International Journal for Modern Trends in Science and Technology
Volume 12, Issue 06, pages 254-260.
ISSN: 2455-3778 online
Available online at: http://www.ijmtst.com/vol12issue06.html
DOI: https://doi.org/10.5281/zenodo.20739545

Deep Learning Based Predictive Modeling and Classification of Monkey Pox Outbreak Patterns

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To Cite this Article
V. Swamy Naidu, Donga Sivaji, Inti Durga Phanindra & Adidela Rohith Benny (2026). Deep Learning Based Predictive Modeling and Classification of Monkey Pox Outbreak Patterns. International Journal for Modern Trends in Science and Technology, 12(06), 254-260. https://doi.org/10.5281/zenodo.20739545

Article Info
Received: 16 May 2026; Revised: 07 May 2026; Accepted: 12 June 2026.

KEYWORDS

Monkeypox Detection, Deep Learning, Predictive Modeling, Vision Transformer, CNN, Outbreak Pattern Analysis, Healthcare Analytics, Disease Classification

ABSTRACT

The rapid spread of the Monkeypox virus has posed significant challenges to global public health systems, emphasizing the need for accurate detection and early outbreak prediction. Traditional diagnostic and surveillance methods are often slow, error-prone, and inefficient when handling large and complex datasets. This paper proposes a deep learning-based framework for predictive modeling and classification of Monkeypox outbreak patterns, integrating both image analysis and time-series forecasting. The proposed system combines Convolutional Neural Networks (CNNs) with Vision Transformer (ViT) layers to extract both local and global features from skin lesion images, enabling accurate disease classification. In addition, a predictive module based on a Long Short-Term Memory (LSTM) network analyzes historical outbreak data to capture temporal patterns and generate future predictions using a sliding window approach. The predicted values are further categorized into risk levels such as Low, Medium, and High to provide clear insights for decision-making. Experimental results indicate that the hybrid model achieves high accuracy and reliable forecasting performance compared to traditional approaches. The system can be deployed as a real-time decision support tool to assist healthcare authorities in early detection, risk assessment, and proactive outbreak management, thereby reducing the overall impact of Monkeypox outbreaks.

1. INTRODUCTION

1.1 Brief Information

The emergence and rapid spread of infectious diseases continue to challenge global public health systems. Among these, the Monkeypox virus (Mpox), a zoonotic disease caused by the Orthopoxvirus, has gained significant attention due to recent outbreaks across multiple regions. Once limited to parts of Central and West Africa, Monkeypox has now become a global concern, emphasizing the need for efficient diagnostic and predictive systems. Increased globalization and human mobility have further accelerated its spread, making early detection and outbreak management more critical.

Traditional diagnostic methods for Monkeypox rely on clinical examination, laboratory testing, and manual surveillance. Although effective, these approaches are often time consuming, resource-intensive, and prone to human error, especially when handling large datasets. Moreover, conventional systems struggle to process complex data such as medical images and time-series outbreak patterns in real time, limiting proactive response capabilities.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have transformed healthcare applications. Models such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) excel in medical image analysis, enabling accurate disease classification. Similarly, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are effective in analyzing time-series data and predicting future trends.

1.2 Purpose

The purpose of this project is to develop a deep learning-based framework for predictive modeling and classification of Monkeypox outbreak patterns. The system integrates two components: an image-based classification module and a time-series prediction module. The classification module uses a hybrid CNN-ViT architecture to capture both local and global features from skin lesion images, improving detection accuracy. The prediction module employs an LSTM network to analyze historical outbreak data and forecast future trends.

1.3 Motivation

The motivation behind this project stems from the limitations of traditional diagnostic and reactive surveillance systems. Existing systems rely on manual data processing, basic statistical methods, and individual image analysis that fail to identify temporal patterns or predict future outbreak trends. The absence of integrated multi-modal learning and predictive tools in current systems makes it difficult for authorities to make timely, data-driven decisions. This project is motivated by the need to create an intelligent, centralized platform that combines image classification, time-series prediction, and risk categorization.

