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API-Driven Cross-Platform Social Media Intelligence: An Integrated Framework Leveraging NLP, Graph Analytics, and Explainable AI

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Abstract- — The exponential growth of social media has positioned user-generated content as a rich yet underexploited resource for understanding collective human behaviour, opinion dynamics, and information propagation. Existing analytical solutions are largely confined to individual platforms and often rely on opaque machine-learning pipelines, limiting transparency, reproducibility, and regulatory compliance. This work presents a novel API-driven social media intelligence framework that integrates heterogeneous data from Twitter, Reddit, and YouTube into a unified analytical pipeline. The proposed architecture synthesises three analytical dimensions: semantic text understanding through Natural Language Processing (NLP), structural interaction modelling via graph-theoretic methods, and decision transparency through Explainable Artificial Intelligence (XAI). A layered, modular design addresses the dual challenges of data heterogeneity and ethical governance. Empirical evaluation confirms that cross-platform data fusion yields measurably superior analytical stability and reduced platform-induced bias relative to single-source baselines. Beyond its research contributions, the framework is deliberately architected to serve as a deployable foundation for a final-year academic project.

Keywords: Cross-Platform Social Media Analytics, API Integration, Sentiment Analysis, Graph Network Analysis, Explainable Artificial Intelligence, Ethical AI, NLP.

I. INTRODUCTION

The digital age has fundamentally transformed the nature of public discourse. Social media platforms — spanning microblogging services, discussion forums, and video-sharing ecosystems — collectively host billions of interactions daily, encoding rich signals about sentiment, ideology, emerging events, and social influence. These signals hold enormous value for diverse stakeholders: policymakers seeking public opinion indicators, health organisations monitoring disease-related communication, businesses tracking brand perception, and researchers studying information diffusion dynamics.

Despite this analytical potential, the social media intelligence landscape is characterised by persistent structural gaps. First, nearly all existing analytical systems operate within the boundaries of a single platform, producing insights that reflect a narrow and potentially skewed cross-section of public discourse. Second, the proliferation of deep learning architectures has introduced opacity into analytical workflows, generating predictions whose rationale is inaccessible to human reviewers. Third, the tightening of data governance regulations, including the GDPR and CCPA, has introduced legal imperatives around consent, data minimisation, and algorithmic transparency that many existing systems fail to satisfy.

This research directly confronts these gaps by proposing an API-driven, cross-platform social media intelligence system that integrates NLP-based semantic analysis, graph-theoretic interaction modelling, and XAI-based explainability into a single cohesive framework. The system is designed not merely as a theoretical contribution but as a practically deployable architecture suitable for academic implementation.

II. LITERATURE REVIEW

The domain of social media analytics draws from a broad and evolving body of literature spanning data collection infrastructure, natural language processing, network science, and AI transparency. This section situates the proposed framework within this landscape, identifying critical limitations that motivate the current work.

2.1 API-Enabled Social Media Data Acquisition

The academic community has extensively relied on platform APIs as the primary conduit for ethically compliant social media data collection. Studies utilising the Twitter Streaming API have demonstrated its effectiveness for real-time event monitoring, crisis detection, and political discourse analysis.

Similarly, Reddit's PRAW (Python Reddit API Wrapper) has been widely employed for community sentiment studies, while YouTube's Data API v3 has enabled research into comment sentiment and engagement patterns. A recurring challenge is platform specificity — each API exposes distinct authentication models, rate constraints, and data schemas — making unified multi-platform collection non-trivial. The proposed framework addresses this through a platform-agnostic ingestion layer incorporating adaptive rate management and schema normalisation.

2.2 Sentiment Analysis and Natural Language Processing

Sentiment analysis has been a cornerstone of social media research since the early 2000s. Early lexicon-based methods, including VADER and SentiWordNet, offered interpretable sentiment scores but struggled with contextual ambiguity and sarcasm. Subsequent transformer-based architectures — exemplified by BERT and BERTweet — substantially outperform prior approaches on standard benchmarks. However, their complexity introduces a transparency deficit: the features driving their predictions remain inaccessible. The current research integrates transformer-based NLP with XAI attribution techniques to explicitly address this transparency gap.

