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PAPER

Automatic Detection of Emotions and Mental Health Conditions from Social Networks in Panama: A Comparative Study of Large Language Models and Transformers

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ABSTRACT

Social media platforms such as X publish millions of emotionally charged comments every day. These posts can be classified into several categories, and automatic emotion recognition (AER) can be applied to identify the human emotions associated with them based on aspects such as text, speech, or facial expressions. From these emotions, we can detect mental health conditions, which represent a complex, multi-layered problem with negative impacts. The aim of this study is to perform an analysis of the emotions expressed via Panama's social networks by extracting a dataset from the X network and evaluating it using some existing lightweight Transformer models to detect mental health conditions that could then be referred to Panamanian hospitals. Methods: Natural language processing (NLP) has undergone major development thanks to the emergence of large language models (LLMs). These models are based on the Transformer, a powerful neural network architecture that has revolutionized the field of deep learning. We show that lightweight models generally outperform alternative approaches. This study demonstrates the potential for automatic emotion detection, with the aim of developing predictive models that can support authorities in decision-making processes.

KEYWORDS

emotions, automatic emotion recognition (AER), mental health, large language models (LLMs), natural language processing (NLP)

1 INTRODUCTION

Every day, social media platforms such as X (formerly Twitter), Facebook, and Instagram are used by the majority of Panamanians [1]. The amounts of content

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generated by the users of these social media platforms are growing rapidly, and the content itself is very valuable, since we can find a diverse range of opinions that can generate different emotions in those who read them. In the current era, in which digital transformation is playing an important role in society, organizations of all kinds are undergoing a digital revolution, as reflected in an exponential increase in the amounts of structured and unstructured data that are created. The ability to transform unstructured data into valuable information for decision-making is very important. This trend, combined with the rapid dissemination of online content, has turned users' online opinions into a very valuable asset [2].

X [3] is a microblogging and social networking service in which huge numbers of emotionally charged messages and opinions are exchanged between users every minute. Certain positive and negative emotions, such as happiness, anger, fear, and depression, are often strongly correlated and are often expressed on social networking sites such as X [4].

Emotions can be defined as "intense and transient mood alterations, pleasant or painful, accompanied by some somatic shock" [5]. They may also be related to mental health conditions. Mental health represents the emotional well-being of each person and includes psychological and social factors that directly affect how an individual feels, thinks, and acts [6]. If health institutions and hospitals can detect mental health conditions in their early stages, they can provide the necessary support, thus preventing more severe problems. Emotions can be classified into a few primary categories. This is a well-researched topic, and existing scales typically include six basic emotions derived from the research work of American psychologist Paul Ekman [7]: these are happiness, surprise, fear, disgust, anger, and sadness and are shared by all human beings. However, little attention has been paid in the literature to studies in the Spanish language. Automatic emotion recognition (AER) is a task in which human emotions are identified based on aspects such as text, speech, or facial expressions, and to achieve this, researchers are focusing on the ability to automatically detect human emotions through information and communication technologies [8].

Recent research in the area of natural language processing (NLP) [9] has yielded positive results in terms of innovative techniques and tools that can facilitate human-computer interaction. Models based on Transformers, such as the one presented in [10], have shown good performance when used for AER from social media platforms. Over the last several years, the field of NLP has undergone a major transformation thanks to the emergence of large language models (LLMs) [11], which are artificial intelligence (AI) systems that are used to model and process human language. These models have hundreds of millions or even billions of parameters and are pre-trained using a massive dataset. NLP problems that previously seemed impossible to address have been solved thanks to LLMs [12]. LLMs form the basis of widely used and popular chatbots such as ChatGPT and Google Bard [13], [14]. These models are based on the Transformer, a powerful neural network architecture that has revolutionized the field of deep learning. A transformer offers an innovative way of handling sequential data more effectively [15].

We were motivated to carry out this study by the growing numbers of people with mental health conditions who express their emotions through social networks and the need to be able to automatically identify these individuals and to provide them with the necessary support via mental health institutions [16].

The aim of this project was to develop an automatic model that could detect emotions and mental health conditions from social networking data in Panama. We extracted a dataset from the X network and evaluated it with some existing LLMs and light Transformers, with a view to being able to send this information to the appropriate mental health institutions.

