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A Study of Stressed Facial Recognition Based on Histogram Information

Barlian Henryranu Prasetio*, Edita Rosana Widasari and Fitra Abdurrachman Bachtiar
E-mail: barlian@ub.ac.id, editarosanaw@ub.ac.id, fitra.bactiar@ub.ac.id
Faculty of Computer Science – University of Brawijaya, Veteran No. 8 Malang, Indonesia

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Stress represents our subconscious emotions. The majority of the unconscious content is unacceptable or unpleasant such as pain, anxiety, or conflict. Most individuals do not realize that they are experiencing stress. Prolonged stressful experiences are likely to lead to health problems and affect one's facial appearance, specifically wrinkles shown in the face. This paper discussed the introduction of facial stress with histogram information. There are three stages in recognizing the stress pattern on the face of the registered image, feature extraction and classification. The registered image process takes three important parts of the face, i.e. the eyes, nose, and mouth. The feature extraction process was performed using the histogram method, i.e. Gabor filter and HOG feature. Each extracted feature was used as the model input to determine whether or not an individual is suffering from stress. Two classification methods were applied to learn stress patterns from the extracted feature. The classification process was performed using SVM with six kernel functions and a Tree algorithm with three numbers of split. Each model is trained using ten cross-fold validation strategies. The test results showed that the Gabor filter and HOG feature accuracy were 55% and 65%, respectively. The effectiveness of the proposed method is evaluated by comparing it with the existing methods in term of accuracy.

Povzetek: Predstavljena je študija ugotavljanja stresa iz obraznih mimik.

1 Introduction

Stress is a non-specific response of the body in every claim [1]. It defines an individual's suppressed psychological state due to limitations and barriers arising in their effort to seize an opportunity [2]. Stress arises due to failure in achieving demands due to an imbalance in demands (physical and psychological) and ability [3]. According to [4] in his book, stress denotes one's physical or psychological response to a change in his environment perceived as disturbing and threatening [4].

Stress is our subconscious emotion. The subconscious mind is the shelter of feelings, thoughts, drives, and memories that are in the subconscious of our consciousness. Much of the unconscious content is unacceptable or unpleasant, such as pain, anxiety, or conflict. The subconscious will be influencing our behavior and experience, even though we are not aware of this fundamental influence [5].

Stress may affect one's physical condition. A prolonged stressful experience may result in heart and circulatory problems. As reported by [6], it can increase heart rate. In 2017, one-three of people reported feeling stressed, meaning that approximately 322 million people worldwide have an anxiety disorder [7]. If this condition continues, one's may suffer from increased blood pressure, affecting their facial appearance. Wrinkles may appear in an individual undergoing stressful experiences [8]. One's facial expression may indirectly show his/her stressed condition. However, it should be noted that stress is known to affect only several face areas such as the eye, nose, and lips [9].

Several methods are known to be helpful for recognizing stress conditions. The medical test is known to be the most accurate method in identifying stress level. However, it is very difficult to identify under-stress person. Most things have used the intrusive method, that is, through facial recognition. Over the past few decades, research on face recognition has been instrumental in computer vision technology [10].

Computer vision is a combination of image processing and pattern recognition. Image processing is a process of image transformation that aims to get good image quality [11]. Pattern recognition is the process of identifying an image object to extract information from the image. In neuroscience, researchers have been mostly concerned with models of the perception and classification of expressions [12], [13]. However, facial expression is a complex element that is difficult to understand. Even in a static pose, a face may present information related to emotion and mood [14]. It investigated how human observers use information from different face areas to successfully recognize the emotion expressed. More than a half of face part presents their conditions. Not only focusing on the perception of facial emotions and human behaviors [15], but the researchers also focused on the methods developed [16].

* Corresponding author

The current study focused on comparing two texture feature extractions. The feature extraction process is the process of encoding images in visual form. The encoding stage used the HOG descriptor (Histogram of Oriented Gradients) and Gabor filter. These two feature extractions were selected since the stress experience is identifiable through the wrinkles in the face area. Furthermore, a classification algorithm was applied to evaluate the effectiveness of the selected feature extractions. Previous studies showed that SVM and Tree-Based algorithm have better recognition rates than other machine learning methods [17]. Considering those findings, this study applied the SVM and Tree algorithm. The vector array of the extracted image features is modeled using SVM (Support Vector Machine) and Tree Algorithm.

