Capstone Project Concept Note and Implementation Plan

Project Title: Snake ID Classification For Myanmar

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Concept Note

1. Project Overview

Snakebite incidents remain a significant public health challenge in many regions, where delayed identification and misinformation often lead to severe injury or death. Existing emergency resources are limited in their ability to recognize snake species quickly and accurately. This project addresses this issue by developing a machine learning–based system capable of classifying snake species from user-uploaded images and instantly providing species-specific safety guidance. The system supports Sustainable Development Goals (SDG) 3: Good Health and Well-being by reducing preventable harm through rapid first-aid recommendations, and SDG 9: Industry, Innovation, and Infrastructure by applying AI technology to enhance public safety tools.

2. Objectives

- Develop a Convolutional Neural Network (CNN) model capable of classifying snake species with high accuracy across varying image conditions.\
- Automatically determine whether the identified snake is venomous or non-venomous.
- Provide real-time, species-specific safety instructions or first-aid steps immediately after classification.
- Improve public awareness and facilitate faster, data-driven responses during snake encounters.

3. Background

Snakebites are a common yet often overlooked medical emergency, particularly in rural and developing regions. Delayed identification of the snake species often leads to improper or delayed treatment. While some mobile applications and guides exist, they generally lack intelligent species recognition and rely heavily on user knowledge or manual comparison, which increases risk.

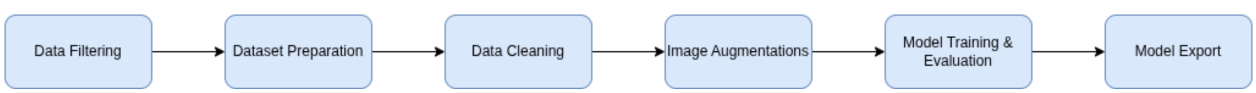
Machine learning provides an efficient solution by enabling automated image-based classification. A CNN model trained on diverse snake image datasets can quickly and accurately recognize species traits that may be difficult for non-experts to identify. Integrating this recognition capability with an immediate safety-response system bridges the gap between real-time observation and informed emergency action, improving the chances of effective first aid and reducing preventable harm.

4. Methodology

This project applies supervised deep learning techniques to perform image classification using convolutional neural networks (CNNs). The primary framework used is PyTorch, which provides the necessary tools for model training, optimization, and evaluation. Pre-trained models from Torchvision, specifically MobileNetV3-Small and EfficientNet-B0, are employed through transfer learning, allowing the project to leverage previously learned visual features and significantly reduce training time. The initial layers of these models will be frozen to retain general image feature extraction, while selected upper layers will be fine-tuned on the snake image dataset to improve classification accuracy for the target species.

To enhance model robustness and reduce overfitting, data augmentation techniques such as random cropping, horizontal flipping, rotation, and color jittering will be applied during preprocessing. The training process will involve splitting the dataset into training, validation, and testing subsets, optimizing the model using stochastic gradient descent (SGD) or Adam, and monitoring performance through accuracy and loss metrics. After achieving satisfactory performance, the final trained model will be exported to ONNX format to enable deployment across various hardware platforms, with optional model quantization applied to reduce size and improve inference speed on resource-constrained devices. This methodology ensures efficient training, strong generalization, and practical real-world deployment.

5. Architecture Design Diagram



1. Data Filtering

This stage removes unnecessary, duplicate, or corrupted images from the dataset. By filtering out low-quality or irrelevant samples early, it ensures that only valid data is passed to later stages, improving training reliability and reducing noise in model learning.

2. Dataset Preparation

At this stage, the filtered dataset is organized and loaded using **PyTorch’s DataLoader**. It handles batching, shuffling, and efficient data feeding to the model during training and validation. This process ensures consistent and reproducible data flow throughout the pipeline.

3. Data Cleaning

This component focuses on verifying image-label consistency and correcting or removing mislabeled entries. Proper data cleaning prevents incorrect supervision signals, leading to more accurate and stable model training results.

4. Image Augmentations

Using **Torchvision transforms**, this step applies operations like random cropping, rotation, flipping, normalization, and resizing. These augmentations enhance the dataset’s diversity and help the model generalize better by simulating real-world variations in the images.

5. Model Training & Evaluation

Here, **pre-trained CNN models** (MobileNetV3-Small or EfficientNet-B0) are fine-tuned using transfer learning. The model is trained on the augmented dataset, validated on a separate set, and adjusted to optimize performance metrics such as accuracy and loss. Evaluation ensures the model meets the desired accuracy before deployment.

6. Model Export

In the final stage, the trained PyTorch model is converted into **ONNX format** for deployment compatibility across platforms. Optional **quantization** may be applied to reduce model size and improve inference speed, making it suitable for edge or mobile applications.

6. Data Sources

Accurate snake species identification requires high-quality, well-annotated image data that captures variations in appearance, lighting, and environment. This data review focuses on selecting and preparing suitable datasets for training a Convolutional Neural Network (CNN) to classify both venomous and non-venomous snakes and support an emergency safety card system. The exploration centers on two areas: identifying reliable public datasets and defining preprocessing and augmentation strategies. The primary dataset used is the SnakeCLEF 2021 dataset, which contains over 300,000 labeled images from more than 700 global species and provides valuable metadata for fine-grained classification. To improve regional accuracy, additional images from local sources such as iNaturalist and HerpMapper will be integrated, resulting in a combined dataset of approximately 10–15 GB after preprocessing.

