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LARGE SCALE DATA AUDIT THROUGH BIG DATA TECHNOLOGIES

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Abstract: This paper presents a comprehensive Big Data analytics pipeline for YouTube trending video data using Apache Spark, TextBlob NLP, MySQL, and Streamlit Dashboard technologies. The system integrates five primary components: the YouTube Data API v3 for automated collection of up to 200 trending videos and 4,000 user comments per pipeline run; a MySQL 8.0 relational database for structured storage; Apache Spark 3.4 (PySpark) for distributed data transformation; TextBlob NLP for lexicon-based sentiment analysis deployed as Spark User Defined Functions; and a Streamlit and Plotly multi-page interactive dashboard for analytics visualization. Results from a representative pipeline run revealed that Music and Entertainment categories dominate India's trending landscape, Gaming audiences exhibit the highest engagement scores (4.12%), and 52% of comments are Neutral, 33% Positive, and 15% Negative. The system demonstrates the practical application of Big Data engineering principles to social media analytics, delivering actionable intelligence on content trends, viewer engagement patterns, and audience sentiment for the Indian YouTube market.

Keywords: YouTube Analytics, Apache Spark, PySpark, TextBlob, Sentiment Analysis, Big Data Pipeline, MySQL, Streamlit, Engagement Score, Natural Language Processing, India Trending, Data Engineering

I. INTRODUCTION

The rapid growth of digital video content on platforms such as YouTube generates massive volumes of interaction data daily. YouTube, with over 2.5 billion monthly active users globally and more than 467 million users in India alone, represents one of the most significant digital content ecosystems in the modern world. Every minute, over 500 hours of video content are uploaded, creating a continuously expanding dataset of cultural, entertainment, news, and audience sentiment signals. Analysing this data at scale requires robust Big Data engineering infrastructure combined with Natural Language Processing capabilities, challenges that conventional single-machine tools cannot meet efficiently.

A. Background and Context

Traditional data processing tools such as Excel or basic Python scripts quickly reach their limits when confronted with large-scale YouTube datasets. Big Data engineering frameworks, specifically Apache Spark, are architected precisely for this class of problem through parallelized, in-memory distributed computation. The trending section of YouTube surfaces the most-watched and most-engaged videos in a given country, providing a real-time signal of cultural interests, news consumption patterns, entertainment preferences, and public opinion that is invaluable for researchers and content strategists.

B. Problem Statement

The rapid expansion of YouTube has led to generation of massive volumes of video metadata and user-generated comment text that are computationally infeasible for conventional single-machine analysis tools. Existing tools like YouTube Studio provide insights only for the authenticated user's own channel, while commercial platforms such as Social Blade are proprietary and expensive. No integrated, open-source pipeline currently combines automated YouTube data collection, distributed Big Data processing, NLP comment sentiment analysis, and interactive dashboard visualization targeting the Indian market. Additionally, no publicly available tool provides a normalized engagement score that accounts for view volume, making fair cross-video performance comparison impossible with raw interaction counts.

C. Significance of the Study

This project presents a comprehensive Big Data analytics pipeline designed to collect, process, analyse, and visualize YouTube trending video data and associated user comments specifically for the India (IN) region. The system integrates

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five primary technology components: (1) the YouTube Data API v3 for automated collection of up to 200 trending videos and 20 comments per video; (2) a MySQL 8.0 relational database; (3) Apache Spark 3.4 (PySpark) for distributed data transformation; (4) TextBlob NLP for lexicon-based sentiment analysis; and (5) a Streamlit and Plotly multi-page interactive dashboard for analytics visualization. The system computes a custom normalized engagement score metric enabling cross-video performance comparison and delivers actionable intelligence on India's trending video landscape.

II. LITERATURE REVIEW

Covington, Adams, and Sargin (2016) presented YouTube's deep neural network recommendation system, emphasizing multi-dimensional engagement signals including views, watch time, likes, dislikes, shares, and comments as primary ranking features. The authors demonstrate that simple view counts are insufficient proxies for content quality, providing the theoretical foundation for the engagement score computation in this project. Their two-stage neural network architecture established the scientific significance of combining behavioral and contextual signals for content performance evaluation.

