

Enhancing University Students' Image Processing Skills through Hybrid Google Colab Training on Image Histogram Analysis

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Abstrak

Mahasiswa umumnya telah memahami konsep dasar citra digital, tetapi jarang mempraktikkan pengolahan citra secara komputasional. Kegiatan pengabdian ini bertujuan meningkatkan keterampilan pengolahan citra mahasiswa melalui pelatihan hibrida berbasis Google Colab dan Python dengan fokus pada analisis histogram citra. Pelatihan dilaksanakan pada 26 September 2026 di laboratorium komputer dan diikuti 20 mahasiswa Program Studi Teknologi Informasi, Universitas Pembangunan Panca Budi (8 luring, 12 daring). Tahapan kegiatan meliputi identifikasi kebutuhan, demonstrasi, praktik langsung dengan notebook Colab bersama, analisis histogram, evaluasi, dan tindak lanjut. Ketercapaian diukur melalui pre-test dan post-test, rubrik tugas praktik, dan angket respons. Rata-rata skor meningkat dari 85 menjadi 95 (10 poin; 11,8%). Sebanyak 18 dari 20 peserta (90%) menyelesaikan tugas analisis histogram sesuai rubrik, yaitu seluruh peserta luring dan 10 dari 12 peserta daring. Skor angket respons mencapai 94%. Koneksi internet yang tidak stabil menjadi kendala utama dan diatasi dengan tethering.

Kata Kunci: Analisis Histogram Citra, Google Colab, Pelatihan Hibrida, Pengolahan Citra, Python

Abstract

University students generally understand basic digital image concepts but rarely practise image processing computationally. This community service activity aimed to improve students' image processing skills through hybrid training based on Google Colab and Python, focusing on image histogram analysis. The training was held on 26 September 2026 in a computer laboratory and involved 20 students of Information Technology Program (8 on-site, 12 online). The activity comprised needs identification, demonstration, hands-on practice with a shared Colab notebook, histogram analysis, evaluation, and follow-up. Outcomes were measured using a pre-test and post-test, a practical task rubric, and a response questionnaire. The mean score increased from 85 to 95 (10 points; 11.8%). Eighteen of 20 participants (90%) completed the histogram analysis task according to the rubric, comprising all on-site participants and 10 of 12 online participants. The questionnaire score reached 94%. Unstable internet connection was the main constraint and was mitigated through mobile tethering.

Keywords: Google Colab, Hybrid Training, Image Histogram, Image Processing, Python

1. INTRODUCTION

Digital images are now part of almost every field that university students enter, from health and agriculture to education, business, and media. Working with images computationally, rather than only viewing or editing them in graphical applications, requires an understanding that an image is a numerical array of pixel intensities that can be read, transformed, and measured with code (Gonzalez & Woods, 2018). This competence is increasingly expected of graduates because many analytical tasks, such as quality inspection, document digitisation, and preprocessing for machine learning, begin with basic image operations. In Python, these operations are made accessible by open-source libraries such as NumPy for array computation (Harris et al., 2020) and scikit-image for image processing (van der Walt et al., 2014).

Among the basic concepts of image processing, the image histogram is a practical entry point. A histogram records how many pixels fall at each intensity level, so its position and spread directly describe the brightness and contrast of an image (Gonzalez & Woods, 2018). The same representation underlies widely used enhancement

methods such as histogram equalization and its contrast-limited variants, which remain an active subject of development (Fan et al., 2022). Because the histogram links a visual impression (dark, bright, flat, high-contrast) to quantities that can be computed and plotted, it is well suited for teaching students to reason about images with data rather than intuition alone.

The participants of this activity were 20 undergraduate students from Information Technology Program, semester 4, Universitas Pembangunan Panca Budi, Medan, Indonesia. Their pre-test mean of 85 indicates that they already understood the basic concepts of digital images. The gap addressed by the activity was therefore not conceptual knowledge but applied practice: During the needs identification stage, it was found that students had learned fundamental image processing concepts but lacked practical competence in executing image analysis workflows. They had limited exposure to Python programming for image loading, conversion, histogram generation, and interpretation, as image processing coursework was mainly delivered through conceptual explanations rather than hybrid, practice-oriented activities using platforms such as Google Colab.. In addition, 12 of the 20 participants could only attend remotely, so the activity had to be accessible from outside the laboratory.

