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Estimation of Emotional Valence toward Politicians using Physiological Signals. A pilot study.

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Abstract*—Emotional valence refers to the positive or negative quality of affective experience and plays a central role in shaping political perceptions, judgments, and participation. However, its objective measurement in political contexts remains underexplored. This article presents a pilot study to evaluate the feasibility of estimating emotional valence from physiological signals elicited by visual stimuli with political content. Physiological data were collected from participants during exposure to images of Colombian political figures. Photoplethysmography (PPG) and galvanic skin response (GSR) signals were recorded using a non-invasive wearable device (EmotiBit). Several machine learning classifiers were evaluated to classify emotional valence (negative, neutral, and positive). Due to class imbalance, the F1 score was used as the primary evaluation metric. The best-performing model was the decision tree-based Extra Trees classifier, achieving 72.73% accuracy and an F1 score of 71.2% in a 3-class classification task. The results show that physiological signals can be used to estimate emotional valence in political contexts, using portable, non-invasive wearable devices.

***Keywords*—Emotional valence, Physiological signals, Machine learning, Political emotions**

I. Introduction

Emotional valence refers to the hedonic quality of an emotion—positive, neutral, or negative—and determines whether an experience is perceived as pleasurable, indifferent, or unpleasant. This dimension systematically shapes fundamental cognitive and behavioral processes, including approach-avoidance tendencies, attentional allocation, and evaluative judgment, functioning as an affective foundation that guides how people interpret information and make decisions in complex environments.

From a psychophysiological perspective, emotions are accompanied by measurable bodily responses, which motivates the study of valence through physiological activity [1]. Classical research has established that emotion, memory, and bodily responses are closely interconnected, so physiological signals are a fundamental tool for understanding affective experience [1]. Emotional perception and representation are inherently multimodal, integrating various bodily signals, such as heart rate, body temperature, muscle electrical activity, galvanic skin response, and brain electrical activity [2].

Emotional valence assessment enables the identification and classification of emotional experiences, and research in this field has seen significant progress in recent years [3].

In politics, the study of emotional valence has received limited attention, despite its central role in shaping political attitudes and judgments. Political stimuli such as speeches, advertising campaigns, audiovisual material, and sociopolitical events not only transmit information but also elicit emotional responses that condition how people interpret, remember, and evaluate that content. These responses can regulate key cognitive processes that influence political decision-making and democratic participation. Several studies have found that specific affective states significantly shape political behavior; for example, negative-valence emotions such as anger have been observed to reinforce support for charismatic or populist leaders. Conversely, states such as fear or anxiety are associated with greater receptiveness to conservative ideological positions. Therefore, accurately measuring emotional responses can be very valuable for predicting political behavior [4].

Political science typically focuses on methods such as surveys and interviews to assess political opinions and attitudes. Although these methods provide an overview of public opinion, they rely on subjective, consciously self-assessed opinions, which may be susceptible to response biases. On the other hand, the analysis of physiological signals provides an objective measure of valence and opinion, enabling deeper analysis and a better understanding of people's emotional responses to political stimuli [5, 6]. It has been observed that during election cycles, declared voting intentions do not always coincide with the results at the polls. The reason is that the electorate can be volatile, and its decision-making is more closely linked to emotional impulses that methods such as surveys cannot capture [7].

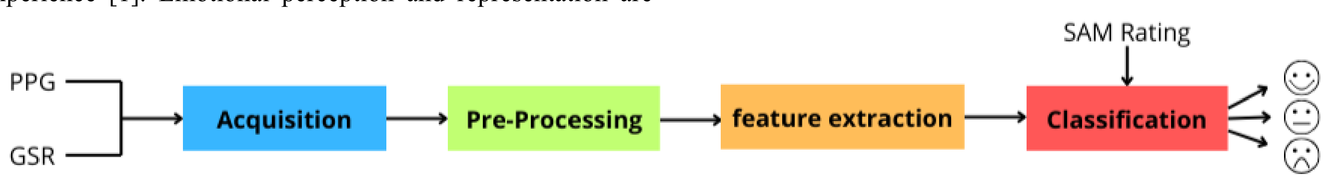

Fig. 1. Methodology

Within this framework, emotional valence acts as a driver of political preference. Several studies demonstrate that voters' affective orientations toward leaders are more stable predictors than party identification itself, which directly influences the probability of voting through mechanisms of enthusiasm or rejection [8].