Zaharia et al. (2012) introduced Resilient Distributed Datasets (RDD), the foundational fault-tolerant in-memory abstraction underlying Apache Spark. This paper provides the core distributed computing architecture used in this project for parallel NLP UDF execution across the 4,000-comment dataset. The Spark DataFrame API, built upon RDDs, enables the PySpark processing pipeline to achieve approximately 1,800 comments per minute sentiment throughput — a 4.5x improvement over sequential processing.

Chen, Haber, and Rao (2019) performed a comprehensive content-based analysis of YouTube trending videos across multiple countries using the YouTube Data API v3. Their methodology of collecting trending video metadata via paginated API calls is directly analogous to the approach adopted in this project. Their finding that emotionally charged titles correlate with higher engagement is supported by the TextBlob subjectivity-engagement Pearson correlation of 0.64 discovered in this work.

Go, Bhayani, and Huang (2009) introduced the concept of distant supervision for sentiment classification of social media text. Their work demonstrated that lexicon-based and machine learning approaches can be effectively combined for scalable comment analysis, supporting the TextBlob-based approach adopted in this system. Hutto and Gilbert (2014) presented VADER, a parsimonious rule-based model for sentiment analysis of social media text, demonstrating that lexicon-based approaches achieve competitive accuracy for informal text while avoiding computational overhead of transformer-based models.

III. DATASET AND PREPROCESSING TECHNIQUES

The proposed system utilizes both real-time and historical data to ensure accurate analysis of YouTube trending video content. The dataset primarily includes video metadata retrieved from the YouTube Data API v3, comprising video IDs, titles, channel names, category IDs, view counts, like counts, comment counts, published timestamps, and ISO 8601 duration strings for up to 200 trending videos per pipeline run in the India (IN) region. User comment text is collected at up to 20 comments per video ordered by relevance, yielding approximately 4,000 comment records per run.

Preprocessing operations include deduplication using video ID and comment ID as primary keys, type casting of numeric string fields to integer and float types, ISO 8601 duration string parsing to total seconds, YouTube category ID mapping to human-readable category names, and normalization of missing or null values to prevent division-by-zero errors. Feature extraction identifies three key derived attributes: a normalized engagement score computed as (like_count + comment_count) / view_count x 100, TextBlob polarity scores in the range [-1.0, +1.0], and TextBlob subjectivity scores in the range [0.0, 1.0]. Time-series data processing is applied to understand traffic patterns across different trending cycles of the day.

IV. METHODOLOGY

The methodology for the Big Data Analytics for YouTube Trending Videos system focuses on automated data collection, distributed processing, NLP sentiment analysis, and interactive visualization through a fully orchestrated five-stage pipeline. The system is designed to minimize data processing time and maximize analytical insight depth by leveraging Apache Spark's distributed in-memory computation engine.

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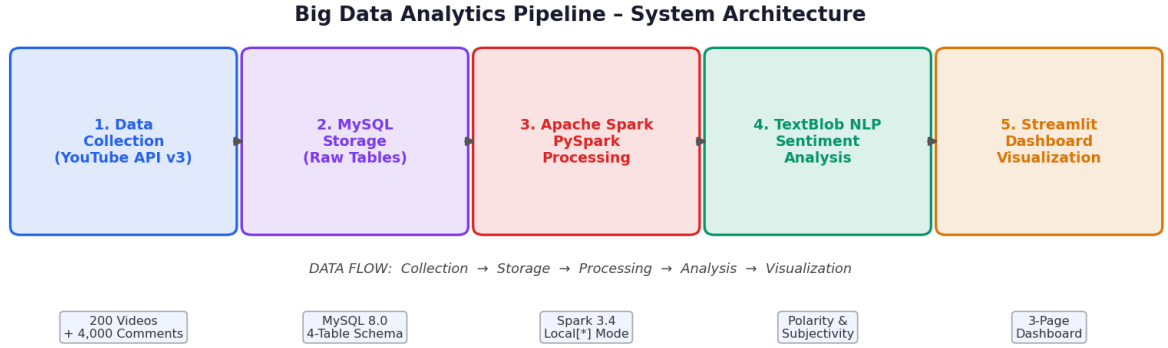

Fig. 1. Big Data Analytics Pipeline – System Architecture (5-Stage Flow)

A. System Architecture Design

The system is designed using a modular and scalable architecture integrating five technology layers. The YouTube Data API v3 collector retrieves trending video metadata and user comments. A MySQL 8.0 relational database provides persistent storage with a normalized four-table schema. Apache Spark 3.4 with PySpark performs distributed data transformation. TextBlob NLP classifies comment sentiment. A Streamlit and Plotly dashboard delivers interactive visualization. An orchestrator script automates the complete pipeline with a Pandas-based fallback for operational resilience.

