



SOCIAL MEDIA BRAND SENTIMENT AND ENGAGEMENT ANALYTICS DASHBOARD WITH PLATFORM COMPARISON AND TREND TRACKING

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Abstract

The Social Media Brand Sentiment and Engagement Analytics Dashboard with Platform Comparison and Trend Tracking is developed to provide comprehensive insights into brand performance and audience perception across multiple social media platforms. In today's digital landscape, understanding user engagement and sentiment is essential for effective marketing strategies and brand positioning. This project leverages Microsoft Power BI to integrate and analyze data from various platforms, enabling a unified view of social media performance. The dashboard evaluates key engagement metrics such as likes, comments, shares, reach, and impressions, along with sentiment analysis that classifies user feedback into positive, negative, and neutral categories. Data modeling and transformation techniques are applied to ensure accurate and structured analysis. The system also includes platform comparison features, allowing organizations to identify the most effective channels for audience interaction and content delivery.

Time-series analysis is used to track trends in engagement and sentiment over different time periods, helping to identify patterns and shifts in audience behavior. Advanced DAX measures are implemented to calculate key performance indicators (KPIs) such as engagement rate, sentiment score, growth rate, and platform contribution.

I. Introduction

In today's digital era, social media platforms have become a vital channel for communication, marketing, and brand building. Organizations increasingly depend on platforms such as Instagram, Twitter, and Facebook to connect with their audience and shape public perception. As a result, analyzing social media data has become essential for understanding user behavior, evaluating campaign performance, and improving brand strategies.

The Social Media Brand Sentiment and Engagement Analytics Dashboard with Platform Comparison and Trend Tracking, developed using Microsoft Power BI, aims to provide a comprehensive analytical solution for assessing social media performance. This project focuses on extracting valuable insights from large volumes of data by analyzing engagement metrics such as likes, comments, shares, impressions, and reach, along with sentiment classification of user-generated content into positive,

negative, and neutral categories. By integrating data from multiple platforms, the dashboard enables comparative analysis to identify high-performing channels and effective content types. It also incorporates trend analysis to monitor changes in engagement and sentiment over time, helping organizations recognize patterns and respond proactively. Interactive visualizations, filters, and drill-down capabilities allow users to explore data at various levels of detail.

II. Literature Survey

The rapid growth of social media platforms such as Instagram, Twitter, and Facebook has resulted in a massive increase in user-generated data, attracting significant attention from researchers and organizations. Many studies have focused on analyzing this data to understand customer sentiment, engagement behavior, and brand perception. Sentiment analysis has been widely explored using machine learning and natural language processing techniques, where user opinions are classified into positive, negative, and neutral categories to evaluate public perception of products and services. At the same time, research in engagement analytics has examined metrics such as likes, comments, shares, reach, and impressions to measure audience interaction and content effectiveness, highlighting their importance in determining the success of marketing campaigns.

Recent advancements emphasize the adoption of business intelligence tools such as Microsoft Power BI for visualizing large and complex datasets. These tools enable the creation of interactive dashboards that allow users to explore data dynamically and derive meaningful insights. However, despite these developments, several gaps still exist in the literature. Many studies focus only on sentiment analysis or engagement metrics separately, lacking an integrated approach that combines both aspects. Additionally, limited attention has been given to cross-platform comparison, making it difficult to evaluate performance across different social media channels. There is also a lack of user-friendly and interactive dashboards, as well as insufficient focus on analyzing trends over time.

To address these limitations, there is a clear need for a unified system that integrates sentiment analysis, engagement tracking, platform comparison, and trend analysis within a single framework. This project aims to bridge these gaps by leveraging the advanced analytical and visualization capabilities of Power BI, providing a comprehensive and interactive solution for social media performance analysis.

III. System Analysis

Social media has become a major platform for marketing, communication, and brand engagement. Organizations generate large volumes of data from platforms like Instagram, Twitter, and Facebook. Managing and analyzing this data is challenging without proper tools. There is a need to understand user sentiment and engagement behavior. Businesses require insights into likes, comments, shares, reach, and impressions. Comparing performance across multiple platforms is essential for strategy optimization. Traditional systems lack real-time analytics and visualization. Data-driven decision-making is important for improving brand performance.

Sentiment analysis helps identify customer opinions and feedback. Trend tracking is required to monitor changes over time. The system should be interactive and user-friendly. It should support dynamic filtering and drill-down features. This project addresses these needs using advanced analytics tools.