The technology of physiological sensors has improved; many are compact, precise, and practical, facilitating the acquisition of these signals in diverse environments [9]. Furthermore, by applying machine learning techniques, the accuracy of affective state recognition, including valence, has been improved [10, 11].

From this perspective, we see that the study of valence can be supported by the identification of coordinated patterns of autonomous activity that emerge during emotional experience. These patterns can manifest as variations in cardiac dynamics (heart rate and PPG-derived heart rate variability), electrodermal activity (EDA/GSR), respiration, and peripheral temperature. These signals are modulated by the subject's contextual and cognitive-affective demands, allowing for an objective assessment of their emotional state [10].

Many studies using these signals have demonstrated that machine learning models can discriminate affective states from biosignals, although in many cases, performance is moderate due to the inherent complexity of physiological responses and interindividual variability. For example, studies comparing classification methods for valence and arousal have found that even with advanced classifiers and wearable sensor data, performance can vary widely, with moderate accuracy and F1 scores depending on the feature set and algorithm used [12]. Studies such as that by Carrasquilla Quintero (2021) used a database (DEAP) with various physiological signals (EEG, ECG, EMG, GSR, respiration) to recognize emotions, achieving a maximum accuracy of 79.46% in valence prediction using an SVM classifier [13]. Another example is Domínguez Jiménez et al. (2019), who tested the feasibility of using machine learning models to classify emotions from physiological signals such as photoplethysmography (PPG) and galvanic skin response (GSR). Their study included an analysis of valence and emotional activation, and their results showed significant accuracy in identifying different emotional states, such as joy, sadness, and neutral states [14].

Other studies that also use combinations of physiological signals reported accuracies of around 60% to 70% for valence classification, highlighting the challenges of inferring emotional valence from physiological measures [15]. Furthermore, systematic reviews on the classification of physiological signals, particularly cardiological ones such as ECG and PPG, have highlighted a wide variety of methodological approaches, although performance levels are generally moderate in the current literature. These results underscore the importance of investigating new signal processing techniques [16] and of incorporating multimodal approaches. Physiological response analysis (EDA/HRV) has begun to be used to study affective and cognitive reactions to complex content, such as disinformation, demonstrating the methodological transferability of these techniques to the study of sociopolitical phenomena [17, 18].

Despite these technological advances, there is a significant research gap in applying objective physiological measurement to the specific context of political leadership perception, particularly in Latin American contexts. This paper is a pilot study that proposes an approach to estimate emotional valence using PPG and GSR physiological signals in response to visual stimuli of Colombian political figures, using a portable device (EmotiBit, Connected Future Labs, USA) equipped with sensors that do not cause discomfort and are not invasive, and provide high-quality signal acquisition [19].

Previous studies have characterized the emotional intensity and activation levels elicited by political stimuli using similar physiological monitoring frameworks [20]. Building on these findings, the present work expands on this analysis by focusing on the classification of emotional valence, which is fundamental to understanding the nature of political responses.

II. Methodology

A block diagram of the methodology is shown in Fig. 1. Computational analysis was performed using Python 3.10, leveraging the PyCaret 3.0 library for machine learning (AutoML) and model optimization. Data manipulation and numerical operations were handled with Pandas 2.0 and NumPy 1.24. For advanced preprocessing and evaluation, scikit-learn 1.3.0 was used, specifically to implement StandardScaler and RobustScaler. To address the inherent class imbalance of the dataset, SMOTE (Synthetic Minority Over-sampling Technique) from the balanced-learn 0.11.0 library was applied. Statistical visualization and performance diagnostics were generated using Matplotlib 3.7 and Seaborn 0.12. Each step and process developed is detailed below.

