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Developing an Artificial Intelligence Chatbot for Snake Image Classification and Accuracy Improvement

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AU2 *Abstract.* Snakebites pose a significant global health challenge. The timely and accurate identification of snake species is essential for guiding antivenom administration. Our goal was to evaluate the effectiveness of a machine learning model for classifying snake species using images collected from the external environment and a preprocessing method to enhance accuracy. In this study, we developed a deep learning model for snake species identification in Taiwan based on the Swin Transformer v2 architecture, applying transfer learning to 12,000 images sampled from a dataset of 30,573 labeled images collected by the authors from sources such as Flickr, iNaturalist, and local databases before AU3 October 2023. An external test set of 2,400 images, collected through the XX (LINE) chatbot and Facebook groups between November 2023 and April 2024, was used to evaluate real-world performance. To address challenges in external test set images, we introduced a preprocessing method called test-time object detection and cropping (TT-ODC). Without preprocessing, the model achieved 95.6% accuracy on the validation set but dropped to 83.3% on the external test set. Applying TT-ODC improved external test accuracy to 89.8%, closely matching human annotation performance (90.3%). These findings revealed that integrating a Swin Transformer v2-based model into the LINE chatbot enhances snake species identification and improves real-world accuracy. The TT-ODC method effectively bridges the gap between experimental (validation set) and real-world (external test set) performance, providing a practical tool for clinical snakebite management.

INTRODUCTION

Snakebites represent a significant global health challenge, causing up to 94,000 deaths annually and affecting millions of people worldwide.[1] The primary treatment of snakebite envenomation is the administration of antivenom, which depends on accurate snake species identification.[2] Although cross-neutralization can occur, antivenoms are primarily specific to the snake species whose venom was used in their production.[3–5] Without accurate identification, administering multiple antivenoms to cover different species increases the risk of adverse reactions.[6] Furthermore, delays in antivenom administration can exacerbate complications, leading to tissue damage, envenomation syndromes, and prolonged recovery times.[7–10] Therefore, the timely and accurate identification of the snake species, followed by species-specific antivenom administration, is crucial for effective treatment.[11]

Among more than 50 native snake species in Taiwan, six are medically significant and have species-specific antivenoms available: *Trimeresurus stejnegeri* (*T. stejnegeri*),[12] *Protobothrops mucrosquamatus*,[13] *Naja atra* (*N. atra*),[14] *Bungarus multicinctus*,[15] *Deinagkistrodon acutus*,[16] and *Daboia siamensis* (*D. siamensis*).[17] Two additional venomous species, *Trimeresurus gracilis*[18] and *Ovophis makazayazaya* (*O. makazayazaya*),[19] are also medically significant but rely on antivenom cross-neutralization. Additionally, certain venomous species, *Sinomicrurus* spp. and *Rhabdophis formosanus* (*R. formosanus*), have not been associated with envenomation cases in Taiwan but have been implicated in incidents abroad.[20–22] The misidentification of snake specimens brought to hospitals in Sri Lanka and Nepal has led to either the inappropriate use or complete omission of antivenom administration, thereby placing patients at risk.[23–25] The accurate identification of these venomous snake species is critical for guiding antivenom administration, ensuring timely and effective treatment, and minimizing the risk of adverse outcomes.

The accurate identification of snake species presents a significant challenge for clinical healthcare providers, with a global review revealing that only 53.0% of snakebite cases were correctly identified.[26] Deep learning (DL) has emerged as a promising tool for snake species identification, achieving an average accuracy of 94.2% per country in some studies.[27,28] However, DL models often perform inconsistently on external test sets compared with internal validation, owing to variations in populations and settings, underscoring the need for robust external testing to evaluate their generalizability.[29] Consequently, the effectiveness of trained snake recognition models in real-world applications remains uncertain.

