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Deep Learning Models for Accurate Snake Species Identification from Bite Marks

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***Abstract*— Snakebite envenomation is a significant medical emergency requiring rapid and accurate identification of the responsible snake species for effective treatment. In this study, we propose a deep learning-based approach for snake species identification using images of snake bite marks. We employed three neural network models: a custom Convolutional Neural Network (CNN), Inception V3, and VGG16. The dataset includes images of bite marks from six snake species: cobra, coral snake, king cobra, krait, sea snake, and viper. Preprocessing steps such as rescaling, denoising, and data augmentation were applied to enhance the quality and diversity of the training data.**

The custom CNN model achieved a test accuracy of 13.3% with a test loss of 4.136, indicating challenges in learning from the bite mark images. Inception V3 significantly outperformed the custom CNN, achieving a test accuracy of 96.7% and a test loss of 0.191. VGG16 demonstrated the highest performance with a test accuracy of 99.3% and a test loss of 0.078, highlighting the effectiveness of transfer learning and pre-trained models in complex image classification tasks.

Our findings underscore the importance of leveraging advanced deep learning architectures for accurate snake species identification from bite marks. Future research could explore ensemble methods, real-time classification systems, and integration with other diagnostic tools to further enhance the applicability and robustness of these models in medical and herpetological applications.

Keywords*— *Snake species identification, Snake bite marks, CNN (Convolutional neural network), Inception V3, VGG16, Deep learning etc.,

I. INTRODUCTION

Snakebites pose a significant public health challenge, particularly in regions where venomous snakes are prevalent. Prompt and accurate identification of the snake species involved is crucial for administering appropriate antivenom and medical treatment, thereby reducing morbidity and mortality associated with snake envenomation. Traditional methods of snake species identification rely on visual observation of the snake or its remains, which can be challenging, especially in cases where the snake is not observed directly or where only bite marks are present.

Advancements in computer vision and deep learning offer promising avenues for automating snake species identification based on bite marks. In this study, we propose a novel approach utilizing convolutional neural network (CNN) architectures, including Inception V3 and VGG16, to accurately classify snake species based on bite mark images. CNNs have demonstrated remarkable success in various image recognition tasks, making them well-suited for the complex patterns present in snake bite marks.

The objective of this research is to develop a robust and efficient system capable of distinguishing between different snake species commonly encountered in snakebite incidents. The targeted species include cobras, coral snakes, king cobras, kraits, sea snakes, and vipers, which pose varying degrees of medical risk based on the toxicity of their venom.

The methodology involves several key steps. Firstly, image preprocessing techniques are applied to enhance the features relevant to snake bite marks. Subsequently, pre-trained CNN models, namely Inception V3 and VGG16, are employed for feature extraction, leveraging their ability to capture intricate patterns in images. The extracted features are then used to train machine learning models for snake species classification.

The evaluation of the proposed models is conducted using a curated dataset comprising bite mark images corresponding to the target snake species. Performance metrics such as accuracy and loss are utilized to assess the efficacy of the models in accurately identifying snake species. Additionally, comparative analysis is performed to evaluate the strengths and weaknesses of each CNN architecture in this context.

The outcomes of this research have significant implications for clinical practice, particularly in resource-constrained settings where access to snakebite treatment facilities may be limited. A reliable automated system for snake species identification based on bite marks could expedite treatment decisions, leading to improved patient outcomes and reduced healthcare burden. Moreover, the insights gained from this study contribute to the broader field of computer vision applications in healthcare and environmental conservation efforts aimed at mitigating the impact of snakebite incidents.

The organizational framework of this study divides the research work in the different sections. The Literature survey is presented in section 2. In section 3 discussed about proposed system methodologies. Further, in section 4 shown Results is discussed and. Conclusion and future work are presented by last sections 5.

II. LITERATURE SURVEY

In the work of Mrugendra [1] the system is used to identify snake species from their visual traits in order to provide suitable treatment, thus preventing from the subsequent deaths. This system involves techniques based on Image Processing, Convolution Neural Networks and Deep Learning for this proposed system. The models which had been fine-tuned and optimized had been measured primarily based on the overall performance metrics and training results. An overall of 3050 images are used for training and validation that are separated into 28 species.

In the work of Nur liy ana [2] it involves the collection of text-based totally description of snake's species based on the provided snake images through the use of questionnaire strategies. Then, important functions had been extracted through the use of term frequency – inverse file frequency (TF-IDF), and those capabilities had been supplied to system through transfer learning algorithms to study and predict the snake species with the help of Weka tool. The result of 180 samples text-based description collected from 60 respondents was used for training and classification. Then, features extraction techniques which includes stop phrase elimination, stemmer, and tokenizer had been done. In this paper the overall performances show that the J48 is the best and suited for text classification task. The drawback of the work is that if the respondents are unable to describe the snake image, the snake species cannot be identified.

