Sketch-based Facial Expression Recognition for Human Figure Drawing Psychological Test

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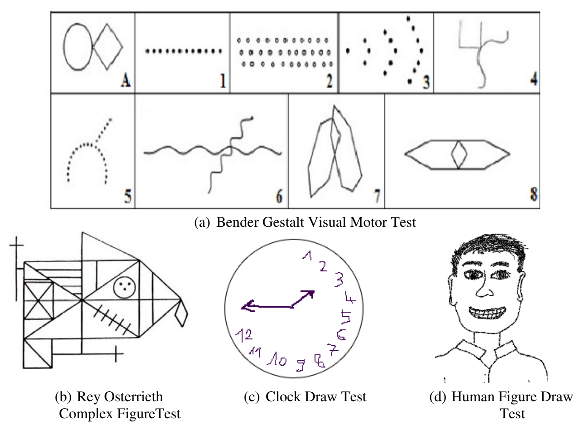
***Abstract*—Drawing tests have been long used by practitioners for early screening of a number of psychological and neurological impairments. These brain functioning tests are used by psychologists to understand feelings, personality and reactions of individuals to different circumstances. Among these, Human Figure Drawing Test (HFDT) is a popular instrument for the assessment of cognitive functioning of individuals. While the HFDT has various dimensions, the focus of this study lies on the face of the drawn figure. A computerized system that analyzes the hand-drawn facial images to extract the expressions from the image is proposed. Sketch of human face is drawn by the subject and then fed to the system, the image is then binarized and segmented into different facial components. Features (based on local binary patterns, gray level co-occurrence matrices and histogram of oriented gradients) computed from the facial components are used to train an SVM classifier to learn to distinguish between four expression classes, 'happy', 'sad', 'angry' and 'neutral'. The system evaluated on a custom developed database of sketches realized promising results. The developed system could serve as a useful module toward development of a complete automated system to score human figure drawing test.**

I. INTRODUCTION

Neuro-psychological evaluations have been widely used by clinical psychologists to measure different cognitive abilities of individuals [40]. The findings of these assessments can be effectively employed for early screening of a number of neuro-psychological disorders. While a number of mature medical procedures have been developed for analysis of brain related disorders, these imaging modalities only indicate *'which'* parts of brain could have abnormalities but do not specify *'how'* the brain functions as a results of these abnormalities. A major proportion of assessments in clinical psychology involve *'pencil-and-page'* based tasks requiring subjects to either write a text or draw a set of shapes (by copying or through recall). Trained practitioners then analyze the produced writings or drawings to measure deviations from the expected models and score a test according the defined scoring criteria. Poor performance on these tests is indicative of a number of cognitive disorders. Correlation, for instance, has been shown to exist between handwriting and neurological disorders like autism [16], [29] Parkinson [49] and Alzheimer [46]. Likewise, drawings tests including Bender Gestalt Visual Motor Test [51], Clock Draw Test [33], Rey Osterrieth Complex Figure Test [47] and Human Figure Drawing Test [20] are widely employed for measurement of visual-motor functioning, developmental disorders, dementia, visuospatial abilities and cognitive development etc. Unlike handwriting based tests which can be conducted on literate population only, sketch-based assessments offer a simpler mechanism for projection of different cognitive attributes covering the literate as well as the illiterate population. Examples of common neuro-psychological drawing tests are illustrated in Figure 1. Among these, the focus of our research lies on the Human Figure Draw Test (HFDT).



