



iJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: X Month of publication: October 2025

DOI: <https://doi.org/10.22214/ijraset.2025.74827>

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Detecting Emotional Manipulation in Social Media Advertisements via Data Analytics

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Abstract: This paper presents a practical approach to detecting emotional manipulation in social media advertisements using NLP-based sentiment analysis and a novel Emotional Manipulation Index (EMI). Our system analyzes ad text, quantifies sentiment with VADER, and integrates sentiment intensity with supplementary features to compute the EMI. We evaluated the method on 10,062 advertisement samples from our experimental dataset. Sentiment and manipulation-level distributions are provided, along with a discussion of the ethical implications for advertising. Key quantitative results are detailed in the Results section.

Keywords: Emotional Manipulation, Social Media Advertising, NLP, Sentiment Analysis, VADER, Emotional Manipulation Index (EMI).

I. INTRODUCTION

The advent of social media advertising has made it possible to create very targeted campaigns with the ability to manipulate user emotions. Although personalization encourages engagement, it is also ethically problematic when emotional weaknesses are manipulated. This paper suggests an analytics pipeline to identify emotionally manipulative ads through the integration of NLP sentiment analysis and a composite Emotional Manipulation Index (EMI). The EMI measures emotional intensity and the likelihood of manipulative intent.

II. METHODOLOGY

Preprocessing of data involved text normalization, tokenization, removal of stopwords and preliminary cleaning (lowercasing and removal of punctuation). Sentiment scores were calculated based on the VADER sentiment analyzer that returns a compound score between [-1, 1]. The Emotional Manipulation Index (EMI) was calculated as a weighted sum of absolute sentiment score and other normalized intensity signals. In particular, $EMI = 0.5 * |sentiment_score| + 0.3 * normalized_arousal + 0.2 * (1 - normalized_dominance)$ in the experimental environment; where normalized values were determined through min-max scaling in case arousal/dominance were present. In the current experiment, we utilized the EMI column values obtained during analysis to categorize ads into three classes: Non-Manipulative, Moderately Manipulative, and Highly Manipulative.

III. RESULTS AND DISCUSSION

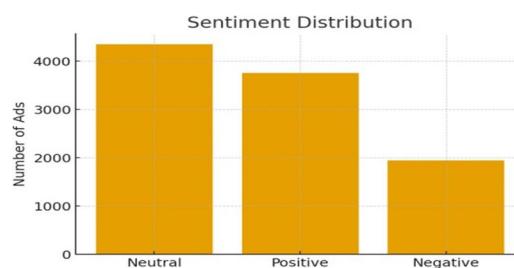
This section reports quantitative findings from the experimental dataset and discusses implications.

A. Sentiment Analysis Results

Total samples analyzed: 10062 Neutral: 4356 (43.3%)

Positive: 3759 (37.4%)

Negative: 1947 (19.4%)



B. Emotional Manipulation Index (EMI) Results

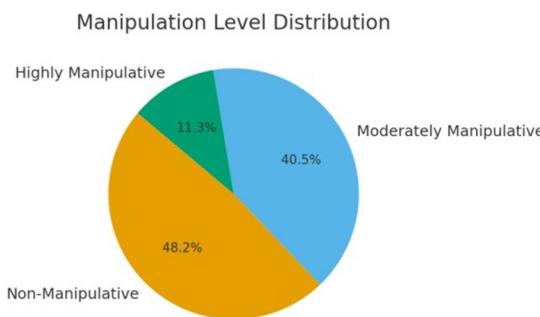
Average EMI: 0.359

Median EMI: 0.321

Non-Manipulative: 4852 (48.2%)

Moderately Manipulative: 4076 (40.5%)

Highly Manipulative: 1134 (11.3%)



