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A Patch-Based Voting Framework with MobileNetV2 for Identifying AI-Generated Visual Content in Digital Poster

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ABSTRACT

This study aims to detect the involvement of the use of AI in digital posters. The algorithm used for this purpose is to use the MobileNetV2 network architecture with evaluation scenarios to determine the best model configuration on the detection of the use of AI involved in digital posters. In this study, a method is proposed that uses a patch-based voting mechanism to model local visual patterns that serve as evidence of creator presence. The dataset used totaled 208 posters, half of which were man-made and the other half were AI-generated. The proposed model based on the CRISP-DM framework consists of six steps: (1) business understanding; (2) understanding data; (3) data preparation; (4) modeling; (5) evaluation; (6) Application. Various permutations of MobileNetV2 training including learning rate tuning, unlocked layers, and enriched data are explored to find the most reproducible architecture with the highest performance. The best models are selected based on their performance on validation data and voting uniformity across patches. The results of the model showed a training accuracy of 94.74%, a validation accuracy of 91.18%, and a test accuracy of 90.48% with a strong ability to distinguish visual features between AI and human work. These results suggest that the selection of appropriate training cases for MobileNetV2 along with a patch-based approach is a good way to filter the influence of AI in contemporary visual content.

Keywords-MobileNetV2; Patch-Based Analysis; AI-Generated Content Detection; Human Involvement Classification; Deep Learning; Model Selection Strategy

I. INTRODUCTION

Machine-generated images are making impressive progress faster with the rapid development of Artificial Intelligence (AI) than ever, which brings huge impacts to a wide range of areas such as graphic design and digital poster creation [1–3]. Generative AI models like GANs and Diffusion possible to produce highly realistic and sophisticated visual works from only textual descriptions, which dramatically changes the way of creative activities [4, 5]. This has led to an enormous proliferation of posters and illustrations on the web and on social media, often appearing as if humans made them with slight differences [6, 7].

Although much development has been made for the generation of AI-generated visual media, the increasing amount of AI-generated images have raised some significant problems, it is harder to visually recognize which are human-created images as opposed to ones created by Deep Learning (DL) algorithms [8, 9]. This lack of discrimination is further enhanced by the absence of ground-truth or metadata that matches images and complicates automatic detection their source [10-12], as it hinders algorithms that rely on metadata analysis [13]. Not only does this challenge give oxygen to copyright and plagiarism debates [14, 15], it also raises concerns about authenticity. To adress this, recently there has been a huge shift in the scientific community towards forensic image analysis and computer vision [16], specially for Convolutional Neural Network (CNN) to detect digital artifacts or other uncommon signals that AI-generative processes leave behind [8, 17-22].

CNN methods are effective for image classification and segmentation tasks, which have been demonstrated, including achieving state-of-the-art results on medical applications such as brain tumors [23-26] and breast histology [27] often through patch-based strategy by focusing on local important details. The patch-based approach design makes the model's texture and only minor artifacts analysis better than other methods, which is proven to be effective in deepfake detection and fingerprint technology of authenticity [28, 29]. One of these, which is related with extensive literature and research use CNN such as MobileNetV2 for AI image classification [8] and other state-of-the-art models (e.g., ViT, EfficientNet) [22], there are still some missing links. First, a few studies have directly measured the level of AI contribution to the end product (e.g., citation vs. whole generation) [2]. Secondly, the use of the patch-based voting mechanism, which has demonstrated good performance on clinical image forensics [29], is also rarely investigated systematically for AI-generated poster detection. Third, model selection methods to determine the optimal CNN architecture and voting for large patches in different detection scenarios need further investigation [30].

To address these gaps, this study sets out to establish and evaluate an effective AI-based image detection approach by integrating the MobileNetV2 architectures with a patch-based voting detection framework. The aim is to find the optimal configuration for obtaining both accuracy, sensitivity and specificity of digital posters generation between human-made and AI-generated work.

II. METHOD

A. Framework of Research

To determine the AI level and human presence in digital posters, this study extracts the features using a MobileNetV2 model trained with multiple scenarios, followed by patch-wise voting. Then use Cross Industry Standard Process for Data Mining (CRISP-DM) as the main framework in data analysis and processing of this work. CRISP-DM can guide the research stages in a systematic way, such as data understanding, data preparation, modeling, and evaluation to implementation [31, 32]. Moreover, the top model is also incorporated into a web-based detection system at deployment phase. The development of the system is based on Rapid Application Development (RAD) to make it possible that the implementation and software development process goes more rapidly and incrementally for user-friendly purpose [27]. By combining CRISP-DM and RAD (see Figure 1), this paper not only establishes a potential predictive detection model but also delivers a practical, ready-to-use application solution..

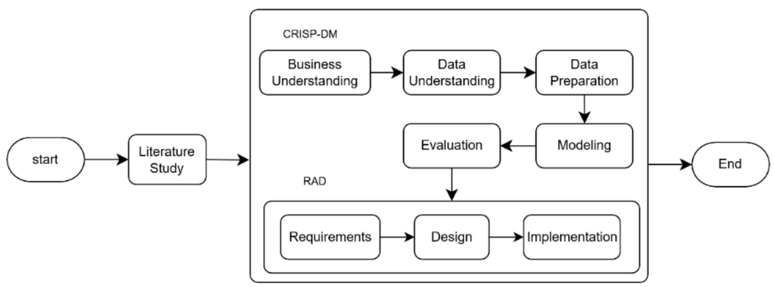


Figure. 1. CRISP-DM Framework

B. Dataset

The dataset is organized into two main categories: human-made posters and AI-generated posters. The dataset consists of a total of 208 digital posters, evenly distributed between the two categories. The human-made posters were collected from multiple sources, including submissions to the “2024 Graphic Design Student Exhibition”, entries from the “INTERAKSI 2025” illustration poster competition, and curated digital graphic design collections from online platforms such as Pinterest. The AI-generated posters were obtained through image generation using the DALL-E model, as well as from publicly available AI-generated image platforms, including Pinterest and Lexica Art.There's a total of 100 human generated ads and 108 AI created posters in JPG, PNG, and WEBP files included. All of the data are quality-controlled, resolution has been checked, file type can be picked, and duplicate detection has been applied. No files were excluded, however, the data was preprocessed into JPG format via WEBP. Table 1 shows the dataset summary for this work.

