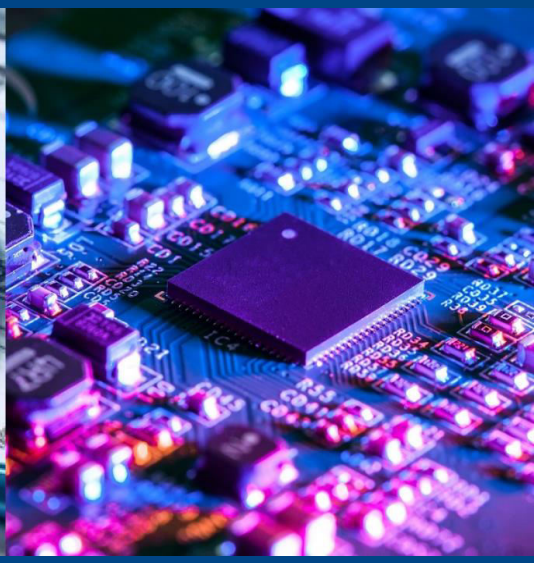
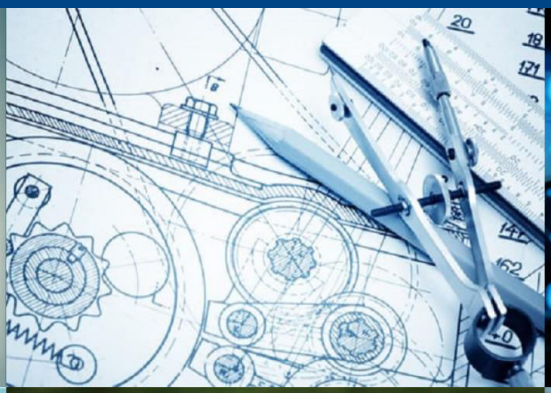
ISSN: 2582-7219

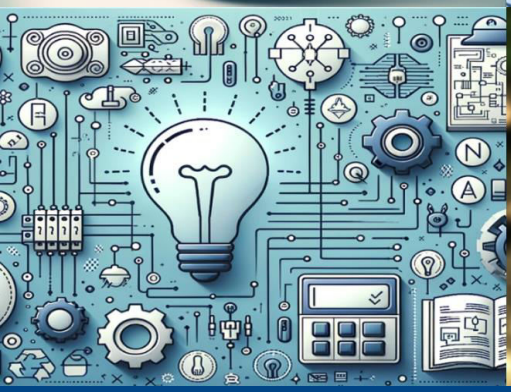




International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 9.864

Volume 9, Issue 5, May 2026

© 2026 IJMRSET | Volume 9, Issue 5, May 2026| DOI:10.15680/IJMRSET.2026.0905048

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

AI Sentiment Analysis Dashboard

Santhosh S C, Ms Pooja Taragar

PG Student, Dept. of MCA, City Engineering College, Bengaluru, India

Assistant Professor, Dept. of MCA, City Engineering College, Bengaluru, India

ABSTRACT: an excessive amount of user-generated content, which makes it difficult for organizations to manually interpret public The rapid growth Using digital channels for communication has led to opinion The creation and execution of an AI-driven Sentiment Analysis Dashboard that allows for the real-time analysis and visualization of textual information collected from several sources, such as social media, reviews, and feedback systems, is presented in this workThe The suggested method makes use of natural language processing and machine learning (NLP). technologies. approaches to categorize attitudes into neutral, negative, and positive groups.

The dashboard integrates data preprocessing feature extraction, and model deployment into a unified interface, allowing users to gain actionable insights through interactive visualizations including charts and trend analysis. The technology is made to manage big datasets effectively and accurately. in sentiment prediction. Additionally, it provides comparative analysis and temporal tracking of sentiment patterns, supporting informed Making decisions for researchers and businesses.

KEYWORDS: Artificial intelligence, sentiment analysis and social media analysis, text mining, opinion mining, dashboard data visualization, machine learning, analytics, and real-time monitoring

I. INTRODUCTION

he widespread use Using digital channels has greatly raised the amount of textual data generated by users via internet reviews, social media,blogs, and forums. This continuous flow of unstructured information contains valuable insights about public opinions, preferences, and experiences. However, manually analyzing such large-scale data is both time-consuming and inefficient, creating a need for automated and intelligent solutions.

Finding and classifying opinions conveyed in text into sentiments like positive, negative, or The primary objective of sentiment analysis, A crucial component of NLP, or natural language processing, is neutrality. Sentiment analysis methods are now more precise and able to handle intricate linguistic patterns like sarcasm, context, and ambiguity due to advancements in machine learning as well as artificial intelligence. Because of these features, sentiment Analysis is a helpful resource for businesses attempting to monitor brand reputation, comprehend client input, and assist with strategic decision-making.

Despite the availability of various sentiment analysis models, many existing systems lack an integrated platform that combines data processing, analysis, and visualization in a user-friendly manner. Decision-makers often demand not just categorization findings but also interactive, lucid depictions of trends and patterns across time.

