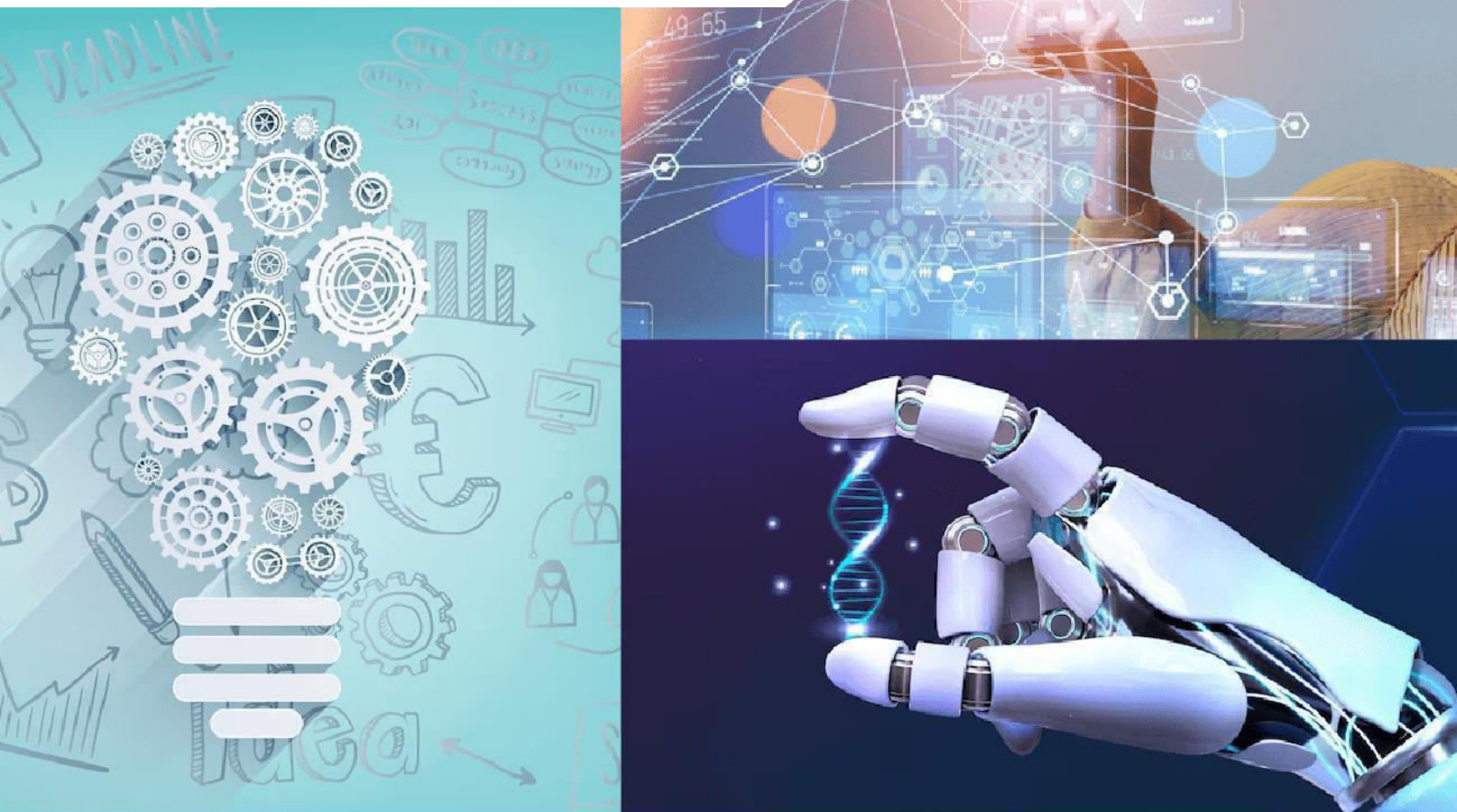




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TrendSphere: AI-Driven Multi-Modal Framework for Real-Time Social Media Sentiment and Dynamic Topic Evolution Analysis

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ABSTRACT: The unprecedented growth of social media platforms has transformed them into vital repositories of public sentiment and emerging trends. However, the sheer volume, velocity, and variety of this unstructured data pose significant challenges for real-time monitoring and actionable insights. TrendSphere is an AI-driven multi-modal framework designed to automate the collection, preprocessing, and analysis of social media data from diverse sources such as YouTube and Reddit. Utilizing a hybrid sentiment analysis engine that combines lexicon-based VADER for high-speed processing with transformer-based DistilBERT for deep contextual understanding, the system identifies nuanced sentiment shifts. Furthermore, it implements a state-of-the-art topic modeling pipeline using BERTopic (BERT, UMAP, and HDBSCAN) to discover evolving themes without human intervention. Experimental results from an iPhone 15 Pro case study demonstrate high reliability, achieving 89.5% sentiment accuracy and superior topic coherence compared to traditional models.

