"A Review on Snake type detection and venomous detection Using Machine Learning Algorithms"

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Abstract -Developing reliable techniques for identifying snake species and determining their venomous nature is critical given the tremendous health danger presented by snakebite venomation in many parts of the world. This study utilizes deep learning to identify snake kinds and categories them as poisonous based on photographs. We offer a multi-task model that employs CNNs to detect and classify snake species as venomous or non-venomous using input photos. The algorithm was trained and tested using snake pictures, yielding good accuracy in species classification and poison prediction. This approach can improve snakebite management by instantly detecting the type of snake and its potential hazard, resulting in faster reaction times during crises. This technique demonstrates the effectiveness of deep learning in identifying animals and improving human safety, with potential for future applications in ecological monitoring and public health.

Key Words: Snake detection, Venom Detection, Farmer deaths, Machine Learning, Feature Extraction.

1. INTRODUCTION

Agriculture plays an essential role for our country and requires investment in technology and growth. Farmers are struggling to increase productivity owing to the impact of pests such as rats, insects, and snakes. There are many poisonous snakes. These snakes pose a significant risk to everyone engaged and imperil the lives of the farmers. Snake bites kill around 46,000 people annually in our nation, accounting for nearly half of all snake bite deaths worldwide. Approximately 5% of these deaths occur in agricultural fields. Farmers, particularly in paddy and cotton fields, require appropriate solutions to address these challenges.
As technology advances, people are increasingly relocating from rural areas to urban centers. Farmers confront challenges such as harmful animals accessing fields and ruining crops due to deforestation. Previously, this disadvantage was present but has now been eliminated. Previously, snake bites were a prevalent cause of mortality. India accounts for around 50% of global snake bite deaths. There should be technology or mechanisms to identify and inform humans if snakes reach their vicinity.
Every day, there are several reports of snake bites in agricultural areas. As agricultural students, we aimed to better the lives of all farmers in the country, having witnessed their struggles. Implementing this approach can alleviate farmers' fear of snake bites and increase their productivity. Due to limited medical resources in rural areas, it is crucial to avoid accidents with deadly snakes in fields. To prevent snake bites and farmer fatalities, it's crucial to discover them before they attack.

2. Existing System

Researchers are especially interested in predicting snake behavior. Predicting the snake group responsible for certain behaviors might be difficult because of the large number of events involved. This study seeks to identify the factors that contribute to snake behavior. Current forecasting methods are inadequate. Machine learning systems can predict the likelihood of identifying snakes based on relevant data. The study's findings can help security agencies and lawmakers devise effective methods to eliminate snakes. Machine learning and snake-specific information may be used to examine snake behavior trends across many areas and nations.
This study system employs deep learning to identify snake photos, detect intruders, and categories them using image processing. The image is then compared to a snake image using a CNN algorithm.

3. Proposed System

Our suggested methodology uses a machine learning technique to detect snakes. The concept incorporates a camera that sends pictures or video streams to a microcontroller. To handle the tremendous processing power required for video processing, we used edge computing. The microcontroller includes a phone-connected module. This module delivers a live feed to the phone.

The phone processes live streams using a machine learning algorithm. If the software detects a snake, it sends a signal to the module.

Also for further development in the hardware system we can make instant response module which can transmits it back to the microcontroller, which forwards it to the alarm system. The microcontroller and camera will be situated at the farmer's knee level and connected to their phone via Bluetooth or Wi-Fi. This type detects snakes and alarms the farmer.

