ICIC Express Letters
Volume **17**, Number **11**, November **2023**

ICIC International ©2023 ISSN 1881-803X
pp. 1217–1224

THE EFFECT OF PSEUDORANDOM PIXEL PLACEMENT ON UNCONSTRAINED FACE RECOGNITION PERFORMANCE USING SINGLE LEARNING IMAGE

Muhammad Sabirin Hadis[1,3,*], Junichi Akita[1], Masashi Toda[2] and Nurzaenab[3]

[1]Department of Electrical Engineering and Computer Science
Graduate School of Natural Science and Technology
Kanazawa University
Kakuma-machi, Kanazawa, Ishikawa 920-1192, Japan
akita@ifdl.jp
*Corresponding author: muhammadsabirinhadis@ifdl.jp

[2]Center for Management of Information Technologies
Kumamoto University
2-39-1 Kurokami, Chuo-ku, Kumamoto 860-8555, Japan
toda@cc.kumamoto-u.ac.jp

[3]Study Program of Informatics Engineering
Universitas Teknologi AKBA Makassar
Tamalanrea Jaya 90245, Tamalanrea, Makassar, Indonesia
nurzaenab@akba.ac.id

Received January 2023; accepted April 2023

Abstract. *The pseudorandom pixel placement (PSE) algorithm has been studied, which has the effect on increasing spatial sampling frequency, in order to improve the image processing accuracy, especially for low resolution images. In this paper, we applied PSE algorithm for the unconstrained face recognition using single learning image and evaluated its performance for ten times to generate random patterns, compared with the conventional regular pixel placement. We used eight constrained face images for eight subjects as training data and unconstrained face images from the converting result of the CCTV video as testing data. We found the average accuracy is improved by 3.25% using the best random pattern.*

Keywords: Image processing, Pixel placement, Preprocessing, Single learning image, Unconstrained face image

1. **Introduction.** One of the famous applications of image processing is the face recognition. The market size value for face recognition technology reaches USD 3.72 billion in 2020, and it is predicted that this value will increase to USD 11.62 billion in 2026 [1]. The application of face recognition can be used in various fields such as security [2-5], health [6-9], and business [10,11].

In some of the face recognition applications, we have to use the low resolution images from CCTV video camera, which results in low accuracy [12].

The authors have studied the pseudorandom pixel placement (PSE) algorithm, where the active area in each pixel is randomly arranged, to increase effective spatial sampling frequency. PSE algorithm has the effect on increasing image processing accuracy, especially for the low resolution images [13,14]. We have already demonstrated that the PSE algorithm in several image problems to enhance the performance, such as color moire [15] and jagged edges [16,17].

DOI: 10.24507/icicel.17.11.1217

We have motived to apply the PSE algorithm for the low resolution face recognition problem, since the PSE algorithm has the potential to increase the effective spatial resolution, that is expected in enhancing the performance. In this paper, we apply the PSE algorithm as the preprocessing step for unconstrained face recognition to emulating low resolution camera, and evaluate its performance compared with the conventional (regular) pixel placement algorithm. We also evaluate the dependency of the performance on random patterns.

We explain the related work in Section 2 and Section 3 explains about the pseudorandom pixel placement with our experimental setting in this research. We present the results in Section 4, and finally in Section 5, we conclude the results of this work.

2. **Related Work.** Several researchers have applied methods at the preprocessing step in order to improve accuracy; for example, Nurzaenab et al. [14] applied the CLAHE (Contrast Limited Adaptive Histogram Equalization) method to determining the contrast limit value in face images carried out in the preprocessing. Their work aims to reduce excessive contrast values in face images. They made several changes to the value of the contrast limit. The result is that their face recognition application's accuracy has increased by 12.25%. Sharma et al. [18] implemented a resizing technique in the preprocessing step to speed up the computational process when detecting disease in plant leaves. Ahmad et al. [19] conducted a comparative study on the effect of color conversion in the image to gray in the preprocessing step. The results show that the application performance when detecting edges from a color to a gray image is higher than without converting. Indrabayu et al. [20] applied brightness enhancement at the preprocessing step to increasing the accuracy of feature classification in the eye with an average accuracy of 93.5%.

