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Deep Learning Model or Identifying Snakes Using Snakes Bite Marks

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Abstract: *In order to save patients, doctors may be able to diagnose the victim and provide the correct anti-venom by recognising snakes by their bite marks. For doctors, aiding patients who have been bitten by snakes is a crucial step. Hence, research was conducted utilising CNN (Convolution Neural Network) model in Deep Learning methods to analyse photos and categorise them as belonging to various snake families. To categorise various snakes as venomous or non-poisonous snakes, the CNN model needs photographs of their bite marks. By analysing images of venomous snakes' bite markings, it is then able to identify the family of venomous snakes. The proposed deep learning model has to be trained repeatedly using all feasible distinct photos of the same snake family and various snake families in order to get correct results. The CNN model's effectiveness depends on its ability to recognise patterns in the input photos and identify the family of snakes. The method may take some time to provide results if the input photographs are many and large in size. It must be taken into account to provide outcomes with shorter execution times.*

Key Word: *CNN, Snake Bite, Machine learning, and Bite Marks.*

I.INTRODUCTION

Snake bites and treating patients to recover from the poisons inflicted by snakes are major threats to human life in India and around the world. Moreover, there are several snake families around the world. They should not be attacked unnecessarily since they have the right to live in this lovely planet. Snakes in agricultural areas are a significant concern for farmers. To catch the rats, they are more present on the agricultural land's side. Unfortunately, doctors have a difficult time treating patients when farmers are bitten by snakes since it is important to know what sort of snakes are biting the formers right now while treating patients.

Material and Method
Non-Venomous Snakes:

Fig.no.1 Non-Venomous Snakes

snakes found in India like, Indian Rat, Common Cat Snake, Checkered Keelbackl, Dog-faced water snake, Banded racer, Sand Boa, Black-headed Royal Snake, Common Trinket, and Banded Kukri. Non- Venomous Snakes They may have a rounded head, round pupils, no heat-sensing pit on their head, and other characteristics.

Venomous Snakes:

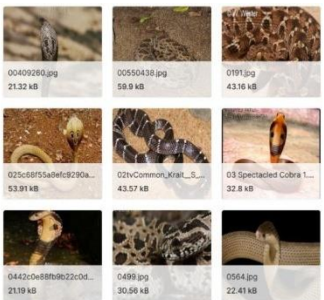
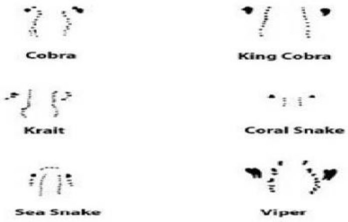


Fig.no.2 Venomous Snakes

Snakes with venom are extremely deadly and can cause fatalities in people. the several families of poisonous snakes like, Indian Krait, King Cobra, Russell’s viper, Indian Cobra, Malabar Pit Viper, Bamboo Pit Vipers, Hump Nosed Pit Viper, Banded Sea Krait and Bamboo Pit Vipers. Venomous snakes have rough triangle-shaped heads, daytime pupils that resemble slits, and they may have heat- sensing pits on their heads. The majority of snakes have a number of similar physical traits.
Nonetheless, they will be distinct when their variations in are plainly visible and recorded. Snakes will bite humans and will attack any kind of prey. When venomous snakes bite their victim, the poison from the gland may be injected into the prey. The prey will be poisoned by that venom and will either become paralysed or die in a short period of time. People need to be able to see the snake's bite marks whenever it bites. People may tell which snakes are "Non-Venomous" or "Venomous" by looking at the bite scars on them.



II.LITREATURE SURVEY

Progga et,al, mentions that the snakes are warm- blooded, curled reptiles belonging to the phylum serpents. Any traits, such as head shape, body shape, physical appearance, skin texture, and eye structure, may be utilised to distinguish between venomous and nonvenomous snakes that are uncommon among non-experts. The automatic classification of snake species based on the image has also been done using a typical machine learning approach, although the features still need to be manually tweaked. This led to the proposal in this study of a Deep convolutional neural network to divide snakes into poisonous and non- venomous groups. Seven neural networks with our suggested model are implemented using a batch of data including 1766 images of snakes. Ultimately, the identification process accuracy is increased even more by using the transfer learning approach. The suggested model can identify the snake photos with a high accuracy of 91.30%, according to five-fold cross-validating for SGD optimizer. Without cross-validation, the model's accuracy is 90.50%. [1]

Rajabizadeh et.al. describes that automated snake picture recognition is crucial for a number of reasons, but managing snake bites is the most crucial. The automatic detection of snakes in photographs may aid in patient care improvement and deadly snake avoidance. For the first time, a comparison of the accuracy of a number of cutting-edge machine learning techniques, from holistic to neural network algorithms, has been made in this study. Six different snake species are
the subject of the study at Iran's Tehran Province's Lar National Park. In this study, the dimension reduction strategy [principle component analysis (PCA) and linear discriminant analysis (LDA)] is combined with the holistic approaches [k-nearest neighbours (kNN), support vector machine (SVM), and logistic regression (LR)] as the feature extractor. The classifier does not provide an accuracy of more than 50% when combined with PCA in holistic approaches (kNN, SVM, LR), but its performance is greatly enhanced when the key features are extracted using LDA. With a kernel value of "rbf," a combination of LDA and SVM results in test accuracy of 84%. This discovery opens the door for developing mobile applications for identifying snake images. [2]

