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Emotion Analysis in Children's Drawings Using Machine Learning Techniques

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Abstract. Emotions are a set of chemical and neural responses that regulate the body to act in various situations. They can be triggered automatically and are fundamental to human life. From an early age, emotions play an important role in the personal development of human beings, as they impact emotional intelligence, social and relational development, mental health, decision-making, academic learning, and overall well-being. This work presents a proposal for the non-invasive detection of emotions in children through the analysis of their drawings, using machine learning techniques, manual feature extraction and deep learning methods. A methodology and a proposal are presented in this work, with all their stages listed in general, following the specifics of each stage. Finally, the conclusions and future work are described.

Keywords: Emotion recognition, children emotion recognition, pattern recognition.

1 Introduction

Emotions are psychological reactions in human beings that occur as a way of adaptation when they face different situations, places, people, objects, and more. These are important because they control impulses, express sentiments, manage feelings, behaviors, and more. Understanding emotions has become essential for the daily functioning of humans, as the acquisition of emotions and experiences is crucial for interpersonal communication in social environments. An emotion influences on the thoughts and interfere in decisions, actions, memories and perceptions [26]. Human emotions can be recognized through studies that analyzed facial expressions, tone of voice, posture, eye movements, appearance, and verbal cues. These analyses are conducted by individuals who understand human behavior, such as psychologists.

Currently, computational techniques allow us to recognize emotions through speech, text, facial images, and electroencephalograms. Facial expressions are the most significant factor for recognizing human emotions and act as a key element in understanding and perceiving the mental state of any individual, thereby guiding subsequent actions. This has become a key reason in numerous research works, where several hypotheses, experiments, and practical studies are still being carried out [15].

On the other hand, speech is a natural form of communication between humans. It provides information about thoughts, feelings, moods, and the context of the speaker's communication. The subtleties of emphasis, tone, phrasing, variations in speed and continuity of expression and the accompanying physical gestures convey something of the inner life of impulse and feeling [12].

Functional neuroimaging techniques such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), or positron emission tomography(PET) can be used. Although EEG has poor spatial resolution and requires many electrodes placed in various locations on the head, it provides excellent temporal information, allowing researchers to study phase changes in response to emotional stimuli. Additionally, EEG is non-invasive, fast, and cost-effective, making it the preferred method for studying brain responses to emotional stimuli [3].

Emotion recognition has potential in the healthcare sector as it can help physicians understand the emotional states of their patients, enabling the delivery of individualized and personalized medical services. Emotion recognition also has the ability to enhance intelligent customer service systems by detecting users' emotional needs and offering more personalized services. Furthermore, emotions have a substantial influence on human cognitive processes, including perception, attention, learning, memory, reasoning, and problem-solving. Emotion has a particularly strong impact on attention, especially modulating attentional selectivity and motivating action and behavior. This attentional and executive control is closely linked to learning processes, as intrinsically limited attentional capacities focus better on relevant information. Emotion also facilitates encoding and aids in the efficient retrieval of information [27], however, analyzing emotions is not the same for adults and infants, and the applications for both may differ. Nevertheless, the importance of understanding and/or analyzing emotions is equally significant at any age.

Analyzing emotions in children is crucial as it helps to recognize their emotional development and emotional intelligence, which can aid in regulating their emotions. Understanding emotions facilitates empathy and social skills, including interpersonal relationships and conflict resolution. Additionally, the ability to express and process emotions contributes to mental well-being, education, and learning. [13]. From the various approaches to identifying emotions, the interest in analyzing emotions in children arises.

Child abuse and neglect are critical issues worldwide, resulting in harm to the child's health, development, and dignity. It can be classified into four categories: physical abuse, psychological abuse, sexual abuse, and neglect. The long-term effects include diminished abilities to trust, form intimate relationships, and engage in healthy behavior, as well as a range of ongoing mental and physical health issues. Additionally, the experience of abuse affects children's social cognition, particularly their ability to understand others [18].

