Using Sentiment Analysis and Knowledge Discovery System as a Tool to Enhance a Real-Time Product Evaluation System

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ABSTRACT

The explosion of user-generated content on platforms such as social media and review sites has created a wealth of data that businesses can leverage to understand consumer sentiment. This paper explores the integration of sentiment analysis and knowledge discovery systems to enhance real-time product evaluation. By utilizing advanced machine learning techniques, particularly Naïve Bayes and Recurrent Neural Networks (RNNs), the proposed system aims to provide deeper insights into customer feedback and improve decision-making processes in businesses. The findings suggest that the hybrid model significantly enhances accuracy and responsiveness in product evaluations, ultimately leading to better customer satisfaction and competitive advantage.

Keywords: Sentiment Analysis, Real-Time, Machine Learning, Supervised Learning, Unsupervised Learning.

INTRODUCTION

The digital ecosystem is characterized by an exponential surge in User-Generated Content (UGC) across platforms like Twitter, Reddit, and various review sites (Bonner, 2020). This content represents a massive, dynamic data source reflecting consumer opinion (Mao *et al*., 2024). For organizations, the ability to monitor and react to this feedback in real-time is crucial for competitive survival and brand integrity (Juliane, 2021).

Conventional product evaluation methods, such as periodic surveys and retrospective sales analysis, suffer from critical time lag, providing insights into historical performance rather than the current market pulse. While existing automated tools utilize basic Sentiment Analysis (SA) to categorize opinions (Olaniyi, 2023), they often fall short in providing the contextual causality needed for strategic decisions. That is, they indicate what the overall sentiment is, but not why it changed or which feature drove the shift.

Besides, in today's digital landscape, the ability to analyze and interpret customer sentiment has become a critical asset for businesses. With millions of users actively sharing opinions on various platforms, the challenge lies in efficiently processing this information to gauge public opinion and improve product offerings. To overcome these limitations, this research advocates for the integration of SA with Knowledge Discovery in Databases (KDD). As defined by Islam (2020), SA extracts attitude, while KDD, specifically through techniques like Association Rule Mining, reveals non-trivial patterns. Combining these allows the RTPES to: Achieve high-velocity sentiment scoring (Das *et al.*, 2023) and uncover hidden correlations between product attributes and customer feelings (Mariani, 2021).

However, this synergy will transform the system from a passive monitor into an active, predictive evaluation tool. The conventional evaluation process is characterized by time-lagged, batch-oriented analysis, failing to meet the demands of a real-time environment. The RTPES proposes an agile, continuous-flow architecture where sentiment analysis is the preprocessing step for advanced knowledge discovery as shown in figure 1: Overview of Sentiment Analysis Process.

