International Journal of Allied Research in Marketing and Management
Volume.9, Number 4; July-August, 2023;
ISSN: 2836-5585 | Impact Factor: 6.65
http://zapjournals.com/Journals/index.php/ijarmm
Published By: Zendo Academic Publishing

EXPLORING BEAUTY BUSINESS INSIGHTS ON INSTAGRAM WITH COMPUTATIONAL VISION

Eduardo Ferreira[1]

Article Info
Keywords: Media consumption, audience engagement, social media, culture, technological shifts.

Abstract
Contemporary audience and media consumption research in the realm of the Internet has witnessed dynamic evolution and complexities. This paper addresses the unfolding landscape of audience engagement and media interaction within the digital sphere. Notably, the interplay between media and culture is underlined by recent social and technological shifts, presenting both prospects and challenges for investigation (Recuero, 2018). A substantial surge in studies exploring the nexus of social media and intelligent analytical tools is evident. This trend is attributed to the escalating significance of these subjects, their amplified adoption, and consequential impact. Concurrently, the accessibility to vast volumes of data has substantially facilitated such research endeavors (Sloan & Quan-Haase, 2017). This article delves into the contextual backdrop of audience-media dynamics, considering emergent paradigms brought about by the Internet age. The ensuing analysis seeks to comprehend the intricate interplay between audience behavior, technological advancements, and cultural influences, offering valuable insights into the contemporary media landscape.

1. Introduction

Audience and media consumption studies on the Internet have been going through a lot of unfolding and tensioning in recent years. Recent social and technological changes have created opportunities and challenges in researching the articulation between media and culture (Recuero, 2018). The growth of research that focuses on social media and intelligence tools is first due to the prominence of the object, whose adoption and impact have grown in recent years, but also by the ease of access to data (Sloan & Quan-Haase, 2017).

The use of crawlers for the different Application Programming Interface (APIs), is a joint of routines and standards set by software for the use of its functionality by apps that do not intend to get involved in the details of software implementation but just use their services, also have created a highly supportive context for this type of study

[1] Teacher and Researcher at Senac University

(Voulodimos et al., 2018). Several methodologies and approaches are applied to social media data such as monitoring, metrics and quantitative measurement with the application of descriptive statistics; content analysis; data mining, sentiment analysis; text analysis; netnography; network analysis; geospatial analysis among others (d'Andrea & Mintz, 2019). User-generated visual media such as shared images and videos on Facebook, Instagram, YouTube, and Flickr open fascinating opportunities to study digital visual culture (Burrell, 2016). Since 2012, Lev Manovich's research lab (Software Studies Initiative, softwarestudies.com) has been using computational and data visualization methods to analyze large numbers of photos of these social media on the Internet by introducing new visualization techniques that can show tens of thousands of individual images sorted by their metadata or visuals extracted by algorithms (Manovich, 2018). In recent years, computational vision has attracted a great deal of research and development and, as a result, significant scientific and technological advances have been made in the inspection, classification and evaluation of social media data and their application in business intelligence (Voulodimos et al., 2018).

According to Manovich (2015) in short, these concepts form the "mind" of the data society - the particular ways of finding, understanding, and acting on the digital world, until the 21st century, we typically compare small numbers of artifacts, and used our human cognitive abilities without the support of machines, and it was considered to be sufficient,

"Anyone who wants to understand how our society "thinks with data" needs to understand these concepts. They are used in tens of thousands of quantitative studies of social media cultural patterns by computer scientists in recent years. In general, these concepts underlie data mining, predictive analytics and machine learning, and their many industry apps." (Manovich, 2015, p. 7).

If we intend to compare tens of thousands or millions of artifacts from user-generated social media content today, there is no choice but to use computational methods. In other words: "seeing" visual social media requires the use of computers and data science (Manovich, 2016). Computational vision is an interdisciplinary scientific field that deals with how computers can be made to gain a high-level understanding from digital images or videos. From an engineering standpoint, it seeks to automate tasks that the human visual system can do (Lemley, Bazrafkan & Corcoran, 2017).

The computational vision is concerned with the automatic extraction, analysis and understanding of useful information from a single image or sequence of images. It involves the development of a theoretical and algorithmic basis to achieve automatic visual comprehension (Burrell, 2016). As a scientific discipline, computational vision is concerned with the theory behind artificial systems that extract information from images. Image data can take many forms, such as video sequences, multi-camera views, or multidimensional data from a scanner. As a technological discipline, computer vision seeks to apply its theories and models to the construction of computer vision systems (Chatzilari et al., 2011).