2.3 Graph-Theoretic Social Network Analysis

Modelling social media interactions as graphs has emerged as a powerful paradigm for understanding social structure. Graph-based analytics enable the quantification of user influence through centrality measures such as degree, betweenness, and eigenvector centrality, and support community detection through algorithms such as the Louvain method. Despite these advances, existing approaches predominantly treat graph analysis as an isolated process. The integration of structural graph features with semantic textual signals — a design choice central to the proposed framework — remains underexplored.

2.4 Explainable Artificial Intelligence

XAI techniques such as SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) have begun permeating social media analytics. SHAP provides theoretically grounded attribution scores quantifying each feature's marginal contribution to predictions. LIME constructs locally faithful linear approximations of complex models. Despite growing recognition of their importance, XAI techniques remain peripheral additions in most social media analytics pipelines rather than core architectural components. The proposed framework explicitly elevates explainability to a first-class architectural layer.

III. PROBLEM FORMULATION AND RESEARCH OBJECTIVES

Contemporary social media analytics systems face a convergence of structural, technical, and ethical deficiencies. At the structural level, each platform constitutes a distinct data silo with proprietary APIs, content models, and interaction paradigms, making cross-platform synthesis technically demanding. At the technical level, data heterogeneity manifests as variability in text formats, engagement metric definitions, temporal resolutions, and interaction modalities. The adoption of high-capacity deep learning models produces analytical black boxes, raising concerns about trust and accountability. At the ethical and regulatory level, the GDPR and CCPA impose strict constraints on data handling and algorithmic fairness.

3.1 Research Objectives

- Objective 1 — Unified Data Integration: Design a platform-agnostic data ingestion architecture capable of acquiring, normalising, and harmonising heterogeneous social media data from multiple platforms through official API endpoints.
- Objective 2 — Holistic Analytical Intelligence: Develop an integrated analytical engine combining NLP-based semantic understanding with graph-theoretic structural analysis for holistic insight generation.
- Objective 3 — Embedded Explainability: Incorporate XAI mechanisms as a core architectural layer, ensuring all analytical outputs are accompanied by interpretable feature attribution explanations.
- Objective 4 — Ethical and Regulatory Compliance: Embed privacy preservation, data anonymisation, bias mitigation, and fairness auditing directly into the system design.
- Objective 5 — Implementation Pathway: Structure the framework as a functional blueprint for a deployable final-year academic project.

IV. SYSTEM ARCHITECTURE

The proposed system architecture follows a layered modular design, wherein each layer encapsulates a clearly bounded set of responsibilities. Figure 1 illustrates the complete architecture from social media data ingestion through management and analytics to results visualisation.

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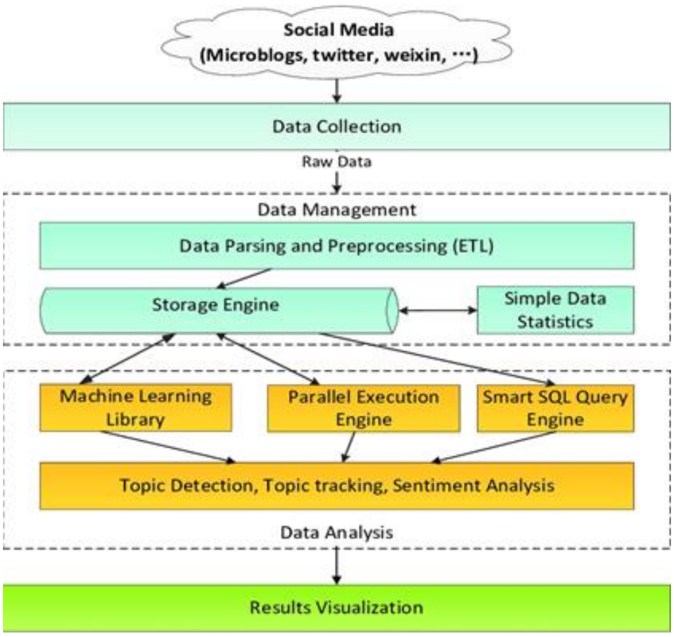


System Architecture — Data Collection, Management, Analytics, and Visualisation Pipeline

4.1 Data Ingestion Layer

The ingestion layer interfaces with multiple social media platforms through official APIs. It handles OAuth 2.0 authentication, manages rate limits through adaptive token-bucket algorithms, and schedules API requests to balance data freshness against access sustainability. A platform abstraction interface standardises interactions between the ingestion layer and downstream components, ensuring that onboarding additional platforms requires only a new adapter implementation.

