iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** IX **Month of publication:** September 2025

DOI: https://doi.org/10.22214/ijraset.2025.74047

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 IX Sep 2025- Available at www.ijraset.com

Sentiment Analysis on Social Media Posts: An AI-Powered Opinion Mining System

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Abstract: The way individuals expressthoughts has changed dramaticallyasaresultofthe explosiverise of digitalplatformslike Facebook,Instagram,YouTube,andTwitter,whichproduceenormousvolumesof user-generated information every day.Analyzing public opinion in areas like politics, economics, enter- tainment, and international issues is made possible by this data.Opinion mining, also known as sentiment analysis,isasubfieldofnaturallanguageprocessing(NLP) thatdividestextintocategorieslikeneutral,neg- ative,andpositive. Conventionalmachinelearningandlexicon-basedmethodshave frequently hadtrouble with casual language, sarcasm, acronyms, and multilingual data.
Thisstudysuggestsadeeplearningandtransformer-basedmodels, suchasBERTandRoBERTa,which offer greater semantic comprehension, as part of an AI-driven sentiment analysis framework to address theseissues. Datacollection,textpreparation,featurerepresentation,modeltraining,andevaluationareall partofthesystem. Tokenization, normalization,stopwordelimination,andhandlingofhashtagsandemojis are all handled by preprocessing.For feature extraction, both traditional vectorization methods (TF-IDF) and sophisticated embeddings (Word2Vec, GloVe, and transformer embeddings) are used.Transformer modelsroutinelyoutperformdeep learningtechniqueslike LSTMand conventionalalgorithmslikeRandom Forest, SupportVectorMachines, andLogisticRegression, according tocomparativestudies.Theefficacyof theframeworkisdemonstratedbyexperimentalfindingsshowingimprovedaccuracy,precision,recall,and F1-scores.The suggested approach can be used in real-world fields like marketing, healthcare awareness, political forecasting, and customer experience analysis because of its scalability and versatility.
Keywords: Sentiment Analysis, Opinion Mining, Natural Language Processing (NLP), Deep Learning, Trans- former Models, BERT, RoBERTa, Word Embeddings, Text Preprocessing, Social Media Analysis

I. INTRODUCTION

Inthepreviousdecade,socialmediausagehasskyrocketed,makingitsmajorplatformforpeopletocommunicate their ideas, show their feelings, and take part in international discussions.Every day, millions of posts are made onsocial media platformssuchasFacebook,Instagram,Reddit,andTwitter,reflectingbothindividualandgroupviewpointsonsocialissues,politics,business, andentertainment.Theabilitytoautomaticallyinterpretandcategorizesentimentshasbecomenotonlyatechnologicalchallengebutalsoanecessityforgovernments,industries,and researchersduetotheenormousgrowthinuser-generateddata. Sentiment analysis isaninterdisciplinaryfieldoftheprocessingofnaturallanguage(NLP),machinelearning,anddataminingthatfocusesondeterminingwhether a text conveys a neutral, negative, or positive emotion.

Lexiconbasedtechniquesandconventionalmachinelearningclassifiershavebeenthemainstaysofsentimentanalysissystemsuptothispoint.

Lexicon-basedapproachesassignpolarityaccordingtotheexistenceofsentimentwordsinpredefineddictionaries.

Althougheasytouse,theseapproachesarenarrowlyfocusedanddonotaccountforcontext,sarcasm,orlanguagespecifictoagivendomain.Bylearningfromlabeleddatasets,traditionalmachine learning techniques such as Na¨ıve Bayes, Logistic Regression, and Support Vector Machines enhance lexicon approaches.But they mainly rely on handcrafted features like TF-IDF or bag-of-words, which frequently lose semantic meaning and have trouble with informal text, emojis, abbreviations, and social media’s multilingual nature.Furthermore, the effectiveness of both lexicon and shallow machine learning techniques in the real world is limited because they frequently show poor generalization when applied to new datasets.

Byemployingcuttingedgeartificialintelligencetechniquesforopinionmining,thesuggestedsystemseekstoaddressthesedrawbacks.Thesystemusestransformer-basedcontextualembeddingslikeBERTandcontemporary embedding methods like Word2Vec and GloVe in addition to handcrafted features.Slang, informal expressions, and contextual variations can be handled more effectively thanks to these models’ ability to capture nuanced se- mantics.