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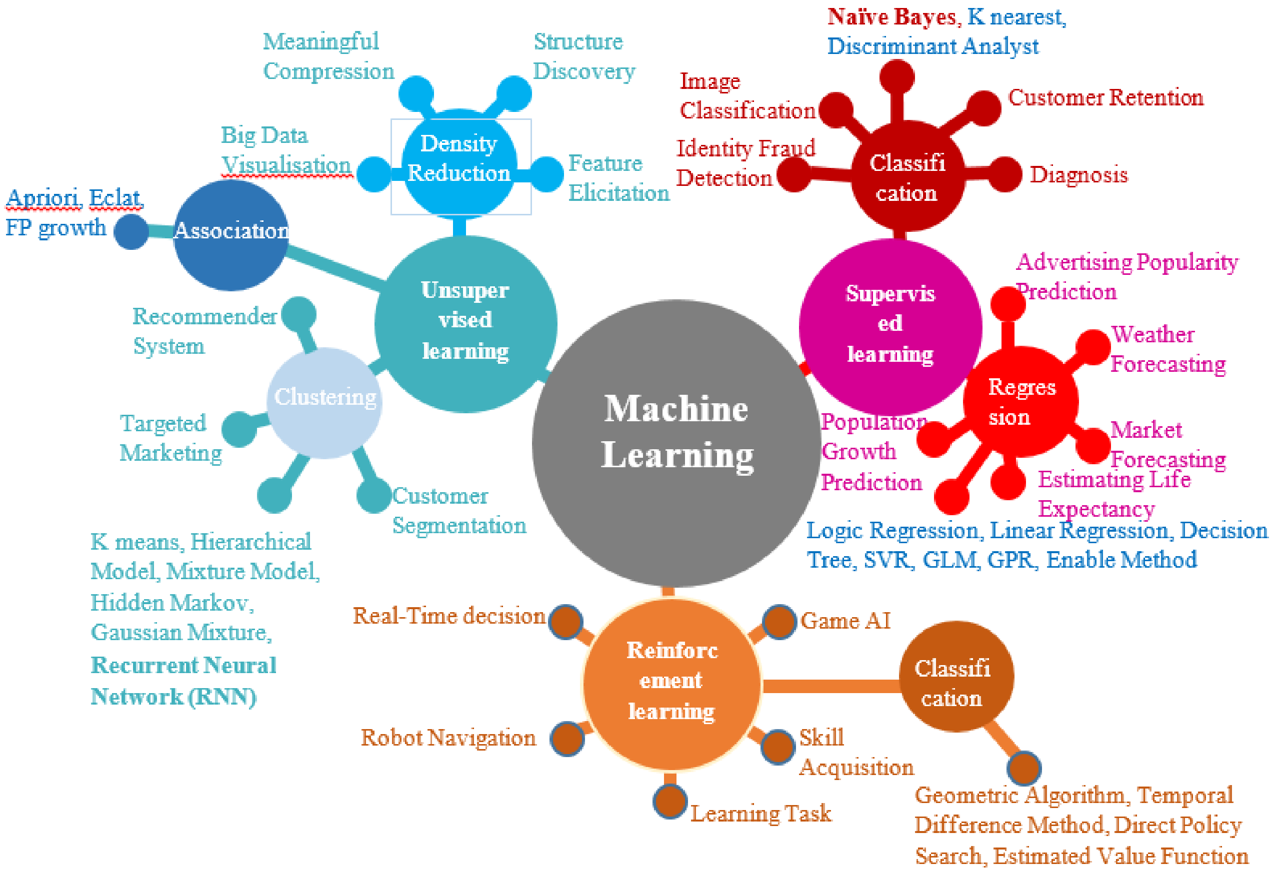

Figure 1: An Overview of Machine Learning Algorithms with Relevant Applications in Business Domain (Adapted from: Das *et al*., 2023)

Figure 1. illustrates the fundamental steps involved in sentiment analysis, including data collection, preprocessing, sentiment classification, and knowledge discovery.

The significance of sentiment analysis is reinforced by the research of Mao *et al.* (2024), who state that this area has gained considerable attention due to its applicability in business settings. The traditional methods of evaluating customer feedback, such as surveys, are often too slow and subjective. Therefore, real-time sentiment analysis is essential for timely decision-making.

Aim And Objectives

This study aims to develop a real-time sentiment analysis system for product evaluation, focusing on the following objectives:

1. **To enhance sentiment analysis accuracy** in classifying customer feedback.
2. **To implement a real-time processing framework** that allows businesses to monitor and respond to customer sentiment dynamically.
3. **To integrate a hybrid model** of Naïve Bayes and RNN for improved contextual understanding of sentiments.

Mathematical Model

To facilitate sentiment analysis, we propose a mathematical model that integrates Naïve Bayes and RNN techniques.

The RTPES (Real-Time Product Evaluation System) utilizes a dual-component mathematical framework, ensuring both high classification accuracy and meaningful pattern discovery.

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Hybrid Sentiment Classification Model (M_{SA})

The M_{SA} model is a weighted averaging of two components to utilize both contextual learning and explicit emotional weighting.