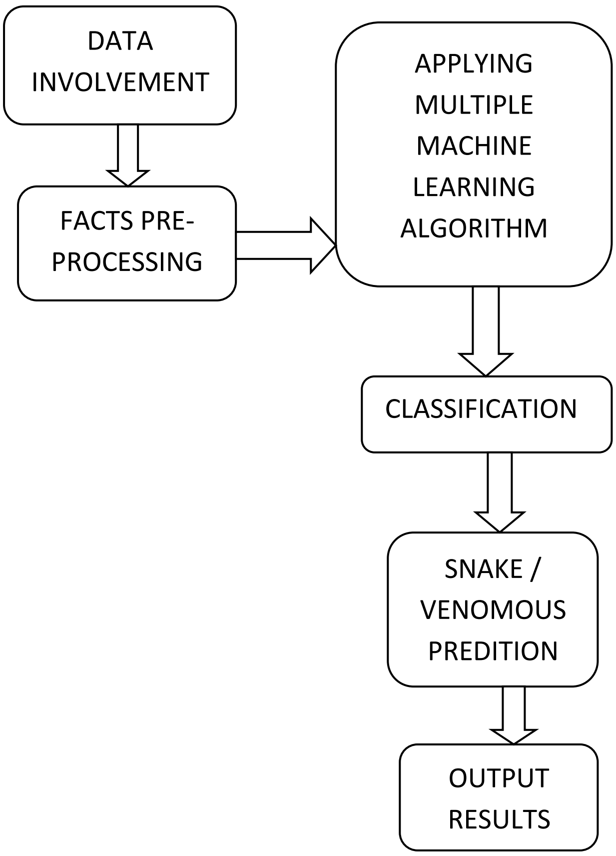

Fig -1: Overall data flow diagram (DFD) of proposed system

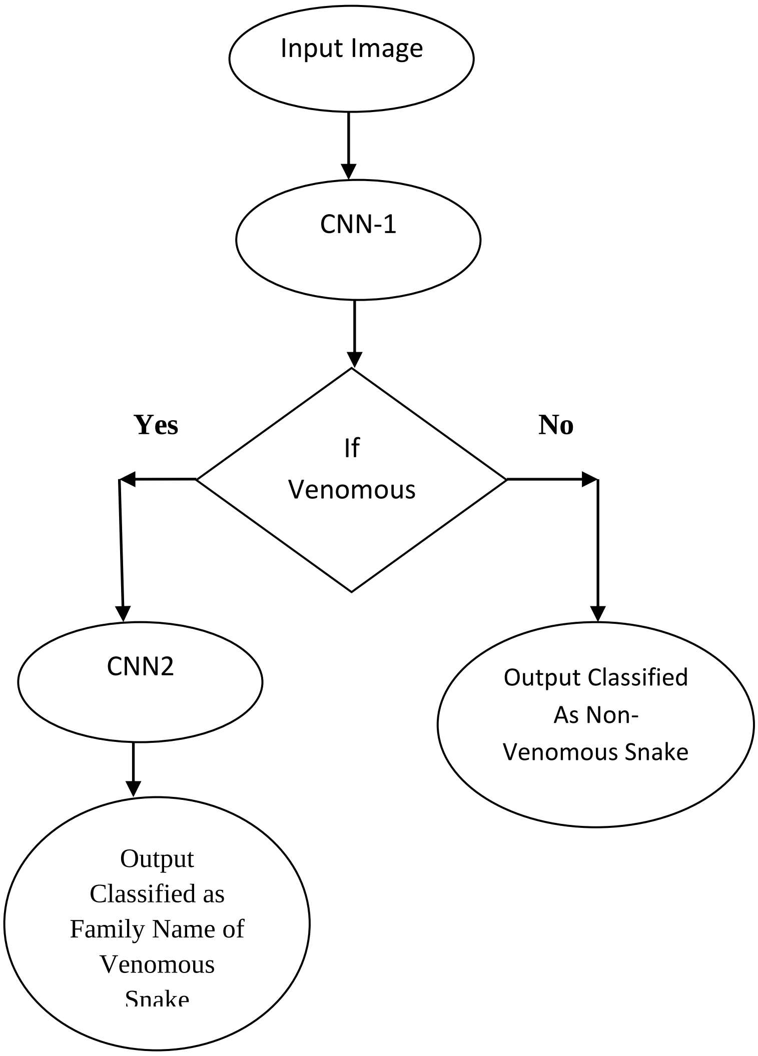

Fig. 2 Proposed architecture for identification of snakes using CNN algorithm

4. Literature Review

To address a lack of research on snake detection models utilizing pattern recognition, we will first conduct a study of works focusing on methods suitable for object or pattern identification. Next, we may compare the suggested model to other animal detection systems that have been developed earlier. We will use the knowledge and details gained from the publications to enhance our suggested research for optimal results. This study aims to explore the socio-cultural and historical significance of snakes and snakebites in Central African forests through anthropological and ethno historical research. The article explores anthropological contributions to the SBE research through literature from Southeast Asia and Latin America.

The study strategy for Central Africa includes ethno biology investigations of snake ecosystems, participatory assessments of human-snake interactions, and interviews and observation of indigenous prevention and treatment approaches. This initiative aims to reduce the burden of SBE by developing policies and practices in collaboration with forest communities, leaders, and regional and national authorities [1].

