Machine Learning in Psychological Drawing Analysis: Shapes, Colors and Symmetry

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Abstract—Psychological analysis of drawings has long been a subject of interest in clinical and research settings, offering insights into an individual's personality, emotional state, and cognitive processes. Traditional methods rely on subjective interpretation, often leading to bias and inconsistency. This study presents a novel approach to psychological drawing analysis by integrating artificial intelligence and computer vision techniques. A Python-based application has been developed, utilizing machine learning algorithms for automated recognition of geometric shapes, color patterns, and symmetry within drawings. The system employs convolutional neural networks for shape detection and a structured color recognition model based on the RGB model. The extracted visual features are analyzed using a generative artificial intelligence model to infer psychological traits and emotional states. While the application does not replace clinical diagnosis, it offers a valuable complementary tool for therapists by providing objective and data-driven insights. The research was designed as a proof-of-concept study, aiming to demonstrate the technical feasibility and potential clinical relevance of AI-assisted drawing analysis. Future work will focus on expanding the dataset, applying statistical validation, and improving accuracy, interpretive depth, and accessibility via mobile and cloud platforms.

Keywords—artificial intelligence, color psychology, computer vision, convolutional neural network, deep learning, drawing analysis, emotion recognition, psychoanalysis, psychological analysis, shape recognition

I. Introduction

IN psychological research, people's drawings are not only a creative way of self-expression, but also provide deep insights into the characteristics, emotional state, and way of thinking of the individual. Drawings reflect both conscious and unconscious aspects, providing rich psychological information. For example, geometric shapes, colors, symmetry, and the harmony between them are all features that can indicate the emotional and mental state of the individual and thus help in psychological analysis.

The psychological analysis of drawings has become a priority over the decades, and various studies have shown that these tools can provide insights into the emotional state, self-image, and mental disorders of individuals. However, this type of analysis has traditionally been subjective and often based on the personal interpretation of the therapist. Advances in automated image processing technologies, computer vision, and artificial intelligence (AI) offer the possibility of more objective and faster analyses.

The application of AI-based algorithms can lead to significant improvements in the psychological analysis of drawings, allowing fast, reliable, and detailed information gathering.

This research aims to develop a computer application for the psychological analysis of drawings using various image processing techniques and artificial intelligence. The application is written in the Python programming language and uses advanced machine learning algorithms. The goal is for the application to be able to recognize geometric shapes and their location, dimensions, color, and symmetry in drawings.

All of them provide information about the psychological state of the individual. This research represents an initial proof-of-concept study demonstrating the technical feasibility and clinical potential of AI-assisted drawing analysis.

This paper is structured as follows. Section II presents the state of the art. Next, Section III details the development process and the application itself. Section IV contains a sample result, while Section V contains user feedback. Section VI shows current limitations and future perspectives. Lastly, conclusions are drawn in Section VII.

II. State of the Art

Machine learning is one of the most dynamically evolving fields, which can be divided into different types based on the

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different goals and data available, [1]. During supervised learning, the model receives labeled data to learn the relationship between input and output variables. It can then predict the output based on the new data. In contrast, unsupervised learning uses unlabeled data, and the model autonomously discovers structures in the data by clustering them.

Deep learning, [2] is inspired by the behavior of the human brain. It uses artificial neural networks to learn from large amounts of complex data and to recognize patterns. The key components of deep learning are the artificial neurons, which are simple computational units that receive input data, generate weighted sums, and then produce output values using activation functions. These neurons are arranged in layers to form artificial neural networks whose complexity and capabilities depend on the number of layers (i.e., the depth of the network). One of the biggest advantages of deep learning is its ability to learn complex patterns from large datasets without the need for manually designed features. Networks typically use backpropagation to minimize errors and refine weights for more accurate predictions.

Convolutional neural networks (CNNs) are one of the major model architectures for deep learning, with excellent performance, especially in processing visual data. CNNs are based on the operation of the human visual cortex, where neurons are sensitive to small, spatially distributed input patterns. The basic operation is convolution, whereby a small filter (kernel) consisting of numerical values runs through the input image and multiplies it pixel by pixel with the corresponding pixel. By summing the resulting values, a new pixel value is obtained. Filters are sensitive to different patterns such as edges, angles, or textures. During convolution, the filter is incremented on the image, so that at each position, a new activation map is created that represents a feature of the input image.

