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Artificial Intelligence for Tattoo Classification in Identity Verification

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Abstract

We recommended designing this system to be as efficient as possible in the detection of tattoos from missing persons, unidentified individuals, and unclaimed bodies for the purpose of gathering biometric data in terms of personal identification. The program will be revising in stages, classifying and labeling different kinds of tattoos to establish a standardized method to record biometric data of tattoos. Consistency, on the other hand, will help the concerned key agencies and departments—the Royal Thai Police, the Ministry of Social Development and Human Security, the Forensic Science Institute, and the Ministry of Public Health—to have all data recorded in organized and appropriate forms. A system with unveiled and standardized processes will enable matching of the database entries with a centralized set controlled by the Missing Persons, Unidentified Individuals, and Unidentified Corpses Tracking System Committee. This is a method that will ensure that success rates in establishing the identity of unidentified persons and their matching with the existing records are accomplished. A process guided by standards will minimize data entry errors, preserve precious time, and even reduce problems linked to personnel shortages. In this way, the program minimizes the need for specialized personnel in data input. This program also hopes to overcome discontinuities evident in 'data recording' by different agencies on a unified basis, in a collaborative manner. Finally, it promises to make tattoo-based identification more efficient, reliable, and accessible across agencies. The initiative would help law enforcement and social services bring clarity and closure to the agencies and the many families and communities affected by cases of missing and unidentified persons.

Keywords: Artificial Intelligence, Transformers, DINO, Image Comparison, Identity Verification

1. Introduction

The introduction highlights the critical challenges in addressing cases of missing persons, unidentified individuals, and unclaimed bodies in Thailand, emphasizing the increasing urgency of the issue due to fragmented data management and an aging population. From 2002 to 2019, over 4,000 unidentified bodies and 628 missing persons were documented by the Central Institute of Forensic Science (CIFS), with 1,438 unidentified individuals reported in 2019 alone. The lack of a unified database across agencies leads to inefficiencies and challenges for both authorities and citizens seeking to navigate multiple systems.

A proposed solution involves leveraging advancements in image processing and machine learning to automate the identification and classification of tattoos, a unique and enduring biometric feature. Such a program would address data inconsistencies and inefficiencies caused by human interpretation and recording differences across agencies. For example, varying descriptions of tattoos such as "bird," "hawk," or "eagle" hinder accurate database searches.

Through the application of Convolutional Neural Networks (CNNs) and other deep learning methods, tattoos can be analyzed and classified with higher accuracy and efficiency. Training these networks involves supervised learning, where labeled datasets allow the model to learn patterns through backpropagation and gradient descent, refining predictions until optimal accuracy is achieved (1). Techniques such as feature extraction using CNNs enable the classification of tattoos and facilitate similarity-based image retrieval, providing a robust framework for forensic and investigative applications.

The introduction also outlines the potential benefits of integrating advanced algorithms like the watershed technique for image segmentation, SIFT for feature extraction, and content-based image retrieval systems for tattoo identification (2-4). Further exploration into machine learning methods, including Support Vector Machines and triplet loss-based systems, demonstrates the significant strides in automating tattoo recognition and matching, even under challenging conditions such as distorted images or varied skin tones (5-7).

Emerging technologies like transformers and Vision Transformers (ViT) offer alternative architectures that can further improve image classification tasks by addressing limitations inherent in CNNs. These innovations, alongside privacy-focused measures like tattoo de-identification, underscore the multidisciplinary approach required to develop a comprehensive tattoo identification system (8-10). By unifying fragmented data and enhancing technical capabilities, this initiative aims to transform the identification process, supporting law enforcement, forensic science, and social services in resolving cases and bringing closure to affected families and communities.

2. Materials and Experiment

2.1 Preparation of image data for developing the artificial intelligence (AI) program

Tattoo images across 14 categories were collected, comprising 2,628 images sourced from the Central Institute of Forensic Science and 1,881 images gathered from public sources, including websites like Pinterest and Tattoodo. This collection resulted in a total of 4,509 images, as detailed in Table 1.