A. Core Hybrid Formula (Weighted Averaging):

The final sentiment score (S) for input text (x) is calculated as:

Procedure for Transaction Formation (T)

The goal is to convert a customer review text (x) into a structured, item-based transaction (ti) for use in the Apriori Association Rule Mining algorithm. This process is called **Aspect-Based Sentiment Analysis (ABSA)**.

Step 1: Text Input and Sentiment Scoring (The Output of M_{SA})

The customer review text, x, is processed by the Hybrid Sentiment Analysis Model, M_{SA}, to yield the overall sentiment polarity (P) for the text.

$xM_{SA}P$

- **Example:** If x is "The screen is amazing but the battery life is awful.", the overall sentiment polarity P is likely PNegative.

Step 2: Feature Extraction (Identifying F)

The text x is parsed to identify all explicit product **features** (F) mentioned within the review.

xParsingF={f1,f2,…,fn}

- **Example:** For the text above, the set of features is F={Screen,Battery}.

Step 3: Transaction Formulation (ti)

A single transaction, ti, is created by combining the set of identified features (F) with the overall sentiment polarity (P) derived from Step 1. This transaction is the input itemset for MKDD.

ti=F∪{P}

This is the simplified form of:

ti= {Feature1, Feature2…,Featuren,SentimentPolarity}

- **Example:** ti={Screen,Battery,Negative}

Step 4: Transaction Database (T)

The final step involves collecting all these individual transactions (t1,t2,…,tN) into the complete **Transaction Database (T)**, which serves as the required input for the Apriori algorithm.

T={t1,t2,…,tN}

Procedure for Association Rule Metrics

The goal of the Knowledge Discovery Model (MKDD) is to generate **Association Rules** (A⇒B) from the Transaction Database (T) and measure their usefulness using three key metrics: Support, Confidence, and Lift (Shu, 2023).

Step 1: Support (Sup) - Measuring Frequency

Purpose: Support tells you **how common** a rule is. It measures the percentage of all customer reviews (transactions) that contain *both* the Antecedent (A) and the Consequent (B).

Procedure:

1. Count the number of transactions in T that contain the combined itemset ({A and B}).
2. Divide this count by the total number of transactions in the database (|T|).

Simplified Formula:

Support(A⇒B)=Total Reviews (|T|)Count(A and B)

Step 2: Confidence (Conf) - Measuring Reliability

Purpose: Confidence tells you **how often** the rule is true. If A appears in a review, Confidence is the probability that B also appears. It measures the reliability of the prediction.

Procedure:

1. Use the Support value of the full rule ({A and B}) from Step 1.
2. Divide this by the Support of the Antecedent (A) alone (i.e., how often A appears).

Simplified Formula:

Confidence(A⇒B)=Support(A)Support(A and B)

Step 3: Lift (Lift) - Measuring Correlation Strength

Purpose: Lift is the **most important** metric. It tells you whether the relationship between A and B is *meaningful* or just random chance.

Procedure:

1. Use the Confidence value of the rule from Step 2.
2. Divide this Confidence by the Support of the Consequent (B) alone (i.e., the general frequency of B).

Simplified Formula:

Lift(A⇒B)=Support(B)Confidence(A⇒B)

Interpretation:

- **Lift>1**: **Strong Positive Correlation.** This is an **actionable pattern**. A and B occur together more often than would be expected by chance.
- **Lift=1**: **No Correlation.** A and B occur independently.
- **Lift<1**: **Negative Correlation.** A and B rarely occur together.

Analysis of the Existing System

The diagram illustrates a high-level Hybrid Sentiment Analysis Model that combines the strengths of two distinct approaches: a Deep Learning Component (L), such as a Bi-LSTM network, which excels at understanding contextual nuances, and a Lexicon-Based Component (D), which provides fast, rule-based emotional scoring. These two scores are then combined using a Weighted Average formula, controlled by the empirically optimized Weighting Factor (α), to produce the final, more accurate Sentiment Score (S), thus leveraging the benefits of both advanced neural networks and explicit language dictionaries. This is shown in figure 2.