Unlike traditional two-step methods that first propose and then classify regions, the YOLO algorithm solves the object detection goal through a single neural network. This approach can result in significant speedups while providing competitive accuracy, [3].

The YOLO model processes the entire image at once, providing a context-aware view that helps to better distinguish objects from the background and reduces sensitivity to partial occlusions and unusual positions. YOLO is designed to represent objects in a more general way, so that the model can flexibly adapt to different datasets and generalize effectively to new, previously unseen objects. YOLO networks typically rely on convolutional neural networks to extract characteristics of the image.

The concept of Region of Interest (ROI), [4] has evolved in parallel with the development of image and signal processing. The application of ROI first became widespread in medical imaging, particularly in the investigation of tumors, malformations, and other pathological lesions. Limiting image analysis to key regions has long been a principle since the 1970s and 1980s. One of the earliest publications to discuss the importance of ROI was in the field of medical imaging and radiology. In the early work of [5], focusing computation on regions of interest optimizes performance and reduces noise, and the influence of noise can be minimized.

The development of psychology was already present in ancient philosophical thought, and by the end of the 19th century, with the establishment of Wilhelm Wundt's laboratory in Leipzig, it had become a discipline in its own, [6]. As discipline continued to develop, several dominant trends emerged: psychoanalysis (which built on Freud's theories and emphasized the role of the unconscious [7]), behaviorism (which studied observable behavior, [8], and cognitive psychology (which also allowed the study and modeling of mental processes using computer simulations, [9]). Humanistic psychology has focused on self-actualization and the unfolding of human potential, [10], while neuropsychology has investigated the relationship between the brain and behavior, using modern tools such as Magnetic Resonance Imaging (MRI) and Electroencephalography (EEG), [11].

In the 21st century, psychology and informatics have become increasingly linked, with artificial intelligence and digital testing platforms providing new perspectives in psychological diagnosis and predictive analysis of behavior, [12].

The psychology of drawing is an important way of expressing ourselves, giving people of all ages the opportunity to express their emotions and thoughts. Young children usually prefer to express themselves through drawing, as it is more comfortable for them than answering questions, as drawing gives them pleasure and is a way of communicating information, [13]. The analysis of children's drawings began in the 19th century, and three main lines of research have emerged. The first approach was that of Sigmund Freud, who tried to reveal personality traits through drawings. The second approach was to explore children's mental states along emotional scales and was based on the work of [14]. The third approach was to explore children's perspectives on global problems that might later affect their lives.

Koppitz's later research, [15] showed that children's choice of drawing as a tool and as a basis for drawing is not random. The shape of the pencil chosen and the size of the drawing board are all factors that may reveal the psychological state of the child. When drawing human figures, their shapes and features – such as the head, eyes, arms, and hands – can also provide important mental cues, such as the presence of aggression, self-worth, desire to connect, or anxiety, [16].

In examining the psychological meaning of shapes, [17], they provide not only symbolic but also contextual, individual experiences and emotional background. In addition to circles, squares, and triangles, other shapes, such as arcs or wavy lines, may also carry more meanings. Size, layout, and relativity can reflect different psychological information. Large shapes, such as a large circle or triangle, can often be a sign of self-confidence, dominance, or emotional compensation, while excessively small shapes can signify insecurity or withdrawal. Asymmetrical or balanced shapes reflect the dynamics and conflicts of emotional states, while the quality, strength, and rhythm of the lines can also reveal the psychological state of the individual. The positioning of shapes and the combination of colors can provide important information about the inner world of the person creating them, while the dynamics expressed by the drawing can trigger emotional responses in the viewer. Art can therefore convey not only aesthetic experience but also the feelings, desires, and fears of the psyche.