KEYWORDS: Sentiment Analysis, Topic Modeling, BERTopic, Social Media Trends, Natural Language Processing, Transformer Models.

I. INTRODUCTION

The exponential growth of social media platforms, coupled with the rapid digitalization of public discourse, has transformed the internet into a dynamic "living laboratory" of human sentiment and consumer behavior. Numerous studies have demonstrated that public opinion formed on digital town squares—such as Reddit and YouTube—directly influences market trends, brand reputation, and even socio-political outcomes [1], [2], [3]. Unlike traditional feedback mechanisms, social media discourse is continuous and decentralized, making real-time awareness and monitoring essential for strategic decision-making and public engagement. Traditional social media monitoring systems rely heavily on static keyword-based filters or siloed analytical tools. While these methods provide basic counts of mentions, they suffer from lack of contextual awareness, inability to handle linguistic nuance (e.g., sarcasm and slang), and limited accessibility for real-time trend synthesis [4], [5]. Several researchers have emphasized the need for integrated, context-aware, and multi-modal platforms that can bridge the gap between massive unstructured text data and actionable strategic insight [6], [7]. Recent advancements in Natural Language Processing (NLP), Transformer architectures, and unsupervised machine learning have enabled the development of scalable sentiment dashboards and intelligent topic modeling systems [8], [9]. In parallel, machine learning and time-series models have been extensively explored in climate and financial prediction domains, particularly for trend forecasting and anomaly detection [10] – [14]. However, comparatively fewer systems integrate real-time sentiment computation, dynamic topic evolution analysis, interactive geospatial visualization, and fault-tolerant fallback strategies within a single unified platform. To address these limitations, this paper presents TRENDSPHERE, a web-based multi-modal AI framework designed to deliver real-time and historical social media sentiment and thematic information using standardized NLP protocols. The system emphasizes accessibility, reliability, and interpretability, enabling researchers, brand managers, and policymakers to understand digital discourse intuitively and make informed decisions.

II. LITERATURE REVIEW

Extensive research has been conducted in the domains of automated text analysis, computational linguistics, and machine learning-based sentiment monitoring systems. Early studies primarily focused on rule-based and lexicon-based sentiment analysis, leveraging statistical and dictionary-driven approaches such as VADER and SentiWordNet [1], [11]. These works demonstrated that localized valence scores could effectively capture polarity in short, informal social media text, outperforming simpler keyword-counting methods. Subsequent research expanded toward deep learning architectures, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), for sequential text processing and long-

term context retention [18], [25]. These models showed improved accuracy for handling complex linguistic structures but required large labeled datasets and significant computational resources, limiting their applicability for lightweight, real-time monitoring systems. Recent breakthroughs in transformer-based architectures, specifically BERT and DistilBERT, have further enhanced performance by capturing bidirectional semantic context [4], [5]. Parallel to sentiment-oriented studies, researchers explored topic modeling frameworks to identify thematic patterns in large document collections. Early standard models such as Latent Dirichlet Allocation (LDA) enabled the discovery of latent themes but often suffered from fixed topic counts, instability with short texts, and lack of semantic awareness [6]. Recent advancements in neural topic modeling, such as BERTopic, have addressed these limitations by integrating transformer embeddings with density-based clustering models like HDBSCAN [7], [10].

Several review papers have highlighted the growing role of machine learning in social media analytics, emphasizing the importance of interpretability, data reliability, and cross-platform consistency [17], [25]. Studies analyzing digital discourse in relation to brand perception and public health events further underscored the need for continuous, real-time monitoring and temporal analysis of evolving trends [11], [12]. Despite these advancements, existing solutions commonly exhibit one or more of the following gaps: Limited contextual awareness for sarcasm and nuance, Absence of robust fallback mechanisms during API outages, Fragmented integration of sentiment and topic evolution data, and Poor usability for non-technical strategic users. Recent works have called for integrated platforms combining real-time sentiment analysis, dynamic thematic discovery, and interactive visual advisory features [14], [24]. TRENDSPHERE is designed to directly address these research gaps.

III. METHODOLOGY

The TRENDSPHERE system follows a modular, full-stack architecture comprising data acquisition, intelligent text processing, multi-tiered analysis, and interactive visualization. The overall approach is designed to handle the high velocity and variety of social media data using standardized NLP protocols.