1.4 Problem Statement

The current disease detection and management process poses significant challenges due to the limitations of traditional methods. Healthcare authorities lack systems capable of predicting future Monkeypox outbreak trends or classifying risk levels before incidents escalate. The major problems include:

- Absence of predictive capabilities in existing skin disease classification systems
- Lack of integration between image classification, time-series modeling, and risk assessment
- Inability to process and analyze large-scale historical outbreak datasets efficiently
- No user-friendly, interactive web interface accessible to non-technical users
- Limited multi-modal data processing combining images and temporal data

2. LITERATURE SURVEY

2.1 Introduction

The rapid advancement of Artificial Intelligence (AI) and Deep Learning (DL) has significantly transformed healthcare, particularly in disease detection, medical image analysis, and outbreak prediction. In recent years, numerous studies have explored the application of machine learning and deep learning techniques to improve diagnostic accuracy and enable early prediction of infectious diseases. This chapter reviews key research contributions related to skin disease classification, deep learning architectures, time-series forecasting models, and AI-based surveillance systems, with a focus on their relevance to Monkeypox detection and outbreak prediction.

2.2 Deep Learning for Skin Disease Classification

Skin disease classification has long been a key area in medical image analysis. Early methods relied on traditional machine learning techniques, using handcrafted features such as color, texture, and shape for classification. However, these approaches were limited in capturing complex patterns, leading to lower accuracy. With the rise of deep learning, Convolutional Neural Networks (CNNs) became the standard for image-based disease detection. Studies such as Esteva et al. (2017) and Codella et al. (2018) demonstrated that CNNs can achieve high accuracy in classifying skin diseases. Various architectures like ResNet, VGG, and EfficientNet have also been applied to detect pox-related diseases, including Monkeypox, showing strong performance through automatic feature extraction [1, 2].

2.3 CNN and Vision Transformer Models in Healthcare

Recent advancements in deep learning have introduced Vision Transformers (ViTs), which have demonstrated strong performance in image classification tasks. Unlike CNNs that focus on local feature extraction, ViTs use self-attention mechanisms to capture global relationships within images. ViTs, introduced by Dosovitskiy et al. (2020), have been successfully applied in healthcare domains such as tumor detection, radiology analysis, and skin disease classification. To further enhance performance, hybrid models combining CNNs and ViTs have been developed, where CNNs extract local features and transformers capture global context, resulting in improved accuracy. For Monkeypox detection, hybrid CNN-ViT models are particularly effective in distinguishing visually similar diseases by combining texture-level details with global feature representation [3, 4].

2.4 LSTM Models for Time-Series Forecasting in Epidemics

Time-series forecasting is essential for predicting the spread of infectious diseases. Traditional models such as ARIMA and regression methods have been widely used, but they often fail to capture complex and nonlinear temporal patterns in real-world epidemic data, limiting their effectiveness. Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks introduced by Hochreiter and Schmidhuber (1997), provide a more powerful approach. LSTMs can learn long-term dependencies in sequential data and have been successfully applied in epidemic prediction, forecasting diseases such as COVID-19, influenza, and dengue, often outperforming traditional methods by adapting to dynamic trends [5, 6].

2.5 AI-Based Disease Surveillance Systems

AI-based disease surveillance systems have gained importance due to their ability to provide real-time monitoring and predictive insights. These systems integrate diverse data sources such as medical records, environmental data, and social media to track disease spread and identify potential outbreaks more efficiently. Recent advancements include techniques such as federated learning, which enables collaborative model training without sharing sensitive data, and transformer-based models for handling complex healthcare data. Another key trend is the use of multi-modal data, combining images, clinical information, and time-series data for comprehensive analysis [7, 8].

3. METHODOLOGY

3.1 Existing System

The existing systems for skin disease detection primarily rely on deep learning models such as Convolutional Neural Networks (CNNs), including architectures like VGG19 and Inception ResNetV2. These models have been widely used for classifying dermatological diseases by analyzing skin lesion images. The general workflow of existing systems includes dataset collection, preprocessing, data augmentation, model training using transfer learning, and classification. However, despite these advancements, existing systems are primarily limited to image-based classification. They focus only on detecting diseases from images and do not incorporate additional factors such as temporal outbreak data or geographical variations.