(a) Bender Gestalt Visual Motor Test

(b) Rey Osterrieth Complex FigureTest

(c) Clock Draw Test

(d) Human Figure Draw Test

Fig. 1. Examples of Neuro-psychological Drawings Tests

The Human Figure Draw Test (also known as Draw a Person Test) was originally introduced by Goodenough in 1926 [17]. HFD is well-known psychological test primarily used to evaluate the cognitive development in children and adolescents. In addition to cognitive attributes, this test is also used as a measure of intelligence in children [39] and can be effectively employed to study anxiety, self-esteem and personality of the subject as well. Many variants of this test are in practice. In some cases, subjects are asked to draw a picture of a person followed by a picture of a person of opposite gender. In some cases, subjects may be asked to draw themselves or any of the family members too. To assess the subject, a quantitative scoring system has been developed by the psychologists. To score a drawing, fourteen different aspects of the drawn figure are analyzed including different body parts and clothing. The analysis

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involves inspecting for the presence or absence of attributes, level of detail and proportions. Once the drawn figure is analyzed, the final score is employed to come to a conclusion about different cognitive and personal attributes of the subject.

The recent developments in areas like image analysis and pattern classification allow computerized system to automate the analysis of these psychological tests. Studies [41], [45], [14], [42] suggest that computerized scoring systems can facilitate professional psychologists in scoring the sheets produced by subjects so that they can focus only on suspected cases. Naturally, the objective is not to replace the human examiners but to facilitate them by reducing the manual investigations. Among different aspects of the HFDT, the focus of this study lies on the face of the drawn figure. We propose a computerized system that analyzes the hand-drawn facial images to extract the expressions from the image, one of the most important components in scoring of the HFDT. The system takes digitized images of hand-drawn sketches, segments the facial components and classifies the sketch into one of the four expression classes (happy, sad, angry & neutral) considered in our study. More specifically, features extracted from eyes and lips of the sketch are employed to train a Support Vector Machine (SVM) that learns to discriminate between the difference expression classes. The system evaluated on a database of 200 hand-drawn sketches reported promising classification rates.

This paper is organized as follows. In the next section, we discuss the notable recent contributions to computerized analysis of various psychological tests as well as facial expression recognition systems. Section III introduces the database employed in our study along with the details of the proposed technique including feature extraction and classification steps. Experimental settings and discussions on the realized results are presented in Section IV. Finally, Section V concludes the paper with a discussion on our further study on this problem.

II. Related Work

Computerized analysis of handwriting and hand-drawn shapes has remained an active area of research for more than three decades targeting a wide variety of applications [38], [4], [9], [2], [23]. Despite these endeavors, such computerized systems have not been fully explored in applications related to health or behavioral profiling of subjects. The primary reason has been the hesitancy of practitioners in accepting computerized systems in their work. The recent years, however, have witnessed a shift in paradigm and psychologists have been more open in embracing the use of computer based technologies in their practices [40], [45], convincing computer scientists to target such problems.

Among notable contributions to computerized analysis of neuro-psychological assessments, Remi et al. [41] discuss identification of learning difficulties through hand-drawn samples of school children. Likewise, Fairhurst et al. [14] present a pilot study to automate clinical tests targeting visuo-spatial neglect and dyspraxia. In another work [42], authors propose techniques for automated analysis of geometrical sketches targeting visuo-spatial classification. Similarly, in a pilot study [8], authors apply image analysis techniques to store parts of the Rey Osterrieth Complex Figure (ROCF) test. Scoring of geometrical shapes including triangles, rectangles, diamonds and lines is carried out using Gestalt laws of perception. Among other well-known studies, Moetesum et al. [36] apply shape context features [3] for classification of shapes in the Bender Gestalt Test and present a heuristic based approach [35] to score a subset of properties in this test. In a number of recent studies, the computerized analysis of Clock Draw Test (CDT) has been investigated [26], [19]. This test is known to be an early indicator for dementia. As opposed to many of the other tests which involve analysis of sketches, this test requires recognition of handwritten digits which is known to be a mature area of research [11].