Although disclosing child abuse can put an end to it, many survivors remain silent due to reasons such as fear and shame, difficulty in expressing their experience, or being silenced by the perpetrator or their supporters. Additionally, the impact of abusive experiences on the brain often results in dissociation and an inability to recall the traumatic events. These factors present significant challenges for investigators and practitioners in developing techniques to encourage victims to disclose their experiences [14].

The self-figure drawing, developed by Lev-Wiesel from the draw-a-person test, was designed to identify important drawing indicators in human figure drawings of individuals with traumatic experiences, as it can be used to assess specific psychological and emotional traits [14]. As Duque [8] states, drawing is considered a fundamental tool for emotional expression in childhood. The act of drawing provides the opportunity to make thoughts and emotions tangible. Through lines, colors, and shapes, feelings and internal states can be expressed creatively and visually. When children draw, they are capturing their emotions on paper in a unique and personal way. In this way, adults can use such drawings to try to better understand children's thoughts, while the children feel more understood and validated.

This work presents a proposal to recognize emotions through family drawings, which currently are used by educators, psychologists, and individuals studying human behavior, often involving a questionnaire to create an individual report. Children drawing analysis via machine learning algorithms is proposed with the aim of serving as a tool for parents and professionals working in the field of emotions. This procedure is non-invasive and could complement current child examinations.

The document is divided into the following sections: first, a background of useful terms for understanding is presented; second, the related works are presented; third, research method to develop the proposal is shown; fourth, the proposal to solve the problem is described; finally, the conclusions are provided.

2 Background

2.1 Emotions

Emotions are a set of chemical and neural responses, as well as physiological reactions that adapt or adjust the organism to face a specific phenomenon. They are useful for survival and arise automatically and spontaneously due to internal or external stimuli, and they can be modulated to some extent voluntarily or through external stimuli [25]. The brain is primarily responsible for processing basic emotions, mainly the limbic system and the prefrontal cortex, and it consists of five factors: motor expression, cognitive components, neurophysiological, motivational, and subjective experience [27].

In recent years, a growing number of studies have attempted to investigate the structure of affect. Most of these studies agree that affective experience has two dominant dimensions, namely, positive affect (PA) and negative affect (NA). In Bradburn's pioneering work, PA and NA have been described as two independent unipolar dimensions of affect, encompassing all affective states with a positive valence (joy, enthusiasm, love, etc.) or a negative valence (anger, fear, anxiety, etc.). The two dimensions of affect (PA and NA) have been crucial in the conceptual differentiation between depressive and anxiety disorders. Furthermore, PA and NA have also been strongly associated with the personality dimensions of Extraversion and Neuroticism, respectively [7]. Therefore, the analysis and recognition of emotions have commonly been studied by specialists such as psychologists, mostly analyzing the complete behavior of human beings, such as facial expressions, body language, tone of voice, among other things, using interviews or data collection instruments in a direct and personal manner where human experience plays a central role in the analysis.

2.2 Emotions Categories

The discrete emotions theory is based on six categories of basic emotions: sadness, happiness, fear, anger, disgust, and surprise. These innate and culturally independent emotions are experienced over a short period of time. Other emotions are derived from combinations of these basic ones. Most existing emotion recognition systems (ERS) focus on these basic emotional categories. However, these discrete categories of emotions are not capable of defining some of the complex emotional states observed in daily communication [2]. Each emotional category is characterized by unique internal experiences, external expressions, and physiological patterns. Basic emotions must possess the following attributes: (1) Emotions originate from innate instincts; (2) Various individuals manifest the same emotion in response to the same circumstances; (3) People tend to express basic emotions in a similar manner; (4) The physiological patterns of different individuals are consistent when experiencing basic emotions. Additionally, some studies incorporate the classification of data into distinct categories, such as positive (i.e., expressing a positive feeling), negative (i.e., indicating a negative feeling), or neutral (i.e., lacking affective impact) [9].