Cloud-based notebooks offer a practical response to the installation problem. Google Colab provides a hosted Jupyter environment in which code, explanations, and outputs are combined in a single document that runs in a web browser without local configuration (Nelson & Hoover, 2020). Reports from programming and artificial intelligence courses show that Colab lowers the setup barrier and allows instructors to distribute ready-to-run notebooks (Nelson & Hoover, 2020; Llerena-Izquierdo et al., 2024), and interactive notebooks have been used to connect image processing theory with practice in engineering courses (Bayindir, 2026). In the Indonesian community service context, Colab-based training has been used to introduce data analysis to university students (Febriansyah et al., 2025), but reports that focus on image processing and histogram interpretation are still scarce.

Delivery mode is a second consideration. Participants who cannot attend in person can still join through a synchronous hybrid format, in which on-site and remote learners follow the same session at the same time. Such designs widen access but require deliberate attention to interaction and technical quality for remote participants (Raes et al., 2020), and blended arrangements are most effective when online components are structured rather than added informally (Müller & Mildenerger, 2021).

Based on these conditions, this community service activity aimed to (1) improve participants' ability to load, visualise, and convert digital images to grayscale using Python in Google Colab; (2) improve their ability to compute and interpret image histograms; and (3) evaluate competency improvement, task completion, and participant response under the hybrid training format. The activity is a downstream application of the authors' work on The needs identification revealed that university students had limited practical experience in implementing image processing techniques using Python-based tools. Although fundamental concepts such as image representation, enhancement, and histogram analysis had been introduced, learning activities remained predominantly theoretical, providing insufficient opportunities for students to load, process, visualise, and analyse digital images through coding environments such as Google Colab..

2. IMPLEMENTATION METHOD

2.1 Participants and Needs

The activity was conducted on 26 September 2026 in the computer laboratory of Universitas Pembangunan Panca Budi, Medan, Indonesia, with a synchronous online room via Google Meet. The participants were 20 undergraduate students from Universitas Pembangunan Panca Budi, Medan, Indonesia, of whom 8 attended on-site and 12 joined online (Table 1). Needs were identified through a pre-test and initial discussion with the participants.

Table 1. Participant characteristics

Characteristic	Category	n	%
Status	Undergraduate student	20	100.0
Mode of participation	On-site (computer laboratory)	8	40.0
	Online (synchronous)	12	60.0
Study programme	Information Technology	20	100.0
Total		20	100.0

2.2 Implementation Stages

The activity followed eight stages (Figure 1). Needs identification produced the participant profile and baseline scores. During preparation, the team developed a Google Colab notebook, slides, a practice image set, the test instrument, and the questionnaire. The hybrid training was delivered in a classroom equipped with a projector, a camera, and a microphone connected to the online room, so that on-site and online participants followed the same demonstration simultaneously. In the demonstration stage, the instructor executed the notebook cell by cell while explaining each output. Participants then ran and modified the same notebook during hands-on practice, completed an image histogram analysis task, and took the post-test and questionnaire. Follow-up consisted of To reinforce the learning outcomes, post-training activities included an individual practical assignment involving image loading, preprocessing, and histogram analysis using Python in Google Colab. Continuous support was provided through an online mentoring group for two weeks, allowing participants to discuss challenges, receive feedback, and improve their implementation skills.