From the view point of specific facial expression recognition systems [15], most of the work has been carried out on images and videos [22] targeting applications like human-computer-interaction [12], implicit customer feedback [24] and human emotion analysis [34]. A number of techniques based on statistical [43], [30] or structural [28] features have been proposed over the years. Recently, deep learning based facial expression recognition systems [31], [32] have also been investigated and have been shown to be more effective than the traditional techniques. Despite these tremendous research efforts, recognition of facial expressions from sketches has remained a relatively less explored area. Though sketch-based face recognition [48], [27], [52] and generalized sketch recognition systems [2], [23] have been researched and developed for forensic and retrieval applications respectively, recognizing expressions from sketches has yet to be investigated. In a relevant study, Bu et al. [7] present a system for sketch based facial expression recognition using Principal Component Analysis (PCA) and Support Vector Machine(SVM). The system, however, does not directly work on hand-drawn sketches but converts camera based grayscale facial images into sketches using Graphical Processing Units (GPU). Evaluations reveal that recognition of expressions from sketches realizes better performances than those reported by grayscale images. Interestingly, similar findings are reported in [6] where children of ages 5 and 7 years recognized emotions more easily from sketches as compared to grayscale human facial images.

III. Methodology

This section presents the details of the proposed methodology for recognition of facial expressions from sketches. The technique relies on extracting the facial components (eyes and lips) characterizing the expressions. Features based on Local Binary Patterns (LBP), Gray-level Co-occurrence Matrices (GLCM) and Histogram of Oriented Gradients (HoG) extracted from different regions of interest are used to train a Support Vector Machine (SVM) classifier that learns to discriminate between the four expressions considered in our study. We first introduce the database employed in our study followed by the details of feature extraction and classification steps.

A. Database

The database was collected by requiring the subjects to draw a sketch of a person (with a given expression) on blank sheet of paper. A total of 60 subjects contributed to data collection and each subject produced one sketch of each of the four expressions making a total of 240 (60×4) facial sketches. The sheets were digitized as grayscale images at 300 DPI. 40 sketches of each expression were employed in the training set and 20 in the test set resulting in a training set of 160 images and a test set of 80 images. It should be noted that the actual Human Figure Draw Test involves complete drawing of a human. Since the focus of current study is on a part (recognition of expressions) of the complete HFDT, the subjects were asked to sketch the face only. Based on the findings of the present study and its acceptance by the clinical psychologists, scoring of complete human figure will be considered in our further work on this problem. Figure 2 illustrates samples of (binarized) facial sketches from the database showing the four expressions considered in our study.

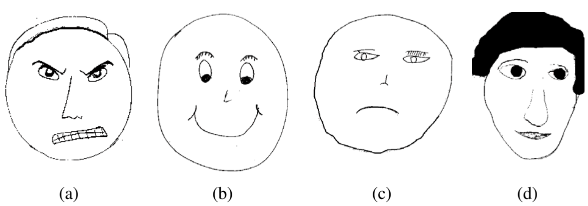


Fig. 2. Sample sketches from the database showing the four expressions (a): Angry (b): Happy (c): Sad (d): Neutral

B. Feature Extraction

Prior to extraction of features characterizing facial expressions, the face image is binarized. Since the pressure of writing instrument on the paper varies during the sketching process, binarization may result in broken lines and components. Morphological closing is therefore applied as a preprocessing step to connect and smooth the boundary of face as well as the facial components. Small noisy components are removed applying an area based filtering. Among different areas on the face, expressions are mainly characterized by eyes, eye brows and lips [25]. These components are even more important in case of sketches where cheeks do not convey any useful information. The components of interest (lips, eyes and eyes brows (if present)) therefore need to be detected and segmented prior to feature extraction.

Among different techniques to detect face and facial components, Haar-like features introduced by Viola-Jones [50] are known to be highly robust and have been most widely used. Such sophisticated techniques report effective detection performances on true images but fail once applied to sketches. Although complete image of face in a sketch can be detected, such techniques cannot be applied for detection of the facial components. The poor performance of such methods can be attributed to the fact that unlike true images, components in sketches comprise lines and curves only. Different components like nose, eyes or lips can all be represented by very similar lines or curves. Consequently, simpler techniques are likely to perform better on such images. We, therefore, first apply morphological dilation on the binarized image of the sketch to group pixels in different regions of the face into single connected components. The largest of these components encompassing other components can safely be considered as the face while other components (eyes, nose and mouth) are identified based on their spatial arrangement (Figure 3).

