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Research Article

Modeling And Detection of Cracks in Earthenware Water Jugs Using Artificial Neural Networks and Image Processing Techniques

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ABSTRACT

Quality control in traditional pottery production is a labor-intensive process that relies heavily on manual visual inspection to detect structural defects. To address this, the present study proposes an automated framework combining image processing techniques with Artificial Neural Networks (ANN) to detect and classify cracks in handmade earthenware jugs. Images acquired via smartphone were preprocessed using Otsu's thresholding and median filtering to effectively isolate defect regions and suppress noise. A dataset of 189 samples was utilized to train and test the ANN model. The proposed model achieved a classification accuracy of 92.98%. Confusion matrix analysis confirmed robust performance, demonstrating high capability in distinguishing between intact and defective samples with no significant bias toward either class. This approach offers potential for modernizing pottery production, enhancing efficiency, and ensuring quality.

1. Introduction

Image processing supports quality control processes in various fields such as medicine, construction, agriculture, and defense [1], [2]. Computer-aided systems facilitate the rapid and accurate detection of defective products. This capability contributes to the widespread adoption of such systems in industrial applications[3], [4]. Businesses aim to provide consumers with durable and flawless products in order to maintain and strengthen brand trust. They achieve this goal by producing high-quality and robust goods. Established companies, which have spent years building trust in their products and brands, always strive to create the most durable and reliable products with minimal defects. Releasing a defective product or product series to the market can lead to serious financial losses for businesses. In severe cases, this situation can even cause the business to cease operations. Today, there are many examples of such failures. Product recalls can shake a brand's reputation and also have negative consequences for consumers. As a result, offering flawless, high-quality products remains a critical priority. Image processing techniques are successfully applied in detecting product damage. The main reason for the effectiveness of these approaches is the ability of computer-aided systems to quickly and accurately identify defective products[5]. Computer vision and image processing techniques have become standard for automated quality control and defect detection across various industries, ranging from road surface inspection [6] to railway anomaly detection [7]. These studies demonstrate that analyzing surface textures via segmentation and filtering can effectively isolate defects. Furthermore, machine learning models have proven robust in classifying these extracted features [8], [9]. In this study, we apply similar principles to the domain of traditional pottery.

Handicrafts, deeply rooted in Anatolian culture, are a traditional craft with a long history. In Turkey, pottery stands out among other handicrafts and holds a distinguished place. Industrial materials such as plastic and metal can pose certain health risks. In contrast, pottery is generally considered a more natural and healthier option. This contributes significantly to the growing popularity of pottery [10]. Pottery production in Anatolia is a legacy

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dating back to the Hittite civilization [11]. This production continues today, adhering to traditional methods with very few changes. The district of Avanos has gained renown in this craft not only in Turkey but also worldwide. Traditional techniques retain their central place in pottery production [12]. The stages of traditional pottery production are shown in Figure 1. In the first stage of production, masters collect clay from the ancient beds of the Kızılırmak River. They mix this clay with other types of clay in specific proportions in a pool to obtain pottery clay (Figure 1a). The master kneads this clay like dough to form lumps. This clay mass is shaped by hand on the potter's wheel (see Figure 1b). Since each product is handmade, no two earthenware pots are physically identical. After shaping, the newly produced pot is left to dry (see Figure 1c).

(a) Preparing pottery clay　**(b)** Shaping pottery on the potter's wheel　**(c)** Drying the newly formed pottery

Figure 1. Stages of traditional pottery production

Unfired pottery remains highly vulnerable to structural damage and mechanical stress until the firing process completes. Pottery production involves multiple stages, each presenting distinct risks of defects such as deformation or cracking. Primary causes of these defects include improper clay composition, rapid drying due to excessive heat or wind, sudden temperature fluctuations, residual moisture, excessive loading during firing, and mechanical impacts during handling [13]. The drying process eliminates moisture from the raw clay body (Figure 2). Upon complete drying, the ware is ready for firing (Figure 2a). However, this phase is critical, as shrinkage stress often induces cracking (Figure 2b).

(a) Pottery left to dry　**(b)** Cracks forming during drying.