Color psychology studies human behavior and the psychological effects of color, as each color has its own psychological associations that can influence mood and emotions, [18]. The role of color is prominent today, as it plays a key role in design, branding, and marketing, [19]. The colors that someone prefers and uses can tell us a lot about their mental state and problems. This can also be demonstrated by the Lüscher color test, which reveals personality traits based on the subject's color preferences, [20]. Colors influence not only behavior but also performance in competitive sports, for example, red suggests dominance over competitors, while blue has been shown to have lower win rates, [21]. In addition, color choice also affects mental performance, with red being associated with failure and danger, which can reduce performance, [22].

Warm and cold colors can also generate behavioral differences; for example, red increases stimulation, [23]. The sensation of eating is also affected by color, as a colored food can create a more intense taste stimulus, [24]. In addition, the emotional effects of color differ, with green conveying calm and harmony, while black evokes sadness and anxiety, [25].

The relationship between psychology and computer science has become increasingly close over the past decades. The development of cognitive sciences and the advances of computer science have made it possible to artificially model human thinking, emotions, and behavior.

With the development of neuropsychology, brain imaging techniques – such as MRI and EEG – have helped psychological research, which is the basis for machine learning models, [11].

The intersection of computer science and psychology includes natural language processing, which models the psychological and cognitive context of spoken and written language, and emotion analysis, which aims to automatically identify human emotions.

The modeling of psychological states has become increasingly accurate with the development of machine learning, with the use of deep learning algorithms. Among the techniques used to analyze and predict human behavior, neural networks play a prominent role, [2], [26]. Computational methods in psychological research are helping to improve our understanding of human behavior, which can be applied to mental health, education, and occupational psychology. Also, psychological interpretations can be automated, but without clinical validation, they remain supportive tools only.

Recent advancements in computational psychology and AI-assisted diagnostics further support the integration of machine learning into psychological evaluation tools. Studies have shown that AI-enhanced systems can aid mental health professionals by processing behavioral and linguistic patterns with high accuracy, providing insights into disorders like ADHD, anxiety, and depression that often elude conventional diagnostics, [27].

Xiaowei et al. emphasized that aligning AI models with human cognitive logic – especially through agent-based modeling – can enhance trust and efficacy in clinical decisions, particularly in high-stakes mental health. scenarios, [28].

Additionally, Liu et al. introduced a deep multimodal system that combines facial micro-expression analysis with vocal biomarkers to identify early indicators of depressive episodes, showing predictive accuracy above 90%, [29].

III. Development

This section contains practical methods for technical implementations. Several technologies and tools were used for the different parts as follows:

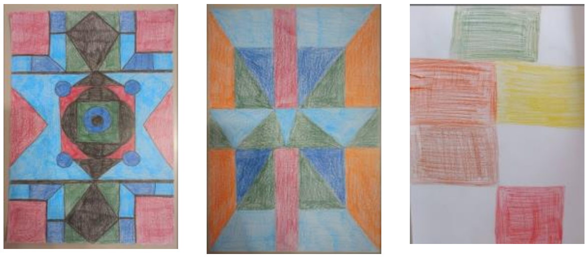
- Roboflow and OpenCV for image preprocessing and shape recognition,
- RGB color space and the 99colors database, [30] for color recognition,
- Gemini AI model for psychoanalysis,
- OAuth 2.0 protocol with Google Auth library authentication.

The analyses and reports were generated in Python using the FPDF library, and the user interface was designed using Tkinter.

A. Preprocessing

The preprocessing included the establishment of the basic data and tools needed for the successful implementation of the project, including the collection and cleaning of datasets, the training of machine learning models, and the preparation of the color table.

The datasets provide the necessary input for the model, while artificial intelligence tools enable accurate and efficient recognition and analysis.

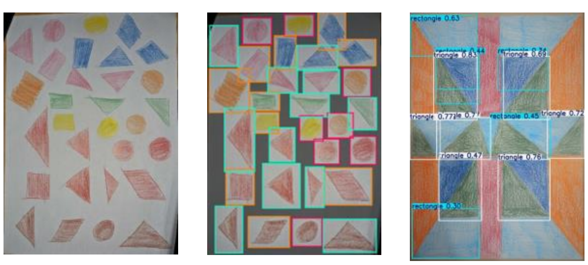


a) b) c)

Fig. 1 Sample images from the dataset used
Source: created by the authors.