The experimental protocol and procedures for acquiring the GSR and PPG signals were implemented using a previously validated methodology for analyzing political stimuli [20], ensuring consistency in the data collection process.

A. *Subjects*

Twenty participants (10 men and 10 women, all over 18 years of age) were recruited at the university. All participants are Colombian. None of them had emotional or psychological disorders, nor were they taking any medications that affect emotional or physiological responses. The study was approved by the institution's Ethics Committee, and all participants provided written informed consent before participating.

B. *Stimuli selection*

The IAPS database [21] was used to evoke different stimuli in the participants. These stimuli were neutral, pleasant, and unpleasant. These same images have already been validated in Colombia [22]. In addition, images of Colombian political figures were selected. In total, our dataset consisted of 12 cycles, each presenting a neutral, pleasant, unpleasant, control, and political image. A 5-second black screen was displayed between images to avoid abrupt transitions in affective responses. The images of the political figures were divided into three main ideologies, resulting in four images for each end of the political spectrum: left, right, and center. All images were standardized to 1024 × 768 pixels, expressed neutral emotions, lacked bright colors or distracting objects, and showed the politicians' faces fully visible.

C. Physiological Signal Acquisition

PPG and GSR were recorded using an EmotiBit device (Fig. 2) placed on the middle finger of each subject's hand. Event markers were automatically inserted at the beginning of the image for precise temporal alignment. PPG and GSR signals were selected because they are widely used in the field of emotion recognition [23] and are also easy to obtain and non-invasive.

Fig. 2. Emotibit device for signal acquisition.

D. Experimental procedure

Each session included: (1) sensor preparation and placement, (2) baseline test, (3) presentation of stimuli (10 seconds duration per image, with 5-second intervals between stimuli), (4) subjective evaluation of valence on a 5-point scale (1 = very negative, 5 = very positive) using a Self-Assessment Manikin (SAM), and (5) information session. Subjects sat 60 cm from a monitor in a temperature- and light-controlled room.

E. Signal Preprocessing

The acquired signals were synchronized with the markers and resampled at a unified sampling rate. PPG signals were filtered using a bandpass filter (0.5–8.0 Hz, 4th-order Butterworth) to detect systolic peaks. GSR signals were decomposed into tonic and phasic components using Empirical Mode Decomposition (EMD): phasic = sum of the first 3 IMFs, tonic = remaining IMFs. For each stimulus, data was extracted from 2 seconds before to 8 seconds after onset (10-second windows).

F. Feature Extraction

The feature extraction process resulted in a set of 22 physiological metrics derived from PPG and GSR signals (8 from PPG and 14 from GSR). As summarized in Table I, cardiovascular analysis focused on heart rate dynamics, variability, and pulse wave morphology, while electrodermal analysis captured both the slow-varying tonic levels and the rapid phasic responses to political stimuli.

Table 1. Physiological Features Extracted from PPG and EDA Signals.

Signal	Domain	Descriptors
PPG	Heart rate	Mean and standard deviation
PPG	HRV (time)	RMSSD, pNN50
PPG	Morphology	Mean amplitude, amplitude variability, range, rise slope
EDA	Tonic	Mean, standard deviation, minimum, maximum, range, slope of SCL
EDA	Phasic	SCR count; mean, maximum, standard deviation of SCR amplitudes; summed absolute differences; energy
EDA	Frequency	Total power, mean frequency

G. Classification model

This study follows a structured methodology for multiclass classification of emotional states. The pipeline used in the implementation is shown in Fig. 3.

