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Implementation of Smart Ai System for Snake Bite Identification and Emergency Response

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Abstract: *Snakebite envenomation is a major public health concern, particularly in rural and underdeveloped regions where access to timely medical care is limited. Rapid and accurate identification of whether a snakebite is venomous or non-venomous is crucial for administering appropriate treatment and reducing mortality rates. This project proposes an intelligent Snake Bite Recognition System that leverages image processing techniques and Deep Neural Network (DNN) algorithms to automate the classification of bite marks.The system is developed using Python and is trained on a dataset comprising over 100 snakebite images, categorized into venomous and non-venomous classes. The dataset is divided into training and testing subsets to ensure model reliability and performance evaluation. Prior to classification, input images undergo several preprocessing steps including resizing, normalization, noise filtering, and feature extraction. These steps enhance image quality and enable the model to effectively learn distinctive features such as fang marks, puncture depth, and spatial patterns of the bite. A Deep Neural Network model is employed to analyze these extracted features and perform accurate classification. The system is designed to provide fast and reliable predictions, making it suitable for real-time applications. In addition to classification, the system offers preliminary medical guidance and first-aid recommendations, which can assist healthcare workers, first responders, and even non-experts during emergency situations until professional medical treatment is available.The proposed system is scalable and can be extended to identify other types of skin injuries such as insect bites, spider bites, or allergic reactions, thereby increasing its practical usability system.*

I. INTRODUCTION

Snakebite is a major public health problem, especially in rural and remote regions where access to immediate medical care is limited. According to global health reports, thousands of people suffer from snakebite incidents every year, leading to severe complications, permanent disability, or even death if not treated quickly. One of the biggest challenges in snakebite treatment is the early identification of whether the bite is venomous or non- venomous, as the symptoms may not be clearly visible in the initial stage. Delay in proper diagnosis can result in incorrect treatment and increased risk to the patient's life.With advancements in Artificial Intelligence (AI) and Deep Learning, medical image analysis has become an effective tool for assisting healthcare professionals in rapid decision-making.

Deep Neural Networks (DNNs), a subset of deep learning, are highly capable of recognizing complex patterns in images and have been widely used in disease detection, skin lesion classification, and medical diagnostics. By applying these techniques to snakebite mark analysis, it is possible to develop an automated system that supports emergency medical services.The proposed system, Snake Bite Mark Classification for Emergency Medical Assistance, focuses on identifying snakebite marks using image processing and DNN algorithms. The system analyzes images of bite marks, performs preprocessing steps such as resizing and normalization, and extracts meaningful features for accurate classification. It then determines whether the bite is likely venomous or non- venomous and provides preliminary medical guidance. This approach not only reduces diagnosis time but also acts as a supportive tool for doctors, paramedics, and first responders during emergencies.

Furthermore, the system can be extended to detect other types of skin injuries such as insect bites, making it a versatile solution for community healthcare.

II.LITERATURE REVIEW

1. **Warrell D.A., Snakebite envenoming: a neglected tropical disease, 2010.**
   - This study highlights snakebite as a major global health issue, especially in rural areas. It explains clinical symptoms and treatment approaches for venomous bites. However, diagnosis depends on expert knowledge and lacks automated detection methods.

2. **Kasturiratne A., et al., The global burden of snakebite envenoming, 2008.**
   - This research provides statistical analysis of snakebite incidents worldwide and emphasizes the need for rapid diagnosis. It

identifies high-risk regions and mortality rates. However, it does not propose any technological solution for classification.

3. **Mohapatra B., et al., Snakebite mortality in India: a nationally representative survey,2011.**
- This paper analyzes snakebite deaths in India and highlights delays in medical treatment as a key issue. It stresses the importance of early identification. However, it lacks real-time diagnostic systems.

4. **Longbottom J., et al., Vulnerability to snakebite envenoming: a global mapping, 2018.**
- This study maps snakebite-prone regions using environmental and demographic data. It helps in understanding risk factors and prevention strategies. However, it does not address bite mark classification or emergency diagnosis

III.METHODOLOGY

1. **Data Collection**
- Collected 100+ snake bite mark images.
- Divided into Training (80%) and Testing (20%) datasets.

2. **Image Preprocessing**
- Resize images (e.g., 128×128 or 224×224).
- Convert to grayscale or RGB.
- Normalize pixel values (0–1).

3. **Feature Extraction**
- Flatten image pixels into feature vectors OR
- Use pre-extracted features before feeding into DNN.

4. **DNN Model Architecture**
- Input Layer (image features)
- Multiple Hidden Layers (Dense + ReLU activation)

5. **Emergency Assistance Output**
- If venomous → Immediate medical guidance.
- If non-venomous → Basic wound care advice.

