# Snake Species identification using Machine Learning

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**Abstract:** *Snakebite poisoning is one of the tropical diseases responsible for many deaths globally and particularly in developing countries. In most cases, identifying the species of the snake following the bite is the life-saving factor for snakebite poisoning patients. However, snake species identification is not a trivial task, it can be misleading and dangerous. That is why this study proposes the use of Machine Learning approaches to automate snake species identification.*

## 1. Introduction

Snakes are vertebrate animals that belong to the group of reptiles, among which approximately 700 species are described as poisonous. Snakes are animals that share physical characteristics between distinct species, have distinctive characteristics than snakes of the same species in different geographic regions, the characteristics of species vary at different ages and in opposite sexes.

Traditionally the snake identification process is carried out by making a visual analysis. This approach proves to be inefficient, as it can be misleading due to the need for in-depth knowledge about these animals. For example, to identify correctly, one needs to be able to distinguish different patterns that can be found in a snake which may vary in age, location, sex, the climate in the region, among other features. Also, visual analysis can be dangerous as it needs certain physical contact or approximation between the snake and the specialist.

Snakebite poisoning is a potentially fatal disease, causes about 81000 - 138000 deaths annually, and about 421000 and 1.2 million poisonings per year [1]. Moreover, the world health organization (WHO) has declared snakebite to be a neglected tropical disease (NTD) that causes a humanitarian crisis [2,3].

According to WHO the snakebit causes over 100,000 human deaths and 400,000 victims of disability and disfigurement globally every year. It affects poor and rural communities in developing countries, which host the highest venomous snake diversity and the highest burden of snakebite due to limited medical expertise and access to antivenoms. ("*SnakeCLEF2021 - Snake Species Identification Challenge*") Death or harmful effects of snakebites can be reversed or prevented by administering antidotes. However, administering an antidote is only efficient when done quickly and correctly -with a positive snake species classification.

## 2. Related work

Artificial Intelligence (AI) and Machine Learning (ML) are two areas of computing that have shown reliable results in solving complex problems such as classifying objects based on RGB photos. Animal classification is one of the application AI and ML as shown in many studies [4–9].

On snake species identification, Amir et al compared [10] five traditional models based on five ML algorithms, namely, k-NN (k=7), Naïve Bayes, Decision tree J48, Nearest Neighbour and Backpropagation Neural Networks, where 349 images of 22 species of snakes were used to train the models. Among the trained models, Nearest Neighbour outperformed the other models with an accuracy of 89%. Their approach consisted in training the model based on the histogram of snake species images. Their approach is not applicable for snake species that can be found in a distinct colour, as is the case of coral snakes.

A Siamese Neural Networks (SNNs) which are networks that work with a limited set of data normally called "One Shot Learning," was used by Abeysinghe et al [11] to classify 84 species of snakes. They used three images by species, where two were used for training and one for classification. The result obtained by the model was 5% accuracy and humans achieved an accuracy of 20% when classifying the test set. This approach is not practical in identifying snake species because snakes have many variations[12] , and two images per species may not cover all the variations.

Also, a Convolutional Neural Network (CNN) was proposed by Abdurrazaq et al [13], where they try to classify 5 venomous snakes, in this approach, a k fold cross validation was performed with 5-fold and the average was measured. The medium CNN performs better than deep CNN with 82% and 78% accuracy for the deep model.

## 3. Dataset and features

In this project we will be using part of the dataset released in the challenge proposed by the world health organization (WHO) for snack identification. The dataset consists of 4 species of venomous snake (table 1).

*Table 1: Distribution of imagens in our dataset*

| ID | Snake Species | Images | Train | Test |
|---|---|---|---|---|
| *000* | *Bitis arietans* | 140 | 112 | 28 |
| *001* | *Dendroaspis polylepis* | 140 | 112 | 28 |
| *002* | *Naja mossambica* | 140 | 112 | 28 |
| *003* | *Dispholidus typus* | 140 | 112 | 28 |
| **Total** | | **560** | **448** | **112** |

To split our dataset into train and test we use the ratio 80:20, where 20% of the images per class was attributed to the test set. Before splitting the dataset in training and test we did some data normalization such as resizing all the images to the same size 256x256.

## 3.1.Data Augmentation

To provide a large data set for training the models, the following augmentation techniques were applied in the training data set. The resulting training data set contains a total of 2240 images, 560 training images by each species, which was resized to 256x256 pixels each image.