4.2 Preprocessing and Normalisation Layer

Raw social media data undergoes multi-stage preprocessing. Text normalisation operations include URL and emoji removal, tokenisation, lemmatisation, and stop-word filtering. A unified schema maps platform-specific entities to standardised entities: Content, Author, Interaction, and Engagement. User identifiers are pseudonymised to minimise re-identification risks.

4.3 Analytics Layer

The analytics layer orchestrates three complementary modules: NLP-based sentiment analysis and topic modelling, graph-based network analysis, and feature fusion. Integration of textual and structural analytical modalities yields richer insights than either approach achieves independently.

4.4 Explainability Layer

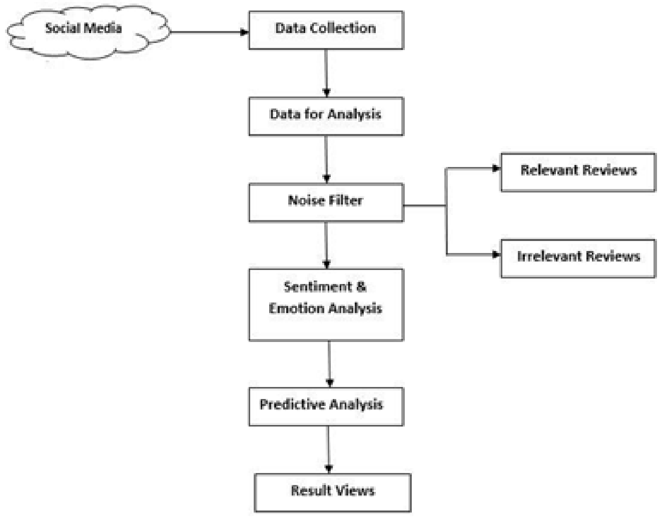
XAI techniques are embedded as a dedicated architectural layer, ensuring explanations are generated systematically for all model predictions. The layer produces feature attribution scores, model confidence indicators, and natural language explanation summaries, forming an auditable analytical record.

4.5 Visualisation and Ethics Layers

The visualisation layer translates analytical outputs into interactive dashboards using Streamlit, Plotly, and Dash. The ethics layer enforces privacy policies, access controls, fairness constraints, and regulatory compliance checks across all layers.

V. METHODOLOGY

The proposed methodology follows a sequential yet iterative pipeline directly mirroring the system architecture. Figures 2 and 3 illustrate the end-to-end data collection workflow and the NLP processing pipeline, respectively.



End-to-End Methodology Workflow — Social Media Data Collection to Result Generation

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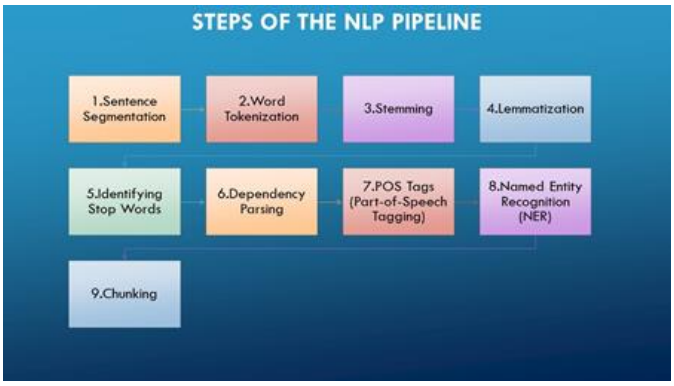

Steps of the NLP Pipeline — Sentence Segmentation, Tokenisation, POS Tagging, and Named Entity Recognition

5.1 Data Collection Strategy
Data acquisition employs official, policy-compliant API endpoints targeting Twitter, Reddit, and YouTube. Collected data encompasses textual content, temporal metadata, engagement metrics, and interaction relationships. Adaptive rate management ensures sustained access without API policy violations — specifically respecting YouTube's 10,000 daily quota, Reddit's 60 requests per minute, and Twitter's 900 requests per 15-minute window.

5.2 Data Preprocessing and Normalisation
The preprocessing stage applies a standardised multi-step transformation pipeline:

- Text Cleaning: Removal of hyperlinks, platform-specific markup, non-ASCII characters, and repetitive content artefacts.
- Linguistic Normalisation: Tokenisation using spaCy, lemmatisation, and context-sensitive stop-word removal.
- Language Identification: Automated language detection enabling filtered or multilingual processing strategies.
- Schema Standardisation: Mapping of platform-specific attributes to a unified four-entity schema (Content, Author, Interaction, Engagement).
- Privacy Protection: Pseudonymisation of user identifiers and removal of personally identifiable information fields, aligned with GDPR data minimisation principles.