IV.TESTING AND IMPLEMENTATION

The phase ensures that the Snake Bite Mark Classification System works accurately, reliably, and efficiently under different conditions. Testing is conducted on both the preprocessed images from the dataset and new unseen images to validate the model’s performance. The system is tested for: accuracy in classification, response time, interface usability, and the reliability of preliminary medical suggestions. Different performance metrics, such as accuracy, precision, recall, and F1-score, are evaluated to measure the effectiveness of the model. Testing also verifies the proper functioning of the database, input-output modules, and user interface.

Dataset Testing: Test the model on a separate set of bite mark images. Evaluate whether the system can correctly classify venomous and non-venomous bites. Ensures that the model generalizes well to unseen data.

Real-Time Image Testing: Upload new bite mark images through the interface. Check if the system produces instant classification results. Verifies real-time functionality for emergency scenarios.

Accuracy Verification: Compare predicted results with the actual labels of the images. Measure how often the system makes correct classifications. Helps determine the reliability of the model.

Performance Metrics: Calculate metrics like accuracy, precision, recall, and F1-score.Quantify the model’s overall performance in classification. Identify areas for improvement in the neural network.

Interface Testing: Ensure the interface allows users to easily upload images. Check if the classification result and medical suggestion are displayed clearly. Verifies usability for doctors, paramedics, and first responders.

Database Testing: Check that input images and prediction results are stored correctly. Verify retrieval of historical data when required. Ensures data integrity and consistency.

Error Handling: Test system with invalid, blurred, or low-quality images. Check if the system gives meaningful warnings or handles errors gracefully. Ensures robustness and prevents system crashes.

Emergency Suggestion Validation: Confirm that preliminary medical guidance matches bite type. Ensure suggestions are **safe**

and actionable for emergency care. Supports quick decision-making in critical situations

System Stress Testing: Test the system with multiple images uploaded consecutively. Check the response time and stability of the system under load. Ensures smooth performance during heavy usage.

Integration Testing: Verify that all modules (input, preprocessing, classification, output, and database) work together.Check seamless communication between each module.Ensures that the full system functions correctly and reliably.

Implementation:
The preparing and preprocessing the bite mark images, including resizing, normalization, and noise removal. The preprocessed images are then fed into a **Convolutional Neural Network (CNN)** or Deep Neural Network (DNN) model designed to extract important features and classify the bites as venomous or non-venomous. The model is trained using a labeled dataset, and its performance is evaluated on a separate testing set using metrics such as accuracy, precision, and recall. Once trained, the model is integrated with the system interface to accept real-time input images, perform classification, and display the results along with preliminary medical suggestions. The implementation also includes database management to store images, predictions.

Dataset Preparation: Collect bite mark images and organize them into training and testing sets. Ensure images are labeled as venomous or non-venomous. Check for quality and consistency before preprocessing.

Image Preprocessing: Resize images to a standard dimension (e.g., 224×224 pixels).Normalize pixel values and remove noise for better model performance. Enhance contrast to highlight bite mark features.

Model Design: Create a CNN or DNN architecture with convolution, pooling, and fully connected layers. Define the input, hidden layers, activation functions, and output layer. Design the model to extract features and perform accurate classification.

Model Training: Train the model using the preprocessed training dataset. Monitor loss and accuracy during training to avoid over fitting. Use validation data to evaluate performance at each epoch.

Model Evaluation: Test the trained model on the testing dataset. Measure performance using accuracy, precision, recall, and F1-score.Ensure the model generalizes well to unseen images.

Integration with Interface: Connect the trained model to the system interface. Allow users to upload images and get real-time classification. Display bite type and preliminary medical suggestions.

Database Management: Store input images, predicted results, and metadata in the database. Ensure easy retrieval for future reference or model improvement .Maintain data integrity and consistency.

Real-Time Operation: Input images are captured or uploaded by users. Model performs classification instantly and outputs results. System provides guidance for emergency medical assistance.

V.RESULTS AND DISCUSSION

The Snake Bite Classification System was developed using deep learning and tested with a dataset of more than 100 images. The model achieved 92% training accuracy and 88% testing accuracy, showing that it can effectively classify bite marks as venomous or non-venomous. The system provides fast results and basic medical suggestions, which can be useful in emergency situations. However, the dataset size is small, which affects the model's ability to handle real-world cases. The slight difference between training and testing accuracy indicates minor overfitting Overall, the system works well as a support tool for quick identification, but it is not reliable enough to replace medical experts. Improving the dataset and model can increase accuracy and performance

VI.CONCLUSION

The efficient and reliable solution for the rapid identification of venomous and non-venomous snakebites. By combining image processing techniques with a Convolutional Neural Network (CNN), the system can accurately classify bite marks and provide preliminary medical suggestions in real time. This approach reduces dependence on manual diagnosis, minimizes human error, and supports doctors, paramedics, and first responders, especially in rural or emergency scenarios. The modular design, including preprocessing, classification, output, and database management, ensures scalability, maintainability, and future adaptability. Overall, the system enhances emergency medical response, improves patient safety, and demonstrates the potential of AI-driven healthcare solutions.

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