Figure 2. Drying process and defects

The final stage, firing, transforms the dried ware into a durable finished product (Figure 3). During this process, the ware is heated gradually to minimize thermal stress and prevent structural failure (Figure 3a). Kiln temperatures typically exceed 800°C (Figure 3b). However, this is a critical stage that poses a significant risk of cracking and deformation.

a) Pottery kiln　**b)** Pottery fired at high temperatures.

Figure 3. Firing process

As noted, defects can occur at any stage of traditional pottery production. Consequently, artisans must continuously inspect the ware for cracks throughout the manufacturing process. This manual detection is labor-intensive and inefficient. To address such challenges, image processing has become a widely adopted technique for automated quality control [14], [15]. Image processing facilitates critical industrial tasks such as automated counting, dimensional sorting, and defect detection, becoming integral to modern production systems [16]. In agriculture, for instance, this technology is employed to analyze the physical properties of wheat for quality assessment and classification. [17]. Image processing techniques are widely utilized for fault diagnosis across diverse industrial sectors. In the railway industry, for example, these methods detect defects in pantograph-catenary systems [18]. Image processing filters enhance feature visibility, thereby facilitating defect detection. For instance, in civil engineering, these techniques significantly improve the identification accuracy of cracks in concrete structures [19], [20]. Images captured under variable illumination were subsequently classified. The paper is organized as follows: Section 2 details the methodology, followed by the experimental results in Section 3, and concluding remarks in Section 4.

2. MATERIAL AND METHODS

2.1. Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational frameworks designed to simulate the learning mechanisms of biological systems [21]. As illustrated in Figure 4, a typical ANN architecture consists of an input layer, one or more hidden layers, and an output layer. Mathematically, inputs $X = \{x_1, x_2, \ldots, x_n\}$ are multiplied by their corresponding $W = \{w_1, w_2, \ldots, w_n\}$, summed with a bias term, and passed through an activation function to generate the output Y [22]. For this study, the network is configured to classify samples into two categories: intact or cracked.

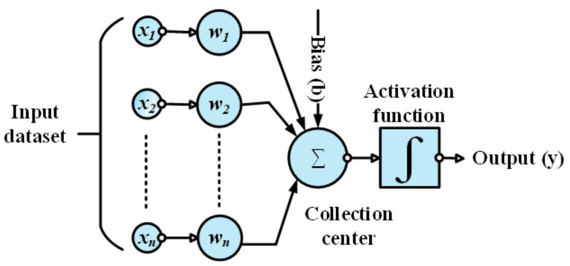


Figure 4. Structure of an ANN neuron [23]

The ANN consisted of an input layer (features from flattened preprocessed images), two hidden layers with 128 and 64 neurons respectively, ReLU activation, and a sigmoid output. Training was performed using Adam optimizer with a learning rate of 0.001 for 50 epochs. The dataset of 189 images was split into training (132 images) and testing (57 images) subsets using stratified random sampling with a fixed seed (seed = 42) to ensure reproducibility. This 70-30 split maintained class balance, with the training set containing 66 cracked and 66 intact samples, while the test set included 27 cracked and 30 intact samples. Similar architectures have proven effective in industrial defect detection application [24].

2.2. Data Set Acquisition

The initial phase of the proposed methodology is image acquisition. Data collection was conducted at a local pottery workshop in the Avanos district of Nevşehir, Turkey. Avanos is a historically significant center for traditional pottery production [25] The dataset comprises 189 images captured using a smartphone camera (8 MP) with a resolution of 1024x768 pixels. Figure 5 presents representative samples of both intact and defective pottery from the dataset.

(a) Cracked and deformed water jugs

(b) Intact jugs.

Figure 5. Cracked and intact pottery used in this study.

This study proposes a method to detect structural defects in pottery and classify as “intact” or “cracked” using a feed-forward (ANN). The proposed framework consists of four primary stages: image acquisition, segmentation, enhancement/cropping, and classification.

1. Image Acquisition: A total of 189 images of both intact and defective jugs were acquired from a workshop in Avanos using a smartphone camera (1024x768 resolution). Due to the artisanal nature of production, significant physical variability exists between samples.
2. Image Segmentation: Defects were isolated using Otsu’s automatic thresholding method to segregate regions of interest from the background.
3. Image Enhancement and Cropping: A median filter was applied to mitigate salt-and-pepper noise, which often persists after binary conversion. This step enhances defect visibility while preserving edge details. Furthermore, images were cropped to the object's bounding box to eliminate non-informative background areas, optimizing input for ANN training.
4. Classification: The ANN was trained on a dataset of 66 defective and 66 intact samples. Subsequent testing on randomly selected images yielded a classification accuracy of 92.98%. Figure 6 illustrates the workflow of the proposed method.