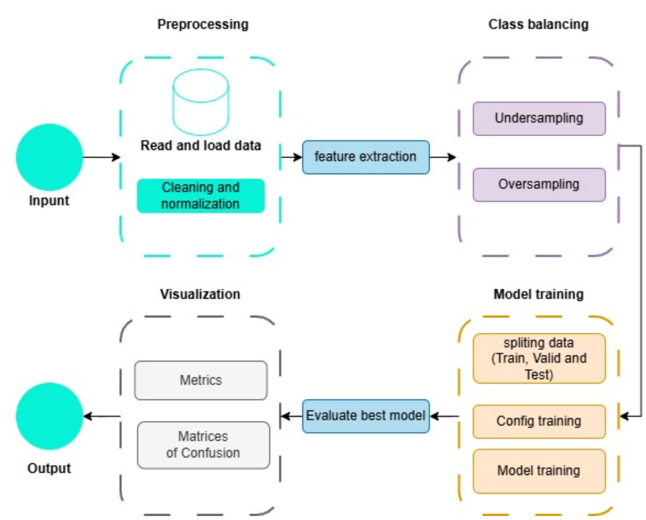

Fig. 3. System Pipeline.

The pipeline comprises several fundamental stages. First, data preprocessing is performed, including loading, cleaning, and normalization of physiological signals. Subsequently, feature engineering, class balancing, and model training are applied using automated machine learning.

To evaluate the model's performance, the metrics of accuracy, precision, recall, and F1-score from [24] were used, with F1-score as the primary metric. To assess the model's performance, the dataset was split into 80% for training and 20% for testing, while maintaining the class proportions.

1. Data Preprocessing

The initial dataset consisted of physiological signals from two sources: PPG and GSR, with a total of 22 base features extracted from these signals. The distribution of the target variable (sam_score) showed a significant imbalance across the five emotional classes, with the extreme classes (1 and 5) being the least represented.

Preprocessing included normalization of all numerical features using RobustScaler, a technique robust to outliers that centers and scales data using quartiles instead of mean and standard deviation.

2. Feature Engineering

From the 22 normalized base features, 10 derived features were created to capture interactions and non-linear relationships between physiological signals:

Cardiovascular features (PPG):

- ppg_amplitude_cv: Coefficient of variation of PPG amplitude, reflecting relative variability of blood flow.
- ppg_hr_cv: Coefficient of variation of heart rate, an indicator of cardiac stability.
- hrv_ppg_ratio: Ratio between heart rate variability (HRV-RMSSD) and mean heart rate, capturing normalized autonomic regulation.
- ppg_amplitude_normalized_range: Normalized range of PPG amplitude.
- ppg_hrv_hr_interaction: Interaction term between HRV and HR, capturing cardiovascular complexity.

Electrodermal activity features (GSR):

- gsr_tonic_cv: Coefficient of variation of the tonic component of GSR, reflecting variability of the baseline activation level.
- gsr_scr_rate: Electrodermal activity rate, combining the frequency and mean amplitude of skin conductance response (SCR) peaks.
- gsr_tonic_normalized_range: Normalized range of tonic GSR, an indicator of relative dispersion.
- gsr_phasic_per_tonic: Ratio of phasic energy to the tonic component, representing the balance between punctual emotional responses and baseline state.
- gsr_scr_density: Normalized density of SCR peaks.

These features were calculated on normalized data, resulting in a final vector of 32 features per sample. Infinite values and NaNs generated during division were replaced with zeros to maintain dataset integrity.

3. *Class Balancing*

The experimental procedure initially generated a total of 240 raw observations of the 12 stimuli viewed by the 20 participants. Following an inspection of the quality of the physiological data, 15 samples were identified and excluded due to missing values caused by physiological signal artifacts and sensor noise during the feature extraction stage, to ensure data integrity, resulting in a final dataset of 225 valid observations. To address the class distribution imbalance in the training set, a hybrid two-stage strategy combining undersampling and synthetic oversampling was implemented. To prevent data leakage and ensure reliable performance estimates, this balancing strategy was applied only to the training set after the 80/20 split between training and test.

In the first stage, undersampling was applied to the majority class (class 3: Neutral), reducing its representation from 150 to 100 samples, which represented a 33.3% reduction. This technique prevented the model from developing excessive bias toward the dominant class while maintaining a reasonable size for the neutral class as a reference.