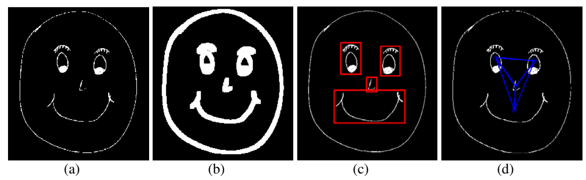


Fig. 3. Detection of facial components in a sketch (a): Original Image (b): Dilated Image (c): Connected Components in the Dilated Image (d): Centers of gravity of facial components

Once the eyes (plus eyebrows if present) and lips are identified, features are extracted from these components to characterize the emotion. The features considered in our study include Local Binary Patterns (LBP) and Gray-Level Co-Occurrence Matrices (GLCM) and Histograms of Oriented Gradients (HoG). For completeness, these features are briefly described in the following.

1) Local Binary Patterns: Local binary patterns (LBP), originally proposed for texture classification [37] have been applied to a number of classification problems [1], [44]. The computation of LBP relies on comparing the value of each pixel with its local neighborhood (8 pixels in the original LBP). All neighboring pixels with a value greater than or equal to the central pixel are assigned a value 1 while others are assigned a value 0. The resulting string is considered a binary number and represents the LBP code of the respective pixel(Figure 4). The LBP codes are computed for all pixels in a region of interest and the (normalized) histogram of the resulting codes is employed as a descriptor. We consider a neighborhood of 8 pixels around each pixel resulting in a histogram with 256 bins.

2) Gray-level Co-occurrence Matrices: Gray-level Co-occurrence Matrices (GLCMs) [18] capture the spatial relationship between pixels in an image representing the frequency of co-occurrence of two pixel values for a given distance and a given direction. The size of the matrix is same as the number of intensity levels in the image (2×2 for binary images). In our implementation, we compute four matrices using a

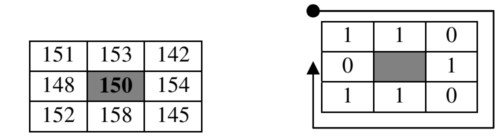


Fig. 4. Computation of LBP

displacement of 1 pixel in the four principal directions $0°$, $45°$, $90°$ and $135°$. Statistics computed from these GLCMs are then employed as features. Features considered in our study include contrast, correlation, homogeneity, entropy and energy of each GLCM (Table I). Finally, the sketch image is represented by a 20 (4×5) dimensional GLCM feature vector.

TABLE I
SUMMARY OF GLCM BASED FEATURES ('P' REPRESENTS THE MATRIX)

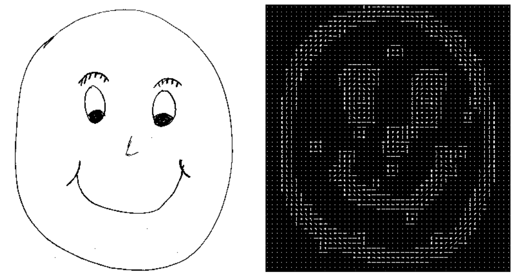
SNo.	Feature	Computational Details
1.	Contrast	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$
2.	Correlation	$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{(\sqrt{(\sigma_i^2)(\sigma_j^2)})}\right]$
3.	Homogenity	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$
4.	Entropy	$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j})$
5.	Energy	$\sum_{i,j=0}^{N-1} (P_{i,j})^2$