### 3.1.1. Key Characteristics

The dataset has some interesting characteristics that make the classification of these species a challenge, some of these characteristics are described below:

a) The dataset contains images of snakes in their habitat (bushes, rocks, etc.), or others objects that we call noise here.

b) Snakes are very diverse animals which make some species patterns (colour, shape etc) very different.

c) The same species can present different characteristics and patterns if the age, location and sex are different.

## 3.2.Features Extration

We use Histogram of gradient to extract features to train the model. The Histogram of gradient counts occurrences of gradient orientation in localized portions of an image. It is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy. Before calculating the histogram of gradient, we converted the image to grayscale, normalize the pixel values and used Gaussian noise.

## 4. Methods

In this study, we will make a comparison between Convolutional Neural Network Xception and some methods of machine learning such as KNN, SVM, MLP, and Decision tree.

### 4.1. Models

a) **Xception**

The Xception model [14] which means “eXtreme Inception”, is a linear architecture network of 36 layers organized in 14 modules that have a residual connection in each module except the first and last module. This architecture uses depth-wise separable convolutions instead of Convolution Layer. The Xception used a modified depthwise separable convolution where the first layer performs a pointwise convolution followed by depthwise convolution as shown in figure 1.

b) **K-NN**

The k-nearest neighbours (KNN) algorithm is a simple, easy-to-implement supervised machine learning algorithm that can be used to solve both classification and regression problems. K-NN - algorithm assumes that similar things exist in proximity. In other words, similar things are near to each other.

c) **Multilayer Perceptron (MLP)**

Multilayer Perceptron is a class of feedforward artificial neural networks. An MLP consists of at least three layers of nodes: an input layer, a hidden layer, and an output layer.

Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training.

d) **Decision tree**

The decision tree can be described by a sequential decision-making process corresponding to the traversal of a binary tree (one that splits into two branches at each node) [15].

e) **Support Vector Machine (SVM)**

Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. The objective of the SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points. The dimension of the hyperplane depends upon the number of features.

### 4.2. Training and testing

The models were trained in the Kaggle taking advantage of Kaggle accelerator TPU and GPU. To evaluate the model performance the following metrics were calculated, accuracy, precision, f1 score, and recall. The metrics described were applied using the scikit-learn library

a) **Precision** is a metric that allows us to determine if the model is correct when the prediction of a snake species is positive when the predicted species is equal to the real species.

b) **Accuracy** is the most widely used measure for classifying models; it is the ratio of the classes correctly predicted to the existing class total.

c) **The recall** metric is a metric that allows you to determine how often the model correctly determines species in the test data set.

d) **F1score** determines the weighted average (harmonic) between Precision and Recall, in this metric the closer to 1, the better the model's performance.

## 5. Experiments and results

The experiment Xception and SVM had a reliable result compared with other models. The results here can be improved with further tests and experiments.

*Table 2: Models performance*

| | **Accuracy** | **F1 score** | **Precision** | **Recall** |
|---|---|---|---|---|
| Xception | 0.746 | 0.745 | 0.758 | 0.746 |
| KNN (k=2) | 0.554 | 0.562 | 0.633 | 0.554 |
| SVM | 0.741 | 0.739 | 0.746 | 0.741 |
| MLP | 0.589 | 0.594 | 0.620 | 0.589 |
| Decision tree | 0.571 | 0.570 | 0.576 | 0.571 |

We describe below with more details about the performance of each model during the training and testing phase.

### 5.1. Xception

We implement Xception Architecture from the scratch based on the description provided by the author in his article. We also add Batch Normalization layer after each Convolution operation to add some noise and bust our training. The Xception was implemented with the following hyperparameters: the loss function *categorical cross-entropy*, the optimizer *adam* with a *learning rate of 1e-5*, and we train for *70 epochs* in each fold. We train the Xception model using the k-fold cross-validation method with k=10, where k estimation points were generated, and the weighted average was calculated for each of the metrics used. The use of cross-validation allows the model to be trained and validated throughout the data set [16].