TABLE 1. DATASET SUMMARY

Data Categories	Data Source	N	Format
Digital Poster by Human	- Graphic Design Student Exhibition 2024 - Illustration Poster Competition “INTERAKSI 2025” - Pinterest	100	JPG, PNG
Digital Poster Generated by AI	- DALL-E - Pinterest - Lexica Art	108	JPG,PNG, WEBP

The labeling process was carried out by separating the dataset into two main directories, namely AI_poster and human_poster. Each file was renamed to ensure consistency, for example ai_poster_001 for AI-generated posters and human_poster_001 for human-made posters. Then the dataset was divided at a ratio of 70 : 20 : 10 into a training set (145 data), validation set (42 data), and testing set (21 data). In addition, an additional test dataset was also created in the form of modified posters, human posters with added AI elements, and otherwise, to evaluate the model's ability to detect the level of AI and human involvement in more complex manner. Figure 2 shows an example of the additional test dataset results from digital poster modification.

Figure. 2. Modification Poster Data Test

C. Data Preparation

The preparation stage includes preprocessing and data augmentation. Preprocessing is carried out to ensure that all digital posters meet the input requirements of the MobileNetV2 architecture. The first step is resizing, which adjusts the size of each image to 224×224 pixels as required by the MobileNetV2 model [33]. This also aims to standardize the input size for both vertically and horizontally oriented posters. Then data augmentation was used here to enhance the diversity of the training set for a better generalization. The on-the-fly augmentation was done during the model training by Keras ImageDataGenerator. The augmentation operations used can be seen in Table 2 and examples of the augmentation results can be seen in Figure 3.

TABLE 2. AUGMENTATION OPERATIONS

Augmentation	Description
Rescaling	Normalized pixel score with range [0-1]
Rotation	Random rotation until 20°
Width Shift	Horizontal shift until 10%
Height Shift	Vertical shift until 10%
Zoom	Zoom in/out until 20%
Shear	Shear distortion until 10%
Horizontal Flip	Random horizontal flip
Fill Mode	Fill the empty area with the nearest pixel

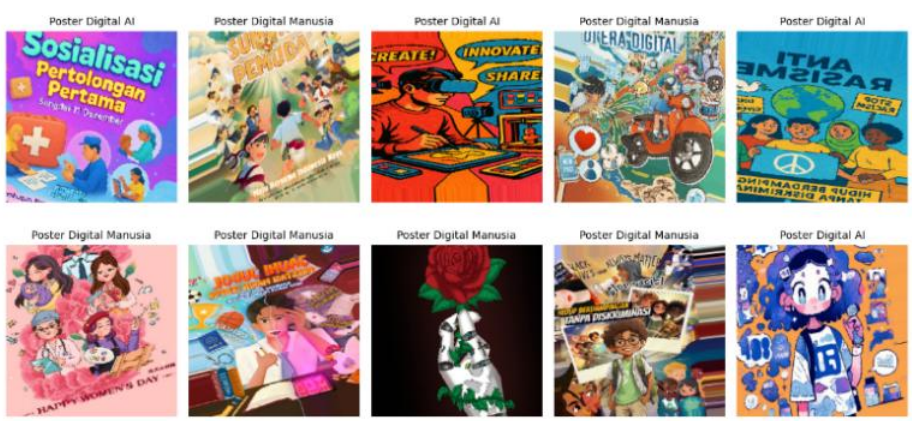


Figure. 3. Augmentation Results

D. Model Architectures

This presents the tools, algorithms, and technical setups that were applied in the modeling, training, and testing process to identify AI and human involvement on digital posters. This study was developed using the Python programming language as the basis for data processing and Machine Learning (ML) implementation. The training and testing processes using TensorFlow and Keras, which serve as the main frameworks for implementing the MobileNetV2 architecture, applying transfer learning, and managing data augmentation. The computing environment use the Google Colaboratory with GPU support to accelerate the computationally intensive model training process. In addition, the web-based detection system was built using Streamlit, which allows the model to be integrated into an interactive and easily accessible application interface (PosterScan).

This study uses a Convolutional Neural Network (CNN), as shown in Figure 4, as the core algorithm that is well known for its reliability in processing image and video data. CNN uses a mathematical linear operation called convolution, contains at least one convolutional layer, and is followed by at least one fully connected layer as in standard multilayer neural networks [34]. The MobileNetV2 architecture was chosen as the model backbone due to its high efficiency and relatively small parameter count. MobileNetV2 uses Inverted Residual Blocks and Linear Bottlenecks, which maintain optimal information flow despite its lightweight architecture. [35], and the MobileNetV2 architecture can be seen in Figure 5. The training process uses transfer learning, with the model's initial weights initialized from pre-trained weights from the ImageNet dataset to improve generalization and accelerate convergence. In addition, a patch-based voting mechanism is used in the detection method, dividing the poster image into several patches so the model can learn visual artifacts in greater detail. The predictions of each patch are then aggregated to calculate the level of AI involvement in a digital poster.