3) Histogram of Oriented Gradients: Histogram of Oriented Gradients (HOG), originally proposed for human detection by Dalal and Triggs [10], is a powerful descriptor that has been applied to a large number of detection and classification problems. Though mostly applied to high level object detection problems in computer vision, HOG has reported promising results on handwriting [13], [5] and sketch based [21] retrieval systems in a number of recent studies. We, therefore, investigate its effectiveness in characterizing expressions from facial sketches. HOG captures the local gradient information in small regions of the image, generally known as cells which are grouped into blocks. Since the dimensionality of the HOG descriptor is a function of image size, we resize all sketches to a fixed size of 512×512. Unlike LBP and GLCM features which are computed from eyes and lips only, the HOG descriptor is computed from the complete image of the sketch as facial components in different sketches may have different dimensions consequently leading to feature vectors of varying dimensions. In our implementation, we employ a cell size of 32×32 and a block size of 2×2 cells leading to a feature vector of dimension 8100. An example sketch and the corresponding HOG features are illustrated in Figure 5. More details on computation of the descriptor can be found in [10].

Table II presents a summary of the features employed in our study along with the dimensionality of each.

C. Classification

For classification we train a Support Vector Machine (SVM) using 'one-against-all' implementation. As discussed earlier,



(a) (b)

Fig. 5. HOG features computed on a sketch image

TABLE II
SUMMARY OF FEATURES EMPLOYED

Feature	Description	Dimensionality
f1	LBP Histogram	256
f2	GLCM Features	20
f3	HOG Descriptor	8100

40 images of each expression are used to train the classifier while 20 images of each expression are used in the evaluation set. Parameter tuning is carried out on the training data and the test data is kept unseen until the evaluation step. Training is carried out for each of the features (LBP, GLCM, HOG) separately as well as by combining all features. The results of these evaluations are discussed in the next section.

IV. EXPERIMENTS AND RESULTS

This section presents the details of the experiments carried out to validate the effectiveness of the employed features in characterizing expressions from the facial sketches. We first report the performance of the individual features on 80 query sketches where classification rates of 79%, 76% and 75% are reported by LBP, GLCM and HOG features as summarized in Table III. It can be seen that the performance of these features is more or less similar with LBP features performing marginally better than the GLCM and HOG features. When all features are combined, a correct classification rate of 82% is realized.

TABLE III
CLASSIFICATION RATES ON INDIVIDUAL AND COMBINED FEATURES

Feature	Correct Classification	Classification Rate
LBP	63/80	79%
GLCM	61/80	76%
HOG	60/80	75%
All Features	**66/80**	**82%**

In order to provide an insight into the type of errors, we present the system confusion matrix in Table IV while expression-wise performance in terms of precision, specificity and sensitivity is summarized in Table V. These results are reported for the combination of all features. It can be seen that a major proportion (around 60%) of errors results from the confusion between the expressions 'sad' and 'angry'. Likewise, in some cases, the expressions 'happy' and 'neutral' are confused with each other. These observations are very much natural and in many cases, human observers may also find it hard to discriminate between these expressions, especially in case of expressions 'sad' and 'angry'. Nevertheless, an overall classification rate of 82% on this challenging problem is indeed promising.

TABLE IV
CONFUSION MATRIX

Expression	Happy	Sad	Angry	Neutral
Happy	**18**	0	0	3
Sad	0	**16**	4	0
Angry	0	4	**16**	1
Neutral	2	0	0	**16**

TABLE V
EXPRESSION-WISE PERFORMANCE

	Expression Class			
	Happy	Sad	Angry	Neutral
True Positives(TP)	18	16	16	16
False Positives(FP)	3	4	5	2
False Negatives(FN)	2	4	4	4
True Negatives(TN)	57	56	55	58
Precision	0.86	0.80	0.76	0.89
Sensitivity	0.90	0.80	0.80	0.80
Specificity	0.95	0.93	0.92	0.97

V. CONCLUSION

We investigated the problem of facial expression recognition from hand-made sketches, an important component of the Human Figure Draw Test, a popular instrument for the assessment of cognitive functioning of individuals. The technique relies on segmenting the facial components in the sketch image and computing a set of features. Local Binary Patterns (LBP), Gray-level Co-occurrence Matrices (GLCM) and Histograms of Oriented Gradients (HOG) are considered as features in our work. LBP and GLCM based features are computed from the eyes and lips while HOG is computed from the complete image of the sketch. Recognition using Support Vector Machine (SVM) classifier reported a correct classification rate of 82% on 80 query images, a promising number considering the challenges offered by this problem.