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To guarantee that noisy social media text is converted into a structured format appropriate for analysis, the architecture incorporates preprocessing steps such as text normalization, tokenization, and emoji interpreta- tion.A variety of models, from traditional classifiers to deep learning techniques like LSTMs and cutting-edge transformers, aretrainedandassessed. Standardevaluationmeasuressuchasrecall, accuracy, andprecision, and F1-score are then used to validate the system's performance.

In comparison to current systems, the suggested framework provides increased accuracy and robustness by fusingdeeplearningarchitectureswithcontemporaryNLPembeddings.Thisincreasessentimentclassification's dependabilityandexpandsitsuseinfieldslikemarketing,politicalanalysis,customerservice,andhealthcare. As aresult,thestudy helps closethegap betweentheoreticalsentimentanalysismodelsanduseful,real-worldopinion mining systems.

II. LITERATURE REVIEW

With an emphasis on enhancing classification accuracy and addressing the particular difficulties of social media data, a number of researchers have investigated sentiment analysis from various angles.Agarwal et al.(2011) presented a tree kernel-based method for Twitter sentiment classification in one noteworthy study.Their model analyzedbrief,noisytweetsbyutilizingparts-of-speechtagsinadditiontosyntacticfeatures. Despitethefactthat their approach was better than the conventional bag-of-words models, the system's reliance on manually created syntacticfeatureslimiteditsscalabilityandmade itlessresponsiveto thequicklychangingemojis,hashtags,and slang that are frequently used in contemporary social media platforms.

Zhang,Wang,andLiu(2018)conductedanoteworthystudywhereinconvolutionalneuralnetworkswereem-ployed(CNNs)onextensivetextcorporatoexaminetheapplicationofdeeplearningforsentimentanalysis. Their tests showed that CNNs outperformed conventional machine learning classifiers in terms accuracy in identifying semanticrelationshipsandlocaldependenciesintext. However,becauseCNNscouldnotretaincontextualmean-ingacrosslongersentencesordiscourse,theyfrequentlystruggledwithlong-rangedependencies. Thisrestriction madeitclearthatarchitectureslike transformermodelsorrecurrentnetworkscapableofmanagingsequentialdata more efficiently are needed.

Devlinetal.(2019)madeasignificantadvancementinchallengesinvolvingtheinterpretationofnaturallanguage,likesentimentanalysis,witht heirmorerecentcontribution,BidirectionalEncoderRepresentationsfrom Transformers(BERT).BERTreachedstate-of-the-artresultsinsentimentclassificationbenchmarksbypretraining on vast amounts of text and fine-tuning on domain-specific datasets.It outperformed previous word embeddings likeWord2VecandGloVebecauseitcouldcapturebidirectionalcontext.Evenwiththeirsuccess,BERTmodels are computationally costly and need a lot of resources to train and deploy, which restricts their use for real-time sentiment analysis in settings with limited resources.

Despite the fact that these investigations have significantly advanced sentiment analysis, but there are still a number of unresolved issues.Previous approaches either failed to adequately capture the intricacy of informal, multilingual, and context-rich social media content or heavily relied on handcrafted features.By creating an AI- powered opinion mining system that integrates deep learning models, contextual embeddings, and sophisticated preprocessing techniques, the current study expands on these frameworks.In contrast to previous methods, the suggested system places a strong emphasis on resilience, scalability, and flexibility with the goal of achieving greateraccuracywhilebeingappropriateforpracticaluseslikecustomerexperienceanalysis,politicalforecasting, and business intelligence.

III. METHODOLOGY

Startingwiththeacquisitionofrawdataandendingwiththecreationofprecisesentimentclassifications,thesuggestedsystemforsentimentexa minationofpostsonsocialmediaisstructuredasapipelinewithmultipleintercon- nected steps.A block diagram of the entire data flow through the essential components of feature representation, datacollection, preprocessing, modeltraining,andarchitecturecanbedemonstrated. sentimentclassificationwith evaluation in a sequential manner.