Miraemiliana Murat et,al., states that It is important and helpful to create an automated categorization system for plant species since it will make it easier for both experts and the general public to recognise different plant species. It has been established that the MSD and HOG combination was effective for classifying the species of tropical shrubs. As far as being invariant to translation, rotation, and scaling, Hu and ZM descriptors also increased the accuracy in the categorization of tropical shrub species. In this study, ANN fared better than the other methods for classifying tropical shrub species. The categorization of tropical shrub species can employ feature selection approaches since equivalent results can be reached with fewer descriptors and at a lower computational and financial cost. [4]

III.METHODOLOGY

Identifying the family of the snake that bit the prey is the key challenge in snake bite cases. If the survivors are aware of the snake family, doctors may treat the patient with the best antivenom and clinical techniques. But, if the snake's family is unknown, it will be difficult for medics to treat the survivor. Research is being done in this region to determine what kind of snake bit the patient and what kind of anti-venom has to be administered. Here, a method based on deep learning is suggested to identify the snake's family using the Convolution Neural Network model.

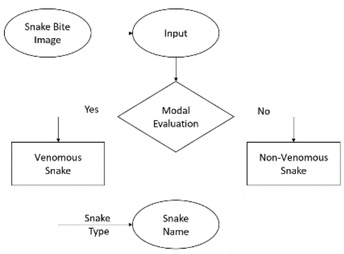


Fig.no.5 Flow Chart

Dataset

This image collection depicts several snake species that may be found in India. The dataset is divided into train and test groups first, followed by non- venomous and venomous categories. There are pictures of rat snakes, cobras, vipers, and green tree vines in it. Each image is 400400 in size. Snake bite marks on pictures or images provide the input to the CNN model. The family of snakes will be the model's output. The fang marks left by the several poisonous snakes are seen in the accompanying fig. 3. The bite patterns or markings of certain snakes appear distinct, as do their fang marks. To train the CNN model to recognise the family of the provided photos of snake bites, this type of bite mark images or data set is required.

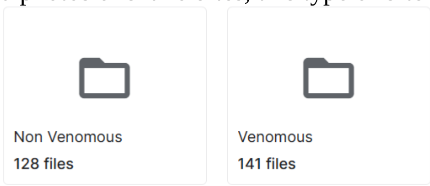


Fig.no.3 Dataset

We prepared the dataset for training and testing. The dataset was gathered from individual w, both male and female, who ranged in age from 20 to 25. For certain dynamic-based isolated motions, we collected the relevant data. Each video sample has an average length of 2 s, a resolution of 1920 x 1080, and a frame rate of 28 FPS. There were 28 terms in the collection, and the 16 participants produced roughly 1100 video clips for each word. This dataset wasn't altered in any way from its original state, including brightness, orientation, Kinect sensor settings, backdrop modifications, gloves, etc.

Feature Extraction using VGG16

The 16-layer design of the VGG16 model, a form of CNN model, is what makes it most useful for automated feature extraction. It is trained using the ImageNet dataset, which has 14 million photos divided into 22,000 categories. For feature extraction, just a few network layers are utilised rather than the whole VGG16 model.

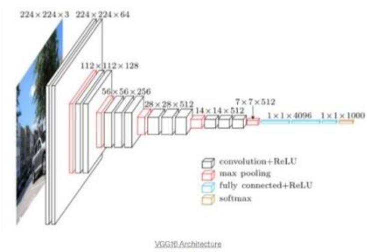


Fig.no. 4 VGG Architecture

Preparing Dataset:

Cleaning and converting raw data before processing and analysis is known as data preparation. Prior to processing, it is a crucial stage that frequently entails reformatting data, making adjustments to data, and fusing datasets to enhance data. The method used to complete blank fields in datasets is called feature imputation. It is crucial since the majority of machine learning models fail when the dataset contains missing data. It is the act of changing raw data so that data scientists and analysts may run it through machine learning algorithms to find insights or make predictions. incorrectly constructed or formatted data.

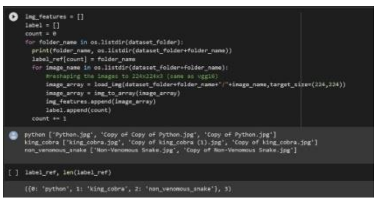


Fig.no. 4 VGG ArchitectureFeature Extraction

The quantity of redundant data in the data collection is decreased with the aid of feature extraction. In the end, the data reduction speeds up the learning and generalisation phases of the machine learning process while also enabling the model to be built with less machine effort. The neural network is often used for multiclass categorization in CNN's output layer. Instead of doing it by hand, CNN utilises a feature extractor in the training phase. The feature extractor used by CNN is made up of unique neural network types, the weights of which are determined during training.