Computational vision analysis has been adopted as a disruptive technology that will reshape business intelligence, which is a domain that relies on data analysis to gain business insights for better decision making (Hosseini, Xiao & Poovendran , 2017). There are several cloud APIs for computational vision available in the market, the main ones being: Google Cloud Vision, Microsoft Azure, Amazon Rekognition, Clarifai, IBM Watson Visual Insights, CloudSight, Sighthound, Face Plus Plus and Kairos.

In this article, we evaluate the Google Vision API to understand which solutions can be used for current or future social media projects. Compared to other APIs, Google Vision is one of the most complete computational vision tools. Google uses these algorithms and applies them to their machine learning processes to improve them (Mancosu and Bobba, 2019). The following is an example of Google Vision image extraction:

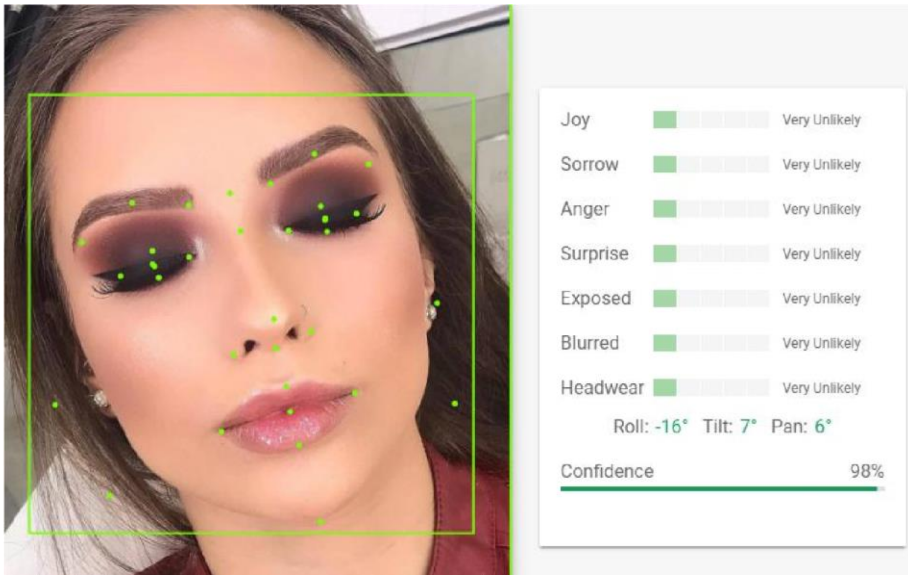

Figure 1: Instagram Beauty hashtag image extraction in the Google Vision API

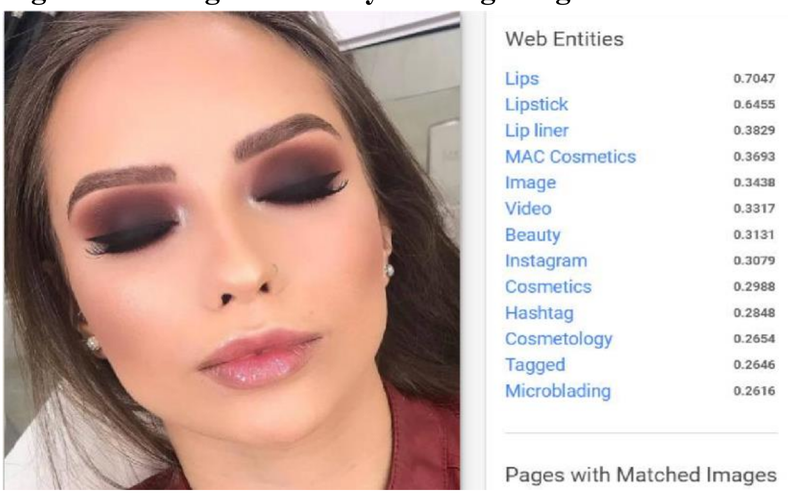

Figure 1: Instagram Beauty hashtag image label analysis in the Google Vision API

These affluent and newly available sources of information often enable the organizations, academic professionals and researchers to identify new gaps or unexplored areas in understanding consumer behavior and its dynamics in the digital environment, particularly in social media (Manovich, 2018).

2. Research objectives

This research aims to study the computational vision technology for the evaluation in the beauty segment discussing in detail the latest advances in the processing and analysis of images in social media.

