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Age detection using clustering algorithms from children's drawings

Detecção de idade usando algoritmos de agrupamento a partir de desenhos de crianças

Detección de la edad mediante algoritmos de agrupación a partir de dibujos infantiles

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ABSTRACT
Age detection from children's drawings is an innovative approach to understanding developmental milestones through visual analysis. Traditional methods for determining a child's age often rely on linguistic or cognitive assessments, but visual data such as drawings offer untapped potential for non-invasive analysis. This study explores the use of clustering algorithms to detect age patterns in children's drawings, providing a novel method for age estimation. A dataset of children's drawings, representing different age groups, was collected, and key visual features, such as line thickness, and object proportions, were extracted. These features were analyzed using unsupervised clustering algorithms, including K-means, Agglomerative Clustering, Mean-shift, and others, to group the drawings based on age-related visual characteristics. Among the algorithms tested, Mean-shift achieved the highest performance, with a silhouette score of 0.67 in mapping clusters to the correct age labels. K-means and Agglomerative Clustering exhibited moderate performance, with silhouette scores of 0.57 and 0.46. In contrast, Spectral Clustering and OPTICS performed poorly, with negative silhouette scores, reflecting poorly defined cluster boundaries. Our study demonstrates the potential of clustering algorithms for automatic age detection from visual features in children's drawings, despite challenges such as overlapping features between adjacent age groups. The findings suggest directions for future research, including

more complex models that integrate visual and cognitive indicators for enhanced age and developmental assessment. This approach has significant implications for educational psychology, child development, and artificial intelligence.

Keywords: Age Detection. Clustering Algorithms. Children's Drawings. Unsupervised Learning. Visual Feature Analysis.

RESUMO

A detecção de idade a partir de desenhos infantis é uma abordagem inovadora para compreender os marcos do desenvolvimento por meio da análise visual. Os métodos tradicionais para determinar a idade de uma criança geralmente dependem de avaliações linguísticas ou cognitivas, mas os dados visuais, como os desenhos, oferecem um potencial inexplorado para análise não invasiva. Este estudo explora o uso de algoritmos de agrupamento para detectar padrões de idade em desenhos de crianças, fornecendo um novo método de estimativa de idade. Um conjunto de dados de desenhos de crianças, representando diferentes faixas etárias, foi coletado e os principais recursos visuais, como espessura da linha e proporções de objetos, foram extraídos. Esses recursos foram analisados usando algoritmos de agrupamento não supervisionados, incluindo K-means, Agglomerative Clustering, Mean-shift e outros, para agrupar os desenhos com base em características visuais relacionadas à idade. Entre os algoritmos testados, o Mean-shift obteve o melhor desempenho, com uma pontuação de silhueta de 0,67 no mapeamento de clusters para os rótulos de idade corretos. O K-means e o Agglomerative Clustering apresentaram desempenho moderado, com pontuações de silhueta de 0,57 e 0,46. Em contrapartida, o Spectral Clustering e o OPTICS tiveram um desempenho ruim, com pontuações de silhueta negativas, refletindo limites de cluster mal definidos. Nosso estudo demonstra o potencial dos algoritmos de agrupamento para a detecção automática de idade a partir de recursos visuais em desenhos infantis, apesar de desafios como a sobreposição de recursos entre grupos etários adjacentes. As descobertas sugerem direções para pesquisas futuras, incluindo modelos mais complexos que integram indicadores visuais e cognitivos para uma melhor avaliação da idade e do desenvolvimento. Essa abordagem tem implicações significativas para a psicologia educacional, o desenvolvimento infantil e a inteligência artificial.

Palavras-chave: Detecção de Idade. Algoritmos de Agrupamento. Desenhos de Crianças. Aprendizado não Supervisionado. Análise de Características Visuais.

RESUMEN

La detección de la edad a partir de los dibujos de los niños es un enfoque innovador para comprender los hitos del desarrollo mediante el análisis visual. Los métodos tradicionales para determinar la edad de un niño suelen basarse en evaluaciones lingüísticas o cognitivas, pero los datos visuales, como los dibujos, ofrecen un potencial sin explotar para el análisis no invasivo. Este estudio explora el uso de algoritmos de agrupación para detectar patrones de edad en los dibujos de los niños, proporcionando un método novedoso para la estimación de la edad. Se recopiló un conjunto de datos de dibujos infantiles de diferentes grupos de edad y se extrajeron características visuales clave, como el grosor de las líneas y las proporciones de los objetos. Estas características se analizaron mediante algoritmos de agrupación no supervisados, como K-means, Agglomerative