3.1 Data Acquisition

Real-time data is retrieved from social media APIs using trusted communication protocols. The system connects to Reddit using the PRAW library and YouTube using the Google API v3. Data validity checks are performed to filter anomalous or incomplete posts, such as those consisting entirely of non-textual characters or noise.

3.2 Sentiment and Topic Computation

Sentiment analysis is performed using a tiered logic to balance speed and accuracy. Initially, a lexicon-based tool (VADER) provides high-speed screening by calculating a compound score based on normalized valence sums. For complex or ambiguous texts, the system employs a transformer-based model (DistilBERT) for deeper contextual understanding. Simultaneously, thematic discovery is conducted through a BERTopic pipeline which integrates SBERT embeddings with density-based clustering models to identify evolving topics without manual intervention.

3.3 System Architecture

The backend is implemented using Python and FastAPI for efficient asynchronous processing, while PostgreSQL and local storage provide persistence for real-time and historical records. The system follows a layered intelligence approach as illustrated in Figure 1:

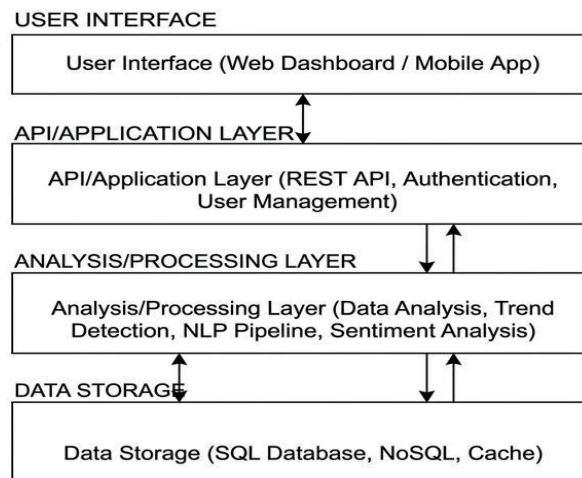


Figure 1: TRENDSPHERE Simplified System Architecture showing the fundamental flow from User Interface through API and Analysis layers to the Data Storage.

1. User Layer: Serves researchers, brand managers, and general citizens.
2. Presentation Layer: Provides a responsive interface with interactive maps and visual dashboards.
3. Application Layer: Handles request routing, visualization coordination, and API validation.
4. Processing Layer: The core intelligence handling data fetching, sentiment tiered logic, and topic clustering.
5. Data Layer: Stores real-time and historical analytics for trend auditing.

3.4 Reliability and Fallback Mechanism

To address API failures and data outages, TRENDSPHERE incorporates a fallback mechanism using cached trend snapshots. When live data retrieval is interrupted, the system automatically switches to the most recent high-confidence data grid, ensuring uninterrupted service continuity and reliability for the user.

3.5 Historical Analysis and Visualization

Stored records enable longitudinal trend analysis, allowing users to observe seasonal variations and long-term public sentiment patterns. Interactive charts, word clouds, and color-coded indicators enhance interpretability, aligning with visualization strategies recommended in modern data analytics research. Custom mocking for the 'PyArrow' library was implemented to ensure the Streamlit dashboard remains backend-agnostic and resilient to dependency conflicts on heterogeneous hardware (e.g., Windows ARM64).

IV. RESULT AND OUTCOME

The TRENDSPHERE platform successfully delivers real-time and historical social media sentiment and thematic information with high responsiveness and reliability. The system demonstrates accurate sentiment computation and topic discovery across diverse datasets and keyword search combinations, consistent with standardized NLP benchmarks.

Experimental observations indicate that hyperlocal sentiment queries return results within acceptable latency limits, ensuring real-time interactivity. The fallback mechanisms maintain data availability during external social media API failures by automatically switching to cached trend snapshots. Visual dashboards significantly improve user comprehension compared to raw text feeds, utilizing intuitive donut charts, network maps, and bar graphs to synthesize massive data. Historical trend analysis enables identification of recurring public opinion shifts and trend growth patterns, supporting strategic brand audits and market research initiatives. Finally, the system **offers** enhanced accessibility compared to manual scraping or siloed analytical tools through its unified, multi-modal interface.