2 Face and stress

Stress is likely to cause sleep difficulty [18]. It may slow down the circulatory system, expanding blood vessels below the eyes and thus creating dark circles around the eyes [19].

Although aging is a natural, common skin experience, stress may accelerate this process. Stress can affect our brain, causing wrinkles to emerge earlier due to anxiety, depression, exhaustion, or lack of rest. These lines or wrinkles may emerge around the forehead, mouth, and eyes [20].

Stress indirectly affects the production of healthy collagen in the skin. Thus, the skin will look dull and create a tired-looking face. Stress also causes the production of melanin, a pigment that gives color to the skin, to decrease [21]. One's signs of stress can be easily detected from his/her face. Figure 1 above displays the lines or wrinkles around the mouth and eyes.

3 Methods

The stressed face recognition system has two main parts: the feature extraction process and the classification [22]. Figure 2 shows the stress recognition system block diagram.

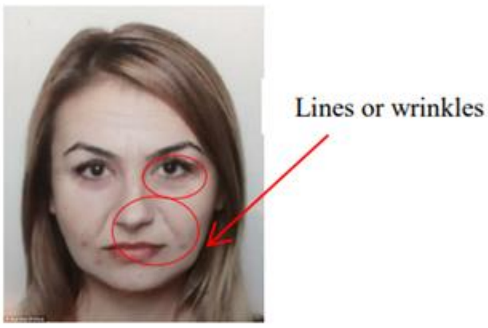


Figure 1: The lines or wrinkles around the mouth and eyes.

As shown in Figure 2, Specific face areas were segmented first before the feature extraction process. This study focused on three areas. The segmented images were extracted to obtain the numerical value for further process.

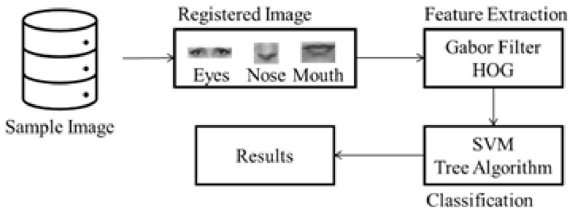


Figure 2: The stressed recognition system block diagram.

Lastly, the extracted features were fed to classification algorithm for facial pattern learning.

3.1 Image dataset

The training phase is the process of providing the images face that is known to the class (stress or neutral). The collection of facial images is called the image dataset. This study employed JAFFE consisting of 213 images of different facial expressions from ten different Japanese female subjects categorized as stress and neutral expression.

3.2 Registered image

The registered image phase has 3 steps to get the needed facial parts to be processed further. The first step is detecting the face area. The next step was to greyscale the image. Finally, the selected area of the image was cropped. In particular, the three areas to be cropped are the eye, nose, and mouth [23]. These areas are chosen as the features since wrinkles may appear in these three regions. The image registration steps are displayed in Figure 3.

Face detection and area cropping is detected and performed using Viola-Jones object detection framework in MATLAB Toolbox.

3.3 Feature extraction

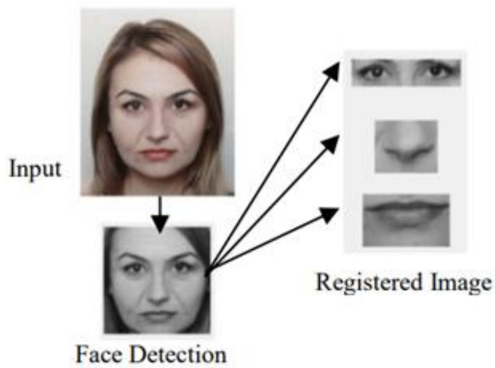


Figure 3: The pre-processing steps of registered image.

3.3.1 Gabor feature

Gabor Filter is a linear filter used to detect edges and frequency decomposition [24]. There are 2 main processes in Gabor feature extraction: the process of making Gabor array and the extraction process, i.e., taking vector feature from the Gabor array [25].

