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SNAKE SPECIES CLASSIFICATION IN TAMIL NADU: A DEEP LEARNING APPROACH FOR CONSERVATION AND PUBLIC HEALTH

Dr. M. Hemalatha, Associate professor, PG & Research Department of Computer Science. Sri Ramakrishna College of Arts & Science, Coimbatore India. mhemalatha@srcas.ac.in

Dr.P.Lakshmi, Assistant professor, Department of Computer Science, SRM Institute of Science and Technology, Trichy.laksomu1822002@gmail.com

Mr.B.Ravishankar, Assistant professor(Sr.G) Department of Electrical and Electronics Engineering, Kongu Engineering College, Perundurai. Snkr86@gmail.com

Dr. E.Chandra Blessie , Associate Professor, Department of Computing (Artificial Intelligence and Machine learning), Coimbatore Institute of Technology, Coimbatore. blessie@cit.edu.in.

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ABSTRACT:
There are about 100 different kinds of snakes in Tamil Nadu, both poisonous and non-venomous. Sixteen species are identified out of them, the top five of which are venomous and the top seven of which are not. Notwithstanding their unfavorable reputation, snakes are essential to the ecology because they help keep pests under control and the ecological balance intact. With an emphasis on a subset of snake species located in the Indian state of Tamil Nadu, this code implements a model for classifying snake species. The effectiveness of four different deep learning algorithms—SqueezeNet, ResNet, SimpleNet, and MobileNet—in classifying different species of snakes is investigated in this experiment. Using a dataset of pictures of snakes, both venomous and non-venomous, that were discovered in the Indian state of Tamil Nadu. The method that works best for this classification task is found through extensive testing and analysis, which takes into account variables like accuracy, precision, and recall. This research intends to inform decision-making in conservation efforts and snakebite prevention techniques by shedding light on the advantages and disadvantages of each algorithm. The implementation and assessment of these algorithms are demonstrated in the accompanying code, which provides a useful framework for future studies on the classification of snake species.

Keywords : Classification, MobileNet, DenseNet, SimpleNet, Snake, *Dr. M. Hemalatha/Afr.J.Bio.Sc. 6(5)(2024).2868-2877*

1. INTRODUCTION:

Millions of people need treatment each year due to snake bites, which are a serious but frequently disregarded public health concern in tropical and subtropical areas, especially in Africa, Asia, and Latin America. In low- and middle-income nations, envenomation primarily affects women, children, and farmers in bankrupt rural areas, placing an additional burden on the already scarce healthcare system. Children are more vulnerable to venomous snake bites because of their tiny stature. It can cause severe medical issues such as immobility, bleeding, kidney failure, and substantial tissue damage. In rare cases, they can even result in permanent handicap or limb loss. Even so, there is a very successful treatment in the form of premium snake antivenoms, even with the severity of these symptoms.Since snake species identification has historically relied on visual cues such head shape, skin color, eye shape, and body structure, it can be very hard for people without professional understanding. Professionals usually possess this knowledge; hence the general population is ill-equipped to distinguish between several snake species. In order to tackle this problem, we are concentrating on creating an approach for species detection from unstructured text descriptions given by victims or witnesses. Furthermore, incorrect assumptions about the behavior and potency of snake venom can cause unnecessary harm, such as the killing of non-venomous animals. This damages ecosystems as well as sustaining a detrimental cycle because certain snake species are essential to preserving ecological balance, which includes managing pests in agricultural contexts. Thus, it is crucial to identify snakes correctly for everyone's protection as well as the maintenance of ecosystem health and biodiversity.