Table 1 Image Data for Developing the AI Program for Tattoo Classification in Identity Verification

Types of Tattoo Image		Number of Images Obtained from		Total Images
		CIFS	Public Sources	
1	Human	101	224	325
2	Gecko	134	196	330
3	Bird	113	205	318
4	Dragon	196	124	320
5	Scorpion	201	120	321
6	Tiger	248	84	332
7	Character	200	120	320
8	Buffalo	205	128	333
9	Father	202	117	319
10	Mother	203	106	309
11	Mystic symbol	200	117	317
12	Heart	208	108	316
13	Flower	208	118	326
14	Graphic Images	209	114	323
Total Images		**2,628**	**1,881**	**4,509**

The dataset of 4,509 tattoo images, divided into 14 distinct categories, is used to train the model. The categories are as follows:

- Human: Images featuring humans, faces, and bodies with distinctive features like head, eyes, arms, and legs

- Gecko: Images of lizards or reptiles, typically showing limbs and tails similar to lizards (330 images)
- Bird: Images of birds and other winged creatures (318 images)
- Dragon: Images of dragons, naga, and snakes (320 images)
- Scorpion: Images of scorpions (321 images)
- Tiger: Images of tigers (332 images)
- Character: Images containing text or lettering (320 images)
- Buffalo: Images depicting buffalo (333 images)
- Father: Images featuring the Thai word "พ่อ" (Father) (319 images)
- Mother: Images featuring the Thai word "แม่" (Mother) (309 images)
- Mystic Symbol: Images of sacred symbols or traditional tattoos (317 images)
- Heart: Images depicting hearts (316 images)
- Flower: Images of flowers (326 images)
- Graphic Designs: Various graphic design elements (323 images)

2.2 Design and Development of the AI Program for Tattoo Classification in Identity Verification

Utilizing Artificial Intelligence Models for Image Classification: The chosen model for this project is DINOv2 from Hugging Face, which has the capability to process images and create vectors representing those images.

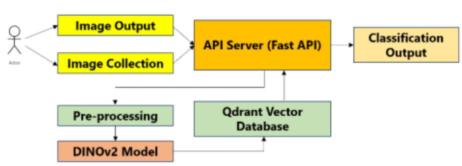


Figure 1 Conceptual Design of the AI Workflow

From Figure 1, The AI program for tattoo image classification follows a structured process from user input to results: User Interaction: The process begins with the user, who can initiate it by uploading tattoo images or receiving classification results. Image Collection: Uploaded images are stored in the "Image Collection" section, which serves as a database for training and testing purposes. Image Output: Processed images and classification results are stored here and then made available for user access. API Server (FastAPI): FastAPI functions as an intermediary server, managing user requests such as image uploads, model training, and image classification, and coordinating interactions between various program components. Preprocessing: Uploaded images undergo essential preprocessing steps, including resizing and normalization, to prepare them for vector representation. Vector Creation Using DINOv2: The DINOv2 model from Hugging Face generates vectors that represent the tattoo images. These vectors are essential for similarity searches and classification. Vector Storage (Qdrant Database): The generated vectors are stored in the Qdrant database, a specialized vector database optimized for fast and efficient searches of similar vectors. Classification Output: The final tattoo classification results, including image categories and similarity scores, are presented in the "Classification Output" section. Results to User: The classification results are then returned to the user via the API server, completing the cycle.

Image Processing and Vector Generation: Uploaded images are processed and converted into vectors by the DINOv2 model. These vectors represent the key features of the images, which are then used to compare and search for similar images within the database with precision. Converting vectors to unit length allows for efficient and rapid similarity calculations.

Connecting to the Vector Database: The program uses Qdrant as the vector database, designed specifically to manage and search for vector data. Searching within Qdrant is fast and accurate, enabling efficient classification of images based on the most similar vectors found in the database.

Training the AI Program with New Data: The program can be trained with new, categorized tattoo images, which are processed to generate vectors that are added to the database, allowing for more accurate and comprehensive classification of new images. The training and testing process includes the following steps:

- Data Preparation: Tattoo images are collected and grouped into 14 distinct categories, each with unique characteristics. For instance, the "Human" category includes images depicting heads, eyes, arms, and legs, while the "Bird" category includes images with wings.