Gabor filter consists of several steps. The first step is the initialization variable. Four variables are initialized, including wavelength (u), number of orientations (v), and two dimensions of Gabor filter bank (m, n) [26], [27]. Each Gabor filter variable used in this study was identified to obtain the maximum extraction results. These four parameters were used to calculate the Gabor filter bank. The visual illustration of the Gabor matrix is displayed in Figure 4.

Fig. 4 shows that the 5x5 filter matrix. Each filter array represents a different wavelength and orientation [28].

3.3.2 Histogram of Gradients (HOG)

Histogram of Oriented Gradients (HOG) is a rotationally invariant descriptor [29]. HOG feature consists of several stages, including gradient calculation, spatial weighting and orientation of cells, normalization of spatial block overlapping and HOG detection windows.

The gradient calculation process is to apply the vertical and horizontal Sobel method with the kernel filter on the greyscale image (Rekha and Kurian, 2014). The magnitude and gradient values can be calculated after obtaining the values of x, y derivatives Equation 1.

$$|G|=\sqrt{I_x^2+I_y^2} \quad (1)$$

Where, I_x and I_y are input image after convolution operation x and y.

The spatial weighting and orientation of the cells process divide the image into small spaces called cells. Each pixel in the cell is grouped in bins based on the

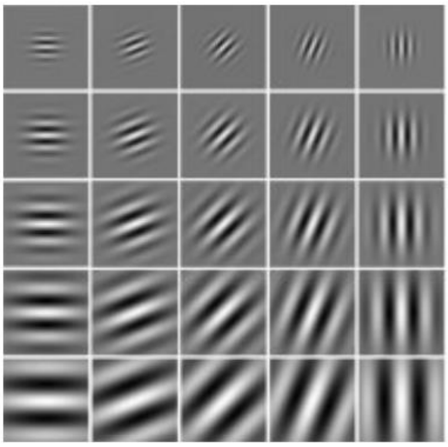


Figure 4: The visual illustration of Gabor matrix (u=5, v=5).

orientation value obtained from the gradient calculation [30]. Each cell creates a histogram with 9 channel histograms distributed into an angular orientation of 0°-180°.

Since the gradient calculation process obtained different values, it is necessary to group each cell into larger groups called blocks. After grouping into a block, any overlapping block should be normalized. All histograms for each block were combined to produce a feature vector. This process is called a HOG detection window. The illustration of the HOG feature stages is presented in Figure 5. All of the HOG parameters in this study were explored to get the most extraction results.

3.4 Classification

SVM is the traditional classification method used in this study because it can find the hyperplane optimally [31]. SVM maps each input and output data to represent the similarity vector [32]. Vector mapping can be either linear or non-linear [33]. For non-linear functions, a kernel is required in the mapping process. Three types of kernels are known, namely Linear (Equation 2), Polynomial (Equation 3) and Gaussian (Equation 4).

$$k(x,y)=x^T y \quad (2)$$

$$k(x,y)=(1+x^T y)^d \quad (3)$$

$$k(x,y)=e^{-(\|x-y\|^2/(2\sigma)^2)} \quad (4)$$

Where x and y represent classes, d represent polynomial degree; if d = 2 then quadratic kernel function; if d = 3 then cubic kernel function; $1/2\sigma = \gamma$; if $\gamma = 0.43$ then fine Gaussian; if $\gamma = 1.7$ then medium Gaussian if $\gamma = 6.9$ then coarse Gaussian.

The second classification method was Tree algorithm. Tree algorithm has influenced machine learning as classification and regression. A tree has presented a node and split of the branch. The splitting number σ (T) of tree T has an effect of successive [34]. In this study, feature extraction data from Gabor filter and HOG feature were classified into three models of Tree algorithm, namely, Fine Tree, Medium Tree, and Coarse Tree. The number of fine tree's split is 100, for medium tree is 20, and for the coarse tree is 4.

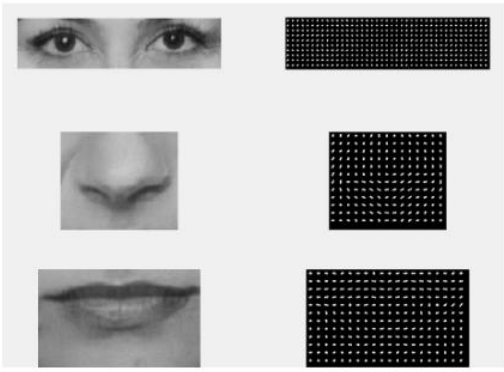


Figure 7: The gradient histogram of eyes, nose, and mouth.