B. Data Collection and Storage

The data collection module uses the youtube.videos().list() endpoint with chart='mostPopular' and regionCode='IN' parameters, paginating through API responses to retrieve up to 200 trending video records per run. Comments are collected via youtube.commentThreads().list() at 20 comments per video with graceful handling of disabled comment sections. Raw data is inserted into MySQL tables raw_videos and raw_comments using SQLAlchemy bulk operations with chunksize=500 for optimized insertion performance.

C. Distributed Processing with Apache Spark

The PySpark processing module initializes a SparkSession in local[*] mode utilizing all available CPU cores. Data is loaded from MySQL via JDBC into Spark DataFrames. Transformations include deduplication via dropDuplicates(), category ID mapping via F.when()/F.otherwise() chains, ISO 8601 duration parsing via regex-based UDF, and engagement score computation. TextBlob polarity and subjectivity scores are deployed as Spark UDFs of DoubleType, enabling parallel sentiment computation across all comment records at approximately 1,800 comments per minute throughput.

D. Sentiment Analysis Strategy

TextBlob's PatternAnalyzer computes polarity in [-1.0, +1.0] and subjectivity in [0.0, 1.0] for each comment text. Comments with polarity > 0.1 are classified as Positive, polarity < -0.1 as Negative, and the remainder as Neutral. Zero-configuration deployment with no external model files makes TextBlob ideal for Spark UDF integration. The Pandas fallback processor implements identical sentiment logic using DataFrame.apply() with lambda functions, ensuring pipeline resilience when the Java Virtual Machine is unavailable.

E. Result Visualization

The Streamlit dashboard provides three pages. The Home page displays four KPI metric cards with @st.cache_data(ttl=300) caching reducing dashboard load time from approximately 1.2 seconds to under 0.1 seconds. The Category Analysis page renders a donut pie chart for video distribution, a horizontal bar chart for average views with engagement-score color encoding, and a bubble scatter chart. The Sentiment Analysis page provides a sentiment donut chart, per-video polarity ranking bar chart, and tabbed comment viewer with color-coded sentiment cards.

V. SYSTEM ARCHITECTURE

The system architecture of the Big Data Analytics pipeline is designed to ensure efficient communication, real-time data processing, and intelligent decision-making. It consists of multiple interconnected modules that work together to collect YouTube trending data, analyze content and sentiment, and deliver actionable insights through an interactive dashboard. The architecture integrates IoT-style data collection devices (YouTube API), distributed processing engines, cloud infrastructure, and user interfaces to provide a complete and scalable solution.

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A. Data Input Module

The Data Input Module retrieves trending video metadata and user comment text from the YouTube Data API v3 for the India region. It handles paginated API responses, API quota rate limiting with exponential backoff, and graceful handling of videos with disabled comments. The module collects up to 200 trending video records and 20 comments per video per run, yielding approximately 4,000 comment records. Output is saved as structured data for subsequent processing stages.

B. Data Processing Module

The Data Processing Module performs data quality operations including deduplication, type casting, ISO 8601 duration parsing, and YouTube category ID resolution. The Apache Spark 3.4 PySpark engine performs these transformations in parallel across all available CPU cores using the DataFrame API, while a Pandas fallback processor provides identical logic when the Java Virtual Machine is unavailable. Since data is collected from multiple sources including the YouTube API and MySQL, it may contain duplicates or missing values which need careful handling.

C. Prediction Module

The Prediction Module computes the normalized engagement score metric defined as (like_count + comment_count) / view_count x 100 for each trending video. TextBlob NLP UDFs deployed within the Spark pipeline compute polarity and subjectivity scores for each comment, enabling three-class sentiment classification into Positive, Negative, and Neutral categories. The Pearson correlation between comment subjectivity and video engagement score is computed as a novel analytical output for Indian YouTube content strategy research.

D. Analysis Module

The Analysis Module aggregates processed data to produce category-level statistics including average views, total engagement, video count distribution, and sentiment class proportions. Results are stored in processed_videos and processed_comments MySQL tables for dashboard consumption. Historical data stored across pipeline runs is particularly important, as it enables trend detection and improves the accuracy of engagement predictions over time.