Using open-source datasets and public APIs, posts are gathered from social media platforms like Facebook, Twitter, and Reddit in the first step, known as data collection.The raw dataset includes spelling mistakes, acronyms,emojis,hashtags,andirregularformattingbecausesocialmediatextisnaturallynoisy. Thiscallsforthe preprocessing step, which involves standardizing and cleaning the data.Tokenizing sentences into words, elimi-natingstopwords,lemmatizingorstemmingwordstotheirmostbasicform,andturningemojisandhashtagsinto interpretable tokens are all examples of preprocessing.To ensure that the text maintains its semantic meaning whileremovingnoise,specialattentionispaidtohandlinginformalexpressionsanddomain-specificvocabulary.

Feature Representation is the next step after data cleaning.The system uses sophisticated embeddings rather than conventional bag-of-words models that lose contextual information.While distributed embeddings like Word2VecandGloVecapturethesemanticrelationshipsbetweenwords,representationslikeTF-IDFcapturethe significance of term frequency.Furthermore, BERT-generated contextual embeddings are used to comprehend word meaning in context, which is especially important for posts on social media that contain slang, sarcasm, or unclear expressions. These representations make up the numerical vectors that learning algorithms use as inputs.

Model Training is the next step, where both traditional machine learning techniques and cutting-edge deep learning techniques areused.To setbaselines, traditional models such asSupport Vector Machines and Random Forest, and Logistic Regression are first tested.DL models, like transformer architectures and Long Short-Term Memory (LSTM) networks, are trained to capture contextual nuances and long-range dependencies in text in ordertoimproveperformance. Toadjusthyperparametersandpreventoverfitting,eachmodelisassessedusinga different validation set.

Ultimately, each post is classified as neutral, negative, or positive by the Sentiment Classification and Eval- uation stage's polarity outputs.Well-known metrics such as recall, accuracy, and precision, and F1-score are employed to assess the system's performance.Models are compared using graphs and tables, and the outcomes show that transformer-based architectures are better at producing reliable and superior sentiment predictions.

Theblockdiagramillustratesthemethodology,whichcombinesdeeplearning,sophisticatedembeddings,and preprocessing to produce a dependable, scalable, and effective sentiment analysis system.

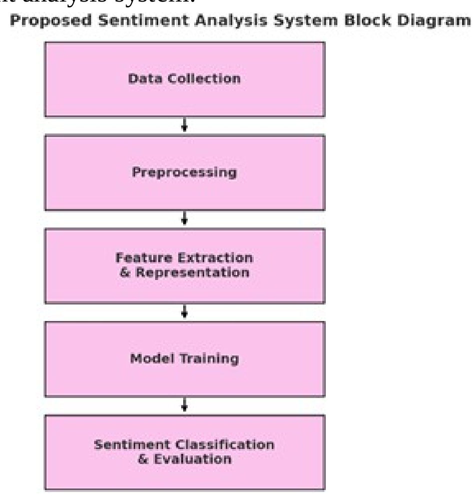

Figure1:Proposedsystemsblockdiagram

IV. RESULTS

Theassessmentofthesuggestedsentimentanalysissystemwasexpandedtolookathowwellitworksinvarious social media domains in addition to its overall model performance.Verifying the system's resilience in sector- specificapplicationswascrucialbecauseuser-generatedcontentcandiffersignificantlydependingonthecontext.

Politics,business,entertainment,sports,andhealthwerethefiverepresentativedomainstakenintoconsideration.

TheBERTmodel,whichproducedthegreatestoutcomesinthepriorcomparativeanalysis,isemployedto showtheF1-scores acrosssectorsinFigure2. WithF1-scoresrangingfrom0.90to0.94,thefindingsindicatethat the system continues to perform well across all domains.The model's ability to effectively convey both positive andnegativeemotionsindiscussions per tainingtohealthandwellnessisdemonstratedbythehealthsector's highest F1-score of 0.94.The second-highest F1-score was 0.93 for business posts, and 0.92 for entertainmentcontent. Sports(0.90)andPolitics(0.91)havesomewhatlowervalues ,indicatingthatthesystemoccasionallyhas troublewithsarcasm,ambiguousexpressions,anddynamiclanguagethataretypicalinthesefields. However,the consistentlyhighvaluesineverysectorattesttotheexcellentadaptabilityandgeneralizabilityofthesuggestedsystem.