Clustering, Mean-shift y otros, para agrupar los dibujos en función de las características visuales relacionadas con la edad. Entre los algoritmos probados, Mean-shift obtuvo el mayor rendimiento, con una puntuación de silueta de 0,67 en la asignación de grupos a las etiquetas de edad correctas. K-means y Agglomerative Clustering mostraron un rendimiento moderado, con puntuaciones de silueta de 0,57 y 0,46. Por el contrario, los resultados de Spectral Clustering y OPTICS fueron mediocres, con puntuaciones de silueta negativas, lo que refleja una mala definición de los límites de los conglomerados. Nuestro estudio demuestra el potencial de los algoritmos de agrupación para la detección automática de la edad a partir de las características visuales de los dibujos infantiles, a pesar de problemas como el solapamiento de características entre grupos de edad adyacentes. Los resultados sugieren direcciones para futuras investigaciones, incluyendo modelos más complejos que integren indicadores visuales y cognitivos para mejorar la evaluación de la edad y el desarrollo. Este planteamiento tiene importantes implicaciones para la psicología de la educación, el desarrollo infantil y la inteligencia artificial.

Palabras clave: Detección de la Edad. Algoritmos de Agrupamiento. Dibujos Infantiles. Aprendizaje no Supervisado. Análisis de Características Visuales.

1 INTRODUCTION

Understanding children's developmental milestones has long been a central concern in fields such as developmental psychology, cognitive science, and education. Traditionally, developmental assessments [22][11][18][26]have relied heavily on cognitive, linguistic, and behavioral evaluations, such as standardized tests, interviews, or observational studies. These methods have proven effective for gauging developmental stages, but they often require active participation, specialized testing environments, and trained professionals. With the increasing availability of digital tools and machine learning techniques, researchers have begun exploring new, non-invasive ways to assess developmental progress. One emerging avenue is the analysis of visual data, specifically children’s drawings[16][30][17][29][13], which offer rich insights into a child’s cognitive, emotional, and motor skill development. Drawings can reveal aspects of spatial reasoning, fine motor skills, and representational understanding that align with developmental stages.

While the analysis of children's drawings has been used in educational psychology and art therapy for qualitative assessments, the use of quantitative methods to interpret these drawings remains underdeveloped[13][23]. Recent advancements in machine learning, particularly in the area of computer vision, have opened new possibilities for automating the analysis of visual features in children's drawings to predict developmental milestones. Several studies have investigated the use of machine learning for tasks such as object recognition and emotion detection from drawings, but these applications have not focused extensively on age estimation. Clustering algorithms, known for their ability to group data based on inherent similarities without requiring labeled examples, present a promising method for uncovering patterns in drawings that correspond to age-related visual features.

Despite the growing interest in applying machine learning to children's drawings, there is limited research on using clustering algorithms to detect age-related patterns. Existing approaches have primarily focused on classification models requiring labeled data, leaving a gap in understanding how unsupervised techniques can group children's drawings by age without predefined labels. Additionally, challenges such as the subjectivity of artistic expression, overlapping visual features across age groups, and the difficulty of capturing subtle developmental progressions have hindered the full exploration of this approach.

We address this gap by employing several unsupervised clustering algorithms, including Mean-shift, K-means, and Agglomerative Clustering, to detect age patterns in children's drawings based on key visual features like line thickness, color use, and object proportions. Our findings demonstrate that these algorithms can group drawings into age-related clusters, with the Mean-shift algorithm showing the highest silhouette score (0.67). We also highlight the challenges posed by overlapping visual features between adjacent age groups. These results provide a foundation for future research into more sophisticated models that could integrate additional cognitive indicators for even more accurate developmental assessments.