- Data Splitting: A set of 100 images per category (from a total of 14 categories) is randomly selected and split into Training Set: Contains 70 images per category. Testing Set: Contains 30 images per category.
- AI Program Training: The tattoo image classification program is developed using the DINOv2 model from Hugging Face, which effectively generates vectors to represent each image. These vectors are stored in the Qdrant database, optimized for finding similar vectors. During this step, the Training Set (70 images per category) is processed to generate vectors, which are then added to the Qdrant database for program training.

2.3 AI Program Design and Development for Tattoo Image Comparison in Identity Verification

The design and development process follows these steps:

- Image Analysis for Comparison: The Vision Transformer (ViT) model is selected for development, using the DINOv2 model specifically for image analysis.
- Model Size Selection for Image Analysis:

- Performance is tested across four model sizes: small, base, large, and giant.

- A target performance criterion is set, with Accuracy@top-N not falling below 0.8, ensuring accuracy remains at or above 80%.

- The model size that meets or exceeds an Accuracy@top-N of 0.8 is selected for further development and use.

This structured approach enables optimal model selection to ensure accuracy in tattoo image analysis.

2.4 Preliminary Testing of the AI Program for Tattoo Image Classification in Identity Verification

The following steps outline the accuracy testing of the tattoo image classification program.

Data Preparation: For the preliminary test, tattoo images from the Central Institute of Forensic Science were used, totaling 2,628 images across 14 categories, as shown in Table 2. Tattoo images collected from public sources, totaling 1,881 images, will be used to test the program again after installation.

Table 2 The tattoo image data from the Central Institute of Forensic Science used for the preliminary testing

Types of Tattoo Image		Total Images
1	Human	101
2	Gecko	134
3	Bird	113
4	Dragon	196
5	Scorpion	201
6	Tiger	248
7	Character	200
8	Buffalo	205
9	Father	202
10	Mother	203
11	Mystic symbol	200
12	Heart	208
13	Flower	208
14	Others (Graphic Images)	209
Total Images		**2,628**

Data Splitting: The data is split into two sets as follows: 1) Training Set: 70% of the images in each category and 2) Testing Set: 30% of the images in each category.

Training the AI Program: The AI program for tattoo image classification is trained using the training set. Each image is processed to generate vectors, which are then added to the Qdrant database.

Testing the Accuracy of the AI Program: Once the AI program has been trained, its accuracy is tested using the testing set, which contains 30% of the images from each category. The performance is measured by calculating the percentage of images correctly classified (on the first attempt) in the testing set. The program must achieve an average accuracy of at least 80%.

2.5 Preliminary Testing of the AI Program for Tattoo Image Comparison with the Database in Forensic Identification

After the design and development of the program using the Vision Transformer (ViT) model, specifically DINOv2, the performance was tested across four model sizes: Small, Base, Large, and Giant. The expected performance benchmark was set to an Accuracy@top-N of no less than 0.8, indicating that the accuracy must meet or exceed 80%.

Data Preparation: Data augmentation techniques are used to increase the diversity and size of training datasets without collecting additional data. Ten images from each of the 14 categories, totaling 140 images, are selected for testing. These images are augmented using the Roboflow platform Roboflow, various techniques were applied to triple the total number of images, reaching a dataset size of 420. To ensure data quality, any transformations-such as flipping or rotating-that result in duplicate images are removed, avoiding bias in performance testing. The augmented images were generated using eight different transformation methods, as detailed in Table 3.

Table 3 Details of the 8 Image Augmentation Methods

Data Augmentation: Process		Data Augmentation: Conditions	Output	Total Sample
1 Flip		Vertical, Horizontal	3	330
2 Rotate 90°		Clockwise, Counter-Clockwise, Upside Down	3	389
3 Crop (zoom)		20-50% Zoom	3	420
4 Blur		≤ 10 Pixels	3	418
5 Noise		≤ 3.2% of pixels	3	420
6 Cutout		5 boxes (random) with 15% size each	3	420
7 Combi-ned V.1	Flip	Horizontal, Vertical	3	420
	Rotate 90°	Clockwise, Counter-Clockwise, Upside Down		
	Crop	0-20% Zoom		
	Blur	≤8 Pixels		
	Noise	≤2% of pixels		
	Cutout	3 boxes with 10% size each		
8 Combi ned V.2	Flip	Horizontal, Vertical	3	420
	Rotate 90°	Clockwise, Counter-Clockwise, Upside Down		
	Crop	0-40% Zoom		
	Blur	≤10 Pixels		
	Noise	≤3.2% of pixels		
	Cutout	5 boxes with 15% size each		