2.3 Techniques

Some methods for investigating emotions primarily focus on physiological aspects, offering quantifiable data on the body's response to emotional stimuli, such as EEG, fMRI, ECG, and skin conductance. The study of emotions can be conducted consciously, using subjective methods and instruments, or unconsciously, by using objective methods and instruments. Objective measures should be used if the goal is to assess the most unconscious level of an individual, which can be achieved by using psychophysiological measures such as electrodermal activity (EDA), heart rate (HR), or electroencephalography. These allow for the collection of physiological and biometric data, providing essential information about how a person feels, even if they are not consciously aware of it. However, they also present some drawbacks, primarily because they are intrusive and noisy [20].

In turn, subjective measures can be used if the goal is to evaluate the emotional experience from the individual's subjective point of view. This includes established user scales, such as the "Visual Analog Scale" (VAS) or the "Self-Assessment Manikin" (SAM), interviews, thinking aloud, and questionnaires (e.g., the "Check-All-That-Apply" procedure, the "Positive and Negative Affect Schedule", or the "State-Trait Anxiety Inventory"). These measures can be pictorial, like the SAM, which presents a representative drawing of the human figure for respondents to express their emotions.

In various areas of engineering with different applications, attempts have been made to analyze emotions. From a computational perspective, human-machine interaction requires understanding user emotions for specific tasks, such as adapting applications as needed. To achieve this, a series of steps are followed, such as acquiring data, preprocessing, analyzing, and applying. However, achieving this requires various sources, such as those mentioned below.

Facial expressions, behavior, voice, text, and physiological signals can all be used to identify human emotions. Although the effectiveness and objectivity of these methods are still under investigation, some studies suggest that physiological cues may provide more objective measures of emotional states in certain contexts than the other approaches. Emotion recognition (ER) involves studying human emotions and developing tools or systems that can track, analyze, understand, and respond to these emotions. A camera can record body postures, gestures, and facial expressions, while a microphone captures speech and sounds. Additionally, sensors are used to monitor physiological data such as heartbeat, skin temperature, blood pressure, pulse rates, and skin's galvanic resistance to detect emotional states. ER requires feature extraction, relevant pattern discovery, and data analysis [9].

2.4 Limitations

Some biases and stereotypes affect the accuracy of diagnoses, and often systems reflect more of the ideas of those who created them than a true classification of the characteristics of the people they aim to help. Cultural context can influence what is considered "healthy" or "pathological," which can lead to misdiagnoses in people from different cultures [11].

From one perspective, it should be easy to determine if someone is experiencing a particular emotion. However, Mauss suggests that measuring a person's emotional state is one of the most complex problems in affective science [21].

3 Related Work

This work presents a proposal to analyze emotions in children's drawings, and in this section, relevant works on machine learning and image-based approaches are discussed.

A master's thesis developed by Brinkman [6] presents a machine learning approach for emotion classification in abstract expressionist paintings. The research explores how abstract shapes, expressive colors, and textures in abstract expressionist paintings evoke emotions in human observers. The study aims to answer whether it is possible to predict people's emotional reactions when viewing these artworks. To this end, an emotion corpus was collected, including ratings on the dimensions of arousal, dominance, and valence, and image features from a set of paintings were analyzed. The machine learning algorithms used correctly classified emotions in the arousal dimension at 73.33%, while the accuracy was lower in the dominance 46.67% and valence 73.33% dimensions.

In 2017, Moetesum et al. developed a study to detect facial expressions in human figure drawings, focusing specifically on the face [22]. A computerized system was proposed to analyze hand-drawn facial images to extract expressions from the image. The subject draws a human face, which is then input into the system, where the image is binarized and segmented into different facial components. Features based on Local Binary Patterns (LBP), Gray Level Co-occurrence Matrices (GLCM), and Histograms of Oriented Gradients (HOG) computed from the facial components are used to train an SVM classifier to distinguish between four expression classes: 'happy,' 'sad,' 'angry,' and 'neutral.'

In 2022, an emotion recognition application was developed by Nasva et al. [4], based on artificial intelligence (AI) and called the Emotion Sensing Recognition App (ESRA) to help parents and teachers understand children's emotions by analyzing their drawings. A total of 102 drawings were collected from a local school in Doha and 521 drawings from Google and Instagram. The deep learning model was trained using the Fastai library and ResNet. The model classifies the drawings into positive or negative emotions, with an accuracy ranging from 55% to 79% in the four experiments.

