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STRENGTHENING MACHINE LEARNING COMPETENCE THROUGH LEAF IMAGE ANALYSIS IN VOCATIONAL EDUCATION

Syafrial Fachri Pane¹, Muhammad Yusril Helmi Setyawan², Amri Yanuar³, Raden Irfan Santika
Rahman⁴, Raditya Rizki Raharja⁵, Muhammad Arif Rivaldi⁶, Rifky Najra Adipura⁷,
Ode Andi Alamsyah⁸

¹School of Information Technology, Universitas Logistik dan Bisnis Internasional

¹syafrial.fachri@ulbi.ac.id

²School of Information Technology, Universitas Logistik dan Bisnis Internasional

²yusrilhelmi@ulbi.ac.id

³School of Logistics and Transport, Universitas Logistik dan Bisnis Internasional

³amri@ulbi.ac.id

⁴Software Engineering Department, SMK Negeri 2 Cimahi

⁴caumenkhel@gmail.com

⁵School of Information Technology, Universitas Logistik dan Bisnis Internasional

⁵radityarzkir@gmail.com

⁶School of Information Technology, Universitas Logistik dan Bisnis Internasional

⁶m.arifrivaldi141105@gmail.com

⁷School of Information Technology, Universitas Logistik dan Bisnis Internasional

⁷rifkyadipura@gmail.com

⁸School of Information Technology, Universitas Logistik dan Bisnis Internasional

⁸odeandialamsyah@gmail.com

ABSTRACT

The rapid advancement of artificial intelligence demands strong Machine Learning and Computer Vision competencies in vocational education, particularly within Software Engineering study programs. Although students at SMK Negeri 2 Cimahi possess adequate programming foundations, they lack hands-on experience in building a complete end-to-end ML pipeline, creating a gap between conceptual knowledge and applied technical skill. This community service activity addresses that gap by strengthening participants' conceptual understanding while transferring it into practical competence for 38 eleventh-grade Software Engineering students, through a fully facilitated learning approach delivered via Google Colab. The activity encompassed leaf image dataset exploration, data preprocessing, ResNet9 model training, model evaluation, and a Streamlit-based prediction application demonstration deployed with Ngrok. Learning outcomes were measured using a 20-item multiple-choice pre-test and post-test, complemented by facilitator observation of participant engagement. Results indicate that the already-high conceptual understanding (mean scores of 96.84 and 97.37, N = 38) was successfully transferred into technical competence, with per-stage achievement ranging between 93.4% and 99.1%, peaking in the Training and Evaluation stages (99.1%) and lowest in Deployment. These findings suggest that time allocation in similar short-duration ML/CV training should be proportional to each pipeline stage's integration complexity.

Keywords: Machine Learning, Computer Vision, Leaf Image Classification, Competency Strengthening, Vocational Education

1. INTRODUCTION

The rapid development of Artificial Intelligence (AI) and Machine Learning (ML) has brought significant transformation across industrial sectors and daily life. Within vocational education, particularly in Software Engineering (*Rekayasa Perangkat Lunak/RPL*) programs, mastery of ML and Computer Vision (CV) competencies has become an urgent requirement to prepare graduates for the demands of the digital-era workforce (Nadzinski et al., 2023). However, a substantial gap remains between the demand for skilled data science and ML professionals and the availability of competent graduates, particularly at the vocational education level, where instruction in these skills is still in its early stages (Nadzinski et al., 2023). Vocational education is expected to provide not only conceptual knowledge but also applicable technical skills that can be directly implemented in developing AI-based solutions. Several digital technology initiatives at Indonesian vocational high schools have shown positive outcomes, such as the integration of IoT and Computer Vision in agricultural vocational learning (Marwan Ramdhany Edy et al., 2025) and the application of generative artificial intelligence to enhance student interest and learning outcomes in vocational high schools (Tofan Dwi Tjahyono et al., 2025). Similar initiatives have also grown within the broader AI/ML domain, including project-based AI implementation training for high school and vocational students (Wibowo et al., 2026). AI application training for Software Engineering students (Hidayat et al., 2026), and the introduction of artificial intelligence concepts to students across various study programs, including accounting (Utomo et al., 2024; Wulandari & Fitrianiingsih, 2024), collectively indicating that the need for strengthened AI/ML literacy at the vocational high school level cuts across study programs.