Image sensors in the camera have pixels as photo receptors, and each pixel has the potential to arrange the position of its "active" area, which samples the incoming image, so called the pseudorandom pixel placement. Researchers have evaluated the pseudorandom pixel placement methods for image processing. Izaki and Akita [13] observed the structural characteristics of pixels between pseudorandom and lattice pixel placement to reduce jaggy lines in an image. The results showed that the pseudorandom pixel placement could reduce image jaggy compared to the lattice pixel placement. Nakamura et al. [16] applied pseudorandom pixel placement to reducing the jaggy effect in moving pictures. Kobayashi and Akita [15] conducted an experiment to solve the problem of color moire and false color in the image. They found that the effect of color moire and false color was reduced when applying pseudorandom pixel placement. Our previous work [21] has implemented pseudorandom pixel placement in face recognition for knowing the accuracy performance based on face image resolutions. The results showed that the accuracy increases as the base of face images' resolution also increases. That work only uses one approach where each image has a different pattern pixel placement from the other images. Thus, in this work, we try to apply another approach and compare the performance with PSE-R [21]. The CMOS image sensor with the pseudorandom pixel placement has been actually designed, fabricated, and evaluated [17].

3. **Method.** This section explains how to apply the PSE method in the algorithm flow of the face recognition that we used. Note that this method based on the down sampling is to emulate the low resolution camera with pixels using PSE for simulation.

3.1. **Pseudorandom pixel placement (PSE).** PSE can be emulated by the down sampling with choosing the pixels by "randomly" from the original image to form a new image structure. Here, we assume the down sampling of the original image into the half size. For example, in Figure 1, where the original image has a size of $4 * 4$ pixels (px). We handle $2 * 2$ px blocks for down sampling. By choosing one pixel at the same position in each $2 * 2$ px block, such as the upper left, we obtain the regular (REG)

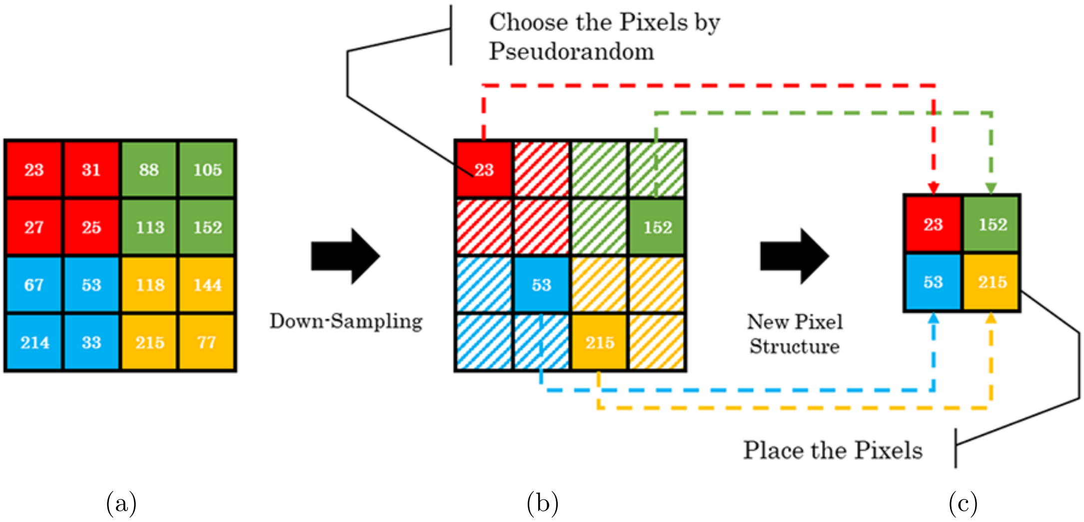


Figure 1. An illustration of PSE algorithm: (a) Pixel structure in the original image; (b) down sampling processing with choosing the pixels from the original image by pseudorandom; (c) place the selected pixel into new image structure

down sampled image. By choosing one pixel in each $2*2$ px block randomly, we obtain the pseudorandom pixel placement (PSE). While the pixel selections are not completely random over the pixel plane, this method is indicated to give a good approximation for completely random selection [13] in terms of the spatial spectrum of sampling points. Thus, we call this algorithm as "pseudorandom".

