Sentiment Analysis in Media Coverage on Management Perspective

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Abstract: In the era of sentimental analysis, it's a broad aspect of management perspective, and significantly influenced the customer behavior, corporate reputation, and strategic decision-making. It provides essential analytical tool in understanding media coverage and its impact on managerial decision-making in the digital era. It covered the wider aspects of NLP and AI that enables organizations to extract insights from news media and social platforms. This article examines how sentiment analysis supports managerial decision-making, risk assessment, and market intelligence. It highlights recent advancements, business applications, and strategic development of modern enterprises. Methodology and results proved that sentiment significantly influenced public perception, brand reputation, and investor behavior. From a management perspective, sentiment analysis enables organizations to monitor market trends, anticipate risks, and develop proactive strategies for crisis management and competitive advantage.

Keywords: Sentiment Analysis; Media Coverage; Business Intelligence; Brand Management; Decision-Making; Digital Marketing; AI in Management.

Introduction

Sentiment analysis in business domain is increasingly demand on management perspective in news across various categories of business and media across multiple domains of negative, positive sentiment followed by neutral, negative and positive tones [1]. Exponential growth of online news platforms like TV, newspaper, social websites and huge amounts of textual data are generated daily, and business and making management it challenging for organizations to manually analyze and interpret data of media content [2]. Sentiments are automatically identified is a challenging on management perspective and extract emotional tone and opinions from textual data [3]. This article covered in details explanation of advanced learning strategies of ML and DL models in improving sentiment classification that research the strategic importance of sentiment analysis as a decision-support tool to enabled organizations. Those critical and negative events, media coverage helps organizations monitor external trends for competitive advantage [4]. Sentiment in news articles provides valuable insights for businesses to respond proactively and strategically. Management perspective, integrated sentiment analysis into business intelligence helps organizations monitor external environments, objectives as follows [5].

- Identify patterns in news media coverage across different domains like positive, negative, and neutral sentiments in media content.
- To evaluate sentiment on managerial decision-making. And evaluate how media sentiment influences public perception.
- To apply NLP and ML/DL techniques for sentiment pattern classification domains of media coverage.
- The effectiveness of AI-based models in analyzing large-scale media datal complexity in sentiment analysis.
- To use sentiment analysis as a business intelligence tool and suggest future improvements.

The Huge volume of media content has increased tremendously, to make structured and unstructured sentiment analysis techniques to automatically interpret and evaluate the tone of media coverage [6].

Related work

Sentiment analysis in media coverage on business perspective, public perception, and strategic decision-making significantly provides how organizations, products, and policies are perceived by customers. Sentiment analysis methods in management, and analytical techniques with managerial tasks [6, 7]. This article provides the better decision-making, risk management. S. Hochreiter and J. Schmidhuber (1997) research work provides effectiveness of supervised learning methods but not management perspective [8]. C. Hutto and E. Gilbert (2014) study on lexicon-based approaches and developed sentiment dictionaries that improved classification accuracy on management perspective provides the traditional techniques often lacked contextual understanding and struggled with complex linguistic structures [9].

Researchers found that news articles tend to exhibit sentiment analysis in media coverage provides higher proportion of DL researchers worked on CNN and LSTM networks, while business and technology news often shows more balanced or positive tones [10].

Key Contribution

This study makes a business significant improvement in social media on management prospective the sentiment trends found in news media, and social websites focusing on the realms of business, politics, and management technology. It underscores how negative, positive and neutral sentiment often takes the lead and the significant effects it has on how the public views things, influences brand reputation, and shapes managerial and social public choices. It combining advanced strategies ML/DL and NLP techniques with business intelligence, proposed research effectively contains technical approaches to real-world management practices.