This study is of enormous relevance to companies, professionals and academic researchers as it discusses new technologies for recognizing objects and extracting quantitative information from digital images in order to provide an objective, assertive, ethical and strategic quality assessment with critical, comprehensive and readily accessible on business intelligence, state of the art and the science of computational vision technology.

3. Background

The computational vision driven by new technologies is reshaping markets and managing marketing activities primarily within social media (Manovich, 2018). However, this data remains largely untapped or unexplored by many companies, suggesting the potential for new research developments. Wide competition requires more efficient ways to address user engagement - after all, users form the core of the business model. Thus, the aim of this study is to promote knowledge about the ways in which computational vision is currently used in social media and how it can be used as a strategic support for business intelligence marketing in the beauty segment (Chaffey & Ellis-Chadwick, 2019).

On the basis of the international market, the Brazilian Association of the Personal Hygiene, Perfumery and Cosmetics Industry – *ABIHPEC* (*Associação Brasileira da Indústria de Higiene Pessoal, Perfumaria e Cosméticos*), as representative of the Brazilian Personal Hygiene, Perfumery and Cosmetics - *HPPC (Higiene Pessoal, Perfumaria e Cosméticos)* industry, in its annual publication that presents an evolutionary history of the HPPC sector of regularized companies in the National Health Surveillance Agency - *ANVISA (Agência Nacional de Vigilância Sanitária).*

In 2018 Brazil came in 4th (fourth) place with revenues of US$ 30bi representing 6,2% of the world consumer market, in the first three positions are: United States (US$ 89.5bi / 18,3%), China (US$ 62.0bi / 12,7%), Japan (US$ 37.5bi / 7,7%) respectively.

This industry overview justifies the attention to research for its expressive representativeness. In this scenario we start from the following research question:

How can computational vision technology combined with business intelligence influence the marketing communication efficiency of the beauty segment?

This research minister as a valid and innovative approach to the academic investigation of consumer behavior and the understanding of consumer culture on social media.

4. Methodological Procedures

This research is characterized as a mixed method of exploratory and descriptive disposition, addressing the computational vision, analysis of social networks, social media and business intelligence combined. According to Recuero (2018), the growth of research that focuses on the analysis of social media networks first occurs by the prominence of the object, whose adoption and impact have grown in recent years, but also by the ease of access to data. Creswell & Creswell (2017) define mixed methods as a procedure for collecting, analyzing and combining quantitative and qualitative techniques in the same research project. The literature suggests two main arguments to justify the importance of integration, either data or techniques: (1) confirmation and (2) complementarity.

Converged and parallel mixed methods are research projects where data are collected qualitatively and quantitatively generally at the same time and converge or are mixed in the analysis. The goal is the complementarity of data for analysis (Creswell & Creswell, 2017). For the research the application of the visual computing resource platform called Google Cloud Vision was chosen for convenience. Cloud Vision offers pre-trained templates through an API or the ability to create custom templates using AutoML Vision (machine learning service type), which helps build custom image recognition templates (Manovich, 2018).

The Cloud Vision API encapsulates advanced machine learning models into a REST API, which enables developers to understand image content. This API quickly classifies images into thousands of categories (for example, “makeup”), detects individual objects and faces, and extracts printed words contained in images (Voulodimos et al., 2018). Also creates metadata in image catalog, moderates offensive content, or enables new marketing scenarios using image sentiment analysis (Kim & Kim, 2018).

The combination of this technology with similar image search makes it possible the outcome of similar images on the web, as shown in the following figure:

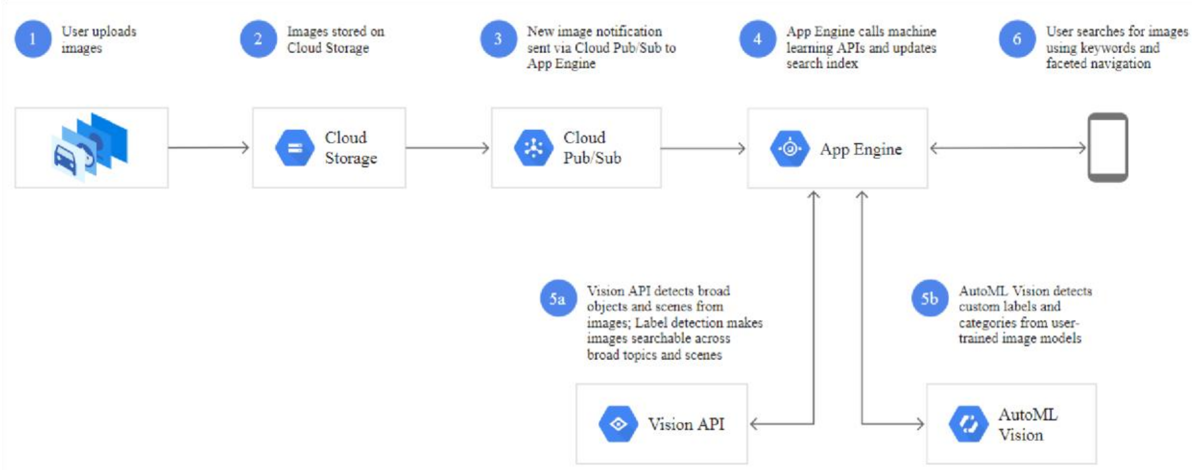

Figure 3: Vision API and AutoML Vision to make images searchable across a wide range of custom topics, scenes, and even categories.

Considering these questions and assumptions, the Netlytic tool will be used to collect images posted with hashtags in the beauty segment on social media, resulting in information and metrics for evaluating processed images (Manovich, 2016). Later, with the resulting data in the spreadsheet it is possible to evaluate the proximity of the markers in the photos allowing to find groupings of entities and themes in the analyzed images (Bosch, Revilla and Paura, 2018). Gephi tool will be used to compile and visualize network analysis with the main hashtag themes and their node distribution with Gephi's Force Atlas 2 algorithm, the visualization provides the significantly images, allowing to discover the thematic groupings in an intuitive way. (Khokhar, 2015).

5. Data collect

Data collection will be performed via Netvizz app which extracts data from different sections of the Instagram platform (Facebook-owned social photo and video sharing service) for research purposes. File outputs can be easily parsed in standard software and later parsed in the program Gephi, Khokar (2015).

The focus of the research is the cosmetics segment, analyzing the hashtag beauty (#beauty) extracted directly from the Instagram API for analysis, given its expressiveness of millions of posts on the social network. The images are collected with the Netlytic tool, leading to 13,174 images, later clearing the dataset, processed Memespector, a simple Python-coupled script to use the Google Vision API and applied according to Bosch, Revilla and Paura methodological procedures. (2018), as follows:

Figure 4: Images rendered in the Google Vision API of the hashtag beauty on Instagram

In the categorization process, semantic criteria will be performed based on the themes of the comments. With the help of Gephi platform we will analyze the grouping of the main hashtags around the posts, obtaining a grouping of the themes in Instagram evidences.

6. Data analysis

For this analysis we use ForceAtlas2, a force-driven layout: simulates a physical system to spatialize a network. In this separation (Figure 5) we see the beauty hashtag network on Instagram around indegree and plotted using the ForceAtlas2 algorithm (Scott, 2013), which is a force driven algorithm that promotes cluster approximation and its removal from each other according to the connections (where clusters act as a gravitational force).

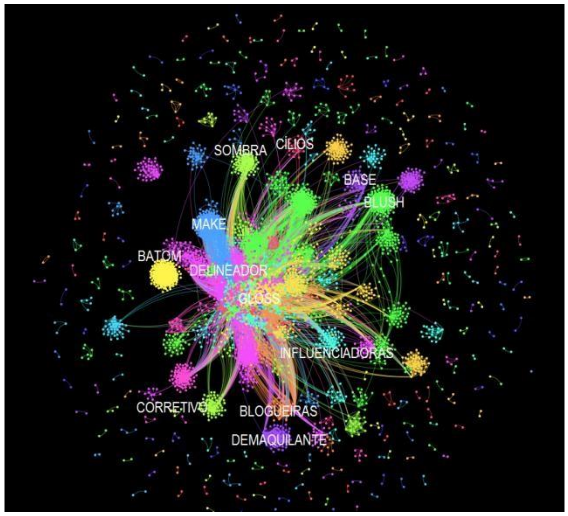

Figure 5 - Gephi Network Clusters with the main hashtag beauty separation

The graph is directed and contains 44,169 (nodes) and 141,872 (edges), 3,422 (average degree), 0,368 (modularity) totaling 11 clusters (Recuero, 2018), which the focus will be on analyzing the effects of computational vision and insights for the beauty segment. Meeting the purpose of this research, beauty-related content was detected in human face images by image processing and pattern-recognition artificial intelligence techniques through Google Cloud Vision (Kim & Kim, 2018). Among the insights it was detected facial changes caused by cosmetics such as eyeshadow, eyelashes, lipstick, liquid foundation, gloss, make-up remover, eyeliner, concealers, blush and tutorials of bloggers and influencers, main targets of this study. Possessing an adequate facial database based on beauty segment information becomes necessary because the facial makeup database was a valuable achievement for this research.