*Table 3: Xception performance*

| | **Mean** | **Std.** |
|---|---|---|
| Accuracy | 0.746 | 0.035 |
| f1_score | 0.745 | 0.035 |
| Precision | 0.758 | 0.036 |
| Recall | 0.746 | 0.035 |

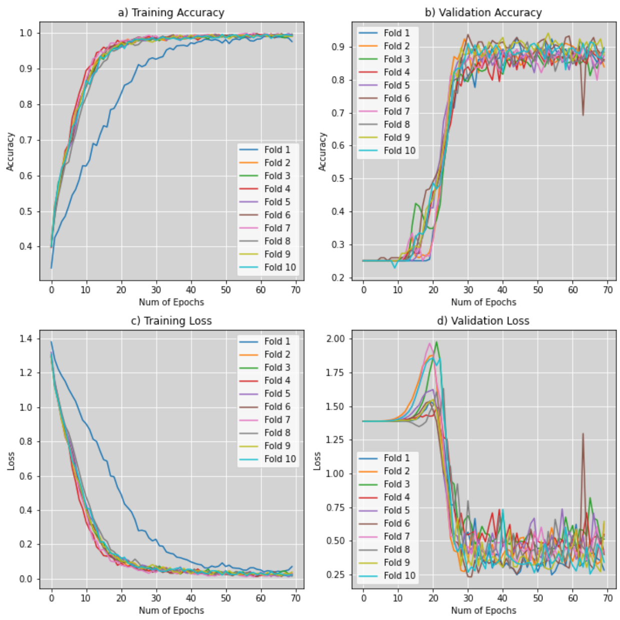


*Figure 1: Xception Performance*

The Xception model performed the best out of all th models giving us an accuracy of almost 75% and also an f1 score of 0.745. We believe Xception performed well due to the fact that it has been especially modelled for image classification which really helped in our case.

### 5.2. KNN

We implement knn using the euclidean distance and for the features extraction, we compute the histogram of the image. The knn algorithm had very low accuracy using histogram colour as features to train the model, we believe that some key dataset characteristics influence this behaviour on the knn model.

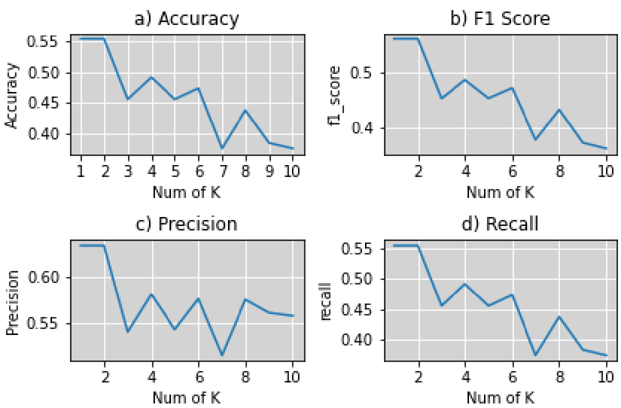


*Figure 2: performance of different k in knn*

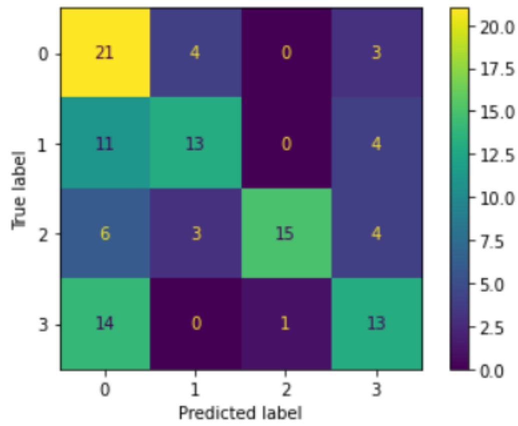


*Figure 3: KNN confusion matrix k=2*

We did not achieve particularly reliable results with knn with an accuracy of 55% and an f1 score of 0.562. One of the reasons we think this might be happening is because of the object which we are trying to classify i.e., the snake. Snakes tend to merge around with their environment like trees, mud, leaves which is what according to us, making it hard for our model to learn just based on the histogram of the images.

### 5.3. SVM

The SVM model achieve a performance like Xception when we put the following parameter *C=5.0, kernel='rbf', degree=3, gamma='scale'*.