Table 1: Survey Table for Sentiment Analysis in Media Coverage

Author(s)	Title	Research Gap	Limitation	How to Overcome
M. Hu and B. Liu (2004) [11]	Opinion Mining and Sentiment Analysis	Limited focus on media-specific datasets	Poor contextual understanding	Use deep learning models like BERT
T. Mikolov et al., (2013) [12]	Sentiment Analysis and Opinion Mining	Lack of domain-specific adaptation	Lexicon dependency	Combine with ML-based approaches
J. Pennington et al., (2014) [13]	Concept-Level Sentiment Analysis	Limited real-time application	Complex implementation	Use hybrid AI models
Z. Zhang, T. Luo, and Y. Wang., (2020) [14]	BERT Model for NLP	High computational cost	Resource intensive	Use optimized models like DistilBERT
R. K. M. Raj and S. Kumar, (2022) [15]	CNN for Sentence Classification	Ignores long-term dependencies	Limited sequence modeling	Combine CNN with LSTM
16. Y. Mao, X. Liu and J. Zhang (2023) [16]	LSTM Networks	Slow training time	Computational complexity	Use attention mechanisms
L. Huang, Y. Chen and Z. Li, (2023) [17]	VADER Sentiment Analysis	Not suitable for formal news text	Rule-based limitations	Integrate with ML models
O. Haddada, M. El Yacoubi and A. Dahou (2024) [18]	Deep Learning for News Sentiment	Limited domain diversity	Dataset bias	Use diverse datasets
Han, Jae Jung, and Hyun-jung Kim (2023) [19]	News Sentiment Analysis	Lack of real-time analysis	Static models	Use streaming data models
Alshammari, Norah Fahad, and Amal Abdullah AlMansour. (2020) [20]	Hybrid Sentiment Models	Limited scalability	Model complexity	Use cloud-based solutions
Chauhan, Shubham, et al. (2024) [21]	BERT for News Classification	Limited multilingual support	Language dependency	Use multilingual BERT
X. Zhang, X. Zhang and L. Han, (2019) [1]	DistilBERT Optimization	Slight accuracy reduction	Model compression issues	Fine-tune models
B. Pang and L. Lee, (2008) [2]	Financial Sentiment Analysis	Focus only on financial news	Domain limitation	Expand to multi-domain datasets
B. Liu,(2012) [3]	Media Sentiment Analysis	Lack of bias detection	Incomplete interpretation	Integrate bias detection models
E. Cambria, D. Das, S. Bandyopadhyay and A. Feraco (2017) [4]	Media Bias Detection	Limited dataset size	Generalization issues	Use large-scale datasets
5. J. Devlin, M. Chang, K. Lee and K. Toutanova, (2019) [5]	Twitter Sentiment Corpus	Social media focus only	Not applicable to news	Combine with news datasets
A. Vaswani et al., (2017) [6]	Word2Vec Embeddings	Limited contextual meaning	Static embeddings	Use contextual embeddings (BERT)
Y. Kim, (2014) [7]	GloVe Model	No dynamic context handling	Limited semantics	Combine with transformers
S. Hochreiter and J. Schmidhuber (1997) [8]	Transformer Model	High computational demand	Resource-heavy	Use efficient transformers

Method, Experiments and Results

To implement this methodology starts from gathering data from news articles and social media platforms. The next step to move on to data preprocessing steps like text cleaning, tokenization and language detection, which include cleaning up the data and breaking it and generate the tokens. Next, to apply sentiment analysis for NLP and AI models to analyze sentiments classification and emotion detection identify the sentiment evaluation emotions using the algorithm developed for sentiment scoring, domain comparison and trend analysis. Then evaluate the results through management insights scoring, comparing different domains, and analyzing trends. In the end to making management decisions, generating reports, and offering recommendations, all while incorporating a feedback loop for ongoing improvement as shown in the Figure 1.