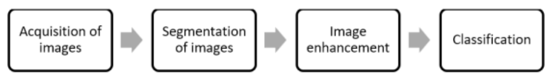


Figure 6. Stages of the proposed method for crack detection and classification.

Prior to processing, all RGB images were converted to grayscale (Figure 7). Figure 7(a) highlights visible structural defects, such as horizontal and vertical cracks, while Figure 7(b) depicts an intact specimen with a uniform surface structure.

(a) Cracked jugs **(b)** Intact jugs

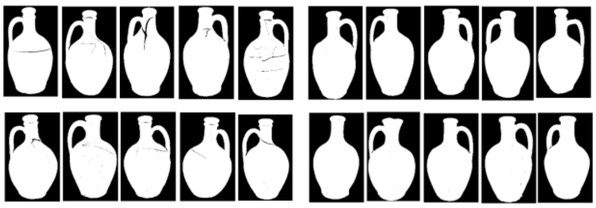
Figure 7. Grayscale transformation

2.3. Otsu's Thresholding Method

Image segmentation is often performed via thresholding, which partitions a grayscale image into distinct regions based on pixel intensity. Typically, a grayscale image comprises intensity values ranging from 0 to $N-1$. In global thresholding, a threshold value T is selected to separate pixels into two classes: background and foreground. Pixels with intensity below T are assigned to 0 (black), while those above are set to 1 (white), as defined in Equation 1 [26].

$$g(x,y)=\begin{cases}1; & f(x,y)>T \\ 0; & f(x,y)\leq T\end{cases} \tag{1}$$

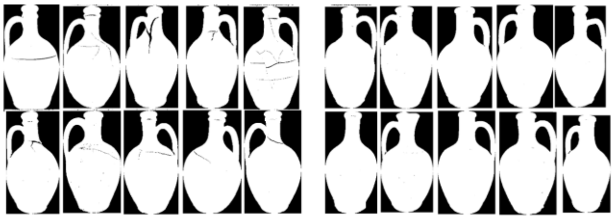
Here, $f(x,y)$ denotes the grayscale intensity at coordinates (x,y). Selecting an optimal T is critical; an inappropriately high threshold may cause information loss, while a low threshold often introduces background noise. To address this, Otsu's method was employed to automatically determine the optimal threshold by maximizing the inter-class variance of the grayscale histogram [27]. This ensures robust isolation of crack regions from the pottery surface. As shown in Figure 8, the method effectively highlights defects: Figure 8(a) reveals distinct fracture patterns on cracked samples, while Figure 8(b) depicts the smooth contours of intact pottery



(a) Cracked jugs showing distinct deformation line **(b)** Intact jugs with smooth contours.

Figure 8. Segmentation results

To mitigate salt-and-pepper noise, a median filter was applied to the segmented images. 3X3 kernel size was employed, selected to maintain an optimal balance between noise suppression and the preservation of fine fracture details. This process effectively clarified structural deformations while eliminating artifacts from intact specimens. As demonstrated in Figure 9, the filter yields distinct fracture patterns on defective samples (Figure 9(a)) and artifact-free surfaces on intact ones (Figure 9(b)). By enhancing feature integrity, this preprocessing stage significantly facilitates the subsequent ANN classification process.



(a) Image enhancement using Median filter on Cracked jugs (b) Image enhancement using Median filter on Crac Intact jugs

Figure 9. Median filter application

3. RESULTS AND DISCUSSION

The experimental evaluation was conducted on a balanced dataset to ensure unbiased performance assessment. Table 1 presents the distribution of samples across training and testing subsets. The training set maintained perfect balance with equal representation of both classes, while the test set showed minimal imbalance (47.4% cracked vs. 52.6% intact). This near-balanced distribution is critical for reliable evaluation, as significant class imbalance can inflate accuracy metrics and mask poor performance on minority classes

Table 1. Distribution of samples across training and testing subsets

Subset	Cracked	Intact	Total
Training	66 (50%)	66 (50%)	132
Testing	27 (47.4%)	30 (52.6%)	57

Table 2 presents the performance metrics of the ANN classifier. These results demonstrate the model's high efficacy in discriminating between cracked and intact samples.