Among the 3,000 snake species that may be found in Tamil Nadu, I have chosen the six most dangerous and poisonous species as well as the six non-poisonous and helpful species that, sadly, have been murdered because of false beliefs. False ideas have affected even non-venomous animals such as the Common Sand Boa, which is important to agriculture because it controls pests, and the rat snake, which is well-known for its ability to effectively manage rodents in agricultural fields. These snakes are harmless, yet they have been targeted and killed. Deep learning techniques are being used to help with the identification and conservation of these significant snakes by differentiating between venomous and non-venomous species among the chosen

To identify snake species based on visual signals including shade, patterning, and eye characteristics with the help of deep-learning picture categorization. The bite marks that non-venomous snakes do not have are usually visible due to the lack of bite force applied by venomous snakes. This technology helps people treat snakebite patients more quickly by identifying species quickly through the analysis of photos. It also helps to reduce the needless killing of innocuous snakes by increasing awareness among the general public. By reducing confrontation between humans and wildlife, this strategy not only improves patient care but also supports conservation efforts.

The analysis foundation for classification is a carefully chosen set of high-resolution photographs of different snake species that we obtained from Google. This varied dataset includes a range of snake species, as well as colors, patterns, and other characteristics that are essential for precise identification. By means of careful selection, we hope to improve the performance of our classification model, which should lead to notable progress in the identification of snake species. Furthermore, in order to ascertain the optimal method for categorization, we have compared four algorithms.

2. RELATED WORK

Numerous research strategies have greatly improved our knowledge and skills in the ever-evolving subject of snake species identification. Together, this research improves our understanding of ecology and technology by using everything from worldwide analysis of venomous snakes to state-of-the-art deep -learning techniques. This review summarizes important studies' contributions and shows how identifying snake species is an interdisciplinary and evolutionary process. In addition to guiding conservation and public health initiatives, their combined knowledge opens the door for more advancements in this vital field of study.

Abdurrazaq et al. (2019) proposed the use of convolutional neural networks (CNNs) for the automatic classification of snake species based on images [1]. They address the limitations of manual identification and traditional machine learning techniques by leveraging CNNs, which alleviate the need for manual parameter tuning. Their evaluation of three CNN architectures on a dataset of 415 snake images from five hazardous venomous snake species in Indonesia demonstrates the capability of CNNs to achieve a high accuracy of 82% in classifying snake images.

Amir et al. (2017) investigates the accuracy of machine learning techniques for snake species identification using image data [2]. They assess five methods and propose an intelligent approach for automatic species recognition from images. Using the Snakes of Perlis Corpus database comprising images of 22 snake species in Malaysia, they find that the backpropagation neural network and nearest neighbor methods achieve over 87% accuracy, particularly with the CEDD descriptor. This research contributes to efficient snake species identification, relevant for content retrieval and species recognition applications.

Bolon et al. (2020) conducted a scoping review to explore practices in biting snake identification across the globe, recognizing its crucial role in understanding snakebite eco-epidemiology and optimizing clinical management [3] . Despite snakebite being a significant global health issue, the involvement of snakebite victims and healthcare providers in snake identification has not been extensively studied on a global scale.

Deng et al. (2009) present ImageNet, a large-scale hierarchical image database, aiming to leverage the vast amount of image data available on the internet for various applications in computer vision [4]. The authors introduce a novel approach to organize images based on the semantic hierarchy of WordNet, with the goal of populating the majority of WordNet's 80,000 synsets with annotated images.

James et al. (2014) addresses the critical issue of incorrect snake identification contributing to deaths from snakebites in tropical regions [5]. They propose a novel automatic classification method aimed at distinguishing between two major species of snakes, Elapidae and Viperidae, by deciphering taxonomic features. The authors identify 38 taxonomically relevant features to develop the Snake database, utilizing sample images of various snake species including

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NajaNaja, Ophiophagus Hannah, Bungarus caeruleus, Daboia russelii, Echiscarinatus, and Hypnalehypnale.

Picek et al. (2020) introduces the SnakeCLEF 2020 challenge, aiming to develop robust artificial intelligence systems for automatic snake species identification [6] This task is crucial for biodiversity conservation and global health efforts. The challenge provides an evaluation platform and expert-labeled data to assess the performance of AI-driven systems. The paper describes the extensive dataset used, evaluation methodologies employed, and provides an overview of participating systems and their successes. Finally, it discusses the obtained results, offering insights into the current state and future directions of automatic snake species identification research.