Program Performance Evaluation: The program's performance is evaluated using the Accuracy@top-N metric to measure the effectiveness of image retrieval. This metric assesses whether the correct result (or relevant items) appears within the top N results of a search. The DINOv2 model is used for image analysis, and tests are conducted with four model sizes: Small, Base, Large, and Giant. The formula for Accuracy@top-N is: Accuracy@top-N = (Number of correct result in top-N) / (Total number of queries)

Testing Steps includes the followings:

Image Search: For each query image, retrieve the top N results from the model. In this test, N is set to 1, 3, 5, 10, 15, 20, 25.

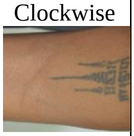
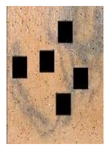
Verify Correct Results: Check if the correct result appears within the top N results:

Count Correct Matches: Count the number of times the correct result appears in the top N results:

Divide by Total Queries: Divide the number of correct matches by the total number of search queries to calculate the accuracy.

Sample Augmented Images: Sample images generated through data augmentation techniques (8 different transformation methods will be used to evaluate the AI program's ability to compare tattoo images to the image database for identification purposes. These techniques enhance the dataset by modifying existing images, ensuring a comprehensive performance test of the AI model.

Table 4 Sample Augmented Images

Process	**Conditions**		
1. Flip	Original 	Vertical 	Horizontal 
2. Rotate 90°	Original 	Clockwise 	Counter-Clockwise 
	Upside Down 		
3. Crop (*zoom*)	Original 	20% Zoom 	50% Zoom (*Max*) 
4. Blur	Original 	10 Pixels (Max) 	
5. Noise	Original 	3.2% of pixels (Max) 	
6. Cutout	Original 	5 boxes (random) with 15% size each 	
7. Com-bined V.1	Original 	Combined 	
8. Com-bined V.2	Original 	Combined 	

3. Results and Discussion

Screenshots of the program "Artificial Intelligence for Tattoo Classification in Identity Verification" are shown in Figures 2-9.