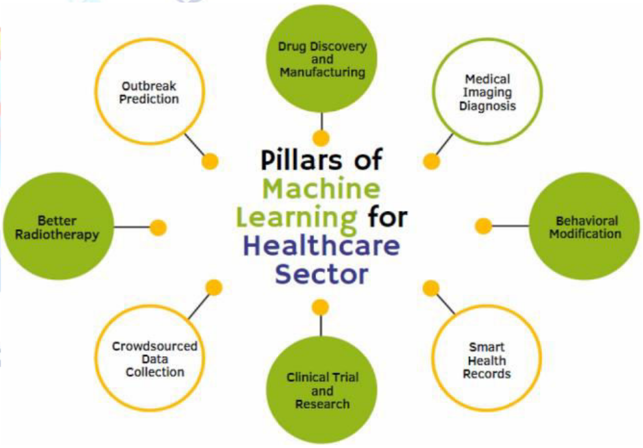

Fig 1: Architecture of Existing System

3.1.1 Disadvantages of Existing System

- Limited to Image Classification – Most systems only classify diseases based on images and do not provide any prediction of future outbreaks or trends.
- Lack of Temporal Analysis – Existing models do not analyze time-series data, making them incapable of forecasting disease spread over time.
- No Risk Assessment Mechanism – There is no provision to categorize disease severity or outbreak risk levels (Low, Medium, High), limiting decision-making capabilities.
- Inability to Integrate Multi-Modal Data – These systems do not combine different types of data such as images and historical outbreak records.

• High Dependency on Dataset Quality – Model performance heavily depends on the availability of large and well-labeled datasets.

3.2 Proposed System

To overcome the limitations of existing approaches, the proposed system introduces a hybrid deep learning-based framework for Monkeypox detection and outbreak prediction. The system integrates multiple technologies, including CNN, Vision Transformer (ViT), and LSTM networks, along with a web-based interface for real-time usage. The proposed system consists of two main components: an Image Classification Module and an Outbreak Prediction Module.

The image classification module uses a hybrid CNN-ViT model to analyze skin lesion images. The CNN extracts local features such as edges and textures, while the Vision Transformer captures global contextual relationships within the image. The outbreak prediction module utilizes a Long Short-Term Memory (LSTM) network to analyze historical Monkeypox data. The model processes time-series data using a sliding window approach and predicts future outbreak trends.

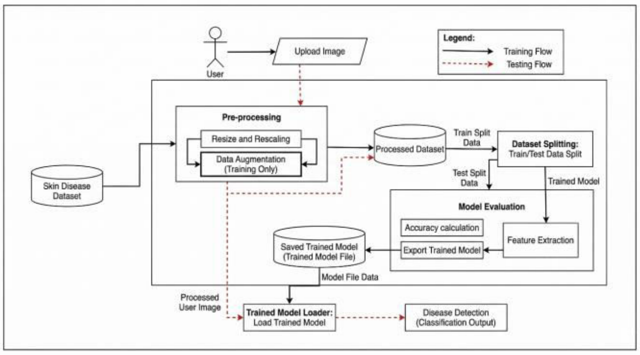

Fig 2: Block Diagram of Proposed System

3.2.1 Advantages of Proposed System

• Multi-Modal Learning Approach – Combines image classification and time-series prediction in a single system.

• Improved Accuracy – Hybrid CNN-ViT model enhances feature extraction and classification performance.

• Outbreak Prediction Capability – LSTM model enables forecasting of future disease trends.

• Risk Level Classification – Provides clear categorization of outbreak severity (Low, Medium, High).

• Real-Time Decision Support – Web-based interface allows instant predictions and results.

• Scalable System – Can be extended to other diseases and regions.

