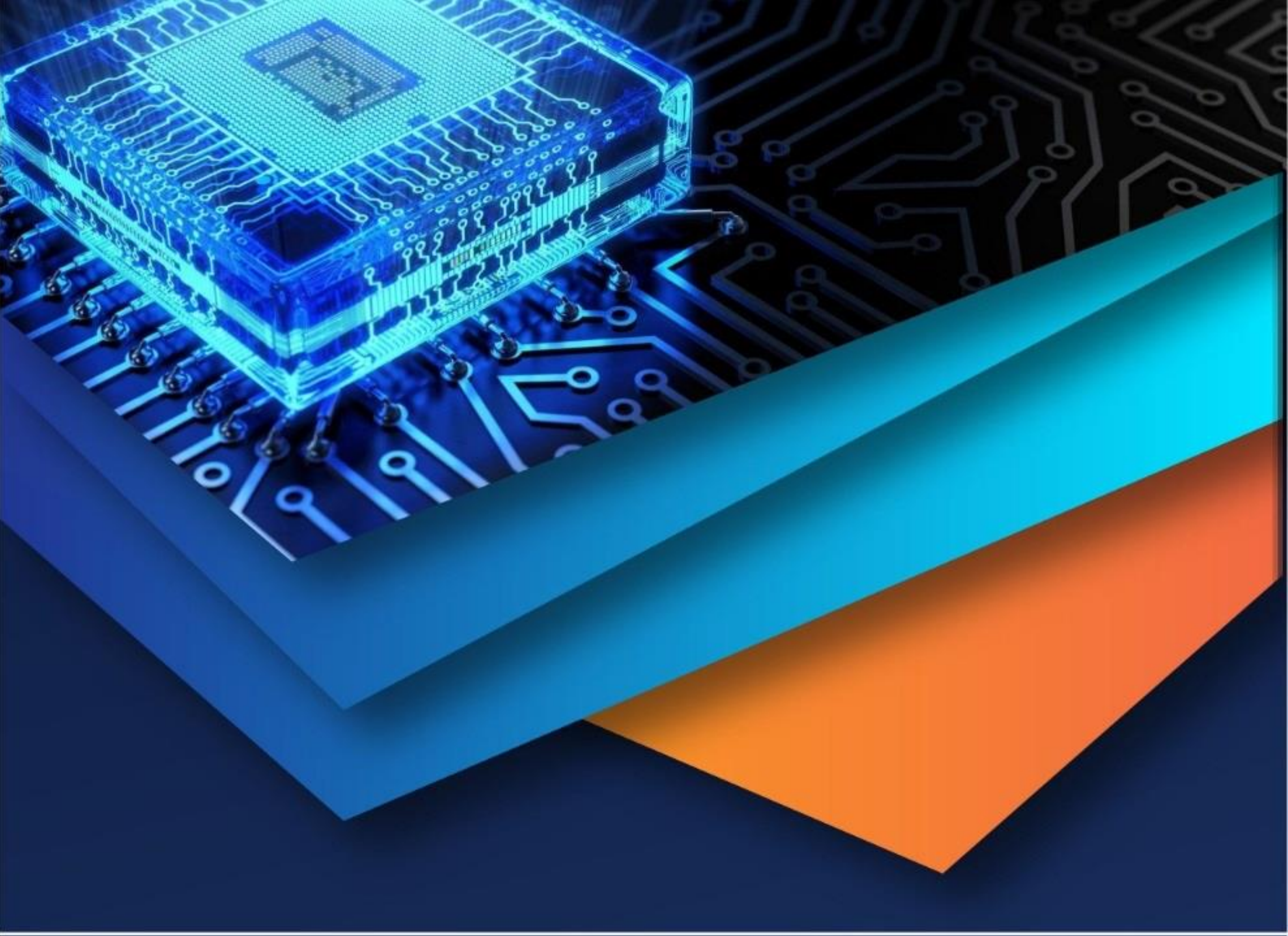

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