Figure 2 Log-in

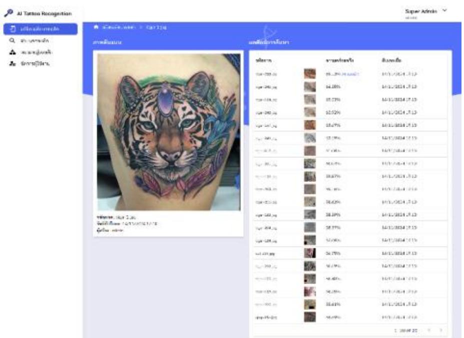


Figure 3 Tattoo image comparison system

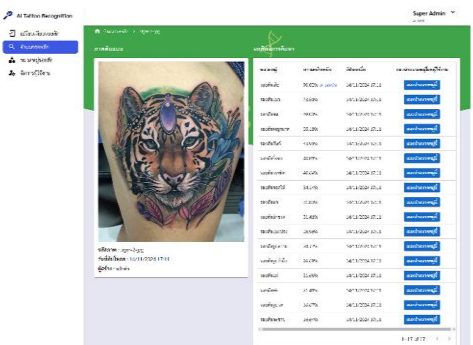


Figure 4 Tattoo image comparison system

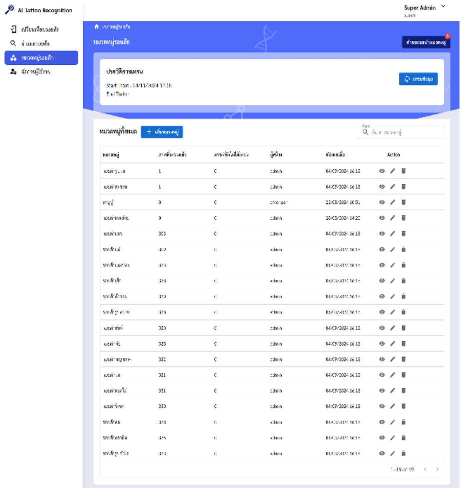


Figure 5 Tattoo category system

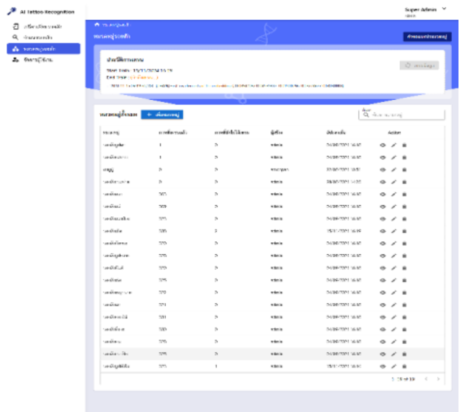


Figure 6 AI training system

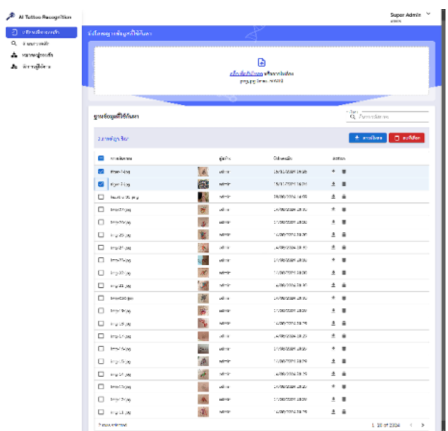


Figure 7 Tattoo database system

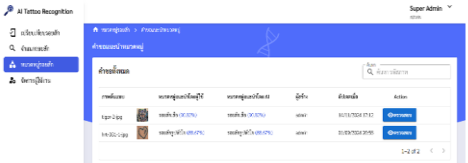


Figure 8 Category suggestion request system

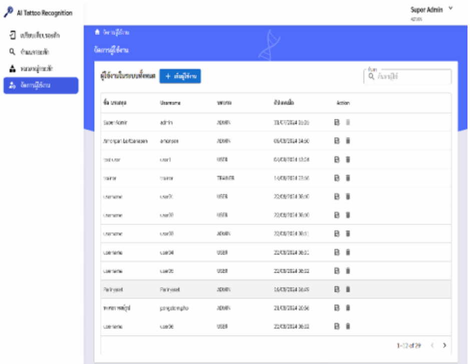


Figure 9 User management system

Test results of the accuracy of the Artificial Intelligence for Tattoo Classification in Identity Verification system: The Artificial Intelligence for Tattoo Classification in Identity Verification system in this research consists of two parts: 1) The AI program for comparing tattoo images with the image database, and 2) The AI program for tattoo classification in identity verification. Details are as follows:

Test results for the accuracy of the AI program for comparing tattoo images with the image database: Table 5 shows details of the test results on the performance of the AI program for comparing tattoo images with the image database.

Table 5 Details of the test results on the performance of the AI program for comparing tattoo images with the image database using the Accuracy@top-N metric