A parallel processed inter-feature product similarity fusion based automatic classification of snake species, including the Spectacled **Cobra, Russel's Viper, and King Cobra, was presented in Alex James and co. [3].** They utilized a dataset of 88 pictures of cobra and 48 pictures of snake for the underlying component scientific categorization investigation and perceived 31 unmistakable systematically significant elements from snake pictures for programmed snake characterization of studies. The K - nearest-neighbor classifier was utilized by the authors in this paper. The class of the unknown data sample is distinguished by this classifier from its nearest neighbor, whose class is already known. Mean variance filtering is used to normalize the taxonomically applicable features chosen from the snake pictures for automated class. Characteristic vectors are constructed from the normalized functions' orientation and gradient histograms. A proposed minimal distance product similarity metric classifier is used to evaluate these characteristic vectors.

A Patel et al. [4] created a smartphone app that uses deep learning to distinguish images of nine distinct snake species that live on the Ecuadorian Galápagos Islands. Algorithms for object detection and classification have been used to accomplish this. The images included in the dataset were sourced from the Tropical Herping image collection as well as from Google and Flickr web scrapings. Various mixes of design models like Quicker R-CNN, Beginning V2, ResNet, MobileNet, and VGG16 have been tried for object discovery and picture characterization. With a classification accuracy of 75%, the Faster R-CNN with ResNet-based model performed the best.

James, Alex Pappachen [5] developed a taxonomy-based function intended for use by computer scientists and herpetologists to solve the automated snake identity problem in his paper. Each sample's 38 taxonomically applicable functions were stored in the function database. Out of those 38 capabilities, top capabilities which affect class not set in stone. To find the top capabilities from the entire information base, twelve trademark evaluators had been utilized. In addition, a collection of distinct search strategies, such as Genetic Search, Greedy Step-wise, and Linear Forward Selection, were utilized. The dataset's function-subset evaluation revealed that snake identity requires at least 15 functions. It became seen that those capabilities had been almost correspondingly dispensed from the coherent gathering of top, side and body perspectives on snake pictures.

Nagifa Ilma [6] A deep convolutional neural network has been proposed in this paper to classify snakes into two categories that is venomous and non-venomous. The dataset is collected from Kaggle of 1766 snake images which contains of both venomous and non-venomous and with the help of the neural network it is able to implemented the proposed model. Fivefold

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cross validation model for SGD optimizer shows that the proposed model is capable of classifying the snake images with high accuracy of 90.50%. They are using transfer learning technique to boost the identification process accuracy.

In the paper of **Isa Setiawan Abdurrazaq [7]** snake species are identified based on the features such as head shape, body shape, texture, skin color, eye shape with the help of convolutional neural network. The classification of images has been developed manually with the help of deep learning technique and the parameters have to be changed manually. The dataset is collected manually by the trimaharani who handles emergency cases in Indonesia. It consists of 415 images for five venomous snake species they are krait 77, cobra 91, viper 72, pit viper 95, Russell’s viper 80. Three different CNN models are used in this model shallow, medium and deep architecture. After testing of three model medium architecture provides the best accuracy of 82%.

Anika patel [8] used object detection and classification for racer snakes in Galapagos islands for developing mobile application which will support the visitors in Galapagos to identify correct snake species from the uploaded images with the help of region based convolutional neural network in deep learning. The model was built using TensorFlow which is connected to API with the python technologies. Four models have been used for image classification inception v2, VGG16, ResNet, MobileNet and dataset has been collected from there different sources tropic herping, google, flickr which consists of 9 species with 247 images. MobileNet achieves the accuracy of 10%, VGG16 and Inception V2 70%, ResNet 75%.

Alex James et al. [9] presented a parallel processed inter-feature product similarity fusion based automatic classification of kinds of snakes such as Spectacled Cobra, Russel’s Viper and King Cobra to name a few. The authors used a database of 88 images of cobra and 48 images of viper for the initial feature taxonomy analysis and identified 31 different taxonomically relevant features from snake images for automated snake classification studies. In this paper, the authors use the nearest-neighbour classifier. This classifier identifies the class of unknown data sample from its nearest neighbour, whose class is already known. For automatic classification, the taxonomically relevant features are selected from the snake images and are normalized using mean-variance filtering. The histograms of gradients and orientation of these normalized features are used as feature vectors..

