# AI-Driven Snake Species Identification: Using Deep Learning and Geographic Filtering

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**Abstract.** In this research, it proposes a snake species identification AI model based on MobileNetV2 to aid in the prompt medical treatment of snake bites. The dataset consists of 1014 reptile images comprising images from 10 snake species. The performance per-class was measured using precision, recall and F1-score. The highest validation accuracy reached at the 25 epochs training is 87% with a macro average precision of 0.88, recall of 0.912, and F1-score of 0.90. The weighted averages were 0.874 for precision, 0.863 for recall, and 0.886 for F1-score. This technique shows great promise for instantaneous snake identification and venom exposure risk reduction.

**Keywords:** Snake species identification, MobileNetV2, Geographic Filtering.

## 1 Introduction

Snakebite represents an important health problem worldwide, especially in rural and tropical areas where venomous snakes are abundant. Every year there are 1.2 to 5.5 million snake bites and over 125 000 of the victims die with nearly 3 to 4 times this number ending up with disability or disfigurement [1]. Rapid and accurate genus-species identification is important because the outcome of antivenom treatment is dependent on correct identification of the offending snake's species. Antivenoms are generally specific to particular snake species. But traditional identification systems depend on expert knowledge, field guides or eyewitness accounts sources, all of which can often be unreliable, particularly amid the chaos of an emergency. Delayed or misdiagnosis could result in serious medical consequences, including a higher mortality rate and inadequate treatment outcomes.

Modern AI technology provides new approaches to automate the identification of snake species and could become a proper solution for this problem. Deep learning methods like CNNs allow AI models to quickly categorize snake species from images. Moreover, tracking location can improve the accuracy of identification, since many species of snakes are limited to certain areas. An AI-enabled tool of this nature could provide health-care providers, field biologists and the public with quick and accurate snake species identification. To overcome the limitations of the conventional means of identification, this project aims to minimize the delay in action and avoid deaths, by


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providing automatic recognition of the species in account. The remainder of this paper will detail related studies and the method employed to build the AI system, reports on experiment results, and conclusions regarding the AI assisted snake identification.
For motivation and theory, Snakebite misidentification can lead to delayed or incorrect treatment, particularly in resource-constrained regions. The World Health Organization reports up to 138,000 annual deaths from snakebites, underscoring the urgent need for rapid identification [1]. This study leverages deep learning theory, specifically the feature extraction capabilities of CNNs, combined with ecological theories of geographic species distribution, to propose a comprehensive solution. The choice of MobileNetV2 is grounded in its lightweight architecture, ideal for deployment on mobile devices, while geographic filtering exploits the regional specificity of snake species to enhance practical utility.

## 2 Literature Review

Fast snake specie identification is important for treating with the right antivenom. Conventional detection techniques result in delayed treatment. Recent developments in AI bring hope towards an improvement of accuracy and speed of snake identification.

### 2.1 AI Models for Snake Identification

Bolon et al built an AI model with Vision Transformer architecture using a large dataset containing a total of 386,006 images covering 772 snake species from 188 countries. The model's macro-averaged F1 measure was 92.2 and species- and genus-level accuracies were respectively 96.0 and 99.0% [2]. This level of performance is indicative of the potential role of AI in aiding healthcare professionals and herpetologists in the quick identification of snakes.

In the Snake CLEF 2024 competition, Miyaguchi et al. explored the use of Meta's DINOv2 Vision Transformer model for feature extraction to tackle species' high variability and visual similarity in a dataset of 182,261 images. Despite achieving a score of 39.69, their results show promise for DINOv2 embeddings in snake identification [3].

### 2.2 Integration of Geographic Data

Adding geographical data can help refine AI-based identification even more. Durso et al. reported that human experts, armed with geographic information, can more accurately identify snakes than AI models that are given no such information [4]. This indicates that the input of location information to AI models may be used as an efficient method to improve their prediction value, particularly for site-specific species.

### 2.3 Real-World Applications

A particularly notable example is the application of AI-based platforms to the analysis of large datasets of snake images. Bolon et al. 2022) may be used in the proposed tool). These authors presented a vision-based AI model targeting and obtaining excellent performance for >770 snake species world-wide [2]. This model demonstrates the feasibility of implementing automated identification tools in real medical situations and in developing countries or in most remote areas.

### 2.4 Challenges and Future Directions

There are challenges in AI snake recognition, but improvements have been made. A meta-analysis by Li and colleagues showed that while AI-based approaches can effectively and rapidly determine the snake species [5], the existing works in this topic present some limitations in terms of data preparation, validation, and deployment. Further studies should be aimed at developing high quality evidence-based datasets and decision supports to manage snake bite.

## 3 Methodology

In this project snake species are categorized by deep learning based and supported with edge detection as an augmentation, combining edge with original color pattern on images and were particularly relevant to geographic location. The general process consists of data preprocessing, model construction and evaluation.