Table 2. Performance metrics of the proposed ANN model for crack detection.

Metric	Cracked Class	Intact Class
Sensitivity	0.9259	0.9333
Specificity	0.9333	0.9259
F1 Score	0.9259	0.9333
Accuracy	92.98%	

The classification performance is further detailed in the confusion matrix shown in Figure 10. Out of 57 test samples, the model yielded 25 True Positives (TP) and 28 True Negatives (TN), while limiting misclassifications to only 2 False Positives (FP) and 2 False Negatives (FN). Collectively, these outcomes demonstrate the model's robust performance and its potential for automated quality control.

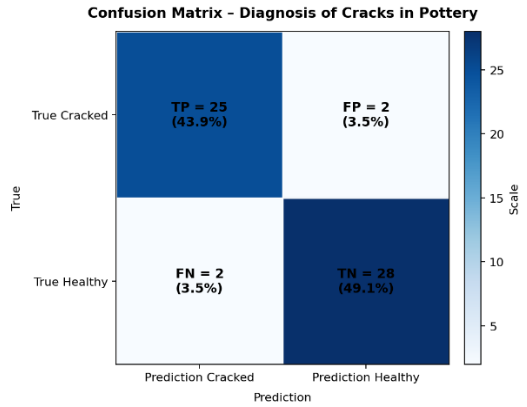


Figure 10. Confusion matrix of the proposed ANN model.

Error analysis revealed that the 4 misclassified samples (2 FP, 2 FN) shared common characteristics: (1) ambiguous surface textures caused by irregular clay composition, and (2) specular highlights from uncontrolled workshop lighting that created false crack-like features. Future work should address these issues through controlled illumination and higher-resolution imaging (minimum 2048×1536 pixels). The model demonstrates balanced performance, distinguishing between cracked (positive) and intact (negative) samples with comparable accuracy and no significant bias. This level of accuracy is particularly notable given the inherent challenges of handmade pottery, such as morphological heterogeneity, surface irregularities, and variable illumination. The applied preprocessing pipeline, combining Otsu's thresholding and median filtering, effectively isolated defect patterns and suppressed noise, thereby facilitating robust feature extraction for the ANN. Error analysis suggests that misclassifications primarily stem from ambiguous surface textures or specular highlights. Consequently, future studies could further enhance performance by utilizing high-resolution imaging and controlled lighting environments.

The study has three main limitations. First, the dataset size (189 samples) is relatively small for deep learning approaches. Second, all images were captured under natural workshop lighting, introducing illumination variability. Third, the simple feedforward ANN may not capture complex spatial hierarchies in crack patterns. Future research should incorporate: (1) dataset expansion to 500+ samples, (2) controlled lighting setups, (3) convolutional neural networks (CNNs) for spatial feature learning (similar to approaches by [22] and [14]), and (4) data augmentation techniques.

4. CONCLUSIONS

This study presents an automated, cost-effective framework for detecting structural defects in pottery. Defect regions were isolated using Otsu's thresholding and median filtering, followed by classification via an ANN. With a classification accuracy of 92.98%, the proposed method demonstrates high reliability and efficacy. These findings underscore that the appropriate selection of preprocessing steps significantly influences classification performance. By reducing the reliance on manual inspection, this approach enhances production efficiency and minimizes operational time for artisans. Future research may further enhance system performance by incorporating high-resolution imaging and deep learning architectures. Ultimately, this automated detection framework holds significant potential for application in both traditional workshops and industrial manufacturing lines.

Declaration of Ethical Standards

The article does not contain any studies with human or animal subjects.

Credit Authorship Contribution Statement

The author individually was responsible for the ideation, modeling, analysis, and writing of this article.

Declaration of Competing Interest

The author claims that there are no conflicts of interest.

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Data Availability

The dataset used in this study will be made publicly available in a data repository upon completion of further research.

References

[1] A. Sioma, "Vision System in Product Quality Control Systems," Applied Sciences, vol. 13, no. 2, p. 751, Jan. 2023, doi: 10.3390/app13020751.