The facial database consists of 13,174 photos of individuals around a hashtag, which is a type of metadata tag used in social networks, allowing users to apply user-generated dynamic tags, enabling others to easily find messages with a specific theme or content. Selecting the best features that lead to the best rating result is a challenging issue, once any head variation, lighting conditions, and face orientation can be complex to properly assess whether or not if any makeup has been applied (Chaffey & Ellis- Chadwick, 2019). Most approaches to analyzing beauty are holistic or feature-based, and until then without a computational vision and machine learning it was difficult to realize a classification algorithm that matches human subjective ratings based on the number of face samples (Hosseini, Xiao & Poovendran, 2017).

The resource-based approach the size and location of the face elements are important. Shape, texture, symmetry and verification are some of the features that have been used in many studies (Fan and Gordon, 2014). In artificial intelligence and computational vision, it is important to design a machine to behave and decide how humans recognize and analyze visual concepts such as object recognition, text reading, geometric resource learning and beauty, and so on (Burrell, 2016). Recently, computer scientists are focusing on automatic makeup apps (Manovich, 2018). An appropriate database plays an essential role in machine learning classification or data mining. Extraction, training and testing is required at all stages of image processing (Voulodimos et al., 2018).

Validation of a technique for a specific problem also depends on the choice of database. Therefore, when comparing results obtained from different methods, the same database should be used. In digital makeup detection, this is the first step in this research due to there is no other database or result available for comparison (d'Andrea & Mintz, 2019). Although many published facial databases are for public use, none of them are specifically designed for makeup detection and related purposes (Varshovi, 2012).

In facial recognition many problems can affect face analysis. Lighting is one of the main problems. Face analysis, excessive brightness or darkness creates undesired patterns on the face. Accessories such as glasses or a hat partially cover the face, causing recognition problems to the face structure. Facial gesture and facial orientation are other problems in facial analysis (Varshovi, 2012). Over this study front faces with interior lighting conditions are used, but the main issue is poor orientation and improper color remains that need to be corrected (Tifentale, & Manovich, 2015). The necessity to have an algorithm to analyze beauty patterns was the motivation to conduct this research.

When it comes to social media, influencers have played a vital role in brand growth. The impact of makeup photos and videos has created a significant range of content across the beauty and related market (Denton, 2019). These types of immersive experiences promote a stratospheric number of makeup fans whether to learn new techniques or keep up with emerging brands (Wang et al., 2015). Consumers who are much more knowledgeable about social networking sites, such as Instagram, can determine what is working and compare them to several channels (Ackland, 2013).

Changing buying habits lead to one of the beauty industry's biggest challenges in anticipating consumer predictions, developing innovative technologies, trends through computer vision aligned with business intelligence and reshaping the beauty market (Ferrarra et al., 2015).

7. Conclusion

Further on the importance of defining beauty, today's modern world demands beauty in the digital world. Today's consumers betake to their social networks for everything from beauty tips and product recommendations to makeup tutorials and online shopping. When it comes to choosing which products to buy, flashy ads and samples no longer have the influence they once had. As social media reaches universal levels, it becomes a hive around cultural and social issues and is being inestimable in driving the changes. Social media offers users one of the biggest platforms for talking about topics they care about, and there is real pressure for brands to get in on the conversation. The impact that social media has on the beauty industry is significant. Brands can be more creative with their platform narratives and consumer touch points throughout the buying journey

References

Ackland, R. (2013). Web social science: Concepts, data and tools for social scientists in the digital age. Sage.

Bosch, O. J., Revilla, M., & Paura, E. (2018). Answering mobile surveys with images: an exploration using a computer vision API. Social Science Computer Review, 0894439318791515.

Burrell, J. (2016). How the machine „thinks": Understanding opacity in machine learning algorithms. Big Data & Society, 3(1), 2053951715622512.

Chatzilari, E., Nikolopoulos, S., Patras, I., & Kompatsiaris, I. (2011). Enhancing computer vision using the collective intelligence of social media. In New Directions in Web Data Management 1 (pp. 235-271). Springer, Berlin, Heidelberg.