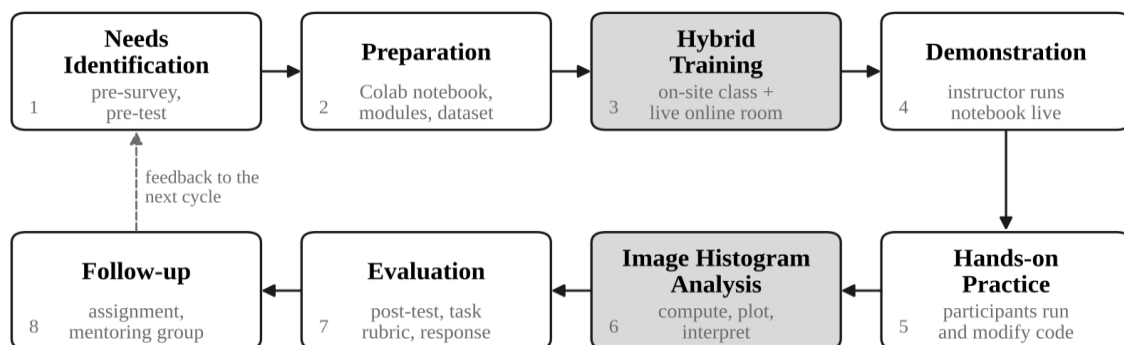


Figure 1. Community service implementation flow

2.3 Training Materials, Tools, and Colab Workflow

The material covered ten topics: digital images; pixels and intensity; Google Colab; basic Python; image loading; image visualisation; grayscale conversion; image histograms; histogram interpretation; and practical image analysis. All practice was carried out in Google Colab using Python with NumPy (Harris et al., 2020), Matplotlib, and scikit-image (van der Walt et al., 2014). Participants needed only a Google account, a browser, and an internet connection. The notebook followed the eight-step workflow in Figure 2: opening the shared notebook, importing libraries, loading an image as an array, visualising it and inspecting pixel values, converting it to grayscale, computing and plotting its 256-bin histogram, interpreting the histogram, and applying histogram equalization to compare the result.

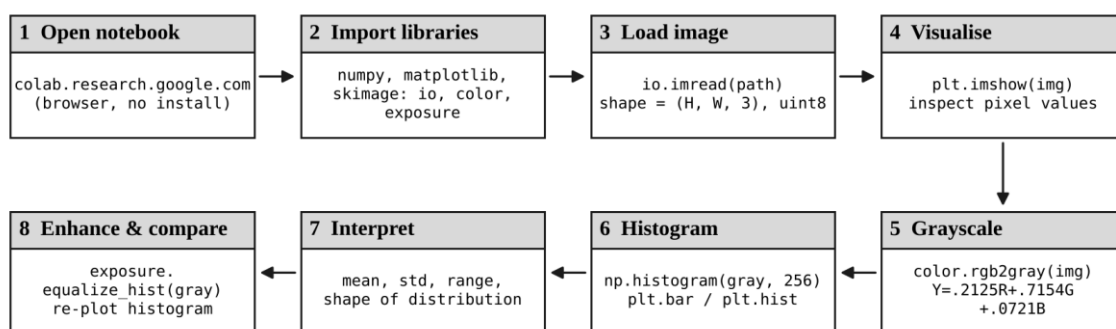


Figure 2. Google Colab image processing workflow used in the training notebook

2.4 Evaluation

Training outcomes were measured with three instruments. First, a pre-test and post-test scored 0–100 covered the training content: digital image concepts, Colab and Python operation, image loading and visualisation, grayscale conversion, histogram computation, and histogram interpretation. Second, a practical task rubric with four criteria (correct image loading, correct grayscale conversion, correct histogram plot, and a correct written

interpretation) determined task completion; a participant was considered to have completed the task when at least three criteria were met. Third, a questionnaire captured participant response to the material, delivery, and tools, reported as an overall percentage score. Improvement was calculated descriptively, without inferential statistical testing, using Equation (1).

$$\text{Percentage Improvement} = ((\text{Post} - \text{Pre}) / \text{Pre}) \times 100\% \quad (1)$$

3. RESULTS AND DISCUSSION

3.1 Implementation of the Hybrid Training

The training was implemented on 26 September 2026 in 7 sessions (Table 2). All 20 participants completed the pre-test, the practical task, the post-test, and the questionnaire. Eight participants worked at laboratory computers and 12 followed the same sessions online from their own devices. Table 2 shows that more than half of the scheduled time was allocated to hands-on activity, because the needs identification showed that the participants' main gap was applied practice rather than conceptual knowledge.

Table 2. Training implementation

No	Session	Mode	Main activity and output	Duration
1	Opening and pre-test	Hybrid	Baseline score	15 minutes
2	Digital image, pixel and intensity	Hybrid	Lecture and Q&A; participants read pixel values of a sample image	20 minutes
3	Google Colab and Python basics	Hybrid	Demonstration; every participant opens and runs the shared notebook	25 minutes
4	Image loading, visualisation, grayscale	Hands-on	Participants load their own image and convert it to grayscale	25 minutes
5	Image histogram and interpretation	Hands-on	Histogram plot and written interpretation of brightness and contrast	25 minutes
6	Practical task and enhancement	Hands-on	Histogram equalization on a low-contrast image; comparison of histograms	25 minutes
7	Post-test, questionnaire, follow-up	Hybrid	Post-test score, response data, follow-up plan	15 minutes

Note: confirm or revise sessions and durations according to the actual rundown.