2 MATERIALS AND METHODS

2.1 General description

The methodology proposed in this article was implemented as a case study, which took the following form. A literature review of state-of-the-art research was carried out in the context of Transformer models applied to AER [17]. We reviewed several related works in the context of emotions and worked on the extraction of a labeled dataset. We regularized the dataset and implemented some techniques for preprocessing of the data. The features were extracted, and existing models were applied, and the results from each model were evaluated. Figure 1 shows the proposed architecture, which is described in detail in the following sections.

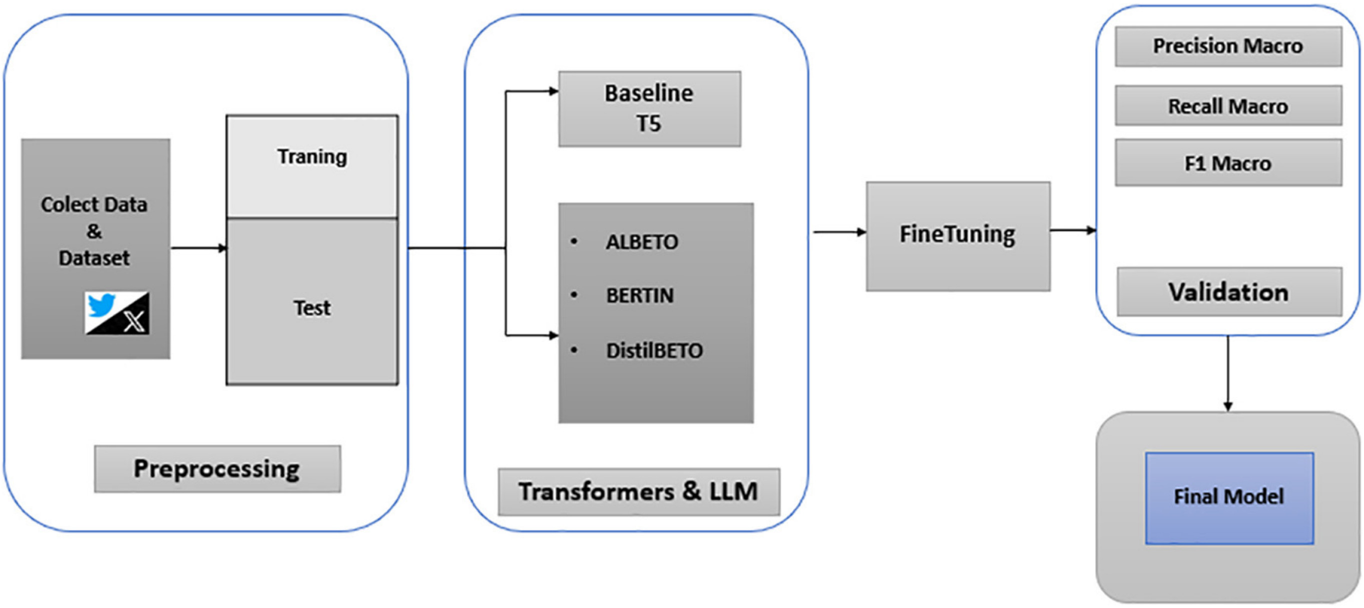

Fig. 1. Proposed architecture

2.2 Dataset

A dataset compiled from X was used as a basis for the study, and Ekman's taxonomy was applied to the keywords, which included positive and negative emotions [18]. Tweets posted between May and July 2024 were extracted using web scraping techniques [19].

2.3 Preprocessing

Each tweet was analyzed and evaluated, and various tasks were performed, including the elimination of unnecessary columns (such as name, handle, media URL, profile link, and date), leaving only those columns with which we were going to work. We also eliminated special characters, hyperlinks, identifiers, hashtags, links in the text, emoticons, leading blanks, blank spaces, tabs, and empty lines [20].

2.4 Annotation and labeling

The tweets were then manually labeled to determine their emotional classification, according to the Ekman scale. Five annotators participated in this manual analysis and applied pre-existing rules to annotate each tweet, taking into account that the annotator who classifies the tweet can understand the context of the tweet and can understand regional slang and current topics [21]. As a result, a new, annotated dataset compiled from X was obtained, containing 7,600 messages in Spanish, which was suitable for the task of AER. Table 1 shows some statistics for the extracted dataset.

Table 1. Statistical summary of the extracted dataset

No	Emotion/Affections	Quantity
1	Happiness	1,987
2	Surprise	1,760
3	Fear	991
4	Disgust	1,098
5	Anger	788
6	Sadness	976
Total		7,600

2.5 Training and test datasets

We used proportions of 80% of the data for training and 20% for testing [22].

