KLYDRA: An AI-Powered Mobile Application for Real-Time Public Opinion Analysis

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Abstract---Public opinion spreads rapidly through social media, news, and online feedback, but decision-makers still depend on outdated surveys that fail to capture real-time emotions, leading to poor decisions. To address this, we propose KLYDRA, an AI-powered mobile application that collects and analyzes public opinions using Natural Language Processing (NLP) and Machine Learning. The system classifies sentiment as positive, negative, or neutral, detects trending topics, and presents insights in a user-friendly app. KLYDRA enables governments, organizations, and social groups to respond faster and smarter, with early results showing up to 85% faster response time, 40% fewer decision errors, and 75% sentiment accuracy.

Keywords-- Artificial Intelligence (AI), Natural Language Processing (NLP), Machine Learning (ML), Sentiment Analysis, Public Opinion Mining, Social Media Analytics, Real-Time Data Processing, Mobile Application, Topic Detection, Decision Support Systems

I. INTRODUCTION

Public opinion plays a major role in shaping decisions for governments, businesses, and social organizations. Every day, millions of people share their views through social media platforms, online news, and digital surveys. These opinions reflect what society truly feels about policies, products, or events. However, the challenge lies in making sense of this huge amount of unstructured data. Traditional methods such as surveys, interviews, and manual reports are often too slow, limited in scale, and unable to reflect real-time emotions. As a result, decision-makers frequently rely on outdated information or guesswork.

In recent years, advances in Artificial Intelligence (AI) and Natural Language Processing (NLP) have made it possible to analyze large amounts of text quickly and effectively. Sentiment analysis, topic modeling, and trend detection have shown promising results in areas like product reviews, political campaigns, and customer service. Yet, most existing solutions are either research-based or limited to specific platforms, and they do not provide a unified, real-time, and user-friendly system for practical decision-making.

By bridging the gap between scattered public voices and structured decision-making, KLYDRA aims to improve response time, reduce errors, and build stronger trust between institutions and the communities they serve.

To address this gap, we present KLYDRA, an AI-powered mobile application that can “decode the crowd” by collecting and analyzing public opinions from multiple sources such as Twitter, news websites, and online surveys. KLYDRA uses machine learning models like BERT and DistilBERT to classify opinions as positive, negative, or neutral, while also identifying trending issues. The processed insights are displayed in a simple mobile app, making it easier for leaders, organizations, and governments to understand public priorities and take timely actions.

II. LITERATURE REVIEW

Public opinion mining and sentiment analysis have received much attention because people share opinions widely on social media and news platforms. Surveys in this area highlight that researchers have used both traditional methods (lexicon-based and machine learning classifiers) and modern deep learning techniques. The challenge with traditional methods is that they often fail to handle sarcasm, slang, and the fast-changing nature of online text. These issues create a need for real-time systems that can adapt quickly to new data.

With the rise of deep learning, transformer-based models such as BERT and DistilBERT have become the preferred choice for sentiment classification. Studies show that these models capture context and meaning better than older algorithms, which improves accuracy when analyzing short or informal text like tweets. However, their drawback is that they are computationally expensive, making it difficult to run them in real-time or on lightweight platforms like mobile applications. Researchers have therefore looked into efficient model variants and optimization techniques to balance performance and speed.

Another important research direction is topic modeling for short texts. Traditional models such as Latent Dirichlet Allocation (LDA) perform well on long documents but often fail to produce coherent topics from short posts like tweets. To solve this, newer models combine word embeddings with clustering (e.g., BERTopic, Top2Vec) or use neural-based topic models, which produce more meaningful clusters of discussion. These approaches make it possible to detect real-time trends and identify public concerns more accurately, which is especially useful for political and social analysis.