Existing System

In the existing system, social media data is analyzed using basic tools or manual methods. Data is often collected separately from different platforms without integration. Analysis is limited to simple metrics like likes and shares. There is no combined analysis of sentiment and engagement. Reports are usually static and lack interactivity. Platform comparison is difficult due to fragmented data. Visualization is limited or absent in many cases. Decision-making relies on incomplete or outdated data. There is no real-time monitoring of trends. Sentiment analysis is either missing or performed separately. Users cannot explore data dynamically. Overall, the system lacks efficiency and comprehensive insights.

Disadvantages of Existing System

- No integration of multiple social media platforms
- Limited sentiment analysis capabilities
- Lack of real-time data monitoring
- Poor visualization of data
- No interactive dashboards
- Difficulty in platform comparison
- Limited trend analysis
- Fragmented and inconsistent data
- Manual and time-consuming processes
- Inaccurate decision-making
- Lack of scalability
- Reduced effectiveness of marketing strategies

Proposed System

The proposed system is an advanced analytics dashboard developed using Microsoft Power BI. It integrates data from multiple social media platforms into a centralized system. The dashboard analyzes engagement metrics such as likes, comments, shares, reach, and impressions. It performs sentiment analysis to classify user opinions into positive, negative, and neutral categories. Platform comparison features help identify the most effective channels. Time-series analysis is used to track trends in engagement and sentiment. The system uses DAX measures to calculate KPIs like engagement rate and sentiment score. Interactive visualizations such as charts and graphs are used for data representation. Users can apply filters and drill down into specific details. The system supports real-time or near real-time updates. It is user-friendly and easy to use. Overall, it enhances decision-making and marketing performance.

Advantages of Proposed System

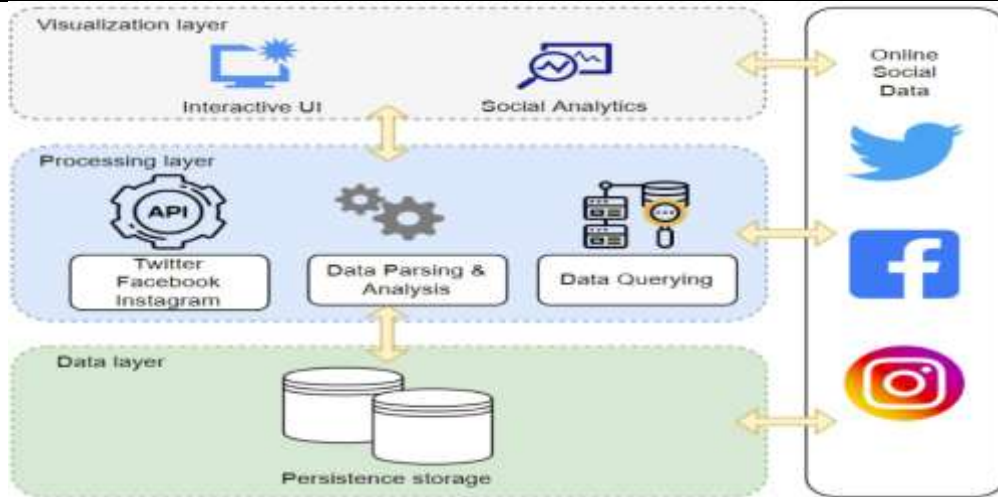
- Integrated analysis of multiple platforms
- Real-time monitoring of social media data
- Advanced sentiment analysis
- Interactive and dynamic dashboards
- Easy platform comparison
- Effective trend tracking over time
- Improved decision-making support
- Better understanding of audience behavior
- Scalable and flexible system
- Enhanced marketing strategy optimization
- User-friendly interface
- Increased efficiency and accuracy

IV. Methodology

The project begins with collecting social media data from various platforms. The data is cleaned and preprocessed to remove inconsistencies. Sentiment analysis is applied using NLP techniques. Data transformation is performed to structure it for analysis. The processed data is loaded into Power BI. Data modeling is carried out to establish relationships between datasets. KPIs such as engagement rate and sentiment score are defined using DAX. Interactive dashboards are designed using charts and graphs. Filters and slicers are added for dynamic exploration. Trend analysis is performed using time-series data. The system is tested for accuracy and performance. Finally, the dashboard is deployed for use by stakeholders.

