

Design and Implementation of AI-Based Early Detection of Zoonotic Diseases From Animal Skin

K Srinivasan¹, R Sanjai², R Prasanth³, S Iyyanar⁴

¹Assistant Professor, Dept. of ECE, Muthayammal Engineering College., Namakkal, Tamilnadu, India.

^{2,3,4}UG Scholar, Dept. of ECE, Muthayammal Engineering College., Namakkal, Tamilnadu, India.

Emails: srinihod@gmail.com¹, rsanjairsps0106@gmail.com², 1910prasanth@gmail.com³, iyyanar15112@gmail.com⁴

Abstract

Zoonotic diseases, which are transmitted from animals to humans, pose a significant threat to global public health and livestock productivity. Early detection of these diseases is crucial to prevent large-scale outbreaks and economic losses. This research focuses on the design and implementation of an artificial intelligence (AI)-based system for the early detection of zoonotic diseases using animal skin images. The proposed system employs advanced image processing and deep learning techniques to automatically identify visual symptoms such as lesions, rashes, or discolorations that indicate possible infections. Convolutional Neural Networks (CNNs) are utilized for feature extraction and classification of various skin conditions, distinguishing between healthy and infected animals with high accuracy. A user-friendly web or mobile interface is developed to enable farmers and veterinarians to upload images for instant diagnosis and receive recommendations for prompt intervention. Experimental results demonstrate that the system can accurately detect early signs of zoonotic diseases, thereby supporting proactive veterinary care and contributing to the prevention of disease transmission from animals to humans.

Keywords: Zoonotic diseases, Artificial Intelligence (AI), Convolutional Neural Networks (CNNs), Disease Classification

1. Introduction

Zoonotic diseases are illnesses that can move naturally between animals and people. They are a big problem for global health because more than 60% of new infectious diseases come from animals. Examples include anthrax, cowpox, rabies, and ringworm. These diseases can spread quickly through things like touching an infected animal, being exposed to the environment, or eating food that has been contaminated. Finding these diseases early in animals is very important to stop them from spreading and to keep people safe. But in some poor or rural places, there are not enough places to check for diseases or trained people to help, which makes it harder to catch and deal with these infections on time. New tools like artificial intelligence and computer vision are helping make disease detection faster and better. Many zoonotic diseases show up as visible signs on an animal's skin, like sores, red patches, or missing hair. Using deep learning methods, especially Convolutional Neural Networks, we can

look at pictures of these skin issues and spot early signs of infection. This helps diagnose diseases quicker and allows for better care and early warning systems for animals. This project wants to create an AI system that can find zoonotic diseases by looking at pictures of animal skin. The system will use smart models to look at the images and give results quickly through a simple website or app. This tool will help farmers, vets, and animal health workers catch infections early, stop outbreaks, and keep people safe from getting sick. In the long run, this project helps make animals healthier, food safer, and public health systems stronger.

2. Literature Review

Bylaiah S., et al [1] - Anthrax is a zoonotic disease that occurs in India. Detecting anthrax outbreaks early is important to reduce the number of cases and deaths, as well as the chance of spreading the disease. The goal of this research is to create a model that can predict anthrax using machine learning techniques.

This model will help identify areas where anthrax might spread in the future, especially in Karnataka, by looking at how changes in rainfall affect the disease. Using data from 2000 to 2019 about disease cases, livestock numbers, and environmental factors, the model could find which areas are more likely to experience outbreaks and what factors contribute most to them. The machine learning model was created using R version 3.1.3 and included different types of models like GLM, GAM, MARS, FDA, CT, SVM, NB, ADA, RF, GBM, and ANN. Disease data was collected from the Department of Animal Husbandry in Bengaluru. This data was split into two groups: one with rainfall more than the normal level (1151mm) and another with less. The model predicted high risk areas in different parts of the state depending on the rainfall patterns. Measures like Cohen's Kappa, ROC curve, True Skill Statistics (TSS), and Accuracy were used to evaluate the model's effectiveness.