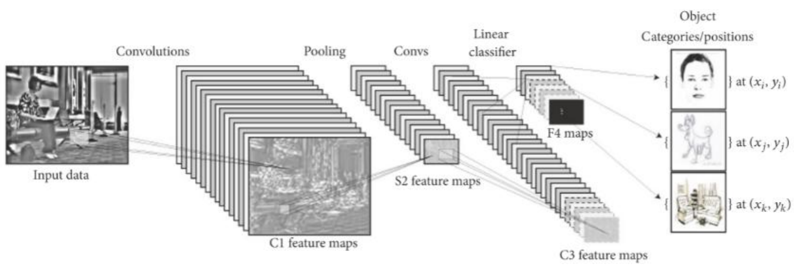


Figure. 4. CNN for Object Detection

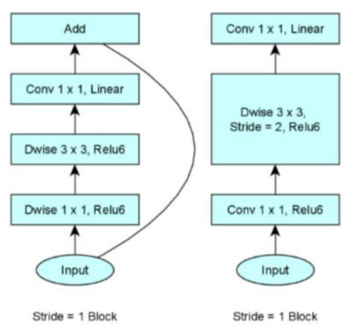


Figure. 5. MobileNetV2 Architecture

E. Machine Learning (ML) Configuration and Model Optimization Scenario

The ML configuration for the model selection process in this study includes preprocessing settings, training hyperparameters, the classification head structure, and MobileNetV2 optimization scenarios. All configurations are designed to ensure that the training process runs consistently and can be replicated. In the preprocessing stage, all images used as model inputs are resized to 224×224 pixels and normalized with range [0–1] to match the specifications of the MobileNetV2 architecture. The training process uses Binary Cross-Entropy as the loss function because this study is a binary classification task. Adam optimizer chosen for its stability and speed in achieving convergence. Model training is conducted with a batch size of 32, and the number of epochs ranges from 15 to 20, depending on the needs of each training scenarioMobileNetV2 is adapted for binary classification by attaching a classification head composed of a Global Average Pooling layer, a Dropout layer (0.3), a Dense layer with 128 neurons and ReLU activation, and an output Dense layer with a Sigmoid activation function. Model performance evaluation uses the metrics Accuracy, Precision, Recall, and F1-score. The model configuration can be seen in Table 3.

TABLE 3. HYPERPARAMETER CONFIGURATIONS

Parameter	Value
Preprocessing	Resize to 224×224, Normalization [0–1]
Loss Function	Binary Cross-Entropy
Optimizer	Adam
Batch Size	32
Epoch	15–10
Classification Head	Global Average Pooling layer, followed by Dropout (0.3), Dense layer with 128 neurons and ReLU activation, and a final Dense layer with 1 neuron and Sigmoid activation
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score

In the optimization stage, several MobileNetV2 training scenarios determine the best configuration to be used in the AI involvement detection system. Each scenario was tested using different combinations of trainable layer settings and learning rates, both with fine-tuning and frozen weights. These scenarios allow for a comprehensive analysis of the model's performance and help determine the most stable and accurate model. These provide an opportunity to assess the model's performance, ensuring a stable, accurate model is selected. The training scenarios are described in Table 4.

TABLE 4. MODEL TEST SCENARIOS

Scenario	Base model trainable	Learning Rate	LR- Fine-Tuning	Epoch
1	True (20% last layer)	0.01	0.00001	15
2	False	0.01	-	20
3	True (20% last layer)	0.001	0.00001	15
4	False	0.001	-	20
5	True (20% last layer)	0.0001	0.00001	15
6	False	0.0001	-	20

F. Performance Evaluation

The purpose of the evaluation stage is to measure how reliable a trained CNN model can be in recognizing AI and human involvement on digital posters. Independent testing data will be used to test the model. The assessment technique is divided into four primary focuses:

1) Model Performance Metrics

Model performance is evaluated using graphical interpretation and confusion matrix based metrics.

- **Accuracy and Loss Graph**: Monitor the model's performance during training and validation stages to know whether it is underfitting or overfitting. The accuracy is computed using (1) to evaluate the proportion of correct predictions relative to all data and the Loss value is calculated with (2), namely Binary Cross-Entropy.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ samples} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\left[y_{true}log\left(y_{pred}\right) + (1-y_{true})log\left(1-y_{pred}\right)\right] \tag{2}$$

- **Confusion Matrix**: Display the comparison between the prediction results and actual labels. Its main components are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Based on the confusion matrix, the evaluation on the test data will also be calculated using accuracy, precision (the model's correctness in classifying positive data), recall (the model's ability to correctly identify positive data), and F1-score (the harmonic mean of precision and recall).

2) Evaluation of AI and Human Involvement Levels

This study explicitly evaluates the model's ability to detect the proportion of AI involvement in digital posters, in addition to binary classification. Therefore, an evaluation using the modified dataset will also be conducted to determine whether the model can sensitively detect contributions from either AI or humans. The materials prepared for this evaluation include posters entirely generated by AI, posters entirely created by humans, and hybrid posters that have been modified by combining AI and human elements.

III. PROPOSED METHOD

The proposed method is an AI involvement detection system for digital posters that integrates the MobileNetV2 architecture with a Patch-Based Voting scheme to determine the level of AI vs. human contribution in a single visual work. This approach represents an innovation in the field of synthetic image detection, which previously focused primarily on binary classification (Real vs. Fake). The proposed method flow can be seen in Figure 6.