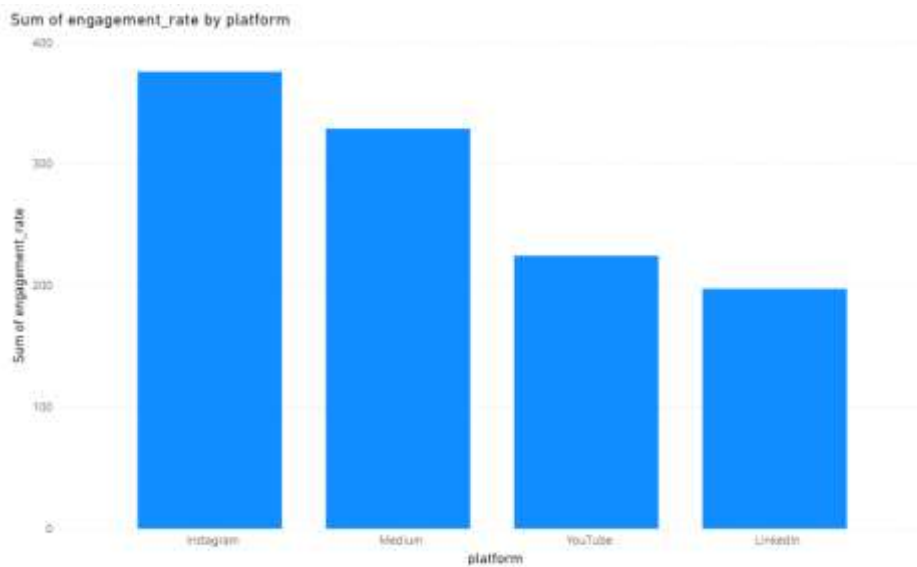
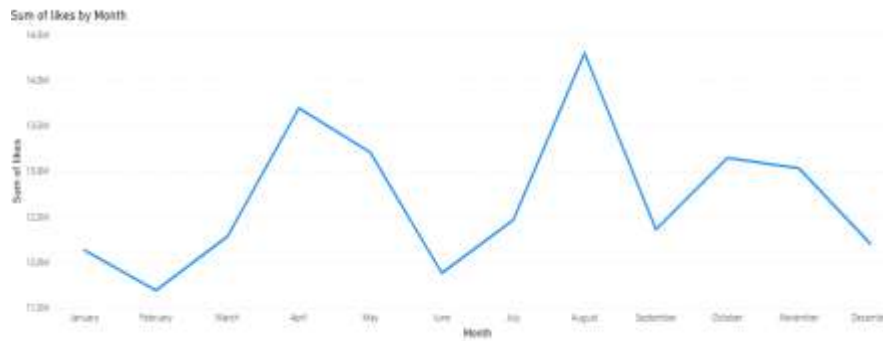
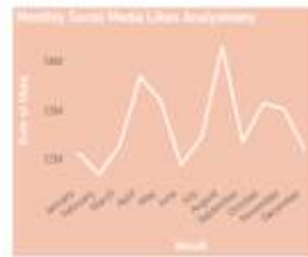
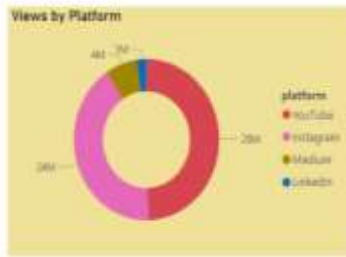
System Architecture

