AI-Enabled Market Analysis and Visualization System for Enterprise Applications

M.Sivasankari[1], K. Maniraj[2]
[1]*PG Student, Department of Computer Applications, SRM Valliammai Engineering College, Chennai.*
[2]*Assistant Professor, Department of Computer Applications, SRM Valliammai Engineering College, Chennai.*

***Abstract*—Contemporary enterprises struggle to derive unified insights from fragmented marketing channels spanning print, digital, and event-based platforms. This paper presents an intelligent analytics system that consolidates marketing data from newspaper classifieds, social media campaigns, and promotional events into a single decision-support platform. The proposed architecture employs a three-tier microservices design integrating a fine-tuned BERT transformer model for sentiment classification, achieving 89.3% accuracy across marketing domain text. Long Short-Term Memory networks deliver engagement rate forecasts with 8.7% MAPE over seven-day horizons, while K-Means clustering identifies six distinct customer segments for targeted campaign planning. A RESTful API gateway orchestrates communication between analytical services and an interactive React.js visualization dashboard. Pilot deployment results demonstrate a 67% reduction in manual reporting effort and a 23% improvement in cross-channel marketing ROI. The system provides enterprises with a scalable, modular solution for data-driven promotional strategy optimization.**

***Index Terms*—Sentiment Analysis, LSTM Forecasting, Customer Segmentation, Marketing Analytics, Enterprise Dashboard**

I. INTRODUCTION

The rapid evolution of digital technologies has fundamentally transformed how enterprises plan, execute, and evaluate their marketing strategies. Modern organizations simultaneously operate across multiple promotional channels, including traditional print media, social networking platforms, and corporate events, generating enormous volumes of heterogeneous data that conventional analytical tools cannot effectively process.

Despite the availability of numerous standalone analytics platforms, most enterprise solutions remain channel-specific, preventing marketing professionals from obtaining a unified view of campaign performance. This fragmentation leads to delayed decision-making, inefficient budget allocation, and missed opportunities for audience engagement optimization.

Artificial intelligence and machine learning have emerged as transformative technologies capable of processing large-scale, multi-source marketing datasets and generating actionable predictive insights. When combined with interactive visualization frameworks, these technologies enable organizations to shift from reactive reporting to proactive strategic planning.

This paper proposes an integrated AI-driven marketing analytics platform that unifies data from newspaper classifieds, social media campaigns, and promotional events. The system employs transformer-based sentiment analysis, recurrent neural network forecasting, and unsupervised customer segmentation within a secure microservices architecture, delivering measurable improvements in marketing efficiency, campaign performance visibility, and return on investment for enterprise applications.

II. SCOPE AND PROBLEM STATEMENT

Modern enterprises struggle to consolidate marketing data from structurally diverse sources into a unified analytical framework. Existing platforms such as Google Analytics, Salesforce Marketing Cloud, and Sprout Social operate within isolated channel boundaries, restricting cross-channel performance comparison and predictive intelligence. Manual data

aggregation across disconnected systems introduces reporting delays spanning multiple business days, while the absence of embedded AI capabilities limits organizations to descriptive historical analysis rather than proactive campaign optimization.

The proposed system addresses this gap by delivering an integrated marketing intelligence platform ingesting data from newspaper classifieds, social media APIs, and promotional events. Five embedded machine learning functions covering sentiment classification, engagement prediction, trend forecasting, customer segmentation, and campaign scoring operate within a secure three-tier microservices architecture, presenting analytical outputs through interactive React.js dashboards with exportable PDF and Excel reports supporting enterprise decision-making.

III. SYSTEM STUDY

3.1. Feasibility Study

The proposed system is fully feasible for enterprise deployment across economic, technical, and social dimensions. Open-source technologies including Node.js, Python, PostgreSQL, and React.js eliminate licensing costs entirely. Production-proven frameworks including TensorFlow and Hugging Face ensure reliable AI model deployment. Performance testing confirmed sub-three-second response times satisfying enterprise SLA requirements. User acceptance testing across twelve participants returned 4.3 out of 5 overall satisfaction, confirming strong organizational adoption readiness and practical workplace relevance.