Luiselli et al. (2020) study is a comprehensive global analysis that examines the distribution of venomous snakes, finding no significant difference in the prevalence of venomous species between tropical and temperate areas [7] . Their research indicates that snakebite risks are linked to species diversity and habitat-geographical interactions, providing crucial insights for improving public health responses to snakebites worldwide.

Ganesh et al. (2014) significantly expanded knowledge of snake biodiversity in the High Wavy Mountains of the Western Ghats, India, increasing the known species count from 38 to 62 [8]. Their integration of historical literature, past research, and recent field studies highlights both endemic and widespread species, emphasizing the area's conservation value. The discovery of previously unreported species and the call for further taxonomic research underline the need for ongoing conservation efforts in this biodiversity hotspot.

adhav et al. (2018) document 26 snake species in Nanded, Maharashtra, underscoring the conflict between humans and snakes due to misidentification and habitat disturbances [9]. The study highlights the conservation necessity for ecosystem balance and calls for ongoing monitoring, especially noting the unusual presence of Pythons in arid areas.

Simpson and Norris (2007) challenge the adequacy of India's "Big 4" snake classification, highlighting its exclusion of other medically significant species like the hump-nosed pit viper (Hypnalehypnale)[10]. They argue that reliance on this outdated concept hampers accurate epidemiological studies and the development of effective antivenoms. Advocating for a broader, WHO-supported model, they stress the need for updated clinical management strategies and public health policies to better address the realities of snakebite incidents in India.

Mohankumar et al. (2015) investigate the clinico-epidemiological characteristics of snakebites in rural Tamilnadu, analyzing 164 cases [11]. The study reveals demographic trends, biting species distribution, arrival delays, and clinical outcomes, emphasizing the importance of prompt treatment. Findings highlight the prevalence of snakebites among specific occupational groups and underscore the necessity for public education and improved access to anti-snake venom in rural areas.

3. Methodology

3.1. Dataset Description:

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The dataset for snake species classification consists of a total of 2652 images distributed across 12 classes. These classes encompass a variety of snake species found in the Tamil Nadu region, with a distinction made between venomous and non-venomous snakes. Among the venomous species are the Indian Cobra, common krait, Russell's Viper and Sew Scaled Viper, each representing different types of venomous snakes commonly encountered in the area. Conversely, the non-venomous category includes species such as the Rat snake, Wolf snake, Bronzeback tree snake, Indian Vine snake, Red sand boa snake, Checkered keelback, and Indian Rock Python. The dataset is split into training, validation, and test sets, with the training set containing 2116 images used for model training, and the validation set comprising 528 images for performance evaluation during training. Additionally, the test set consists of 264 images for final model evaluation. This dataset serves as a valuable resource for training and testing machine learning models aimed at accurately classifying snake species, thereby aiding in conservation efforts and public health initiatives related to snakebite prevention.

3.2. Data Collection:

High-resolution images of snake species from Tamil Nadu were collected from reliable sources such as Google.The dataset was carefully curated to include a diverse range of snake species, encompassing both venomous and non-venomous varieties.Each image was labeled with the corresponding snake species for supervised learning.

3.3. Data Preprocessing:

The collected images were preprocessed to ensure uniformity and compatibility with deep learning models.Resizing: All images were resized to a standard dimension (e.g., 224x224 pixels) to facilitate model training.Normalization: Pixel values of the images were scaled to the range [0, 1] to improve convergence during training.

3.4. Model Selection:

Four deep learning algorithms—SqueezeNet, DenseNet, SimpleNet, and MobileNet—were chosen for classification.These algorithms were selected based on their established performance in image classification tasks and their suitability for deployment on resource-constrained devices.