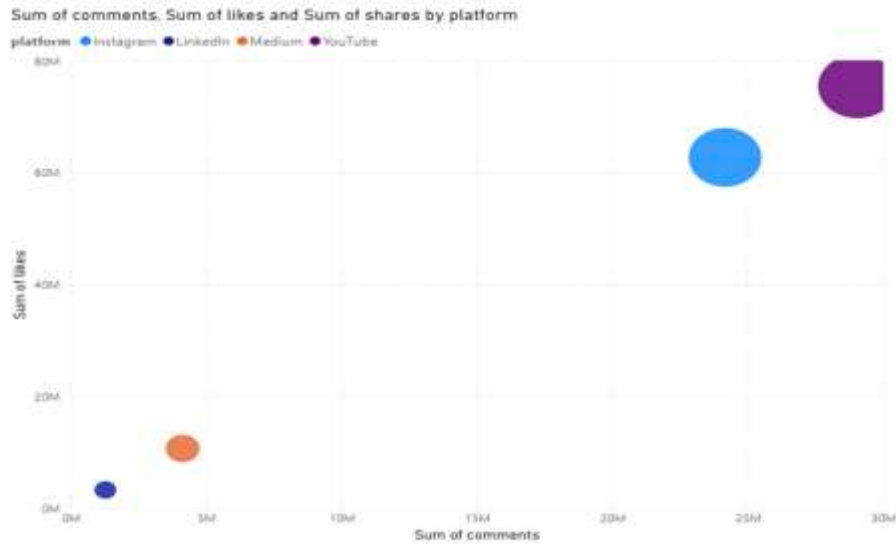
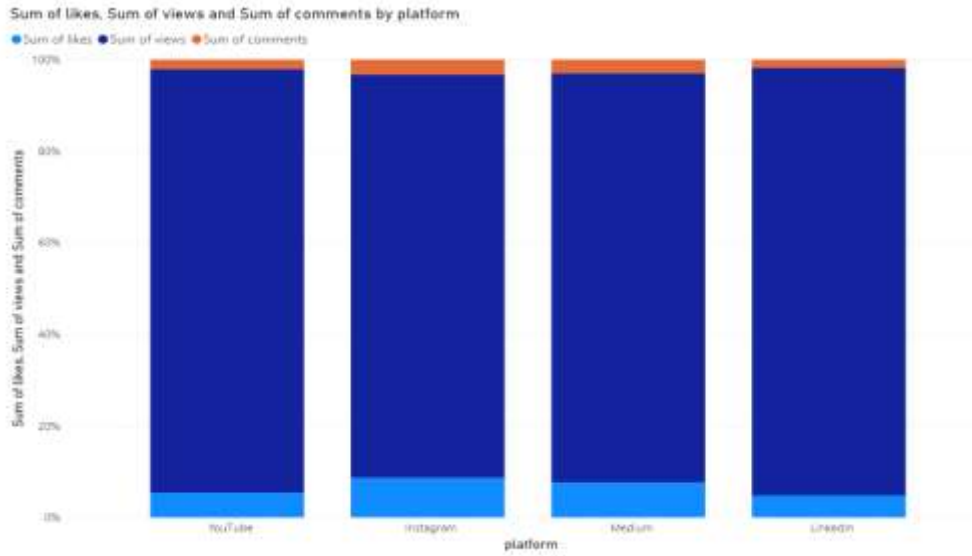
The system architecture consists of multiple layers for efficient data processing and visualization. The first layer is the Data Source Layer, which includes social media platforms and APIs. The second layer is the Data Preprocessing Layer, where data cleaning and transformation are performed. The third layer is the Data Integration Layer, which combines data from different platforms. The fourth layer is the Data Storage Layer, where structured data is stored. The fifth layer is the Data Analysis Layer, where sentiment analysis and KPI calculations are performed. The sixth layer is the Visualization Layer, implemented using Power BI dashboards. The seventh layer is the User Interaction Layer, where users explore insights. The system supports real-time updates. It ensures data consistency and accuracy. The architecture is scalable and flexible. Overall, it provides a complete analytics solution.