3.5 Validation method

In these experiments, the stress classification is validated using a k-fold cross-validation method. This is a technique to validate the accuracy of a model built on a particular dataset. The development of a model usually aims to predict and classify new data [35]. The data used in the model development process is called training data. The data used to validate the model is called the test data. In this study, we evaluated the effectiveness of the proposed system by applying some “k” value.

4 Result and discussions

4.1 Gabor filter

Initially, we created a Gabor filter matrix (m=7, n=5). This matrix was filled by the Gabor array with the number of wavelengths of 5 and the number of orientations of 7. The wavelengths were 3, 6, 13, 28, and 58. The orientations were 0, 30, 45, 90, 120, 135, and 150. Every face part of a registered image (eyes, nose, and mouth) is convoluted its magnitude based on Gabor array. So, each face part has 7x5 arrays of images. The Gabor magnitude image array for the eye can be seen in Figure 6.

The next step was converting those magnitudes matrices to feature vectors. The feature vector consists of Local Energy and Mean Amplitude [36]. Local energy is the mean of the sum of squares of the magnitude matrix. Mean Amplitude is the mean of the absolute values of the magnetic matrix.

Furthermore, both local energy and mean amplitude are input of SVM and Tree Algorithm.

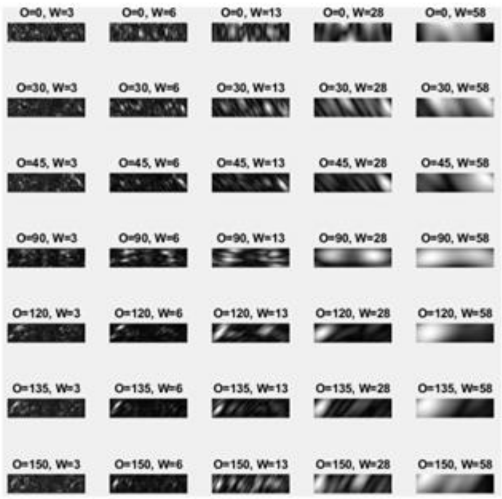


Figure 6: The Gabor magnitude image array for the eye.

4.2 HOG feature

The first step of the HOG feature is calculating a HOG descriptor. We need the horizontal and vertical gradients. The next step is to divide the image into a 16x16 cell. Then the gradient histogram is counting on each cell. Each gradient histogram consists of 2 matrix values, i.e. magnitude and direction. A gradient histogram of three face areas (eyes, nose, and mouth) can be seen in Figure 7.

As shown in Figure 7, the calculation of the feature vector values was performed after the gradient histogram matrix value was normalized into dimensional vectors. The dimensional vectors in each face area will take the average value of each cell and will be as the input of SVM and Tree Algorithm.

4.3 Support Vector Machine

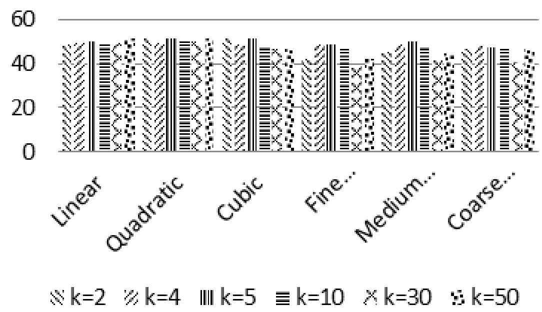
The result data from feature extraction was classified using SVM algorithm. The classification was performed with 6 SVM kernel functions, i.e. linear, quadratic, cubic, fine Gaussian, medium Gaussian, and coarse Gaussian. Each classification was validated using a cross-validation method with some “k” values. The accuracy of SVM algorithm can be seen in Figure 8.

Figure 8 (a) displays the SVM accuracy for Gabor filter feature extraction. The highest accuracy was around 50%. Fig. 8 (b) shows the SVM accuracy for HOG feature extraction. The highest accuracy was around 60%. Based on the classification results, the combination of SVM and HOG feature shows higher recognition result compared to SVM and Gabor Filter by showing accuracy of 62.8%.