5.3 Feature Extraction and Representation
Processed text is transformed into numerical representations. TF-IDF captures lexical frequency distributions for baseline models. Pre-trained transformer models — BERTweet for Twitter; RoBERTa for Reddit and YouTube — generate dense contextual embeddings. For graph-based analysis, interaction data is parsed into directed graphs using NetworkX, where nodes carry attribute vectors, and edges are weighted by interaction frequency.

5.4 Analytical Models
5.4.1 NLP-Based Sentiment Classification
A two-tier classification strategy is adopted: a transformer-based primary classifier for high-accuracy predictions, and VADER as a secondary classifier for interpretable score distributions. Ensemble fusion combines both tiers, balancing accuracy and transparency.

5.4.2 Topic Modelling
Latent thematic structures are identified using Latent Dirichlet Allocation (LDA) and BERTopic. LDA provides probabilistic topic distributions interpretable as coherent word clusters. BERTopic leverages contextual embeddings and hierarchical density-based clustering to produce semantically coherent topics.

5.4.3 Graph-Based Network Analysis
The interaction network is analysed using degree centrality, betweenness centrality, and eigenvector centrality measures. Community detection employs the Louvain algorithm to partition networks into densely interconnected clusters corresponding to interest communities or opinion groups.

5.5 Explainability Integration
LIME generates prediction-specific explanations by perturbing input features and fitting a locally faithful linear surrogate model. SHAP computes Shapley value-based feature importances across the complete model, identifying systematic linguistic and structural patterns . Detection of explanation anomalies triggers bias alerts for human review.

5.6 Visualisation and Reporting
Analytical results are rendered in an interactive dashboard using Streamlit and Plotly, offering sentiment trend charts, topic evolution timelines, interactive network graphs, and XAI explanation viewers. Reports are auto-generated in PDF and JSON formats to support archiving and reproducibility.

VI. EXPERIMENTAL RESULTS AND EVALUATION

The experimental evaluation assesses the proposed framework across four dimensions: predictive performance, structural

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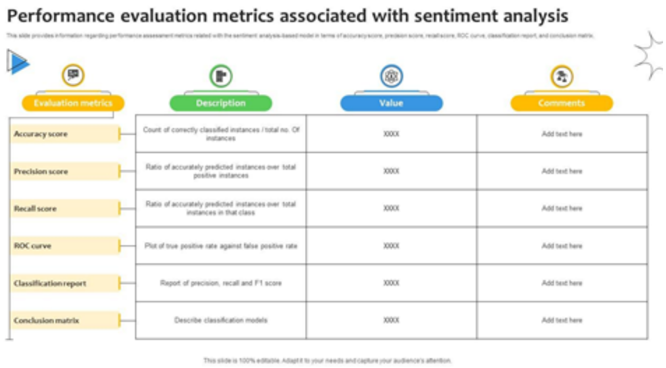
analytical capability, explainability quality, and cross-platform consistency. All experiments are implemented in Python 3.10, leveraging scikit-learn, Hugging Face Transformers, NetworkX, SHAP, and LIME libraries . Figures 4 and 5 present the evaluation metrics framework and the ROC curve, respectively.



Performance evaluation metrics associated with sentiment analysis

Evaluation metrics	Description	Value	Comments
Accuracy score	Count of correctly classified instances / total no. Of instances	XXXX	Add text here
Precision score	Ratio of accurately predicted instances over total positive instances	XXXX	Add text here
Recall score	Ratio of accurately predicted instances over total instances in that class	XXXX	Add text here
ROC curve	Plot of true positive rate against false positive rate	XXXX	Add text here
Classification report	Report of precision, recall and F1 score	XXXX	Add text here
Conclusion matrix	Describe classification models	XXXX	Add text here