We use Equation (1) in the down sampling process. The parameter p_O is the pixel in the original image (virtual pixel, or $2*2$ px block in Figure 1), and p_L is the pixel in the new image (active area). (x, y) determine the pixel position. The pixel movement for choosing the selected pixel uses the parameters d_x for the x-axis and d_y for the y-axis. The values of d_x and d_y is randomly determined as 0 or 1. Note that REG down sampling is represented as $d_x = d_y = 0$.

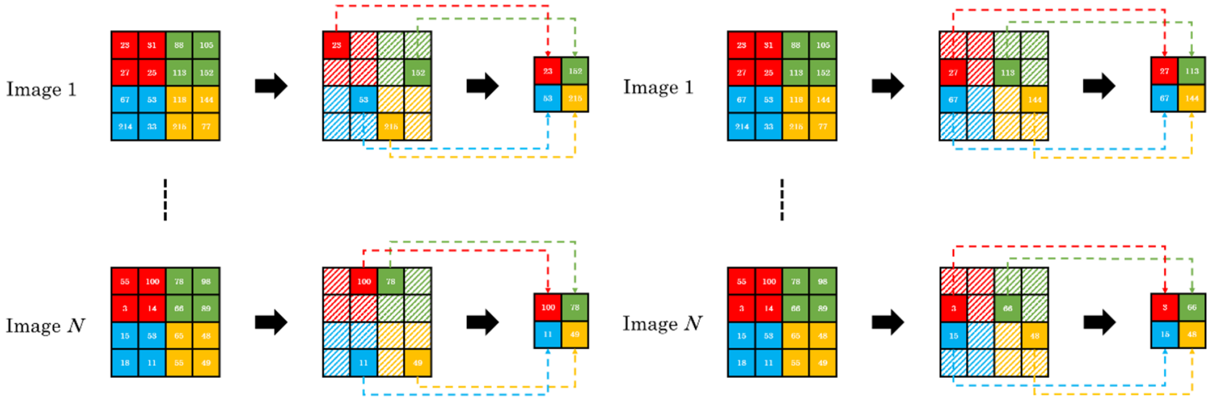
$$p_L(x, y) = p_O(2x + d_x, 2y + d_y) \tag{1}$$

Our previous work [21] has applied the PSE method where different random patterns are applied to each image in all subject test, which we call PSE-R. We evaluated that algorithm against face image resolution by using four variations, namely, $110*130$ px, $220*260$ px, $440*520$ px, and $880*1040$ px. We obtained the result that the PSE-R method has better accuracy with the base highest resolution at $880*1040$ px compared to REG.

In this paper, we carried out the accuracy evaluation using different strategies for treating random number in order to emulate the physical implementation of CMOS image sensor with pseudorandom pixel placement. We generate ten random patterns from PSE1 to PSE10. Each PSE-i is applied for each image of subject, from T1 to T8, and the accuracy is calculated. We call this algorithm as PSE-S. Figure 2 shows an illustration of the difference between PSE-R with PSE-S. We will evaluate the accuracy of PSE-S in comparison with PSE-R in [21] and REG.

We measure the accuracy, defined as the ratio of the face images successfully recognized over all the face images. The accuracy is calculated for each subject, and the averaged accuracy is also calculated as the average of the accuracy for all the subjects.

The equation used to determine the accuracy for each face object can be seen in Equation (2) with an explanation of the term NCI for number of correct images, and NTI is



(a) (b)

FIGURE 2. The implementation model of (a) PSE-R, and (b) PSE-S

number of testing images.

$$Accuracy = (NCI/NTI) \times 100\% \tag{2}$$

Averaged accuracy using Equation (3) where AVG means average, AT1 is the accuracy value at T1 as the first subject until AT8 as the last subject for the accuracy value at T8.

$$AVG\ Accuracy = (AT1 + \cdots + AT8)/Number\ of\ Subjects \tag{3}$$

3.2. **Face recognition.** We used the same face recognition (FC) program in our previous work [21], where the PSE-R was applied in the pre-processing. Figure 3 shows the main diagram flow of the FC program. Figures 4 and 5 show the pre-processing step in training and testing data. In the case of REG, we omit the PSE step.

