054

055

056

057

058

059

060

061

062

063

064

065

066

067

068

069

070

071

072

073

074

075

076

077

078

079

080

081

082

083

084

085

086

087

088

089

090

091

092

093

094

095

096

097

098

099

100

101

102

103

104

105

106

107

# 002 003 004 005 006

# 007 008 009 010 011 012 013 014 015 016 017 018 019

031

032

# 039

## **Snake Specie Recognition using CNN**

### A. Problem Statement

Snakebites envenoming is one of the life threatening disease caused by snakebites, especially in developing countries. As per WHO around 4.5 to 5.4 million people get bitten by snake every year, of this around 81,000 to 138,000 people die each year. To treat the venomous snake bite you need to find the right antivenom and correctly identifying snake is very difficult since there are more than 3700 different species of snakes, also it's not very common to have knowledge on snakes in general. We are addressing this challenge by training our model to identify different snake species which can help victim to quickly identify if, the snake was venomous or nonvenomous, also for healthcare personnel to correctly choose antivenom based on the snake species.

There would be many challenges in solving the above problem statement such as: Pixel resemblance between the foreground and background may result in categorization errors. The considerable variation in the same attributes among objects in different photos makes it difficult for the model or architecture to generalise object features. Furthermore, a bias originates from the unequal number of images for the various classes. Additionally, generalising pre-processing transformations and procedures would be challenging due to the variation in image sizes between datasets..

Our application's objective is to conduct comparative analysis on the proposed CNN architectures and see how they are performing on the different datasets to identify the right snake species. On that premise, we will determine how the models have changed over time, which parameters provide various results, and how the model's depth affects the outcomes.

### **B.** Datasets

| Name          | Total Images | Image Size | Classes |
|---------------|--------------|------------|---------|
| Dataset 1 [1] | 12250        | 384*384    | 35      |
| Dataset 2 [2] | 15000        | 384*384    | 5       |
| Dataset 3 [3] | 20000        | 512*512    | 30      |

DataSet 1 - This dataset includes 15000 snake images which are divided into 5 classes of different species namely Northern Watersnake, Common Garter snake, DeKay's Brown snake, Black Rat snake, Western Diamondback rattlesnake. The classes are imbalanced and having an average of 3400 images per class.

DataSet 2 - This dataset consist of 13000 images which are classified into 35 classes, with an average of 350 images per class. The images have been scraped from Google Images. DataSet 3 - This dataset includes 20000 images from 30 different classes. The classes are categorised on the bases

of country, continent, genus and family. Additionally, this dataset classifies the species according to whether they are poisonous or not.

### C. Methods

We will be using three CNN models respectively, In which we will do a comparative analysis of below given models and observe difference in results.

- VGGNet16: Our aim is to perform initial study on VG-GNet having 16 no of layers, as it is relatively simpler architecture and focus on increasing the depth of the network and do not include advance blocks such as skip-connections as in ResNet.Therefore we feel the need of analysing how these simpler architectures perform in our case study.
- ResNet18: We aim to study the functionalities of Skip layers, how they improve the performance of the neural network and how it addresses Vanishing gradient problem. We intend to analyze the perturbation issues of the architecture and ways to overcome the same.
- ResNet32: In this, we want to compare outcomes based on network depth and examine how results change as we delve further into the network.

### C.1. Preprocessing Steps

As part of preprocessing we are using k-fold cross validation technique since results are less biased and it will provide the average of k folds evaluation to split our data into train and test set. Then we will be using data-augmentation to perform transformations like flipping, scaling, rotation, etc and this will help in preventing our model from learning irrelevant features.

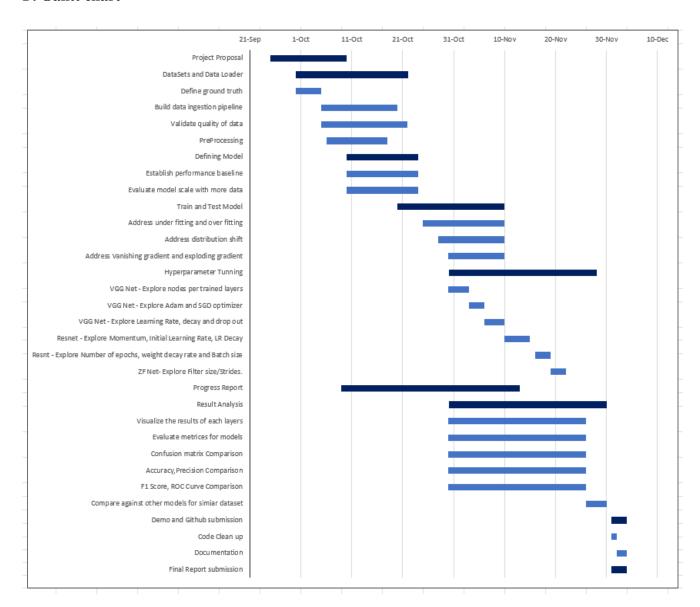
### D. Evaluation matrix

In order to classify our model, we will be using metrices like Accuracy, precision, recall, F1 score and ROC curve. Further, confusion matrix can also be plotted to determine the performance of the model.