7. Literature Review

The literature review supports utilizing Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), as the chosen methodology for automated snake identification, with studies by Nandwani et al. (2021) and Chamidullin et al. (2021) demonstrating their high accuracy across diverse species and patterns. The key finding from existing research is that while these CNN models (like MobileNetV2 and ResNet) are experimentally effective, they are primarily confined to controlled settings and lack integration into real-time public safety systems. This project directly builds upon and extends this work by taking the proven DL classification accuracy and translating it into a practical, real-world application: developing a machine learning model that not only identifies the snake from a user image but also automatically generates a dynamic safety card with instant, toxicity-based first-aid recommendations, thereby bridging the critical gap between research and immediate emergency management.

Implementation Plan

1. Technology Stack

Programming Language : Python (primary development language)

Machine Learning & Model Development

- PyTorch: Building and training the CNN model
- Torchvision: Pre-trained models (MobileNetV3, EfficientNet) and image transforms
- scikit-learn: Evaluation metrics (accuracy, confusion matrix)

Data Handling & Utilities

- NumPy: Numerical operations
- DataLoader & ImageFolder (PyTorch): Dataset loading and splitting
- tqdm: Training progress visualization

Model Export & Optimization : ONNX Runtime: Model export and INT8 quantization for optimized inference

Hardware/Environment : CPU (default) with optional GPU support for faster training

2. Timeline

Phase	Tasks	Duration	Deliverables (Estimation)
Phase 1: Data Collection & Preprocessing	Collect global and regional snake datasets (SnakeCLEF, iNaturalist, HerpMapper); perform image cleaning, resizing, labeling, and augmentation (rotation, flipping, color jitter).	Weeks 1-3	Cleaned and augmented dataset, ready for model training
Phase 2: Model Development	Implement CNN model using transfer learning (MobileNetV3, EfficientNet); freeze base layers, fine-tune upper layers; experiment with hyperparameters.	Weeks 4-6	Trained CNN model achieving baseline accuracy
Phase 3: Model Training & Evaluation	Split dataset (train/validation/test); train using SGD or Adam optimizers; evaluate with accuracy, loss, and confusion matrix; perform tuning and quantization.	Weeks 7-10	Optimized, validated model exported in ONNX format
Phase 4: Deployment & Integration	Develop user interface prototype; connect model inference with safety card generation module; test real-time prediction and latency.	Weeks 11-14	Working prototype with image upload, classification, and safety response display

Task Distribution
Pyae Sone Kyaw: Model design, training optimization, and ONNX deployment.
Aye Moh Moh Khin: Backend integration, API development, and testing.
San San Maw: Data preprocessing, augmentation, and dataset management.
Htwe Myat Cho: UI/UX design and integration of emergency response interface.
Kaung Myat Tun: Documentation, performance evaluation, and report preparation.

3. Milestones

Milestone	Expected Output	Target Week
Dataset finalized and cleaned	Complete dataset of global + regional snake images	Week 3
Baseline CNN model trained	Model achieves ≥85% classification accuracy	Week 6
Model fine-tuned and optimized	Improved accuracy ≥90% with balanced performance	Week 9
Model exported and integrated into prototype	Functional ONNX model running with UI	Week 12
Final testing and presentation	Working end-to-end system demonstration	Week 14

4. Challenges and Mitigations

Challenge	Description	Mitigation Strategy
Data Quality and Imbalance	Snake datasets often contain uneven class distribution and poor-quality field images.	Apply extensive data augmentation and under/over-sampling to balance species classes; filter out low-quality images.
Model Performance	Risk of low accuracy due to inter-species similarity or small local dataset.	Use transfer learning with EfficientNet/MobileNetV3; fine-tune final layers; apply early stopping and learning rate scheduling.
Technical Constraints	Limited computational resources for model training.	Use lightweight pre-trained CNN architectures; apply model quantization and ONNX runtime optimization.
Deployment Latency	Real-time inference on low-end devices may lag.	Optimize inference using ONNX Runtime with INT8 quantization; test across devices for speed-performance balance.

Metadata Inconsistency	Missing or mismatched venomous status in dataset metadata.	Verify metadata using verified open sources (HerpMapper, iNaturalist); manually correct mismatched entries where necessary.

5. Ethical Considerations

Our project prioritizes ethical and responsible AI practices throughout data collection, training, and deployment.

- **Data Privacy:** All datasets used are open-source and non-personal, ensuring no violation of privacy or copyright.
- **Bias Mitigation:** Model training will include diverse regional snake species to minimize geographic bias and ensure fair performance across different environments.
- **Accuracy and Safety:** As the system provides health-related information, first-aid recommendations will strictly follow medically verified protocols from credible public health sources. Users will be explicitly advised that the app provides preliminary guidance only and does not replace professional medical treatment.
- **Transparency:** The project documentation will disclose all datasets, model architectures, and performance metrics to ensure transparency and reproducibility.
- **Sustainability:** The solution aims to support public health and safety without environmental harm, aligning with SDG 3 and SDG 9.

6. References

- https://github.com/chamidullinr/snake-species-identification
- https://journals.plos.org/plosntds/article?id=10.1371/journal.pntd.0010647