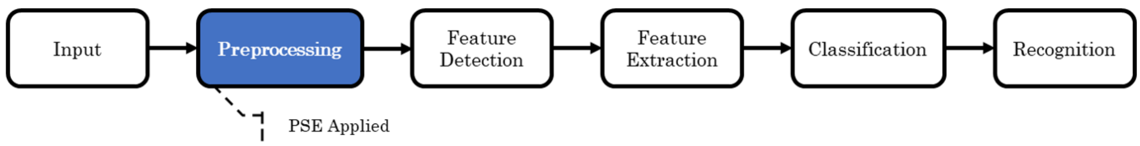


FIGURE 3. The main steps flow in face recognition

FIGURE 4. The steps flow in pre-processing for training data

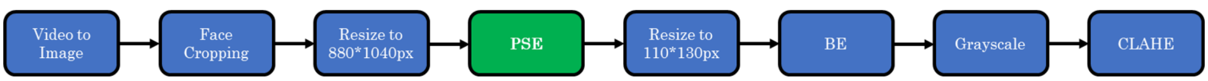


FIGURE 5. The steps flow in pre-processing for testing data

We use single learning image per person (SLIPP) for training data. There are 8 subjects for test, we called T1 for the first subject, T2 for the second subject to T8 for the last subject, as shown in Figure 6. In the testing data, we use unconstrained faces from the converting result of the CCTV Video, as shown in Figure 7. We use the biggest resolution at $880 * 1040$ px for the testing data because that resolution achieves the highest average accuracy when applying PSE-R [21]. The details of training and testing data specification can be seen in Table 1.

Figure 6. The training data based on SLIPP concept for 8 subjects where T1 is in the far left to T8 in the far right

Figure 7. The testing data using unconstrained face images from CCTV Video

Table 1. Training and testing data specification

Subject	Training		Testing		FPS CCTV Video
	Amount (pcs)	Resolution (px)	Amount (pcs)	Resolution (px)	
T1	1	$1023 * 1441$	351	$880 * 1040$	30
T2	1	$888 * 1193$	381		
T3	1	$1012 * 1338$	406		
T4	1	$1078 * 1575$	360		
T5	1	$1023 * 1441$	373		
T6	1	$2019 * 3192$	248		15
T7	1	$2869 * 4227$	254		
T8	1	$1758 * 2900$	299		

The term of pcs is pieces, px is pixel, and FPS is frame per second.

4. **Result and Discussion.** The accuracy performance in each PSE-S variation, as well as REG and results from PSE-R [21] are shown in Figure 8. We found the accuracy is different for the variations of random patterns; however, most PSE-S gives better accuracy than REG.

We got the most significant improvement in accuracy when applying PSE-S in T6 at PSE8 by 22.98% compared to REG and by 12.50% compared to PSE-R [21]. That case also becomes the lowest performance on REG. For the lowest accuracy, we found in T5 at PSE3 with a decrease by 9.38% and 16.09% compared to REG and PSE-R [21], respectively.