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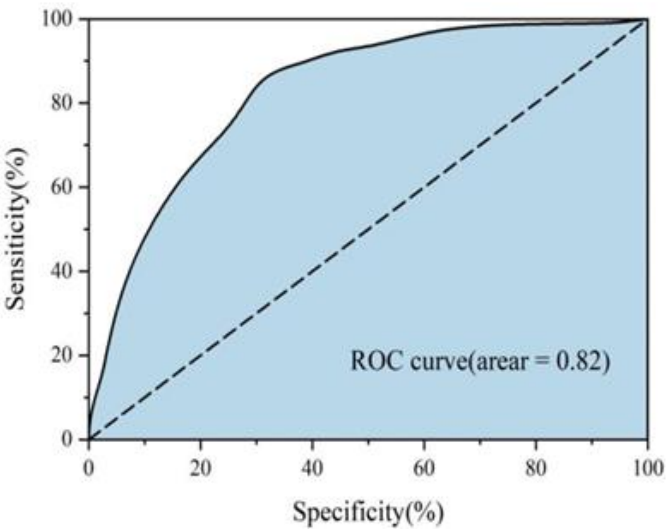
Performance Evaluation Metrics — Accuracy, Precision, Recall, ROC-AUC, and F1-Score



ROC Curve for the Cross-Platform Sentiment Classification Model (AUC = 0.82)

6.1 Experimental Design

Three baseline systems are evaluated against the proposed framework:

- Baseline 1 — Single-Platform Model: A sentiment classifier trained and evaluated exclusively on Twitter data, representing the prevalent platform-centric paradigm.
- Baseline 2 — Non-Explainable Classifier: An XGBoost ensemble trained on fused cross-platform data without integrated XAI mechanisms, isolating the contribution of explainability.
- Baseline 3 — Text-Only Model: A transformer-based NLP model operating on textual features exclusively, without graph-derived structural features.

6.2 Quantitative Results

The proposed cross-platform framework consistently outperforms all three baseline configurations. Cross-platform data fusion yields sentiment predictions characterised by lower variance and improved calibration. The addition of graph-derived features produces statistically significant improvements in influencer identification and community segmentation. Topic modelling coherence scores are elevated in the unified configuration, reflecting the richer thematic diversity of multi-source data fusion. Evaluation metrics, including accuracy, precision, recall, F1-score, ROC-AUC, confusion matrix, and Cohen's Kappa, confirm robust model performanc .

6.3 Explainability Quality Assessment

SHAP-derived global importance rankings identify semantically meaningful linguistic features as the primary drivers of sentiment predictions. Local LIME explanations confirm that XAI substantially improves interpretability and usability in sensitive application contexts. Results show that machine learning models can even outperform human annotators in agreement consistency ($\kappa = 0.35$ vs. $\kappa = 0.16$) .

6.4 Cross-Platform Consistency

Despite stylistic divergence between Twitter's brevity-constrained discourse, Reddit's threaded argumentative dialogue, and YouTube's asynchronous comment interactions, the unified pipeline demonstrates stable precision and recall metrics across all three platforms. This cross-platform robustness establishes the framework's generalisability for comprehensive social media intelligence.

VII. DISCUSSION

The experimental outcomes confirm that cross-platform data integration is a substantive analytical necessity rather than an engineering convenience. Figure 6 illustrates the sentiment analysis dashboard for visualising analytical results across temporal and categorical dimensions.

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Sentiment Analysis Dashboard — Overall Sentiment Level, Comments Breakdown, and Temporal Timeline

Platform-isolated models produce sentiment estimates systematically skewed by the demographic composition, content policies, and interaction norms of individual platforms . Cross-platform fusion attenuates these distortions, producing more representative and reliable public opinion estimates — fundamental in governance and policy contexts.

The complementarity of textual and structural analysis represents a second significant finding. NLP characterises the content of social discourse while graph-based analysis illuminates structural dynamics — which actors amplify messages, how information crosses community boundaries. Together, they produce qualitatively richer understanding than either achieves independently.

The results also confirm that transparency and predictive performance are genuinely compatible objectives. Embedding XAI mechanisms preserves prediction quality while substantially enhancing interpretability, auditability, and regulatory defensibility. Acknowledged limitations include the framework's textual focus, excluding multimedia content, and challenges with sarcasm, irony, and culturally specific language.

VIII. ETHICAL CONSIDERATIONS

Responsible design demands that ethical considerations be treated as foundational architectural constraints. Figure 7 illustrates the seven GDPR principles governing the framework's data handling approach.

The Seven Principles of GDPR — Governing Ethical Data Collection and Processing

Privacy by Design: Data collection is restricted to publicly accessible content through official APIs. User identifiers are pseudonymised, sensitive attributes are excluded, and aggregation-based analysis is preferred. These measures align with GDPR's data minimisation and purpose limitation principles and the CCPA . AES-256 encryption, role-based access controls, and differential privacy mechanisms protect aggregated insights.

