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Examining visual impact: predicting popularity and assessing social media visual strategies for NGOs

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Abstract

Purpose: This research aims to analyze the role of visuals posted on the social media of NGOs and to predict the popularity of a post based on the characteristics of the visual it contains.

Design/methodology/approach: Two social media platforms, namely Facebook and Instagram, were selected as the empirical study environments. Specifically, all visuals posted on 12 child-related Non-Government Organizations during the period of 2020–2021 (4,144 in total) were collected and subsequently subjected to automatic characterization using visual recognition and artificial intelligence tools. Machine learning algorithms were then employed to predict the popularity of a post solely based on the visuals it contains, as well as to identify the most significant features that serve as predictors for post popularity.

Findings: The Support Vector Classifier performed best with a prediction accuracy of 0.62 on Facebook and 0.81 on Instagram. For the explanation of the model, we used feature importance metrics and found that features like the presence of people and the emotions of joy and calmness are important for the prediction.

Practical implications: Companies and organizations serve a large part of their communication strategy through social media. Given that every advertiser would like to use their funds in the most efficient way, the ability to predict the performance of a post would be a very important tool.

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Social implications: The methodology can be used in the non-profit sector, whereby knowing what visual will perform better they could promote their mission more effectively, increase public awareness, raise funds and reduce expenses on their communication strategy.

Originality/value: The novelty of this work regarding popularity prediction on social media lies in the fact that to make the prediction, it focused exclusively on the visual and its characteristics and achieved high accuracy scores in the case of Instagram. Additionally, it provided important information about visual characteristics and their importance in predicting popularity.

Keywords: social media; popularity prediction; machine learning; Non-Governmental Organizations; visual content analysis; social media engagement

1 Introduction

In recent years, there has been an explosion of data, with millions of posts being posted daily on social media. However, not all posts receive the same attention. Some garner many reactions, while others are ignored. This raises both curiosity and the need to predict the popularity of a post (Mazloom et al. 2018). Popularity is the measure of whether a person, idea, object, or place is liked and accepted by other people. Nowadays, digital content posted on various social media platforms has created a new measure of popularity. Specifically, user popularity is measured by the cumulative count of followers, friends, and diverse social interactions, encompassing likes, shares, retweets, and comments. This amalgamation reflects the extent to which individuals resonate with a user's content, forming a dynamic measure of their social influence and reach. In contrast, the popularity of multimedia content is gauged through a multifaceted lens, encompassing the frequency of views, likes, and the depth of engagement in the form of comments.

This comprehensive evaluation delves into both the quantitative and qualitative dimensions of user interaction, shedding light on the resonance and impact of the content. It is worth noting that distinct social media platforms employ varying metrics to ascertain the prevalence of content. Each platform employs a tailored amalgamation of metrics, such as Facebook's reactions, Instagram's heart symbols, and Twitter's retweets and favorites, among others. These distinct approaches underscore the nuanced nature of content engagement and its interpretation within the diverse landscape of social media. Visual popularity is influenced by several key factors. Visual appeal, emotional resonance, relevance, and uniqueness all play a crucial role in capturing viewers' attention and provoking their engagement. Additionally, visuals that effectively tell a story, incorporate humor, or leverage

influencer endorsement tend to garner higher interaction. Timing, platform-specific strategies, and incorporating a variety of visual formats also contribute to visual popularity (Deza and Parikh 2015).

1.1 The need to predict popularity

The popularity of a post is particularly important as it helps increase brand awareness and confirms the loyal relationship the page has developed with users. However, choosing the right content, among millions of potential posts, is a challenge. In other words, the content must be designed in a way that creates value for users and seeks a stronger level of engagement (Malthouse et al. 2013). Therefore, automating the above process, through data collection and pattern identification, is both an important facilitation (Gelli et al. 2018) and can contribute to the strategic decisions of organizations to manage their resources more efficiently (Zohourian et al. 2018).

At this point, it is worth mentioning that according to Facebook, the number of comments and likes a post receives determines its frequency of appearance in the user feed (Kim and Yang 2017). Consequently, the interaction with the post, in terms of likes, comments, and shares, determines the number of users likely to see it. Similarly, the frequency of its appearance influences the user's potential interaction with it. According to Lavidge and Steiner 1961 outcomes hierarchy model, the path to purchase includes three stages: knowledge, emotion, and action. Srinivasan et al. (2016) argued that a user clicks on an advertisement in the knowledge stage, perceives whether they like or dislike the product/service in the emotional stage, and make purchases in the action stage. According to previous studies, the knowledge stage is particularly important, because, through this stage, the user's first contact with the product takes place. In the case of social media, this stage is identified with posts. This means that the user, after seeing the post and its content, will decide whether to click on it to proceed to the next stages. Thus, if companies/organizations could predict the popularity of a post, they could control consumer engagement and disengagement in a faster and more cost-effective way. In a world where companies spend up to 30 % of their budget on online marketing, early identification of popular or unpopular content can maximize their revenue through better ad placement. Moreover, given the continuous growth of online consumers, content distribution networks can rely on popularity prediction methods to proactively allocate resources according to the demand of future users (Tatar et al. 2014).

1.2 The power of visuals

Previous research on social media popularity focuses mainly on the text of posts, not recognizing the importance of visual content. Comparing visual and textual popularity depends on the platform, the audience, and the nature of the content. Generally, visual content tends to grab attention quickly and can generate a lot of engagement in terms of likes, shares, and views. It's often more shareable, especially on platforms that prioritize visual elements. Textual content, on the other hand, might require more time and attention to consume, but it can provide more in-depth information and engage users who are looking for detailed insights or discussions. In many cases, a combination of both visual and textual elements can be the most effective approach, as it caters to a wider range of preferences and consumption habits among users. For example, a blog post with well-designed visuals or an infographic alongside informative text can have a strong impact. However, the visual is the main communication tool of the new generation. In fact, according to Facebook's 2021 data, visuals garnered the highest engagement rate compared to other types of posts (Beard 2021).