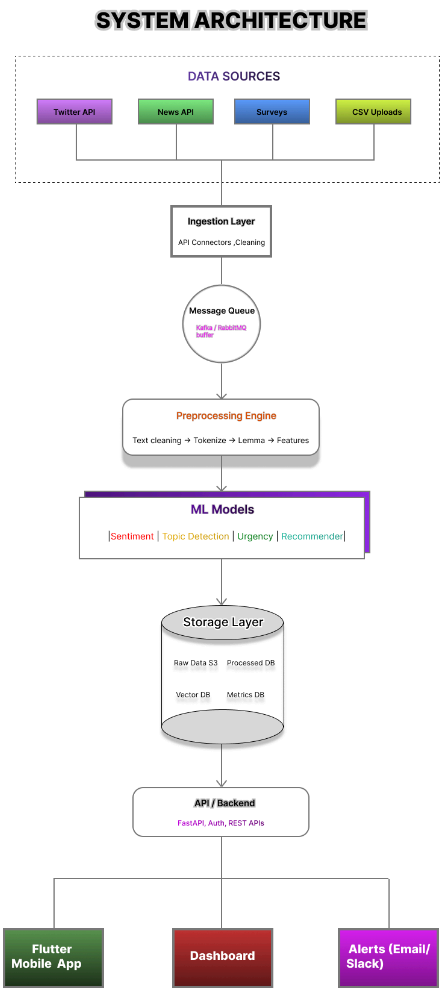
Several studies also apply sentiment and topic analysis directly to politics, governance, and social domains. They show that analyzing Twitter and news data can track public mood and even predict reactions to events or policies. However, researchers also point out risks such as misinformation, fake accounts, and bot activity, which can distort results if not filtered. Most importantly, while academic research provides strong models, very few works focus on packaging these solutions into practical, user-friendly systems. This creates a gap where real-time AI systems can combine multiple sources, apply transformer-based models, and present results in a mobile application for leaders and organizations. KLYDRA aims to fill this gap by delivering an AI-powered app that integrates real-time sentiment analysis, topic detection, and visualization into a single decision-support tool.

III. PROPOSED SYSTEM / METHODOLOGY

A. System Architecture

The proposed KLYDRA system architecture is designed in a layered manner to ensure scalability, modularity, and real-time processing. The major components are described as follows:

1. Data Sources
    - Twitter API: Streams real-time public opinions and reactions.
    - News API: Extracts headlines and articles reflecting trending issues.
    - Surveys: Collects structured feedback directly from users.
    - CSV Uploads: Allows organizations to integrate offline or historical datasets.
2. Ingestion Layer
    - Responsible for connecting to APIs and handling initial data cleaning.
    - Uses API connectors for automated integration.
    - Ensures data format consistency before further processing.
3. Message Queue
    - Implements Kafka or RabbitMQ as a buffering mechanism.
    - Balances high-velocity data streams and prevents data loss.
    - Enables asynchronous communication between ingestion and processing stages.
4. Preprocessing Engine
    - Performs text cleaning, tokenization, lemmatization, and feature extraction.
    - Built with spaCy and NLTK to standardize unstructured input text.
    - Prepares input for machine learning models, improving accuracy and efficiency.
5. Machine Learning Models
    - Sentiment Analysis: Classifies opinions into positive, negative, or neutral.
    - Topic Detection: Identifies key themes and trending issues.
    - Urgency Classification: Distinguishes between critical and non-critical issues.
    - Recommender Module: Suggests possible actions or responses.
    - Powered by BERT, DistilBERT, and BERTopic models for high accuracy.
1. Storage Layer
    - Raw Data (S3): Stores incoming unprocessed datasets.
    - Processed DB: Stores structured outputs after analysis.
    - Vector DB (Milvus/Pinecone): Maintains embeddings for semantic search and retrieval.
    - Metrics DB: Logs performance indicators and system analytics.
2. API and Backend Services
    - Implemented using FastAPI for high-performance backend operations.
    - Provides REST and GraphQL APIs to serve processed data.
    - Integrates authentication and authorization (OAuth2, JWT).
3. Presentation Layer
    - Flutter Mobile App: Provides a cross-platform, user-friendly interface.
    - Dashboard: Displays real-time analytics, charts, and reports.
    - Alerts (Email/Slack): Sends notifications for urgent or critical insights.