SMK Negeri 2 Cimahi is a vocational education institution in Cimahi City with a substantial Software Engineering study program. The school has established a partnership with Universitas Logistik dan Bisnis Internasional (ULBI) through a prior community service activity, namely the Laravel Bootcamp for Improving Web Programming Competence conducted in 2025 (PANE et al., 2025). The continuity of this partnership reflects both institutions' commitment to enhancing the quality of vocational education through the transfer of knowledge and skills grounded in current technology. Sustained community service activities contribute positively to strengthening the learning ecosystem within partner schools.

Although Software Engineering students at SMKN 2 Cimahi already possess an adequate programming foundation, they lack practical experience in building a complete end-to-end ML pipeline. An end-to-end ML pipeline encompasses a series of stages, from dataset acquisition and exploration, data preprocessing, model selection and training, model performance evaluation, to prediction application deployment. This gap between conceptual understanding and technical implementation skills poses an obstacle for students in building AI-based portfolios that could support their competitiveness in the workforce.

The selection of leaf image classification as the case study for this activity was guided by several technical and pedagogical considerations. First, image classification is one of the most fundamental Computer Vision applications and produces clearly interpretable results, facilitating participants' conceptual understanding. Second, leaf image datasets are freely and widely available through public platforms such as [vip00000l/new-plant-diseases-dataset](https://www.kaggle.com/datasets/vip00000l/new-plant-diseases-dataset) on Kaggle, eliminating the need for data acquisition costs. Third, training a leaf image classification model does not require specialized computing infrastructure, as it can be performed using free cloud platforms such as Google Colab. Fourth, plant health classification through leaf image analysis carries high social relevance in the context of food security and precision agriculture, thereby offering genuine applied value for participants. Convolutional Neural Network (CNN) architectures have been shown to be effective for image-based plant disease classification with high accuracy (Imanulloh et al., 2023).

Based on a situational analysis and discussions with the partner school, the problems addressed in this activity can be formulated as follows: limited practical materials for applying ML and Computer Vision despite prior introduction of basic concepts, restricted access to appropriate tools and datasets for learning, and the absence of hands-on experience in building an end-to-end ML pipeline that could serve as an AI-based competency portfolio.

This community service activity aims to strengthen the conceptual understanding already possessed by students while transferring it into practical skills for implementing ML and Computer Vision. This competency strengthening is expected to improve the readiness of SMKN 2 Cimahi's Software Engineering students in meeting workplace AI competency demands and to contribute to the development of technology-based portfolios.

Prior studies have demonstrated the effectiveness of practice-based learning and guided approaches in enhancing technical competence within vocational education. However, a combination of guided learning, a Computer Vision case study applied to local agriculture, and the integrated use of free cloud tools within a single learning activity has not been widely and systematically applied in the Indonesian vocational high school context. The novelty of this activity lies in integrating all these components into a single structured learning package, spanning from dataset exploration to prediction application demonstration, utilizing the Google Colab and Streamlit platforms, both accessible without requiring dedicated infrastructure investment.

2. METHOD OF IMPLEMENTATION

2.1 Location And Time

This community service activity was conducted at SMK Negeri 2 Cimahi, in the Software Engineering department, located at Jalan Kamarung No. 69, RT.2/RW.5, Citeureup, Cimahi Utara, Kecamatan Cimahi Utara, Cimahi City, West Java 40512. This location was selected based on the continuing partnership previously established between ULBI and SMKN 2 Cimahi (PANE et al., 2025). The activity was carried out on August 10, 2026, from 09.00 to 14.30 West Indonesia Time (WIB). The main venue was the Software Engineering department's computer laboratory, equipped with internet access and a projector to support the demonstration and guided practice sessions.



Figure 1. Software Engineering computer laboratory at SMKN 2 Cimahi



Figure 2. SMKN 2 Cimahi campus environment and activity participants

2.2 Target Audience

The target audience of this activity comprised Software Engineering students of class XI RPL A at SMKN 2 Cimahi. A total of 38 students participated, confirmed through name-based matching of pre-test and post-test respondent data. Participants were selected based on the consideration that they already possessed an adequate programming foundation. This prerequisite ensured that participants had a sufficient knowledge base to follow the practical implementation of the end-to-end ML pipeline.