3.2 Results of Google Colab Practice

Every participant ran the shared notebook in a personal Colab session, whether at a laboratory computer or on a personal device at home. Because the code executed on Google's servers, no participant had to install Python or image libraries, and on-site and online participants worked with identical software. This is consistent with earlier reports that Colab allows students to run instructor-prepared notebooks without configuring packages and dependencies (Nelson & Hoover, 2020; Llerena-Izquierdo et al., 2024). For a hybrid community service activity, this property is essential: without it, the 12 online participants would have needed individual installation support that could not be provided remotely within one day.

3.3 Results of Image Histogram Analysis

The image histogram analysis activity demonstrated that participants were able to apply fundamental image processing techniques using Python through the Google Colab platform. During the hands-on session, participants successfully loaded digital images, converted RGB images into grayscale representations, and generated histogram plots to observe the distribution of pixel intensity values. The activity allowed participants to directly relate numerical pixel information with visual characteristics observed in the images.

The histogram results showed variations in intensity distribution among different image samples. Images with balanced brightness levels generally produced histograms distributed across a wider intensity range, indicating better contrast and clearer visual information. In contrast, low-contrast images tended to show concentrated intensity values within a limited range, resulting in reduced visual details. Through histogram interpretation, participants were able to identify the relationship between pixel intensity distribution and perceived image quality.

Furthermore, participants implemented histogram equalization as an image enhancement technique to improve the contrast of low-quality images. The comparison between the original and enhanced images showed that histogram equalization redistributed pixel intensity values more evenly, resulting in improved visibility of image details. The corresponding histogram changes provided visual evidence of the enhancement process and helped participants understand how mathematical operations can influence image appearance.

The results of this activity indicated that Google Colab-based practical training effectively supported students in transforming theoretical knowledge into computational skills. By analysing histogram patterns and interpreting the resulting image changes, participants developed a deeper understanding of image representation, intensity distribution, and basic enhancement techniques in digital image processing.

Figure 3 shows the output of the histogram analysis exercise produced in the training notebook. The colour image (Figure 3a, 400×600 pixels, three channels) was converted to grayscale (Figure 3b) using the weighted luminance formula in scikit-image. Its histogram (Figure 3c) spans almost the entire intensity range, with a mean of 98.8 and a standard deviation of 58.9. About 27.4% of the pixels lie below intensity 64 and only 7.4% above 191, while distinct peaks appear in the dark region (the shadowed background and saucer), the middle region (the wooden table), and near intensity 235 (the white cup). Participants were asked to translate these quantities into a statement about the image; the expected interpretation is that the image is moderately dark overall but has good contrast, because its pixels are spread widely across the intensity range.