In the second stage, SMOTE (Synthetic Minority Over-sampling Technique) was applied conservatively to the minority classes. SMOTE generates synthetic samples by interpolating between nearby examples in the feature space, creating new data points that share similar characteristics with real samples without duplicating existing instances. This technique increased the representation of classes 1, 2, 4, and 5 to 50 samples each, while class 3 remained at 100 samples. As a result of this hybrid strategy, the final distribution of the balanced training set consisted of 300 samples in total.

4. Model Training

Training was performed using PyCaret, an automated machine learning library that enables systematic comparison of multiple algorithms. More than 15 different classification models were evaluated through 5-fold stratified cross-validation, sorting results by macro F1-score.

5. Model Evaluation

Model evaluation was performed in two stages:

5-class classification: The performance of the best model was evaluated on the original multiclass classification task (sam_score: 1-5), reporting accuracy, precision, recall, and macro F1-score, along with the confusion matrix and classification report per class.

Valence-grouped classification: this analysis was implemented by grouping the five classes into three valence categories: Negative (classes 1 and 2), Neutral (class 3), and Positive (classes 4 and 5). This grouping allows evaluation of the model's ability to discriminate general emotional polarity, a relevant task in affective monitoring applications. The same metrics were calculated and compared with the results from the 5-class classification.

III. Results and Discussion

To identify the best models for emotion classification, several machine learning algorithms were evaluated with cross-validation using Accuracy and F1 metrics. The best models for estimating emotional valence with five classes are listed in Figs. 4 and 5. The Extra Trees classifier achieved the best performance with an accuracy of 0.6970 and an F1-Score of 0.6503, followed by CatBoost and Random Forest.

The five best models were all tree-based and outperformed linear-based models. These results are consistent with the nature of physiological data, where the relationship between autonomic signals and emotional states is inherently nonlinear. Therefore, tree-based models can be effective at capturing nonlinear interactions between features—such as the coupling between heart rate and skin conductance—without assuming normality in the data. As highlighted by Cai et al., tree-based methods tend to outperform linear models in affective computing due to their ability to handle high-dimensional, noisy data, which is typical of autonomic responses [10]. Given the distribution of classes, the F1 score was considered a more robust metric than accuracy. Therefore, the results obtained suggest that the model achieves a reasonable balance between accuracy and sensitivity, especially after applying the SMOTE technique to address class imbalance.

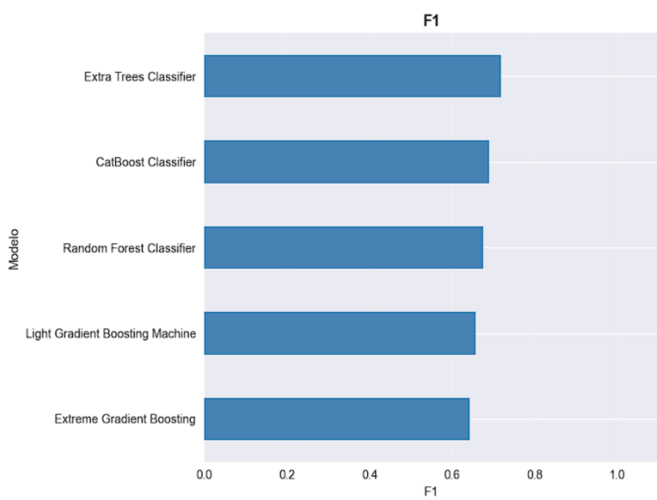

Fig. 4. F1 score by model

After identifying Extra Trees as the best-performing architecture through cross-validation, the model was retrained and tested with the task of classifying valence into three classes to verify its generalizability. For this evaluation, the accuracy and F1 score were 72.73% and 71.2%, respectively. Fig. 6 shows the confusion matrix obtained from this independent test set, where the 45 total samples (15 per class) provide a clear view of the model's performance. The model correctly classified 12 of the 15 stimuli with negative valence. The detection of positive and neutral stimuli showed a slightly higher error rate. This result confirms greater physiological consistency in responses to negative political stimuli, such as rejection or outrage, which tend to trigger more pronounced and uniform autonomic activations. Therefore, this greater accuracy for negative valency is a very relevant finding, since in the political context, rejection or aversion are stronger predictors than sympathy, so much so that some studies, as mentioned by Greys (2006), indicate that negative campaigns can increase electoral participation by providing a substantial load of information that helps voters to build distinctive images of the candidates and at the same time, generate affective responses [25].

