



Hybrid CNN - LSTM Model for Visual and Behavioral Rabies Detection

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ABSTRACT: Rabies is one of the most serious zoonotic viral diseases and is one of several viral zoonotic diseases that can be transmitted from animals to humans. Approximately 59,000 people die from rabies each year. Almost all rabies cases in people are caused by transmission of rabies virus (RabV) from rabid domestic dogs (99% of rabies cases in people worldwide), the primary rabies virus reservoir. Rabies can be diagnosed using a recognized "gold standard" method of diagnosis, the Fluorescent Antibody Test (FAT), which is based on the post-mortem examination of brain tissue of the infected animal. However, because FAT diagnosis requires the collection of animal post-mortem brain tissue for laboratory analysis, rabies cannot be diagnosed in an animal until after death. This paper describes a dual modal artificial intelligence (AI) based screening system that uses complementary image classification (deep learning) and text classification (deep learning) to simultaneously identify rabies in dogs based on classical ('textbook') clinical signs. The dual modal AI based screening system consists of: (1) a fine-tuned Convolutional Neural Network (CNN) based on the ResNet50 architecture is used to classify visual signs associated with furious rabies such as: excessive salivation, abnormal behaviour and frothy saliva, and (2) a Long Short Term Memory (LSTM) Recurrent Neural Network (RNN) is used to semantically classify written signs describing clinical manifestations of dumb (paralytic) rabies. In addition, because of the variance of the symptoms chosen for training the models, each of these models ultimately achieved a final predicted accuracy of 100% during the validation iterations; Both of these CNN models share their outputs in a single Streamlit application that calculates an overall risk score for the use of rabies vaccines and provides recommendations on the use of rabies vaccines to prevent further rabies infections. This study is an important advancement toward allowing for a quick and easy method for non-expert healthcare providers to diagnose rabies in developing countries worldwide.

KEYWORDS: Rabies Diagnoses, CNNs, ResNet50, LSTMs, Transfer Learning, Zoonotic Diseases, Deep Learning, Multimodal Classification Systems, Veterinarian AI Applications, Public Health Screening



I. INTRODUCTION

Rabies is a serious zoonotic disease that remains a source of hundreds of thousands of deaths each year due to rabies. Rabies is not only a serious global health issue but also has a significant public health impact on developing countries. The main cause of human rabies cases is the bite of a rabid dog, which emphasizes the significance of diagnosing the infected animal as soon as possible to ensure the health and safety of the general public [12, 13]. Rabies in dogs occurs in two forms: the "furious" form of rabies (living with rabies) and the "dumb" form (a combination of rabies and paralysis). The furious form of rabies in dogs can have aggressive and hypersalivating reactions, as well as other abnormal behaviors, while the dumb form of rabies in dogs will have a general muscular weakness or appear to be lethargic or have difficulty swallowing, and therefore can be confused with other diseases and accordingly treated for other diseases, which increases the risk of rabies transmission [14, 16]. Conventional rabies diagnosis can only be carried out through laboratory procedures such as the Fluorescent Antibody Test (FAT), which involves the collection of post-mortem specimens of brain tissue from the suspected rabies victim in order to perform the test. Although these tests are accurate, they are invasive and do not offer the ability to quickly and easily test for rabies in the field [15, 17]. Thus, there is a need to develop low-cost and non-invasive rabies diagnostic tools that can be used by veterinarians or animal control officers to quickly and easily test for rabies in the field while conducting routine veterinary or animal control work. Much progress has been made in the use of artificial intelligence (AI) in a number of fields, such as computer-aided diagnosis through the analysis of medical images, computer-based prediction of the incidence of infectious diseases based on disease incidence data, and use of AI by veterinarians and community health workers to help in the identification of suspected rabies cases [20, 21, 23]. The use of computer vision algorithms in animal identification, breed identification, and the monitoring of animal diseases has long been established [1, 6, 22], and much progress has been made in the development of models based on natural language processing algorithms for the automated classification of rabies signs and symptoms.