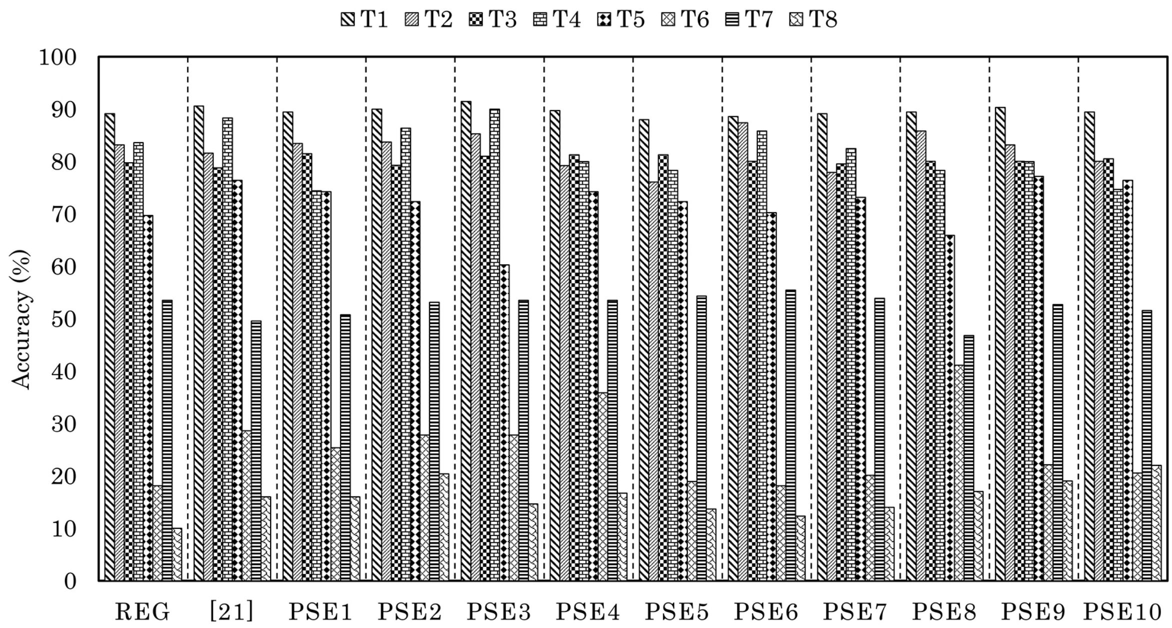


FIGURE 8. The accuracy for all subjects over the pixel placement patterns

In the case of REG, the best accuracy is on T3. Compared to the highest PSE-S at PSE1 in the same subject, the PSE-S is better with a difference by 1.72%. In case of the lowest PSE-S at PSE2, the PSE-S accuracy decreases by 0.49% while compared to PSE-R [21] increasing at same value by 0.49%. The highest accuracy in PSE-R [21] obtains in T5. That value is higher by 6.70% compared to REG and 0.80% lower compared to the highest PSE9 at the same subject. The big difference shows up when we compare REG to the highest PSE-S at PSE8 for T6, the PSE-S accuracy increasing by 22.98%.

In the accuracy for each subject based on the overall experiment, we can see a significant difference between two groups of subjects, group 1 with members T1 to T5 and group 2 with members T6 to T8. In the case of REG, Group 1 has an average accuracy of 81.10%, while Group 2 has 27.24%. The difference is 53.86%. The cause is the differences in the training and testing data used and the differences between devices used to take face photos, also shooting angles.

The CCTV Video shooting angle in Group 2 is at a slope of $\pm 15°$, while Group 1 is straight to the subject. The training data for both groups of subjects have the same model, the face facing perpendicular to the front. The difference in the angle of taking testing data in Group 2 is one of the reasons why the accuracy value of Group 2 is lower than Group 1. However, after applying the PSE-S, we can increase the average accuracy in Group 1 by 1.27% with a total value 82.37% and Group 2 by 6.55% with a total value 33.79% based on the best pattern at PSE2.

In the case of the average accuracy, we got the results for the highest obtained in PSE2 with 64.15%. The performance increased by 3.25% against REG and 0.39% compared to PSE-R [21]. In this work, with ten variations of PSE-S pattern in all face image, the decrease in accuracy is no more than 0.51% for REG and 3.37% compared to PSE-R [21]. The graph of average accuracy performance can be seen in Figure 9.

Based on the best average PSE performance in PSE2, we can see that this method can provide a lot of improvement in Group 2, which includes 3 subjects, namely T6, T7, and T8. These subjects have a test image with lower resolution, and the testing data collection environment is more challenging than Group 1. The placement of patterns influences the feature classification process to determine whether an image can be recognized. The performance difference obtained was 5.28% higher than Group 1.