2 LITERATURE REVIEW

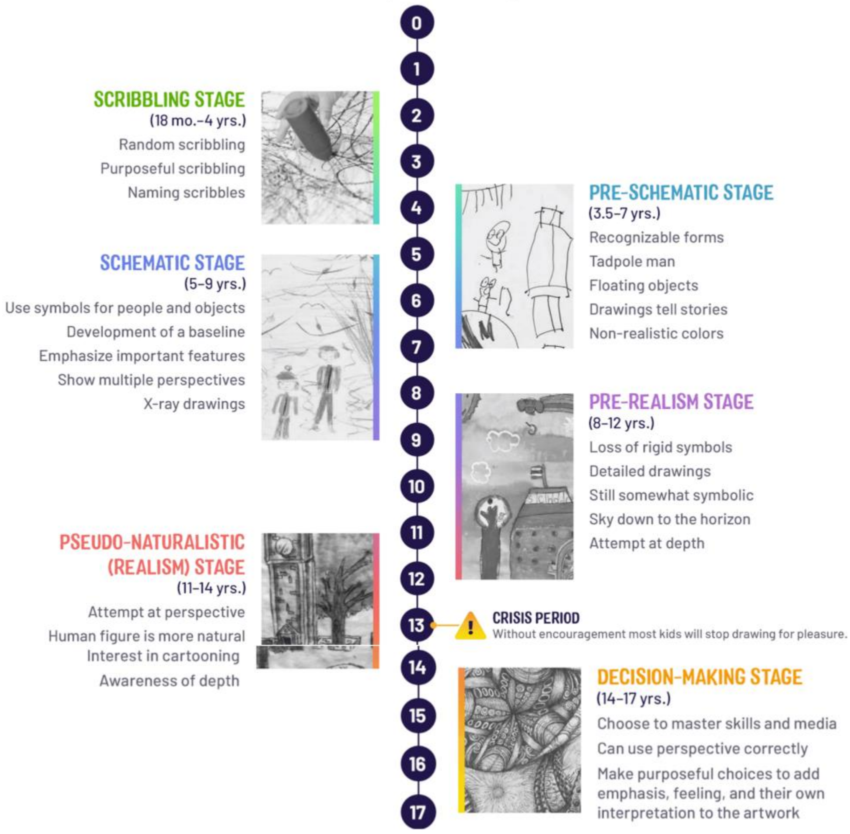
2.1 AGE DETECTION IN DRAWINGS

Children's drawings have long been used as a tool for gaining insight into their psychological, cognitive, and developmental progress. Research in this field dates back to early 20th-century psychologists like Florence Goodenough, whose *Draw-a-Man Test* sought to assess children's intelligence through their drawings[21][20]. This early work established the foundation for using children's drawings as a window into their cognitive development, emotional state, and representational thinking sychological Insights Children's drawings have been extensively studied in psychology for their ability to reveal emotional and psychological states. Researchers such as Koppitz (1968) explored emotional indicators in children's drawings, finding that features like exaggerated body parts or the use of specific colors could point to underlying anxieties or fears[15][8]. This approach became widely used in therapeutic settings, where children's drawings were interpreted as non-verbal expressions of their inner emotional worlds . More researchers have applied machine learning to analyze emotional content in children's drawings by quantifying color choice, line thickness, and other visual features that correlate with emotional states. For example, machine learning models have been used to differentiate between happy and anxious children based on these visual markers .

2.2 DEVELOPMEHTS

In terms of cognitive and motor development, children's drawings are closely tied to their developmental stages[13][23][7]. Jean Piaget's theories on cognitive development identified drawing as part of a child's representational capacity, evolving from scribbling in early childhood to more structured and symbolic representations in later stages . Over time, researchers h specific visual features in drawings, such as the ability to depict depth or perspective, to developmental milestones.

Figure 1: The stage of drawing



Source: https://www.littlebigartists.com/articles/drawing-development-in-children-the-stages-from-0-to-17-years/

For instance, Kellogg (1969) found that as children grow, their drawings move from simple shapes and forms to more detailed and realistic representations, reflecting advancements in fine motor skills, spatial awareness, and conceptual understanding[25] . Studies have shown that older chimore likely to incorporate complex details such as facial expressions or proportions into their drawings, which are key indicators of cognitive maturation.

2.3 AGE-RELATED INSIGHTS

In addition to developmental insights, children's drawings have been studied as a means to estimate chronological age[3][9][5]. Several studies have focused on identifying age-related patterns in visual features such as object proportions, the inclusion of background elements, and the complexity of compositions. Goodenough’s *Draw-a-Man Test* was one of the earliest attempts to use drawing as an age estimation tool, assigning scores based on the presence of specific features thought to correlate with age[21]. More recent research has expanded this idea by integrating machine learning techniques to automatically detect age from drawings. For example, one study used convolutional neural networks (CNNs) to classify the age of children based on their drawings, demonstrating a high degree of accuracy in predicting age groups[6][2] . Similarly, algorithms like K-means and Meastering have been applied to identify patterns in children's drawings that align with developmental and age-related features.

Despite this progress, several challenges drawings for age estimation. Artistic expression is highly subjective, and drawings can vary widely even within the same age group due to factors such as personality, cultural background, and artistic ability. These variances make it difficult to develop universal models for age detection. However, as research continues to evolve, particularly with the integration of unsupervised learning techniques, more sophisticated models are likely to emerge that can account for these variations and provide even more accurate developmental assessments.