With this study, we aimed to develop a DL model for public and clinical use to identify snake species in Taiwan based on user-submitted photographs. By analyzing real-world images, we evaluated the performance of the model and proposed methods to enhance its reliability in practical applications, addressing the gap between experimental results and real-world performance.

MATERIALS AND METHODS

Classification of snake species in Taiwan.

In this study, snake species native to Taiwan were classified into 11 classes on the basis of their clinical relevance. Ten classes represent venomous species with reported envenomation cases, whereas an “Others” class includes nonvenomous species or those with no documented envenomation cases. The 11 defined classes are as follows: 0 = *T. stejnegeri*; 1 = *Protobothrops mucrosquamatus*; 2 = *N. atra*; 3 = *Bungarus multicinctus*; 4 = *Deinagkistrodon acutus*;

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5 = *D. siamensis*; 6 = *Trimeresurus gracilis*; 7 = *O. makazayazaya*; 8 = *Sinomicrurus* spp.; 9 = *R. formosanus*; and 10 = others.

Data collection, labeling, and cleaning.

Data for the training and validation sets were collected before October 2023 from Flickr,[30] iNaturalist,[31] and two Taiwan-based websites: the Taiwan Reptile Report Program[32] and the Taiwan Roadkill Observation Network.[33]
AU4 The external test set images were gathered from the XX (LINE) chatbot and Facebook groups between November 2023 and April 2024.

All snake images were labeled by researchers specializing in Taiwanese snakes from the Herpetology Laboratory in the Department of Biological Science and Technology at National Pingtung University of Science and Technology. Images that could not be identified were removed.

Data preprocessing.

The data were divided into three subsets based on dataset type: training, validation, and external test sets. For the training set, we applied an extensive data augmentation process to enhance model generalization by diversifying the images. This included random flipping, applying perspective transformations, and center cropping. For the validation set, we applied simple transformations to ensure consistency with real-world testing scenarios. For the external test set, test-time object detection and cropping (TT-ODC) was applied. All images were resized to a standard dimension of 224 × 224 pixels and normalized to the RGB channels. AU5

Transfer learning for the image classification model.

The Swin Transformer is a computer vision backbone that incorporates visual priors into the transformer encoder, enabling tasks such as image classification and object detection.[34] In this study, we used the pre-trained Swin Transformer v2 model, specifically the swinv2-base-patch4-window12-192-22k variant made available by Microsoft on Hugging Face, which was pretrained on the ImageNet-21k dataset at a resolution of 192 × 192.[35] We applied transfer learning to adapt the model for snake species classification by using images from the training set. The model was trained for 20 epochs, with the best performance on the validation set achieved during the seventh epoch, when the validation accuracy reached 95.6%.

User interface.

The DL model was deployed via a LINE chatbot as the user interface.[36] Using the Django framework, images submitted through LINE were stored and processed.[37] The Swinv2-base model, which is a variant of the Swin Transformer v2, predicted the snake species according to the classes established for the study, and the results were returned to users through the LINE chatbot (https://line.me/R/ti/p/%40069qmkhj).

Test-time object detection and cropping.

Images from the LINE chatbot or Facebook (external test set) exhibited lower classification accuracy than validation images because of the lower quality and smaller relative size of the snakes within the frame. To address this issue, we propose a TT-ODC method. Among several zero-shot object detection models tested and compared, the owlv2-large-patch14-finetuned variant from Google exhibited the best performance.[38] Using this model, the snake region was detected on the basis of the text query "snake." The detected area was then cropped and passed through a classification model. If multiple snake regions were detected, the largest was selected for cropping. When no snakes were detected, the original image was processed directly for classification.

Overview of workflow and dataset preparation.