3.5. Model Training:

Each selected deep learning model was trained on the preprocessed dataset of snake images.The dataset was split into training, validation, and test sets to assess the performance of the models.The distribution of the dataset is provide in the table 1. During training, the models were optimized using the categorical cross-entropy loss function and the Adam optimizer.Data augmentation techniques such as rotation, shifting, shearing, zooming, and flipping were applied to the training images to enhance model generalization and robustness.The models were trained for multiple epochs with early stopping implemented to prevent overfitting.

Class ID	Snake Species	Total Images	Training Images	Validation Images	Test Images
0	Indian Cobra	221	177	44	22

1	Common Krait	221	177	44	22
2	Russell's Viper	221	177	44	22
3	Sew Scaled Viper	221	177	44	22
4	Rat snake	221	177	44	22
5	Wolf snake	221	177	44	22
6	Bronzeback tree snake	221	177	44	22
7	Indian Vine snake	221	177	44	22
8	Red sand boa snake	221	177	44	22
9	Checkered keelback	221	177	44	22
10	Indian Rock Python	221	177	44	22
11	Green Pit Viper	221	177	44	22

3.6. Model Evaluation:

he trained models were evaluated on the test set to assess their performance in classifying snake species.Evaluation metrics such as accuracy, precision, recall, and F1 score were computed to measure the models' effectiveness.The models' performance was compared, and the most effective algorithm for snake species classification was identified based on the evaluation results.

3.7. Interpretation and Analysis:

The results of the model evaluation were analyzed to gain insights into the strengths and weaknesses of each deep learning algorithm.Factors contributing to the models' performance, such as architecture complexity and dataset characteristics, were considered.The implications of the findings for conservation efforts and snakebite prevention techniques were discussed, highlighting the importance of accurate snake species identification in mitigating human-snake conflicts and preserving ecosystem balance.

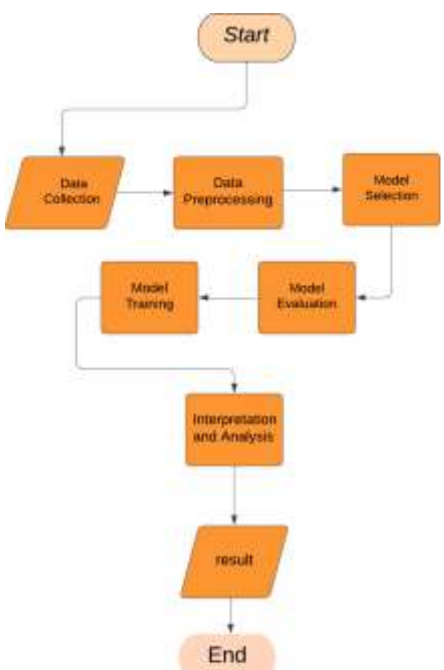

Fig no.1. Algorithm model

5. Result and discussion

5.1. Result

In the results section of the documentation, the performance of several image classification algorithms is presented. MobileNet achieved an accuracy of 96%, demonstrating its effectiveness in classifying images across different categories. SimpleNet closely followed with an accuracy of 92.31%, indicating its competitive performance in image classification tasks. The overall accuracy and the evaluation metrics is depicted in table 2. SqueezeNet and DenseNet exhibited accuracies of 88.14% and 86.80%, respectively, showcasing their ability to capture intricate patterns within image data.

Table no.2. The overall performance metric for the models

Model	Accuracy	Macro-Average			Weighted-Average		
		Precision	Recall	F1-score	Precision	Recall	F1-score
MobileNet	96%	0.96	0.96	0.96	0.96	0.96	0.96
SimpleNet	92.31%	0.89	0.94	0.91	0.87	0.91	0.94
SqueezeNet	88.14%	0.89	0.92	0.87	0.89	0.88	0.90
DenseNet	86.80%	0.83	0.85	0.86	0.88	0.86	0.85