II. METHODOLOGY

Data collection, preprocessing, sentiment classification, and visualization are all integrated into the structured pipeline of the suggested AI Sentiment Analysis Dashboard. Through an interactive interface, the methodology is intended to effectively handle massive amounts of textual data and transform it into insightful knowledge.

1. Data Collection

Textual data is gathered from a variety of sources, including internet reviews, social networking sites, and feedback systems. APIs Various web scraping methods are employed to extract real-time or historical data. The collected dataset may include user comments, ratings, and timestamps, which are essential for sentiment and trend analysis.

© 2026 IJMRSET | Volume 9, Issue 5, May 2026| DOI:10.15680/IJMRSET.2026.0905048

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

2. Data Preprocessing

Unprocessed Text data frequently contains noise, including special characters, URLs, and irrelevant symbols. To improve data quality, preprocessing steps are applied, such as:

- Removal of stop words, punctuation, and duplicates
- Tokenization and normalization (lowercasing, stemming, or lemmatization)
- Handling missing or incomplete data

These steps make certain that the input data is clean and suitable for additional examination.

3.FeatureExtraction

After preprocessingImportant elements are taken out of the text. Word embeddings, Bag-of-Words (BoW), and TF-IDF, or Term Frequency–Inverse Document Frequency are some of the techniques used to convert textual data into numerical representations. This Modification enables algorithms for machine learning to read and analyze the material eff

4.Sentiment Classification

For sentiment predictionAfter processing, the data is sent into machine learning or deep learning models. Naïve Bayes Assistance Vector Machines (SVM), and neural network-based models like LSTM are examples of common algorithms. Text is categorized by the model into sentiment groups like neutral, negative, and positive. To guarantee accuracy and dependability The model has been trained and verified. using labeled datasets.

5. Dashboard Development and Visualization

The classified results are integrated into a dashboard interface that offers visual information through charts, graphs, and trend lines. Visualization tools are used to display sentiment distribution, time-based trends, and comparative analysis. The dashboard is designed to be interactive, allowing users to filter data and explore specific patterns.

6. Performance Evaluation

The sentiment classification's efficacy model is assessed using criteria including F1-score, recall, accuracy, and precision. These indicators aid in evaluating the model's effectiveness and pinpointing areas in need of development.

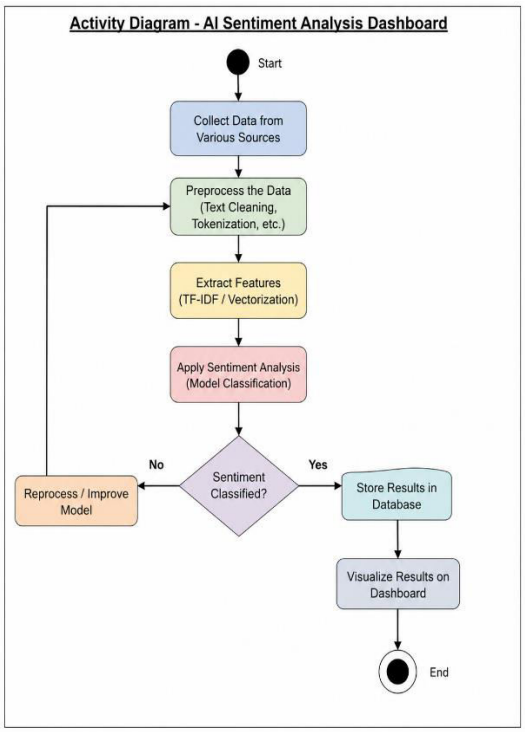


Fig 3.1 Activity Diagram

© 2026 IJMRSET | Volume 9, Issue 5, May 2026| DOI:10.15680/IJMRSET.2026.0905048

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

III. SYSTEM DESIGN

The AI Sentiment Analysis Dashboard's architecture is founded on the notion of using a series of computer procedures to convert unstructured textual information into organized and comprehensible knowledge. Each part of the system's layered, modular architecture is in charge of a particular task inside the larger analytical workflow.

At the core of the system lies the concept of data abstraction, in which raw textual inputs are progressively refined into meaningful representations. Initially, data acquisition mechanisms collect large volumes of text from diverse digital sources. This raw data is inherently noisy and unstructured, requiring systematic preprocessing to enhance its quality and usability. The preprocessing stage applies linguistic normalization techniques to standardize the text and eliminate irrelevant elements, thereby preparing it for analytical operations.

The next conceptual layer involves feature representation, which plays a critical role in enabling machines to interpret human language. Since computational models cannot directly process textual data, the system uses statistical and mathematical techniques to change text into vectors of numbers. This transformation captures the semantic and syntactic properties of the text, forming the foundation for subsequent analysis.

IV. SYSTEM ARCHITECTURE AND DESIGN

The AI Sentiment Analysis Dashboard is structured using a multi-layered architecture that supports efficient data processing, intelligent analysis, and intuitive visualization. The design emphasizes modularity, scalability, and seamless data flow, enabling the ability of the system to manage substantial amounts of textual data while maintaining performance and accuracy.