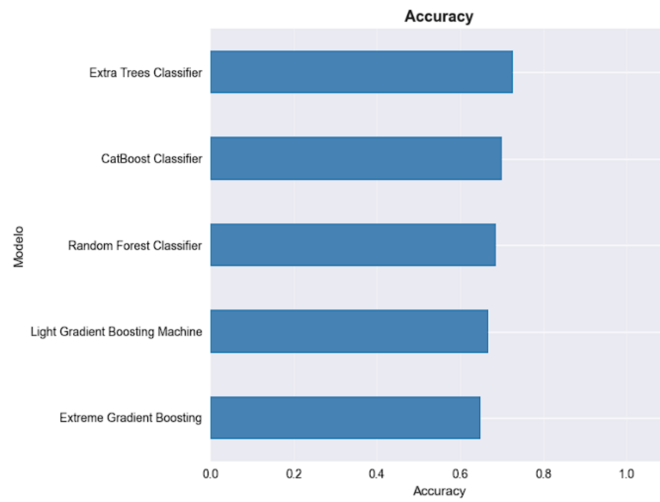

Fig. 5. Accuracy by model.

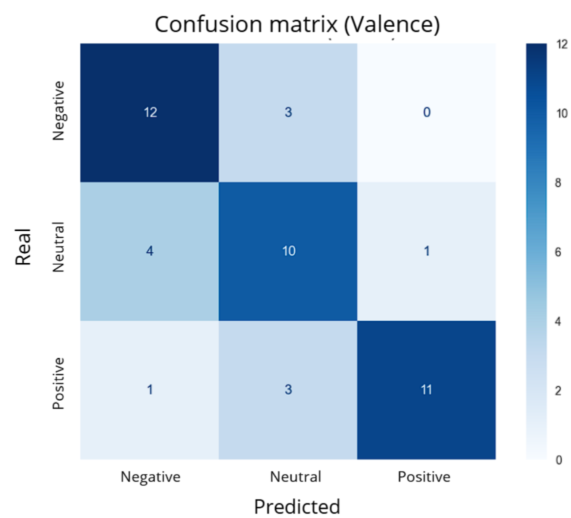

Fig. 6. Confusion matrix for valence classification performance.

The decision to simplify the classification from five to three classes (Positive, Neutral, and Negative) aimed to improve the model's stability and promote the practical applicability of the findings. In the field of political science, voter turnout is largely driven by existing political polarization:

the divide between rejection and acceptance. This phenomenon is quite evident in the current sociopolitical landscape of Latin American countries, where ideological polarization generally shapes voter behavior through antagonistic affective responses [26]. By focusing on these three core states and considering current voting behavior, the model achieves a more robust performance (F1 score of 71.2%), making it more reliable for real-world political sentiment analysis.

These results suggest that physiological signals such as PPG and GSR, when processed using optimized classification models, offer a viable source for assessing emotional valence in the political sphere. While differentiating positive valence remains a challenge, the high accuracy achieved in identifying negative responses is highly relevant in the context of political science, since these emotions are generally the main drivers of voter behavior and, in turn, help them define their ideological positioning. Furthermore, they pave the way for more in-depth studies using these biomedical signals, which can be acquired conveniently.

Another key aspect to highlight is that, although this study focuses on the political aspect, it is not limited to that area. There are several applications in which studies of a similar nature can be developed, since by changing the stimuli that the participants receive, a different analysis can be focused on. For example, it could be seen how certain specific content, such as advertisements, products, programs, people, etc., affects people's emotional state. Therefore, it can be considered a multidisciplinary study based on the proposed approach.