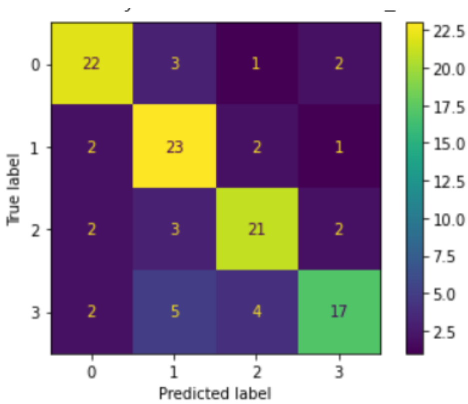


*Figure 4: SVM best performance confusion matrix*

We were able to achieve an accuracy as good as 74% with an f1 score of 0.739. We were able to achieve good result with SVM because in SVM the result is a hyperplane that separates the classes as best as possible. The weights represent this hyperplane, by giving you the coordinates of a vector that is orthogonal to the hyperplane

### 5.4. Decision Tree

We achieved an accuracy around 58% from 50%. We were able to improve the accuracy by setting the max depth parameter of decision tree classifier to 31. The low accuracy could be due to the fact that decision tree model is greedy and deterministic, hence they tend to overfit.

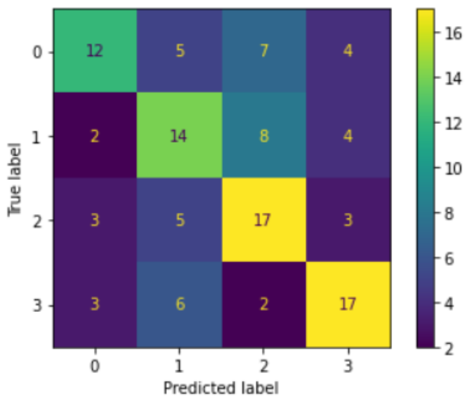


*Figure 5: Confusion matrix Decision tree*

### 5.5. Multilayer Perceptron

We implemented the Multilayer Perceptron by setting the maximum number of iterations to 300 and tweaking the parameters a little. The key difference between the MLP with a linear perceptron is the nonlinear activation function that help the MLP distinguish if the data is linearly separable.

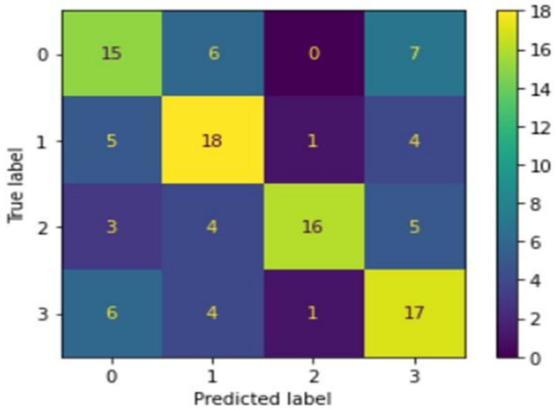


*Figure 6: Confusion matrix MLP*

We were not able to achieve satisfactory results with MLP with an accuracy of just 58% and an f1 score of 0.594. It was initially overfitting but after some tweaks we were not able to achieve good result with MLP.

## 6. Conclusion

The process of snake identification can be an extremely hard and a challenging process considering the vast factor that can change their pattern, so the results achieved were influenced by those factors. We were able to achieve descent results with Xception and SVM because of the advantage that these two models provide over the other models for image classification. It turned out to be a challenge since snakes tend to merge with the environment around them because of which it was difficult for the models to classify them based on the images. But at the same time with the help of data cleaning and feature extractions, we had 2 models which showed particularly reliable results on the image dataset and with time and a few more changes those two could end up providing excellent results going forward.

### 6.1.Future works.

We think that some of the methods here implemented could have better accuracy so, if we had more time, we would like to try the following:

- Increase the depth of decision tree
- Try different kernel for support vector, we try only the linear and rgf.
- Use the last layer of a Neural Network to extract features and train models like KNN and SVM.
- Research and try others feature extraction and Engineering.
- Increase the number of species in our dataset.
- Work more on the hyperparameter optimization.
- Try different distance for the knn.

## 7. Contribution

The group work as nice team during all process of this project, and each of us put their hand in a little of everything. The details of what each of us focus on most of time are detailed bellow per member

a) Emerson Cardoso
   - Dataset preparation, data augmentation cleaning, features extraction and Decision tree.
b) Sameer Hans
   - Implementation and improvement of the KNN and SVM.
c) Mohd Aamir
   - Implementation and improvement of the Xception and MLP.

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