[2] T. Prabaharan, P. Periasamy, V. Mugendiran, and Ramanan, "Studies on application of image processing in various fields: An overview," IOP Conf. Ser.: Mater. Sci. Eng., vol. 961, p. 012006, Nov. 2020, doi: 10.1088/1757-899X/961/1/012006.

[3] Y. Chen, Y. Ding, F. Zhao, E. Zhang, Z. Wu, and L. Shao, "Surface Defect Detection Methods for Industrial Products: A Review," Applied Sciences, vol. 11, no. 16, p. 7657, Aug. 2021, doi: 10.3390/app11167657.

[4] M. Raisul Islam et al., "Deep Learning and Computer Vision Techniques for Enhanced Quality Control in Manufacturing Processes," IEEE Access, vol. 12, pp. 121449–121479, 2024, doi: 10.1109/ACCESS.2024.3453664.

[5] S. A. Singh and K. A. Desai, "Automated surface defect detection framework using machine vision and convolutional neural networks," J Intell Manuf, vol. 34, no. 4, pp. 1995–2011, Apr. 2023, doi: 10.1007/s10845-021-01878-w.

[6] B. Akarsu, M. Karaköse, K. Parlak, E. Akin, and A. Sarimaden, “A Fast and Adaptive Road Defect Detection Approach Using Computer Vision with Real Time Implementation,” International Journal of Applied Mathematics, Electronics and Computers, pp. 290–290, Dec. 2016, doi: 10.18100/ijamec.270546.

[7] M. Karaköse, E. Akın, and O. Yaman, “A Fault Diagnosis Approach for Rail Surface Anomalies Using FPGA in Railways,” ijamec, vol. 1, no. SpecialIssue, pp. 42–46, Aug. 2017, doi: 10.18100/ijamec.2017SpecialIssue30469.

[8] S. B. Çelebi, A. Aslan, and M. Canpolat, “Predicting Gelation in Copolymers Using Deep Learning Through a Comparative Study of ANN, CNN, and LSTM Models with SHAP Explainability,” in Database Engineered Applications, vol. 15928, G. Bergami, P. Ezhilchelvan, Y. Manolopoulos, S. Ilarri, J. Bernardino, C. K. Leung, and P. Z. Revesz, Eds., in Lecture Notes in Computer Science, vol. 15928. , Cham: Springer Nature Switzerland, 2026, pp. 85–95. doi: 10.1007/978-3-032-06744-9_7.

[9] M. E. Sönmez, K. Sabancı, and N. Aydın, “Classification of Wheat Rootstock and Their Hybrids According to Color Features by Machine Learning Algorithms,” International Journal of Applied Mathematics Electronics and Computers, vol. 10, no. 2, pp. 39–48, June 2022, doi: 10.18100/ijamec.1098276.

[10] D. Wang et al., “Comparison of Risk of Silicosis in Metal Mines and Pottery Factories,” Chest, vol. 158, no. 3, pp. 1050–1059, Sept. 2020, doi: 10.1016/j.chest.2020.03.054.

[11] I. Lazaridis et al., “Ancient DNA from Mesopotamia suggests distinct Pre-Pottery and Pottery Neolithic migrations into Anatolia,” Science, vol. 377, no. 6609, pp. 982–987, Aug. 2022, doi: 10.1126/science.abq0762.

[12] S. Karacaoğlu, “A Comprehensive Outlook of Culture, Creativity and Sustainability in Rural Areas Through Tourism Development,” in Niche Tourism and Sustainability, A. Farmaki, P. Singh, and V. Hassan, Eds., GB: CABI, 2024, pp. 94–104. doi: 10.1079/9781800626669.0008.

[13] M. Yada, G. Tanaka, K. Isono, N. Kamochi, and H. Ichinose, “Ultra-reduction of drying and firing shrinkage on pottery slip casting by adding mullite fiber,” Journal of the European Ceramic Society, vol. 44, no. 4, pp. 2677–2684, Apr. 2024, doi: 10.1016/j.jeurceramsoc.2023.11.012.