2.3 Service Methods

This activity employed a fully facilitated learning approach that combined guided demonstration and guided practice. This approach was selected in consideration of time constraints during implementation (a condensed single-day schedule from 09.00 to 14.30 WIB), which did not allow for independent practice sessions or an independent mini-project as would be expected under a Project-Based Learning (PjBL) approach. Although PjBL has been proven effective within vocational education (Wahyudi et al., 2024), the time limitations of this activity required the adoption of a fully facilitated learning approach instead. The activity was carried out through six main stages, as follows.

2.3.1 Technical Preparation

The preparation stage included coordination with the school for scheduling and laboratory facility provision, development of instructional modules, configuration of Google Colab accounts for each participant, and preparation of access to the vip00000l/new-plant-diseases-dataset via the Kaggle platform. Google Colab was selected as the learning platform based on its effectiveness in providing free GPU access, a cloud-based environment requiring no complex configuration, and ease of notebook sharing for collaborative learning (Lahulima et al., 2023). The use of Google Colab as a medium for programming and AI/ML literacy training in community service activities has also been widely adopted in other contexts, such as Python training for teachers and students (Handayani et al., 2025; Nugrahanti et al., 2025), further reinforcing the platform choice for this activity. The facilitator team also prepared a structured Google Colab notebook to guide participants through each stage of the ML pipeline.

2.3.2 Introduction to AI/ML/CV and CNN Concepts

This session was delivered through interactive lectures and discussion to introduce the fundamental concepts of artificial intelligence, Machine Learning, Computer Vision, and Convolutional Neural Network (CNN) architecture. Material was presented using a visual approach with real-world application examples to strengthen participants' understanding of the relevance of ML technology across various domains.

2.3.3 Dataset Exploration and Data Preprocessing

Participants were guided to explore the vip00000l/new-plant-diseases-dataset leaf image dataset from Kaggle, covering various plant health categories. This stage included Exploratory Data Analysis (EDA), understanding of the dataset's directory structure, class labeling, image resizing to standard dimensions, splitting the dataset into training and validation sets, and pixel value normalization. All stages were carried out under guidance, with direct demonstration from the facilitator.

2.3.4 Image Classification Model Training

At this stage, participants followed guided demonstration and practice to build and train an image classification model based on the ResNet9 architecture using Google Colab. The training process covered configuration of the learning rate, number of epochs, loss function, and model optimization. The facilitator explained the interpretation of training loss and validation accuracy curves during the training process. The trained model achieved a validation accuracy of approximately 96% after 2 epochs.

2.3.5 Streamlit-Based Prediction Application Demonstration

The facilitator demonstrated the development of a simple web application for plant health prediction using the Streamlit framework. This application integrated the trained model and allowed users to

upload a leaf image and receive a classification prediction result. The demonstration also covered application deployment using Ngrok for temporary public access. Participants followed this stage in a facilitated manner rather than through independent development.

2.3.6 Evaluation

Evaluation was conducted through a pre-test and post-test to measure participants' conceptual understanding and technical competence. In addition, the facilitator observed participants' engagement and active participation throughout the demonstration and guided practice sessions.



Figure 3. Student practice activity during the guided practice session

2.2 Success Indicators

The success indicators of this activity were established based on three main evaluation aspects, adjusted to the actual implementation conditions. Table 4 presents the evaluation aspects and their corresponding success indicators.

Table 1. Activity Success Indicators

No	Evaluation Aspect	Success Indicator
1	Basic conceptual understanding	Pre-test scores indicate good prior mastery (result of earlier instruction)
2	Technical implementation competence	Post-test scores per ML pipeline stage indicate strong applied understanding
3	Participant engagement	Active involvement in discussion and practice during the demonstration and guided practice sessions

2.5 Evaluation Methods

Evaluation was conducted quantitatively through pre-test and post-test instruments, each consisting of 20 multiple-choice questions. The pre-test was designed to measure participants' basic conceptual understanding of Machine Learning acquired through prior instruction, while the post-test focused on the technical application of ML pipeline stages, covering Data Loading, Exploratory Data Analysis (EDA), Data Preparation, Modeling, Training, model Evaluation, and application Deployment. In addition to the quantitative evaluation, the facilitator directly observed participant engagement during the demonstration and guided practice sessions to assess active participation and contextual understanding.