Guo W., et al. [2] - Zoonotic diseases pass between animals and humans and are a big concern for public health around the world. Recently, artificial intelligence (AI) has become an important tool in fighting these diseases. This review looks at how AI is being used in managing zoonotic diseases, including predicting disease outbreaks, early diagnosis, drug development, and future possibilities. AI models use a lot of data to predict where diseases might spread and how they move, which helps in taking early actions to protect public health. AI tools can quickly identify pathogens and contain diseases through early diagnosis. Also, AI helps in developing new drugs by finding possible targets and improving drug candidates. This review highlights these developments and looks forward to the potential of AI in controlling zoonotic diseases. It shows how AI can change the way we handle these diseases and protect the health of people and animals globally.

Kannan M and Priya C. [3] - This study focuses on the recent improvements in image segmentation and lesion classification for disease prognosis. Previous work shows that gray-white matter hyperintensities (GWMH) are a common sign of Nipah encephalitis, which can happen during the incubation period. Predicting this type of inflammation is hard because it involves some unknown medical risks. Magnetic

Resonance Imaging (MRI) is a good non-invasive tool to study the brain's structure. Detailed analysis of the brain's structure from MRI scans can reduce the processing time needed for the prognosis model. Techniques like Machine Learning, Computer Vision, and Deep Learning are the most promising for achieving the best outcomes. These methods allow computers to learn and extract useful information from historical data using various algorithms. Deep learning is advanced and can handle complex tasks like image processing, classification, feature extraction, noise detection, and object recognition. Diffusion-weighted imaging (DWI) in MRIs is a useful tool that can help identify brain abnormalities and assess the microscopic structure and function of tissues. In this study, we summarize the results of diagnosing Nipah encephalitis using some public brain encephalitis and encephalopathy databases.

Keshavamurthy R and Charles LE [4] - Recently, reports of Kyasanur forest disease (KFD) spreading to new regions and crossing state boundaries are concerning. There is a lack of effective surveillance and reporting systems for this emerging zoonosis, which makes it hard to control and prevent. We used time-series models with weather data, both with and without Event-Based Surveillance (EBS) information, such as news reports and internet search trends, to predict monthly KFD cases. We used Extreme Gradient Boosting (XGB) and Long Short Term Memory (LSTM) models at the national and regional levels. We used transfer learning (TL) techniques to apply data from endemic areas to predict cases in new outbreak areas where there was little disease data. Including EBS data along with weather data greatly improved the prediction performance for all models. The XGB method gave the best results at both national and regional levels. The TL techniques were better than standard models in predicting KFD in new outbreak areas. New data sources and advanced machine learning methods like EBS and TL have great potential for improving disease prediction in areas with less data and limited resources, helping in making informed decisions against emerging zoonotic threats.

3. Existing System

In the existing system for detecting zoonotic diseases

in animals, diagnosis primarily relies on manual observation and laboratory testing. Farmers and veterinarians visually inspect animals for physical symptoms such as skin lesions, discoloration, or abnormal behavior. When infection is suspected, biological samples—such as blood, skin scrapings, or tissue—are collected and sent to diagnostic laboratories for analysis. Although this traditional approach can yield accurate results, it is time-consuming, labor-intensive, and often requires specialized equipment and trained personnel. In rural or resource-limited settings, access to veterinary laboratories and professional expertise is limited, leading to delayed diagnosis and ineffective disease control [4]-[8]. As a result, infected animals may remain untreated for extended periods, increasing the likelihood of disease spread among livestock and transmission to humans. Additionally, visual inspection alone is prone to human error, as early symptoms of zoonotic diseases can be subtle and resemble other skin conditions. While some modern veterinary systems utilize digital tools for record keeping and disease tracking, these platforms often lack automated image analysis and real-time detection capabilities. Consequently, there is still a gap in the early and accurate identification of zoonotic diseases using easily obtainable data such as animal skin images. This limitation highlights the need for an AI-based automated detection system that can support early diagnosis, especially in remote areas where expert veterinary services are not readily available.