A study developed in 2024 by Khan et al. [16] to analyze emotions specifically uses behavioral metrics such as drawing and handwriting to determine a person's emotional state, recognizing these actions as physical functions that integrate motor and cognitive processes. The study proposes an attention-based transformer model as an innovative approach to identify emotions from handwriting and drawing samples, thereby advancing the capabilities of ER into the domains of fine motor skills and artistic expression. The proposed method achieved cutting-edge results with 92.64% accuracy on the benchmark dataset known as EMOTHAW (Emotion Recognition via Handwriting and Drawing).

The art of drawing is a substantial conduit for delving into the rich complexities of human emotions, facilitating unique insights into non-verbal emotional expressions. In the work developed by Weng [28], it is mentioned that drawings function as a means to reveal emotional expressions. Moreover, obtaining family drawings presents a non-invasive instrument compared to other methods and represents a projective technique widely used by clinical and developmental psychologists to access a child's inner world [24].

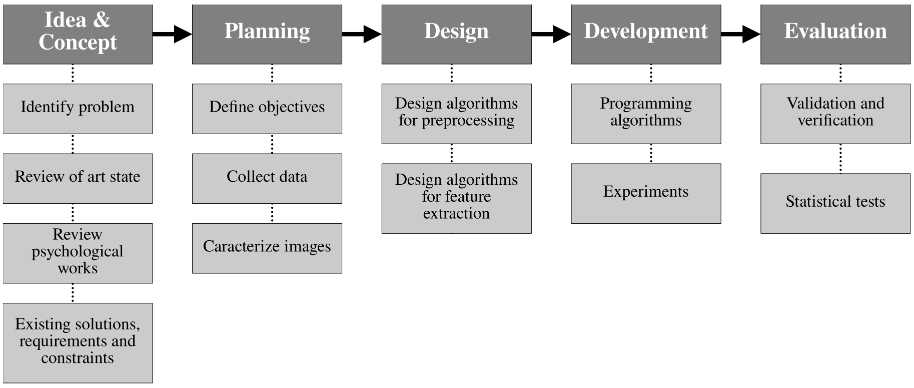

Fig. 1. Methodology of work for the development of research proposal.

As observed in the different studies, it currently presents a challenge due to the lack of information. However, the advancements made have shown that drawings can give us a perspective on emotions. Most studies attempt to evaluate basic emotions, some grouping them into positive or negative categories, or based on the dimension they represent. Among the studies found, most present approaches based on manual feature extraction, such as color, shape, texture, time, frequency, and statistics. Only Khan's work [16] presents a methodology implementing transformers, similar to what is intended for the proposed methodology, and they also use an available database (EMOTHAW) consisting of images and text that represent adult emotions. Generally, working with children's datasets is challenging due to data collection issues; despite being a useful method for detecting emotions through drawings, it may have certain limitations because drawing skills depend on gender and age.

4 Research Methodology

This section describes the steps shown in Fig. 1, where the research stages for the development of the proposal are presented.

Idea and Concept: In this stage, the problem is defined, and identified through interviews in schools about various issues, with a particular focus on the emotional state of children. This is difficult to identify because they do not express it concretely, and it is challenging to approach them without involving their parents. After identifying the problem, related works were reviewed, specifically on the automatic identification of emotions from drawings using machine learning techniques, as well as studies in the psychological field. Finally, existing solutions were reviewed, including their requirements, limitations, advantages, disadvantages, and how current methods address the problem from the proposed approach.

Planning: In this stage, the general and specific objectives are defined. The main objective is to recognize basic emotions in grayscale drawings using machine learning techniques, with two options presented. A dataset of children's drawings will be created with quick direct labeling by the children themselves; however, the drawings will also be analyzed by experts to ensure the reliability of the emotions in the drawings. Finally, some of the images will be characterized to design automatic description algorithms.

Design: Based on the proposed objective, there are two approaches to achieve it. The first is through emotion analysis using manual feature extraction methods, and the second option involves the implementation of deep learning methods, in particular via a transformer. To achieve this, an algorithm will be developed for the preprocessing of images, including enhancement and scaling. Subsequently, feature extraction techniques will be implemented.