The present system is designed to recognize four common expressions including 'happy', 'sad', 'angry' and 'neutral'. In our further work, we intend to increase the number of expressions and enhance the robustness of the recognition technique. Being a pilot study, the current system assumes that the all facial components are present in the sketch. This assumption may not hold in all cases, especially if the sketches are produced by subjects with cognitive impairments. The system may encounter missing or noisy components which have to be handled accordingly. Moreover, recognition of expressions is only a part of the complete HFDT. We plan to design algorithms to provide a complete scoring of this test and compare the computerized scoring with the one carried out by practitioners. The authors expect that the findings of this study would be interesting both for computer scientists and clinical psychologists.

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REFERENCES

[1] Timo Ahonen, Abdenour Hadid, and Matti Pietikäinen. Face recognition with local binary patterns. *Computer vision-eccv 2004*, pages 469–481, 2004.

[2] Christine Alvarado and Randall Davis. Sketchread: a multi-domain sketch recognition engine. In *Proceedings of the 17th annual ACM symposium on User interface software and technology*, pages 23–32. ACM, 2004.

[3] Serge Belongie, Jitendra Malik, and Jan Puzicha. Shape context: A new descriptor for shape matching and object recognition. In *Advances in neural information processing systems*, pages 831–837, 2001.

[4] Ameur Bensefia, Thierry Paquet, and Laurent Heutte. A writer identification and verification system. *Pattern Recognition Letters*, 26(13):2080–2092, 2005.

[5] Nesrine Bouadjenek, Hassiba Nemmour, and Youcef Chibani. Histogram of oriented gradients for writer's gender, handedness and age prediction. In *Innovations in Intelligent Systems and Applications (INISTA), 2015 International Symposium on*, pages 1–5. IEEE, 2015.

[6] Claire Brechet. Children's recognition of emotional facial expressions through photographs and drawings. *The Journal of Genetic Psychology*, 178(2):139–146, 2017.

[7] Jiajun Bu, Mingli Song, Qi Wu, Chun Chen, and Cheng Jin. Sketch based facial expression recognition using graphics hardware. *Lecture notes in computer science*, 3784:72, 2005.

[8] RO Canham, Stephen L Smith, and Andrew M Tyrrell. Automated scoring of a neuropsychological test: the rey osterrieth complex figure. In *Euromicro Conference, 2000. Proceedings of the 26th*, volume 2, pages 406–413. IEEE, 2000.

[9] Krzysztof Cpałka, Marcin Zalasiński, and Leszek Rutkowski. New method for the on-line signature verification based on horizontal partitioning. *Pattern Recognition*, 47(8):2652–2661, 2014.

[10] Navneet Dalal and Bill Triggs. Histograms of oriented gradients for human detection. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, volume 1, pages 886–893. IEEE, 2005.

[11] Markus Diem, Stefan Fiel, Angelika Garz, Manuel Keglevic, Florian Kleber, and Robert Sablatnig. Icdar 2013 competition on handwritten digit recognition (hdrc 2013). In *Document Analysis and Recognition (ICDAR), 2013 12th International Conference on*, pages 1422–1427. IEEE, 2013.

[12] Fadi Dornaika and Bogdan Raducanu. Facial expression recognition for hci applications. *Encyclopedia of Artificial Intelligence*, 2:625–631, 2009.

[13] Reza Ebrahimzadeh and Mahdi Jampour. Efficient handwritten digit recognition based on histogram of oriented gradients and svm. *International Journal of Computer Applications*, 104(9), 2014.

[14] Mr C Fairhurst, T Linnell, Stephanie Glenat, RM Guest, Laurent Heutte, and Thierry Paquet. Developing a generic approach to online automated analysis of writing and drawing tests in clinical patient profiling. *Behavior Research Methods*, 40(1):290–303, 2008.