Data Augmentation	**Model Size DINO v2**	**Accuracy (Number of correct result/Total number of queries)**						
		@top-1	**@top-3**	**@top-5**	**@top-10**	**@top-15**	**@top-20**	**@top-25**
1. Flip	Small	0.946 (317/335)	0.976 (327/335)	0.976 (327/335)	0.976 (327/335)	0.976 (327/335)	0.976 (327/335)	0.976 (327/335)
	Base	0.922 (309/335)	0.964 (323/335)	0.967 (324/335)	0.970 (325/335)	0.970 (325/335)	0.970 (325/335)	0.973 (326/335)
	Large	0.928 (311/335)	0.958 (321/335)	0.961 (322/335)	0.964 (323/335)	0.967 (324/335)	0.967 (324/335)	0.967 (324/335)
	Giant	0.928 (311/335)	0.958 (321/335)	0.967 (324/335)	0.973 (326/335)	0.973 (326/335)	0.973 (326/335)	0.973 (326/335)
2. Rotate 90°	Small	0.946 (368/389)	0.969 (377/389)	0.974 (379/389)	0.974 (379/389)	0.977 (380/389)	0.979 (381/389)	0.979 (381/389)
	Base	0.897 (349/389)	0.951 (370/389)	0.961 (374/389)	0.964 (375/389)	0.969 (377/389)	0.972 (378/389)	0.972 (378/389)
	Large	0.910 (354/389)	0.941 (366/389)	0.954 (371/389)	0.961 (374/389)	0.961 (374/389)	0.969 (377/389)	0.972 (378/389)
	Giant	0.895 (348/389)	0.949 (369/389)	0.956 (372/389)	0.956 (372/389)	0.964 (375/389)	0.964 (375/389)	0.967 (376/389)

Data Augmentation	Model Size DINO v2	Accuracy (Number of correct result/Total number of queries)						
		@top-1	**@top-3**	**@top-5**	**@top-10**	**@top-15**	**@top-20**	**@top-25**
3. Crop (zoom)	Small	0.910 (382/420)	0.964 (405/420)	0.967 (406/420)	0.971 (408/420)	0.971 (408/420)	0.971 (408/420)	0.974 (409/420)
	Base	0.883 (371/420)	0.929 (390/420)	0.933 (392/420)	0.948 (398/420)	0.948 (398/420)	0.952 (400/420)	0.955 (401/420)
	Large	0.857 (360/420)	0.914 (384/420)	0.921 (387/420)	0.933 (392/420)	0.938 (394/420)	0.940 (395/420)	0.940 (395/420)
	Giant	0.919 (386/420)	0.960 (403/420)	0.964 (405/420)	0.969 (407/420)	0.969 (407/420)	0.971 (408/420)	0.971 (408/420)
4. Blur	Small	0.940 (393/418)	0.974 (407/418)	0.974 (407/418)	0.974 (407/418)	0.974 (407/418)	0.974 (407/418)	0.974 (407/418)
	Base	0.938 (392/418)	0.969 (405/418)	0.969 (405/418)	0.969 (405/418)	0.971 (406/418)	0.971 (406/418)	0.971 (406/418)
	Large	0.940 (393/418)	0.967 (404/418)	0.967 (404/418)	0.969 (405/418)	0.969 (405/418)	0.969 (405/418)	0.974 (407/418)
	Giant	0.945 (395/418)	0.974 (407/418)	0.974 (407/418)	0.974 (407/418)	0.978 (409/418)	0.978 (409/418)	0.978 (409/418)
5. Noise	Small	0.781 (328/420)	0.840 (353/420)	0.857 (360/420)	0.883 (371/420)	0.900 (378/420)	0.910 (382/420)	0.919 (386/420)
	Base	0.848 (356/420)	0.883 (371/420)	0.893 (375/420)	0.902 (379/420)	0.912 (383/420)	0.917 (385/420)	0.924 (388/420)
	Large	0.883 (371/420)	0.929 (390/420)	0.933 (392/420)	0.940 (395/420)	0.948 (398/420)	0.948 (398/420)	0.948 (398/420)
	Giant	0.924 (388/420)	0.969 (407/420)	0.971 (408/420)	0.974 (409/420)	0.974 (409/420)	0.974 (409/420)	0.974 (409/420)
6. Cut-out	Small	0.943 (396/420)	0.974 (409/420)	0.974 (409/420)	0.974 (409/420)	0.976 (410/420)	0.979 (411/420)	0.979 (411/420)
	Base	0.917 (385/420)	0.962 (404/420)	0.967 (406/420)	0.969 (407/420)	0.976 (410/420)	0.979 (411/420)	0.979 (411/420)
	Large	0.933 (392/420)	0.971 (408/420)	0.971 (408/420)	0.976 (410/420)	0.976 (410/420)	0.979 (411/420)	0.979 (411/420)
	Giant	0.950 (399/420)	0.979 (411/420)	0.979 (411/420)	0.979 (411/420)	0.979 (411/420)	0.979 (411/420)	0.979 (411/420)
7. Com-bined V.1	Small	0.643 (270/420)	0.705 (296/420)	0.733 (308/420)	0.752 (316/420)	0.760 (319/420)	0.774 (325/420)	0.786 (330/420)
	Base	0.671 (282/420)	0.729 (306/420)	0.738 (310/420)	0.769 (323/420)	0.786 (330/420)	0.805 (338/420)	0.814 (342/420)