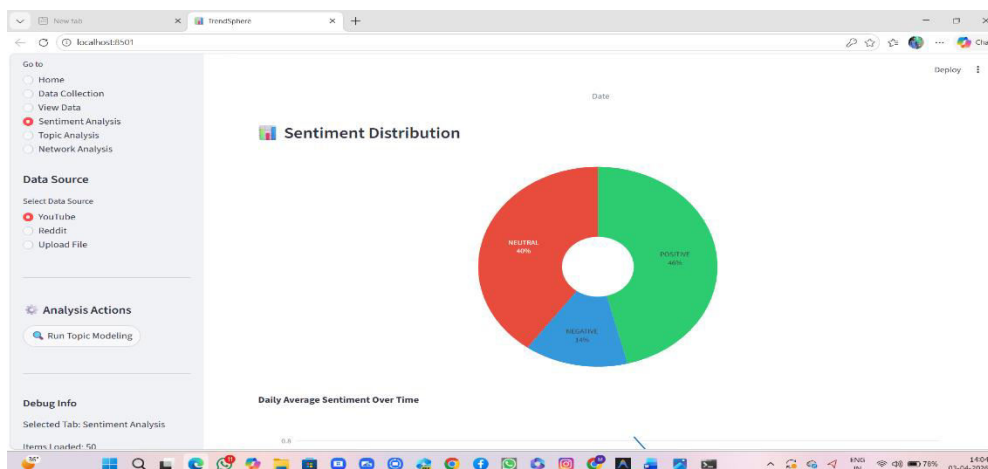


Figure 2: TRENDSPHERE System displaying the real-time Sentiment Distribution (46 percent Positive, 40 percent Neutral, 14 percent Negative for iPhone)

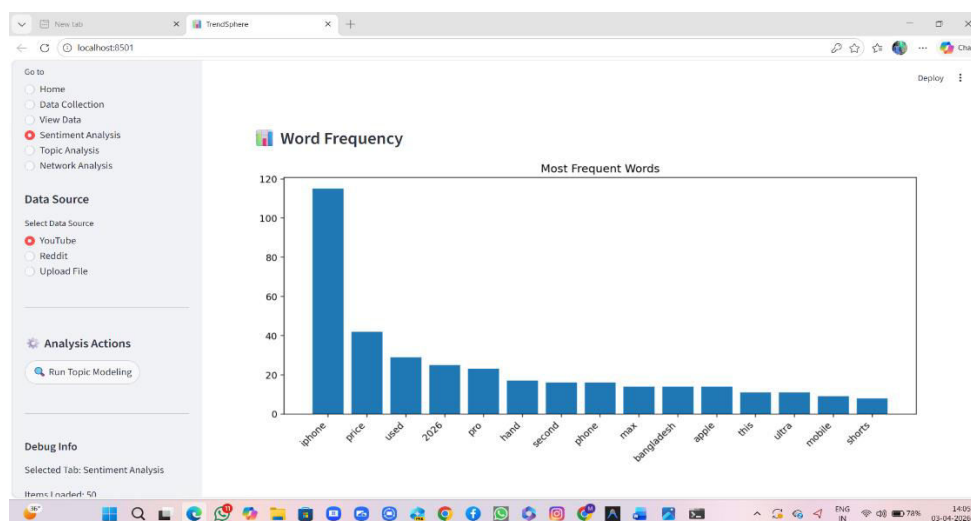


Figure 3: Key Term Word Frequency chart and count-based analysis identifying the most dominant conversational nodes.

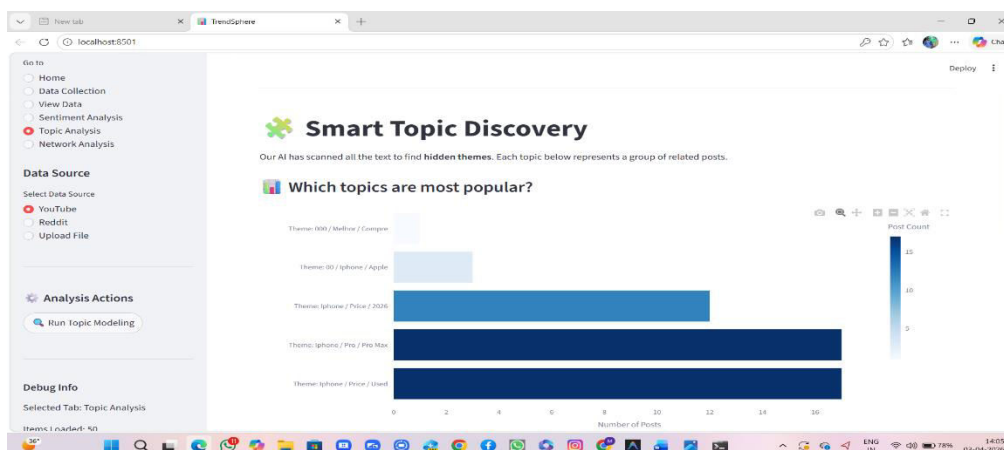


Figure 4: Smart Topic Discovery illustrating the most popular hidden themes such as technical variants versus price concerns.