The software was developed using real images drawn by patients following instructions during examinations by professionals. The drawings were then scanned or photographed. The available dataset contains a total of 17 images showing different colors, patterns, and shapes. The images are stored in JPG and PNG formats (see sample images in Fig. 1).

A hand-drawn dataset of colored shapes was needed to properly train the program for shape recognition. This dataset is extremely important, as the program must learn to recognize inaccurate human hand-drawn shapes. This required not only the different basic shapes (circles, triangles, rectangles), but also their "variations", such as parallelograms or trapezoids. The internet offers many options for searching datasets (e.g., Kaggle, Roboflow, GitHub); however, none of the available datasets proved to be optimal for this goal, as the program could not successfully perform shape recognition on the resulting test images after learning from the available datasets.



a) b) c)

Fig. 2 Sample images from the a) created training dataset and the b) labeled dataset; c) Example for shape recognition
Source: created by the authors

As a result, a custom dataset was created from different components: unfilled "empty" shapes; filled versions of the same shapes; and filled images with colored contours. (Fig. 2.a).

Perfect geometric accuracy was not necessary, as hand-drawn imperfections were purposely preserved to reflect real-world conditions. The resulting images form a diverse and varied dataset.

B. *Shape recognition*

The next step was to label the shapes using Roboflow with manual annotation by selecting the bounding box for each shape. These were used to identify individual objects: purple frames mark rectangles, red frames mark circles, and turquoise frames mark triangles (Fig. 2. b), with 166, 211, and 180 annotations, respectively.

After that, auto-orientation was implemented, a function that automatically determines and sets the correct orientation of the images (portrait/landscape). Its importance lies in the fact that the algorithms process images with consistent orientation much more efficiently. Auto-orientation uses EXIF (Exchangeable Image File Format) data to rotate images automatically. Within the bounding boxes, a Gaussian blur with σ=1.5 was applied, which was designed to give the shapes a blurred effect while keeping their positions within the bounding boxes unchanged. For datasets with limited available data (such as ours), this technique can be applied to artificially expand both the size and diversity of the dataset, generating new images while retaining the original ones.

After extensive empirical testing, the final version of the neural network achieved satisfactory accuracy. It was trained with a batch size of 8 over 50 epochs, and predictions were made using a confidence threshold of 0.25. The confidence score, ranging from 0 to 1, indicates the model's certainty in a given prediction – 0 meaning complete uncertainty and 1 indicating full confidence. Test results show that the applied method correctly identifies the shape type with an accuracy of 87% when the object is recognized. The overall efficiency of shape recognition is 71%, meaning that in certain cases the algorithm either fails to detect shapes or misclassifies them (see Fig. 2.c). This performance is expected to improve with further developments, particularly using a larger and more diverse training dataset. With continued testing and data expansion, both the accuracy and reliability of the recognition method can be enhanced.

C. *Color table*

Color recognition is complex and depends mainly on algorithm quality and sample representativeness. There are different color models; in our case, the RGB color space was chosen. Due to the large variety of color shades, further refinements were necessary; thus, color groups were created based on the main colors (red, green, blue) and their dark and light shades. The hierarchical structure of the color groups contributes to the algorithm providing increasingly accurate color estimates – for example, dark blue and light blue represent significantly different emotions, thus, distinguishing them is essential. The extensive color palette from the 99colors website, [30] provides an excellent basis for the color recognition algorithm.

D. *Artificial intelligence preparation*

The Gemini system instructions are special instructions that can be used to fine-tune the behavior of the model. They can be used to control the style and length of responses; the resources used, or even to give the model specific tasks. One of the most important parameters is the so-called temperature, which is fundamental because it influences probability distributions. A low temperature refers to decreasing the probabilities of predictions, where the model tends to choose the most likely outcomes, thus minimizing the potential for error. In contrast, high temperature increases the differences in output probabilities and allows for sparser or more creative responses, which can be particularly useful for generating varied outputs. The role of the temperature parameter is important not only in controlling the diversity of outputs but also in how irrelevant or unusual information is handled.