Alex Pappachen James et al. [10] in his paper presented the automatic snake identification problem by developing a taxonomy-based feature, targeted for use by computer scientists and herpetologists. The feature database contained 38 taxonomically relevant features of each sample. Out of these 38 features, top features that have highest impact on classification were determined.

III. DATASET

For this method focused on snake bite mark identification, we have meticulously curated a dataset comprising snake bite marks from six distinct snake species: cobra, coral snake, king cobra, krait, sea snake, and viper. Each species represents a unique and potentially hazardous threat to human health, making accurate identification crucial for prompt and effective medical treatment. Our dataset encompasses a diverse range of bite marks, captured under various environmental conditions and from different geographical locations where these snake species are prevalent. We have ensured that the images are of high resolution and quality, allowing for detailed analysis of the bite marks' characteristics. Annotations have been meticulously applied to each image, indicating the species of snake responsible for the bite. Additional metadata, such as the location and date of the incident, severity of the bite, and any other pertinent details, have also been included to provide comprehensive context for each image.Ethical considerations have been paramount throughout the data collection process, with a focus on ensuring the responsible and humane treatment of animals and adherence to relevant regulations. Our dataset not only serves as a valuable resource for training machine learning models to identify snake species based on bite marks but also contributes to the broader understanding of snakebite management and treatment. By making this dataset openly accessible to the research community, we aim to foster collaboration and innovation in the field of snakebite identification and healthcare. Figure 1, 2 and 3 shows the dataset and image sizes and resolutions.

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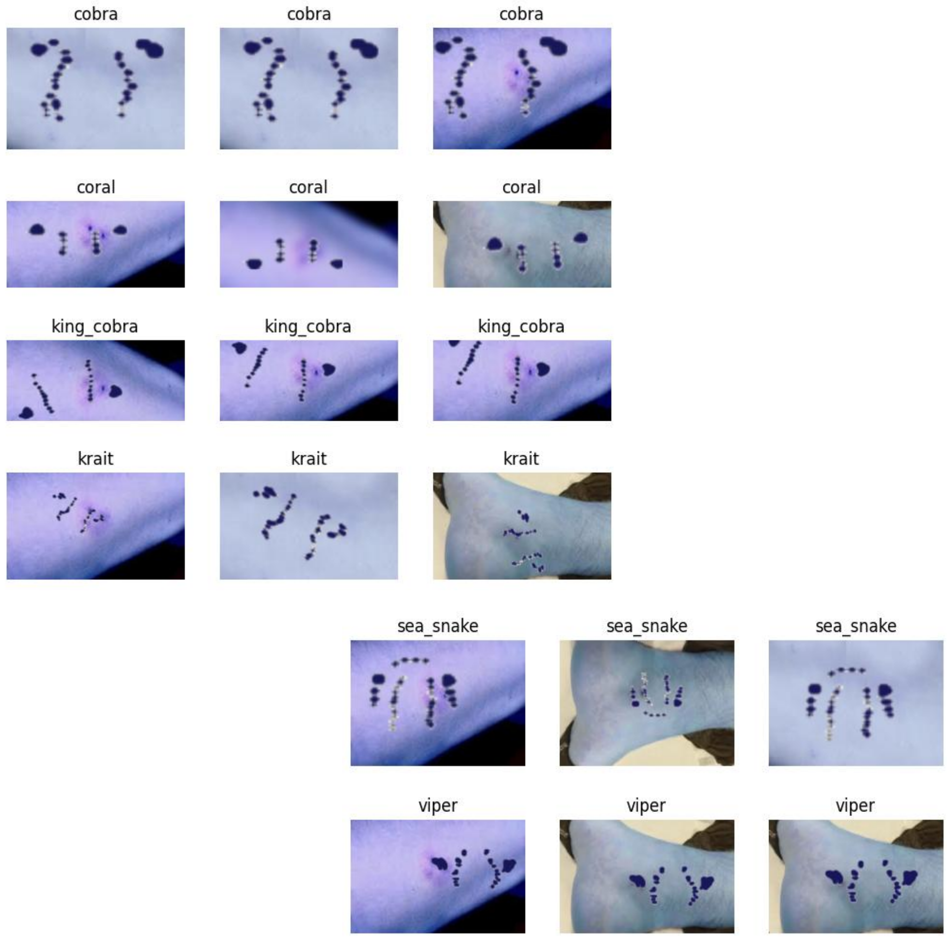

Fig. 1. Data set

The dataset contains a variety of images showcasing different conditions of snake bytes shown in fig.2 to fig.7.