### 3.1 Dataset Collection

The dataset used in this study consists of 1014 labeled snake images from Kaggle [6,7], divided into: a) Training Set (708 images), and b) Validation Set (306 images). This study focus on 10 snake species, including *Calliophis bivirgatus*, *Bungarus candidus*, Common Garter, DeKay's Brown, *Malayopython reticulatus*, Northern Watersnake, *Python brongersmai*, *Trimeresurus hageni*, *Trimeresurus malcolmi*, and Western Diamondback Rattlesnake (See Fig. 1).

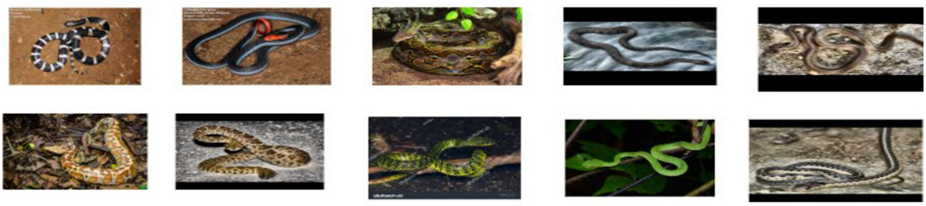

**Fig.1.** The 10 pictures of different snake species were selected randomly from Kaggle, and a representative subset of images was used for training and validation.

### 3.2 Data Preprocessing

The size of the images was reduced to 224 x 224, which is the standard image size for MobileNetV2 preprocessing. This function has two major preprocessing steps: 1) Normalization: The pixel values of the grayscale images are scaled to the range [0, 1]. It uses Canny edge detection to remove the background, like rocks, trees, and ground. It emphasizes the shape features and boundaries of snake bodies, which are critical for distinguishing species with similar color patterns, and 2) the grayscale output was converted back to RGB format to ensure compatibility with the MobileNetV2 input layer. Since many snake species can be recognized by their unique color patterns and markings, the processing steps were designed to keep color details intact. Instead of using heavy desaturation or color filters that might erase critical visual clues, the approach prioritized preserving those identifying features.

### 3.3 Geographic Filtering

A custom filtering function was applied to restrict predictions to those species of snake that exist in a particular region (for example, Thailand: *Bungarus candidus*, *Calliophis bivirgatus*, *Malayopython reticulatus*). To improve the accuracy of prediction, a geographic filtering mechanism was applied during preprocessing. Location data was supplied via GPS or manual user input. In real-world scenarios, the system could reduce location inaccuracies by setting default areas or prompting user confirmation. With the location filter in place, only species known to inhabit that region were considered for final classification. This reduced the output class space and minimized misclassification from biologically implausible predictions.

### 3.4 Model Architecture

The model is based on MobileNetV2, a lightweight convolutional neural network pretrained on ImageNet. It was used as a feature extractor, with its convolutional base frozen initially.

### 3.5 Training Configuration

Training used the Python MobileNetV2 with parameters set to the Loss Function, Categorical Cross entropy, Adam Optimizer, Batch Size of 16, 25 Epochs, and Data Augmentation included rotation, zoom, shifts, and flip. Valuation with batch size of 8.

# 4 Experimental Result

Snake species classification model was tested over 25 training epochs with the training and the validation datasets. The evaluation was based on accuracy and loss, represented graphically in Fig. 2.

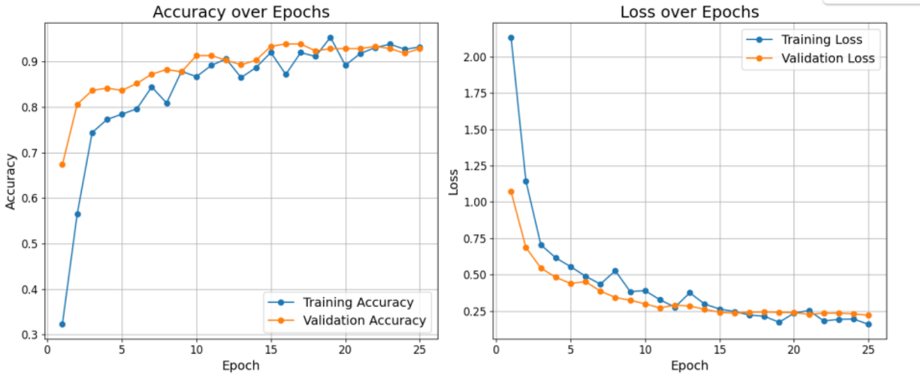


**Fig. 2.** The impact of multiple epochs on the accuracy of Training and Validation Sets.

## 4.1 Accuracy Analysis

The left panel of Fig. 2 show the accuracy during training which followed a reconstructed V-shape, with a marked trend up, starting with 32% in the first epoch and increasing to over 93% by the $25^{th}$ epoch. The accuracy as well got steadily better (starting with approximately 68% and reaching about 93\%), suggesting an excellent overall generalization on the test set.