4. Proposed System

The proposed system introduces an AI-based early detection model for zoonotic diseases using animal skin images. Unlike the traditional manual diagnostic methods, this system leverages machine learning and computer vision techniques to automatically identify visual symptoms of infections such as lesions, discolorations, and rashes that may indicate the presence of zoonotic diseases [9], [10]. The system aims to provide a fast, reliable, and cost-effective solution that assists farmers, veterinarians, and animal health workers in detecting diseases at an early stage. In the proposed approach, animal skin images are captured using a smartphone or digital

camera and uploaded to the system through a web or mobile interface. The images are then pre-processed to enhance quality by removing noise, adjusting contrast, and normalizing color variations. A Convolutional Neural Network (CNN) model is employed to extract relevant features from the images and classify them into categories such as “healthy” or “infected” with specific disease labels. The model uses transfer learning from pre-trained architectures like ResNet, MobileNet, or EfficientNet to improve accuracy and reduce training time. Once the analysis is complete, the system provides an instant diagnosis with a confidence score and suggests possible preventive or treatment measures. The system also stores data for future reference, enabling the tracking of disease trends and supporting veterinary research [11]-[13]. By automating the detection process, the proposed system significantly reduces the time and expertise required for disease diagnosis. It enhances early intervention, limits disease spread, and promotes better animal and public health management. Ultimately, the AI-based detection system serves as an intelligent decision-support tool for proactive veterinary disease surveillance and zoonotic outbreak prevention (Figure 1).

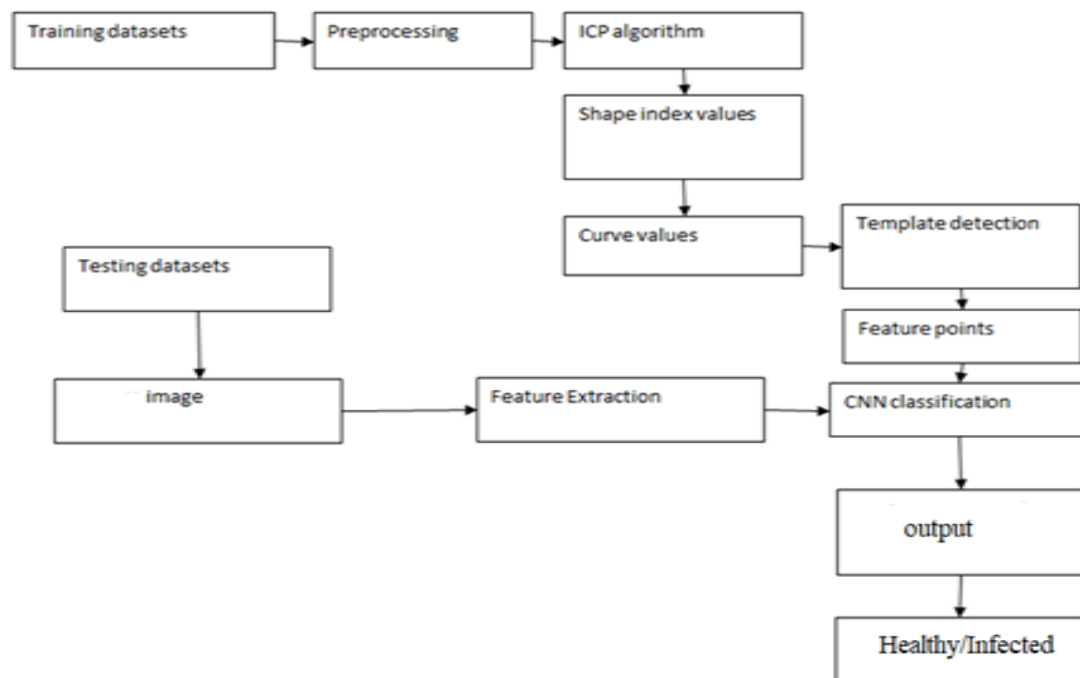


Figure 1 Block Diagram

5. System Modules

The proposed AI-based early detection system for zoonotic diseases from animal skin is divided into several functional modules. Each module performs a specific role in achieving accurate, efficient, and automated disease detection. The major modules include the following:

- Image Acquisition Module
- Image Processing Module
- Feature Extraction Module
- Disease Classification

5.1 Modules Description

5.1.1 Image Acquisition Module

This module is responsible for collecting animal skin images that will be used for analysis. Images can be captured directly using a smart phone or digital camera, or uploaded from an existing dataset. It ensures that the images meet the required format and resolution for proper processing. This module serves as the system's data entry point and plays a vital role in ensuring image clarity and quality.