A. Exploratory Data Analysis

Through this exploratory analysis, we gained insights into the relative abundance of different snake species in our dataset. This understanding serves as a crucial foundation for further analysis and model development, ensuring that our subsequent efforts are informed by the dataset's inherent characteristics.

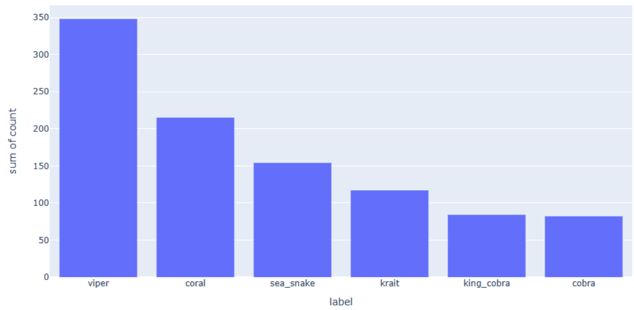

Fig. 2. Data Analysis

Extract Image Properties (Size, Resolution, Color Distribution)

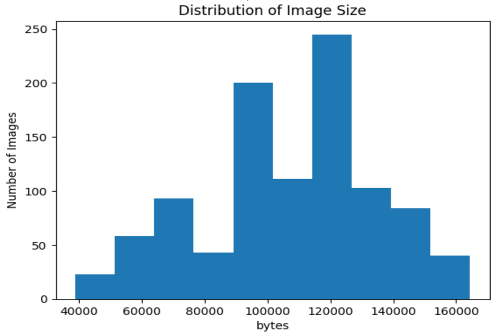

Fig. 3. Distribution of images

B. Distribution of images size

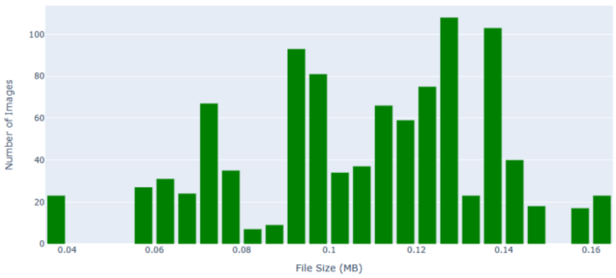

Fig. 4. Distribution of image size

C. Distribution of image resolution

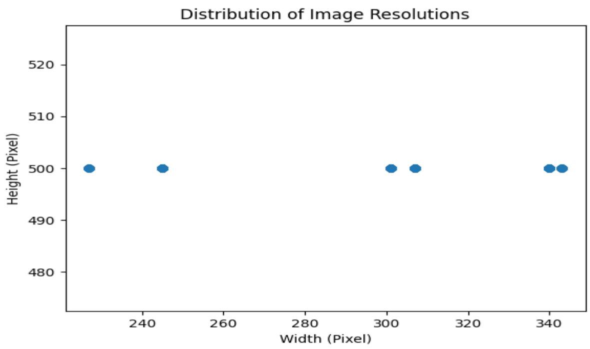

Fig. 5. Distriibution of image resolution

D. Distibution of image resolution

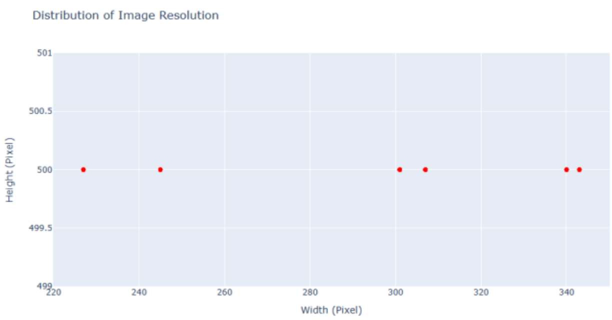

Fig. 6. Distribution of image resolution

E. Mean color distribution

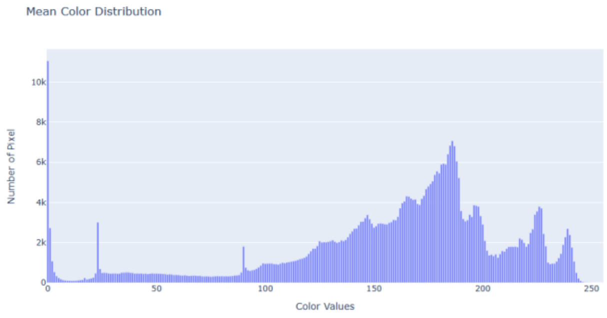

Fig. 7. Color Distribution

IV. PROPOSED METHOD

For our proposed method, we aim to train a deep learning model to classify snake bite marks based on the images of bite marks. We employ convolutional neural network (CNN) architecture, leveraging image data augmentation techniques to enhance the model's robustness and generalization capabilities. We begin by defining the input image dimensions to be 224x224 pixels, which is a common size for many pre-trained CNN models. This ensures compatibility with widely used architectures such as VGG16 and Inception V3. We set the batch size to 32, which represents the number of images processed simultaneously during model training. This value strikes a balance between computational efficiency and model stability. The data generators are configured to read image paths from the DataFrame columns specified by "img_path" and label information from the "label" column. Images are resized to the specified target size (224x224) and converted to RGB color mode. By employing this method, we can efficiently train a CNN model to classify snake bite marks, leveraging data augmentation to enhance model performance and robustness. This approach allows us to effectively handle the challenges posed by limited and imbalanced datasets, ultimately leading to improved classification accuracy and reliability.

A. System Architecture

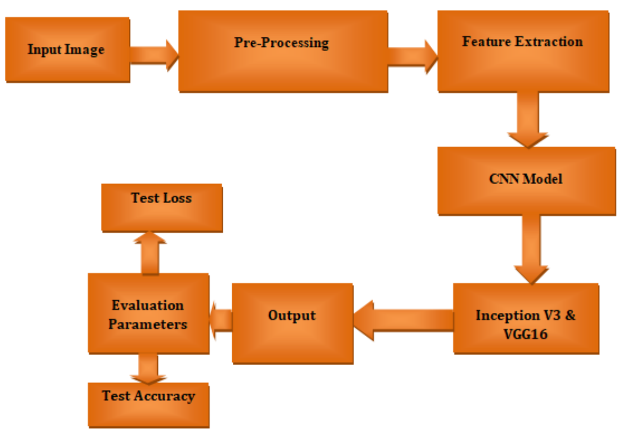

Fig. 8. System Architecture

1. Input Image:

This block represents the collection of images of snake bite marks. The images are initially stored in a directory and their paths are recorded in a DataFrame along with their corresponding labels (species of the snake).

2. Preprocessing:

The preprocessing block involves several steps to prepare the images for training: Scaling pixel values to the range [0, 1]. Applying a preprocessing function to reduce noise in the images. Applying transformations such as rotation, width/height shifts, shear, zoom, and horizontal flip to artificially increase the diversity of the training data. ImageDataGenerator from Keras is used for this purpose.

3. *Feature Extraction:*

In this step, the preprocessed images are fed into feature extraction layers of the neural network models. These layers are responsible for identifying and extracting key features from the images that are crucial for differentiating between different snake species. Convolutional layers of the CNN, Inception V3, and VGG16 models perform feature extraction.

4. *CNN Model:*

A convolutional neural network (CNN) model is trained on the preprocessed images to learn to classify the snake bite marks. The CNN architecture typically includes several convolutional layers followed by pooling layers, and finally, fully connected layers. Custom-designed CNN model specific to the task.

5. *Inception V3 & VGG16 Models:*

In addition to a custom CNN, two pre-trained models, Inception V3 and VGG16, are fine-tuned for the snake bite mark classification task. These models have been previously trained on large image datasets and can be adapted to our specific task through transfer learning.

- **Inception V3**: Known for its inception modules that capture multi-scale features.
- **VGG16**: Characterized by its simplicity with 16 layers and known for its performance in image classification tasks.

6. *Output:*

The output of the models is the predicted class labels for the input images. These predictions indicate the snake species responsible for the bite marks. Predicted labels and probabilities for each class.

7. *Evaluation Parameters:*

After training the models, their performance is evaluated using the test dataset. Key metrics include:

- **Test Accuracy**: The proportion of correctly classified images out of the total number of test images.
- **Test Loss**: The loss value computed on the test set, indicating how well the model's predictions match the true labels.

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B. Methodology

The methodology for our project involves several key steps, ranging from data collection and preprocessing to model training and evaluation. Below is a detailed description of each step in the methodology.

1. Data Collection

- **Image Dataset**: We collected a comprehensive dataset of snake bite mark images, focusing on six snake species: cobra, coral snake, king cobra, krait, sea snake, and viper. The dataset includes high-resolution images annotated with the species labels.
- **Data Splitting**: The dataset is split into three subsets: training, validation, and test sets. This ensures that we can train the model, tune its hyperparameters, and evaluate its performance on unseen data.