Development: This stage involves programming the designed algorithms, as well as conducting various experiments, such as evaluating different classification algorithms, their parameters, and data partitions (i.e., all classes or the division of positive and negative emotions).

Evaluation: An evaluation will be conducted using training, test, and validation sets, as well as the implementation of cross-validation techniques, area under the curve (AUC), and confusion matrices. Statistical metrics such as accuracy, precision, F-score, and others will be obtained.

5 Proposal

Emotion recognition has garnered growing interest from researchers across various fields. Human emotions can be identified through facial expressions, speech, behavior (such as gestures and posture), or physiological signals. However, the first three methods can be unreliable because individuals may unintentionally or intentionally hide their true emotions, a phenomenon known as social masking [29].

Therefore the use of physiological signals have become more attractive because it offers a more objective and reliable approach to emotion recognition. Compared to peripheral neurophysiological signals, electroencephalogram (EEG) signals are more sensitive to changes in affective states and can respond in real-time, providing valuable insights into emotional states. As a result, numerous EEG-based emotion recognition techniques have been developed in recent years [29]. However, these types of methods are intrusive and uncomfortable for many people, and, the commercialization and development of applications for regular users are still limited.

Since the approaches described can either conceal a person's true emotions or rely on invasive devices with limited accessibility for the general population, the alternative of using drawings, where each child expresses their ideas, is explored. This makes it an attractive, non-invasive, and personal option. As mentioned, datasets [1, 19] have been developed that utilize drawings made by children, leading to various studies [5, 10, 17, 23]. However, the disadvantage of these datasets and studies is that the drawings are part of psychological tests

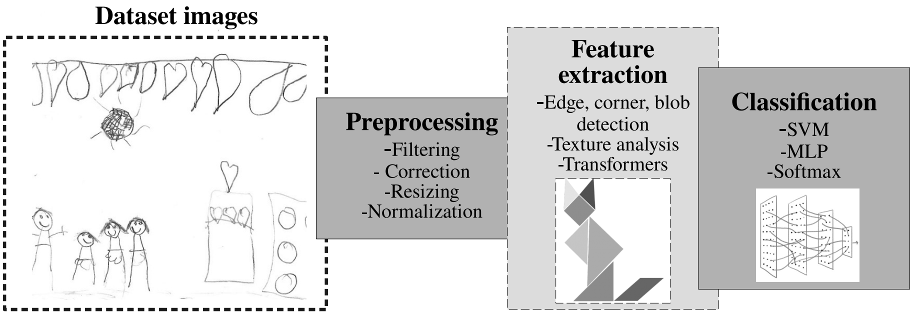

Fig. 2. Design of the proposal.

where the child is directed on what to draw, meaning that feelings and emotions are not allowed to be expressed naturally.

Taking into account all of this, the proposed approach for analyzing emotions in children based in drawings is depicted in Fig. 2. The first stage is data acquisition. At this point, the protocol for acquiring a new dataset will be established. The main difference between this dataset and existing ones is that the drawings will be requested freely and as part of a routine activity. Subsequently, with the expert knowledge of a mental health professional, the data will be labeled, and the emotions present will be identified. Doing it in this way ensures that the children are not directed, so unlike other studies, the data will be grouped later based on the identified emotions.

Since the drawings are going to be done on paper, not digitally, they need to be converted into a digital format. This process often results in an inherent loss of information. Additionally, it's common that the materials used by children to create the drawings to vary in their characteristics (color, graphite quality, etc.), so the graphical representations may not always have the same quality in terms of the information contained. For these reasons, a preprocessing stage is necessary, during which various filters and operations will be applied to maximize and standardize all the data in the dataset. These issues can be observed in the Fig. 3, which shows a couple of examples of the data captured in the ongoing work.