More specifically, visual holds a very important role in social media. The pictures posted daily are the key factors of users' engagement in emotional and behavioral activities (Stepaniuk 2015). According to the existing image advertising literature, the visual elements of a post can influence users' attitudes, preferences, and intentions. Using eye-tracking methodology, Pieters (2004) found that the visual element in print advertisements attracted readers' attention more than the text. Several studies of banner ads have even shown that intrusive ads are more effective because they grab the viewer's attention (Bruce et al. 2017). In line with these findings, we expect that the presence of a visual in a social media post helps the post stand out from many posts that include only text and, as a result, attract more attention.

The term "visual" has been applied to consumer psychology for many years. Finn, as early as 1985, sees visual as the collection of symbolic associations with a product. Another definition by Kosslyn et al. (1983) perceives visual "as a representation in the mind that generates the experience of "seeing" on the occasion of eye stimulation". Although this definition is limited to visuals, it also applies to other senses (Mandler 1984). Furthermore, according to the dual coding theory (Paivio 1986, 1991, 2004), visual cues take precedence over verbal ones. This theory assumes that people use two cognitive subsystems to process visuals and text and that visuals, in particular, can be processed by both subsystems, leading to higher communicative effectiveness (Edell et al. 1983).

It is worth noting that, especially in recent years, there has been a shift from text to visuals. This turn towards visual communication is mostly due to the rapid

increase in the popularity of smartphones and the improved experience they offer. Smartphones and social media have created a new generation of users whose main characteristic is the use of visuals. Any user can easily take a picture with their mobile phone and post it on social networks, either in the form of a post or story or forward it to a friend with a direct message. At the same time, in addition to the pictures that the user may have taken, other iconic elements are often used as a means of communication, such as gifs, memes, or stickers. It can therefore be noted that visuals are the primary means of communication and networking for the current generation. As Mirzoeff (1999) pointed out, the role of visuals is not just a part of everyday life, it is everyday life. The daily lives of individuals, their experiences, and emotions are now reflected through visuals on social media.

Therefore, the study of visuals and the development of visual methodologies is an essential, and currently under-examined step in enhancing the capacity of media analysis (Pearce et al. 2018). For this reason, a concerted effort in visual research was deemed necessary.

1.3 The use of social media by NGOs

NGOs are being challenged to strengthen and re-establish their identity as strong and recognizable brands. The sustainability of today's NGOs depends on their ability to publicly advocate an issue and to be seen by stakeholders as the vehicle for working on and resolving that issue. To achieve this, NGOs must reach their audience with two objectives. First, to communicate the values, ideas, and beliefs that give meaning and entity to the organization. Second, to ensure that stakeholders are aware and feel involved and committed to the organization.

Thus, NGOs can reach out to stakeholders to contribute to their cause, both through voluntary and financial involvement. However, for this to happen, they need to adopt a strategy through which long-term social objectives are promoted and internal cohesion is built. These objectives require communication, through which the NGO can attract public attention, to the issue it serves or interpret the problem by summarizing the diagnosis of the situation, risks, and possible solutions (Radu and Şele 2015). If an NGO fails in its communication strategy, the public trust may disappear, resulting not only in a loss of reputation but also in a reduction of financial support (Del Mar Gálvez-Rodríguez et al. 2019).

In the context of the NGO Communication Camp, trainers Radu and Şeler (2015) suggest that NGOs should use social media to promote their mission, raise public awareness of their cause, raise funds necessary for their operation and reach new members and supporters. In addition, through social media, they can create a community of people who support their actions and implement call-to-action

campaigns, where the user is invited to “click” to accomplish a specific action. It is worth noting that social media is a communication channel that organizations can leverage to enhance their communication strategy.

Although most NGOs have social media pages, not all have managed to ensure two-way engagement with stakeholder groups. Social media is a tool through which many stakeholders can be reached quickly and effectively. For this reason, organizations should include social media in their broader communication strategy with the aim of increasing supporters. This can be achieved through the right choice of posts and their features.

1.4 Visuals & popularity

In a communication process, content usually refers to a message that the sender sends to potential recipients. A way to further deconstruct a communication process was proposed by Lasswell (1948), who stated that the answers to the following questions represent the main characteristics of a communication act: (1) who, (2) says what, (3) through which channel, (4) to whom, (5) with what result. By investigating the content of a visual and its characteristics, we focus on the “what”, since the content is created by the sender before it is “sent” to the receivers (Schreiner et al. 2019).

Cappallo et al. (2015) showed how visual characteristics can help predict post popularity by exploring visual features that determine the popularity and extracting content from popular and unpopular visuals. McParlene et al. (2014), performed a classification of visuals based on content, context, user interface and hashtags to predict whether a visual will receive a high or low number of views and comments. They separated the visual features into low- and high-level features. Regarding low-level features, they studied color and texture. The correct distribution of colors in a visual, on one hand, attracts the viewer’s attention and, on the other hand, helps to identify and understand the objects in the visual. The texture on the other hand can define the homogeneity of the colors or tones of a visual. It can also be used to identify the most interesting objects or areas. In terms of high-level features, the quality and aesthetic appearance of a visual is important to its popularity. Based on the various photography techniques and aesthetic standards used by professional photographers, some aesthetic features were adopted to predict popularity.

The low- and high-level characteristics of a visual are developed below.