An overview of the data collection, dataset splitting, and model training workflow is provided in Figure 1. Before October 2023, we collected and labeled 30,573 images from international platforms (Flickr and iNaturalist) and local websites (the Taiwan Reptile Report Program and the Taiwan Roadkill Observation Network). From this collection, 12,000 images were sampled by species and used to create the training and validation sets, with an 80:20 split ratio. F1

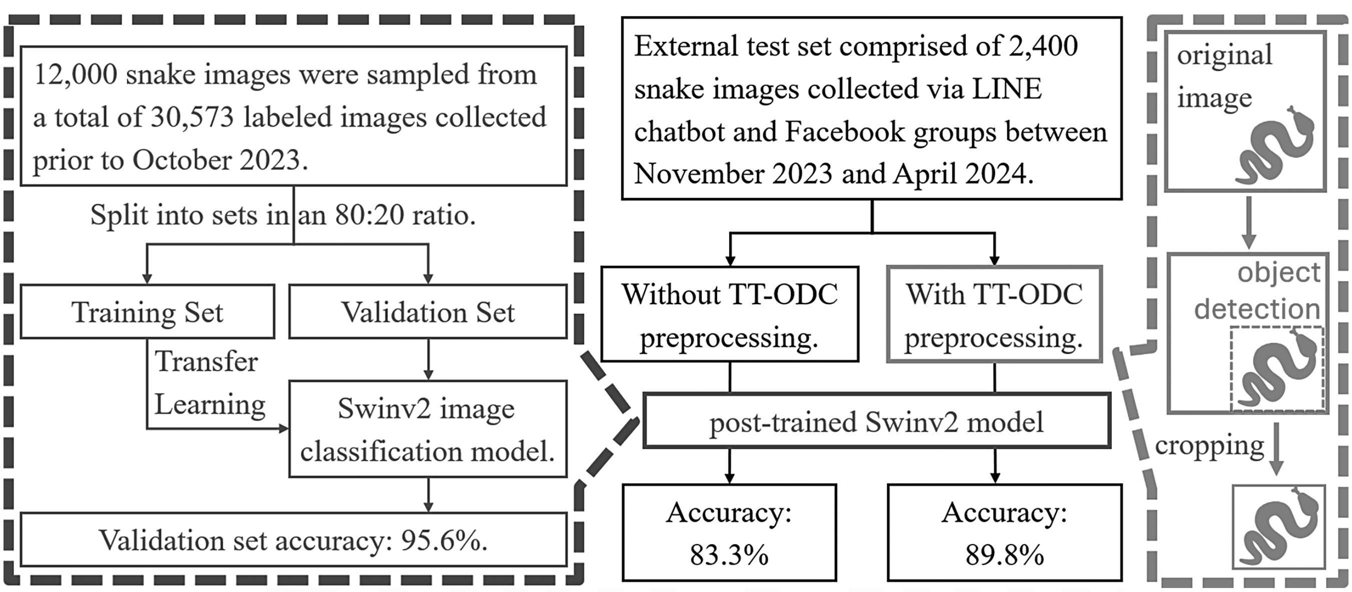

FIGURE 1. Data collection and model training flowchart. TT-ODC = test-time object detection and cropping. This figure appears in color at www.ajtmh.org.

RESULTS

The sampling process and the distribution of images across snake species in these sets are summarized in Table 1. A total of 9,600 images were included in the training set for transfer learning, and the post-trained Swin Transformer V2 model achieved a validation accuracy of 95.6%.

To assess the performance of the model under real-world conditions, it was deployed on a LINE chatbot, attracting ~4,000 users. Duplicate and unidentifiable images submitted by users were excluded. Between November 2023 and April 2024, 730 unique and identifiable images were collected through the LINE chatbot. Additionally, 1,670 images were gathered from Facebook groups where users inquired about snake species. After appropriate labeling and annotation, these 2,400 images formed an external test set. However, the accuracy of the model on the external test set was only 83.3%.

Analysis of the misclassified images revealed two main factors that contributed to the lower accuracy. First, the external test set contained a higher proportion of challenging images compared with the validation set. For instance, cyan blue variants of *T. stejnegeri*, which are typically green with a red tail, were not represented in the training and validation sets.[39] Many users submitted these rare cyan blue variants, leading to lower classification accuracy for this species. Second, the small size of the snake in some images reduced the accuracy of the model (Figure 2A and B).