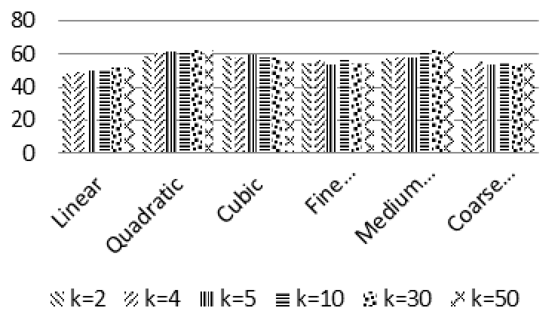
4.4 Tree algorithm

Each feature extraction (Gabor Filter and HOG Feature) was classified using the Tree algorithm. The accuracy value was cross-validated. The accuracy of the Tree algorithm can be seen in Figure 9.

Figure 9 shows that the average accuracy using Tree's algorithm is above 65%. Figure 9 (a) shows that the best accuracy of the Tree's algorithm classification for the Gabor feature is the 30-folds Fine Tree. Figure 9 (b) shows that the most accurate of the tree algorithm classification for the HOG feature is the 50-folds Medium Tree. The combination of Medium Tree and HOG Feature was found to be more accurate than other combinations with a 70.4% accuracy.



(a) Gabor Filter



(b) HOG Feature

Figure 8: The accuracy of SVM algorithm.

4.5 Comparison performance

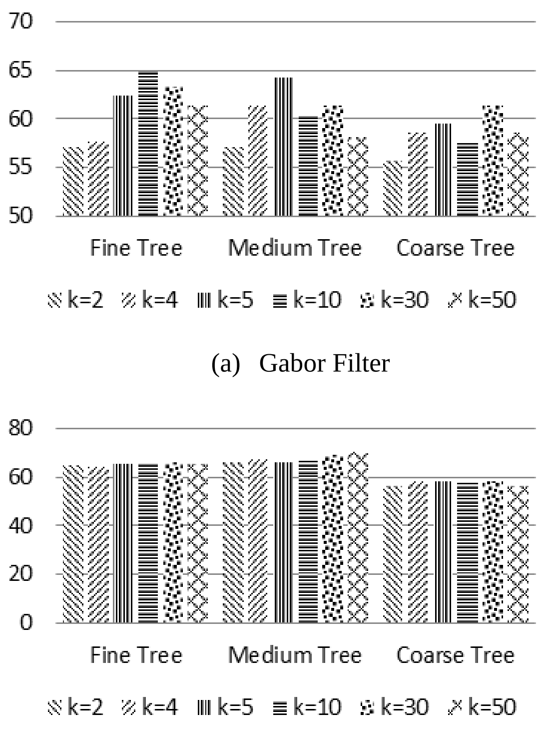
The effectiveness of the proposed method is evaluated in term of accuracy and compares it to baseline methods, as showed in Table 1.

The evaluation result shows that Bayesian Network (BN) able to incorporate the past information about a event parameters. However, BN sometimes produce a posterior distribution that is strongly influenced by priors, it might difficult to assure the validity of the selected priors. On the other hand, the DNN based technique (ResNet and SOTA) outperforms the BN. DNN better to represent complicated patterns of emotions. However in a simple case, such as binary classification of stress, our work more accurate than DNN due to a low set of categorical values in training data. DNN and Tree has a same mechanism in finding non-linear solutions by interacting between independent variables. Thus, decision trees are better when the scenario demands an explanation over the decision. It is because its deterministically one, whereas DNN take a probabilistic view towards the piece-by-piece model fitting.

4.6 Summary

The summary of classification performance can be seen in Figure 10.

As shown in Figure 10, the accuracy of SVM-Gabor filter feature was 51.9%, while that of SVM-HOG feature was 62.8%. The accuracy of Tree algorithm and Gabor filter feature was 64.8% and that of Tree algorithm and HOG feature was 70.4%. The results indicated that the HOG feature is more efficient for classifying stress extracted from facial elements. HOG feature extracted the orientation of the histogram which can extract nonlinear pattern in the image. The registered images used in this study were not linear. Thus, nonlinear feature extraction would be suitable in this situation.