2. Data Preprocessing and Augmentation

- **Image Rescaling**: All images are rescaled to have pixel values in the range [0,1]. This normalization step is essential for effective model training.
- **Denoising**: We apply a preprocessing function to reduce noise in the images, enhancing the quality and clarity of the bite marks.
- **Data Augmentation**: For the training set, we apply various augmentation techniques to increase the diversity of the data. These include:
  - **Rotation**: Randomly rotating images within a range of 30 degrees.
  - **Width and Height Shifts**: Randomly shifting images horizontally by up to 10% and vertically by up to 20%.
  - **Shear Transformation**: Applying shear transformations up to 10%.
  - **Zooming**: Randomly zooming in on images up to 20%.
  - **Horizontal Flipping**: Randomly flipping images horizontally.

Model Training

- **Model Selection**: We utilize three different models: a custom Convolutional Neural Network (CNN), Inception V3, and VGG16.
- **Custom CNN**: A CNN model is designed specifically for this task, including multiple convolutional layers followed by pooling layers and fully connected layers.
- **Transfer Learning**: Pre-trained models (Inception V3 and VGG16) are fine-tuned on our dataset. Transfer learning leverages the pre-existing knowledge in these models, allowing for faster training and potentially higher accuracy.
- **Training Process**: The models are trained using the training data generator, validated using the validation data generator, and optimized by adjusting hyperparameters such as learning rate, batch size, and the number of epochs

4. Model Evaluation

- **Performance Metrics**: The models are evaluated on the test set to determine their accuracy and loss.
  - **Test Accuracy**: Measures the proportion of correctly classified images.

  - **Test Loss**: Measures the discrepancy between the predicted and actual labels.
- **Comparison**: The results from the custom CNN, Inception V3, and VGG16 models are compared to identify the best-performing model for snake bite mark classification

C. Implementation

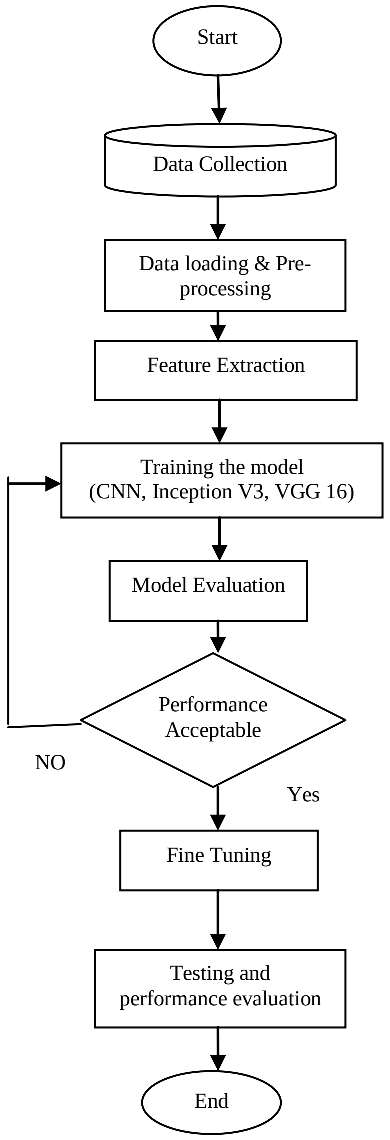

Fig. 9. Implmentation Flow Diagram

This flowchart in figure 5 represents the sequential steps involved in the implementation process:

Data loading and Preprocessing: This initial step involves loading the dataset and preparing it for analysis by pre-processing the images.

Feature Extraction: Features are extracted from the pre-processed images, either using pre-trained CNN models or handcrafted feature extraction methods.

Model Training: The extracted features are used to train a deep learning model (e.g., CNN) on the dataset.

Model Evaluation: The trained model's performance is evaluated using evaluation metrics on a validation set.

Fine Tuning and Optimization: Hyperparameters are tuned to optimize model performance, ensuring convergence and generalization.

Testing and Performance Analysis: The final trained model is tested on a separate test set to assess its performance and analyze potential areas for improvement.

Deployment and Integration: The trained model is integrated into a practical application or system for automated date palm disease detection.

Iterative Improvement: Feedback from domain experts and end-users is gathered to iteratively improve the model's performance and usability over time.