II. RELATED WORK

There has been a tremendous increase in the application of artificial intelligence for animal surveillance and veterinary health analysis in the past few years. Computer vision methods have been employed for the classification of animal species, breeds, and behaviors through convolutional neural networks, proving their efficiency in recognizing visual features from images [1], [6], [7]. Detection models like YOLO-based models have also been employed for the surveillance of stray dogs in urban areas, assisting the authorities in monitoring animal populations and ensuring public safety [5]. This indicates that deep learning methods are capable of efficiently processing visual data related to animals, opening up possibilities for disease screening applications. Machine learning has also been investigated for the purpose of animal health condition identification. Some research has employed support vector machines and natural language processing for the identification of skin diseases in pet dogs and suggested their treatment, emphasizing the effectiveness of joint image and text data in veterinary applications [4]. Other research has employed deep learning-based image classification for the identification of animal diseases in various species, verifying the effectiveness of automatic disease identification based on visual symptoms [22]. Hybrid neural networks that integrate convolutional and recurrent networks have also enhanced the effectiveness of biomedical image classification, implying their effectiveness in multimodal learning techniques [9]. Regarding rabies, there have been studies aiming at enhancing the accuracy of diagnosis and surveillance. Systematic reviews have assessed the current state of rabies diagnostic techniques and underlined the importance of developing faster and more accessible diagnostic tools [2]. Portable devices based on PCR have been suggested for the detection of rabies virus genes in field samples, providing faster results but still requiring the collection of biological samples and the necessary expertise [3]. Machine learning approaches have been applied for the analysis of rabies epidemiology and the prediction of risks of outbreaks in areas with limited surveillance data [10], [18]. However, many current methods are based on a single type of data, such as images or epidemiological data. But the symptoms of rabies include both observable symptoms and descriptive clinical symptoms. Thus, a multimodal approach that combines visual and text data may offer a more comprehensive screening tool. The new CNN-LSTM system proposed here builds on previous work by combining image analysis for symptom detection with text analysis.

III. METHODOLOGY

The proposed rabies detection system employs a two-modality deep learning model to examine visual symptoms and text descriptions of dog behavior. The proposed methodology is broken down into several steps, including data preparation, model development, training, and system implementation.



A. Data Collection and Preparation

For text analysis, symptom descriptions were gathered from veterinary reports and mock case files. The text was preprocessed, tokenized, and zero-padded to a fixed length. A vocabulary dictionary was constructed to represent words as numbers for model training.

B. Visual Classification Model

The image processing component was implemented using transfer learning with the ResNet50 model. A pre-trained model was employed as a feature extractor, and a new classification head was appended with global average pooling, a dense layer with ReLU activation, dropout for regularization, and a sigmoid output layer for binary classification. The model was trained in two phases. First, the layers of the pre-trained model were frozen during training of the new classification head. Next, the upper layers of the model were fine-tuned with a lower learning rate to adjust the model to rabies-specific visual cues.

C. Textual Classification Model

The second module applied a Long Short-Term Memory network for the classification of the symptom descriptions. An embedding layer transformed words into vector space representations, accompanied by spatial dropout for enhanced generalization. The LSTM layer identified relationships among symptoms in sequence, and a softmax layer generated the final classification output.

D. Model Training and Evaluation

The models were trained on labeled datasets with validation for accuracy and loss assessment. Accuracy and confusion matrix analysis were employed for the evaluation of the reliability of the models.

E. System Integration and Deployment

The trained models were then integrated into a web application using Streamlit. The web application allows users to upload images of dogs and input descriptions of symptoms. The system then processes the two inputs and provides a combined risk score and safety advice. The system allows for rapid and non-invasive testing that can help veterinarians and health officials detect rabies early.