1.4.1 Low-level features

According to research conducted by Ibarra et al. (2017), regarding the role of low- and high-level features in users’ aesthetic preferences, high-level visual features play a

prominent role in predicting aesthetic preference but do not eliminate the predictive power of low-level visual features. Moreover, several of the effects of low-level visual features on aesthetic preference are mediated by high-level features, with elements of full and partial mediation. These results suggest that the role of low-level features in guiding aesthetic preference is complex, with some low-level visual features influencing aesthetic preference through high-level semantics. The contribution of these features, therefore, may be particularly important in predicting the popularity of a publication.

1.4.1.1 Colors

The perception of visual elements in marketing and advertising is of major importance. Shapes, forms, textures, colors, graphics, and logos play a very important role in attracting consumers. Focusing on colors, can attract the user's attention, convey specific messages, communicate information, evoke emotions, and stimulate our memory. More specifically, colors work through sensory and cognitive mechanisms (Zailskaitė-Jakštė et al. 2017). In the sensory mechanism, color helps to distinguish an object from its background or from a set of other similar objects. In the cognitive mechanism, color helps to associate the visual with a specific message (Ghaderi et al. 2015).

Furthermore, the right choice of colors can determine the attitude, emotions, reactions, and intentions of consumers, differentiating products. Particularly for similar products, visual features are an important factor in consumers' decision-making process, whose final decision is strongly influenced by the colors they include. Research by Lindgaard et al. (2006) showed that consumers' first impression of the product is formed in the first 50-thousandths of a second and about 62–90 % of the evaluation is based on colors.

Regarding the use of colors on corporate pages in social media, according to research by Fortin and Dholakia (2005), vibrant colors are more effective in improving consumers' attitude towards the brand and in increasing the popularity of the page posts, while according to Lv et al. (2017), colorful visuals can attract more visual attention. Moreover, it is worth pointing out that colors are directly related to the science of psychology. Colors can stimulate, arouse and evoke different emotions. Each color can lead to a different psychological reaction and can be associated with a specific ability. For example, orange indicates friendliness, while grey indicates professionalism (Zailskaitė-Jakštė et al. 2017).

1.4.1.2 Symmetry and contrast

Researchers have hypothesized that certain structural properties of visuals (e.g. simplicity, symmetry, or visual contrast) directly influence aesthetic responses (e.g. the aesthetic appreciation and judgment that a visual is beautiful) on the part of

consumers. Symmetry in social media, is defined as self-similarity within a visual. In general, symmetrical objects are usually preferred over non-symmetrical ones. The preference for symmetry is intrinsic and strong and applies to both realistic and abstract items. Symmetry can positively influence users' preference, pleasure, or liking (Bode et al. 2017). Moreover, in marketing, mirror symmetry in brand logos is related to consumer liking and interest. The above is also confirmed by the research of Kostyk and Huhmann (2021). Therefore, social media visuals with symmetry will evoke more liking than non-symmetrical visuals.

Another structural property of visuals is contrast. Visual contrast is the measure of the difference in brightness between the bright and dark areas of the visual. Contrast can apply to several elements of the visual. In general, contrast enables the distinction between an object in the foreground and the background of the visual. The ability to distinguish the object from the background reduces visual noise and contributes to visual clarity. Further, such contrast can be enhanced through differences in color or brightness between visual elements (Ahn et al. 2018).

1.4.2 High-level features

High-level features bear semantic information. Semiotics enables us to interpret the meaning of visuals. Barthes (1977) argued that all visuals consist of two levels of meaning or duality of messages: a symbolic message, which is the analogical meaning, and a conscious message, which is the way society communicates its beliefs about it in a code system. Co-signifying codes allow a visual to signify, in addition to its signifying reference, other additional implicit meanings that are forms of social knowledge or codes derived from social practices, knowledge of institutions, beliefs, and so on (Hall 1997). The “reading” or the process of decoding any visual is done by people in different ways often based on their identity and experiences, and there may be a “preferred” or “dominant” reading that is the purpose of the “author”. More generally, the contribution of visuals is particularly important in conveying meanings and engaging the reader emotionally.

1.4.2.1 Faces

Three hundred million visuals are posted every day on Facebook, while 46,740 visuals are posted every minute on Instagram. These numbers are particularly interesting, and identifying the mechanisms by which users engage with visual content is a challenging task. Understanding how visual content is associated with user engagement and the popularity of a post, could have a significant impact on the science of communication through social media and influence the design, production, and distribution of this content.

One of the most common contents of posted visuals is people. In fact, several studies have shown that human faces are the most powerful channels of non-verbal communication. The human brain can recognize faces within hours of birth, and by the age of two months, infants acquire the ability to differentiate specific visual features of the face and to process facial expressions. It is worth noting, that our brain has a specific area, the right spindle gyrus, which specializes in recognizing faces. This region is particularly important, not only because it enables us to distinguish between different faces, but also because it helps us to recognize emotions and expressions (Kanwisher et al. 1997).

In the field of advertising, research has shown that attractive faces are more effective as far as consumers are concerned. Research by Bakhshi et al. (2014), led to the conclusion that visuals containing faces are 38 % more likely to receive likes and 32 % more likely to receive comments. The number of faces, their age and gender do not affect the popularity of the post. According to research by Ding et al. (2019), features such as nice architecture, pretty faces, cute children and cute animals often lead to high popularity predictions. In contrast, low-quality visuals, with empty backgrounds, or with objects that are not easily distinguishable, lead to low popularity predictions.