To address the second issue, we introduced a preprocessing method called TT-ODC. The OWLv2 model, a zero-shot object detection framework, was used to detect snake regions in the images without requiring prior training on snake datasets. Using this model, snake regions were successfully detected in 2,289 of 2,400 images (95.4%), which were then cropped and input into the classification model. For the remaining images, in which no snake regions were detected, the original images were directly input into the classification model without cropping. This preprocessing method significantly improved the external test set accuracy from 83.3 to 89.8% while maintaining a validation set accuracy of 96.3%.

The accuracy of the post-trained Swinv2-base model on the validation and external test sets, both with and without cropping preprocessing, is compared in Table 2. The application of TT-ODC (examples shown in Figure 2C and D) improved the accuracy of the external test set from 83.3 to 89.8%. This performance is comparable to human annotation accuracy, which was 90.3%. The per-class precision, recall, and F1-score for each snake species are presented in Table 3.

To further examine the impact of TT-ODC, the confusion matrices, which reveal the classification accuracy on the external test set with and without preprocessing, are presented in Figure 3. The results reveal improved accuracy across nearly all species after applying the preprocessing method.

DISCUSSION

The categorization and classification strategy used in this study is outlined in Table 1, focusing on 10 categories of venomous snakes in Taiwan, with some categories encompassing multiple species, and an “Others” category that includes nonvenomous snakes or species with no documented envenomation cases. This approach was chosen because accurately classifying nonvenomous snakes within the “Others” category does not have clinical significance. In snakebite treatment, the primary objective is to identify medically important venomous snakes that require specific antivenoms.[2,3] Misidentifying a nonvenomous snake would not alter clinical decisions.

To improve the quality of the training and validation sets, we performed selective downsampling rather than including all collected images. With this approach, we aimed to mitigate the impact of imbalanced class proportions on model predictions because the prevalence of snake species in online databases may not accurately reflect their occurrence in actual snakebite cases in clinical settings. A previous study revealed good performance in DL-based snake species identification worldwide, with an average accuracy of 92.2%.[27] However, *Indotyphlops braminus*, a nonvenomous snake native to Taiwan, was highly represented in the training (1,296 images) and validation (184 images) sets, whereas medically important snakes such as *D. siamensis* and *O. makazayazaya* were entirely absent. This disparity highlights the mismatch between the prevalence of data in online sources and the clinical relevance of certain species in snakebite cases.

To address this limitation, we downsampled ~1,000 images for each of the eight medically important venomous snakes

Table 1
Image collection and distribution across training, validation, and external test sets

	Training and Validation Set*				
	Collected	Sampled	Training	Validation	External Test Set†
Trimeresurus stejnegeri	3,166	1,000	793	207	230
Protobothrops mucrosquamatus	1,952	1,000	787	213	302
Naja atra	1,950	1,000	796	204	97
Bungarus multicinctus	1,160	1,000	810	190	131
Deinagkistrodon acutus	3,588	1,000	797	203	96
Daboia siamensis	1,891	1,000	804	196	43
Trimeresurus gracilis	960	960	771	189	30
Ovophis makazayazaya	1,394	1,000	803	197	80
Sinomicrurus spp.	677	500	399	101	31
Rhabdophis formosanus	418	418	350	68	23
Others‡	13,417	3,122	2,490	632	1,337
Total images	30,573	12,000	9,600	2,400	2,400

* The training and validation sets initially comprised 30,573 images. To ensure an even distribution across species, 12,000 images were randomly sampled.
† The external set consisted of 2,400 images, which were used in their entirety without adjustments to group proportions.
‡ Additional details regarding the species and numbers included in the “Others” category are provided in the appendix table.