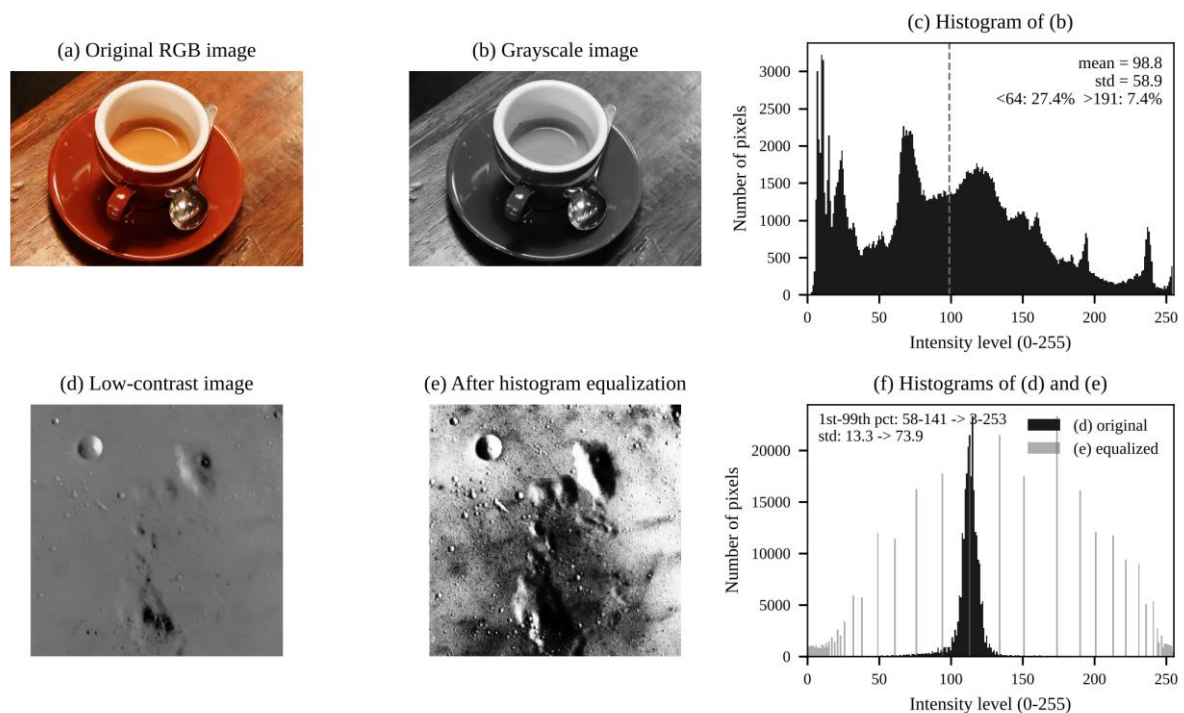


Figure 3. Example of image histogram analysis in Google Colab: (a) original RGB image, (b) grayscale image, (c) histogram of (b), (d) low-contrast image, (e) image after histogram equalization, and (f) histograms of (d) and (e)

The second part of the exercise used a low-contrast image (Figure 3d). Its histogram (Figure 3f, dark bars) is concentrated in a narrow band: 98% of the pixels lie between intensities 58 and 141, and the standard deviation is only 13.3. After histogram equalization (Figure 3e), the same 98% of pixels spread from 3 to 253 and the standard deviation increased to 73.9, which makes the crater edges and surface texture visible. The equalized histogram (grey bars) also appears as separated spikes rather than a smooth curve, because equalization redistributes existing intensity levels but cannot create new ones. This observation was used to discuss why enhancement methods continue to be refined to control over-enhancement (Fan et al., 2022).

3.4 Participants' Competency Improvement

Table 3 summarises the training outcomes. The mean score increased from 85 before training to 95 after training, an absolute gain of 10 points or 11.8% according to Equation (1) (Figure 4). The relative gain is modest because the baseline was already high: with a pre-test mean of 85, the maximum possible gain was only 15 points, so the participants closed two-thirds of the remaining gap. The score therefore mainly confirms that the participants consolidated what they already knew; the stronger evidence of skill acquisition comes from the practical task, which required them to produce and interpret histograms with code rather than answer test items.

Table 3. Summary of training outcomes (n = 20)

Outcome indicator	On-site (n = 8)	Online (n = 12)	All (n = 20)
Mean pre-test score (0–100)	–	–	85
Mean post-test score (0–100)	–	–	95

Outcome indicator	On-site (n = 8)	Online (n = 12)	All (n = 20)
Improvement, Equation (1)	–	–	11.8%
Practical task completed (≥ 3 of 4 rubric criteria)	8 (100.0%)	10 (83.3%)	18 (90.0%)
Questionnaire score	–	–	94%

Note: test and questionnaire scores were recorded for the whole group only.

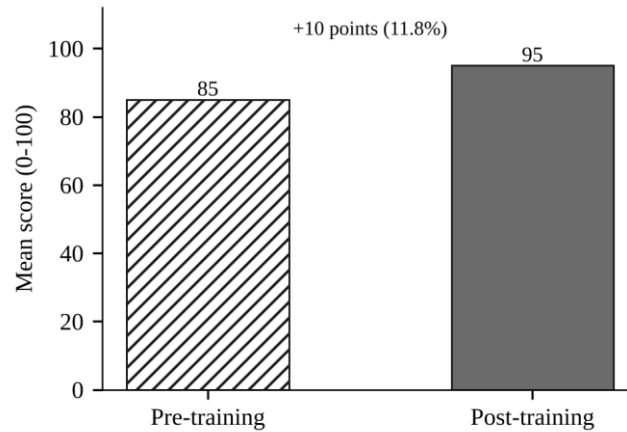


Figure 4. Comparison of participants' mean competency score before and after training (n = 20)

Figure 5 shows practical task completion by participation mode. All 8 on-site participants met at least three of the four rubric criteria, compared with 10 of the 12 online participants (83.3%), giving an overall completion rate of 90%. The two participants who did not complete the task both joined online. Given that unstable internet connection was the main constraint of the activity (Section 3.6), the most plausible explanation is that interruptions in the Colab session cost online participants practice time, although the small group size does not allow this difference to be generalised. Compared with the Colab-based data mining training reported by Febriansyah et al. (2025), which recorded a 38% increase in conceptual understanding among ten students, the relative gain here is smaller, but the present participants started from a much higher baseline and the two activities measured different content, so the comparison should not be taken beyond this general level.