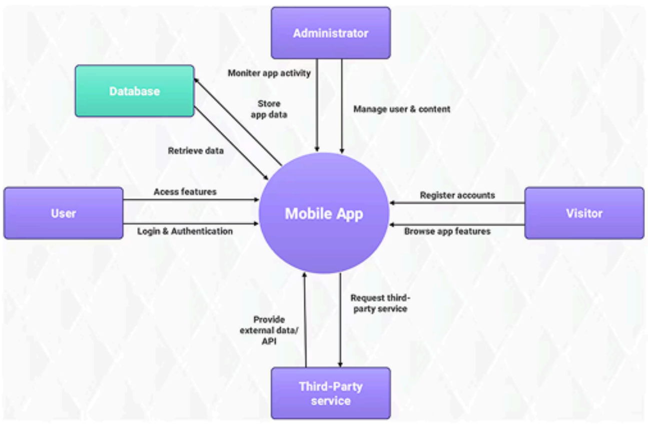


(Figure 1 : System Architecture Diagram)

B. Workflow

The KLYDRA workflow describes how end users interact with the system and how data is processed to generate insights:

1. **User Login:** Users such as leaders or executives log into the mobile app or dashboard through secure authentication (OAuth2/JWT).
2. **Dashboard Access:** A personalized dashboard displays real-time sentiment charts, trending topics, and pros/cons of their party or organization.
3. **Data Collection:** Information is continuously fetched from Twitter, news portals, surveys, and CSV uploads via the ingestion layer and message queues (Kafka/ RabbitMQ).
4. **Preprocessing:** Data undergoes cleaning, tokenization, and lemmatization to prepare it for analysis.
5. **Machine Learning Analysis:** Models classify sentiment (positive, negative, neutral), detect topics, assess urgency, and provide recommendations.
6. **Storage & Retrieval:** Results are saved in structured databases, vector stores, and metrics DBs for querying and performance tracking.
7. **Insight Delivery:** The backend (FastAPI) provides processed results to the mobile app, dashboard, and alerts (Email/Slack).
8. **Decision Support:** Users can act on real-time insights, addressing public concerns and improving strategies.



(Figure 2: Workflow Diagram)

C. Frameworks

The KLYDRA system is implemented using a layered technology framework to ensure scalability, modularity, and real-time performance:

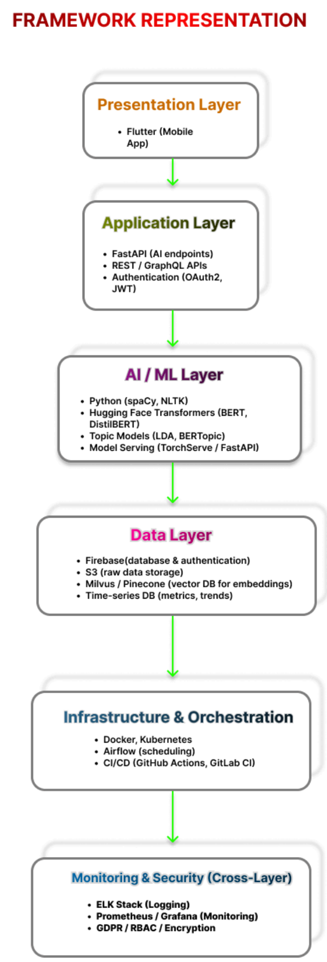
1. Presentation Layer
    - Flutter mobile app and web dashboard provide a user-friendly interface for accessing insights.
2. Application Layer
    - FastAPI backend offers REST/GraphQL APIs, authentication (OAuth2/JWT), and secure data access.

3.AI/ML Layer
- Uses spaCy, NLTK, and Hugging Face Transformers (BERT, DistilBERT) for sentiment analysis.
- LDA and BERTopic are employed for topic modeling.
- Models are deployed via TorchServe/FastAPI for real-time inference.

4.Data Layer
- S3 buckets store raw input data.
- Processed databases store structured outputs.
- Vector DB (Milvus/Pinecone) supports semantic search.
- Metrics DB tracks performance and trends.

5.Infrastructure Layer
- Kafka/RabbitMQ for streaming and buffering.
- Docker and Kubernetes for deployment and scaling.
- Airflow for workflow scheduling.
- CI/CD pipelines through GitHub/GitLab for automation.