(a) Gabor Filter

(b) HOG Feature

Figure 9: The accuracy of Tree algorithm.

We also evaluated the proposed method effectiveness by comparing it with the existing methods such as Bayesian Network (BN) and Self Organizing Tree Algorithm (SOTA). The evaluation result shows that our work outperforms the existing methods because decision trees explicitly fit parameters to direct the information flow.

Stress, anxiety, and depression were the highest mental health problems with 74% for stress, 28% for anxiety disorders, and 48% for depression [38]. Currently, mental health problems are increasing and worrying, especially because of the COVID-19 pandemic, affecting individuals and society in an increasingly diverse nature. The pandemic has also given rise to a wide-ranging mental health crisis. This is forcing decision makers to turn to technology to open up research opportunities into a coherent framework that serves as an initial effort to develop interdisciplinary research between technology and mental health [39][40].

5 Conclusion

In this paper, we have recognized the facial signs caused by stress. Three face areas (i.e., eyes, nose, and mouth) were selected as stress features. We applied a Gabor filter and HOG feature extraction methods. The classification

Table 1: The comparison performance evaluation.

Reference	Dataset	Method and Classifier	Accuracy (%)
L. Surace [10]	GAF (positive/negative event)	Bayesian Network	64.68
S. D. Viet [15]	FERC-2013 (7 expressions)	Multi-task ResNet	69.33
B. H. Prasetio [37]	SUSAS (5 classes of stress)	SOTA	68.72
Our work	Jaffe (stress/neutral)	Tree	70.4

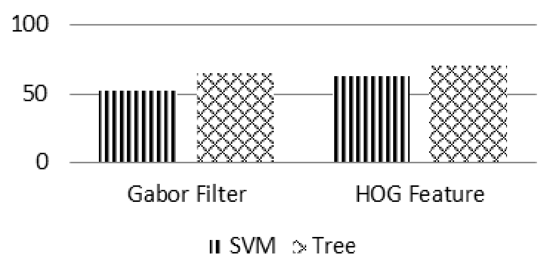


Figure 10: The summary of classification performance.

process was performed by SVM and Tree algorithm. The effectiveness of the proposed system was evaluated using k-fold cross-validation method with some “k” value. The experimental result showed that SVM and Tree algorithm with Gabor filter feature exhibit an average accuracy of 55% while the combination of SVM and Tree Algorithm with HOG exhibited a 67% accuracy. The current study achieved satisfactory results by recognizing stress from facial images by involving three face areas, namely eyes, nose, and mouth. Future studies might consider adding more face areas as additional features. It is also recommended to explore other algorithm methods as the model could affect the recognition accuracy. In a simple classification, decision tree better than DNN based method due to its explicitly fit parameters to direct the information flow and deterministically one.

References

[1] H. Selye, Stress in health and disease. Butterworth-Heinemann, 2013. https://doi.org/10.1016/C2013-0-06263-9

[2] S. P. Robin, “Organizational Behavior,” New York Prentice Hall, 2001.

[3] R. S. Weinberg and D. Gould, Foundations of sport and exercise psychology, 7E. Human Kinetics, 2019.

[4] H. Yaribeygi, Y. Panahi, H. Sahraei, T. P. Johnston, and A. Sahebkar, “The impact of stress on body function: A review,” EXCLI J., vol. 16, p. 1057, 2017. https://doi.org/ 10.17179/excli2017-480

[5] B. J. Carducci, The psychology of personality: Viewpoints, research, and applications. John Wiley \& Sons, 2009.

[6] B. . Tovian, S.; Thorn, B.; Coons, H.; Susan, L.; Matthew, B.; Richard, S.; Daniel, “Stress effects on the body,” Am. Psychol. Assoc.

[7] W. H. Organization and others, “Depression and other common mental disorders: global health estimates,” 2017.