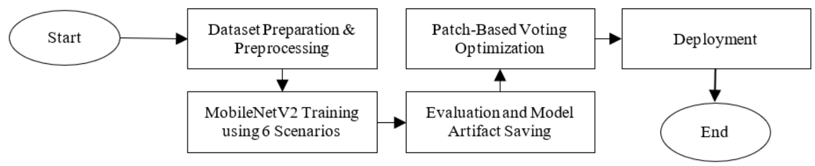


Figure. 6. Proposed Method

A. *Workflow Method*

The process begins with the data preparation stage, in which all digital posters undergo a resize process (224×224 pixels) and normalization to ensure uniform input quality. After the data is ready, the MobileNetV2 model is trained using transfer learning by applying on-the-fly data augmentation to enrich data variation during the training process. The model is then tested through six training scenarios with variations in learning rate configurations and the degree of fine-tuning of the model layers. The goal of this stage is to find the most stable and accurate model for the AI vs Human classification task.

The trained model is then evaluated using accuracy, F1-score, and confusion matrix metrics. The best-performing model is stored as a model artifact and used in the next stage, namely Patch-Based Voting. At this stage, several grid patch configurations are tested to determine the most optimal setting, both in terms of accuracy and processing time efficiency. This best configuration will used to calculate the level of AI involvement in the digital poster.

B. *Patch-Based Involvement Measurement Method*

The Patch-Based Involvement Measurement is applied to yield more precise knowledge on the involvement of AI in a digital poster. While traditional image classification approaches mostly come to a binary decision on whether the poster is generated by AI or human, this can take further advantage of evaluating how many areas in the poster could be produced by AI. The involvement assessment process is shown in Figure 7, where several experiments are carried out using the whole dataset by splitting images into grids of 4×4, 6×6, 8×8, and 10×10, and then into an overfitting-removed grid to specify the best patch grid configuration. By testing each variant for prediction accuracy and execution time, a configuration that balances performance and efficiency can be found. The poster is then split into the chosen grid, and the model processes every patch to get an AI or Human label. The final prediction for all patches is obtained by majority voting, allowing the model not only to predict a class but also to estimate the proportion of areas as AI.

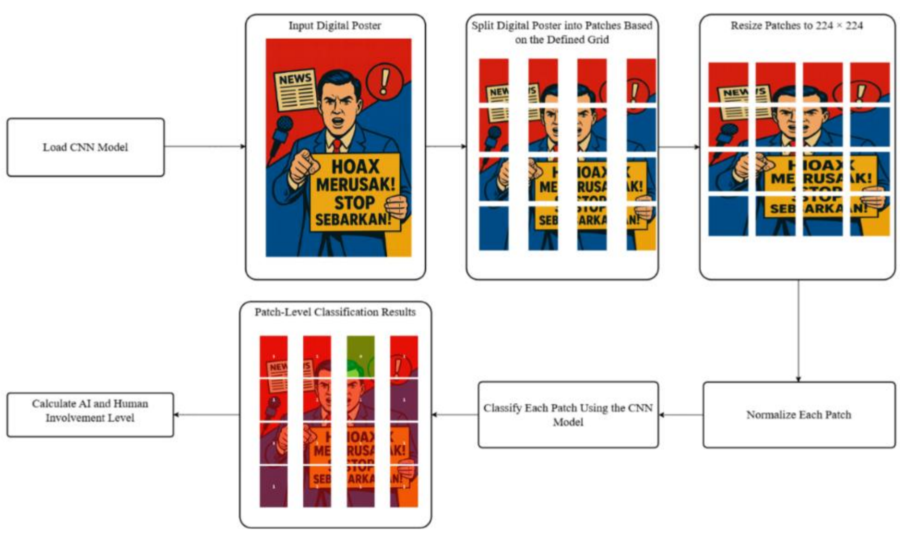


Figure. 7. Patch-Based Method

The level of AI involvement is calculated using (3):

$$\text{AI Involvement } (\%) = \left(\frac{\text{Number of AI-labeled patches}}{\text{Total number of Patches}}\right) \times 100 \qquad (3)$$

This function gives a quantitative sense of how much of the poster was suspiciously created by AI. Therefore, the Patch-Based Involvement Measurement method not only delivers a classification result but also provides an estimated value that can be used to assess content formation, verify visual forgery, and examine the human-AI collaboration ratio for each digital poster. This approach produces a richer interpretation and aligns with contemporary analysis needs for increasingly complex digital media.

C. *Deployment*

The deployment stage in this research was carried out by referring to the RAD method, which is used to develop a web-based system from the best CNN model obtained from the evaluation stage in the CRISP-DM framework.

1) *Requirement planning*

The requirement planning stage was conducted to identify the needs of the AI involvement detection system for digital posters. The system is designed to be able to receive input in the form of poster images through a web interface, run the CNN model (MobileNetV2) to analyze AI and human involvement, and display the prediction results in the form of percentages and patch visualizations. The functional requirements include the ability to upload images, perform detection processes, and display visualization results. Meanwhile, the non-functional requirements include ease of use, accessibility via the web, application responsiveness, and a prediction processing time that does not exceed 30 seconds.

2) *Web Design*

The design stage in the development of the PosterScan application (Figure 8) focuses on designing the user interaction flow and a simple, responsive, and easy-to-use interface. The first user interface is designed to present an application title and a short description of system functionality. A file upload control was provided for users to choose their digital posters in either JPG or PNG format. Uploading the image once a user uploads an image, we show them the poster previews to know if they have chosen right file before doing detection. At the results page, two parts of the interface are presented: a patch visualization depicting regions of detection AI or human in the poster and a percentage graphic to show how much AI is involved overall. Everything is also include so that users can easily understand what's going since the uploading image, preview display, detection, to a nice and easy to understand analyzing the results.