Regarding the age of the depicted persons, according to a study by Polaino et al. (2018), who studied the visuals posted on NGO profiles on Instagram, 63.6 % were either babies or children and 9.2 % were young people or teenagers. The elderly paged for only 2.2 %, 23.7 % were middle-aged and the remaining 1.3 % were undetermined. Regarding the number of people depicted in the visuals, the “compassion arithmetic” strategy predominates, which states that the fewer the number of help recipients, the greater the intentions and willingness to help (Kogut et al. 2015). Västfjäll et al. (2014) indeed demonstrate that the intention to act starts to decrease when more than one person is depicted in a picture. Moreover, close-up and medium shots with an emphasis on the emotional expression of the faces seem to “engage” users to a greater extent. That is, close-ups help to reduce distance and create a sense of intimacy between the subjects and the viewers. Eye-level shots promote a neutral power relationship, while the direct gaze attempts to elicit an emotional engagement from potential supporters (Lipovsky 2016).

1.4.2.2 Emotions

Emotions play a prominent role in marketing. In particular, the emotional context of an advertisement has a significant impact on its popularity and evaluation. Through an experiment conducted by Bakalash and Riemer (2013), during which brain activity was recorded, it was found that memorization of an advertisement is positively related to induced emotional stimulation.

More specifically, posts often target users' emotions. Emotional posts, evoke stronger emotions and thus help to create stronger emotional ties between the brand and the recipients, while combining emotional posts with other communication strategies can significantly contribute to increasing the popularity of a post (Tafesse and Wien 2016). This is because, compared to posts with neutral emotional content, posts with emotional content are more likely to attract users' attention and trigger a reaction (like, comment or share). Moreover, it is worth noting that positive and negative emotions are related to persuasion. Therefore, it is argued that positive and negative emotions of a post are associated with its popularity (She et al. 2021). However, according to research by Klassen et al. (2018), positive emotion stimulation strategies and the use of an optimistic tone were associated with more interactions on Facebook and Instagram. Thus, users who experience positive emotions when viewing a social media post are much more likely to engage with that post than those who do not experience positive emotions.

1.4.2.3 The presence of the brand identity in the visual

Mazloom et al. (2016) attempted to identify the aspects of posts that determine their popularity. The proposed model was based on the hypothesis that posts containing the brand may be more popular, as they are often associated with the user's emotions and brand loyalty. More specifically, some social media pages seek to draw the user's attention to the brand's identity. For this reason, they include in their posts elements that link them to the brand. Brand resonance posts seek to differentiate and favorably position the core brand in the minds of consumers (Tafesse and Wien 2016). Posts in this category focus on visual and include elements of the brand's visual identity, such as its logo, slogan, and "character".

Further, van Riel and Fombrun 2007 describe a corporate visual as "the development of perceptions of the brand that are ingrained in the minds of observers". Changes in these perceptions can lead to changes in attitudes regarding purchasing behavior, loyalty, and competitiveness of users.

1.5 Relevant research

Most of the research to date on social media has focused on unimodal, text-focused approaches rather than multimodal approaches. A multimodal approach to communication practices is one that considers textual, aural, linguistic, and visual elements, each of which contributes to the production of meaning. Language is but one part of this multimodal set.

Each element, whether words, visuals, or sound, performs a specific communicative process and is interpreted differently within different cultural, historical,

and social contexts. It is worth mentioning that recognizing the potential impact of culture on the interpretation of visual characteristics and their implications for post popularity is of paramount importance. Cultural backgrounds shape individuals' perceptions, values, and preferences, which can significantly influence how visual elements within social media posts are understood and engaged with (Hall 1976). Visuals laden with symbolic meanings or cultural references may resonate differently across diverse audiences, impacting their likelihood of engagement (Kim and Markus 1999).

However, as mentioned above, most research on social media focuses mainly on text. Popularity research in the context of text-based content has witnessed extensive investigation, shedding light on the factors that drive engagement and virality. Notable studies by Bakshy et al. (2012) have explored the role of linguistic style, emotions, and topics in predicting the spread of textual information within online social networks. Their research highlights the intricate interplay between textual attributes and user interactions. Similarly, the work of Goel et al. (2016) has unveiled the social influence dynamics underlying the diffusion of textual content. These studies collectively emphasize the multifaceted nature of text-based popularity and provide insights into how linguistic cues can impact content virality. The visual, although presenting particular challenges in terms of its analysis, is an integral part of social networking platforms and therefore a very interesting object of study. Visual content on social media is an important part of daily activity on platforms such as Facebook and Twitter and the main part of Instagram activity.

Some scholars, recognizing the importance of visuals, have challenged linguistic dominance and emphasized the “visual intelligence” of images and their everyday meaning as central to meaning-making (Pearce et al. 2018). Begley (2017), for instance, argues that the importance of visuals is gradually increasing, taking as an example the growing prevalence of visuals in New York Times' front pages.

Further, research has shown that visuals influence attention, attitude, emotion, or purchase intention through their various features. In particular, it has been found that colorfulness in advertisements increases a viewer's attention (Finn 1988) and helps them to understand the meaning of the advertisement. Huma visuals contained in print advertisements also increase the effectiveness of the advertisements Li and Ding (2014). Visual quality has been shown to influence viewers' evaluation of products (Lv et al. 2017). Based on the above, it is considered that visual colorfulness, the presence of human faces and expressions, and visual quality are features that can influence the popularity of a social media post.

The above was confirmed by Li and Xie's (2019) research, which identified four features of visuals in Twitter posts – color, the presence of the human face and its emotional state, the source of the visual and its quality, and evaluated their contribution to user engagement. The results showed that visuals with more color

variations lead to a higher number of retweets. It was also found that the presence of a human face in the visual content increases user engagement. Surprisingly, visuals with happy faces are associated with a lower number of retweets than visuals containing other facial expressions. However, looking further into this finding, it was found that visuals with “happy” facial expressions are mostly selfies and contain only personal information that is not useful or relevant to readers. Furthermore, tweets containing screenshots received a significantly lower number of retweets than those with professionally taken photos. Finally, the findings showed that high-quality visuals can improve user engagement in social media posts.