Data Augmentation	Model Size DINO v2	Accuracy (Number of correct result/Total number of queries)						
		@top-1	@top-3	@top-5	@top-10	@top-15	@top-20	@top-25
	Large	0.714 (300/420)	0.762 (320/420)	0.790 (332/420)	0.824 (346/420)	0.840 (353/420)	0.850 (357/420)	0.860 (361/420)
	Giant	0.771 (324/420)	0.819 (344/420)	0.836 (351/420)	0.855 (359/420)	0.869 (365/420)	0.888 (373/420)	0.890 (374/420)
8. Com-bined V.2	Small	0.517 (217/420)	0.543 (228/420)	0.557 (234/420)	0.583 (245/420)	0.605 (254/420)	0.631 (265/420)	0.650 (273/420)
	Base	0.538 (226/420)	0.598 (251/420)	0.617 (259/420)	0.650 (273/420)	0.674 (283/420)	0.688 (289/420)	0.705 (296/420)
	Large	0.629 (264/420)	0.676 (284/420)	0.693 (291/420)	0.733 (308/420)	0.755 (317/420)	0.769 (323/420)	0.776 (326/420)
	Giant	0.655 (275/420)	0.693 (291/420)	0.714 (300/420)	0.755 (317/420)	0.781 (328/420)	0.800 (336/420)	0.807 (339/420)

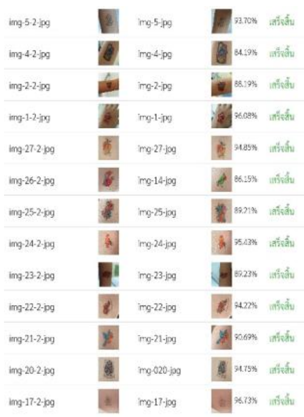


Figure 10 Image showing the test results of the AI program for comparing tattoo images with the image database

Example images of the test results of the AI program for comparing tattoo images with the image database are shown in Figure 10. The test results for the tattoo classification program, as shown in Table 6, indicate an average accuracy of 82.85%, meeting the defined threshold of no less than 80%. However, accuracy in specific categories, such as "dragons/serpents", "father", and "heart", fell below 80%. With additional training and exposure to a broader range of tattoo images, the AI program's accuracy in these categories could potentially improve.

Table 6 Test results of the accuracy of the AI program for tattoo classification in identity verification

Types of Tattoo Image	Total Images				Accuracy (%)
	Total (100%)	Training Set (70%)	Testing Set (30%)	Correctly classified	
1 Human	101	71	30	25	83.33
2 Gecko	134	94	40	32	80.00
3 Bird	113	79	34	31	91.18
4 Dragon	196	137	59	47	79.66
5 Scorpion	201	141	60	52	86.67
6 Tiger	248	174	74	67	90.54
7 Character	200	140	60	48	80.00
8 Buffalo	205	144	61	50	81.97
9 Father	202	141	61	47	77.05
10 Mother	203	142	61	49	80.33
11 Mystic symbol	200	140	60	50	83.33
12 Heart	208	146	62	45	72.58
13 Flower	208	146	62	58	93.55

Types of Tattoo Image	Total Images				Accuracy (%)
	Total (100%)	Training Set (70%)	Testing Set (30%)	Correctly classified	
14 Graphic Images	209	146	63	51	80.95
Total	**2,628**	**1,841**	**787**	**652**	-
Average	-	-	-	-	**82.85**

Example images of the test results of the AI program for tattoo classification in identity verification are shown in Figure 11.