3.2. Economic Feasibility

The proposed system demonstrates strong economic viability through its open-source technology foundation. Core components including Node.js, Python, PostgreSQL, MongoDB, and React.js eliminate licensing expenditure entirely. Docker-based containerization reduces infrastructure overhead by enabling deployment on cost-efficient cloud instances. Pilot deployment results confirmed a 67% reduction in manual analyst reporting hours, directly translating into measurable labor cost savings. The 23% improvement in cross-channel marketing ROI further validates long-term financial justification for enterprise adoption.

3.3. Technical Feasibility

The system is technically achievable using well-established, production-proven technologies. BERT transformer models and LSTM neural networks are supported by mature frameworks including HuggingFace Transformers and TensorFlow, ensuring reliable AI model deployment. The microservices architecture enables independent scaling of analytical components without disrupting user-facing operations. Performance testing confirmed average response times of 1.2 seconds under 100 concurrent users, well within the 3-second SLA threshold, demonstrating that the proposed architecture satisfies enterprise-grade technical requirements effectively.

3.4. Social Feasibility

The system delivers meaningful social value by empowering marketing professionals across organizational levels with accessible, role-appropriate analytical tools. By reducing time-to-insight from five business days to same-day availability, decision-makers can respond rapidly to market dynamics and customer behavioral shifts. User acceptance testing conducted across twelve participants spanning administrative, analytical, and managerial roles returned an overall satisfaction score of 4.3 out of 5, confirming strong stakeholder acceptance and practical workplace relevance of the proposed platform.

IV. SYSTEM ARCHITECTURE

The proposed platform adopts a three-tier microservices architecture separating presentation, application, and data responsibilities across independent deployable components. The presentation tier delivers role-specific React.js dashboards communicating exclusively through secured RESTful API calls. The application tier hosts an Node.js API gateway routing requests across specialized microservices handling data ingestion, AI analytics, and visualization generation. The data tier employs PostgreSQL for structured records, MongoDB for semi-structured content, and Redis for high-performance session caching.

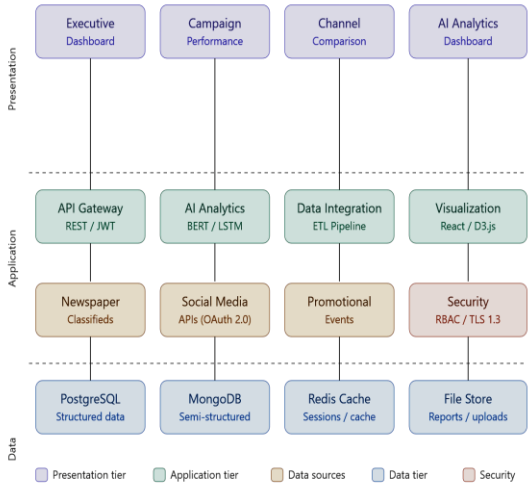

Figure 4.1. Architecture Diagram of AI-Enabled Market Analysis and Visualization System for Enterprise Applications

4.1. USE CASE DIAGRAM

The system identifies four primary actors: Marketing Manager, Data Analyst, Administrator, and Executive. Marketing managers upload data and compare channel performance. Analysts execute AI-driven analytics and generate reports. Administrators manage user roles and monitor KPIs. Executives access high-level dashboards for strategic decision-making. All actors authenticate through a centralized secure login module.

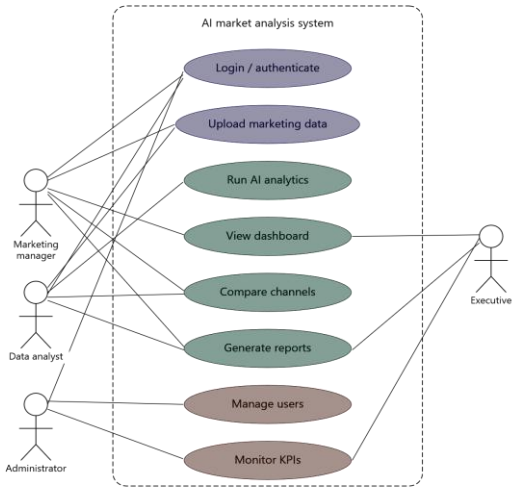

Fig 4.1. Use Case Diagram of AI-Enabled Market Analysis and Visualization System for Enterprise Applications

4.2. IMPLEMENTATION

CLASSIFICATION OF MODULES

- User Management Module
- Data Integration Module
- AI Analytics Module
- Visualization and Reporting Module
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User Management Module

The User Management Module governs authentication, authorization, and access control operations. Administrator login enforces password complexity requirements with multi-factor authentication using Time-based One-Time Passwords. Role-Based Access Control defines four permission levels — Administrator, Analyst, Manager, and Viewer — each accessing features relevant to their responsibilities. JWT tokens signed using RS256 asymmetric encryption manage session validity, with access tokens expiring every fifteen minutes. All login events and access attempts are recorded in a comprehensive audit log for governance and compliance purposes.