3. RESULTS AND DISCUSSION

3.1 Preparation and Basic ML/CV Concept Instruction

The activity began with a session introducing the fundamental concepts of artificial intelligence, Machine Learning, Computer Vision, and Convolutional Neural Network (CNN) architecture. Material was delivered through interactive lectures supported by visual presentations explaining the distinction between supervised and unsupervised learning, the concept of image classification, and the role of

CNNs in extracting visual features from images. The facilitator also explained the end-to-end ML pipeline workflow that participants would subsequently practice, from data acquisition through to application deployment. This session lasted approximately 45 minutes with active discussion from participants, who demonstrated enthusiasm for the topic. Participants raised questions related to ML applications across various domains, such as facial recognition, object detection, and medical image classification.

3.2 Dataset Exploration and Leaf Image Preprocessing

At this stage, participants were guided to access and explore the `vipooool/new-plant-diseases-dataset` leaf image dataset available on the Kaggle platform. This dataset contains thousands of plant leaf images across various health categories (healthy and various disease types). The facilitator demonstrated the installation and configuration of KaggleHub to download the dataset directly into the Google Colab environment. Participants then carried out Exploratory Data Analysis (EDA) to understand class distribution, image dimensions, and the visual characteristics of each category. The preprocessing stage included resizing images to 256×256 pixels to meet the ResNet9 model's input requirements, normalizing pixel values to the $[0, 1]$ range, splitting the dataset into a training set (80%) and validation set (20%), and applying simple data augmentation such as random flipping and rotation to increase training data variation. All stages were carried out under guidance, with each participant executing code in their own notebook while following the facilitator's explanation.

3.3 Model Training and Visualization

The model training stage formed the core of the practical activity. Participants followed a demonstration of building a CNN model architecture based on ResNet9, consisting of 9 convolutional layers with residual connections. The model was configured with a cross-entropy loss function, the Adam optimizer with a learning rate of 3×10^{-4} , and was trained for 2 epochs. The facilitator explained the importance of hyperparameter selection and the interpretation of training loss and validation accuracy curves, which were displayed in real time throughout the training process. The trained model successfully achieved a validation accuracy of approximately 96% after 2 epochs, indicating strong performance on the `vipooool/new-plant-diseases-dataset`.

Participants were also taught how to save the trained model in `.pth` format for use in the subsequent deployment stage. The training process lasted approximately 60 minutes and included discussion of overfitting, underfitting, and regularization strategies.

3.4 Deployment and Demonstration

The facilitator demonstrated the development of an interactive web application for plant health prediction using the Streamlit framework. This application integrated the trained ResNet9 model and provided a simple interface for users to upload a leaf image and receive a classification prediction result. The demonstration covered an explanation of the Streamlit code structure, the model loading process, preprocessing of input images to match the model's expected format, and visualization of prediction results. The facilitator also demonstrated application deployment using Ngrok, enabling temporary public access through a unique URL. Participants followed this stage in a facilitated manner rather than through independent development, given the time constraints of the activity. This demonstration provided participants with a comprehensive picture of how an ML model can be integrated into an application usable by end users.

3.5 Learning Evaluation Results (Pre-test vs Post-test)

Learning evaluation was conducted through a pre-test and post-test involving 38 participants. Both instruments consisted of 20 multiple-choice questions with differing focuses: the pre-test measured basic conceptual understanding of Machine Learning, while the post-test measured the technical application of the ML pipeline stages practiced during the activity. Table 5 presents the descriptive statistics of the evaluation results.

Table 2. Descriptive Statistics of Pre-test and Post-test Scores (N = 38)

Statistic	Pre-test	Post-test
Mean	96,84	97,37
Standard Deviation	5,25	3,44
Minimum Score	80,00	90,00
Maximum Score	100,00	100,00

The mean pre-test score was recorded at 96.84 (SD = 5.25) and the post-test at 97.37 (SD = 3.44), a difference of 0.53 points that appears nominally small. This pattern is consistent with a ceiling effect: a pre-test score already close to the upper bound of the scale limits the measurable room for improvement, meaning the mean difference alone cannot serve as a sole indicator of the activity's impact. A more informative indicator instead emerges from the change in score distribution, as illustrated in Figure 6.