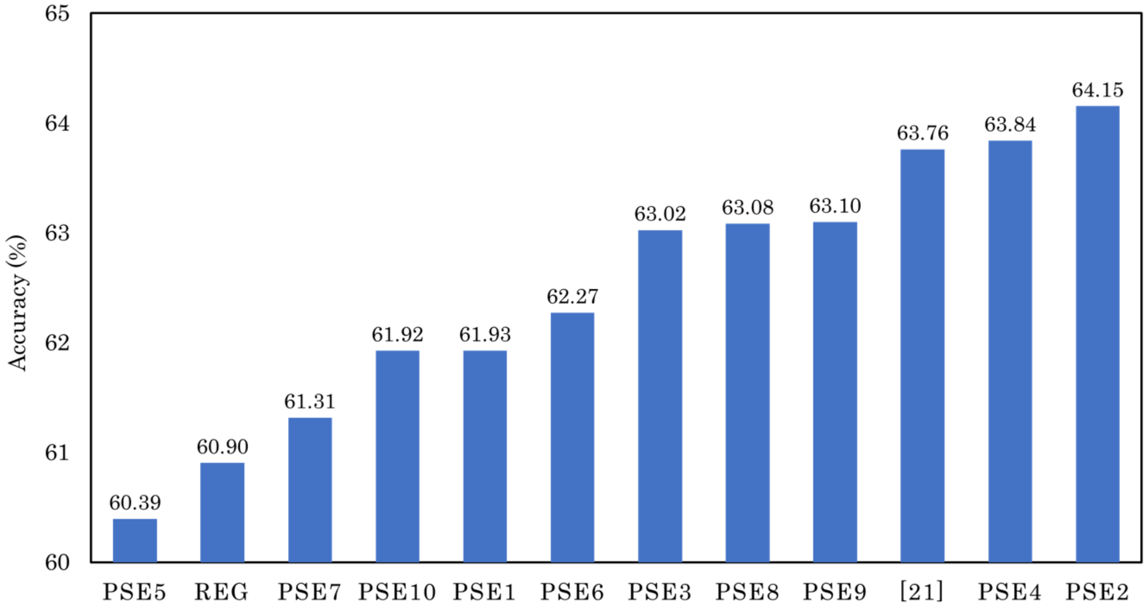


FIGURE 9. The averaged accuracy for pixel placement patterns

5. **Conclusions.** We confirmed that the accuracy of our proposed algorithm (PSE-S) depends on the pattern variation, as in the case of PSE-R. The highest performance of PSE-S was achieved on T6 at PSE8, with accuracy increasing by 22.98% compared to the REG and 12.50% compared to PSE-R [21]. We got the lowest performance of PSE-S on T5 at PSE3, with accuracy decreased by 9.38% compared to REG and 16.09% compared to PSE-R [21]. From the random patterns in this simulation, the PSE-S has better performance accuracy in all subjects. In the case of average accuracy, PSE-S can increase face recognition performance by 3.25% against REG and 0.39% compared to PSE-R [21] at the highest value obtained in PSE2. This result indicates that our proposed algorithm, which emulates the actual CMOS image sensor with pseudorandom pixel placement, performs better than REG. In the future research, we want to evaluate the PSE-S performance in another face recognition framework model that uses more subjects.

REFERENCES

[1] M. Intelligence, *Facial Recognition Market Size, Growth, Analysis 2022*, 2022.

[2] H. Ai and X. Cheng, Research on embedded access control security system and face recognition system, *Measurement*, vol.123, pp.309-322, DOI: 10.1016/j.measurement.2018.04.005, 2018.

[3] P. M. Kumar, U. Gandhi, R. Varatharajan, J. R. G. Manogaran and T. Vadivel, RETRACTED ARTICLE: Intelligent face recognition and navigation system using neural learning for smart security in Internet of Things, *Cluster Computing*, vol.22, no.S4, pp.7733-7744, DOI: 10.1007/s10586-017-1323-4, 2019.

[4] R. Raghavendra, K. B. Raja and C. Busch, Presentation attack detection for face recognition using light field camera, *IEEE Transactions on Image Processing*, vol.24, no.3, pp.1060-1075, DOI: 10.1109/TIP.2015.2395951, 2015.

[5] P. Tome, J. Fierrez, R. Vera-Rodriguez and M. S. Nixon, Soft biometrics and their application in person recognition at a distance, *IEEE Transactions on Information Forensics and Security*, vol.9, no.3, pp.464-475, DOI: 10.1109/TIFS.2014.2299975, 2014.

[6] B. Jin, L. Cruz and N. Goncalves, Deep facial diagnosis: Deep transfer learning from face recognition to facial diagnosis, *IEEE Access*, vol.8, pp.123649-123661, DOI: 10.1109/ACCESS.2020.3005687, 2020.

[7] H. Zhang, A. Jolfaei and M. Alazab, A face emotion recognition method using convolutional neural network and image edge computing, *IEEE Access*, vol.7, pp.159081-159089, DOI: 10.1109/ACCESS.2019.2949741, 2019.