D. Performance Metrics

Performance measures are used to evaluate the network performance of the proposed model. This work uses Test accuracy and Test loss.

a) Test Accuracy:

Test accuracy measures the proportion of correctly classified instances out of the total instances in the test dataset. It is calculated as the ratio of the number of correctly classified samples

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ Number\ of\ Predictions} \quad (1)$$

b) Test Loss:

Test loss is typically calculated using a loss function that measures the discrepancy between the predicted outputs (*y^i*) and the actual labels (*yi*) for each sample in the test dataset. The loss function can vary depending on the task (e.g., classification, regression). For classification tasks commonly used loss functions include categorical cross-entropy and binary cross-entropy. For a classification task with *n* samples in the test dataset, the test loss (test*L*test) can be calculated as the average of the loss values over all samples..

$$L_{\text{test}} = \frac{1}{n}\sum_{i=1}^{n} \text{Loss}(y_i, \hat{y}_i) \quad (2)$$

Where Loss(*yi*,*y^i*) represents the loss function applied to the actual label *yi* and the predicted output *y^i* for the *i*th sample

V. RESULTS AND DISCUSSION

The results of this method demonstrate the effectiveness of different deep learning models in classifying snake species based on bite mark images. We evaluated three models: a custom Convolutional Neural Network (CNN), Inception V3, and VGG16.

The custom CNN model achieved a test accuracy of 13.3% and a test loss of 4.136. This relatively low accuracy suggests that the custom CNN struggled to learn discriminative features from the bite mark images. Possible reasons for this performance could be the complexity of the dataset and the limited depth and capacity of the custom CNN model compared to more advanced architectures.