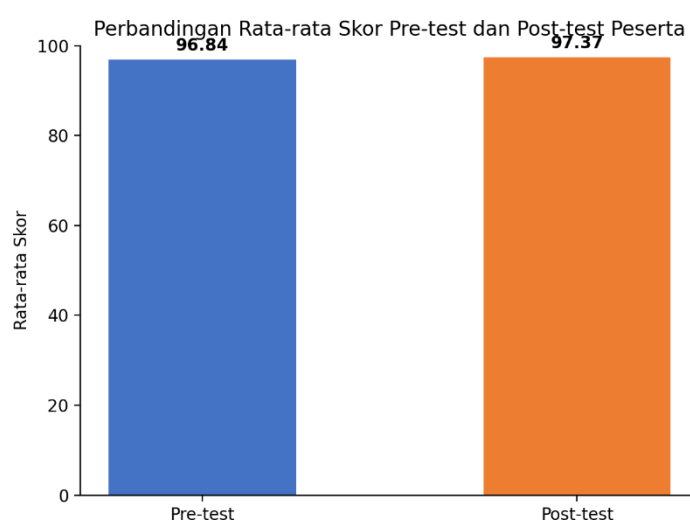


Figure 4. Comparison of mean pre-test and post-test scores

The narrowing of the standard deviation from 5.25 to 3.44, accompanied by an increase in the minimum score from 80.00 to 90.00, indicates a leveling of understanding: the gap between participants with low and high initial achievement narrowed following the activity. At the individual level, 7 participants (18.4%) recorded an increase in score, 24 participants (63.2%) remained at the same level, and 7 participants (18.4%) experienced a decrease. This decline in the latter group is likely related to a shift in question focus, from conceptual understanding in the pre-test to technical application in the post-test: the transfer of conceptual understanding into practical skills does not always occur uniformly or immediately. This pattern serves as a consideration for designing evaluation instruments for similar activities in the future, rather than being dismissed as a negligible deviation.

To provide a more comprehensive picture of participants' technical competence achievement, an analysis was conducted per ML pipeline stage based on the post-test question grouping. Table 7 presents the percentage of correct answers for each stage.

Achievement per stage ranged from 93.4% to 99.1%, following a fairly consistent pattern: the highest performance occurred in stages that were procedural in nature and had been repeatedly practiced directly, namely Training and model Evaluation (99.1% each), followed by Data Loading and EDA (98.2% each), reflecting strong understanding of the data acquisition and exploration process.

Table 3. Participant Competency Achievement per ML Pipeline Stage (Post-test)

Stage	Percentage of Correct Answers
Data Loading	98,2%
EDA	98,2%
Data Preparation	95,6%
Modeling	96,5%
Training	99,1%
Evaluation	99,1%
Deployment	93,4%

The lowest achievement occurred in the Deployment stage (93.4%). This pattern aligns with the cognitive complexity of each stage: Training and Evaluation followed a linear instructional sequence that had been repeatedly demonstrated, whereas Deployment required cross-component integration namely the trained model, the Streamlit interface, and Ngrok configuration introduced only in the final session with the most limited time allocation. This eight-point gap carries pedagogical value: integration stages require proportionally greater time allocation and repetition compared to other stages if similar activities are to achieve a more even level of achievement across the entire pipeline. This finding complements the results in Table 5 and confirms that the transfer of conceptual understanding into technical competence occurs gradually, with varying levels of success at each node of the end-to-end ML pipeline.

The small mean difference observed in this activity contrasts with similar AI/ML training PkM activities that reported considerably larger score increases, for example from 68 to 89 and from 69 to 90 in basic Python-based AI training (Panjaitan et al., 2025), from 71.85 to 87.15 in machine learning and big data training for vocational high school students (Andriani et al., 2025), and a 25% average increase in large language model-based AI literacy training (Utomo et al., 2024). This comparison reinforces the interpretation that the small difference observed in this activity does not indicate a weaker training impact, but rather reflects participants' substantially higher initial scores compared to those in the aforementioned studies; in other words, participants' starting position on the understanding scale also determines the magnitude of improvement that can be statistically observed.