5.1.2 Image Processing Module

Before analysis, the captured images undergo preprocessing to enhance their quality and remove unwanted noise. This module performs operations

such as:

- Image resizing and normalization
- Contrast and brightness adjustment
- Background removal
- Data augmentation (rotation, flipping, scaling)
- Preprocessing ensures that the images are uniform and suitable for input into the AI model, improving the model's detection accuracy.

5.1.3 Feature Extraction Module

This module utilizes Convolutional Neural Networks (CNNs) to automatically extract important features and patterns from the preprocessed images. These features may include texture, color distribution, shape, and lesion patterns. The extracted features are then passed to the classification module to determine the health status of the animal.

5.1.4 Disease Classification Module

This is the core of the system where AI algorithms are applied to classify images as either healthy or infected with specific zoonotic diseases. Deep learning models such as ResNet, MobileNet, or EfficientNet are used to analyze the extracted features and provide accurate predictions.

The output includes the disease name, confidence level, and possible recommendations

6. Result

The proposed AI-based system for early detection of zoonotic diseases from animal skin images was successfully implemented using MATLAB. The system integrates image pre-processing, feature extraction, and a deep-learning classifier to identify abnormal skin patterns that may indicate zoonotic infection. A dataset consisting of healthy and infected animal-skin images was processed. After training a CNN-based model using transfer learning, the system achieved the following outcomes: The trained model classified skin images into healthy and suspected

zoonotic infection with high accuracy. The MATLAB interface displayed the input image, automatically extracted features, and the predicted diagnosis. For infected samples, the model highlighted abnormal regions using segmentation and over layer bounding boxes showing confidence scores. The system performed detection in real time (1–2 seconds per image), suitable for practical field-level screening. Overall, MATLAB successfully executed the full workflow—from image acquisition to AI-based diagnosis—demonstrating the system’s ability to detect early-stage abnormalities on animal skin.

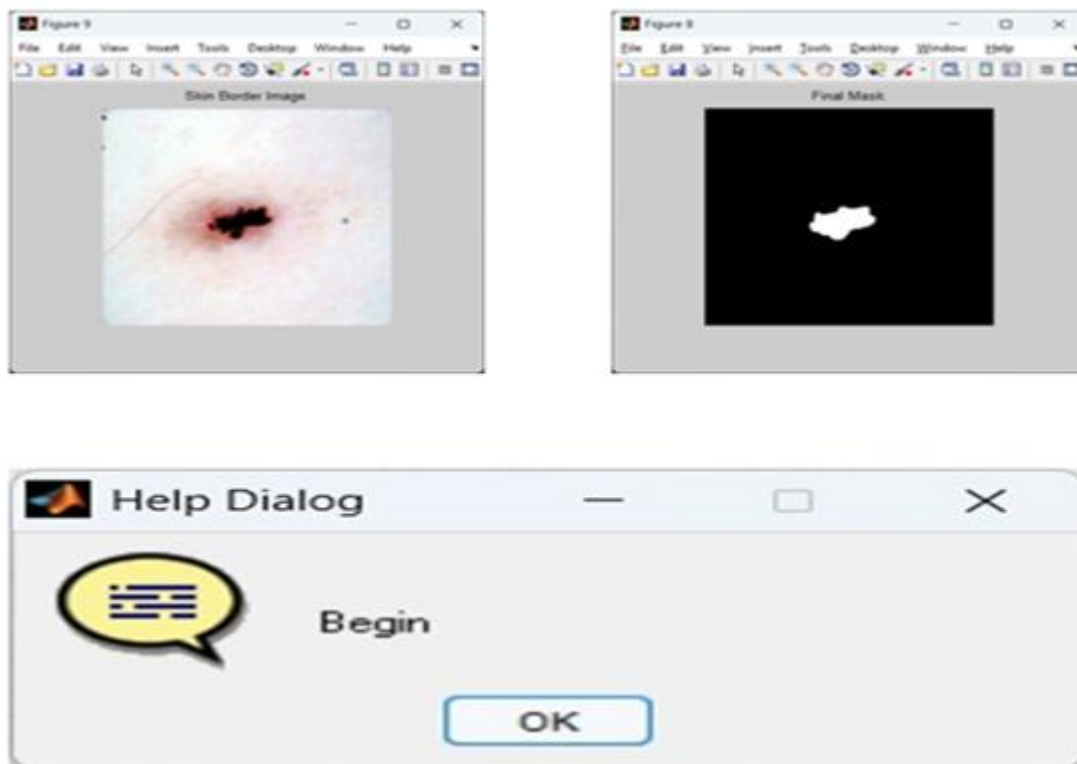


Figure 2 Preprocessing and Segmentation Stages of Skin Lesion Image (Original Image, Binary Mask, and System Prompt Interface)