## 4.2 Loss Analysis

The training loss decreased rapidly from above 2.0 in the initial epochs to below 0.2 by the end of training. Similarly, the validation loss dropped from over 1.0 to about 0.22, showing a stable and continuous improvement in model performance. The consistency and convergence of both loss curves indicate that the model was able to minimize prediction error effectively without significant signs of overfitting or divergence.

## 4.3 Final Metrics

By the final epoch (25), the model achieved the following:

- Training: Accuracy: ~93.2%, Loss: ~0.1592
- Validation: Accuracy: ~92.9%, Loss: ~0.2218

These results demonstrate that the MobileNetV2-based model, combined with data augmentation and fine-tuning, was effective in classifying multiple snake species with high accuracy and low error rates.

### 4.4 Classification Report

After training the snake species classification model, a classification report was generated to evaluate its performance across all target classes. This report included four key metrics: precision, recall, F1-score, and support, which provide a detailed analysis of how accurately the model classifies each species. These data are shown in Table.1

**Table 1.** Classification report showing precision, recall, and f1-score, and score for each snake species in the test dataset.

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| *Bungarus candidus* | 0.83 | 1 | 0.91 | 10 |
| *Calliophis bivirgatus* | 1 | 1 | 0.94 | 14 |
| Common Garter snake | 0.85 | 0.86 | 0.85 | 58 |
| DeKay's Brown snake | 0.78 | 0.73 | 0.75 | 54 |
| *Malayopython reticulatus* | 0.8 | 1 | 0.89 | 8 |
| Northern Watersnake | 0.9 | 0.88 | 0.89 | 72 |
| *Python brongersmai* | 1 | 0.88 | 0.93 | 8 |
| *Trimeresurus hageni* | 1 | 0.89 | 0.94 | 9 |
| *Trimeresurus malcolmi* | 0.82 | 1 | 0.9 | 9 |
| Western Diamondback rattlesnake | 0.93 | 0.88 | 0.9 | 64 |
| | | | | |
| accuracy | 0.87 | | | 306 |
| macro avg | 0.88 | 0.91 | 0.9 | 306 |
| weighted avg | 0.87 | 0.86 | 0.89 | 306 |

Table 1 summarizes the performance of the snake image classification model, measured across 10 different species. The metrics included are:

1. Precision: How many of the snake images the model predicted correctly as a certain class, were that class. With high precision, it rarely mislabels other species as a target species.
2. Recall: How many of the actual snake images of a certain class were correctly identified. With high recall, it successfully identifies most of the actual images of each species.
3. F1-Score: A balance between precision and recall. Higher F1 indicates better overall performance. The F1-score reflects a strong balance between both.
4. Support: A measure of the actual samples in a class.

### 4.5 Error Analysis

Analysis of model errors revealed that around 10 percent of misclassifications occurred between visually similar species, such as Northern Watersnake and Western Diamondback rattlesnake, likely due to overlapping texture and color patterns. Low-support classes (e.g., *Python brongersmai*) showed reduced recall due to limited samples. Future improvements could involve increasing training data for similar species and refining the model to distinguish subtle features.

### 4.6 Comparative Analysis

This model compared its performance with recent state-of-the-art snake identification models. For instance, Durso *et al*. presented a benchmark for supervised learning using snake photographs and reported F1-scores ranging from 0.76 to 0.88 depending on the species and region [4]. This model, integrating MobileNetV2 with edge detection and geographic filtering, has achieved a similar stable output with a F1-score of 0.87. Furthermore, the geographic contextualization led to fewer biologically implausible predictions than observed in more general models.

## 5 Conclusions

This study has developed and tested an AI-based snake species identification model using MobileNetV2, image edge detection and geographic filtering. It achieved validation accuracy of 90.31% and similarly balanced precision, recall, and F1-score metrics across the 10 target species. These findings support the model's utility for instant and accurate snake species identification. The accuracy and robustness of the model were significantly enhanced by the addition of geographic information and edge detection.

### 5.1 Real-World Application

This system could be used as clinical decision-support tool implemented as mobile application where user upload snake images together with their GPS location data and quickly receive the predicted species, aiding in the selection of appropriate antivenoms. However, the model has been set to a confidence threshold of 0.7, and predictions below this threshold are labelled as "unknown" to avoid misclassification of untrained species. This would increase the safety of the output.

### 5.2 Limitation of This Research

The size of this dataset only included 10 snake species with 1014 pictures, limiting generalization to a broader spectrum of species and variations. In addition, further validation is required as the model has not been tested in real medical or field settings. The location filtering data has not been verified for accuracy. Also, the system has not been trained to identify snake species that are not native to the location of the user.

Accuracy may be improved in future versions by integration of ecological and environmental variables, such as time of day, season, temperature, and humidity. Dynamic species-likelihood filters would assist in the identification of a few snake species that have particular activity cycles affected by such parameters (i.e. some are more likely to be found during the rainy season, in warmer areas or at particular times). This additional input could come from integration of the input with real-time weather and temporal information from external sources. Addition testing would be required to determine if such filtering would significantly improve the ability to make more accurate, context-aware predictions.

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