3.6 Activity Success

All three success indicators in Table 4 were achieved, though with varying strength of evidence. Basic conceptual understanding is reflected in the high pre-test scores (mean 96.84), which simultaneously served as a prerequisite for the success of subsequent stages. Technical implementation competence, as the core indicator of this activity, is reflected in the post-test achievement per pipeline stage of 93.4–99.1%, as presented in the preceding section. The third indicator, participant engagement, was assessed through facilitator observation of discussion and practice activity; unlike the two preceding indicators, which are based on measurable scores, this assessment is qualitative in nature and not yet supported by a structured observation instrument, so its result high engagement throughout the activity should be read as a descriptive note rather than a measure equivalent to the other two indicators.

Implementation of the activity encountered a technical constraint in the form of unstable internet connectivity on some participants' devices, which hindered the dataset download process and access to Google Colab. This constraint was addressed by sharing hotspot connections from facilitators' devices and providing a pre-downloaded copy of the dataset as a backup. In addition, the condensed single-day schedule (09.00–14.30 WIB) limited the room for independent practice; this condition was a key consideration in selecting the fully facilitated learning approach over Project-Based Learning, as explained in the Method section.

The achievement pattern above aligns with the literature demonstrating the effectiveness of guided learning approaches for strengthening technical competence in vocational education. Within the constraints of implementation time, fully facilitated learning provided participants with a clear structure for following the end-to-end ML pipeline systematically, although this approach also limited the room for independent exploration that typically strengthens long-term retention in other activities. The structured Jupyter notebook produced as an outcome constitutes a reusable asset for the partner school, both for students' independent learning and as a starting point for follow-up activities offering greater room for independent practice.

4. CONCLUSION

This community service activity, a Machine Learning workshop on leaf image classification for Software Engineering students at SMKN 2 Cimahi, successfully achieved its main objective of strengthening participants' conceptual understanding and transferring it into technical competence for implementing an end-to-end ML pipeline. The consistently high pre-test and post-test scores (means of 96.84 and 97.37) confirm strong basic conceptual understanding, while the per-stage pipeline achievement of 93.4–99.1% demonstrates that this understanding was successfully transferred into technical competence, with varying levels of success across stages. The Training and Evaluation stages achieved the highest results (99.1%), while Deployment recorded the lowest (93.4%) a pattern that, as discussed in the previous section, reflects differences in cognitive complexity between stages rather than a learning failure.

The fully facilitated learning approach, combining guided demonstration and guided practice, proved suitable for a single-day implementation with a condensed schedule. Participants followed the entire pipeline systematically: exploration of the `vip00000ol/new-plant-diseases-dataset`, data pre-processing, training of a ResNet9-based classification model with a validation accuracy of approximately 96%, and demonstration of a Streamlit-based prediction application made publicly accessible via Ngrok. Intensive guidance from the facilitator team ensured that all participants could follow this process despite the limited implementation time, at the cost of reduced room for independent exploration, which would ideally accompany technical learning of this kind.

This activity produced a complete practicum module encompassing basic Machine Learning conceptual material, a structured Google Colab notebook for the leaf image classification case study, and a trained, reusable ResNet9 model. This module provides the partner school with an independent learning resource for students and a starting point for similar community service activities in the future, ensuring the activity's benefits extend beyond the day of implementation.

Beyond its technical achievements, this activity offers one methodological finding relevant to the design of short-duration ML/CV training PkM programs: the difference in achievement between pipeline stages correlates with the integration complexity of each stage, not with the order in which it is delivered. The implication is that time allocation in similar activities should be proportional to the cognitive complexity of each stage, with a larger share allocated to integration/deployment stages rather than divided evenly by number of stages. This principle may serve as a practical reference for designing short ML/CV training curricula in vocational education more broadly, complementing the fully facilitated learning framework applied in this activity.

For program sustainability, similar future activities are recommended to allocate a longer duration, particularly for the deployment stage, to give participants room for independent practice or an independent mini-project. Expanding collaboration with other vocational education institutions also has the potential to broaden the impact of AI competency strengthening among vocational high school students, while the development of advanced material such as object detection, image segmentation, or Computer Vision applications in other domains could become the topic of subsequent community service activities to further deepen participants' competence.

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