A team of scientists from MIT’s Computer Science and Artificial Intelligence Lab, eBay Research Labs and DigitalGlobe, led by MIT PhD candidate Aditya Khosla (2014), created an algorithm that predicts how popular a visual will be on a scale of 1–10. Specifically, they collected data from 2.3 million visuals from Flickr and ultimately concluded that they could predict the popularity of a visual based on its content and social context. The algorithm examines many features, from colors and textures to the objects present in the visual, aiming to predict its popularity. To make the prediction, the data were randomly split into two, where one half was utilized as a training and the other half as a test data set. Performance was averaged over 10 random divisions to ensure consistency of results. In conclusion, it was observed that objects with semantic meaning, such as people, tend to contribute positively to the popularity of a visual. Also, visuals with low predicted popularity tend to be less “busy” and likely to lack interesting features and contain plain backgrounds with few to no significant objects in the foreground, compared to high popularity visuals. Moreover, it was noted that low-popularity visuals, which were predicted to be highly popular, tend to resemble highly popular visuals but may be unpopular due to various aspects of the user’s social network, such as the user’s total number of posts, the user’s contacts, the average number of views of visuals posted by the user, etc.

Cappallo et al. (2015) developed a model for predicting popularity on social media based only on visual content. Specifically, they proposed a latent ranking approach, which takes into page not only the distinctive visual features in popular posts but also those in unpopular ones low and high engagement popularity measurements as well. The results indicated that the level of engagement of a popularity measure has an impact on its popularity. Low popularity engagement metrics are more promising in both datasets than high popularity engagement metrics. Low-engagement measures are easier to predict than high-engagement measures, probably due to the wider context of a picture that plays a more significant role in recipient engagement for high-engagement metrics. While Zohourian et al. (2018) collected a dataset of visuals and videos from Instagram, to which they applied different regression and classification methods to predict the popularity of posts. Specifically, they divided the features into 5 categories, which included temporal features, shared features, text

features, video-only features, and visual features. In addition, as for the popularity index, the number of likes, comments, and views were taken into page. Based on the above, a method for predicting the popularity of a post was created using the regression model, achieving RMSE of 0.002. In addition, the decision tree model was used to make a prediction with an accuracy of 90.77 %.

The research by Purba et al. (2020) compared different regression techniques for predicting the user engagement rate of posts using a global dataset. Model features were extracted from hashtags, visual feature analysis, and user history. It was found that visual quality, posting time, and visual type greatly affect the accuracy of the prediction. In fact, the accuracy of the prediction reached up to 73.1 % using Support Vector Regression (SVR), which is higher than previous studies on a global dataset.

Lv et al. (2017) presented an approach that focused on studying multiple attributes, e.g., visual, user, and temporal, to predict the popularity of a visual using a Flickr dataset. For visual features, they extracted items such as color, texture, and shape, as well as high-level features. In addition, user and post features were taken into page. Regression models were used to predict popularity.

Abousaleh et al. (2021) developed a multimodal machine learning framework for predicting the popularity of visuals on social media. First, they analyzed and extracted different types of visual content features and social context information that significantly affect popularity. Then, they proposed a visual-social computational model based on convergent neural networks for visual popularity prediction and proceeded to train the model. Experimental results on the provided dataset showed the effectiveness of the proposed model in predicting visual popularity. Further experiments showed that the model achieved a remarkably superior prediction performance. Specifically, it outperformed the four traditional machine learning schemes with an MSE (Mean Absolute Error) of 0.73 and MSE (Mean Squared Error) of 0.97.

Finally, it is worth noting the research of Zohourian et al. (2018), who collected visual and video data from Instagram, which they processed to predict their popularity. They then proceeded to utilize the methods of regression and classification. Afterwards, they predicted the popularity score using regression methods and predicted the popularity category using classification methods. In addition, preprocessing methods were applied. By comparing the results obtained for the prediction of popularity score and classification of popularity category, it was concluded that the Local Polynomial Regression and Decision Tree algorithms outperformed the other methods tested.

2 Purpose

This study aims to answer the overarching question of what makes a visual popular on social media in the context of child-related Non-Governmental Organizations,

which visual characteristics contribute to predicting the popularity of a post, and to what extent. Some more specific questions are: Which colors are most important? Which emotions are most important? Is the presence of a smile important? Is the presence of faces important? Is the presence of a logo important? Is high contrast more important than low contrast? Is the inclusion of text important? Are high-level features more important than low-level features? To answer those research questions, the objective was to develop a machine learning model to predict the popularity of a post based on the features of the visual it contains.

3 Methodology

To achieve the research objective, a specific methodology was adopted, which was divided into four stages. In the first stage the data collection was carried out, in the second stage the features were extracted from the post visuals, in the third stage the required data cleaning and processing was implemented and finally the prediction models were developed.

3.1 Data collection

Researchers studying a social media phenomenon face at least three critical sampling decisions. First, they must choose a particular social networking channel as an empirical environment. In this study, the social platforms of Facebook and Instagram were chosen as empirical study environments due to their high popularity, despite the differences between Facebook and Instagram in terms of visual usage. Instagram places a stronger emphasis on visual content, with images taking a central role in conveying messages and engaging users. Facebook tends to incorporate a more balanced mix of visuals and textual content in its posts. Despite these disparities, our study intentionally chose to collect data from both platforms precisely because of these distinct characteristics. By examining both Instagram, where visuals are more pronounced, and Facebook, which integrates various content types, we aim to provide a comprehensive analysis of how different platforms leverage visuals for engagement. This approach allows us to capture a holistic view of visual popularity across diverse social media contexts.