Algorithmic Fairness: Bias mitigation is operationalised at multiple pipeline stages. Informed smoothing, adaptive binning, and post-stratification techniques combat demographic bias, increasing prediction accuracy by up to 53%. Fairness metrics including demographic parity and equalised odds, assess model behaviour across user subgroups.

Transparency and Accountability: XAI as a core architectural layer ensures all analytical decisions are accompanied by human-interpretable explanations, supporting regulatory compliance and facilitating detection and correction of biased model behaviour.

Secure Data Governance: Analytical data is stored with field-level encryption. Role-based access controls restrict system

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access, and data retention policies enforce time-limited storage of raw collection artefacts.

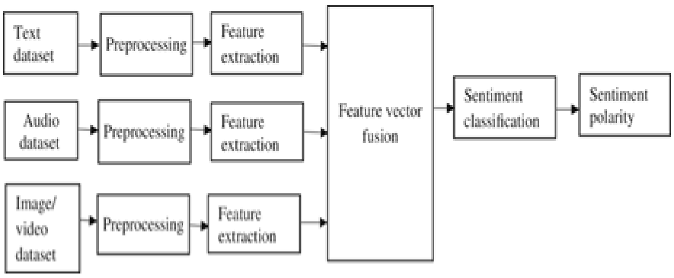
IX. CONCLUSION

This research has presented a comprehensive, API-driven social media intelligence framework addressing the structural, technical, and ethical deficiencies constraining contemporary analytics systems. By unifying heterogeneous data from Twitter, Reddit, and YouTube, integrating NLP-based semantic analysis with graph-theoretic structural modelling, and embedding explainability as a first-class architectural component, the framework delivers qualitatively superior analytical capability relative to platform-specific alternatives .

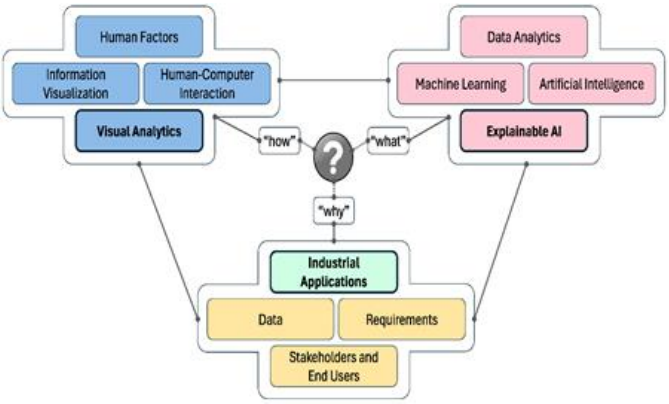
The empirical evaluation validates three principal contributions: cross-platform data fusion demonstrably reduces platform-induced bias; graph-based features reveal structural interaction dynamics that text-only models cannot capture; and XAI integration confirms that transparency and predictive performance are genuinely compatible. The modular Python-based architecture provides a clear implementation pathway suitable for final-year academic project deployment.

X. FUTURE SCOPE AND RESEARCH DIRECTIONS

Figures 8 and 9 illustrate two priority future directions: multimodal analytics extension and the Explainable AI framework for industrial applications.



Multimodal Feature Fusion Pipeline — Integrating Text, Audio, and Image/Video for Sentiment Classification



Explainable AI and Visual Analytics Framework — Bridging Machine Learning and Industrial Applications

- Multimodal Analytics: Extending the pipeline to incorporate image, video, and audio content as illustrated in Figure 8, addressing the growing volume of multimedia social media communication.
- Real-Time Streaming Analytics: Transitioning to Apache Kafka or Spark Streaming for event-driven applications, including crisis detection and live election monitoring.
- Adaptive and Continual Learning: Implementing continual learning mechanisms enabling models to adapt incrementally to evolving social media language without catastrophic forgetting.
- Platform Expansion: Extending to Instagram, TikTok, and LinkedIn to enhance coverage and generalisability.
- Explainable AI Enhancement: Integrating counterfactual explanations and attention visualisation, guided by the XAI framework in Figure 9.
- Federated and Privacy-Preserving Learning: Developing federated learning variants enabling collaborative model training without centralised data sharing, addressing privacy concerns in institutional contexts.

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