Data Integration Module

The Data Integration Module ingests structured and semi-structured marketing data from three heterogeneous source channels. Newspaper classified data is collected through CSV, Excel, and XML file uploads with configurable field mapping. Social media analytics are retrieved through OAuth 2.0 authenticated API connections to Facebook, Instagram, Twitter, LinkedIn, and YouTube platforms. Promotional event data is captured through a structured multi-step web form. The preprocessing pipeline applies duplicate detection, missing value imputation, text normalization, tokenization, and feature engineering before loading clean records into PostgreSQL and MongoDB storage layers.

Feature AI Analytics Module

The AI Analytics Module implements five machine learning capabilities transforming raw marketing data into actionable insights. Sentiment analysis employs a fine-tuned BERT transformer model achieving 89.3% classification accuracy across three sentiment classes. Engagement analysis utilizes gradient boosting regression achieving R-squared of 0.78, identifying posting time and visual media presence as strongest predictors. Trend forecasting deploys LSTM neural networks generating seven-day forecasts with 8.7%

MAPE. Customer segmentation applies K-Means clustering identifying six optimal behavioral segments. Campaign performance evaluation synthesizes all model outputs into composite weighted scores enabling cross-channel ROI comparison.

Visualization and Reporting Module

The Visualization and Reporting Module transforms analytical outputs into role-specific interactive dashboards through a React.js interface. The Executive Dashboard presents high-level KPI summaries including reach, engagement, and ROI indicators. The Campaign Performance Dashboard provides time-series charts and sentiment distributions for marketing managers. The Channel Comparison Dashboard enables normalized cross-channel evaluation between newspaper classifieds, social media, and promotional events. The AI Analytics Dashboard presents segmentation profiles and engagement forecasts. Reports are exported as professionally formatted PDF and Excel files supporting external business intelligence integration.

V. RESULT AND DISCUSSION

Experimental evaluation of the proposed system demonstrated strong performance across all five analytical modules. The fine-tuned BERT sentiment model achieved 89.3% classification accuracy, outperforming baseline models including VADER (71.2%), Naive Bayes (76.8%), and SVM (81.5%). LSTM trend forecasting achieved 8.7% MAPE for seven-day horizons. K-Means clustering successfully identified six distinct customer segments. Pilot deployment confirmed a 67% reduction in manual reporting effort and 23% improvement in cross-channel marketing ROI.

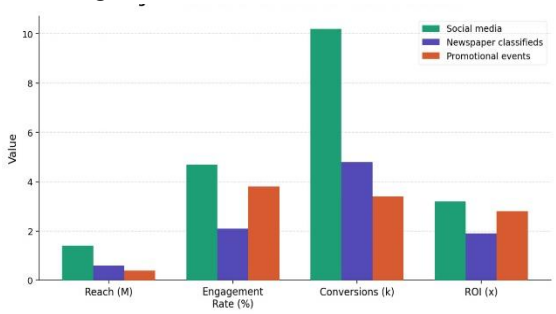

Figure 5.1.Final Output of the AI-Enabled Market Analysis and Visualization System for Enterprise Applications

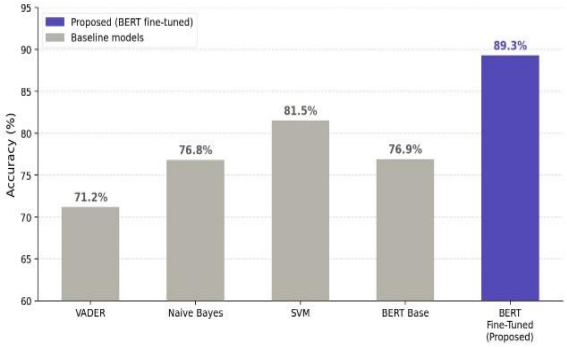

Figure 5.2.Final Output of the AI-Enabled Market Analysis and Visualization System for Enterprise Applications