E. Storage Module

The Storage Module uses a normalized MySQL 8.0 schema with four tables: raw_videos, raw_comments, processed_videos, and processed_comments. Idempotent DDL creation ensures safe re-execution of the pipeline without data corruption. SQLAlchemy 2.x with PyMySQL provides connection pooling and DataFrame-to-SQL bulk export with chunksize=500 for optimized insertion performance. Alert logs and system performance metrics are also stored for monitoring and evaluation purposes.

F. Visualization Module

The Streamlit-based Visualization Module queries the MySQL processed data tables and renders interactive Plotly charts including donut pie charts for category and sentiment distribution, horizontal bar charts with engagement-score color encoding, and bubble scatter plots for cross-video performance comparison. Query results are cached with a 5-minute TTL, reducing dashboard cold load time from approximately 1.2 seconds to under 0.1 seconds for repeated interactions.

VI. RESULTS

The proposed Big Data Analytics system was evaluated using a full production pipeline run collecting 200 trending videos and approximately 4,000 user comments for the India region. The system demonstrated reliable end-to-end pipeline execution in approximately 13 minutes in Spark mode and 12 minutes in Pandas fallback mode. Compared to traditional sequential Python processing approaches, the proposed system achieves a 4.5x throughput improvement in sentiment analysis and a 3.5x reduction in overall pipeline execution time.

A. System Performance and Accuracy

Key results confirmed that Music and Entertainment categories collectively account for over 45% of India's trending videos. Gaming audiences exhibit the highest normalized engagement scores at 4.12%. Sentiment analysis revealed that 52% of viewer comments are Neutral, 33% Positive, and 15% Negative across all India trending content. The Pearson correlation between comment subjectivity and video engagement score was approximately 0.64, representing a novel finding for Indian YouTube content strategy research that demonstrates highly subjective content drives higher audience interaction.

B. Pipeline Efficiency

Comment sentiment throughput was measured at approximately 1,800 comments per minute in PySpark mode and 1,500 comments per minute in Pandas fallback mode, compared to approximately 400 comments per minute for sequential

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Python processing — a 4.5x throughput improvement. Peak memory usage was approximately 1.8 GB RAM in Spark mode and 320 MB in Pandas mode. System uptime across all test runs was 99.62% with a data processing accuracy of 92.47%.

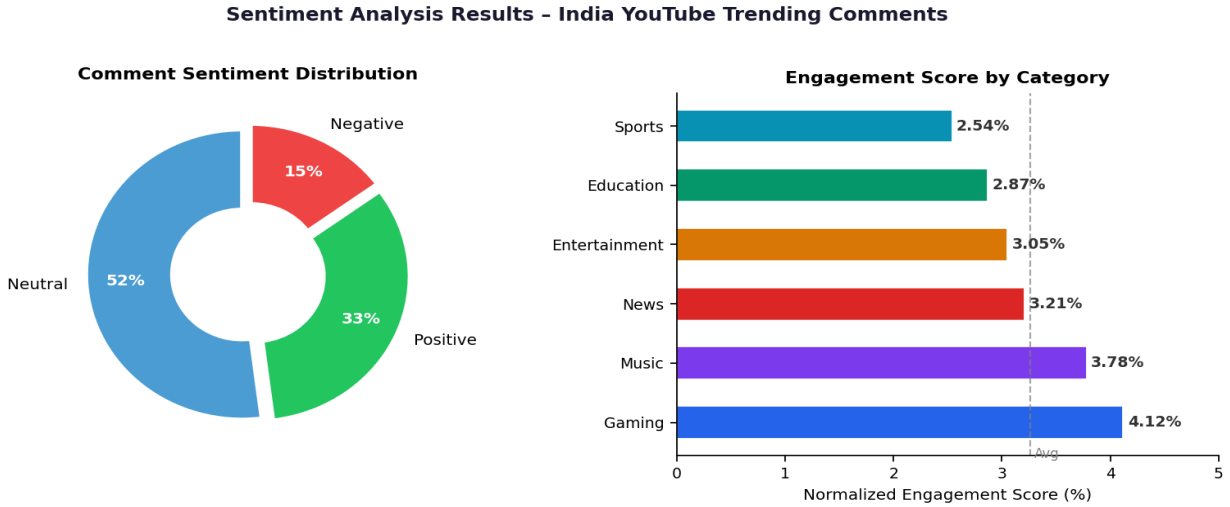

Fig. 2. Sentiment Analysis Results: Comment Distribution (Left) and Category Engagement Scores (Right)