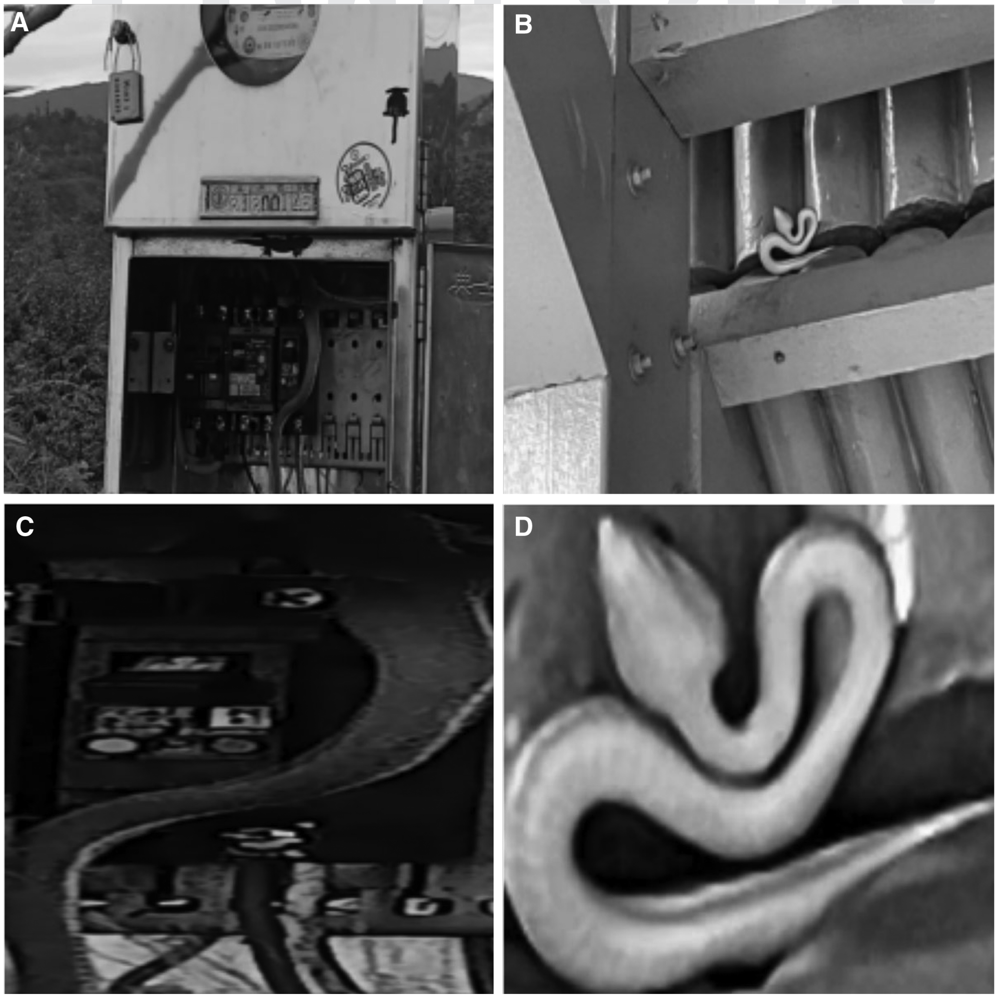

FIGURE 2. Examples of test-time object detection and cropping preprocessing. (**A** and **B**) Original images from the external test set. (**C** and **D**) Images after object detection, cropping, and resizing. This figure appears in color at www.ajtmh.org.

and ∼500 images for *Sinomicrurus* spp. and *R. formosanus*. This strategy ensured that the predictions of the model were minimally influenced by data prevalence. To evaluate the trade-off between dataset size and performance, we also trained the model using the entire dataset of 30,573 images with an 80:20 training–validation split. By using ∼2.5 times more images, the model could achieve an accuracy of 92.9% with TT-ODC. However, our primary objective with this study was to develop a method that could attain sufficient performance using a manageable number of well-balanced images.