# E. Expectation

We expect to develop a snake classification system which can help victims to quickly check if the snake was venomous or not and if they need medical attention or not, also for doctors to choose a correct anti-venom based on the snake type.

### F. Gantt chart



### Milestones

- Milestone 1: In this stage, we are matching the required prerequisites with our problem statement and by the end of this stage we would have our data sets and models and would also have finalized the team as well as their roles.
- Milestone 2: This stage is very important as we will explore our data-set in-depth, find the number of classes, and the size of the image and then will present it in the proposal.
- Milestone 3: In this stage, we are going to study 3 different frameworks, build data pipeline and train our models using 3 different data set.
- Milestone 4: This stage will define the success of our project, we are going to fine tune our model with various hyperparameters. We will compare different matrices obtained from testing and evaluate how different models work with same data and different hyperparameters.
- Milestone 5: At the last stage we will have our final project ready along with a report and presentation on the detail of our model and code and how it works.

References

| 046                               |  |
|-----------------------------------|--|
| 216                               |  |
| 217                               |  |
| 218                               |  |
| 219                               |  |
| <ul><li>220</li><li>221</li></ul> |  |
|                                   |  |
| 222                               |  |
| <ul><li>223</li><li>224</li></ul> |  |
|                                   |  |
| 225                               |  |
| 226                               |  |
| 227                               |  |
| 228                               |  |
| 229                               |  |
| <ul><li>230</li><li>231</li></ul> |  |
|                                   |  |
| 232                               |  |
| <ul><li>233</li><li>234</li></ul> |  |
|                                   |  |
| 235                               |  |
| <ul><li>236</li><li>237</li></ul> |  |
|                                   |  |
| 238                               |  |
| 239                               |  |
| <ul><li>240</li><li>241</li></ul> |  |
|                                   |  |
| 242                               |  |
| 243                               |  |
| 244                               |  |
| <ul><li>245</li><li>246</li></ul> |  |
| 246<br>247                        |  |
|                                   |  |
| <ul><li>248</li><li>249</li></ul> |  |
| 249<br>250                        |  |
| 250<br>251                        |  |
| 251<br>252                        |  |
| 252<br>253                        |  |
| 253<br>254                        |  |
| 254<br>255                        |  |
| 255<br>256                        |  |
| 256<br>257                        |  |
| 25 <i>i</i><br>258                |  |
| 258<br>259                        |  |
| 209                               |  |

| [1] Identifying | different | breeds | of  | snakes. | https://   |
|-----------------|-----------|--------|-----|---------|------------|
| www . kag       | gle.com   | m/dat  | ase | ets/dut | tadebadri/ |
| identify        | ing-di    | fferen | t-1 | oreeds- | of-snakes? |
| select=d        | lataset.  | 1, 4   |     |         |            |

- [2] Pre-processed snake images. https://www.kaggle.com/datasets/sameeharahman/preprocessed-snake-images?datasetId=578272.1,4
- [3] Snakes species. https://www.kaggle.com/ datasets/goelyash/165-different-snakesspecies. 1, 4
- [4] Sharada P. Mohanty Isabelle Bolon Marcel Salathé Andrew M. Durso, Gokula Krishnan Moorthy and Rafael Ruiz de Castañeda2. Supervised learning computer vision benchmark for snake species identification from photographs: Implications for herpetology and global health. In https://www.frontiersin.org/articles/10.3389/frai.2021.582110/full, 2021. 4
- [5] Kamron Bhavnagri. Modern algorithms: Choosing a model. In https://www.kamwithk.com/modern-algorithms-choosing-a-model, 2020.
- [6] Andrew Zisserman Karen Simonyan. Very deep convolutional networks for large-scale image recognition. In arXiv preprint, 2014. 4
- [7] Rob Fergus Matthew D. Zeiler. Visualizing and understanding convolutional networks. In *paper*, 2013. 4
- [8] Mohammad Shahadat Hossain Raihan Ul Islam Nagifa Ilma Progga, Noortaz Rezoana and Karl Andersson. A cnn based model for venomous and non-venomous snake classification. In Communications in Computer and Information Science book, volume 1435, 2021. 4
- [9] Abhishek Verma. Zfnet: An explanation of paper with code. In https://towardsdatascience.com/zfnet-an-explanation-of-paper-with-code-flbd6752121d, 2020. 4
- [10] Richard O. Sinnott Zihan Yang. Snake detection and classification using deep learning. In Proceedings of the 54th Hawaii International Conference on System Sciences, 2021.