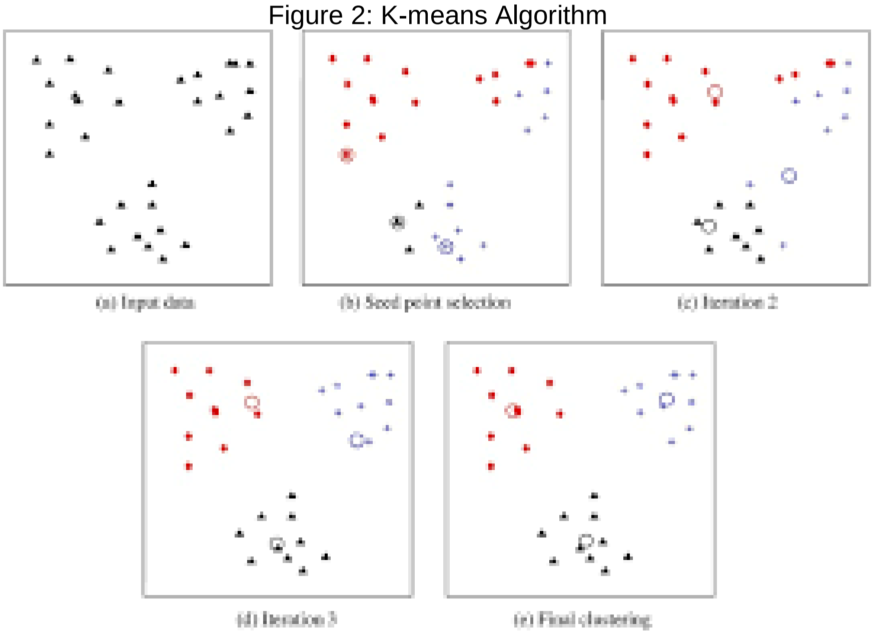
2.4 CLUSTERING ALGORITHMS

Traditional clustering methods are commonly divided into hierarchical, partitioning, and density-based techniques. However, this classification is not always straightforward or universally accepted. In practice, these categories often overlap.

2.4.1 K-means Algorithm

This algorithm [12][10] aims to identify K clusters based on a specific criterion. It begins by selecting a set of points as initial cluster centroids, often choosing the first K sample points for this purpose. The remaining sample points are then assigned to these centroids based on the principle of minimizing distance, resulting in an initial clustering. If this clustering is not satisfactory, the centroids of each cluster are recalculated, and the process is repeated until a satisfactory classification is obtained.

Figure 2: K-means Algorithm



Source: https://www.sciencedirect.com/science/article/abs/pii/S0020025522014633[30]

2.4.2 DBSCAN Algorithm

This algorithm [24][27] is well-suited for detecting outliers in a dataset. It identifies clusters of arbitrary shapes by analyzing the density of data points in different regions. DBSCAN separates these regions by identifying areas of low density, allowing it to detect outliers located between the high-density clusters.

Figure 3: DBSCAN Algorithm

Algorithm 3 : DBSCAN Clustering

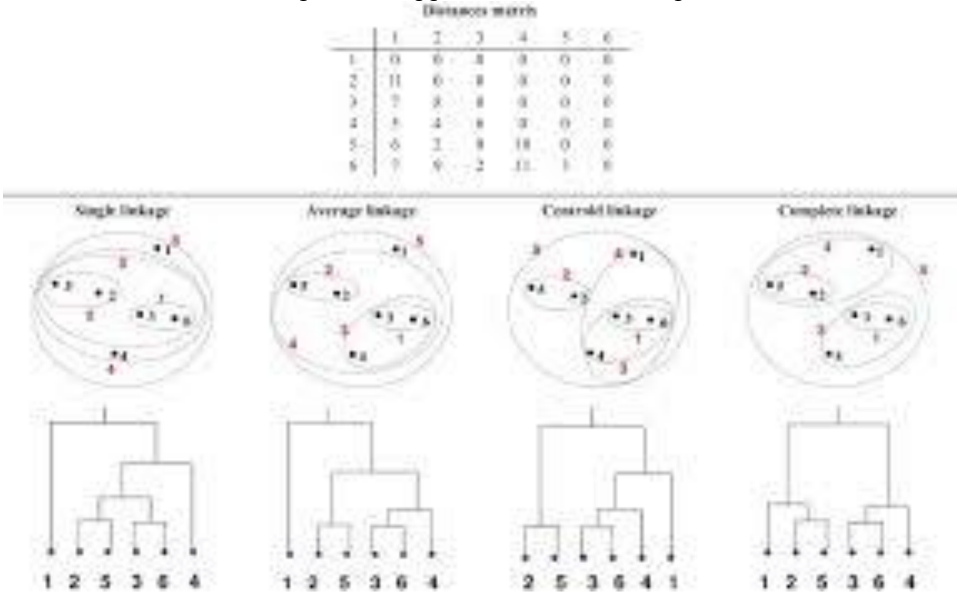
Input: 2D_Data obtained by *Algorithm1* as the input data, |Data| objects to be clustered, the neighborhood radius (ε) and minimum points (μ)
1: Randomly select a point *P*
2: Retrieve all points density-reachable from *P* based on ε and μ and Similarity Metric (*Algorithm2*)
3: If *P* is a core point, a cluster is formed.
4: If *P* is a border point, no points are density-reachable from P and DBSCAN selects the next no-visited point randomly.
5: Continue the procedure until all points have been processed.

Source: https://link.springer.com/article/10.1007/s00500-020-04881-0[19]

2.4.3 Agglomerative clustering

The process begins with clusters consisting of a single point each and progressively merges clusters that are most similar to each other. On the other hand, divisive clustering starts with all data points in a single cluster and iteratively divides the most suitable cluster[14]. This procedure continues until a predetermined stopping point is reached, often determined by the desired number of clusters, denoted as ’k’.