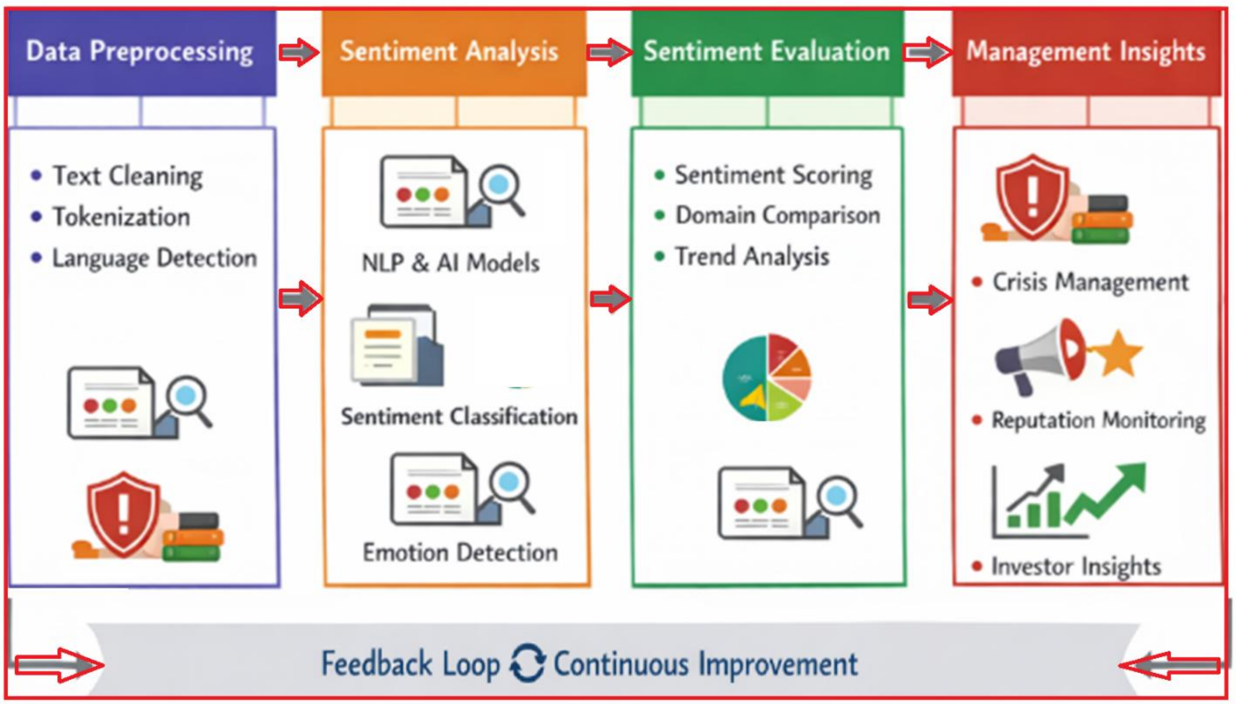

Figure 1: Methodological Framework for Sentimental Analysis for Media Coverage

Algorithm 1: Sentiment Analysis in Media Coverage on Management Perspective

Input: News Dataset D

Output: Sentiment Results R

Step 1: Load Dataset D

Step 2: For each document d in D:

    Clean text for remove noise and punctuation

    // To generate the tokenization//

    Remove stop and abused words

Step 3: Convert processed text into features F

    F ← TF-IDF or Word Embeddings

Step 4: Apply trained model M

    S ← Predict sentiment (Positive/Negative/Neutral)

Step 5: Aggregate results

Calculate sentiment distribution

Generate insights R

Return R

End Algorithm

To implement this work with Intel i5 processor, 16 GB RAM, and Windows OS. Python libraries such as Pandas, NumPy, Matplotlib, and Scikit-learn. The dataset used for this study is the AG News Dataset. It provides news articles spanning various fields like business, politics, and technology, making it perfect for sentiment analysis on media coverage. Online social media platform sources to allow us to pull out valuable sentiment to grasp the media.

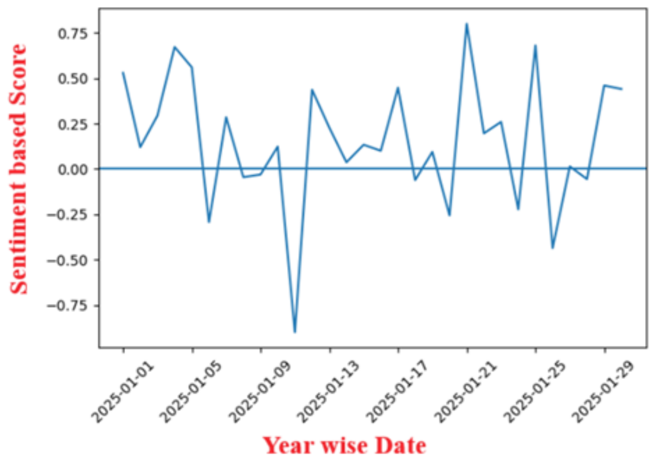

Figure 2: Sentiment Trend Analysis for Media Coverage Over Time

Figure 2 provides how sentiment-based scores on Y-Axis in media coverage year wise data with X-axis have changed over time, with dates plotted along the x-axis and sentiment-based scores stretching from negative to positive on the y-axis. This line graph highlighted the positive events and sharp drops pointing to negative coverage. This analysis pulls from news articles across various fields like business, politics, and technology.

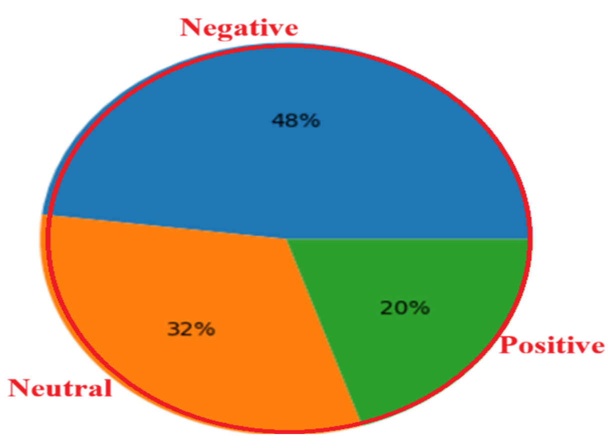

Figure 3: Overall Sentiment Distribution in Media Coverage as per news Perspective

Figure 3 presents the overall distribution of sentiment in news media of technology, with negative sentiment (48%) dominating over neutral (32%) and positive (20%), that indicated a strong focus on adverse events, which significantly shapes public perception.