The second critical point in the sampling process is how to create a working sample of NGO pages on the two channels. To extract the required data, a purposive sample of 12 pages was collected. Specifically, pages of international child-related NGOs (UNICEF, Make a Wish, Save the children, Terre des hommes, NSPCC, Children International, SOS Children's Villages, World of Children, Feed the Children, NYSPCC,

The Home Project, Innocence In Danger), were selected. These pages and the organizations to which they belong represent a wide variety of topics surrounding the issue of children and advocate for various children's rights. Such a diverse set of pages enhances our chances of discovering different types of posts and different characteristics of the visuals they contain. We employed a set of specific keywords, including terms such as "child welfare", "child education", "child healthcare", "child protection", "child abuse", and other pertinent topics, to identify NGO pages on both Facebook and Instagram. These keywords were carefully chosen to encompass a wide range of child-related nonprofit organizations. Choosing child-related NGOs as the focus of a study on predicting visual popularity and evaluating social media visual features offers compelling advantages. These NGOs often share emotionally resonant content that garners widespread engagement due to its heartwarming nature. Highlighting the positive impact on children's lives evokes empathy and prompts sharing, amplifying their message. Moreover, the universal appeal of children's causes transcends borders, ensuring diverse engagement. By analyzing the visual elements contributing to their social media success, these NGOs can optimize their strategies for greater outreach and support.

The third sampling decision concerns how many posts to analyze from each page. This decision, unlike other sampling decisions, must balance the need for generality with the time and effort of collecting data. In this case, a one-year period was chosen as the reference period.

Then, through the Crowdtangle platform, data on the posts of the above-mentioned visuals were collected. This data includes likes, comments, shares and user reactions to these posts. By selecting the links leading to these Facebook posts, which were also included in the file extracted from Crowdtangle, a manual download of 2,587 visuals was performed. The manual saving of the visuals was chosen, since a specific name was assigned to each of them, based on which, in the next step, the matching with the other features was carried out. Regarding Instagram, since the platform does not allow the downloading of visuals posted on it, 1,557 visuals were downloaded manually through the online tool IGDownloader.

3.2 Feature extraction

In the second stage, using automatic visual recognition and artificial intelligence tools and based on the existing literature, the characteristics of each visual were extracted, on the basis of which the prediction was carried out in the next stage. At this point, it is worth noting that the visuals of posts with multiple visuals were examined separately. The selection of the features to be extracted was carried out based on the existing literature. More specifically, the features were divided into

low-level and high-level features. As for the low-level features, the following aspects were identified: the primary color of the visual, the presence of contrast, whether it is a portrait, the inclusion of text, and whether the visual was taken indoors or outdoors. In terms of high-level features, the search was focused on faces, specifically whether the visual depicted one or more faces, whether a child was depicted, and whether a man or a woman was depicted. Additionally, the emotions of the individuals portrayed were identified, along with whether they were smiling. Finally, regarding the presence of the corporate identity, it was investigated whether the logo of the organisation was included in the visual. Regarding the tools, which were used to extract the above-mentioned features, these were mainly Amazon Rekognition, as well as various Python libraries. Amazon Rekognition, part of the Amazon AI platform, analyzes images, detecting objects, faces, and more. It uses machine learning and deep learning like other Amazon AI services. It's commonly used for item identification and facial emotion/ demographic analysis (Table 1).

Table 1: The image's features.

Features	Scale of measurement	Detection tools
<i>Low level features</i>		
Colors	For each dominant color 0: No, 1: Yes	ColorThief
Low contrast	0: No, 1: Yes	Skimage.exposure
High contrast	0: No, 1: Yes	Skimage.exposure
Text	0: No, 1: Yes	Amazon Rekognition Label detection
Indoor	0: No, 1: Yes	Amazon Rekognition Label detection
Outdoor	0: No, 1: Yes	Amazon Rekognition Label detection
<i>High level features</i>		
Faces:		
Are faces depicted?	0: No, 1: Yes	Amazon Rekognition Face detection
One or more (faces)?	0: 0 faces, 1: 1 face, 2: >1 faces	Amazon Rekognition Face detection
Is a child depicted?	0: No, 1: Yes	

Table 1: (continued)

Features	Scale of measurement	Detection tools
Sex	Man (0: No, 1: Yes) Female (0: No, 1: Yes)	Amazon Rekognition
		Face detection
		Amazon Rekognition
Is it close-up?	0: No, 1: Yes	Face detection
		Amazon Rekognition
		Label detection
Emotions:		
Smile	0: No, 1: Yes	Amazon Rekognition
Emotions	Emotion, e.g. Joy (0: No, 1: Yes)	Face detection
		Amazon Rekognition
Corporate identity: does the image include an element of the organization's corporate identity (e.g. logo)?	0: No, 1: Yes	Face detection
		Manually

3.3 Data cleaning & processing

During the process of cleaning and processing the data, the variables, which were decided not to be used in the prediction process, such as the date and time of posting, the caption, the comments, the name of the page, etc., were removed from the Facebook & Instagram datasets. Also, empty values were removed. Then, by checking the type of each variable, it was identified that some values were “object” or “boolean”. Since machine learning algorithms work most effectively with numeric data types, the necessary actions were taken to convert these values into numbers. As a result, all variables in the dataset, were assigned values of 0 & 1. In the next step, the outliers of the predictor variable “Total Interactions”, were removed. Specifically, in the Facebook dataset, this variable received the lowest value of 5 and the highest value of 5,750.308. It was therefore necessary to remove these outliers from the dataset, making a cut of 10 %.