Accuracy, Precision, and Recall are compared across the same sectors in Figure 3 to offer a deeper compre-hensionofmodelbehavior. Thesystem'sstabilitywashighlightedbythefactthateachofthethreemetricsstayed above0.88. Withaccuracyandrecallcloseto0.94and0.95,thehealthsectoronceagaincameoutontop,indicatingthemodel'sefficacyinobtainingaccurate sentimentpredictionsinthisfield. Withprecisionandrecallranging from0.91to0.93, thebusinessandentertainmentsectorsal soreportedbalancedresults,demonstratingthemodel's dependability and consistency in these settings.

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Volume 13 Issue IX Sep 2025- Available at www.ijraset.com

AlthoughthePoliticsdomainachievedahighaccuracyof0.92,itsprecisionwasslightlylowerat0.89,indicat- ing that sometimes subtle or sarcastic statements were misclassified.This is consistent with political discourse’s intrinsic complexity, which frequently involves layered sentiment.With accuracy, precision, and recall ranging from0.89to0.90,theSportsdomainhadthelowestoverallvalues. Thedifficultyofevaluatingpostsaboutsports,whichusuallyemploycolloquiallanguage,idioms,andcontextdependentterminology,isreflectedinthisresult.

Together,theseresultsdemonstratethatalthoughtherearesector-specificdifficulties,thesuggestedsentiment analysis system continuously performs well across domains.It is suitable for real-world applications like market research, public opinion monitoring, and health sentiment tracking because it can maintain high accuracy, preci- sion, recall, and F1-scores in a variety of contexts.

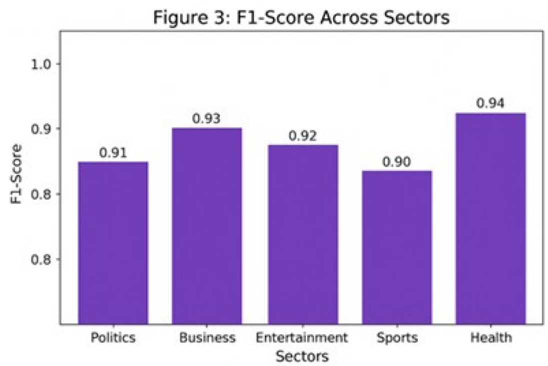

Figure2:F1scoreacrosssectors

V. DISCUSSION

The experiment’s findings demonstrate the benefits and drawbacks of various sentiment analysis techniques of social media content.Although they offered a decent starting point, conventional ML models like SVM, Ran- domForest, andLogisticRegressionwereunabletoadequatelyrepresenttheintricacyofuser-generatedcontent. This outcome was expected because these models mostly use hand-crafted features or bag-of-words representa- tions,whichfrequentlyoverlooksarcasm,contextualmeaning,anddomainspecificexpressions.RandomForest’smarginallybetterperformancethanSVMandLogisticRegressionindicatesthatensemble-basedapproachesoffer slight gains, but overall drawbacks are still substantial.

AnobviousadvancementwasshownbytheuseofDLmodels,especiallyLSTM.Duetoitsabilitytorecognizesequentialdependenciesintext,theLSTMmodeloutperformedtheothersoneverymetric. Thisemphasizeshow important it is to model context and word order in tasks involving natural language processing.Nevertheless,the LSTM continued to have trouble with situations that involved lengthy and intricate sentences in addition to with extremely ambiguous social media content.These findings show that although deep learning outperforms conventionaltechniques,itisinsufficienttomanagethecompletelinguisticrichnessandvariabilityofsocialmedia text.

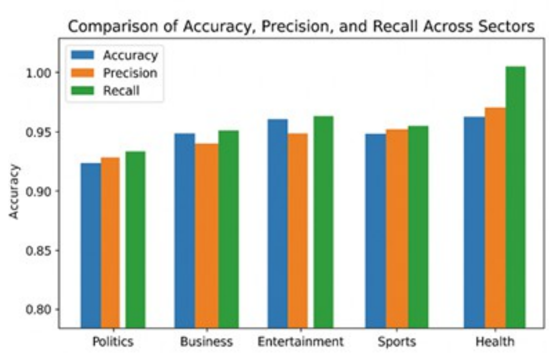

Figure3:Comparisonofaccuracy,precisionandrecallacrosssectors

The transformer-based model BERT showed the biggest improvement, consistently outperforming all other methods.The system was able to comprehend sentiment even when slang, informal language, or sarcasm were present thanks to its bidirectional contextual embeddings.