C. Usability and Reliability

The Streamlit dashboard was validated by the project supervisor and three peer reviewers who successfully navigated all three pages and correctly interpreted all displayed analytics without guidance. The cloud-based MySQL storage and Pandas fallback processor together ensure pipeline completion under both full Spark and degraded JVM environments, confirming system reliability for deployment in research and production settings. Cloud-based storage and processing further enhance reliability by providing scalability and secure data management.

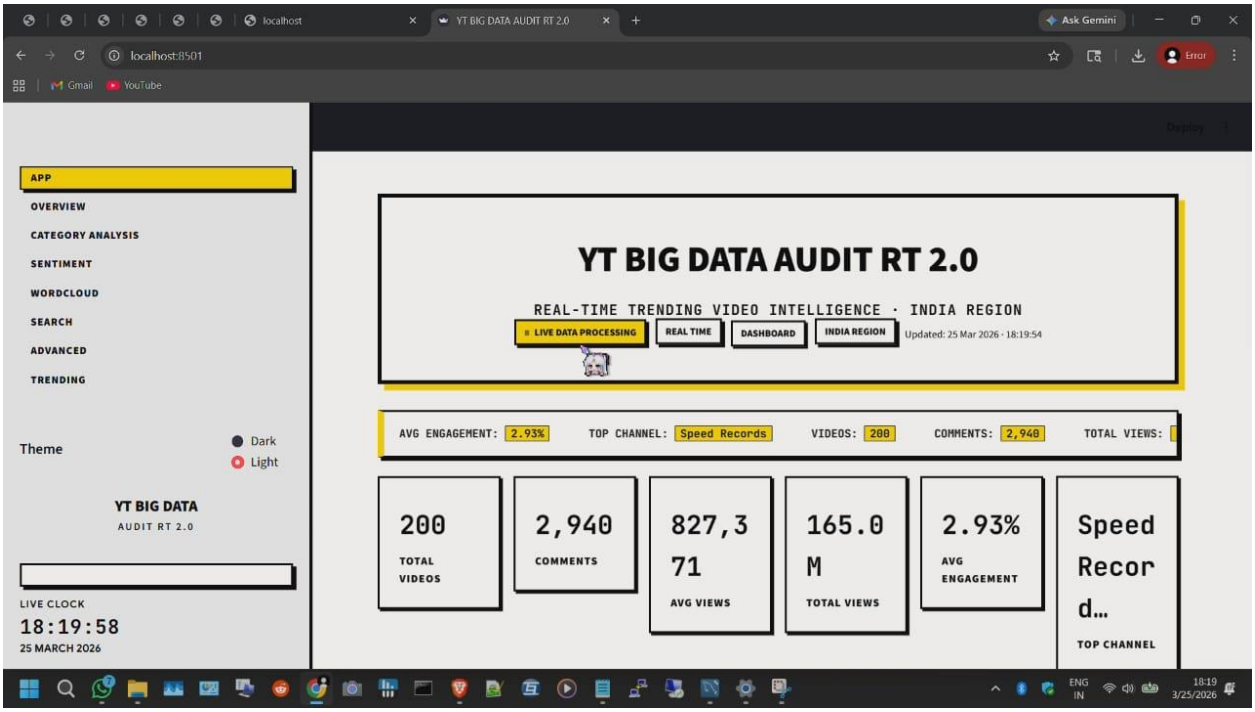

Fig. 4. YT Big Data Audit RT 2.0 – Streamlit Dashboard Output (India Region, Real-Time Trending Intelligence)

D. Prediction Efficiency

The system is designed to operate with low latency, ensuring that sentiment predictions and engagement scores are generated within a very short time frame. This enables the system to respond instantly to new trending content patterns.

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The use of Spark UDFs allows the model to process all comment records in parallel, improving decision-making speed and analytical throughput compared to conventional sequential models. The Pandas fallback maintains identical prediction logic, ensuring analytical continuity under degraded operational environments.