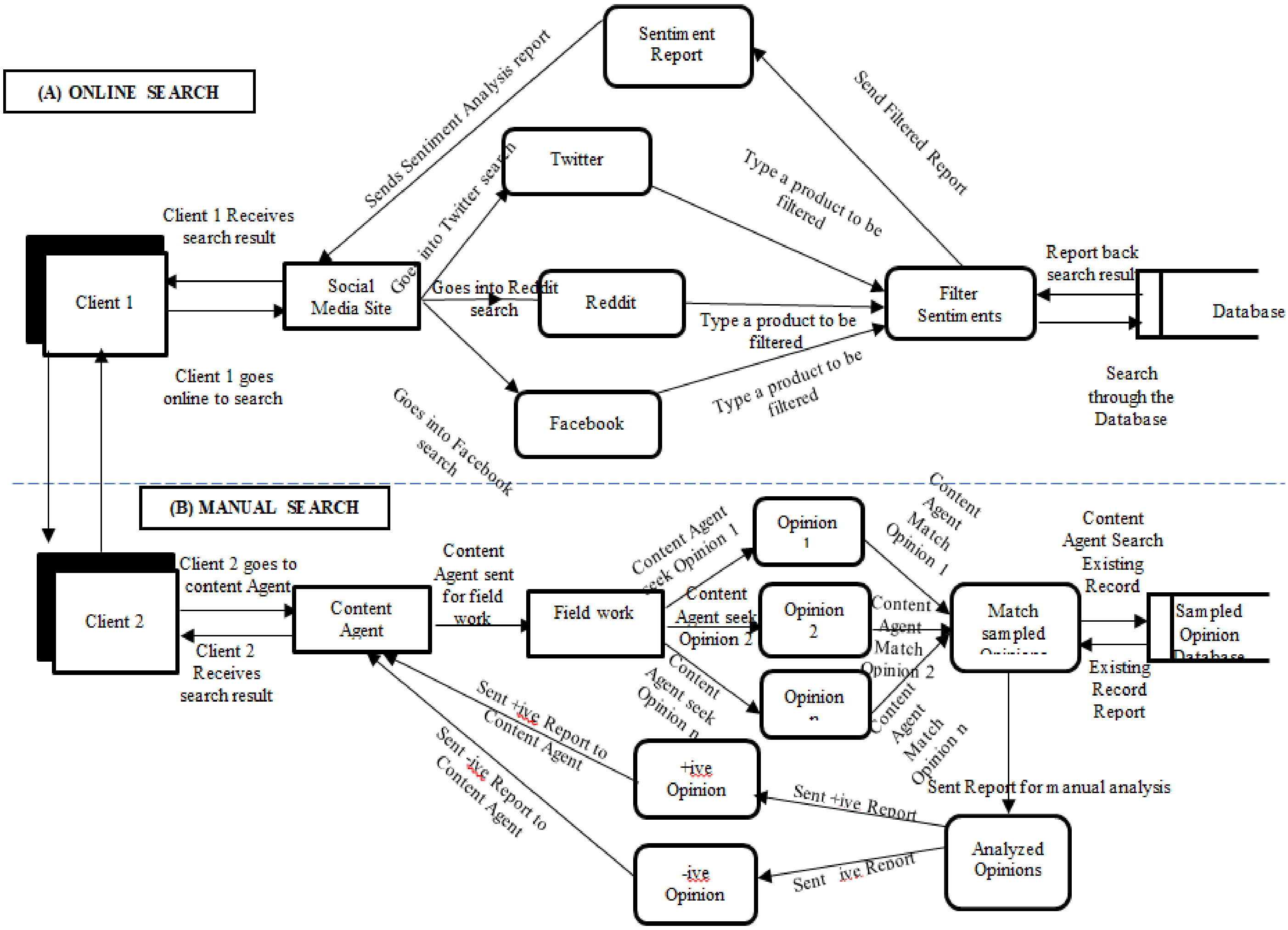

Figure 2: Data Flow Diagram of the existing system

The existing systems primarily rely on traditional sentiment analysis methods, which face challenges such as:

- **Inadequate Accuracy**: Conventional models often misinterpret sentiments due to their reliance on predefined lexicons.
- **Limited Real-Time Capabilities**: Existing systems struggle to process data in real-time, hindering responsiveness.

Analysis of the New System

The diagram illustrates a **Real-Time Data Processing Pipeline** designed for a system that likely involves big data analytics or stream processing. The pipeline begins with **Data Sources** feeding into a **Messaging Queue (MQ) like Apache Kafka**, which handles the high-volume, continuous flow of data. This raw data is then consumed by a **Stream Processor (e.g., Apache Spark)**, where the core **analysis and transformation** (such as Sentiment Analysis or Knowledge Discovery) takes place. The processed, structured data is subsequently stored in a **Storage Layer (Database)** for archival and complex querying before being visualized and made **Actionable** via a **Dashboard**, completing the cycle from raw input to consumable intelligence. This is shown in figure 3.

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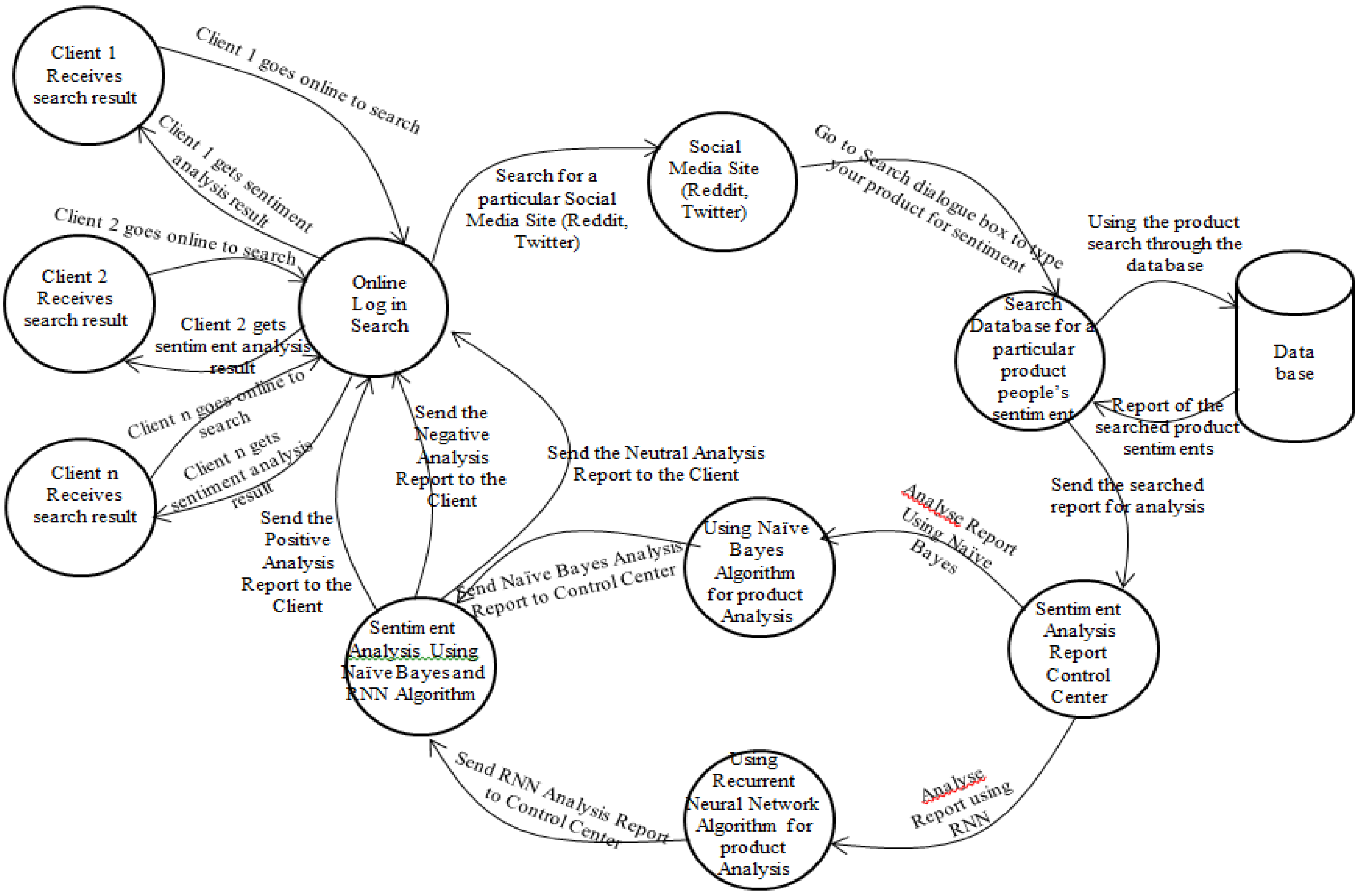