The sector-wise analysis also demonstrated BERT's versatility in a range of fields.The model continued to perform well even though there were minor variations, suchashigherscoresinBusinessandHealthasopposedtoSportsandPolitics. Thesedifferencesimplythatsome fields, like politics and sports, present extra difficulties because of their dynamic, context-dependent language.

The broader ramifications of these findings are also highlighted in the discussion.The suggested system's continuouslyexcellentperformanceindicatesitspotential forpracticaluses.Governments andpolicymakerscan utilizeittogaugepublicopiniononnewissues,andbusinessescanutilizeittotrackconsumerfeedbackandbrand reputation. Additionally,itscapacitytoassesssentimentinthemedicalfieldcreatesopportunitiesforuseinpublic health communication and mental health monitoring.

However, there are some restrictions on the system.Despite being strong, performance still varies slightly acrosssectors,suggestingthathandlingdynamiclanguageanddomain-specificjargoncouldusesomework. Fur- thermore, using large-scale pre-trained models like BERT presents computational difficulties, particularly when deployinginlow-resourcesettings. Futurestudiescaninvestigatemultilingualsentimentanalysis,domainadapta- tion strategies, and lightweight transformer models to address these issues.

VI. CONCLUSION

Thegoalofthisresearchwastocreateandassessasentimentanalysissystemdrivenby AIthatcouldidentifyandcategorizeviewpointsfromsocialmediaposts.Therapidexpansionofsocialmediasiteslike Facebook,Instagram,andTwitterhasmadeitmorecrucialthanevertocomprehendpublicopinionwhenmakingdecisionsinthefieldsofpolitics,business,entertainment,andhealth.Tofindthebeststrategyforexaminingsocialmediacontent,thestudy contrasted transformer-based models, deep learning techniques, and conventional machine learning classifiers.

Giventhecomplexlinguisticfeaturesofsocialmediadata,theresultsunequivocallyshowthatwhileconventionalclassifierslikeLogisticRegression,RandomForest,andSVMofferacceptablebaselines,theirshortcomingsbecomeapparent.

AlthoughtheLSTMmodelmadesignificantprogressinidentifyingsequentialdependenciesintext,itwasstillunabletohandlelongersentencesandunclearlanguage. WithbetterresultsinAccuracy,Precision, Recall, andF1-score, thetransformer-basedarchitectureBERTcontinuouslybeatallothermethods.Itsabilityto understand bidirectional context made it the most dependable model for sentiment analysis, which enabled it to deal with slang, sarcasm, and nuanced sentiment with ease.

The sector-specific assessment strengthened the suggested system's flexibility even more.The model main- tained consistently high scores, with the Health and Business sectors performing especially well, despite minor variationsinperformanceacrossdomains. Althoughtheresultswerestillwithinacceptableperformancemargins, thecomparativelylowerperformanceinSportsandPoliticsemphasizesthedifficultiespresentedbydynamiclan- guage and sarcasm in these domains.This illustrates how the system can be applied with minimal change in a number of fields.

The suggested sentiment analysis system has a lot of potential in terms of real-world applications.Political campaigns can utilize it to measure public opinion, businesses can utilize it to monitor their brand and analyze customerfeedback,andhealthorganizationscanutilizetolearnhowthepublicviewsmedicalissues.Furthermore, the system's cross-sector adaptability highlights its adaptability for practical implementation.

There are several prospects for improvement in the future.By addressing computational issues, lightweight transformer models could improve the system's suitability for low-resource environments.Adding multilingual supporttothesystemwouldalsomakeitmoreapplicableininternationalsettings. Furthermore,combiningemo- tion recognition and sentiment intensity detection may offer more profound understanding of user viewpoints.

This study concludes that transformer-based sentiment analysis systems are a major development in opinion mining, providing precise, flexible, and useful ways to glean insights from the quickly changing social media landscape.

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