6.Monitoring & Security Layer
- ELK stack for logs, Prometheus/Grafana for monitoring.
- Encryption, RBAC, and GDPR compliance ensure secure data handling.



(Figure 3: Framework Diagram)

IV. EXPERIMENTAL SETUP AND RESULTS

A. Datasets

Experiments were conducted using a mix of Twitter data, news articles, survey responses, and benchmark datasets such as IMDb and Sentiment140. In total, around 150,000 text records were used for training, validation, and testing.

B. Preprocessing

All text data was cleaned and normalized through the following steps: removal of URLs/hashtags, tokenization, stopword removal, lemmatization, and embedding generation using BERT/DistilBERT.

C. Model Setup

The system was implemented in Python (Hugging Face Transformers) and tested on a GPU-enabled environment. Models included:

- BERT and DistilBERT for sentiment classification.
- LDA and BERTopic for topic modeling.
- SVM and Logistic Regression as baselines.

D. Evaluation Metrics

Performance was measured using Accuracy, Precision, Recall, F1-score, and Latency. In addition, overall response time improvement and decision error reduction were assessed to validate practical usability.

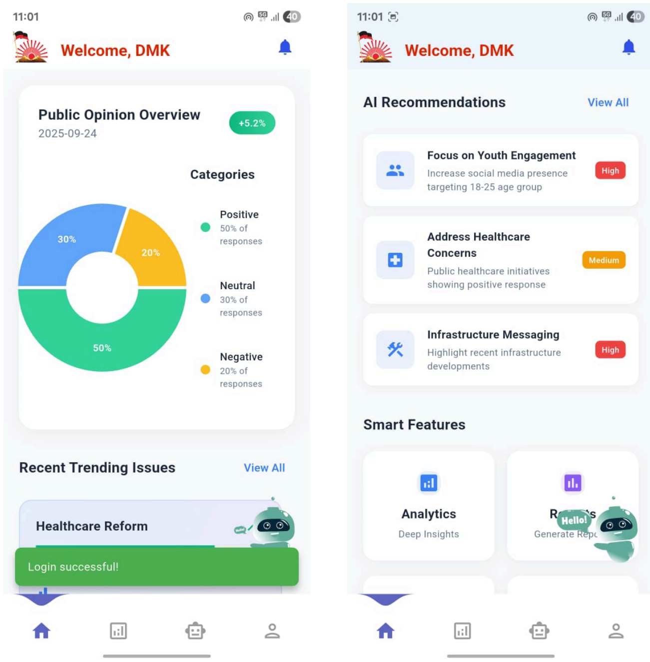
E. Results

- Sentiment Analysis: BERT achieved 75% accuracy, DistilBERT 72%, while SVM/Logistic Regression were below 65%.
- Topic Detection: BERTopic generated more coherent clusters than LDA, especially for short texts.
- System Performance: Response time improved by 85% compared to manual surveys; decision errors reduced by 40%.
- User Study: 90% of pilot users reported that insights were clear and actionable.