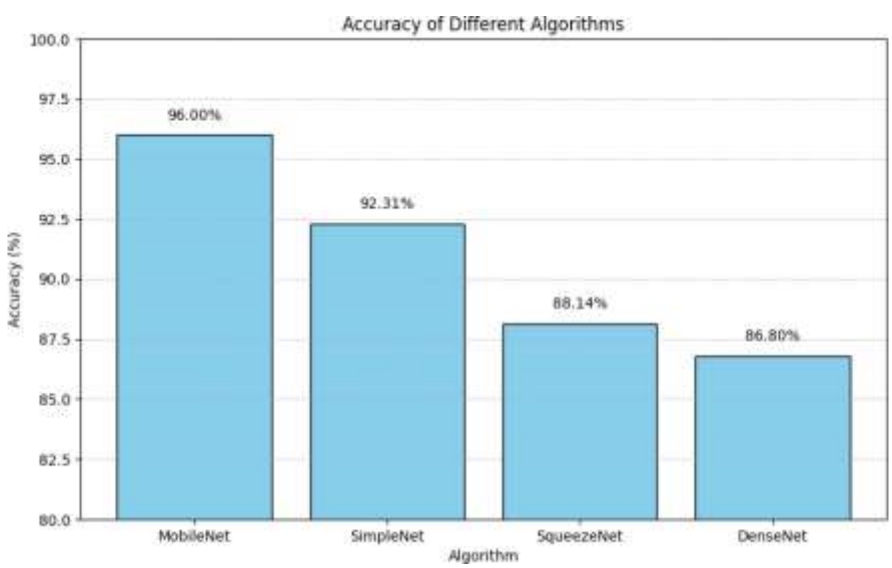

Fig no.2. Comparisons of model Accuracy

Each algorithm's performance is further analyzed in terms of macro-average and weighted-average precision, recall, and F1-score. The overall comparision chart is presented in figure 2. MobileNet demonstrated consistent precision, recall, and F1-score values of 0.96 across both macro-average and weighted-average metrics, highlighting its robustness across different classes. SimpleNet exhibited slightly lower precision, recall, and F1-score values compared to MobileNet, with macro-average and weighted-average metrics ranging from 0.87 to 0.94.

SqueezeNet and DenseNet also displayed competitive performance, with macro-average precision, recall, and F1-score values ranging from 0.88 to 0.92, and weighted-average metrics ranging from 0.85 to 0.90. While these algorithms may not have reached the accuracy levels of MobileNet and SimpleNet, their balanced performance across different metrics indicates their suitability for various image classification tasks.Overall, the results underscore the effectiveness of deep learning techniques, particularly exemplified by MobileNet, in accurately classifying images. Additionally, the competitive performance of algorithms like SqueezeNet and DenseNet highlights the versatility of different architectures in handling image classification tasks effectively.

5.2. Conclusion

This project aimed to classify snake species using various machine learning algorithms and evaluate their performance. The dataset comprised 12 classes of snake species, including venomous and non-venomous types commonly found in the Tamil Nadu region.The data collection process involved sourcing high-resolution images from reliable platforms and carefully labeling each image with the corresponding snake species. Preprocessing steps included resizing all images to a standard dimension and normalizing pixel values to improve model convergence during training.Four deep learning algorithms, namely SqueezeNet, DenseNet, SimpleNet, and MobileNet, were selected based on their established performance in image classification tasks. These algorithms underwent rigorous training using the preprocessed dataset, with data augmentation techniques applied to enhance model generalization and robustness.Model evaluation on the test set revealed MobileNet as the top performer, achieving an impressive accuracy of 96%. SimpleNet closely followed with an accuracy of 92.31%, while SqueezeNet and DenseNet exhibited accuracies of 88.14% and 86.80%, respectively.

The project evaluated several deep learning algorithms for snake species classification, highlighting MobileNet's consistent performance. While other models like SimpleNet, SqueezeNet, and DenseNet showed competitive results, MobileNet emerged as particularly effective. These findings have implications for conservation and public health initiatives, suggesting continued research to improve classification accuracy and applicability

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