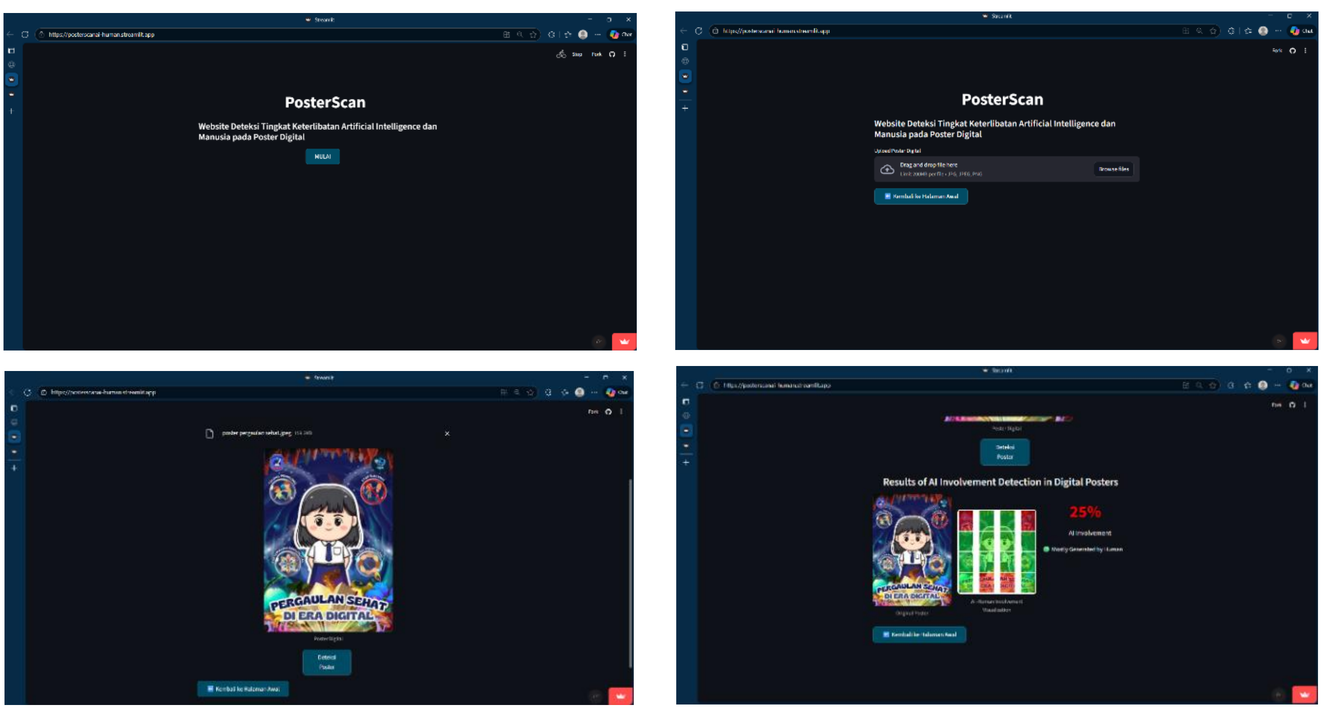


Figure. 8. Website Design

3) *Implementation*

The implementation stage by building a web-based application using Streamlit. The best MobileNetV2 model is saved in .h5 format and integrated into the application file (app.py) to perform direct predictions without retraining. The interface development is carried out in VSCode, and then the entire project is uploaded to GitHub to facilitate the deployment process. The application is subsequently deployed by Streamlit Cloud so that it can be publicly accessed. When the user uploads an image, the system automatically resizes it to 224×224 pixels, runs the model inference, and displays the level of AI involvement along with patch visualization through the web interface. The Implementation flow can be seen in Figure 9.

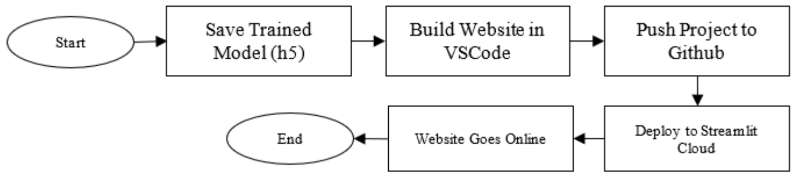


Figure. 9. Deployment

IV. RESULT AND DISCUSSION

This section showcases the experimental results across the entire research pipeline: model selection of best MobileNetV2, classification performance summary, patch grid optimization outcomes, and AI involvement analysis with modified test data. These included a critical analysis of these results, evaluating model performance and advantages of the patch-based approach as well as interpreting research outcomes.

A. *Model Training Performance*

Figure 10 illustrates the comparison of training, validation, and testing accuracy across six experimental scenarios. Overall, Scenarios 1 to 4 demonstrate relatively high and stable performance, with training and validation accuracies consistently above 90%.

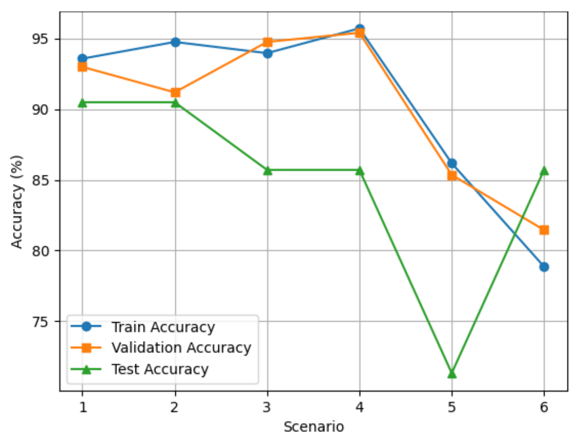


Figure. 10. Accuracy Comparison Across Scenario

According to Table 5, among all tested scenarios, two achieved the highest test accuracy: Scenario 1 and Scenario 2, both equal to 90.48%. These two representations are the closest competitors, as they not only achieve high test accuracy but also provide extensive and stable training and validation values. Scenario 2 becomes the best scenario. This is evidenced by the second-best training accuracy (94.74%), perfect validation accuracy (91.18%), and test accuracy numerically as high as in Scenario 1 (90.48%). The consistency of these three measures indicates that the model under Scenario 2 generalizes well and does not evidence overfitting. Scenario 1 also shows excellent performance, with 93.56% training accuracy and the highest validation accuracy (92.89%). It is similarly to Scenario 2, but its stability across the complete set of training metrics is lower.