Label: Graphics tattoo
Probability: 0.92
Predicted: Graphics tattoo

Label: human tattoo
Probability: 0.81
Predicted: human tattoo

Label: flower tattoo
Probability: 0.88
Predicted: flower tattoo

Label: bird tattoo
Probability: 0.90
Predicted: bird tattoo

Figure 11 Image showing the test results of the AI program for comparing tattoo images with the image database

4. Conclusions

The AI program developed for tattoo image comparison performs effectively in image analysis according to the defined criteria, achieving an Accuracy@top-N of no less than 0.8, meaning accuracy is at least 80%. In the program, the similarity percentage between the test image and images in the database is displayed. The result can be interpreted as follows: 1) When the similarity percentage is high, it indicates that the test image closely resembles an image in the database. 2) When the similarity percentage is low, it suggests that the test image is either new (not present in the database or bears minimal resemblance to any database images. In such cases, the program will attempt to display the most similar image, though it may not be an exact match, merely the closest available.

Limitations of the AI program for tattoo image comparison

1) The program demonstrates optimal performance and efficiency under specific conditions: High-Quality Database Images: Tattoo images stored in the database should be of high quality and clarity, with any irrelevant parts removed to focus solely on the tattooed areas. High-Quality Comparison Images: Tattoo images used for comparison should also be clear, high-quality, and cropped to highlight only the relevant tattoo sections. Interpreting Similarity Percentages: When the similarity percentage between the test image and the database images is high, it suggests a strong resemblance between the test image and the images in the database.

2) The program may encounter errors due to the following factors: Low Similarity Percentage: This occurs when the test image is either new and not yet included in the database or has minimal resemblance to any existing images. In such instances, the program will attempt to display the closest match, which may not always be accurate. Poor Quality of Tattoo Images in the Database: Low-resolution or unclear images in the database can result in incorrect matching outcomes. Low Quality of Comparison Images: When comparison images are of poor quality, unclear, or contain irrelevant elements mixed with the tattoo image, the program's accuracy may be further compromised.

Summary and analysis of the test results of the AI program for tattoo image classification

The test results for the tattoo image classification program indicate an average accuracy of 82.85%, meeting the defined threshold of no less than 80%. However, some categories, such as "dragons/serpents", "father", and "heart", had accuracies below 80%. This discrepancy could be due to factors such as the quantity of images (data) used to train the AI, the quality of the images, and the specificity of the images.

Training the AI with a larger dataset, ensuring high-quality training images that are clear, and maintaining consistency in appearance within the same category can help the AI learn and classify images more accurately. Additionally, refining the categorization by creating more specific subcategories may further enhance the AI's performance.

Limitations of the AI program for tattoo image classification

Sufficient Quantity of Training Images: The AI requires a large number of tattoo images for training to enhance its classification accuracy.

High-Quality Training Images: Tattoo images used for AI training must be of high quality and clarity to support effective learning.

Consistency Within Categories: Tattoo images within the same category used for training should not be overly diverse. For instance, within the "human" category, extreme variations such as cartoonish figures, skeletons, and realistic portraits can negatively impact classification accuracy.

Creating Specific Subcategories: When significant diversity exists within a category, it may be beneficial to establish more specific subcategories, such as "Human (Realistic)", "Human (Skeleton)", and "Human (Cartoon)", to improve the AI's accuracy in classifying tattoo images.

Conclusion and recommendations for the tattoo classification system

1) The DINOv2 model, a smaller yet effective model, is sufficiently capable of supporting the AI program in comparing tattoo images with the image database for identity verification, achieving an accuracy of no less than 80%, thereby meeting the defined threshold.

2) Recommendation: In cases where a search using the small DINOv2 model with top-50 (the first 50 results) does not yield the desired image, it is recommended to perform the search with a larger model.

Finally, researchers want to declare regarding data privacy that the Central Institute of Forensic Science Thailand (CIFS) owns the data, and privacy concerns are addressed in the policy of the CIFS.

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This AI program is expected to enhance identity verification processes, helping confirm identities and, ultimately, reunite missing individuals with their families.

Declaration of Conflicting Interests

The authors declare they have no conflicts of interest for this article, and they alone are responsible for the content.

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