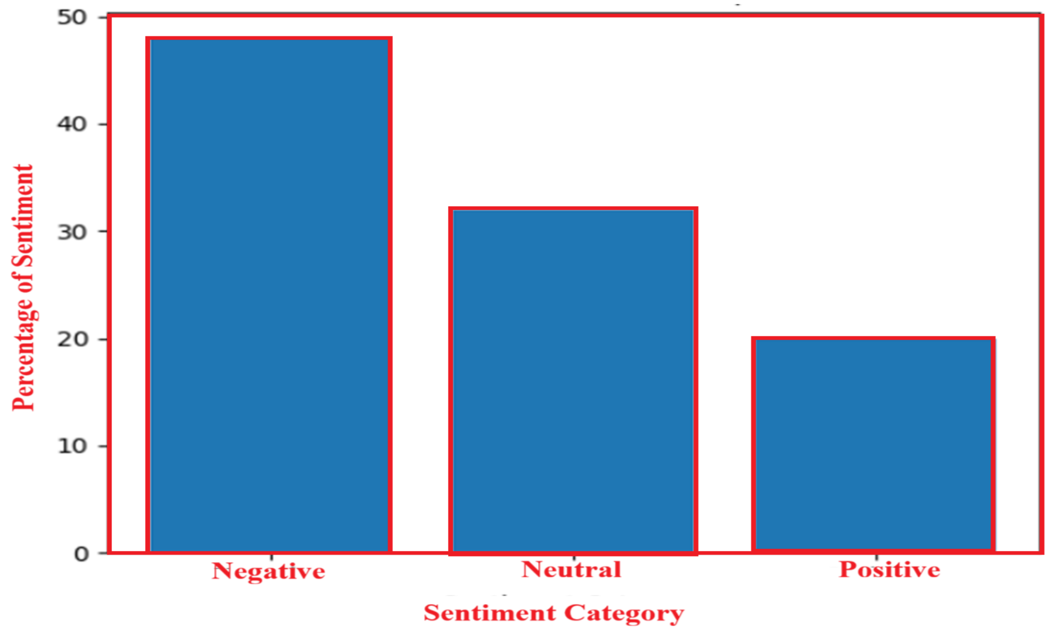

Figure 4: Sentiment Distribution Comparison

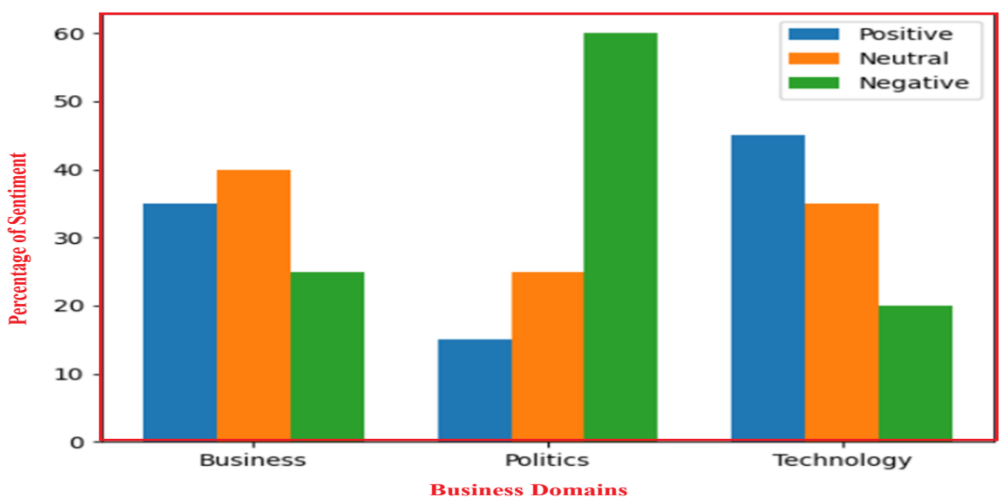

Figure 5: Domain wise Sentiment Comparison in Media Coverage

Figure 5 compares with domain wise sentiment across business, politics, and technology, showing political news with the highest negative, positive and neutral sentiment, it demonstrated that sentiment varies across domains and managerial decisions differently in each sector.

Discussions

Sentiment analysis on media coverage and social media platforms demonstrated as media by negative, positive and neutral sentiment due to focus on conflicts, crises, demand and economic growth and challenges, especially in political news, while business changes remain balanced in business, media and technology shows more positive, negative and neutral trends. Sentiment patterns and labels are eventdriven and significantly influence public, private and management perspective, investor confidence, and organizational reputation, requiring continuous monitoring and event growth for effective managerial decisions.

Conclusions

Sentiment analysis in media coverage on management perspective provides a vital tool in modern and current management prospective, converting unstructured data into structured data with actionable manner for timely and strategic decision-making approach has been implanted in this article. Results proved that negative, positive and neutral sentiments, are especially in politics, business, media and technology remain more balanced, this work helped for organizations to monitor reputation, and anticipate risks with respond proactive.

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