Feature extraction is the next stage and it can be categorized into shallow and deep features. Shallow features are hand-crafted and derived from various analysis domains, such as spatial-domain, time-domain or frequency-domain. Higher-dimensional features are often reduced using techniques like principal component analysis (PCA) or empirical cumulative distribution functions. Some studies [5, 17, 19, 23] that have utilized drawings have focused on features related to the stroke, analyzing it in terms of its temporal aspects, such as the time a stroke remains uniform or is sustained, as well as through ductus (ductus is the way how strokes are drawn including stroke order, direction and speed) analysis. These descriptors will be evaluated; however, it is also proposed to analyze the spatial domain of the data through shape or texture using statistical descriptors.

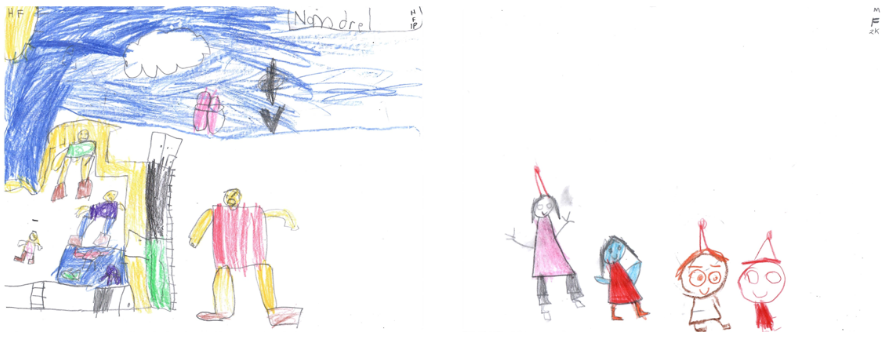

Fig. 3. Examples of acquired data and their characteristics.

To address the challenges of extracting effective and robust features, many researchers have turned to deep learning (DL) approaches. DL reduces the need for manually extracting features for machine learning models, as it can automatically learn a hierarchical feature representation [29]. This approach eliminates the need for data preprocessing and feature space reconstruction typically required in a standard machine learning pipeline. Feature extraction can be performed through convolutional neural networks or transformers, which is the second approach proposed for obtaining descriptors from the dataset.

After any type of feature extraction method, a classification stage will be carry out. Several machine learning methods will be employed, e. g. Support Vector Machine, Multilayer Perceptron or Random Forest. An optimization stage it must need in this part of the proposal in order to obtained the best results for every method. For evaluation, accuracy and precision metrics will be used, applying cross-validation and partitioning the dataset for training, testing, and validation.

6 Conclusions

Emotions are an inherent part of all humans that help regulate physical stimuli, express feelings, and communicate personal ideas and sensations. Emotions can be expressed in multiple ways, through physical reactions, texts, drawings, or neurologically. Recognizing them helps in understanding what a person is thinking at a specific moment. Unlike adults, children do not always have the confidence or vocabulary to express themselves, therefore, analyzing drawings developed by them could facilitate the analysis of their emotions.

Drawings are a pictorial tool for the manifestation of emotions that has been researched through theoretical approaches; however, their analysis and recognition through technological developments have not been explored in depth. Analyzing emotions through children's drawings is a useful and accessible alternative for understanding the emotional behavior of children. However, computationally it presents a significant challenge, as the development of sketches, lines, drawings, and other elements that a drawing may contain varies greatly among children due to their skills and ages, leading to marked differences between individuals when drawing elements or objects.

This proposal presented a methodology for analyzing drawings made by children in a non-invasive way using machine learning techniques. The first point emphasized is the importance of collecting a dataset validated by mental health experts. Additionally, the proposal aims to use drawings with colors and other types of scenarios that will represent an even greater challenge due to all the differences that images may present based on the subjects' personalities for the study, so a preprocessing stage it must be performed. The study of related works to define feature extraction methods and recognition methods is also fundamental. Finally, defining appropriate metrics for evaluation and comparing with related works are necessary steps to carry out.

Future work involves completing the data collection and labeling with the guidance of mental health experts. Subsequently, an analysis of the data needs to be conducted and the most appropriate preprocessing operations defined. Once this is done, methods and techniques for feature extraction can be defined and implemented. Finally, recognition methods should be implemented, experiments designed, and the results evaluated.

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