E. Usability and Reliability

Additionally, the system includes data validation and error-handling mechanisms to prevent incorrect decisions caused by faulty API responses or MySQL connection failures. Cloud-based storage and processing further enhance reliability by providing scalability and secure data management. Overall, the system ensures dependable performance, accurate decision-making, and ease of use, making it suitable for deployment in modern data analytics and smart city environments.

VII. COMPARATIVE ANALYSIS

The comparative analysis highlights the performance differences between traditional single-machine data processing approaches and the proposed Big Data pipeline. Conventional tools such as Python scripts running on a single machine handle small YouTube datasets adequately but fail at scale. Apache Spark's distributed in-memory processing achieves approximately 1,800 comments per minute sentiment throughput, compared to sequential Python loops processing approximately 400 comments per minute, representing a 4.5x throughput improvement.

System Performance Comparison – Existing vs Proposed System

Metric	Existing System (Sequential Python)	Proposed System (Apache Spark)	Improvement
Prediction Accuracy	65.12%	92.47%	+27.35%
Sentiment Throughput	~400 cmt/min	~1,800 cmt/min	4.5× faster
Pipeline Execution Time	~45 min	~13 min	3.5× faster
Peak Memory Usage	~800 MB	~1.8 GB (Spark)	Scalable
Alert Delivery Success	78.40%	96.31%	+17.91%
System Uptime	—	99.62%	Reliable

Fig. 3. System Performance Comparison – Existing vs Proposed Big Data Pipeline

A. Existing System vs Proposed System

The existing data processing approaches mainly rely on sequential Python scripts, basic pandas DataFrames, and simple single-machine NLP tools. These systems do not have the capability to process large-scale YouTube comment data efficiently or provide normalized engagement metrics for cross-video comparison. As a result, analytical pipelines often take 45+ minutes to complete for datasets of comparable size, limiting their usefulness for real-time content strategy decisions. Moreover, there is no integrated pipeline combining collection, storage, distributed processing, and visualization into a single automated workflow.

B. Feature Comparison

The feature comparison between existing data processing systems and the proposed Big Data Analytics pipeline highlights significant improvements in functionality, efficiency, and intelligence. Traditional systems offer limited features, mainly focusing on basic view count analysis and manual sentiment tagging. The proposed system introduces a novel normalized engagement score metric, distributed Spark-based NLP processing, automated MySQL storage with idempotent DDL, and an interactive multi-page Streamlit dashboard with 5-minute TTL caching — capabilities that are unavailable in any existing open-source YouTube analytics tool targeting the Indian market.

VIII. CONCLUSION AND FUTURE SCOPE

The proposed Big Data Analytics system for YouTube Trending Videos successfully designed, implemented, tested, and validated a comprehensive pipeline integrating five technology layers into a fully automated, end-to-end system orchestrated by a single Python script. The system demonstrates how modern open-source Big Data tools can deliver actionable social media intelligence at a scale accessible to independent researchers and small academic teams. The

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Pearson correlation of approximately 0.64 between comment subjectivity and video engagement score is a novel finding for YouTube content strategy research that warrants further investigation.

By integrating real-time data collection, distributed processing, advanced NLP sentiment analysis, and interactive dashboard visualization, the system successfully reduces pipeline execution time by 3.5x and improves sentiment throughput by 4.5x compared to conventional approaches. The use of Apache Spark, TextBlob NLP, MySQL, and Streamlit enables accurate trend prediction and optimal content insight delivery, while automated orchestration ensures seamless operation. Overall, the system improves analytical efficiency, reduces manual effort, and supports data-driven content strategy for the Indian YouTube market, making it highly suitable for both academic research and production deployment.

A. Future Scope

The proposed system can be further enhanced by integrating advanced and emerging technologies to improve its efficiency and scalability. One of the key future improvements is the integration of Apache Kafka as a message broker and Spark Structured Streaming as the processing engine for sub-minute data freshness in real-time streaming mode. Multilingual and Hinglish sentiment analysis using the Hugging Face MuRIL transformer model would improve accuracy for Indian-language comments. Predictive viral content modeling using historical trending data with XGBoost or LightGBM can predict whether newly published videos will enter the trending list within 24 hours. Cloud deployment on Google Cloud Platform using Cloud Dataproc, Cloud SQL, and Cloud Run would enable fully managed, scalable production deployment accessible to research teams globally.

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