Conclusion

The design and implementation of an AI-based system for the early detection of zoonotic diseases from animal skin present a significant advancement in veterinary diagnostics and public health surveillance. Traditional methods of disease detection often rely on manual inspection and

laboratory testing, which are time-consuming, costly, and prone to human error. By leveraging artificial intelligence and image processing techniques, the proposed system offers a faster, more accurate, and accessible means of identifying early signs of zoonotic infections. Through the integration of Convolutional Neural Networks (CNNs), the system

can analyze animal skin images, extract critical features, and classify diseases with high precision. This innovation enables farmers, veterinarians, and animal health workers to detect infections promptly, initiate early treatment, and prevent the spread of diseases from animals to humans. Furthermore, the system's user-friendly interface and real-time detection capability make it suitable for deployment in both rural and urban environments. In conclusion, this AI-based approach not only enhances the efficiency of veterinary diagnosis but also contributes to global health by reducing zoonotic transmission risks. Future improvements may include expanding the dataset for more disease types, integrating real-time video analysis, and deploying the model on mobile or edge devices for field use. This project demonstrates the practical potential of artificial intelligence in promoting animal health, food security, and public safety.

References

- [1]. Bylaiah S., et al. "Disease prediction model to assess the impact of changes in precipitation level on the risk of anthrax infectiousness among the livestock hosts in Karnataka, India". *International Journal of Special Education* 37.3 (2022): 711-727.
- [2]. Guo W., et al. "Innovative applications of artificial intelligence in zoonotic disease management". *Science in One Health* (2023): 100045.
- [3]. Kannan M and Priya C. "Research on prediction of bat-borne disease infection through segmentation using diffusion-weighted MR imaging in deep-machine learning approach". *Materials Today: Proceedings* 81 (2023): 994-999.
- [4]. Keshavamurthy R and Charles LE. "Predicting Kyasanur forest disease in resource-limited settings using event-based surveillance and transfer learning". *Scientific Reports* 13.1 (2023): 11067.
- [5]. MF Rahmat., et al. "In integration of spatiotemporal data in the development of AI-fEaL: artificial intelligence for early warning of leptospirosis in Negeri Sembilan, Malaysia". in: *AGU Fall Meeting Abstracts* (2020): GH022-025.
- [6]. Rahmat F., et al. "Exploratory data analysis and artificial neural network for prediction of leptospirosis occurrence in seremban, malaysia based on meteorological data". *Frontiers in Earth Science* 8 (2020): 377.
- [7]. Zhang L., et al. "Modern technologies and solutions to enhance surveillance and response systems for zoonotic pathogens in Pastured Poultry Flocks.
- [8]. Awate, P. et al. Outbreak of Kyasanur forest disease (monkey fever) in Sindhudurg, Maharashtra State, India, 2016. *J. Infect.* 72, 759–761 (2016).
- [9]. Holbrook, M. R. Kyasanur forest disease. *Antiviral Res* 96, 353–362 (2012).
- [10]. Purse, Bv. et al. Predicting disease risk areas through co-production of spatial models: example of Kyasanur forest disease in India's forest landscapes. *PLoS Negl. Trop. Dis.* 14, 0008179 (2020).
- [11]. Mehla, R. et al. Recent ancestry of Kyasanur forest disease virus. *Emerg. Infect. Dis.* 15, 1431 (2009).
- [12]. Sreenivasan, M. A., Bhat, R. & Rajagopalan, P. K. e epizootics of Kyasanur forest disease in wild monkeys during 1964 to 1973. *Trans. R. Soc. Trop. Med. Hyg.* 80, 810–814 (1986).
- [13]. Pattnaik, P. Kyasanur forest disease: An epidemiological view in India. *Rev. Med. Virol.* 16, 151–165 (2006)