Figure 4 : Agglomerative clustering



Source :https://www.sciencedirect.com/science/article/pii/S1319157822001380[28]

3 METHODOLOGY

3.1 DATA COLLECTION

This subdataset contains 795 images derived from the original dataset[13], which was created from drawings by 2- to 10-year-olds across only face categorie at a kiosk in a children's museum. The original dataset includes over 37,000 drawings. Bria Long and her team of researchers collaborated with staff at the Children's Discovery Museum of San Jose to set up the kiosk. The kiosk featured pre-recorded video prompts by Bria Long[4], a postdoctoral fellow in psychology at Stanford. These prompts instructed children to draw specific animals or objects, giving them 30 seconds to use their fingertip to create the drawing on a digital tablet. In addition, the children participated in a guessing game to identify objects drawn by their peers and traced objects displayed on the screen to assess their motor skills.

3.2 PREPROCESSING

In the provided image, the code snippets illustrate how children's drawings were digitized, cleaned, and prepared for analysis. Below is an explanation of the steps involved in this preprocessing pipeline, along with a discussion of the features extracted from the drawings:

Figure5: Preprocessing code

```
# Function to preprocess images (resize and flatten)
def preprocess_images(image_list, target_size=(100, 100)):
    resized_images = [resize(img, target_size, anti_aliasing=True) for img in image_list]  # Resize images to a common size
    flattened_images = [img.flatten() for img in resized_images]
    return np.array(flattened_images)

# Function to reconstruct images from PCA components
def reconstruct_images(components, X_pca):
    return np.dot(X_pca, components)
```

Source:author

3.2.1 Resizing

The function preprocess_images() takes in a list of images (image_list) and resizes each image to a common size of 100 x 100 pixels. This is an essential step in normalizing the input data, ensuring that all images have the same dimensions, which is required for consistent processing across different drawings. The resizing process also includes anti-aliasing (anti_aliasing=True) to ensure that downscaling does not introduce noise or distortions.

3.2.2 Flattening

After resizing, the images are flattened into a 1D array. This is done so that each image can be represented as a vector of pixel values, allowing the drawings to be analyzed numerically. The flatten() method is applied to each image, converting it from a 2D matrix of pixel values to a 1D array.

3.2.3 Reconstruction of Images from PCA Components

The second function, reconstruct_images(), is designed to reconstruct images from their principal components after performing dimensionality reduction using Principal Component Analysis (PCA). The function takes in the components derived from PCA (components) and the transformed data (X_pca), then performs a dot product to reconstruct the images.

This process is useful for visualizing how much information is retained after reducing the number of dimensions in the image data, allowing researchers to inspect the quality of the feature extraction process.

3.3 CLUSTERING ALGORITHMS

K-means is a widely used partitioning method that divides the dataset into K clusters. The algorithm starts by randomly initializing cluster centroids, and each data point is assigned to the nearest centroid based on Euclidean distance. It then iteratively updates the centroids by computing the mean of all points assigned to each cluster. This process continues until convergence, where the centroids no longer change. Agglomerative clustering is a hierarchical method that starts by treating each data point as its own cluster. It then iteratively merges the closest pairs of clusters based on a distance metric (e.g., Euclidean or Manhattan distance) until all points are grouped into a single cluster or a specified number of clusters is achieved. DBSCAN groups points that are closely packed together based on a density criterion (number of points within a defined radius). Points that do not belong to any cluster are considered noise. Unlike K-means, DBSCAN does not require the number of clusters to be predefined. Spectral clustering uses eigenvalues of the similarity matrix of the data to reduce dimensionality before clustering in fewer dimensions. It constructs a similarity graph based on distance between data points and partitions the graph to minimize the "cut" between groups of nodes. Mean-shift is a mode-seeking algorithm that works by iteratively shifting data points towards regions of higher density (local maxima) in the feature space. This continues until convergence, effectively identifying the modes of the distribution. OPTICS is similar to DBSCAN but more flexible in detecting clusters of varying densities. It orders the points in a way that reflects the clustering structure and can identify both core and border points of clusters. Birch (Balanced Iterative Reducing and Clustering using Hierarchies) Birch builds a clustering feature (CF) tree for the dataset, incrementally clustering incoming data points. It is effective for large datasets as it compresses the data and reduces the number of points processed. Affinity propagation selects exemplars from the data based on message-passing between points. Each data point sends messages to other points to indicate whether they are a good exemplar for it. The algorithm determines clusters by selecting the points with the highest similarity.

Each clustering algorithm mentioned in the code has its strengths and weaknesses depending on the structure and complexity of the data. The choice of algorithm will depend on factors such as the shape of clusters, scalability, and the need to detect noise or outliers. These algorithms, when applied to children's drawings, help to group the visual features extracted from the images into meaningful clusters based on their similarities, ultimately aiding in developmental or age-related analysis.