IV. SYSTEM ARCHITECTURE

The proposed rabies detection framework follows a dual-modality architecture that processes both visual and textual inputs to identify suspected rabies cases in dogs. As illustrated in Fig. 1, the system consists of four major components: the Input Layer, the Visual Engine, the Semantic Engine, and the Streamlit Integration Layer. These modules work together to provide a unified risk assessment and safety recommendation.

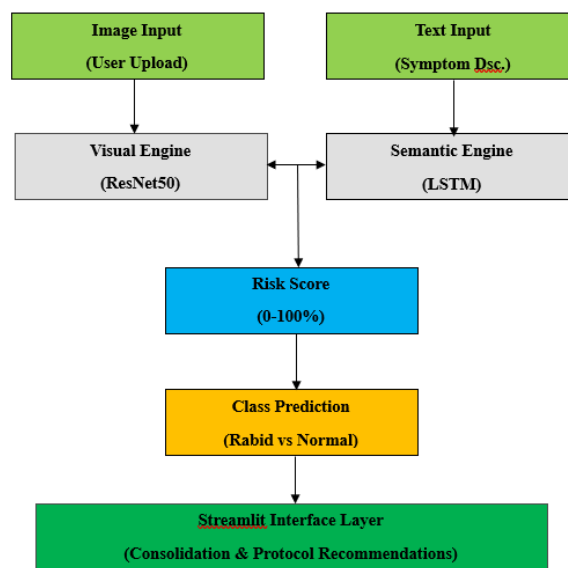


Fig.1. Overall Architecture of the Dual-Modality Rabies Detection System

A. Input Layer

The system accepts two types of user inputs:

1. **Image Input** – A photo of the suspected dog uploaded by the user.
2. **Text Input** – A written description of observed symptoms.

These inputs represent visual symptoms such as hypersalivation and behavioral symptoms such as lethargy or paralysis.

B. Visual Engine (ResNet50)

The uploaded image is processed by a ResNet50-based convolutional neural network. The model extracts important visual features such as mouth posture, saliva presence, eye expression, and aggressive stance. After feature extraction, the model outputs a probability score indicating the likelihood of rabies infection. This score is represented as a risk percentage (0–100%).