[14] S. B. Çelebi and B. G. Emiroğlu, “Leveraging Deep Learning for Enhanced Detection of Alzheimer’s Disease Through Morphometric Analysis of Brain Images,” TS, vol. 40, no. 4, pp. 1355–1365, Aug. 2023, doi: 10.18280/ts.400405.

[15] O. Yaman and M. Karakose, “Development of image processing based methods using augmented reality in higher education,” in 2016 15th International Conference on Information Technology Based Higher Education and Training (ITHET), Istanbul, Turkey: IEEE, Sept. 2016, pp. 1–5. doi: 10.1109/ITHET.2016.7760723.

[16] K. Palanikumar, E. Natarajan, and A. Ponshanmugakumar, “Application of machine vision technology in manufacturing industries—a study,” in Machine Intelligence in Mechanical Engineering, Elsevier, 2024, pp. 91–122. doi: 10.1016/B978-0-443-18644-8.00018-6.

[17] D. Hande Yıldız;DURSUN, “Buğday Tanelerinin Bazı Fiziksel Özelliklerinin Görüntü İşleme Tekniğiyle Belirlenmesi*,” Tarım Bilimleri Dergisi, vol. 13, no. 3, p. 1, 2007, doi: 10.1501/Tarimbil_0000000544.

[18] I. Aydin, O. Yaman, M. Karakose, and S. B. Celebi, “Particle swarm based arc detection on time series in pantograph-catenary system,” in 2014 IEEE International Symposium on Innovations in Intelligent Systems and Applications (INISTA) Proceedings, Alberobello, Italy: IEEE, June 2014, pp. 344–349. doi: 10.1109/INISTA.2014.6873642.

[19] S. B. Çelebi and B. G. Emiroğlu, “A Novel Deep Dense Block-Based Model for Detecting Alzheimer’s Disease,” Applied Sciences, vol. 13, no. 15, p. 8686, July 2023, doi: 10.3390/app13158686.

[20] M. Yavuz Celikdemir and A. Akbal, “Examining the structure cracks in concrete structures exposed to high temperatures,” in 2015 23nd Signal Processing and Communications Applications Conference (SIU), Malatya, Turkey: IEEE, May 2015, pp. 2033–2036. doi: 10.1109/SIU.2015.7130265.

[21] A. Baba, “Neural networks from biological to artificial and vice versa,” BioSystems, vol. 235, p. 105110, Jan. 2024, doi: 10.1016/j.biosystems.2023.105110.

[22] A. Aslan, “DEEP LEARNING IN NEUROLOGICAL IMAGING: A NOVEL CNN-BASED MODEL FOR BRAIN TUMOR CLASSIFICATION TÜRKİYE AND HEALTH RISK ASSESSMENT,” İnönü Üniversitesi Sağlık Hizmetleri Meslek Yüksek Okulu Dergisi, vol. 13, no. 2, pp. 457–474, June 2025, doi: 10.33715/inonusaglik.1645318.

[23] B. Birecikli, Ö. A. Karaman, S. B. Çelebi, and A. Turgut, “Failure load prediction of adhesively bonded GFRP composite joints using artificial neural networks,” J Mech Sci Technol, vol. 34, no. 11, pp. 4631–4640, Nov. 2020, doi: 10.1007/s12206-020-1021-7.

[24] S. A. Singh and K. A. Desai, “Automated surface defect detection framework using machine vision and convolutional neural networks,” J Intell Manuf, vol. 34, no. 4, pp. 1995–2011, Apr. 2023, doi: 10.1007/s10845-021-01878-w.

[25] “Chez hakan pottery | the pottery shop | avanos, cappadocia, turkey.” Accessed: Nov. 29, 2025. [Online]. Available: https://www.chezhakan.com/english/

[26] N. Otsu and others, “A threshold selection method from gray-level histograms,” Automatica, vol. 11, no. 285–296, pp. 23–27, 1975.

[27] O. Yaman, E. Karaköse, İ. Aydın, M. Karaköse, and E. Akın, “Pantograf-Katener Sistemler için Bulanık Mantık Tabanlı Belirlenen Pantograf Modeli Kullanılarak Ark Tespiti Yaklaşımı,” SAÜ Fen Bilimleri Enstitüsü Dergisi, vol. 21, no. 4, pp. 1–1, Aug. 2017, doi: 10.16984/saufenbilder.327098.