Despite the variability among subjects, mediated by ideological beliefs and personal experiences, the findings suggest that it is possible to classify physiological patterns related to emotional valence in a political context.

IV. Limitations and Future Work

This study has several limitations that should be considered when interpreting the findings, given that it is a pilot study. First, the sample size was limited to 20 participants, which limits the generalizability of the results to a broader population.

Second, we used three valence levels: Negative, Neutral, and Positive, which represent a discrete simplification of emotional valence, which is inherently continuous and multidimensional. By grouping the classes, the model achieved an accuracy and F1 scores of 72.73% and 71.2%, respectively. However, the transition between neutral and polarized states could not be studied. On the other hand, the exclusive use of visual stimuli with a political context could have generated diverse emotional reactions, whether influenced by cognitive factors or by individual sociopolitical factors of the subjects that were not fully controlled during this experimental phase.

Finally, the exclusive focus on physiological cues such as PPG and GSR may have also limited the ability to capture the purely cognitive and subjective components of emotion. Furthermore, a methodological challenge arises from using the SAM rating as the ground truth reference. While physiological cues aim to provide a more objective measure of emotion, the model was trained using subjective self-reports. This introduces a potential circular dependency and the possibility of bias in self-reports, where the SAM rating may not accurately match the physiological responses measured during the 10-second window of stimulus duration. Moreover, since the ratings are based on individual perception, no inter-rater reliability measure was applied. This suggests that implementing even more diverse multimodal approaches, such as incorporating additional cues or independent expert validation, could enrich the results in future studies.

For future work, the study will be expanded to a larger and more diverse group of subjects to reduce inter-individual variability, further improve the robustness of the model, and explore the use of consensus-based labeling or expert annotation to reduce reliance on a purely subjective reference. In addition, emotional arousal and dominance will be integrated with valence. This will allow for a much more detailed mapping of emotions in political contexts, such as distinguishing between "anger" (high arousal, negative valence) or "sadness" (low arousal, negative valence) responses to political content.

Regarding the technical framework, while the Extra Tree Classifier yielded satisfactory results, future research will explore more architectures of different types to see if any of them might be better able to capture the temporal dynamics and sequential patterns of physiological signals that are often lost in static feature extraction, as well as explore more physiological features.

The proposed approach presents a wide range of potential applications in various academic and applied contexts. In fields such as political psychology and behavioral science, recognizing and identifying emotions using physiological cues can provide complementary information about emotional reactions that cannot be fully captured through traditional surveys, interviews, or self-report instruments.

In the field of electoral studies, these methods could support the analysis of voters' emotional responses to political campaigns, advertisements, or media content, thereby providing more objective indicators of emotional valence and activation. This could be highly beneficial when analyzing and conducting political campaigns. It could contribute to a better understanding of the affective factors related to political preferences and decision-making processes, thereby enabling the development of proposals or campaigns that are highly beneficial to voters. Beyond the political context, the proposed methodology could be adapted to other areas that involve affective responses to visual stimuli, such as advertising, education, and human-computer interaction.

V. Conclusions

The findings of this pilot study showed that physiological signals, specifically PPG and GSR, can estimate the emotional valence induced by visual stimuli with Colombian political content, achieving 72.73% accuracy and an F1 score of 71.2%. A key technical contribution of this study is confirmation that ensemble tree-based models, in this case led by the Extra Tree Classifier, significantly outperform linear methods. This superiority can be explained by the inherently nonlinear and complex nature of autonomic physiological reactions, which cannot be adequately captured by simple linear decision boundaries.

While identifying positive valence proved somewhat more complex, the model demonstrated a consistent ability to recognize stimuli with negative valence, which is consistent with the prevalence of negative emotional responses in political situations, such as rejection or stress, commonly found in these contexts. The results obtained position this research as a promising exploratory study, which provides objective evidence on the capacity of physiological signals to perform emotional analysis in sociopolitical contexts, offering a methodological bridge between affective computing and political science.

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