On the another hand, Scenario 3 and Scenario 5 are the worst test accuracy (71.34%), which have lower value during training and validation compared to any other scenarios. This implies that the hyperparameter settings in these two cases are not appropriate to guide the model in learning conserved motifs. It can be seen that model under scenario 4 exhibits an overfitting behavior where the training accuracy becomes unreasonably high (95.70%), while test accuracy is relatively lower (81.34%). The Scenario 6 is also weaker compared to the remaining scenarios with training and test accuracy at level of 78.86% and 85.7%.

TABLE 5. MODEL ACCURACY RESULTS

Scenario	Train Accuracy	Validation Accuracy	Test Accuracy
1	93,56%	92,98%	90,48%
2	94,74%	91.18%	90,48%
3	93,95%	94,74%	85,7%
4	95,70%	95,39%	85,7%
5	86,17%	85,35%	71,34%
6	78,86%	81,45%	85,7%

From the best model of Scenario 2, grid experiment in Table 5 shows that there is a direct correlation between patch grid size and prediction accuracy as well as running time. For smaller grid sizes, especially 4×4 and 6×6, greater accuracy is also obtained with respect to other grids. The 4×4, and 6×6 grids both give the best accuracy, which is 83.65% and 79.33% respectively. In such settings the number of generated patches is low, as a result each patch can still have a relatively wide visual context. This condition significantly facilitates the MobileNetV2 model to recognize unique visual features regardless of generated AI elements or human-drawn parts. Larger dimensions of grid size, such as 8×8, 10×10 and 12×12, have instead considerably lower accuracy. Smaller patches leads to incomplete visual patterns and loss of global features or useful textures for accurate decision-making. In the maximum grid size (12×12) we obtain an accuracy of 60.10%, which shows that our model is not effective at taking context into account when predicting in a very narrow area.

In addition to reducing accuracy, increasing the grid size also affects execution time (Table 6). The greater the number of generated patches, the more processes must be performed, such as resizing, normalization, and model inference on each patch. This results in a significant increase in execution time, from 84.64 seconds on the 6×6 grid to 164.75 seconds on the 12×12 grid. Based on these overall results, it can be concluded that the 4×4 grid is the most optimal configuration because it offers the highest accuracy with an execution time that is still efficient. Therefore, this study uses the 4×4 grid for this research.

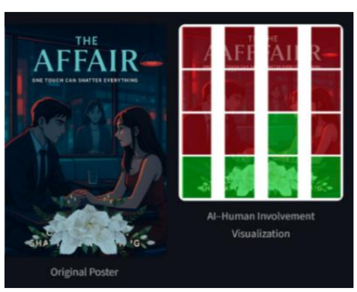
TABLE 6. GRID EXPERIMENT RESULTS

Grid	Accuracy	Time (s)
4	83,65%	117.18
6	79,33%	84.64
8	71,63%	102.09
10	65,38%	134.14
12	60,10%	164.75

Table 7 shows that the model is able to distinguish variations in the level of AI involvement in each test poster. The original human-made poster (No. 1) is detected as having 25% AI involvement, in accordance with its visualization which is dominated by green patches. In poster No. 2, where AI elements were added to two characters in the front area, the level of involvement increased to 38%, indicating that the model can identify the addition of synthetic elements in specific areas.The involvement score for the model was the highest among all AI-generated results at 88% in No. 3 and this corresponded with red being dominant on the visualization. On the other hand, for poster No. 4 (AI-generated poster with additional human-made flower elements at the bottom), shows a reduction of involvement to 69%. This reduced accuracy score indicates that the model not only is unable to perform classification at a global level, but also can identify important human elements in local areas of posters.

In summary, in this evaluation shows that the Patch-Based Involvement Measurement can give a more detailed estimation about how much AI and human are involved. The patch visualization also helping validate the proposed models approach by showing which areas that contribute to the classification process.

TABLE 7. TEST RESULTS ON MODIFIED DATASET

No	Prediction Results	AI Involvement	Modifiy Notes
1		25%	Original Poster by Human
2		38%	Poster no 1 with AI-generated element modifications on the mother sitting in the front and the boy in the front.
3		88%	Poster Generated AI DALL E
4		69%	Poster AI with the modification of adding artificial flower elements at the bottom of the poster

V. CONCLUSION

In this work, we explore the possibility of detecting AI involvement in digital posters using MobileNetV2 and the Patch-Based Involvement Measurement method to provide a granular-level analysis beyond traditional binary classification. Among the six training scenarios tried, MobileNetV2 in Scenario 2 had the most stable test accuracy of 90.48%. Additional experiments with different patch grid settings revealed that the 4×4 grid was more accurate (83.65%) in involvement estimation and had an acceptable execution time, so we used it as the chosen configuration for the detection pipeline. Testing on manipulated posters, in which elements of AI were added or removed in a controlled manner, showed that it could reliably and accurately measure shifts in the degree of AI content.