The architecture is conceptually divided into interconnected components that operate in a pipeline model. The first component focuses on data acquisition where textual information is gathered from a variety of internet resources, such as social networking sites, review systems, and user feedback channels. This component ensures continuous data inflow, supporting both real-time and batch processing mechanisms.

Following data acquisition, the system transitions into the preprocessing module, which is responsible for refining raw input data. Since collected text often contains inconsistencies, noise, and irrelevant elements, preprocessing techniques are applied to standardize the data. This includes normalization, tokenization, and elimination of redundant or insignificant terms. This stage's goal is to improve data quality and prepare it for computational analysis.

V. IMPLEMENTATION

The application of the AI Sentiment Analysis Dashboard involves The incorporation of data processing techniques, machine learning models, and a web-based visualization interface. The system is created utilizing a mix of programming frameworks and tools that support efficient data handling, model deployment, and user interaction.

Setting up the data gathering module is the initial stage of the development process. Textual data is gathered from specific sources, including social media networks, review datasets, or user feedback systems, using APIs and data extraction tools. In order to facilitate effective access and management, the gathered data is organized and stored in a database.

Natural language processing libraries are utilized in the execution of the preprocessing module. This stage includes text cleaning, tokenization, removal of stop words, and normalization. These operations ensure that the textual data is transformed into a consistent format suitable for analysis. Libraries such as Python-based NLP frameworks are utilized to streamline these processes and reduce computational complexity.

Feature extraction is utilized for translating text that has been altered into numerical forms. Techniques like vectorization and TF-IDF are used to generate feature matrices. These attributes serve as inputs for the machine learning models. The implementation ensures that the dimensionality of the data is suitably regulated to maintain model performance.

© 2026 IJMRSET | Volume 9, Issue 5, May 2026| DOI:10.15680/IJMRSET.2026.0905048

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 9.864| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

VI. RESULTS AND DISCUSSION

The proposed AI Sentiment Analysis The dashboard was assessed using a dataset consisting of textual inputs collected from online reviews and social media sources. The system was tested to assess its ability to accurately classify sentiments and present meaningful insights through visualization.

Standard assessment criteria The sentiment categorization The efficacy of Metrics like accuracy, precision, recall, and F1-score were used to assess the model. The findings show that a high level of precision in differentiating between positive, negative, and neutral attitudes was attained by the implemented model. Machine learning-based methods consistently performed well across the studied algorithms, and Better results were observed when suitable feature extraction techniques were used.

The examination of the confusion matrix showed that the model effectively identifies clearly expressed sentiments, while minor misclassifications occur in cases involving ambiguous language, sarcasm, or context-dependent expressions. Despite these challenges, the overall classification performance remains reliable for practical applications.

The dashboard visualization component was evaluated based on usability and responsiveness. The system successfully displayed sentiment distribution through graphical representations such as bar charts and pie charts, allowing users to quickly interpret the results. Time-series analysis enabled the observation of sentiment trends over particular times, offering insightful information about changes in user opinions.

VII. CONCLUSION

This study detailed the creation and deployment of an AI-based Sentiment Analysis Dashboard for the analysis and visualization of textual information from several digital sources . The recommended approach integrates machine learning models that use natural language processing techniques to automatically classify attitudes and convert unstructured material into meaningful information. By offering concise and engaging visual depictions of sentiment patterns and trends, the dashboard interface further improves the system's usability.

The experimental findings show that the system performs consistently, accurately, and efficiently in sentiment categorization tasks. Predictive modeling, data preparation, and feature extraction combined within a unified framework ensures smooth data flow and effective analysis. Additionally, the visualization component enables users to interpret results بسهولة and make informed decisions based on sentiment trends.

Despite its effectiveness, the system has serious shortcoming especially when it comes to managing complex linguistic expressions such as sarcasm and context-dependent sentiments. These challenges highlight The necessity of further advancements in model design and data representation.

REFERENCES

1. B. Liu Morgan & Claypool Publishers, 2012.
2. . Natural Language Processing with S. Bird, E. Klein, and E. Loper *Python*. O'Reilly Media, 2009.
3. T. Mikolov, K. Chen, G. Corrado, and J. Dean, "Efficient estimation of word representations in vector space," *Learning Representations (ICLR)*, 2013.
A. Pak and P. Paroubek, "Twitter as a corpus for sentiment analysis and opinion mining," in 2010.
4. P. D. Turney, "Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews, the necessity in the Association for Computational Linguistics (ACL) Annual Meeting Proceedings, 2002.

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INTERNATIONAL JOURNAL OF MULTIDISCIPLINARY RESEARCH

IN SCIENCE, ENGINEERING AND TECHNOLOGY

| Mobile No: +91-6381907438 | Whatsapp: +91-6381907438 | ijmrset@gmail.com |

www.ijmrset.com