V. Result and Output



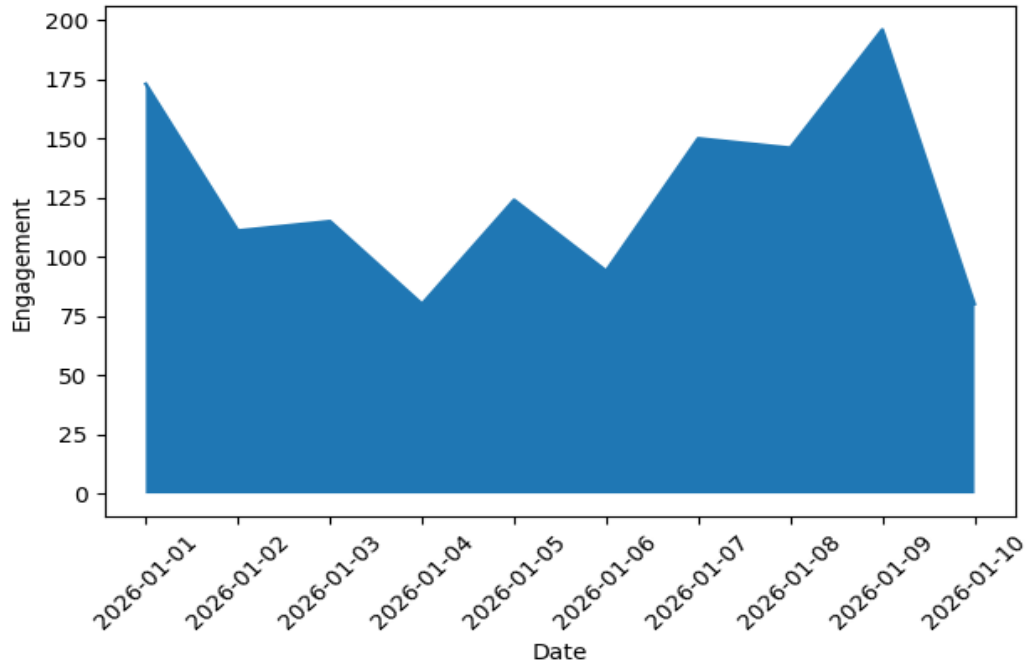




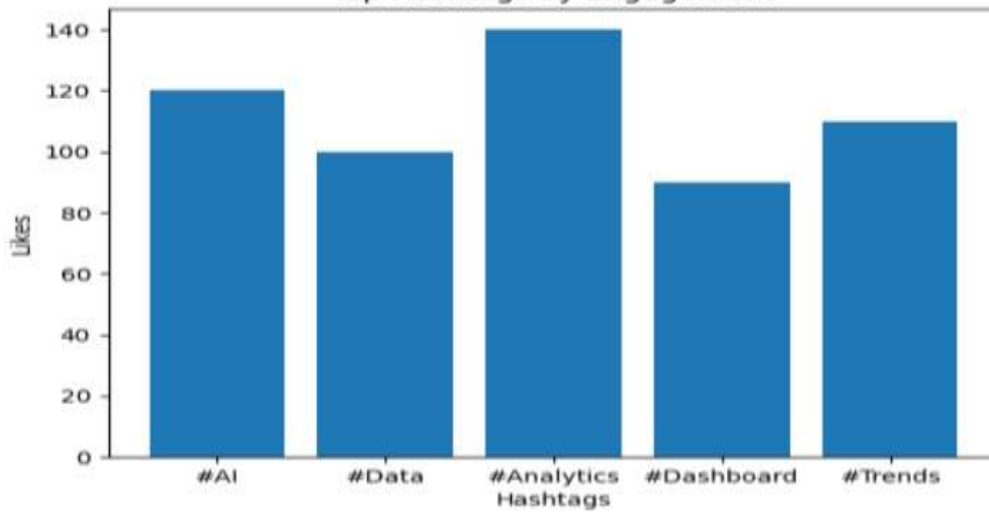
Content Performance Metrics by Post Type

Sum of comments	content_type	Sum of engagement_rate	Sum of likes	platform	Sum of views
262476	article	39.98	682715	LinkedIn	13271542
262885	image	39.56	683741	LinkedIn	13005078
267035	poll	41.34	694546	LinkedIn	13676020
1995107	article	160.13	5187917	Medium	60983665
2131048	story	168.87	5541372	Medium	63851211
4485620	carousel	72.95	11662830	Instagram	118326835
4849801	reel	73.79	12609779	Instagram	133282866
4857709	story	77.96	12630334	Instagram	129832010
4900268	image	75.91	12740945	Instagram	128780045
58601396		1,126.67	152368747		2121421581

Engagement Trend Over Time



Top Hashtags by Engagement





First platform, First region and First topic by topic

Business Instagram	Education Instagram	Entertainment Instagram
Fashion Instagram	Food Instagram	Health Instagram
Lifestyle Instagram	Sports Instagram	Technology Instagram

VI. Conclusion

The Social Media Brand Sentiment and Engagement Analytics Dashboard with Platform Comparison and Trend Tracking plays a crucial role in helping businesses understand and enhance their online presence in an effective and structured manner. By integrating sentiment analysis with engagement tracking, the system provides a comprehensive view of how audiences perceive a brand and how they interact with its content across platforms such as Instagram, Twitter, and Facebook.

The dashboard not only identifies whether audience sentiment is positive, negative, or neutral but also provides insights into the underlying reasons through user interactions, comments, and trends. The platform comparison feature enables organizations to evaluate the performance of different social media channels, helping them allocate resources more efficiently. Additionally, trend tracking allows businesses to monitor changes over time, assess campaign effectiveness, and respond quickly to emerging issues.

By leveraging advanced visualization tools such as Microsoft Power BI, the system presents data in an interactive and user-friendly manner, supporting better analysis and decision-making. Overall, the dashboard enhances marketing strategies, improves customer engagement, and strengthens brand image.

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