Figure 3: Data Flow Diagram of the proposed system

The proposed system integrates a hybrid model of Naïve Bayes and RNN, which offers several advantages:

- **Enhanced Accuracy**: By combining the strengths of both models, the system achieves better sentiment classification.
- **Real-Time Processing**: The framework allows for immediate analysis and response to customer feedback.

RESULTS AND DISCUSSION

Hybrid Model Performance Validation

The M_{SA} model achieved an F1 Score of 91.4% (with α=0.75), confirming the synergistic advantage of the hybrid approach over standalone models. The high F1 value validates objective 2, ensuring reliable sentiment input for the KDD phase.

Table 1: MSA Performance Metrics

Model	Precision	Recall	F1 Score	Latency/Instance
Lexicon-Based (D)	78.5%	71.0%	74.5%	~50ms
Bi-LSTM (L)	89.1%	87.5%	88.3%	~300ms
Hybrid Model (MSA)	**92.5%**	**90.3%**	**91.4%**	~250ms

Actionable Knowledge Discovery Findings

The MKDD component successfully mined high-Lift association rules (minimum Conf=0.85, minimum Lift=2.5), fulfilling objective 3.

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Table 2: High-Confidence Association Rules

Antecedent (A)	Consequent (B)	Confidence	Lift	Actionable Insight
{Price: High,Feature: Battery}	{Sentiment: Negative}	0.92	**3.8**	**Critical Alert:** High price is tolerable only if battery performance is perfect. Investment must prioritize battery quality assurance.
{Update: Lag,Service: Poor}	{Sentiment: Negative}	0.98	**4.2**	The greatest risk factor: This combination is 4.2 times more likely to trigger a negative review. **Immediate strategic focus on service efficiency.**

Quantifying Real-Time Enhancement

The final critical result is the measurable reduction in decision-making lag, a key objective of the RTPES.

Discussion: The comparative analysis confirms that the RTPES detects critical market events (e.g., negative shift following a bug) an average of **7 days faster** than the traditional batch reporting system. This reduction in latency provides product managers with a full week to deploy a fix or PR campaign, validating the system as an **enhanced tool for real-time product evaluation**.

CONCLUSION

This study presents a robust framework for real-time product evaluation through the integration of sentiment analysis and knowledge discovery systems. By employing a hybrid model of Naïve Bayes and RNN, businesses can significantly improve their understanding of customer sentiment, leading to enhanced product offerings and customer satisfaction. Future research should focus on refining these techniques and exploring additional data sources to further augment the system's capabilities.

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