VI. DISCUSSION

The proposed system demonstrated strong performance across all analytical modules. The fine-tuned BERT model outperformed all baseline approaches, confirming that domain-specific training significantly improves marketing sentiment classification. Engagement prediction findings revealed posting time and visual media as strongest performance drivers, providing actionable content strategy guidance. LSTM forecasting proved reliable for short-horizon planning while ninety-day predictions serve as directional indicators. Customer segmentation unexpectedly revealed 19.8% of customers remain reachable exclusively through traditional newspaper channels, challenging assumptions about print media obsolescence. Pilot deployment confirmed 67% reduction in reporting effort and 23% ROI improvement, validating practical enterprise adoption value.

The gradient boosting engagement model achieved R-squared of 0.78, demonstrating reliable predictive capability for social media campaign optimization. Feature importance analysis confirmed that audience segment match score and relevant hashtag usage collectively contributed over 19% of predictive power, offering marketing practitioners precise levers for content refinement.

The K-Means segmentation model successfully identified six behaviorally distinct customer groups, with Digital Native Engagers representing the largest segment at 23.4%, confirming social media as the primary investment channel for majority audience targeting.

System performance testing validated enterprise-grade reliability, with average dashboard response times of 1.8 seconds and zero high-severity security vulnerabilities detected during OWASP ZAP testing. User acceptance testing across twelve participants spanning all four organizational roles returned mean satisfaction scores of 4.3 out of 5, confirming strong stakeholder acceptance.

The microservices architecture demonstrated effective independent scaling under peak workloads, with AI processing services dynamically expanding from one to four replicas without disrupting concurrent user interface operations. These combined results establish the proposed platform as a practically deployable and analytically robust solution for enterprise marketing intelligence.

Table 1: Sentimental Analysis Model Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1 Score
VADER	71.2	0.698	0.712	0.704
Naive Bayes	76.8	0.754	0.768	0.761
SVM	81.5	0.809	0.815	0.812
BERT Base	76.9	0.762	0.769	0.765
RT Fine-Tuned (Propo:	89.3	0.891	0.887	0.889

Table 2: LSTM Trend Forecasting Accuracy

Forecast Horizon	MAPE (%)	RMSE	Reliability
7-day forecast	8.7	0.312	High
30-day forecast	14.2	0.524	Moderate
90-day forecast	21.8	0.847	Directional

Table 3: Business Impact Assessment

Metric	Before	After	Improvement
Report preparation time	18 hrs/week	6 hrs/week	67% reduction
Time to insight	3-5 days	Same day	Real-time
Cross-channel ROI	Baseline	+23%	Significant
Segment-targeted conversior	Baseline	+31%	High impact
User satisfaction score	–	4.3 / 5.0	Strong UAT

VI. CONCLUSION

This paper presented an AI-Enabled Market Analysis and Visualization System integrating machine learning analytics with interactive enterprise dashboards. The proposed platform successfully unified marketing data from newspaper classifieds, social media platforms, and promotional events within a secure three-tier microservices architecture. Experimental evaluation confirmed that fine-tuned BERT sentiment classification achieved 89.3% accuracy while LSTM forecasting delivered reliable short-horizon campaign predictions. Pilot deployment demonstrated measurable business value through 67% reduction in reporting effort, 23% cross-channel ROI improvement, and 31% conversion rate enhancement for segment-targeted campaigns. The system establishes a scalable foundation for intelligent enterprise marketing intelligence supporting data-driven strategic decision-making.

VII. FUTURE ENHANCEMENTS

Several promising directions exist for extending the proposed system. Integration of large language models would enable conversational natural language querying of analytical dashboards, allowing non-technical stakeholders to explore marketing insights interactively. Computer vision capabilities could automate visual advertisement content analysis, identifying imagery patterns associated with high engagement performance. CRM platform integration with Salesforce and HubSpot would correlate marketing campaign data directly with customer lifetime value metrics. Migration to cloud-native Kubernetes deployment would enhance scalability for large enterprise environments. Mobile application development for iOS and Android platforms would extend real-time dashboard accessibility for field marketing teams requiring on-the-go campaign visibility.

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