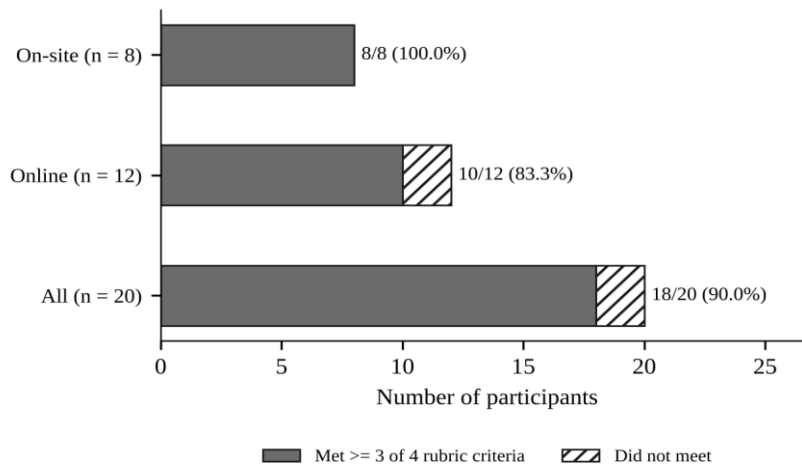


Figure 5. Practical task completion by participation mode

3.5 Participant Response

The questionnaire produced an overall score of 94%, indicating a strongly positive response to the material, delivery, and use of Google Colab (Table 3). The questionnaire responses indicated that participants positively perceived the training approach, particularly the combination of conceptual explanations and hands-on practice using Google Colab. Participants highlighted that direct implementation of image loading, histogram generation, and image enhancement techniques helped them better understand fundamental image processing concepts. The positive response should be read together with the lower task completion of online participants: synchronous hybrid learning widens access, but remote participants depend on connection quality and receive fewer spontaneous interactions with the instructor (Raes et al., 2020).

3.6 Constraints and Solutions

The main constraint during implementation was unstable internet connection. Because Google Colab executes code on remote servers, a dropped connection interrupts the running session and image uploads, and participants must reconnect and re-run earlier cells before continuing. The team addressed this by switching affected devices to mobile tethering, which allowed the sessions to continue. These constraints indicate that cloud notebooks remove the software barrier but not the connectivity barrier; for future hybrid sessions, a backup connection should be prepared in advance, and online participants should receive the notebook and a session recording beforehand.

3.7 Sustainability

The notebook, slides, and practice images remain available to participants and can be reused the training activity was conducted as part of the Digital Image Processing course at [Institution Name]. Following the training, participants were assigned an independent project to implement image analysis techniques using Google Colab. Further development activities are planned through advanced sessions on image filtering, edge detection, and image segmentation to expand students' computational image processing competencies. Because the materials run entirely in Colab, they can be adopted by other study programmes without laboratory investment, and the structured online component can be retained as a blended learning resource rather than a one-off event (Müller & Mildenerger, 2021).

4. CONCLUSION

The hybrid Google Colab training was implemented for 20 students (8 on-site and 12 online) on 26 September 2026 through eight stages, from needs identification to follow-up. The mean score increased from 85 to 95 (11.8%), and 18 of 20 participants (90%) completed the practical task by correctly computing and interpreting grayscale histograms, including the change in histogram spread after equalization. All on-site participants completed the task, compared with 10 of 12 online participants. The questionnaire score of 94% indicates a strongly positive response. Google Colab allowed every participant to practise without installing software, while unstable internet connection was the main constraint and was mitigated through mobile tethering. Future activities should prepare backup connections and pre-shared materials for online participants, use a more demanding pre-test to avoid a ceiling effect, and extend the material to image filtering and segmentation.

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