Chaffey, D. e Ellis-Chadwick, F. (2019). Marketing digital. Pearson, Reino Unido.

Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications. d'Andrea, C., & Mintz, A. (2019). Studying the Live Cross-Platform Circulation of Images with Computer Vision API: An Experiment Based on a Sports Media Event. International Journal of Communication, 13, 21.

Denton, K. (2019). How social media uses the psychology of persuasion to influence the purchase of beauty products to the young generations (Doctoral dissertation, Southern New Hampshire University).

Ertekin, S., Muller, R., & Pryor, S. (2016). You are Beautiful! Promoting Beauty Products through Social Media in the United States, Germany and Brazil. 2016 SMA Proceedings, 209.

Fan, W., & Gordon, M. D. (2014). The power of social media analytics. Commun. Acm, 57(6), 74-81.

Fan, S., Lau, R. Y., & Zhao, J. L. (2015). Demystifying big data analytics for business intelligence through the lens of marketing mix. Big Data Research, 2(1), 28-32.

Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. Communications of the ACM, 59(7), 96-104.

Freeman, W., Perona, P., & Scholkopf, B. (2008). Guest Editorial: Machine Learning for Computer Vision. International Journal of Computer Vision, 77(1).

Freeman, L. C. (2017). Research methods in social network analysis. Routledge.

Hosseini, H., Xiao, B., & Poovendran, R. (2017, December). Google's Cloud Vision API Is Not Robust to Noise. In 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA) (pp. 101-105). IEEE.

Kim, Y., & Kim, J. H. (2018). Using computer vision techniques on Instagram to link users‟ personalities and genders to the features of their photos: An exploratory study. Information Processing & Management, 54(6), 1101-1114.

Khokhar, D. (2015). Gephi cookbook. Packt Publishing Ltd.

Kurnia, P. F. (2018). Business Intelligence Model to Analyze Social Media Information. Procedia Computer Science, 135, 514.

Lemley, J., Bazrafkan, S., & Corcoran, P. (2017). Deep Learning for Consumer Devices and Services: Pushing the limits for machine learning, artificial intelligence, and computer vision. IEEE Consumer Electronics Magazine, 6(2), 48-56.

Lu, Y., Wang, F., & Maciejewski, R. (2014). Business intelligence from social media: A study from the vast box office challenge. IEEE computer graphics and applications, 34(5), 58-69.

Mancosu, M., & Bobba, G. (2019). Using deep-learning algorithms to derive basic characteristics of social media users: The Brexit campaign as a case study. PloS one, 14(1), e0211013.

Manovich, L. (2015). Data science and digital art history. International Journal for Digital Art History, (1).

Manovich, L. (2016). Instagram and contemporary image. Manovich. net, New York.

Manovich, L. (2018). Digital Traces in Context| 100 Billion Data Rows per Second: Media Analytics in the Early 21st Century. International journal of communication, 12, 16.

Mintz, A. (2018). Image Networks: Automated Analysis of Visual Content. In Workshop realizado no# DigitalMedia Winter Institute, promovido pelo iNOVA Media Lab. Lisboa, Portugal.

Recuero, R. (2018). Estudando discursos em mídia social: uma proposta metodológica. ESTUDANDO CULTURA E COMUNICAÇÃO COM MÍDIAS SOCIAIS, 13.

Ruhi, U. (2014). Social Media Analytics as a business intelligence practice: current landscape & future prospects. Umar Ruhi (2014)," Social Media Analytics as a Business Intelligence Practice: Current Landscape & Future Prospects", Journal of Internet Social Networking & Virtual Communities, 2014.

Sebe, N., Cohen, I., Garg, A., & Huang, T. S. (2005). Machine learning in computer vision (Vol. 29). Springer Science & Business Media.

Sloan, L., & Quan-Haase, A. (Eds.). (2017). The SAGE handbook of social media research methods. Sage.

Tifentale, A., & Manovich, L. (2015). Selfiecity: Exploring photography and self-fashioning in social media. In Postdigital aesthetics (pp. 109-122). Palgrave Macmillan, London.

Varshovi, S. (2012). Facial makeup detection using HSV color space and texture analysis (Doctoral dissertation, Concordia University).

Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep learning for computer vision: A brief review. Computational intelligence and neuroscience, 2018.

Wang, J., Zhang, S., & Martin, R. R. (2015). New advances in visual computing for intelligent processing of visual media and augmented reality. Science China Technological Sciences, 58(12), 2210-2211.