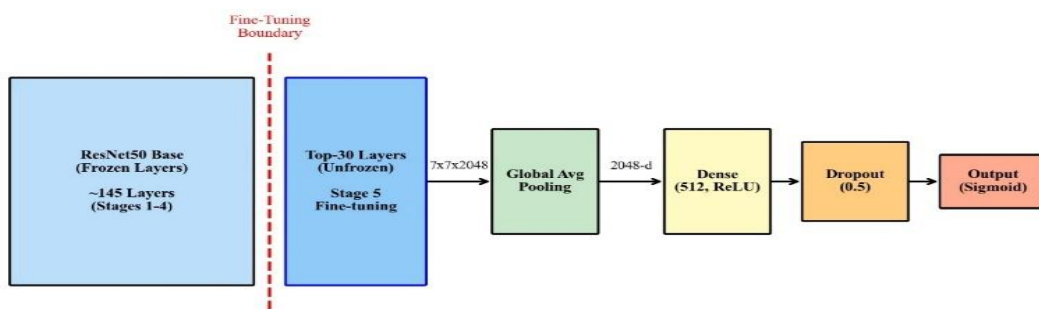


Fig. 2 Fine-Tuned ResNet50 Architecture for Visual Rabies Detection

- **ResNet50 Base (Frozen Layers – Stages 1–4)**
This module consists of about 145 layers of the pre-trained ResNet50 model. These layers are frozen during the training process to ensure that the weights learned by these layers remain unchanged. The frozen layers form a general feature extractor that is capable of detecting basic image patterns such as edges, textures, shapes, and color transitions. The use of frozen layers saves training time and prevents overfitting, particularly when dealing with a small dataset.
- **Top-30 Layers (Unfrozen – Stage 5 Fine-Tuning)**
The last layers of ResNet50 are unfrozen and trained on the rabies dataset. The process of fine-tuning helps the model learn disease-specific features such as excessive salivation, open-mouth posture, inappropriate eye expression, and aggressive posture. Fine-tuning enhances accuracy without affecting the previously learned features.
- **Global Average Pooling Layer**
This layer transforms the large feature map into a vector of size 2048 by averaging the feature channels. It decreases the complexity of the model and prevents overfitting.
- **Dense Layer (512 Neurons, ReLU)**
The dense layer learns about the higher-level relationships among the extracted features. With 512 neurons and a ReLU activation function, it identifies rabies-specific patterns and enhances the classification ability.
- **Dropout Layer**
The dropout layer randomly shuts down 50% of the neurons during training. This ensures that the model does not overemphasize particular features.
- **Output Layer (Sigmoid Activation)**
The final layer gives a probability value between 0 and 1. A value close to 1 represents a high probability of rabies, and a value close to 0 represents a normal dog. This binary output helps in real-time risk prediction.

C. Semantic Engine (LSTM)

The text description is processed by an LSTM-based recurrent neural network. The model analyzes the sequence of words to understand symptom patterns like weakness, dropped jaw, or abnormal behavior. Based on semantic understanding, the model predicts whether the symptoms correspond to Rabid or Normal conditions.

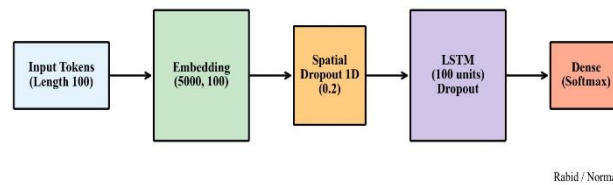


Fig.3. LSTM-based semantic classification architecture for rabies symptom analysis

D. Decision and Integration Layer

Outputs from both the visual and semantic engines are combined to produce a final prediction. If either module indicates high risk, the system flags the case for further veterinary examination. This high-sensitivity strategy reduces the chance of missing infected animals.

E. Streamlit Interface Layer

The final results are displayed through a Streamlit web interface. This layer consolidates predictions, shows the risk score, and provides precautionary guidelines such as isolation or veterinary consultation. The interface enables easy use by veterinarians, animal handlers, and public health workers.

This architecture allows fast, non-invasive rabies screening by combining complementary visual and textual analysis, making it suitable for real-time field deployment.

VI. EXPERIMENTAL SETUP AND RESULT ANALYSIS

The proposed rabies detection model was tested using different data sets for visual and text symptoms of canine rabies. The visual data set consisted of images and extracted frames from videos of confirmed rabid dogs, as well as healthy dogs, all of which were resized to 224 × 224 pixels and preprocessed based on ResNet50 requirements, with rotation and flip augmentation methods included. The visual model employed transfer learning with a pre-trained ResNet50 model, in which the base layers were initially frozen and later fine-tuned with the Adam optimizer and a batch size of 32 to learn rabies-specific features. For the text model, the symptom descriptions were tokenized, padded to have the same length, and processed with an LSTM network with embedding and dropout layers for rabies and normal narrative classification. The visual model reached a validation accuracy of about 97.6%, while the text model reached 100% accuracy on the prepared symptom descriptions. The confusion matrix analysis indicated excellent rabies detection, but some healthy dogs that exhibited panting symptoms were sometimes confused with hypersalivation symptoms due to their visual similarity.

When both models were integrated, the dual-modality approach yielded more accurate screening outcomes compared to the individual models. The proposed system was built with high sensitivity to avoid missing any rabies cases, as false positives can always be checked by veterinarians, but false negatives could lead to severe public health threats. In general, the experimental results have shown that the rabies screening solution using transfer learning with ResNet50 and text analysis using LSTM can be an accurate, rapid, and non-invasive approach.