[15] Beat Fasel and Juergen Luettin. Automatic facial expression analysis: a survey. *Pattern recognition*, 36(1):259–275, 2003.

[16] Christina T Fuentes, Stewart H Mostofsky, and Amy J Bastian. Children with autism show specific handwriting impairments. *Neurology*, 73(19):1532–1537, 2009.

[17] Florence Laura Goodenough. *Measurement of intelligence by drawings.* World Book Co., 1926.

[18] Robert M Haralick, Karthikeyan Shanmugam, et al. Textural features for image classification. *IEEE Transactions on systems, man, and cybernetics*, (6):610–621, 1973.

[19] Zainab Harbi, Yulia Hicks, and Rossitza Setchi. Clock drawing test digit recognition using static and dynamic features. *Procedia Computer Science*, 96:1221–1230, 2016.

[20] Eleanor Holtz-Eakin and Ida Sue Baron. Human figure drawing tests. In *Encyclopedia of Clinical Neuropsychology*, pages 1269–1271. Springer, 2011.

[21] Rui Hu and John Collomosse. A performance evaluation of gradient field hog descriptor for sketch based image retrieval. *Computer Vision and Image Understanding*, 117(7):790–806, 2013.

[22] Takeo Kanade, Jeffrey F Cohn, and Yingli Tian. Comprehensive database for facial expression analysis. In *Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on*, pages 46–53. IEEE, 2000.

[23] Levent Burak Kara and Thomas F Stahovich. An image-based, trainable symbol recognizer for hand-drawn sketches. *Computers & Graphics*, 29(4):501–517, 2005.

[24] Zolidah Kasiran and Saadiah Yahya. *Facial expression as an implicit customers' feedback and the challenges*. IEEE, 2007.

[25] Zolidah Kasiran, Saadiah Yahya, and Zaidah Ibrahim. Facial expression recognition as an implicit customers' feedback. In *Advances in Human Computer Interaction*. InTech, 2008.

[26] Hyungsin Kim, Young Suk Cho, and Ellen Yi-Luen Do. Computational clock drawing analysis for cognitive impairment screening. In *Proceedings of the fifth international conference on tangible, embedded, and embodied interaction*, pages 297–300. ACM, 2011.

[27] Scott Klum, Hu Han, Anil K Jain, and Brendan Klare. Sketch based face recognition: Forensic vs. composite sketches. In *Biometrics (ICB), 2013 International Conference on*, pages 1–8. IEEE, 2013.

[28] Irene Kotsia and Ioannis Pitas. Facial expression recognition in image sequences using geometric deformation features and support vector machines. *IEEE Transactions on Image Processing*, 16(1):172–187, 2007.

[29] Azadeh Kushki, Tom Chau, and Evdokia Anagnostou. Handwriting difficulties in children with autism spectrum disorders: A scoping review. *Journal of autism and developmental disorders*, 41(12):1706–1716, 2011.

[30] Shu Liao, Wei Fan, Albert CS Chung, and Dit-Yan Yeung. Facial expression recognition using advanced local binary patterns, tsallis entropies and global appearance features. In *2006 International Conference on Image Processing*, pages 665–668. IEEE, 2006.

[31] André Teixeira Lopes, Edilson de Aguiar, Alberto F De Souza, and Thiago Oliveira-Santos. Facial expression recognition with convolutional neural networks: Coping with few data and the training sample order. *Pattern Recognition*, 61:610–628, 2017.

[32] Yadan Lv, Zhiyong Feng, and Chao Xu. Facial expression recognition via deep learning. In *Smart Computing (SMARTCOMP), 2014 International Conference on*, pages 303–308. IEEE, 2014.

[33] Brian J Mainland and Kenneth I Shulman. Clock drawing test. In *Cognitive Screening Instruments*, pages 79–109. Springer, 2013.

[34] Tomas Matlovic, Peter Gaspar, Robert Moro, Jakub Simko, and Maria Bielikova. Emotions detection using facial expressions recognition and eeg. In *Semantic and Social Media Adaptation and Personalization (SMAP), 2016 11th International Workshop on*, pages 18–23. IEEE, 2016.