3.4 Model development

In the final stage, the machine learning models were developed. The features (X values) used by the models were: the dominant color, low or high contrast, text,

indoor or outdoor, faces (number, sex, age, close-up), as well as their emotions and logo and the target variable was the “Total Interactions”, which includes total likes, shares & comments in Facebook’s case and total likes & comments in Instagram’s case and “Followers at Posting”, which refers to the total followers of the page at the time of posting. Moreover, the variable used for the classification task was “Total Interactions” per 1,000 followers. The number of followers holds a very important role in the interactions a post will receive. It was therefore considered useful to include it in the predictor variable. It is worth noting that to perform the prediction, the data was split into training and test, where 80 % was utilized as a training and 20 % as a test data set.

Regarding the classification, initially, the classification of the values was performed considering the median value of the target variable (y value). In particular, it was defined that the values above the median are characterized by high popularity, while values below the median are characterized by low popularity. In the second phase, a classification of the values was performed, taking into page the mean of the y values (mean). Again, it was defined that the values of y above the mean are characterized by high popularity, while the values below the mean are characterized by low popularity. However, in this case, a large imbalance was observed between the values with high and low popularity. For this reason, an attempt was made to balance the data in two ways. On the one hand, a random trimming of the low values was performed so that they were equal to the high ones and on the other hand, several data for the high values were generated so that they were equal to the low ones, by randomly copying some data.

The coefficient of determination R^2 , reflecting the linear correlation between observations and expected values was used to measure regression and for classification the classification accuracy metric was used, where the ratio of the total number of correct predictions to the total number of predictions is shown.

4 Findings

4.1 The prediction

Aiming to predict whether social media posts would achieve high or low popularity levels, we initially employed linear regression to forecast the number of reactions to these posts. However, this approach faltered due to the intricate and non-linear nature of the problem. As social media engagement is influenced by a complex interplay of factors, linear regression struggled to encapsulate these dynamics effectively (Table 2). Consequently, we reframed the problem as a classification task,

Table 2: Prediction results with regression – R^2 .

Model	Facebook (2,587 visuals)	Instagram (1,557 visuals)	Facebook & Insta (4,144 visuals)
Random Forest Regressor	–0.2041	–1.9005	–0.2406
Linear Regression	0.0276	0.1562	0.0129

considering models such as Logistic Regression, Random Forest, Ada Boost Classifier, and KNeighbors Classifier. Notably, the Support Vector Classifier (SVC) outperformed linear regression and other models, owing to its capability to handle intricate, non-linear decision boundaries and high-dimensional data. This transition to classification yielded markedly improved results, with the algorithm achieving a classification accuracy of 0.62 for Facebook and 0.81 for Instagram, underscoring its effectiveness in categorizing content by popularity. In both cases, the Support Vector Classifier emerged as the superior prediction model, echoing findings from the research of Purba et al. (2020) (Table 3). In general, it was observed that Facebook tends to score lower accuracy rates compared to Instagram. This is probably since Instagram primarily supports visual posting, unlike Facebook which allows textual posts and link sharing, which may facilitate visual-based prediction. Visuals, in other words, are a category of digital objects that have different capabilities on different platforms. In particular, the structures and cultures of each platform play a key role in facilitating or inhibiting the sharing of visuals between users and as a result can influence prediction (Pearce et al. 2018).

4.2 The importance of the features

Regarding the importance of features in prediction, on Facebook, the most important feature was the presence of people in the visual. This particular feature had been identified as particularly important in existing literature sources as well (Ding et al. 2019). In addition, the presence of a man and a woman in the visual, a smile, and the inclusion of text also appeared to be particularly important, supporting the existing literature (Ding et al. 2019; Klassen et al. 2018). The presence of a child (39 % of the visuals), the feeling of disgust, or low contrast did not contribute at all to this prediction, as shown in Table 4. The non-importance of the child in this study is contrary to existing literature, which states that the visual of a child can “engage” the viewer (Polaino et al. 2018). The logo, also seems to hold an important role in the prediction, as expected (Mazloom et al. 2016), with green, brown and blue appearing as the most

Table 3: Classification accuracy prediction results by Classification Models.

Model	Classification accuracy			
	Dataset	Facebook	Instagram	Facebook & Instagram
Random Forest Classifier	Original – mean	0.7288	0.7883	0.6519
	Balanced dataset – mean	0.6111	0.7876	0.5481
	Oversampling – mean	0.4861	0.5890	0.4496
	Original – median	0.606	0.625	0.5149
	Median (without outliers)	0.62	0.6642	0.5400
Random Forest Classifier – cross validation	Original – mean	0.7120	0.7340	0.6064
	Balanced dataset – mean	0.6087	0.7671	0.5578
	Oversampling – mean	0.4953	0.5082	0.5029
	Original – median	0.5552	0.5868	0.4554
	Median (without outliers)	0.5955	0.6242	0.4662
Ada Boost Classifier	Original – mean	0.76	0.76	0.6524
	Balanced dataset – mean	0.6203	0.7945	0.5760
	Oversampling – mean	0.4722	0.5342	0.4925
	Original – median	0.584	0.6677	0.5261
	Median (without outliers)	0.62	0.6970	0.5110
Ada Boost Classifier – cross validation	Original – mean	0.7555	0.7758	0.6425
	Balanced dataset – mean	0.5864	0.7733	0.6029
	Oversampling – mean	0.5176	0.5027	0.4987
	Original – median	0.5344	0.6631	0.4388
	Median (without outliers)	0.564	0.7214	0.4438
KNeighbors Classifier	Original – mean	0.68	0.7737	0.6602
	Balanced dataset – mean	0.5787	0.7191	0.5182
	Oversampling – mean	0.4814	0.5616	0.4561
	Original – median	0.576	0.5789	0.5199
	Median (without outliers)	0.58	0.6532	0.5110
KNeighbors Classifier – cross validation	Original – mean	0.6928	0.6923	0.4781
	Balanced dataset – mean	0.5427	0.6662	0.5210
	Oversampling – mean	0.5	0.4794	0.5055
	Original – median	0.5324	0.5296	0.4716
	Median (without outliers)	0.5417	0.5671	0.4723
Support Vector Classifier	Original – mean	0.76	0.8357	0.6781
	Balanced dataset – mean	0.6068	0.8150	0.5781
	Oversampling – mean	0.4675	0.4726	0.4946
	Original – median	0.56	0.6710	0.5385
	Median (without outliers)	0.6244	0.7116	0.5179
Support Vector Classifier – cross validation	Original – mean	0.7608	0.8014	0.6777
	Balanced dataset – mean	0.6203	0.7871	0.6041
	Oversampling – mean	0.5186	0.4985	0.5054
	Original – median	0.5304	0.6763	0.4226
	Median (χωρίς ακραίες τιμές)	0.568	0.7265	0.4414