Identifying the biting snake in a communal setting might be difficult, but the outcome of snakebite is dictated by the species responsible. We developed a clinical grading system for epidemiological surveys to identify probable biting species in patients with systemic envenomation requiring therapy.
The score was based on 10 parameters associated to bites from Sri Lanka's five medically important snakes. An algorithm was developed with different weightings for each aspect for different species [2].

Snakes have an important function in the ecology, yet they are not essential. Deforestation harms snake habitat. Identifying snakes is necessary for treatment planning in numerous regions of the world, but not always achievable. Snake bites are becoming increasingly prevalent, and understanding your surroundings may not help identify the snake. To solve this issue, a proposed approach for identifying snake species is presented [3].

India has constantly been ranked first in the world for snakebite sickness.
The inability to get antivenin and delay in spreading the infection determines the timing of death. Snake CLEF 2020: Automatic Snake Species Documentation Challenge offers an evaluation platform with labeled data (including geographic information) for biodiversity and health research. Snake CLEF 2020 aims to establish a valuation stage for AI-driven snake class recognition firms [4].

Using an AI-driven system to identify snake classes has the potential to significantly reduce fatalities and incapacities from snakebite. The Snake CLEF 2021: Instinctive Snake Classes Identification Test with Country Level Emphasis evaluates end-to-end AI-driven snake class classification systems, with a focus on overall country performance [5].

Snakebite deaths and healthcare breadwinners can help to freeze snake documentation and develop new ways [6].

The cylinder uses a non-linear feature change on descriptors, combining the findings into image-level images, and applying a class-section model. Our approach improves the theory, scalability, and categorization of all three processes through novel explanations. Pascal employs the concept of temperament.
Topics covered include object identification, finding, organization, the YOLO method, and picture processing [7].

Maharashtra had the greatest incidence of occurrence, with 70 tastes per 100,000 individuals and 2.4 per 100,000 annually [8].

The future organization uses two modules: object detection and cataloguing. The discovery module detects snakes and the group module classifies them accordingly [9].

Ensuring the independence, geographic distribution, and evolution of species is crucial for human survival and biodiversity conservation. The difficulty in discriminating between plants and animals in yield hinders the application of modern CNN technology [10].

Snake classification has been challenging for zoologists due to their lack of limbs and other regions prone to change. An order that goes back to the Cretaceous era and has spread globally is likely to have developed in structure, as shown in other Vertebrata orders. Anatomists have identified only four suborders and maybe a dozen families. The Colubridae category includes three-quarters of all species and has a global range. As long as this was the predominant effect, it was clear that the order's stronghold had not yet been overcome [11].

The FHDO Biomedical Computer Science Group (BCSG) participated in the competition outlined in Mask R-CNN. Machine learning workflows include picture pre-processing, categorization using Efficient Nets, and integration of location information [12].

The NLP processing of unstructured text

descriptions involved pre-processing, feature extraction, and classification. We used four machine learning algorithms for training and classification: Naive Bayes, k-Nearest Neighbour, Support Vector Machine, and Decision Trees J48. The J48 algorithm achieved a maximum classification accuracy of 71.6% for the NLP Snake data set [13], demonstrating great precision and recall.

CNN is frequently used for automated image categorization. Typically, extracted attributes are utilized for classification. Because artificial neural networks are utilized to accomplish deep learning, it is effective at identifying objects in photographs. Deep learning techniques have led to increased popularity in picture classification challenges. Snakes have yet to be classified using an automated approach. The proposed technique will aid in accurately identifying snake species and taking suitable action [14].

The variety of venomous snakes and their ability to harm people has been extensively documented. This knowledge serves as a foundation for preventive measures against snake toxins and their effects on the body and health.
High intervention in epidemiological and clinical contexts globally leads to around 19,000 fatalities annually [15].

Security is a key concern in e-commerce and intranets. This chapter discusses various hacking attempts against corporations and techniques for countering them. The chapter covers integrated security systems (ISS), which automatically secure communication between two parties against various network threats. The chapter addresses legal implications for firms who fail to safeguard their systems and experience damages [16].

The initiative aims to integrate snake farming into the Animal Production curriculum at Colleges of Agriculture in South-East Nigeria to promote long-term health and security. The study had 130 participants: 93 animal science academics from universities and 37 animal production teachers from agricultural schools. Due to the tiny population, the research had a limited sample size [17].

It is estimated to cause 128,000 fatalities and 300,000 long-term impairments, including blindness, per year and restricted movement. People living in poisonous snake-infested areas with limited access to healthcare and treatment are particularly susceptible [18].

Educational efforts to enhance public understanding of snake identification and bite management in the field are urgently needed [19].