2.6 Feature extraction

We applied the skip-gram method, one of a set of widely used vectorization techniques that includes word embedding. This approach takes into account the context of the text being analyzed, with each word considered in relation to the neighboring words, as this is an effective feature for AER [23].

2.7 Classifier selection

In this study, we employed Transformer-type architectures, since they have great precision and efficiency when applied to tasks related to NLP [24], [25]. The Transformer architecture has two main components, known as the encoder and decoder [26]. We used the Hugging Face tool [27] and Transformer models based on BERT (Bidirectional Encoder Representations from Transformers) [28], such as RoBERTa, ALBERT, and DistilBERT in Spanish, and applied a fine-tuning approach that involved taking a model that had been previously trained on a large amount of text data and adjusting it using our dataset once it had been labeled [29].

We used these models because they have been proven effective in classification tasks and because they can be adapted to specific tasks. In this case, we fine-tuned the model using data from tweets extracted from the X social network to improve their ability to identify users' emotions and mental health conditions. Some important characteristics of this technique are that it offers relatively good model accuracy and reduces the time and resources required compared to training a model from scratch [30], [31].

3 RESULTS

For the evaluation of our model, we used a baseline involving the T5 model (Text-to-Text Transfer Transformer) [30]. The T5 model uses the Transformer approach, and a unified framework for NLP tasks is introduced, as this allows each language problem to be converted into a text-to-text format. This model is also based on the concept of transfer learning, where a model is first pre-trained on a data-intensive task before being fine-tuned for a specific task. The architecture of the T5 model relies on self-attention mechanisms to process and generate text sequences.

The reference metrics used to compare the model performance were the precision (Equation 1), recall (Equation 2), and F1-score (Equation 3) (refer to Table 2). Furthermore, we use the accuracy (Equation 4); we chose these metrics because they enabled a balanced evaluation of the model performance across all classes, regardless of the sample distribution [31].

Table 2. Reference metrics

Precision = TP/(TP + FP)	**Equation** 1
Recall = TP/(TP + FN)	**Equation** 2
F1-score = 2 × Precision × Recall/Precision + Recall	**Equation** 3
Accuracy = TP + TN/TP + TN + FP + FN	**Equation** 4

Where True Positives (TP) are those assessments where the model and human experts agree for a label assignment, False Positives (FP) are those labels assigned by the model that do not agree with the expert assignment, False Negatives (FN) are those labels that the model failed to assign as they were given by the human expert, and True Negatives (TN) are those non-assigned labels that were also discarded by the expert [32].

The results for the baseline model (T5) and each of the Transformers used in the model are shown in Table 3. The best result was obtained with DistilBETO, which yielded much better performance than the rest of the LLMs and the baseline. It is also worth highlighting that only the lightweight models (ALBETO, BERTIN, and DistilBETO) outperformed the baseline, with the model based on T5 achieving lower performance.

Table 3. Results for the baseline (T5) and transformers

Model	Accuracy	Precision Macro	Recall Macro	F1 Macro
Baseline (T5)	75.457	52.445	58.554	56.447
ALBETO	78.423	62.334	67.453	66.652
BERTIN	70.566	61.349	70.452	65.982
DistilBETO	78.56	63.987	75.876	68.341

The results presented here leave us with several clear observations. (1) The Transformer model evaluated on the extracted, developed, and adjusted dataset demonstrated a better capacity for understanding and classifying the texts in the dataset, since it achieved better percentages than the T5 model that we took as a baseline; it also used fewer resources, thus making it more efficient. (2) The attention mechanisms of the Transformers used in the model enabled the capture and treatment of the most significant elements of the text thanks to the self-attention mechanism [33].

We also analyzed the errors or limitations observed in the model studied to better predict categorization in the dataset. Using the confusion matrix, we were able to gain a better idea of how our model is classifying, as it provided us with a count of correct and incorrect answers for each of the classes we classified. We were able to check whether our model was confusing classes and to what extent. We used the confusion matrix that evaluates those tweets misclassified by the best classification model (DistilBETO) for the dataset. The confusion matrix indicates, for each classified tweet, the distribution of predictions made by the classification model. The diagonal of the matrix contains the proportion of known instances correctly classified, while the off-diagonal elements indicate the proportion of instances that were misclassified. We then categorized the 7,600 tweets and divided them into two categories, separating them into positive and negative emotions. Figure 2, represents the confusion matrix of the best model for the dataset. Regarding the model, a proportion of negative instances are misclassified as positive. This may be primarily due to an underfitting problem, as there is little data in the training set. However, we can indicate that as the number of training data increases, the number of these errors decreases.