Table 3: (continued)

Model	Classification accuracy			
	Dataset	Facebook	Instagram	Facebook & Instagram
Logistic Regression	Original – mean	0.7644	0.8394	0.6809
	Balanced dataset – mean	0.6157	0.8013	0.5867
	Oversampling – mean	0.4629	0.5041	0.4925
	Original – median	0.57	0.6677	0.5286
	Median (without outliers)	0.6177	0.7080	0.5082
Logistic Regression – cross validation	Original – mean	0.7564	0.7707	0.6406
	Balanced dataset – mean	0.5938	0.7870	0.6163
	Oversampling – mean	0.5130	0.5547	0.5017
	Original – median	0.5351	0.6664	0.4409
	Median (without outliers)	0.5653	0.7243	0.4452

The bold values are the best scores for the platform.

Table 4: The importance of features in Instagram posts – feature importance scores.

Features	Importance
PeopleNumber	0.17
Female	0.11
Male	0.11
Smile	0.09
close_up	0.04
LOGO	0.04
CALM	0.04
Child	0.03
HAPPY	0.03
Text	0.02

important colors. The literature even mentioned that popular visuals contain colors close to shades of black, grey, blue and brown (Zailskaitė-Jakštė et al. 2017). The emotions with the greatest importance seem to be those of sadness and calmness. Finally, contrast, either low or high, does not seem to contribute much to prediction, contrary to the results of the research of Bode et al. (2017) and Kostyk and Huhmann (2021).

Regarding the importance of features in prediction, in the case of Instagram, in which mean was set as a classification factor, the most important predictor was again that of the presence of people in the visual, followed, as in Facebook, by the

presence of a woman and a man. In addition, the smile was also prominent in this case, while the logo was among the five most important features, highlighting the importance of the presence of the corporate identity (Tafesse and Wien 2016). Regarding colors, blue seems to dominate, while grey did not help at all in the prediction, refuting the hypothesis developed in the theoretical part of the research, which was mentioned above (Zailskaitė-Jakštė et al. 2017). The dominant emotions are joy and anger. In particular, emotions have an influential role, as expected based on the literature (She et al. 2021). The presence of a child (44 % of the visuals) ranked higher than the case of Facebook, but without very high importance. Finally, the importance of the high contrast of the visual and the portrait is noteworthy.

The most popular visual on Facebook

The most popular visual on Instagram

Github files: <https://github.com/elinakout/PopularityPrediction>

5 Discussion

In conclusion, nowadays, companies and organizations serve a large part of their communication strategy through social media, posting daily posts related to their products and services and implementing paid advertising campaigns. Given that every advertiser would like to use their funds in the most efficient way, the ability to predict the performance of a post would be a very important tool. Most research has focused on predicting the popularity of posts based on text, while very few have delved into visuals. For this reason, this study emphasized the significance of the visual, which is the main communication tool in social media. Specifically, a prediction task was implemented based solely on the characteristics of visuals published by NGOs. The findings of this work may be particularly important for these organizations, whose budget resources for communication are very limited.

Regarding the limitations of the study, the findings might be limited in their applicability due to potential biases in the sample of NGOs and their social media posts. The results may not generalize well to all NGOs or social media platforms, as different organizations may have varying posting habits and audience demographics. Furthermore, the analysis of visual characteristics might overlook nuances in visual content, sentiment, or cultural context. Some visuals might carry complex meanings that are not captured by the chosen features, impacting the

accuracy of the prediction model. It is worth noting that the selection of variables for this research predominantly aligns with the WEIRD (Western, Educated, Industrialized, Rich, and Democratic) framework, which may introduce a cultural bias in the interpretation of visual characteristics. While the chosen variables have shown relevance within Western contexts, they might not be applicable across different societies and regions.

What is more, the novelty of this work regarding popularity prediction on social media lies in the fact that in order to make the prediction it focused exclusively on the visual and its characteristics and achieved high accuracy scores in the case of Instagram. Additionally, it provided important information about visual characteristics and their importance in predicting popularity. Moreover, it envisages contributing to the non-profit sector, by discovering the most important visual characteristics that can lead to high popularity for their social media posts. Therefore, NGOs can promote their mission more effectively, increase public awareness of their cause, raise funds necessary for their operations and save resources from their communication strategy. In future research, it is suggested that both visual and textual elements of the posts, along with a deeper analysis of visual characteristics and aesthetics, should be used to enhance prediction accuracy.

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Bionotes

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