Higher temperature increases output diversity and reduces the dominance of the most probable responses, allowing more diverse and possibly more unusual alternatives to emerge. Conversely, at low temperatures, responses tend to be less creative, building on previously experienced patterns. For Gemini, this number can be defined between 0 and 2, which in our case is set at 0.75.

The following textual instructions have been provided to prepare Gemini for later analysis of the information contained in the images (in Hungarian language).

"You are a psychologist. Your job is to perform psychoanalysis on a patient. You are part of a Python program.

This program will tell you how the patient feels based on the shapes they have drawn, the dominant colors in the image, and where these shapes are located in the image (based on a matrix sized 3×3 matrix). You will also get information about the level of symmetry of the drawing. Based on these factors, make a complete psychoanalysis, including the personality traits of the patient! Be a professional! Finally, give tips to the psychologist on what treatment to recommend to the patient! State clearly that the analysis is AI-assisted and for clinical review only. Always answer in Hungarian!"

The interpretive suggestions generated by Gemini are used as supportive insights only. To improve transparency, each analysis report explicitly states that AI results require professional verification by licensed psychologists before therapeutic application.

E. Authentication

OAuth 2.0 is the industry-standard protocol chosen for authentication. The modules required to connect the developed application to the Google Generative Language API were imported, such as the *InstalledAppFlow* component of the Google Auth library to support interactive authentication. The list of privileges was defined in a SCOPES variable.

This function is generally used to enable a generative language model to retrieve, organize, and process information. To start the local web server, *InstalledAppFlow* was used, which automatically opens a browser where the user has the option to allow API access to the application. Once the user has granted access, the credentials are stored in an object called creds, which allows secure and smooth API access to the application. The storage of authentication tokens allows the user to avoid having to re-authenticate each time.

F. Experimental setup and processing

The application is currently launched via a script and involves multiple user interactions, which we plan to improve in the future.

After starting the application and completing authentication, the user is prompted to select an image for analysis through a simple interface built with the Python Tkinter library. This interface allows users to choose JPG/JPEG or PNG files from their file system. Once a file is selected, it is opened and validated using the Pillow library to ensure it is a proper image file. If validation succeeds, a confirmation message is displayed. If validation fails (e.g., the file is not a valid image), an error message is shown. In that case, the user can retry selecting a valid file or exit the program.

a) *b)* *c)*

Fig. 3 Example of object detection and labeling results: a) ROI points; b) Binary mask after preprocessing; c) Detected geometric shapes with bounding boxes
Source: created by the authors

The next step is cropping the image to define the ROI, as images often contain irrelevant or distracting elements along their edges. To simplify this process, default crop points are predefined as percentages of the image dimensions, ensuring they correspond to consistent regions within the image.

The user can move these points by clicking with the left mouse button. A slider is also provided to resize the image in real time, helping users position the points accurately. In the visualization, the selected points appear as yellow circles, and the connecting lines are shown in red (Fig. 3.a). The visualization is rendered in an OpenCV window that updates continuously as the user interacts. A bounding box is generated from these points, which also serves as a binary selection mask. The area outside the ROI is identified using this binary mask through a bitwise AND operation (Fig. 3.b).

The preprocessed image is then analyzed using the previously described machine learning algorithm to detect geometric shapes such as circles, squares, and triangles (Fig. 3.c).

After detection, the data corresponding to the identified shapes are extracted for further processing. Therefore, the shapes, their positioning, and dominant colors are examined, and the results are given to the Gemini AI for analysis.

During color analysis, the mean RGB value of each detected shape is computed and assigned a color name based on the previously defined color table. The output also includes the bounding boxes and class labels of the detected shapes. For further spatial analysis, the image is divided into nine regions; thus, a 3×3 matrix is generated to record the shapes located within each region.