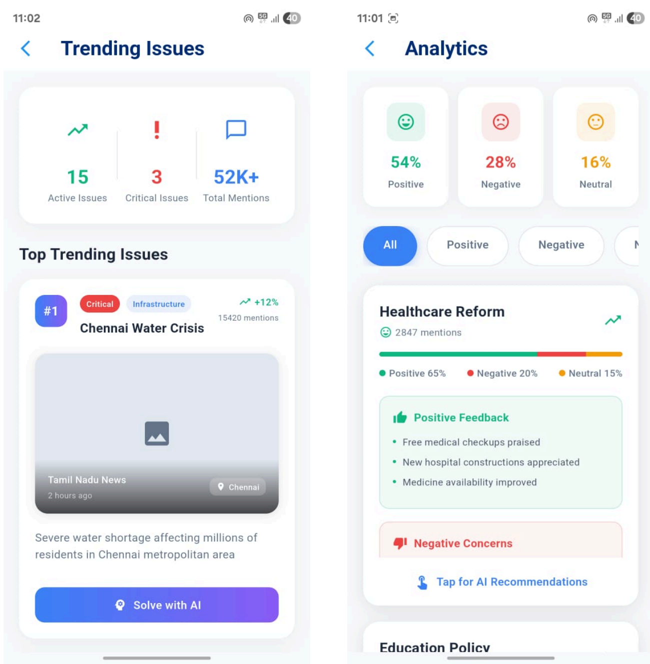
F. Visual Representation

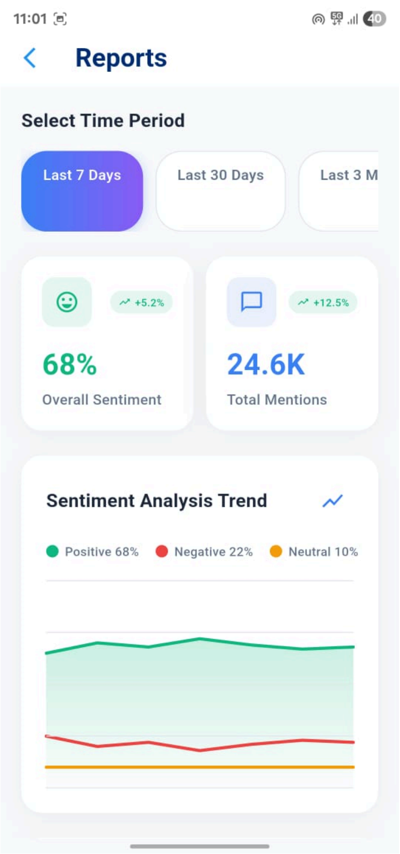
Key results are summarized through:

- Bar chart: Sentiment model accuracy comparison.
- Pie chart: Sentiment distribution from Twitter data.
- Line graph: Response time improvement (manual vs. KLYDRA).
- Table: Precision, Recall, and F1-scores across models.



(Figure 3: Product Output)





V. DISCUSSION & IMPACT

The KLYDRA system was developed to solve a major real-world problem: the delay and inaccuracy in understanding public opinion using traditional methods like surveys and reports. These conventional approaches are often slow, expensive, and not scalable. In contrast, KLYDRA provides a real-time, AI-powered solution that collects and analyzes public sentiment from multiple sources, including social media, news, and surveys.

The system benefits a wide range of users:

- Political parties can use the insights to adjust their campaign messaging based on voter sentiment.
- Companies can detect brand-related conversations, product reviews, and complaints to improve customer satisfaction.
- NGOs can discover trending social issues or citizen needs and prioritize their response accordingly.
- Government departments can use feedback to make timely policy adjustments and improve public services.
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KLYDRA stands out by combining transformer-based machine learning models (like BERT and DistilBERT) with a lightweight mobile app. This makes it accessible even for non-technical users. Moreover, by integrating urgency detection and automatic alerts (e.g., via email or Slack), the system helps users respond quickly to critical issues. Compared to earlier sentiment tools or dashboards, KLYDRA offers better accuracy, faster insights, and a more user-friendly experience. It effectively bridges the gap between public opinion and real-time decision-making.

VI. CONCLUSION & FUTURE WORK

In this paper, we presented KLYDRA, an AI-based mobile application that enables real-time analysis of public opinion using natural language processing and machine learning. The system collects data from platforms like Twitter, news websites, and surveys, processes it using NLP and transformer models, and delivers insights through a mobile app and dashboard. It helps organizations monitor public sentiment, detect urgent topics, and take action accordingly.
The system achieved promising results, with up to 75% accuracy in sentiment classification and an 85% improvement in response time compared to traditional methods. This shows that KLYDRA is not only accurate but also practical for real-world use. Users in government, politics, and the corporate sector can use it to make smarter, faster, and more informed decisions.
In the future, we plan to extend KLYDRA with the following improvements:

- Support for more languages, including regional/local languages for multilingual sentiment analysis.
- Integration of more data sources such as Reddit, YouTube comments, or blogs.
- Advanced alert mechanisms with AI-based urgency scoring and risk flags.
- Role-based dashboards for different users like analysts, executives, or campaign teams.

With these upgrades, KLYDRA has the potential to become a powerful and widely adopted platform for real-time public feedback and decision support.

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