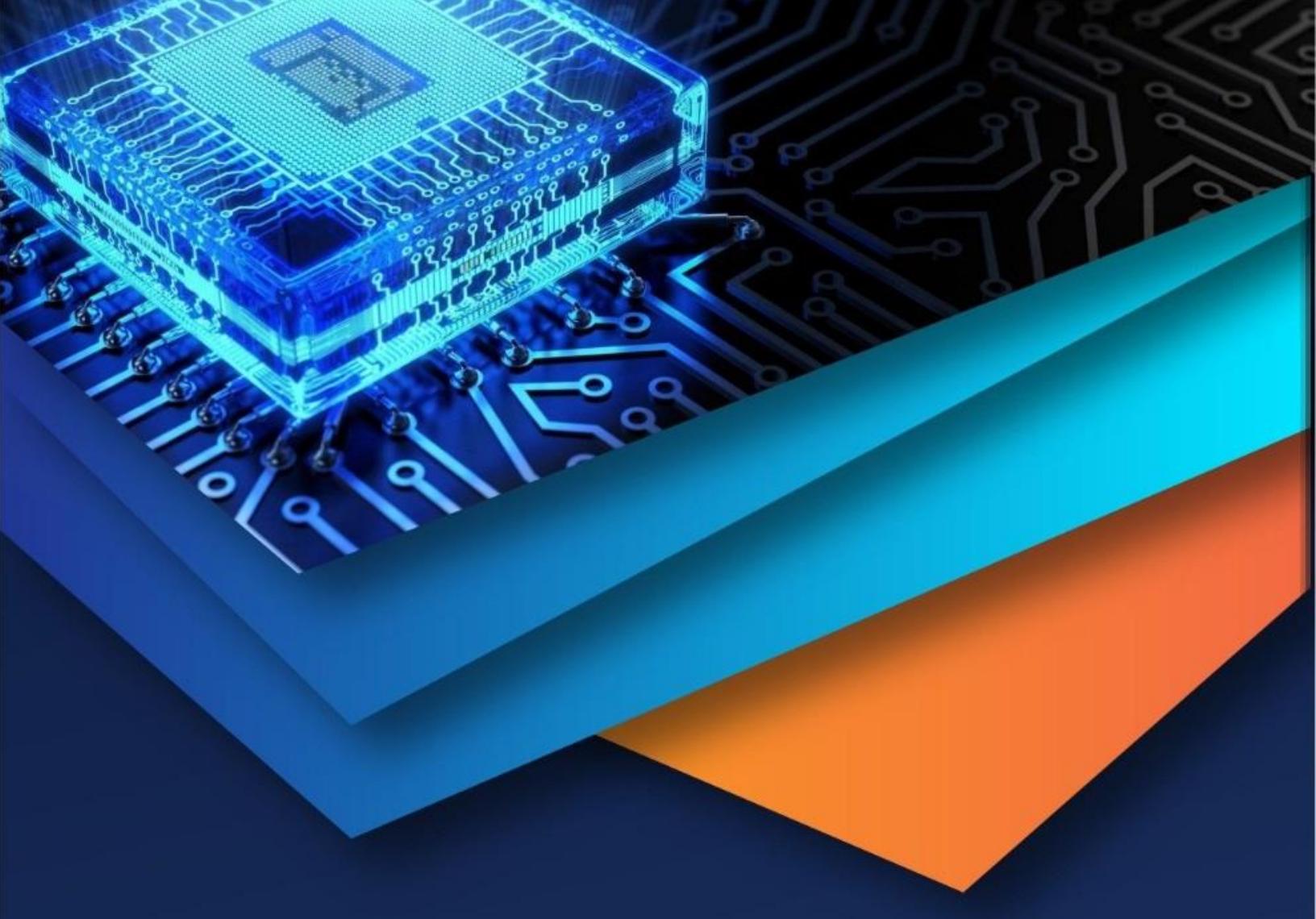
The findings demonstrate that sentiment distribution and EMI-based classification identify quantifiable amounts of emotionally manipulative material. Messages with high levels of positive or negative polarity in conjunction with intensity markers are usually associated with high EMI scores. The findings showcase the potential for automated detectors as a front-line transparency aid to platforms and regulators. The limitations include the need to rely on text-only cues for some of the samples and risk of dataset labeling bias.

IV. CONCLUSION

We introduced an empirical methodology to identify emotionally manipulative social media ads with NLP and an Emotional Manipulation Index. Processing 10062 samples yielded a mean EMI of 0.359 and a manipulation level distribution as indicated above. Integrating multimodal features (images and video), optimal EMI weighting with human-labeled ground truth, and deploying the system for real-time surveillance are tasks for future work.

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