[8] J. H. Dunn and J. Koo, “Psychological Stress and skin aging: a review of possible mechanisms and potential therapies,” Dermatol. Online J., vol. 19, no. 6, 2013. https://doi.org/10.5070/D3196018561

[9] C. Daudelin-Peltier, H. Forget, C. Blais, A. Deschênes, and D. Fiset, “The effect of acute social stress on the recognition of facial expression of emotions,” Sci. Rep., vol. 7, no. 1, pp. 1–13, 2017. https://doi.org/10.1038/s41598-017-01053-3

[10] L. Surace, M. Patacchiola, E. Battini Sönmez, W. Spataro, and A. Cangelosi, “Emotion recognition in the wild using deep neural networks and Bayesian classifiers,” in Proceedings of the 19th ACM international conference on multimodal interaction, 2017, pp. 593–597. https://doi.org/10.1145/3136755.3143015

[11] A. Adriyendi, “A Rapid Review of Image Captioning,” J. Inf. Technol. Comput. Sci., vol. 6, no. 2, pp. 158–169, 2021. https://doi.org/10.25126/jitecs.202162316

[12] A. Martinez and S. Du, “A model of the perception of facial expressions of emotion by humans: research overview and perspectives.,” J. Mach. Learn. Res., vol. 13, no. 5, 2012.

[13] I. Azam and S. A. Khan, “Feature extraction trends for intelligent facial expression recognition: A survey,” Informatica, vol. 42, no. 4, 2018. https://doi.org/10.31449/inf.v42i4.2037

[14] M. Wegrzyn, M. Vogt, B. Kireclioglu, J. Schneider, and J. Kissler, “Mapping the emotional face. How individual face parts contribute to successful emotion recognition,” PLoS One, vol. 12, no. 5, p. e0177239, 2017. https://doi.org/10.1371/journal.pone.0177239

[15] S. D. Viet and C. L. T. Bao, “Effective Deep Multi-source Multi-task Learning Frameworks for Smile Detection, Emotion Recognition and Gender Classification,” Informatica, vol. 42, no. 3, 2018. https://doi.org/10.31449/inf.v42i3.2301

[16] M. K. Benkaddour, “CNN based features extraction for age estimation and gender classification,” Informatica, vol. 45, no. 5, 2021. https://doi.org/10.31449/inf.v45i5.3262

[17] D. S. Trigueros, L. Meng, and M. Hartnett, “Face recognition: From traditional to deep learning methods,” arXiv Prepr. arXiv1811.00116, 2018. https://doi.org/10.48550/arXiv.1811.00116

[18] D. A. Kalmbach, J. R. Anderson, and C. L. Drake, “The impact of stress on sleep: pathogenic sleep reactivity as a vulnerability to insomnia and circadian disorders,” J. Sleep Res., vol. 27, no. 6, p. e12710, 2018. https://doi.org/10.1111/jsr.12710

[19] R. Sarkar, R. Ranjan, S. Garg, V. K. Garg, S. Sonthalia, and S. Bansal, “Periorbital hyperpigmentation: a comprehensive review,” J. Clin. Aesthet. Dermatol., vol. 9, no. 1, p. 49, 2016.

[20] C. Parrado, S. Mercado-Saenz, A. Perez-Davo, Y. Gilaberte, S. Gonzalez, and A. Juarranz, “Environmental stressors on skin aging. Mechanistic insights,” Front. Pharmacol., vol. 10, p. 759, 2019. https://doi.org/10.3389/fphar.2019.00759

[21] A. Sitek, E. Zadzinska, and I. Rosset, “Effects of psychological stress on skin and hair pigmentation in Polish adolescents,” 2012. https://doi.org/10.2478/v10044-012-0001-7

[22] M. Usman, S. Latif, and J. Qadir, “Using deep autoencoders for facial expression recognition,” in 2017 13th International Conference on Emerging Technologies (ICET), 2017, pp. 1–6. https://doi.org/10.1109/ICET.2017.8281753

[23] K. Tsuchida and M. Kobayashi, “Oxidative stress in human facial skin observed by ultraweak photon emission imaging and its correlation with biophysical properties of skin,” Sci. Rep., vol. 10, no. 1, pp. 1–7, 2020. https://doi.org/10.1038/s41598-020-66723-1

[24] L. El Shafey, R. Wallace, and S. Marcel, “Face verification using gabor filtering and adapted gaussian mixture models,” in 2012 BIOSIG-Proceedings of the International Conference of Biometrics Special Interest Group (BIOSIG), 2012, pp. 1–6.