This demonstrates that the patch-based combination with MobileNetV2 is also a promising, more interpretable way to investigate AI's contributions to visual works. The proposed system can spatially identify AI or human-generated areas, making it applicable to verifying digital artwork, assessing originality, and estimating the contribution of AI to creative work. Furthermore, the findings of this work also contribute to our knowledge about lightweight CNN architectures like MobileNetV2 as they can be adequately applied to AI-driven visual content analysis applications.

Overall, this study contributes to the development of patch-based detection for AI accountability threats and provides an implementation-ready model for integration into a web application. Future research can be directed toward expanding the dataset to include more diverse design styles, exploring more advanced architectures such as Vision Transformers, and further optimizing the patch process to accelerate inference time. The development of multi-source or multi-level involvement methods may also be the next step toward enhancing the system's ability to analyze increasingly complex digital works.

REFERENCES

[1] T. Z. Alam and J. Haikal, "Dampak Produksi Desain Grafis Pada Penggunaan Teknologi Artificial Intelligence (AI) Dengan Menggunakan Grounded Theory," *Jurnal Seni Nasional Cikini*, vol. 10, no. 1, pp. 15–26, Jun. 2024, doi: 10.52969/jsnc.v10i1.265.

[2] M. Muhaemin and G. Artikel, "Analisis Pemanfaatan Artificial Intelligence (AI) sebagai Referensi dalam Desain Komunikasi Visual Analysis of Utilizing Artificial Intelligence (AI) as a Reference in Visual Communication Design Article Info ABSTRAK," *SASAK: Desain Visual dan Komunikasi*, vol. 5, no. 1, pp. 71–80, 2023, doi: 10.30812/sasak.v5i1.2966.

[3] Y. A. Reza and H. Kristanto, "Perkembangan Teknologi AI dalam Desain Grafis: Sebuah Tinjauan Literatur," 2024.

[4] Chen Zihan, Chen Lianghong, Zhao Zhiyuan, and Wang Yue, *AI Illustrator: Art Illustration Generation Based on Generative Adversarial Network*. IEEE, 2020. doi: 10.1109/ICIVC50857.2020.9177494.

[5] A. W. Fadhlan Ramdhani and A. Susanti, "Pemanfaatan Teknologi Openai Dall-E 2 dalam Meningkatkan Kreativitas Desainer Grafis pada Komunitas Desain Grafis Indonesia," *Jurnal Bisnis dan Komunikasi Digital*, vol. 1, no. 2, p. 8, Nov. 2023, doi: 10.47134/jbkd.v1i2.1916.

[6] L. Bellaiche *et al.*, "Humans versus AI: whether and why we prefer human-created compared to AI-created artwork," *Cogn Res Princ Implic*, vol. 8, no. 1, Dec. 2023, doi: 10.1186/s41235-023-00499-6.

[7] D. A. Panjaitan, M. Aulia, Y. Juliana, M. Afdol, and R. Kurniawan, "Persepsi Mahasiswa terhadap Isu Penggunaan Ghibli Art AI di Media Sosial sebagai Mata Pencaharian," *JOSH : Journal of Sharia*, vol. 04, no. 02, pp. 167–178, 2025, doi: 10.55352/josh.v4i02.1927.

[8] D. B. Santosa, A. Wahana, and W. Uriawan, "Implementation of Convolutional Neural Network Using MobileNetV2 to Distinguish Human and Artificial Intelligence Painting," *Jurnal Teknik Informatika (Jutif)*, vol. 6, no. 1, pp. 441–452, Feb. 2025 doi: 10.52436/1.jutif.2025.6.1.3827.

[9] J. J. Bird and A. Lotfi, "CIFAKE: Image Classification and Explainable Identification of AI-Generated Synthetic Images," *IEEE Access*, vol. 12, pp. 15642–15650, 2024, doi: 10.1109/ACCESS.2024.3356122.

[10] M. A. Rahman, B. Paul, N. H. Sarker, Z. I. A. Hakim, and S. A. Fattah, "ArtiFact: A Large-Scale Dataset with Artificial and Factual Images for Generalizable and Robust Synthetic Image Detection," in *IEEE International Conference on Image Processing (ICIP)*, Feb. 2023, doi: 10.48550/arXiv.2302.11970.

[11] Y. Zhang, Z. Pang, S. Huang, C. Wang, and X. Zhou, "Unmasking AI-created visual content: a review of generated images and deepfake detection technologies," Aug. 01, 2025, *Springer International Publishing*. doi: 10.1007/s44443-025-00154-8.

[12] S. Teilmann-Lock and A. Savin, "Beyond the AI-copyright Wars: Towards European Dataset Law?," Computer Law & Security Review, vol. 58, 2025, doi: 10.1016/j.clsr.2025.106190.

[13] D. Ghiurău and D. A. Popescu, "Distinguishing Reality from AI: Approaches for Detecting Synthetic Content," *Computers,* vol. 14, no. 1, 2025, doi: 10.3390/computers14010001.

[14] C. P. Tanujaya, "Analisis Karya Ciptaan Artificial Intelligence Menurut Undang-Undang Nomor 28 Tahun 2014 Tentang Hak Cipta", *Journal of Law Education and Business,* vol. 2, no. 1, 2024, doi: 10.57235/jleb.v2i1.1763.

[15] S. Deniesa, D. R. Putri, A. Amrullah, A. binti M. Farid, and N. A. D. binti M. Hassan, "Copyright Protection for Creators of Digital Artwork," *Indonesian Comparative Law Review*, vol. 4, no. 1, pp. 43–58, Sep. 2022, doi: 10.18196/iclr.v4i1.15106.

[16] J. Deng, W. Dong, R. Socher, L.-J. Li, Kai Li, and Li Fei-Fei, "ImageNet: A large-scale Hierarchical Image Database," in *2009 IEEE Conference on Computer Vision and Pattern Recognition*, IEEE, Jun. 2009, pp. 248–255. doi: 10.1109/CVPR.2009.5206848.