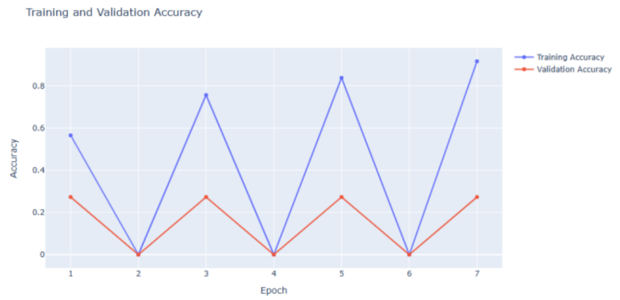

Fig. 10. Training and Validation Accuracy by CNN Model

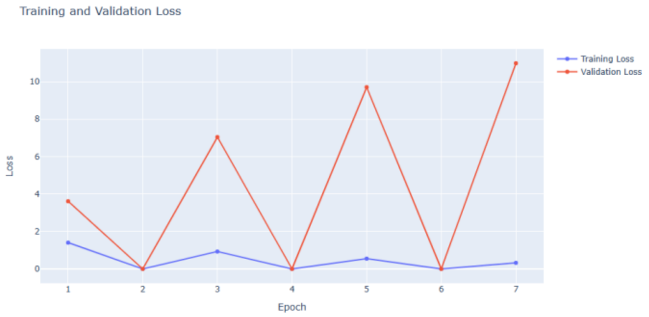

Fig. 11. Training and validation Loss by CNN Model

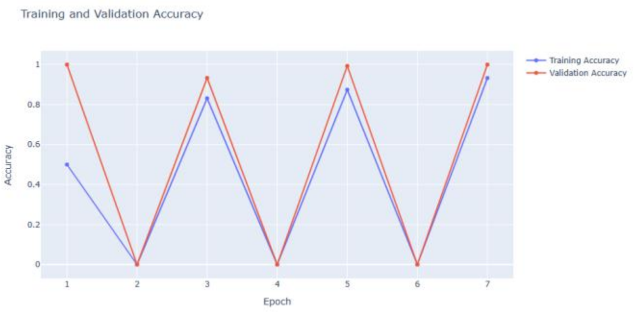

Fig. 12. Training and Validation Accuracy by Inception V3 Model

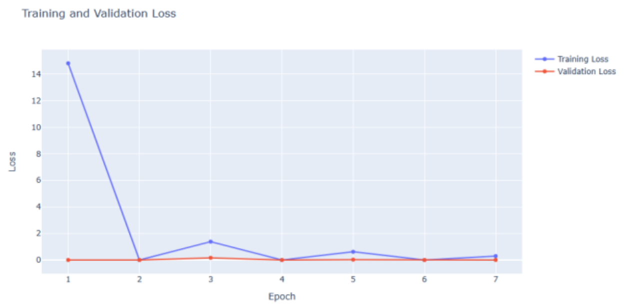

Fig. 13. Training and validation Loss by Inception V3 Model

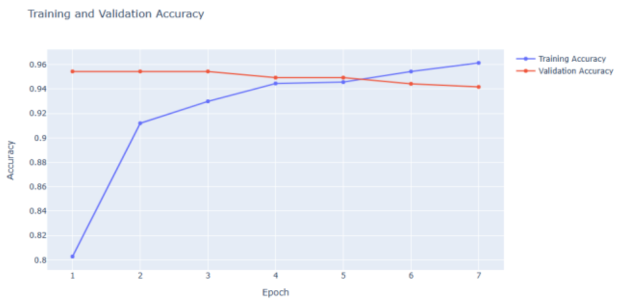

Fig. 14. Training and Validation Accuracy by VGG16 Model

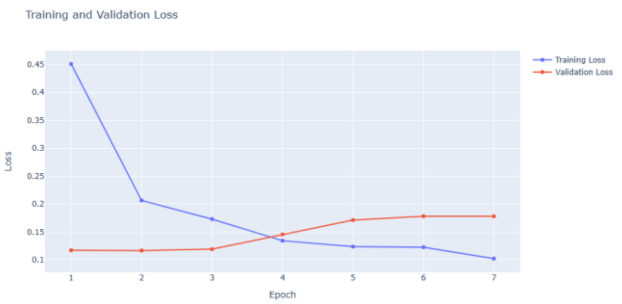

Fig. 15. Training and validation Loss by VGG16 Model

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A. Comparision Table

TABLE I. COMPARISON OF ACCURACY PERFORMACE WITH DIFFERENT DEEP LEARNING MODELS

S. No	Model	Test Loss	Test Accuracy (%)
1	CNN	0.133	4.136
2	Inception V3	0.967	0.191
3	VGG 16	0.996	0.078

In contrast, the Inception V3 model significantly outperformed the custom CNN, achieving a test accuracy of 96.7% and a test loss of 0.191. The superior performance of Inception V3 can be attributed to its sophisticated architecture, which includes inception modules that capture multi-scale features, making it highly effective in extracting relevant features from the images.

The VGG16 model delivered the highest accuracy, achieving a remarkable test accuracy of 99.3% and a test loss of 0.078. VGG16's deep architecture, with 16 layers, allows it to learn complex patterns and features, resulting in excellent performance on the snake bite mark classification task. The success of VGG16 underscores the advantage of using pre-trained models with fine-tuning, as they bring pre-existing knowledge from large-scale datasets that enhance performance on specific tasks.

Our results highlight the critical role of model architecture and pre-training in achieving high accuracy in image classification tasks. The discussion also suggests that while custom models can be tailored to specific tasks, leveraging pre-trained models like Inception V3 and VGG16 can provide substantial performance benefits, especially when dealing with complex image data. Future work could explore further fine-tuning of these models and combining their strengths through ensemble methods to potentially achieve even higher accuracy and robustness in snake bite mark classification.

B. Performance Analyze Graph

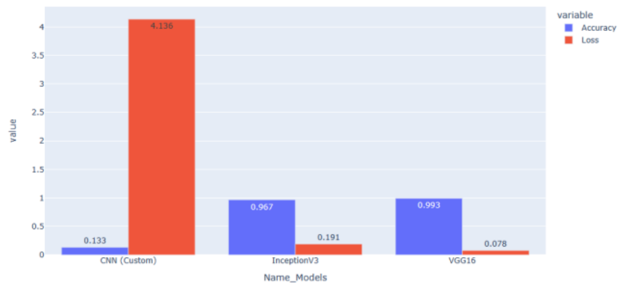

Fig. 16. Performance Analyze graph for different models

VI. CONCLUSION

In this study, we explored the use of deep learning models for snake species identification based on bite mark images, utilizing three different neural network architectures: a custom Convolutional Neural Network (CNN), Inception V3, and VGG16. Our findings demonstrate the significant performance variations among these models. The custom CNN model achieved a modest test accuracy of 13.3%, indicating its limitations in handling the complexity of the dataset. In contrast, the Inception V3 model exhibited a substantial improvement with a test accuracy of 96.7%, thanks to its advanced architecture that captures multi-scale features. The VGG16 model emerged as the best performer, achieving an impressive test accuracy of 99.3%, which highlights the effectiveness of deep, pre-trained models in complex image classification tasks.

The high accuracy and low test loss achieved by the Inception V3 and VGG16 models underline the importance of leveraging sophisticated and pre-trained architectures for specific classification challenges like snake bite mark identification. These results suggest that deep learning can be a powerful tool in medical and herpetological applications, providing accurate and timely identification of snake species based on bite marks, which is crucial for administering appropriate treatment

Future Scope

In future the proposed method can be extended with investigate the use of ensemble techniques to combine the strengths of multiple models, potentially improving the robustness and accuracy of snake species identification.

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