Using Object Detection to Identify Associations Between Brands and Symbolically Relevant Subjects: A New Tool for Analyzing Brand Perception and Purpose in the Digital Age

Abstract

Object detection, a machine learning (ML) technique, offers a powerful approach to understanding how brands are perceived when associated with specific visual content on social media. This study proposes using object detection to identify symbolically relevant subjects in images and videos, and cross-referencing these visuals with brand mentions or tags in the accompanying text. By analyzing posts where fire or smoke appears, the goal is to explore which brands are cited in these contexts and how these associations influence brand perception.

Through automated detection of fire and smoke across large-scale social media content, the tool captures instances where brands are mentioned in posts containing crisis-related imagery. This enables researchers to examine the impact of these associations on brand identity and purpose, revealing how brands are linked to moments of crisis, environmental events, or industrial incidents. By correlating the frequency and context of such posts with brand mentions, the propose a framework to provide insights into public perceptions of brands when they are tied to negative or emergency situations.

This approach offers a novel method to navigate the digital environments and how brands associations with critical imagery affect their reputation and alignment with their stated purpose.

Keywords: Object Detection, Brand Perception, Crisis-Related Imagery, Social Media Analysis, Natural Language Processing (NLP), Brand Reputation Management

1. Introduction

In today's digitally connected society, brands are shaped not only by their marketing efforts but also by public interactions and perceptions, often through user-generated content on social media (Swaminathan et al., 2020; Nuji et al., 2023). Brands can be tied to social issues, crises, or disasters simply by being mentioned or tagged in posts featuring crisis-related imagery like fire or smoke.

The symbolic weight of fire and smoke—representing danger or disaster—can significantly influence public perception of brands associated with such imagery. Companies may inadvertently be linked to negative events, such as industrial accidents or protests, which can affect their identity, trust, and reputation.

This paper presents a tool that uses object detection (Zou et al., 2019) to identify fire and smoke in social media content, cross-referencing these visuals with brand mentions. Using the Faster R-CNN algorithm (Ren et al., 2015), trained on the D-FIRE dataset, and natural language processing (NLP) for brand identification, this tool analyzes how these associations impact public perception of brand purpose and identity. The paper outlines the methodology and explores the broader implications for brand reputation management.

2. Object Detection for Fire and Smoke in Social Media

2.1 The Role of Object Detection in Brand Perception

Object detection, a fundamental task in computer vision, involves identifying specific objects within images or videos (Zou et al., 2019). When applied to the analysis of brand perception, object detection enables researchers to automatically identify visual elements—such as fire and smoke—that can significantly shape the context in which brands are mentioned. By linking these objects to brands cited in the same posts, the tool can systematically explore how these visual cues influence public perception and brand identity.

Fire and smoke often serve as potent symbols of crisis or risk (Byerly et al., 2022). When these elements appear in social media content, they can trigger strong emotional responses, making the association with any brand mentioned in the post particularly impactful. Whether it's a wildfire, industrial fire, or public protest involving smoke, the appearance of these objects can alter the audience's perception of a brand's responsibility, accountability, or involvement in such events.

The ability to detect fire and smoke in real-time across vast amounts of user-generated content allows for continuous monitoring of brand associations with critical events. This tool not only provides a technical solution for tracking these associations but also contributes to the broader understanding of how brands are perceived in moments of crisis or tension.

2.2 Faster R-CNN ResNet-101: The Core Object Detection Model

In this study, the Faster R-CNN (Region-Based Convolutional Neural Network) model with a ResNet-101 backbone is employed for object detection. Faster R-CNN is known for accurately identifying and localizing objects by generating region proposals and classifying them into predefined categories (Pham et al., 2020). The ResNet-101 backbone, a deep network with 101 layers, enhances the model's ability to detect complex patterns, making it ideal for detecting fire and smoke in diverse, real-world environments.

The model is trained on the D-FIRE dataset, a specialized and validated dataset (Venâncio et al., 2022, 2023) that contains annotated images of fire and smoke in various contexts, including wildfires, industrial fires, and urban settings. This dataset ensures the model's accuracy in detecting fire and smoke across different types of social media content, where variables like lighting, framing, and image quality often fluctuate. The fire and smoke detection process includes several steps: 1) Data Collection: Images and videos are sourced from platforms like Twitter, Instagram, and YouTube using APIs and web scraping, filtering posts with keywords and hashtags related to fire or smoke. 2) Preprocessing: Visual content is resized, pixel values normalized, and frames extracted from videos to ensure compatibility with the model. 3) Object Detection: The pre-trained Faster R-CNN ResNet-101 model detects fire and smoke, generating bounding boxes around the objects and assigning confidence scores to each detection. 4) Post-Detection Validation: The system reduces false positives by validating results with metadata, such as geolocation and timestamps, to confirm the relevance of the detected imagery.

Sample detection: **Red** box for fire. **Blue** box for smoke.