To assess symmetry, the image is divided vertically into two halves. If necessary, the right half is rescaled to match the dimensions of the left half to ensure accurate comparison. The right half is then horizontally mirrored, allowing direct evaluation of symmetry between the two sides. A pixelwise difference is computed between the mirrored right half and the left half, producing a difference map that visualizes variations at each pixel. The degree of asymmetry is quantified by the mean intensity of this difference image. The resulting symmetry value is expressed as a percentage, where 100% represents perfect symmetry. For evaluation, the mean difference is compared to the mean of the maximum possible difference (a fully asymmetric case), yielding an objective measure of the image's symmetry level.

In addition to visual data, textual information is required for a complete analysis. Professionals can use the application with randomly generated usernames and passwords, while patient data remains anonymized – only the therapist can link results to the correct patient, ensuring data protection. A text input interface has been developed to collect this information, incorporating validation rules that verify the accuracy and format of the entered data.

For proper analysis, the following data are required:

- Symptoms of the patient,
- Diagnosis (including the BNO code, if applicable),
- Current condition: a description by the therapist of the patient's present state
- Detected shapes, listed in descending order of occurrence
- Dominant colors: the three most frequent colors and their respective counts
- Shape locations based on the 3×3 matrix
- Symmetry percentage of the drawing.

G. *Analysis*

At the end of the process, the program generates a PDF-formatted report summarizing the analysis results in a clear and user-friendly format, implemented using the FPDF library.

Before analysis, the algorithm validates the data formats, organizes all information into predefined sections, and then presents the detailed outcomes of the analysis within the generated document. The generated document is clearly structured and easy to read. Each section includes a descriptive title that highlights its main content and organizes the data in a logical, coherent order.

H. *Workflow*

The overall workflow of the proposed framework is illustrated in Fig. 4. The process begins with input image acquisition, followed by preprocessing and automated image analysis. The analyzed visual data are interpreted by the Gemini AI model, whose psychological outputs are then reviewed by therapists to provide final feedback and validation.

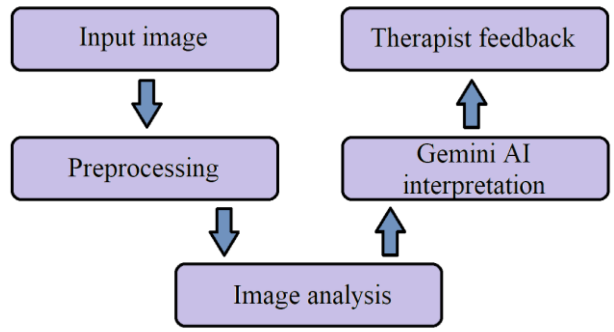


Fig. 4. Workflow of the proposed framework
Source: created by the authors

IV. Sample Result

In the presentation of the results, all data is presented in a visually separated way, allowing for an easy overview. Since the analyses often span multiple pages, only a selected portion of one specific analysis – translated into English – is presented below due to space limitations.

Analysis of the drawing:

The predominant use of light blue suggests a sad, melancholic mood, while black reinforces the depth of depression and hopelessness. The use of red, on the other hand, is ambivalent: on the one hand, it can suggest inner tension and aggression, and on the other, it can indicate a residual vitality and a desire for change.

The large number of rectangles (22) indicates a firm, rational mind, and a desire for control, but it can also indicate rigidity and inflexibility. Fewer circles (10) may indicate uncertainty in social relationships, emotional instability. The presence of triangles (7) indicates ambition and determination but can also indicate aggression.

The location of the shapes is also informative. The large number of shapes in the first row (16) may indicate both intensity of contact with the outside world and excessive nervousness. The emptiness of the middle row may symbolize the current emotional emptiness, the lack of motivation. In the bottom row, the circles clustered on the left indicate repressed emotions, unconscious tension.

The high symmetry (89%) points to perfectionism, a strong desire for control, which can lead to internal conflicts in the context of depression.

<u>*Personality traits:*</u>

Based on the drawing test, the patient is likely to be a rational, control-seeking personality who has difficulty managing their emotions. Perfectionism, high expectations and internal tension may all contribute to their depressive state.