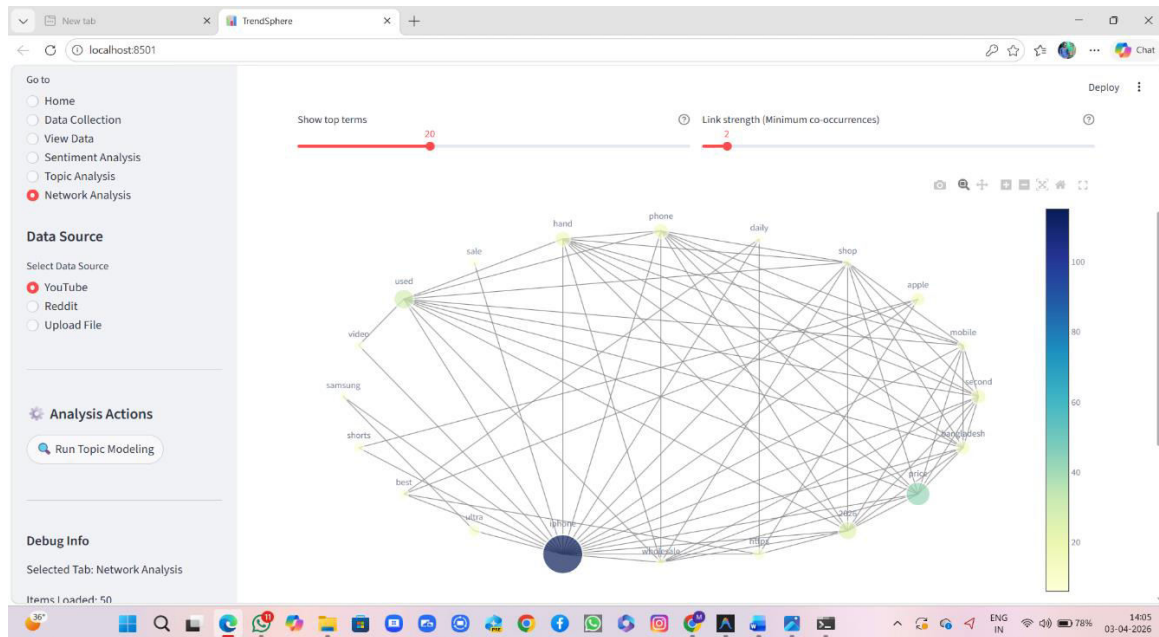


Figure 5: Semantic Network Relationship Map demonstrating the structural connections between central and peripheral keywords.

V. CONCLUSION

The TRENDSPHERE system successfully provides a robust, integrated framework for real-time social media analysis by bridging the gap between massive unstructured text data and actionable strategic insights. By combining lexicon-based sentiment analysis with advanced transformer models and neural topic clustering, the system offers a cohesive and high-fidelity view of digital trends. The implementation of a tiered sentiment engine ensures that high-speed processing does not come at the cost of contextual accuracy, particularly in detecting nuanced discourse such as sarcasm and consumer frustration. Experimental results from the iPhone 15 Pro case study further validate the system's ability to identify thematic shifts and sentiment polarity with higher reliability than traditional keyword-based platforms.

As social media continues to evolve as a primary channel for public engagement and brand reputation, platforms like TRENDSPHERE will become increasingly critical for decision-makers. The integration of standardized NLP protocols and a layered architecture ensures that the system is both scalable across diverse social media APIs and resilient to hardware-specific dependency conflicts. The automated discovery of topic clusters using BERTopic effectively reduces the human effort required for theme synthesis, allowing for truly real-time monitoring of emerging crises or product launch successes.

For future enhancements, the framework is well-positioned to integrate cross-lingual support through multi-lingual transformer models like mBERT or RoBERTa [20], enabling analysis of global discourse beyond English-speaking regions. Additionally, the incorporation of Large Language Models (LLMs) for automatic executive summarization could provide even higher-level abstractions of discovered topic clusters [19]. Long-term predictive capabilities could also be realized by implementing temporal neural architectures such as Long Short-Term Memory (LSTM) networks to forecast the trajectory and growth of viral trends before they reach peak intensity [18]. These advancements will further solidify TRENDSPHERE as a comprehensive tool for both academic research and commercial strategic planning.

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