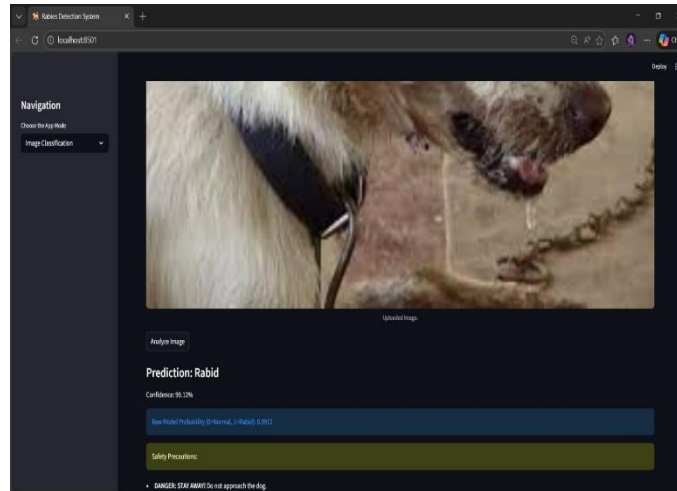


Fig.6. Output of the Image-Based Furious Rabies Detection Module

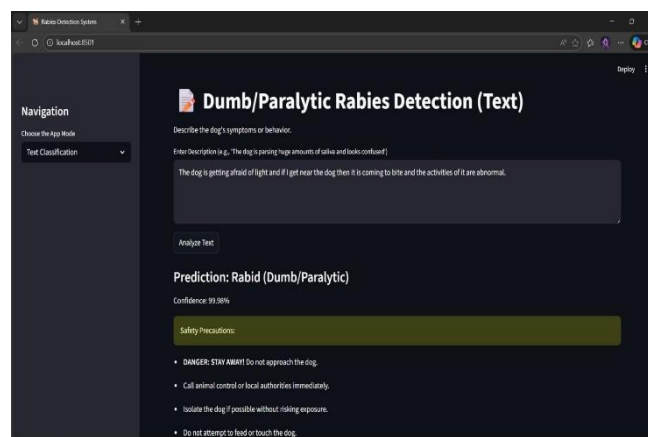


Fig.7. Output of the Text-Based Dumb Rabies Detection Module

VII. CONCLUSION

This research work aimed to develop a dual-modality artificial intelligence framework for the early screening of rabies in dogs using image and text modalities. A fine-tuned ResNet50 model was employed for the detection of Furious Rabies symptoms, while an LSTM model was used for the analysis of Paralytic Rabies symptoms. The experimental results showed the effectiveness of both components, and their combination using a Streamlit interface allowed for real-time risk evaluation and cautionary warnings. The proposed framework was designed with high sensitivity to minimize the chances of missing infected animals, making it more appropriate for use as a screening tool rather than a substitute for laboratory testing. The proposed framework is expected to help veterinarians and public health officials quickly identify suspected rabies cases. Future research will be aimed at improving the robustness of the models and developing a mobile-based implementation for large-scale rabies surveillance in resource-constrained settings.

VIII. FUTURE WORK

Future development of this system will focus on improving accuracy, adaptability, and real-world usability. Expanding the diversity of training data across different dog breeds, lighting conditions, and geographic regions will help the model generalize better to unseen cases. Enhancing the multimodal framework to analyze continuous behavior patterns instead of single observations can provide more reliable predictions. Integrating contextual information such as environmental conditions and animal history may also improve diagnostic confidence. Further research can explore methods to reduce false positives while maintaining high sensitivity, ensuring safe and practical screening performance. In addition, validating the system through large-scale field studies with veterinary professionals will help refine



prediction reliability and user trust. With continuous improvement in data quality, model learning strategies, and deployment adaptability, the system can evolve into a scalable solution that supports early rabies detection and contributes to long-term public health surveillance.

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