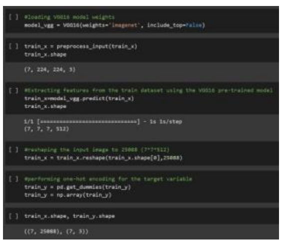
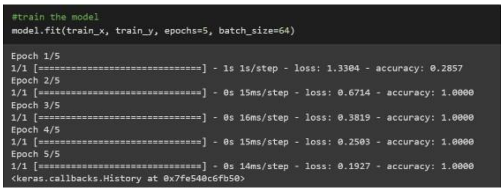


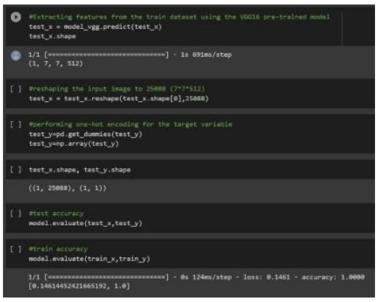
Fig.no. 4 Feature ExtractionTraining the Model

Simply said, training a model entail learning (deciding) appropriate values for each weight and bias from labelled samples. Empirical risk minimization is the technique by which a machine learning algorithm constructs a model in supervised learning by analysing several examplesand looking for a model that minimises loss.



```
#train the model
model.fit(train_x, train_y, epochs=5, batch_size=64)

Epoch 1/5
1/1 [==============================] - 1s 1s/step - loss: 1.3304 - accuracy: 0.2857
Epoch 2/5
1/1 [==============================] - 0s 15ms/step - loss: 0.6714 - accuracy: 1.0000
Epoch 3/5
1/1 [==============================] - 0s 16ms/step - loss: 0.3819 - accuracy: 1.0000
Epoch 4/5
1/1 [==============================] - 0s 15ms/step - loss: 0.2503 - accuracy: 1.0000
Epoch 5/5
1/1 [==============================] - 0s 14ms/step - loss: 0.1927 - accuracy: 1.0000
<keras.callbacks.History at 0x7fe540c6fb50>
```

Fig.no. 4 Training

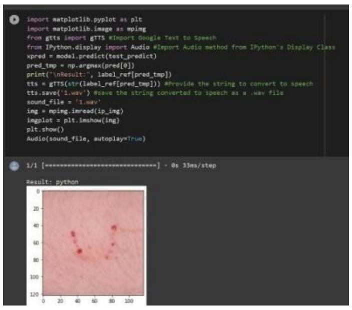


```
#Extracting features from the train dataset using the VGG16 pre-trained model
test_x = model_vgg.predict(test_x)
test_x.shape

1/1 [==============================] - 1s 691ms/step
(1, 7, 7, 512)

[ ] #reshaping the input image to 25088 (7*7*512)
    test_x = test_x.reshape(test_x.shape[0],25088)

[ ] #performing one-hot encoding for the target variable
    test_y=pd.get_dummies(test_y)
    test_y=np.array(test_y)

[ ] test_x.shape, test_y.shape

    ((1, 25088), (1, 1))

[ ] #test accuracy
    model.evaluate(test_x,test_y)

[ ] #train accuracy
    model.evaluate(train_x,train_y)

    1/1 [==============================] - 0s 124ms/step - loss: 0.1461 - accuracy: 1.0000
    [0.14614452421665192, 1.0]
```

Fig.no. 4 Accuracy

IV.RESULT

The Deep Learning with CNN model may readily assist in object identification in the provided photos. Yet, the model must occasionally be trained with fresh patterns using the same objects and colours. The snakes' bite marks must also be processed in order to identify them. There are already various snake identification applications available that list each body characteristic of the snakes one by one. Snakes must either be in human hands or be with humans for a time in order to trace everything. Yet once a snake has bitten someone, it cannot be stopped in a community or in a field of crops. Such people might wish to leave the field.



```
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
from gtts import gTTS #Import Google Text to Speech
from IPython.display import Audio #Import Audio method from IPython's Display Class
xpred = model.predict(test_predict)
pred_tmp = np.argmax(pred[0])
print("\nResult:", label_ref[pred_tmp])
tts = gTTS(str(label_ref[pred_tmp])) #Provide the string to convert to speech
tts.save('1.wav') #save the string converted to speech as a .wav file
sound_file = '1.wav'
img = mpimg.imread(ip_img)
imgplot = plt.imshow(img)
plt.show()
Audio(sound_file, autoplay=True)

1/1 [==============================] - 0s 33ms/step

Result: python
```

Fig.no.5 Snake Detection

V.CONCLUSION

The concept put out here is based on the "Deep Learning" methodology to regularly train the system for analysing fresh input images to identifythe kind of snake family to start treating the victimappropriately. In order to locate objects in the input photos, the CNN model is particularly designed for image processing. After the system has previously been trained using a sufficient set of input photographs concerning the snake bite marks, this model can assist in identifying the suitable snake bite patterns.

Future Scope

The user interface webpage can be developed with login pages where user can login and give snake bite images as input. When searched, the input image will be verified with the model which trained and based on that results will be displayed along with name of the snake. With the help of this webpage, user can easily analyse the bite mark.

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