Images from two local sources, one of which featured roadkill events, were included in this study. This decision reflects real-world scenarios in which patients may bring a dead snake to the hospital for identification.[40] Limiting the training set to images of live snakes might not fully capture the diversity needed for accurate species identification in such situations. Therefore, roadkill snake images were specifically included to better represent the appearance of snakes commonly brought to hospitals after being killed.

In SnakeCLEF 2023 and SnakeCLEF 2024, the Top-1 accuracy reached 91.3% across ∼1,600 to 1,800 snake species.[41,42] Although our model achieved a validation accuracy

TABLE 2
Accuracy of snake species image classification in validation and external test sets

Validation Set (n = 2,400)		Without Image Cropping	With Image Cropping by Owlv22
Accuracy		95.6%	96.3%
External Test Set (n = 2,400)	Without Image Cropping	With Image Cropping by Owlv2	With Image Cropping by Human
Accuracy	83.3%	89.8%	90.3%

Owlv2 refers to the Google model owlv2-large-patch14-finetuned.

TABLE 3
Performance of snake species image classification

	Precision	Recall	F1-Score
Trimeresurus stejnegeri	93.1%	81.7%	87.0%
Protobothrops mucrosquamatus	86.8%	91.7%	89.2%
Naja atra	66.4%	81.4%	73.2%
Bungarus multicinctus	86.3%	96.2%	91.0%
Deinagkistrodon acutus	100.0%	91.7%	95.7%
Daboia siamensis	95.4%	95.4%	95.4%
Trimeresurus gracilis	58.3%	93.3%	71.8%
Ovophis makazayazaya	100.0%	91.3%	95.4%
Sinomicrurus spp.	100.0%	83.9%	91.2%
Rhabdophis formosanus	74.1%	87.0%	80.0%
Others	92.3%	90.4%	91.3%