There has been no systematic attempt to identify and categories common snakes across Indian states, and there is a lack of definitive data on the issue. Research suggests that some snake species, such as saw-scaled vipers in Rajasthan, are more prevalent in specific areas. Our analysis of published literature from several areas in India revealed a North-South split in snake bite prevalence.
North India experiences more neurotoxin envenomations than South India, which has a greater rate of hepatotoxic envenomations. Russell's viper causes symptoms such as local necrosis, gangrene, and compartment syndrome [20].

5. METHODOLOGY

A review on snake type and venomous detection using machine learning algorithms typically involves collecting and analyzing a large dataset of snake images, then applying various image processing techniques to extract key features like head shape, body patterns, scale arrangement, and eye characteristics, followed by using machine learning algorithms (often deep learning based like Convolution Neural Networks) to classify the snakes into different species and identify venomous snakes based on these features, with evaluation metrics like accuracy, precision, and recall used to assess the model's performance.

Key steps in the methodology:

1. Data Acquisition and Preprocessing:

• Image Collection: Gather a diverse and large dataset of snake images, including various species and angles, ensuring proper labeling for both snake type and venom status.
• Image Annotation: Manually annotate each image with the corresponding snake species and venom category (venomous/non-venomous).
• Image Preprocessing: Resize, normalize, and augment images to improve data quality and prevent over fitting.

2. Feature Extraction:

• Manual Feature Engineering: Extract relevant features based on snake morphology like head shape (triangular for venomous), pupil shape, scale patterns, body color, and relative head size.
• Deep Learning Feature Extraction: Utilize convolution neural networks (CNNs) to automatically learn features from the image data, capturing complex patterns and relationships between pixels.

3. Model Selection and Training:

• Classification Algorithms: Choose appropriate machine learning algorithms like Support Vector Machines (SVM), Random Forests, or deep learning models like CNNs depending on the complexity of the dataset and desired accuracy.
• Model Training: Train the chosen model on the prepared dataset, optimizing hyper parameters like learning rate and network architecture to maximize performance.

4. Evaluation and Validation:

• Testing on Holdout Set: Evaluate the model's performance on a separate test dataset that was not used during training.
• Performance Metrics: Calculate metrics like accuracy, precision, recall, F1-score to assess the model's ability to correctly classify snake species and venom status.

Potential Challenges:

• Data Availability: Obtaining a large, diverse, and high-quality snake image dataset can be challenging.
• Intra-species Variation: Significant visual variations within the same snake species can make identification difficult.
• Image Quality: Factors like lighting, angle, and background clutter can impact the accuracy of the model.

Advanced Approaches:

• Transfer Learning: Utilize pre-trained CNN models on large image datasets (like Image Net) to improve model performance with limited snake image data.
• Ensemble Methods: Combine multiple machine learning models to further enhance classification accuracy.
• Real-time Detection: Develop systems for live snake detection in field environments using video analysis techniques.

Applications:

• Snakebite Management: Assist healthcare professionals in identifying venomous snakes from bite marks to administer appropriate ant venom.
• Conservation Research: Monitor snake populations and distribution patterns.
• Public Safety: Develop educational tools to help people identify potentially dangerous snakes in their region.

6. CONCLUSIONS

A review of snake type and venom detection using machine learning algorithms demonstrates the significant potential of deep learning models, particularly convolution neural networks (CNNs), to accurately classify snake species and identify venomous snakes from images, achieving high accuracy rates, making them a valuable tool for rapid identification in situations where immediate medical response to snakebites is crucial; however, challenges remain regarding data quality, regional variations in snake morphology, and the need for robust datasets to ensure reliable performance across diverse environments and snake species.

Key takeaways:

• High accuracy potential: Studies have shown that machine learning models can achieve high accuracy in identifying snake species and classifying venomous snakes, with some reaching near-expert level performance.
• CNNs as primary method: Convolution neural networks are the most commonly used deep learning architecture for snake image classification due to their ability to extract intricate features from images like color patterns and head shapes.
• Data quality concerns: The effectiveness of these models heavily relies on the quality and diversity of the training dataset, which can be a limitation due to the challenges of collecting comprehensive snake images from various regions.
• Regional variations: Snake morphology can vary significantly across different geographic regions,

necessitating tailored models for specific locations to ensure accurate identification.

• Future directions: Further research should focus on developing more robust datasets, incorporating additional features like bite marks or environmental context, and exploring real-time detection systems for immediate snake identification in field situations.

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