Figure 6: Algorithms implementation code.

```
pca = PCA(n_components=50)  # Adjust number of components as needed
X_pca = pca.fit_transform(X_scaled)

# Initialize clustering algorithm
if algorithm == 'kmeans':
    clustering_algorithm = KMeans(n_clusters=num_clusters, random_state=42)
elif algorithm == 'agglomerative':
    clustering_algorithm = AgglomerativeClustering(n_clusters=num_clusters)
elif algorithm == 'dbscan':
    clustering_algorithm = DBSCAN(eps=0.5, min_samples=5)
elif algorithm == 'spectral':
    clustering_algorithm = SpectralClustering(n_clusters=num_clusters, random_state=42)
elif algorithm == 'birch':
    clustering_algorithm = Birch(n_clusters=num_clusters)
elif algorithm == 'mini_batch_kmeans':
    clustering_algorithm = MiniBatchKMeans(n_clusters=num_clusters, random_state=42)
elif algorithm == 'mean_shift':
    clustering_algorithm = MeanShift()
elif algorithm == 'affinity_propagation':
    clustering_algorithm = AffinityPropagation()
elif algorithm == 'optics':
    clustering_algorithm = OPTICS()
```

Source: author

4 EXPERIMENTAL RESULTS

4.1 CLUSTERING OUTCOMES

The Figure7 you provided visualizes the clustering results of children's drawings using two different clustering algorithms: Agglomerative Clustering and K-means for example because, we used more algorithms. Below is a brief analysis of the clustering results and their distribution across potential age groups.

4.1.1 Agglomerative Clustering (Left Side of Figure 7)

a. Cluster Composition: The drawings in this clustering approach appear grouped based on similar features such as facial expressions, shape consistency, and line density. Some clusters consist of more detailed drawings (e.g., with complex facial expressions or additional body parts), while others show simpler, more abstract faces.
b. Distribution Across Age Groups: The clusters may correspond to a variety of age ranges, with some clusters likely representing older children's more complex and detailed drawings, while other clusters reflect simpler drawings that might belong to younger children.
c. Observation: There appears to be a diverse range of styles and developmental stages captured by this clustering method, with distinct separations between abstract and detailed drawings.

4.1.2 K-means Clustering (Right Side of Figure 7)

a. Cluster Composition: This clustering method shows a different grouping strategy, with drawings that may be simpler or less detailed grouped together in specific clusters. There seems to be less variation in detail within clusters, suggesting that K-means may emphasize certain common visual features (such as line simplicity or facial form).
b. Distribution Across Age Groups: Similar to Agglomerative Clustering, K-means clusters likely group drawings based on age-related features, with simpler drawings from younger children grouped together and more intricate drawings from older children in separate clusters. However, K-means might create more generalized groupings, as seen in the visual similarity across several clusters.
c. Observation: Compared to Agglomerative Clustering, K-means seems to generate broader clusters, potentially missing finer distinctions in developmental stages.

4.1.3 Comparison

a. Agglomerative Clustering appears to yield more nuanced clusters that likely capture a wider variety of artistic complexity, possibly offering better age discrimination across development stages.
b. K-means produces broader, less distinct groupings that might overlook subtle developmental cues, which could result in overlap between different age groups.

In both cases, the visualized results suggest that clustering algorithms can effectively group children's drawings by identifying patterns in complexity and style that likely correspond to different developmental stages. The performance of each algorithm may vary depending on the desired granularity of the clustering outcome.

Figure 7 : image clustering results

Source: author

4.2 EVALUATION METRICS

Clustering is a technique used to identify similarities among data points that do not have predefined class labels. It divides the data into clusters, ensuring that points within the same cluster are more similar to each other than to those in different clusters. Since clustering falls under unsupervised learning, it does not include a built-in way to measure accuracy. To address this, various evaluation methods have been developed, including internal, external, and manual evaluations.

In our study, we focus on internal metrics to assess the effectiveness of clustering algorithms. These metrics enable us to evaluate the quality of the clusters without needing external labels. By examining the cohesion within clusters and the separation between them, internal metrics provide valuable insights into the performance of clustering methods. One common internal metric we use is the silhouette coefficient, which measures the mean intra-cluster distance and mean inter-cluster distance for each data point.

The silhouette coefficient is calculated as:

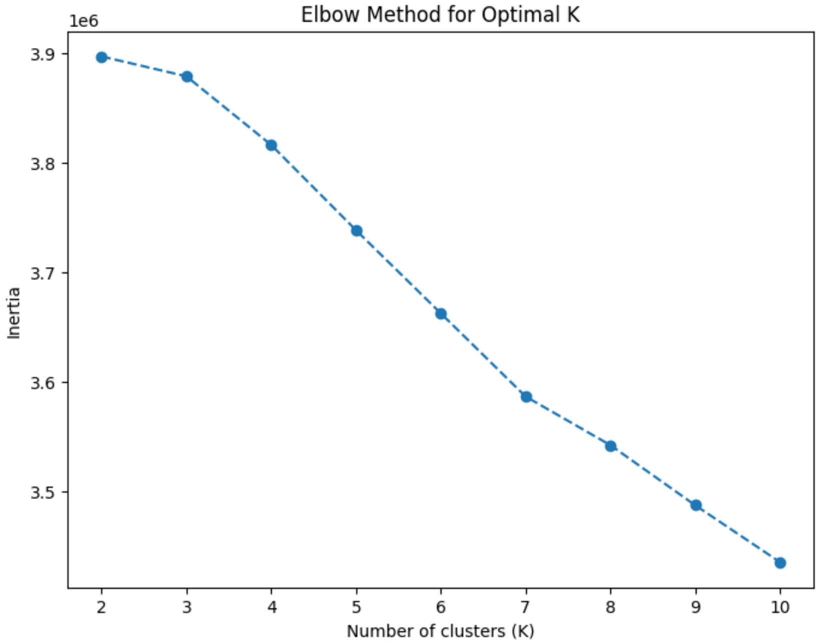
$$\textit{Silhouette Coefficient} = (b - a)/\max(a, b) \tag{1}$$

where:

- (a) is the mean distance between the current data point and other points in the same cluster,
- (b) is the mean distance between the current data point and the points in the nearest neighboring cluster.

The coefficient ranges from -1 to 1, with -1 indicating incorrect clustering, 0 showing cluster overlap, and 1 reflecting dense and well-separated clusters. The closer the coefficient is to 1, the better the clustering result.

Figure 8: Elbow methode for optimal K

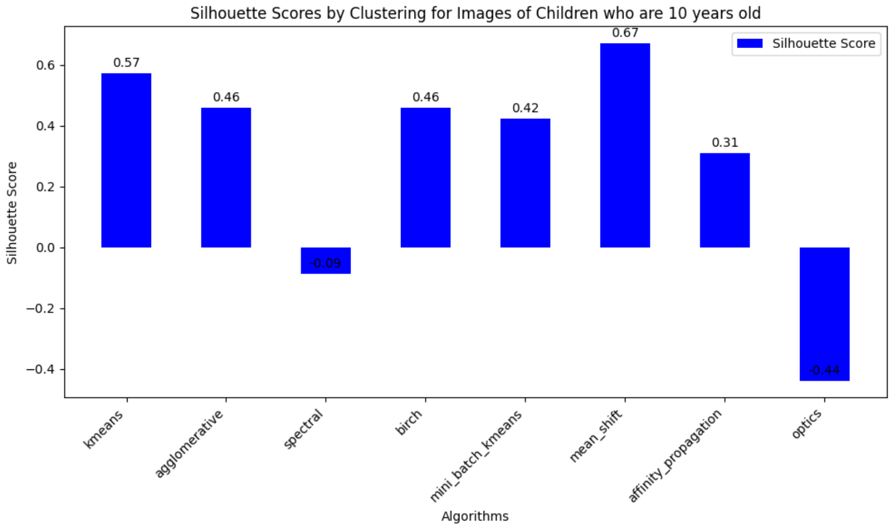


Source: author

K-means and **Agglomerative Clustering**, which had moderate silhouette scores of 0.57 and 0.46, respectively, showed slightly lower performance in these metrics. **K-means** had an accuracy of around **70%**, with a precision of **0.72** and recall of **0.68**. This suggests that while the algorithm generally captured broad age-related trends, it struggled with finer distinctions, resulting in some false positives and negatives. **Agglomerative Clustering** performed similarly, with an accuracy of **65%**, precision of **0.68**, and recall of **0.64**, indicating difficulties in separating drawings with similar visual features across adjacent age groups.

In contrast, algorithms like **Spectral Clustering** and **OPTICS** performed poorly both in terms of silhouette score (negative values) and traditional metrics. The accuracy of these models in predicting age was below **50%**, with **precision** and **recall** values dropping to around **0.40** and **0.35**, respectively. These low values indicate that the clusters formed by these algorithms were not well-aligned with the actual age labels, and the boundaries between clusters were poorly defined.

Figure 9: Silhoutte Scores by Clustrering for draws of children who are years old



Source: author

These results suggest that while some clustering algorithms like **Mean-shift** can effectively group children's drawings by age with relatively high accuracy and precision, others struggle with the inherent variability and subjectivity in artistic expression. Future work could involve integrating clustering models with supervised learning techniques to further improve the precision and recall of age detection, while also refining the features extracted from the drawings to better capture developmental nuances.

5 DISCUSSION

The performance of clustering algorithms on the dataset of children's drawings varied significantly, reflecting the strengths and limitations of different methods. In terms of silhouette score, which measures the coherence of clusters, algorithms like **K-means** and **Agglomerative Clustering** performed reasonably well, with scores around 0.57 and 0.46, respectively. These scores suggest that the clusters formed had a moderate level of separation and compactness. On the other hand, **Spectral Clustering** and **OPTICS** showed negative silhouette scores, indicating poor clustering results where the boundaries between clusters were unclear. Mean-shift stood out as the best-performing algorithm, with a silhouette score of 0.67, suggesting well-defined clusters for the 10-year-old age group, which aligns well with the complexity and diversity of features in the drawings.