[17] S. S. Baraheem and T. V. Nguyen, "AI vs. AI: Can AI Detect AI-Generated Images?," *J Imaging*, vol. 9, no. 10, p. 199, Sep. 2023, doi: 10.3390/jimaging9100199.

[18] Z. N. Ashani, I. S. C. Ilias, K. Y. Ng, M. R. K. Ariffin, A. D. Jarno, and N. Z. Zamri, "Comparative Analysis of Deepfake Image Detection Method Using VGG16, VGG19 and ResNet50," *Journal of Advanced Research in Applied Sciences and Engineering Technology*, vol. 47, no. 1, pp. 16–28, May 2025, doi: 10.37934/araset.47.1.1628.

[19] R. A. Prawiratama, "Design of a Generative AI Image Similarity Test Application and Handmade Images Using Deep Learning Methods," *Jurnal Informatika dan Teknologi Informasi*, vol. 20, no. 3, pp. 326–342, 2023, doi: 10.31315/telematika.v20i3.10096.

[20] S. W. Kusuma, F. Natalia, C. S. Ko, and S. Sudirman, "Detection of AI-Generated Anime Images Using Deep Learning," *ICIC Express Letters, Part B: Applications*, vol. 15, no. 3, pp. 295–301, Mar. 2024, doi 10.24507/icicelb.15.03.295.

[21] I. T. Erwin, Abdul Latief Arda, Imran Taufik, Muhammad Erwin Rosyadi. S, and Hilyatul Auliyah Erwin, "Implementasi Model DeiT untuk Membedakan Gambar Buatan AI dan Manusia pada Ilustrasi Animasi 2D," *INTI Nusa Mandiri*, vol. 19, no. 2, pp. 172–180, Feb. 2025, doi: 10.33480/inti.v19i2.6306.

[22] M. S. A. Aria, C. Slamet, and M. D. Firdaus, "Klasifikasi Fake dan Real Menggunakan Vision Transformer dan EfficientNet-B0 pada Gambar Asli dan Generatif AI," *SMATIKA JURNAL*, vol. 15, no. 01, pp. 179–192, Jun. 2025, doi: 10.32664/smatika.v15i01.1531.

[23] X. Zhao, Y. Wu, G. Song, Z. Li, Y. Zhang, and Y. Fan, "A Deep Learning Model Integrating Fcnns And Crfs For Brain Tumor Segmentation," *Med Image Anal*, vol. 43, 2018, doi: 10.1016/j.media.2017.10.002.

[24] K. Roy, D. Banik, D. Bhattacharjee, and M. Nasipuri, "Patch-based system for Classification of Breast Histology Images Using Deep Learning," *Computerized Medical Imaging and Graphics*, vol. 71, 2019, doi: 10.1016/j.compmedimag.2018.11.003.

[25] N. Cordier, H. Delingette, and N. Ayache, "A Patch-Based Approach for the Segmentation of Pathologies: Application to Glioma Labelling," *IEEE Trans Med Imaging*, vol. 35, no. 4, pp. 1066–1076, Apr. 2016, doi: 10.1109/TMI.2015.2508150.

[26] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks For Biomedical Image Segmentation," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer Verlag, pp. 234–241, 2015, doi: 10.1007/978-3-319-24574-4_28.

[27] R. Aulianita, A. Mukhayaroh, "Metode Rapid Application Development (RAD) Dalam Merancang Website Top Up," *Information Management for Educator and Professionals: Journal of Information Management,* vol. 10, no. 1, pp83-92, 2025, doi: 10.51211/imbi.v10i1.3473.

[28] A. Toosi, S. Cumani, and A. Bottino, "CNN Patch–Based Voting for Fingerprint Liveness Detection," in *International Joint Conference on Computational Intelligence*, 2017, doi: 10.5220/0006582101580165.

[29] J. V. Manjón *et al.*, "MRI white matter lesion segmentation using an ensemble of neural networks and overcomplete patch-based voting," *Computerized Medical Imaging and Graphics*, vol. 69, 2018, doi: 10.1016/j.compmedimag.2018.05.001.

[30] D. Murdiani and M. Sobirin, "Perbandingan Metodologi Waterfall dan RAD (Rapid Application Development) dalam Pengembangan Sistem Informasi," 2022. doi: 10.51401/jinteks.v4i4.2008.

[31] D. Kurniawan and M. Yasir, "Optimization Sentimen Analysis using CRISP-DM and Naive Bayes Methods Implemented on Social Media," *Cyberspace: Jurnal Pendidikan Teknologi Informasi*, vol. 6, no. 2, p. 74, Oct. 2022, doi: 10.22373/cj.v6i2.12793.

[32] C. E. D. Vanegas, J. C. G. Mejía, F. A. V. Agudelo, and D. E. S. Duran, "A Representation Based on Essence for the CRISP-DM Methodology," *Computación y Sistemas*, vol. 27, no. 3, pp. 675–689, Sep. 2023, doi: 10.13053/cys-27-3-3446.

[33] A. Dharmaputra, M. Cahyanti, M. R. D. Septian, and E. R. Swedia, "Aplikasi Face Mask Detection Menggunakan Neural Network MobileNetV2 Berbasis Android," *Sebatik*, vol. 25, no. 2, pp. 382–389, Dec. 2021, doi: 10.46984/sebatik.v25i2.1503.

[34] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, "Deep Learning for Computer Vision: A Brief Review," *Comput Intell Neurosci*, vol. 2018, 2018, doi: 10.1155/2018/7068349.

[35] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," Mar. 2019, doi: 10.48550/arXiv.1801.04381.