3. Associating Detected Fire and Smoke with Brands

3.1 Natural Language Processing for Brand Identification

After detecting fire and smoke, the tool identifies brands mentioned or tagged in the same posts using natural language processing (NLP), specifically named entity recognition (NER) techniques trained for multilingual contexts (Tedeschi et al., 2021). NER efficiently extracts company names or brand mentions from captions, comments, and hashtags. It identifies: 1) Direct Brand Mentions: Instances where a brand is explicitly named (e.g., "BrandX factory fire"), 2) Social Media Tags: User-generated tags using the "@" symbol to directly mention companies (e.g., @BrandName).

3.2 Cross-Referencing Visual and Textual Data

The tool then cross-references the detected fire or smoke imagery with brand mentions in the text to establish associations. This enables the system to map the frequency and context of brand associations with crisis-related imagery. Visual Evidence: Detected fire or smoke forms the core visual data. Brand Mentions: Textual data identifies any brands mentioned or tagged. Association Mapping: The tool links the visual evidence to the mentioned brand, creating a record of the association. For example, a post showing smoke from an industrial accident might tag the company responsible, or a protest involving fire may mention brands connected to the event.

4. Implications for Brand Purpose and Perception

4.1 The Influence of Crisis-Related Imagery on Brand Perception

Fire and smoke in social media posts typically signal crisis, and brands mentioned alongside such imagery may experience negative associations. Brands repeatedly linked to incidents like industrial accidents or protests might be seen as irresponsible, especially if they claim to be socially or environmentally conscious. Additionally, brands may face polarized reactions depending on the context, with some consumers supporting them and others criticizing. Responsiveness to these crises can either reinforce a brand's authenticity or, if poorly managed, damage its credibility.

4.2 Brand Purpose in the Context of Public Scrutiny

This tool helps evaluate whether a brand's stated purpose aligns with public perception. Brands claiming environmental responsibility may suffer reputational harm if they are repeatedly associated with crises like factory fires or pollution, revealing inconsistencies between their messaging and real-world actions (Kapri & Professor, 2023). Conversely, brands that respond positively to crises, such as by providing aid, can strengthen their identity and public trust.

5. Conclusion

This study introduces a scalable tool that combines object detection and natural language processing to analyze how brands are perceived when associated with crisis-related imagery on social media. By detecting fire and smoke in visual content and linking them to brand mentions, the tool provides insights into how these associations impact public perception of brand purpose and identity. Its scalability overcomes traditional limitations in analyzing visual media, offering valuable data for marketers and researchers. As real-time events and user-generated content continue to shape brands, understanding these dynamics is essential for maintaining a consistent, authentic brand identity.

Bibliography

Byerly, H., Champ, P. A., Meldrum, J. R., & Brenkert–Smith, H. (2022, October 4). Wildfire imagery reduces risk information-seeking among homeowners as property wildfire risk increases. *Nature Portfolio, 3*(1). https://doi.org/10.1038/s43247-022-00505-7

Kapri, S., & Professor, A. (2023, June 3). Role of Ethical Decision Making in Business on Corporate Branding: An Empirical Study. *Pacific Northwest Economic Region, 55*(1). https://doi.org/10.48047/pne.2018.55.1.57

Nuji, M. N. N., Ali, A., Noordin, W. N. W., Thaheer, B. A. N. M., & Mathiew, V. (2023, June 7). Of Trust and Influence: A Look At Social Media Influencers and Brand Promotion. *International Journal of Academic Research in Business and Social Sciences, 13*(6). https://doi.org/10.6007/ijarbss/v13-i6/15444

Pham, V., Pham, C., & Dang, T. (2020, December 10). Road Damage Detection and Classification with Detectron2 and Faster R-CNN. https://doi.org/10.1109/bigdata50022.2020.9378027

Ren, S., He, K., Girshick, R., & Sun, J. (2015, January 1). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *Cornell University*. https://doi.org/10.48550/arxiv.1506.01497

Swaminathan, V., Sorescu, A., Steenkamp, J. E., O'Guinn, T. C., & Schmitt, B. H. (2020, January 28). Branding in a Hyperconnected World: Refocusing Theories and Rethinking Boundaries. *SAGE Publishing, 84*(2), 24-46. https://doi.org/10.1177/0022242919899905

Tedeschi, S., Maiorca, V., Campolungo, N., Cecconi, F., & Navigli, R. (2021). WikiNEuRal: Combined neural and knowledge-based silver data creation for multilingual NER. In *Findings of the Association for Computational Linguistics: EMNLP 2021* (pp. 2521–2533). Association for Computational Linguistics. https://aclanthology.org/2021.findings-emnlp.215

Venâncio, P. V. A. B., Campos, R. J., Rezende, T. M., et al. (2023). A hybrid method for fire detection based on spatial and temporal patterns. *Neural Computing and Applications, 35*, 9349–9361. https://doi.org/10.1007/s00521-023-08260-2

Venâncio, P. V. A. B., Lisboa, A. C., & Barbosa, A. V. (2022). An automatic fire detection system based on deep convolutional neural networks for low-power, resource-constrained devices. *Neural Computing and Applications, 34*, 15349–15368. https://doi.org/10.1007/s00521-022-07467-z

Zou, Z., Shi, Z., Guo, Y., & Ye, J. (2019, January 1). Object Detection in 20 Years: A Survey. *Cornell University*. https://doi.org/10.48550/arxiv.1905.05055