[8] J.-D. Lin, H.-H. Lin, J. Dy, J.-C. Chen, M. Tanveer, I. Razzak and K.-L. Hua, Lightweight face anti-spoofing network for telehealth applications, *IEEE Journal of Biomedical and Health Informatics*, vol.26, no.5, pp.1987-1996, DOI: 10.1109/JBHI.2021.3107735, 2022.

[9] M. Awais, C. Chen, X. Long, B. Yin, A. Nawaz, S. F. Abbasi, S. Akbarzadeh, L. Tao, C. Lu, L. Wang, R. M. Aarts and W. Chen, Novel framework: Face feature selection algorithm for neonatal facial and related attributes recognition, *IEEE Access*, vol.8, pp.59100-59113, DOI: 10.1109/ACCESS.2020.2982865, 2020.

[10] F. M. Andiani and B. Soewito, Face recognition for work attendance using multitask convolutional neural network (MTCNN) and pre-trained facenet, *ICIC Express Letters*, vol.15, no.1, pp.57-65, DOI: 10.24507/icicel.15.01.57, 2021.

[11] S. M. Bah and F. Ming, An improved face recognition algorithm and its application in attendance management system, *Array*, vol.5, DOI: 10.1016/j.array.2019.100014, 2020.

[12] T. Marciniak, A. Chmielewska, R. Weychan, M. Parzych and A. Dabrowski, Influence of low resolution of images on reliability of face detection and recognition, *Multimedia Tools and Applications*, vol.74, no.12, pp.4329-4349, DOI: 10.1007/s11042-013-1568-8, 2015.

[13] C. Izaki and J. Akita, Pixel parameter optimization for jaggy reduction in line representation using pseudorandom pixel placement, *ITE Transactions on Media Technology and Applications*, vol.3, no.4, pp.263-267, DOI: 10.3169/mta.3.263, 2015.

[14] N. Nurzaenab, M. S. Hadis and R. Angriawan, The optimal clip limit value for CLAHE method to improve face recognition accuracy on CCTV video, *INSTEK Journal (Informatics Science and Technology)*, vol.5, no.2, 178, DOI: 10.24252/instek.v5i2.16201, 2020.

[15] M. Kobayashi and J. Akita, *Effect of Decreasing Color Moire of False Color Using Pseudorandom Pixel Placement*, ITE Technical Report, pp.1-5, 2021.

[16] Y. Nakamura, M. Kawasaki, J. Akita and T. Komatsu, Evaluation of jaggy elimination effect in moving pictures using pseudorandom pixel placement, *The Journal of the Institute of Image Information and Television Engineers*, vol.66, no.12, pp.J492-J494, DOI: 10.3169/itej.66.J492, 2012.

[17] J. Akita, CMOS image sensor with pseudorandom pixel placement for jaggy elimination, *IEICE Electronics Express*, vol.14, no.9, DOI: 10.1587/elex.14.20170154, 2017.

[18] P. Sharma, P. Hans and S. C. Gupta, Classification of plant leaf diseases using machine learning and image preprocessing techniques, *2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence)*, pp.480-484, DOI: 10.1109/Confluence47617.2020.9057889, 2020.

[19] I. Ahmad, I. Moon and S. J. Shin, Color-to-grayscale algorithms effect on edge detection – A comparative study, *2018 International Conference on Electronics, Information, and Communication (ICEIC)*, pp.1-4, DOI: 10.23919/ELINFOCOM.2018.8330719, 2018.

[20] Indrabayu, R. A. Tacok and I. S. Areni, Modification on brightness enhancement for simple thresholding in eyelid area measurement, *Proc. of the 6th International Conference on Bioinformatics and Biomedical Science*, New York, NY, USA, pp.101-104, DOI: 10.1145/3121138.3121197, 2017.

[21] M. S. Hadis, J. Akita, M. Toda and Nurzaenab, The impact of preprocessing on face recognition using pseudorandom pixel placement, *2022 29th International Conference on Systems, Signals and Image Processing (IWSSIP)*, pp.1-5, DOI: 10.1109/IWSSIP55020.2022.9854474, 2022.