[35] Momina Moetesum, Imran Siddiqi, Uzma Masroor, and Chawki Djeddi. Automated scoring of bender gestalt test using image analysis techniques. In *Document Analysis and Recognition (ICDAR), 2015 13th International Conference on*, pages 666–670. IEEE, 2015.

[36] Momina Moetesum, Imran Siddiqi, Uzma Masroor, Nicole Vincent, and Florence Cloppet. Segmentation and classification of offline hand drawn images for the bgt neuropsychological screening test. In *Eighth International Conference on Digital Image Processing (ICDIP 2016)*, pages 100334N–100334N. International Society for Optics and Photonics, 2016.

[37] Timo Ojala, Matti Pietikainen, and Topi Maenpaa. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *IEEE Transactions on pattern analysis and machine intelligence*, 24(7):971–987, 2002.

[38] Réjean Plamondon and Sargur N Srihari. Online and off-line handwriting recognition: a comprehensive survey. *IEEE Transactions on pattern analysis and machine intelligence*, 22(1):63–84, 2000.

[39] Ratanotai Plbrukarn and S Theeramanoparp. Human figure drawing test: validity in assessing intelligence in children aged 3-10 years. *J Med Assoc Thai*, 86(S3):S610–17, 2003.

[40] Amir M Poreh. *The quantified process approach to neuropsychological assessment*. Psychology Press, 2012.

[41] Céline Rémi, Carl Frélicot, and Pierre Courtellemont. Automatic analysis of the structuring of children's drawings and writing. *Pattern Recognition*, 35(5):1059–1069, 2002.

[42] Ney Renau-Ferrer and Céline Remi. A method for visuo-spatial classification of freehand shapes freely sketched. *arXiv preprint arXiv:1305.1520*, 2013.

[43] Adin Ramirez Rivera, Jorge Rojas Castillo, and Oksam Oksam Chae. Local directional number pattern for face analysis: Face and expression recognition. *IEEE transactions on image processing*, 22(5):1740–1752, 2013.

[44] Amit Satpathy, Xudong Jiang, and How-Lung Eng. Lbp-based edge-texture features for object recognition. *IEEE Transactions on Image Processing*, 23(5):1953–1964, 2014.

[45] Philip Schatz and Jeffrey Browndyke. Applications of computer-based neuropsychological assessment. *The Journal of head trauma rehabilitation*, 17(5):395–410, 2002.

[46] A Schröter, R Mergl, K Bürger, H Hampel, H-J Möller, and Ulrich Hegerl. Kinematic analysis of handwriting movements in patients with alzheimers disease, mild cognitive impairment, depression and healthy subjects. *Dementia and Geriatric Cognitive Disorders*, 15(3):132–142, 2003.

[47] Min-Sup Shin, Sun-Young Park, Se-Ran Park, Soon-Ho Seol, and Jun Soo Kwon. Clinical and empirical applications of the rey–osterrieth complex figure test. *Nature protocols*, 1(2):892–899, 2006.

[48] Xiaoou Tang and Xiaogang Wang. Face sketch recognition. *IEEE Transactions on Circuits and Systems for Video Technology*, 14(1):50–57, 2004.

[49] Hans-Leo Teulings and George E Stelmach. Control of stroke size, peak acceleration, and stroke duration in parkinsonian handwriting. *Human Movement Science*, 10(2):315–334, 1991.

[50] Paul Viola and Michael Jones. Rapid object detection using a boosted cascade of simple features. In *Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on*, volume 1, pages I–I. IEEE, 2001.

[51] Robert Walrath. Bender visual motor gestalt test. In *Encyclopedia of Child behavior and Development*, pages 233–234. Springer, 2011.

[52] Bing Xiao, Xinbo Gao, Dacheng Tao, and Xuelong Li. A new approach for face recognition by sketches in photos. *Signal Processing*, 89(8):1576–1588, 2009.