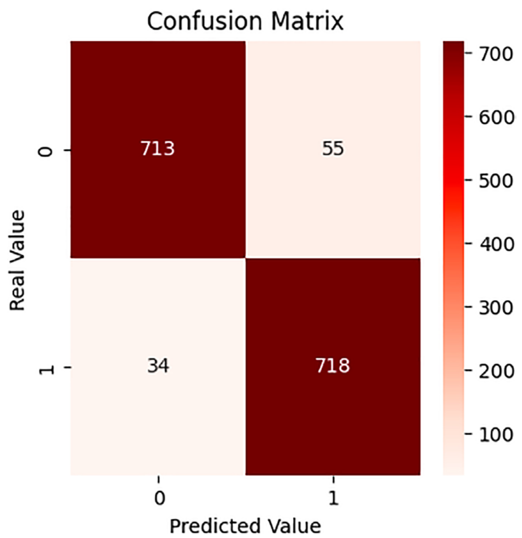

Fig. 2. Confusion matrix of the model evaluated with the extracted dataset

4 DISCUSSION

This study highlights the potential for the automatic detection of emotion and mental health conditions and was carried out with the aim of developing predictive models that could support authorities in their decision-making processes. In this article, we have presented a dataset extracted from the social networking platform X, which enabled the task of classifying emotions and mental health conditions to be performed for users in Panama. The dataset was evaluated, and good results were obtained using a baseline based on T5 architecture and some lightweight LLMs in Spanish. Fine-tuning these models made them much more effective, and better versions of the model were obtained with lightweight LLMs (ALBETO, DistilBETO, and BERTIN).

It is clear that there is still a great deal of work to be done. Our dataset is limited and could perform much better if it was complemented with more tweets, which represents an avenue for future work. In further studies, we aim to feed the dataset with more elements to evaluate and obtain better performance in the evaluations of the model.

5 CONCLUSIONS

Taken together, our results suggest that the incorporation of LLMs, NLP, and transformer approaches using advanced algorithms succeeds in facilitating a significant advance in language research and its application to the study of emotions within the social network X, promoting a more holistic framework that considers both linguistic structures and their interaction with social factors. The importance of these findings lies in their ability to provide a first comprehensive assessment of how new research directions can transform the field of language studies and its application to emotions. These results are particularly relevant for scholars and researchers seeking to expand the frontiers of psychological knowledge of emotions, as they provide a solid foundation for the integration of cultural and technological perspectives in linguistic research. In addition, this study provides valuable insights into the need for adopting software architectural approaches as innovative methods that can address the inherent complexities of human language. More work is needed to deepen the understanding of how cultural and contextual variations influence language use and evolution by holding hands with software tools. Although this study has provided a solid foundation, more research is needed to expand the understanding of language use and evolution. We present a dataset extracted from the social network X, on which we perform tasks such as classification of emotions and identification of mental health conditions among users in Panama. This dataset was evaluated with good results, with a baseline modeled on the T5 architecture and some light LLMs. Fine-tuning was performed on these models, resulting in much more effective networks than models using light LLMs (ALBETO, DistilBETO, and BERTIN), with values for the macro precision of 63.987%, macro recall of 75.876%, and macro F1 of 68.341%.

5.1 Limitations and future work

One limitation of this study is that we are still exploring multilingual and translingual models to find new research avenues that offer a deeper and more nuanced understanding of linguistic phenomena within social media. We must employ a methodological approach that integrates grounded theory and data analysis from social media. Furthermore, the proposed architecture still needs to be validated in other psychological contexts and with a larger number of users. However, the proposal is capable of accurately identifying and quantifying emotions within social network X. Future studies will focus on identifying emotional states and their levels using this same architecture or developing adaptations to the current one within the clinical psychological context. We will also make improvements to the architecture proposed in the article, considering aspects such as data extraction and cleaning models. In addition, we will focus on new studies on NLP, LLMs, and transformers. Thus, these topics provide us with new lines of research with a focus on the clinical psychological emotional states of social media users. Given the difficulties in data processing, architecture must implement improvements using high-performance computational models.

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