<u>*Therapeutic suggestions:*</u>

- *Cognitive behavioral therapy: identifying and changing negative thought patterns and behaviors.*
- *Developing emotional regulation: practicing the recognition and management of emotions.*
- *Relaxation techniques: reducing tension and anxiety.*
- *Art therapy: promoting non-verbal communication and self-expression.*
- *Reviewing the need for medication: consultation with a psychiatrist.*

It is important to create a patient, supportive, therapeutic atmosphere in which the patient feels safe to express and process their emotions. The aim of therapy is to change negative thought patterns and behaviors, to improve emotional regulation and to regain the patient's self-confidence and joy in life.

V. User Feedback

To evaluate the application, feedback was collected from users as follows. The analysis was conducted by therapists (with assistance in launching the program), who provided detailed feedback after use. They were asked to rate their satisfaction with the analysis results on a scale from 1 to 10, where 1 indicated strong disagreement with the results and 10 indicated full agreement.

Due to the current limitations of the application, large-scale testing was not feasible; therefore, only 11 cases were evaluated. In 81% of the cases (9 instances), users rated the results as 7 or higher. One case received a score of 5, and another received a score of 3. Although the sample size is small, these preliminary findings suggest promising acceptance and usability among therapists. A larger-scale validation involving at least 50 participants is planned to statistically confirm these initial observations.

In addition to numerical feedback, several therapists provided qualitative comments emphasizing the application's potential usefulness in supporting therapy sessions and enhancing diagnostic insight. Some noted that automation and visualization features reduced manual workload, while others suggested improving the interface for smoother interaction. These insights will directly inform future development and usability improvements.

Given the limited sample, the results were analyzed descriptively rather than statistically, as inferential statistical methods would not yield meaningful conclusions. The reported values (e.g., satisfaction percentages) are therefore intended as indicative observations only.

VI. Current Limitations and Future Plans

Although the application is not suitable for clinical diagnosis, and inferential statistical analysis was not possible at this stage, it can still serve as a complementary tool in psychological therapy.

The next development goal is to design an intuitive, user-friendly graphical interface, making the application accessible not only to professionals but also to non-specialist users. Future improvements will focus on automatic paper detection, recognition of more complex shapes, and enhanced psychoanalytical accuracy. The integration of more advanced neural networks will further improve the precision of the analysis.

With the expansion of the database, the application may eventually be capable of generating increasingly accurate predictive models to support psychologists in assessing and managing patients' emotional and mental health. This research could enhance the efficiency and reliability of psychological analysis and offer new perspectives in visual psychoanalysis.

The current research phase has focused on system development and technical validation. Statistical inference will become feasible once sufficient data have been collected. At present, the limited sample size and study design do not allow for testing parametric or non-parametric hypotheses; therefore, statistical procedures cannot yet be performed. In the next research phase, we plan to expand the dataset and conduct statistical analyses.

VII. Conclusion

Machine learning-based analysis of shapes, colors, and symmetry in drawings provides new opportunities for objective psychological evaluation. By integrating artificial intelligence and computer vision, this study demonstrates how automated image processing can complement traditional, often subjective, psychological assessments. The developed application achieved 87% accuracy in shape recognition and received positive feedback from professionals, suggesting its potential as a supportive tool in psychological analysis.

Although the system is not intended to replace clinical diagnosis, it can assist therapists by offering data-driven insights into patients' emotional states and personality characteristics. Future development will focus on expanding the dataset, refining the psychological interpretation model, and improving accessibility through mobile and cloud-based solutions. As AI technologies continue to advance, such tools are expected to play an increasingly significant role in psychological research and practice, enhancing both efficiency and reliability in mental health assessment.

This pilot study introduces a data-driven framework for interpreting psychological drawings through AI-assisted analysis. The system is designed to complement human expertise rather than substitute for it. Further empirical validation using larger datasets and clinical collaboration will be necessary to confirm its reliability, interpretive accuracy, and long-term applicability in therapeutic contexts.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors wrote, reviewed and edited the content as needed and verifies that none utilized artificial intelligence (AI) tools were used. The authors take full responsibility for the content of the publication.

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