[25] K. Yan, Y. Chen, and D. Zhang, “Gabor surface feature for face recognition,” in The first asian conference on pattern recognition, 2011, pp. 288–292. https://doi.org/10.1109/ACPR.2011.6166553

[26] T. Barbu, “Gabor filter-based face recognition technique,” Proc. Rom. Acad., vol. 11, no. 3, pp. 277–283, 2010.

[27] A.-A. Bhuiyan and C. H. Liu, “On face recognition using gabor filters,” World Acad. Sci. Eng. Technol., vol. 28, 2007. https://doi.org/10.1109/ICCITECHN.2008.4803030

[28] M. Sharif, A. Khalid, M. Raza, and S. Mohsin, “Face Recognition using Gabor Filters.,” J. Appl. Comput. Sci. \& Math., no. 11, 2011.

[29] T. I. Dhamecha, P. Sharma, R. Singh, and M. Vatsa, “On effectiveness of histogram of oriented gradient features for visible to near infrared face matching,” in 2014 22nd International Conference on Pattern Recognition, 2014, pp. 1788–1793. https://doi.org/10.1109/ICPR.2014.314

[30] S. Paisitkriangkrai, C. Shen, and J. Zhang, “Face detection with effective feature extraction,” in Asian Conference on Computer Vision, 2010, pp. 460–470. https://doi.org/10.1007/978-3-642-19318-7_36

[31] M. G. L. Putra, W. Ariyanti, and I. Cholissodin, “Selection and Recommendation Scholarships Using AHP-SVM-TOPSIS,” JITeCS (Journal Inf. Technol. Comput. Sci., vol. 1, no. 1, pp. 1–13, 2016. https://doi.org/10.25126/jitecs.2016111

[32] L. Muflikhah and D. J. Haryanto, “High performance of polynomial kernel at SVM Algorithm for sentiment analysis,” JITeCS (Journal Inf. Technol. Comput. Sci., vol. 3, no. 2, pp. 194–201, 2018. https://doi.org/10.25126/jitecs.20183260

[33] I. Oktanisa, W. F. Mahmudy, and G. Maski, “Inflation Rate Prediction in Indonesia using Optimized Support Vector Regression Model,” JITeCS (Journal Inf. Technol. Comput. Sci., vol. 5, no. 1, pp. 104–114, 2020. https://doi.org/10.25126/jitecs.202051173

[34] P. Hansen, A. Hertz, and N. Quinodoz, “Splitting trees,” Discrete Math., vol. 165, pp. 403–419, 1997. https://doi.org/10.1016/S0012-365X(96)00187-2

[35] Y. Bengio, Y. Grandvalet, and others, No unbiased estimator of the variance of K-fold cross-validation. Citeseer, 2003.

[36] N. Joshi, “Combinational neural network using Gabor filters for the classification of handwritten digits,” arXiv Prepr. arXiv1709.05867, 2017. https://doi.org/10.48550/arXiv.1709.05867

[37] B.H. Prasetio, H. Tamura, K. Tanno, K. "Semi-Supervised Deep Time-Delay Embedded Clustering for Stress Speech Analysis". Electronics. vol. 2019, no. 8, 1263. https://doi.org/10.3390/electronics8111263

[38] T. Kolenik and M. Gams, "Persuasive Technology for Mental Health: One Step Closer to (Mental Health Care) Equality?," in IEEE Technology and Society Magazine, vol. 40, no. 1, pp. 80-86, March 2021. https://doi.org/10.1109/MTS.2021.3056288.

[39] Kolenik, T. (2022). Methods in Digital Mental Health: Smartphone-Based Assessment and Intervention for Stress, Anxiety, and Depression. In: Comito, C., Forestiero, A., Zumpano, E. (eds) Integrating Artificial Intelligence and IoT for Advanced Health Informatics. Internet of Things. Springer, Cham. https://doi.org/10.1007/978-3-030-91181-2_7

[40] X. Peng. "Research on Emotion Recognition Based on Deep Learning for Mental Health," Informatica, vol. 45, no. 1, 2021. https://doi.org/10.31449/inf.v45i1.3424