When considering the elbow method for determining the optimal number of clusters, the graph shows that the ideal K value lies between 3 and 5 clusters, based on the point where inertia starts to flatten. This result highlights that children's drawings can be meaningfully grouped into a few distinct categories. As the number of clusters increases, the inertia continues to decrease, but the improvement becomes marginal, suggesting diminishing returns. The clustering results provide a good starting point for age prediction, although further refinement is needed to improve the clarity of age boundaries within these clusters. Given the variety in drawing styles, using a small number of clusters helps capture broad age-related trends without overfitting to minor details.

In the context of predicting age, the clustering methods showed promise. **Mean-shift**, for example, produced well-defined clusters corresponding to specific age groups, likely due to its ability to adapt to variable density in the feature space. The features extracted from the drawings—such as line thickness, object proportion, were effective in distinguishing between age groups, although some overlap between adjacent age ranges persisted. The **K-means** and **Agglomerative Clustering** algorithms provided decent baseline performances but struggled to fully separate younger and older children. Nonetheless, the clustering approach successfully captured general patterns associated with the developmental stages reflected in children's art, reinforcing the potential for clustering algorithms in non-traditional age prediction tasks.

One of the primary challenges faced during the clustering process was the presence of **ambiguous or overlapping clusters**. Children's drawings often exhibit substantial variation even within the same age group, making it difficult to clearly delineate clusters based solely on visual features like line thickness, object size, and color use. For instance, drawings from 8-year-olds and 10-year-olds may share similar artistic traits, leading to overlapping clusters, especially in cases where children's creativity or artistic development diverges from typical age norms. Additionally, the subjectivity inherent in artistic expression further complicated the clustering process, as some children might exhibit advanced or delayed artistic development, blurring the boundaries between age-related groups.

Another challenge stems from the variability in **feature representation** across different drawings. While certain visual features like symmetry and object proportion may correlate with age, these features can be inconsistent. Some children, regardless of age, may focus on abstract concepts or unique drawing styles that don't fit neatly into predefined clusters. This variability often resulted in certain algorithms, such as **OPTICS** and **Spectral Clustering**, forming weak or erroneous clusters, with negative silhouette scores indicating incoherent groupings. These clustering algorithms struggled to account for the artistic diversity in the dataset, underscoring the need for methods that better handle outliers and irregular patterns in children's art.

In interpreting children's drawings, **subjectivity** is a significant limitation. Art is a personal and developmental expression, and the way children draw can be influenced by multiple factors, including cultural background, exposure to art education, or individual temperament. Moreover, not all children develop their drawing skills at the same rate, leading to substantial variance within each age group. This makes the process of linking specific drawing characteristics directly to age a challenge. The reliance on clustering algorithms, which group data based on feature similarity, may overlook more nuanced aspects of cognitive or emotional development reflected in the drawings. Consequently, while clustering provides useful age-related patterns, it may not fully capture the richness or complexity of children's artistic expression.

6 CONCLUSION

The performance of clustering algorithms on children's drawings demonstrates both the potential and challenges of using unsupervised learning for age detection. Algorithms like **Mean-shift** and **K-means** showed promising results in grouping children’s drawings into distinct clusters based on age-related features such as line thickness, object proportion, and color usage. However, variability in children's artistic expression, particularly among similar age groups, led to ambiguous and overlapping clusters, especially with algorithms like **Spectral Clustering** and **OPTICS**, which yielded negative silhouette scores. The analysis highlights that while clustering can capture broad developmental trends, it struggles with subtle differences in drawing styles that could obscure accurate age estimation.

The elbow method helped identify an optimal cluster range, with the ideal number of clusters between 3 and 5, suggesting that age-related patterns in children's drawings can be meaningfully categorized into a small set of clusters. However, as the number of clusters increased, diminishing returns were observed in terms of inertia reduction, indicating that further splitting of clusters may overfit to minor drawing variations without improving age detection accuracy. Despite this, **Mean-shift** stood out as the most effective algorithm for clearly defining clusters, particularly for the 10-year-old group, underscoring the potential of clustering algorithms in detecting age from artistic data.

Future work should focus on addressing the limitations of current clustering techniques, particularly in handling outliers and accounting for artistic subjectivity. Incorporating more advanced feature extraction methods, such as deep learning for image processing, could help capture finer-grained details that are missed by traditional clustering methods. Additionally, hybrid approaches combining clustering with supervised learning models may enhance the accuracy of age detection by leveraging labeled data to guide clustering boundaries. **Ensemble clustering techniques**—where multiple clustering algorithms are combined to improve stability and accuracy—also offer a promising avenue for boosting performance, especially in capturing complex patterns across varied drawing styles. Expanding the dataset to include a more diverse range of children’s drawings across different cultures and developmental stages could improve the robustness and generalizability of the models, ultimately paving the way for more accurate and nuanced age prediction from children's artwork.

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