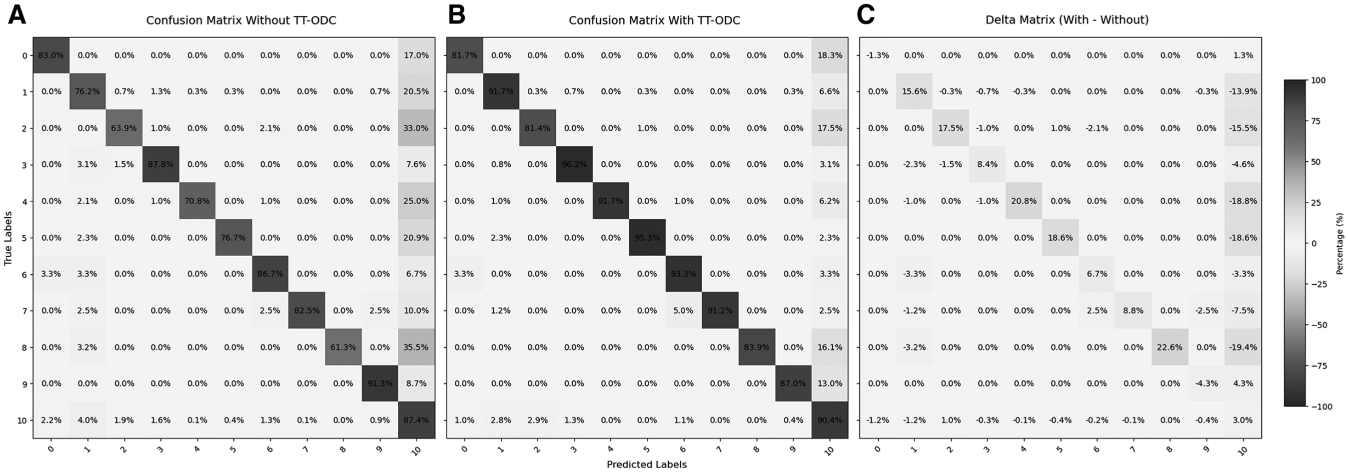

FIGURE 3. Confusion matrices on the external test set. (**A**) Without test-time object detection and cropping (TT-ODC), (**B**) with TT-ODC, and (**C**) percentage difference (with–without). Each matrix reveals the percentage of correct and incorrect classifications. Species labels: 0 = *Trimeresurus stejnegeri*; 1 = *Protobothrops mucrosquamatus*; 2 = *Naja atra*; 3 = *Bungarus multicinctus*; 4 = *Deinagkistrodon acutus*; 5 = *Daboia siamensis*; 6 = *Trimeresurus gracilis*; 7 = *Ovophis makazayazaya*; 8 = *Sinomicrurus* spp.; 9 = *Rhabdophis formosanus*; and 10 = others. This figure appears in color at www.ajtmh.org.

of 95.6% for 11 categories, this result is not particularly remarkable when compared with these benchmarks. However, our primary focus with this study was not on maximizing validation accuracy but on assessing real-world performance and clinical applicability.

To facilitate real-time clinical use, we deployed our model on a LINE chatbot, allowing public users to submit images for snake species identification. By analyzing these user-submitted images, we found that the accuracy of the model on real-world data decreased to 83.3%. To address this limitation, we introduced a preprocessing method, TT-ODC, which improved the accuracy on real-world images to 89.8%. The average inference time using the Swin Transformer v2 alone is 0.0371 seconds per image on an RTX 4090 graphics processing unit (Nvidia, Santa Clara, CA). When TT-ODC is added, the total processing time increases by 0.7 seconds. In contrast, manual cropping by a human takes 17.2 seconds. Although TT-ODC increases the inference time by ~20 times, it still takes only ~4.3% of the time compared with manual cropping, and the accuracy is comparable (89.8% versus 90.3%). In this study, we focused on real-world applications, and the development of preprocessing methods distinguishes our approach from other DL models designed for snake species identification.

Limitations.

The proposed TT-ODC method is novel but has not yet been widely validated; its performance should be further evaluated in other fine-grained image classification tasks. As shown in Figure 3, even with the application of the TT-ODC method, the accuracy of the model remained between 80% and 90% for certain species: *T. stejnegeri*, *N. atra*, *Sinomicrurus* spp., and *R. formosanus*. The reduced accuracy for the first two species likely stems from their significant variability in coloration and patterns, whereas the poor performance for the latter two species may be attributed to the limited number of available training images.

Additionally, in many real-world envenomation cases, an image of the culprit snake is not available. In such scenarios, wound image classification becomes a critical alternative. To more comprehensively address the issue of misidentification, multimodal inputs should ideally be incorporated in future models, including wound characteristics and laboratory test results. However, collecting and accurately labeling wound images presents significant challenges, underscoring the importance of this direction for future research.

CONCLUSION

In this study, we collected two distinct datasets of snake images in Taiwan: one for training and validation, and the other for use as an external test set. Using the Swin transformer image classification model, we achieved a validation accuracy of 95.6%. However, the accuracy decreased to 83.3% on the external test set, which consisted of user-submitted images representing real-world scenarios. To address this issue, we introduced a preprocessing method, TT-ODC, which improved the accuracy for the external test set to 89.8%.

By deploying the model through a chatbot platform such as LINE, we created a user-friendly interface for real-time snake species identification. This approach represents a significant step toward bridging the gap between experimental and real-world performance. We believe that this system can provide clinicians with a timely and accurate reference for selecting appropriate antivenom when treating patients with snakebites.

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Author's contributions: P.-C. Chuang designed the study, collected data, conducted data analysis, drafted the manuscript, and ensured data accuracy and integrity. Y.-I. Chang supervised data analysis. T.-S. Tsai ensured data collection accuracy. C.-H. Hung conducted data analysis. C.-E. Li supervised data analysis and revised the manuscript. All authors participated in the revision of the manuscript.

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