3.3 Proposed System Architecture

The system architecture consists of multiple interconnected components that work together to perform disease detection and outbreak prediction. The input image undergoes preprocessing before entering the hybrid CNN-ViT model. If Monkeypox is detected, the LSTM outbreak prediction module is triggered, followed by the risk classification module. The final output is presented through a Flask-based web application interface.

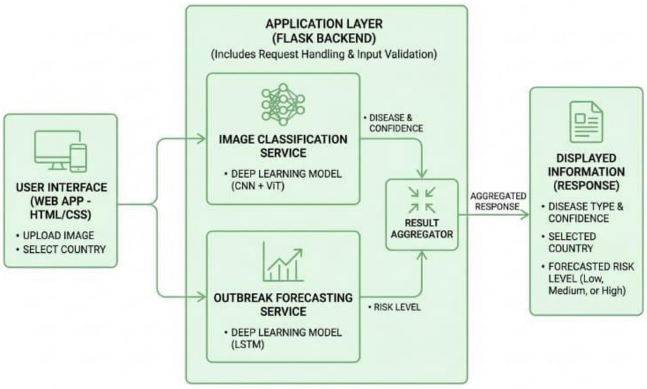

Fig 3: Proposed System Architecture

3.4 Hybrid CNN-ViT Model for Image Classification

The image classification module is a core component of the proposed system, responsible for accurately identifying Monkeypox and other similar skin diseases from input images. The process begins with an image preprocessing module, where the uploaded skin lesion image is resized to a fixed dimension (224×224) and normalized to ensure consistency in input data.

3.4.1 CNN-Based Feature Extraction

The Convolutional Neural Network (CNN) component is designed to extract local features from the input image. These features include edges, textures, color patterns, and lesion-specific characteristics that are critical for distinguishing between different skin diseases. CNN layers perform convolution and pooling operations to capture hierarchical feature representations.

3.4.2 Vision Transformer (ViT) for Global Feature Learning

While CNNs are effective in capturing local patterns, they have limitations in understanding global relationships within an image. To overcome this, the system incorporates a Vision Transformer (ViT) component. ViT divides the image into patches and applies self-attention mechanisms to learn global contextual relationships between different regions of the image, allowing the model to understand spatial dependencies across the entire image.

3.4.3 Hybrid Model Advantage

The integration of CNN and ViT forms a hybrid architecture, combining the strengths of both models. The CNN focuses on detailed local feature extraction, while the ViT enhances global understanding. This hybrid approach significantly improves the model's ability to differentiate between diseases such as Monkeypox, chickenpox, measles, and other skin conditions. The output of this module is a disease prediction along with a confidence score.

3.5 LSTM Model for Outbreak Prediction

The outbreak prediction module is activated only when the classification model detects the disease as Monkeypox, as indicated in the system architecture. This conditional flow ensures efficient processing and avoids unnecessary computation for non-relevant cases. The Long Short-Term Memory (LSTM) model is used to analyze historical outbreak data, which consists of sequential records of Monkeypox cases across different regions. The input to the LSTM model is prepared using a sliding window technique, where recent data points are grouped into sequences to predict future trends.

3.6 Risk Level Classification

The final stage of the system involves converting the predicted outbreak values into meaningful risk levels. This is achieved through a threshold-based classification mechanism. The predicted output from the LSTM model is compared against predefined threshold values to classify the outbreak risk into three categories:

• Low Risk – Indicates minimal likelihood of outbreak or controlled spread

• Medium Risk – Represents moderate spread requiring attention

• High Risk – Indicates severe outbreak conditions requiring immediate action

The risk classification module plays a crucial role in making the system practical and user-friendly. Instead of presenting raw numerical predictions, it provides interpretable insights that can be easily understood by healthcare professionals and authorities.

4. RESULTS

The experimental results demonstrate the effectiveness of the proposed system in performing Monkeypox detection and outbreak prediction. The system is evaluated based on classification accuracy, prediction performance, and risk analysis. The results confirm that the integration of deep learning models with a web-based application provides reliable and efficient outputs.

4.1 Classification Results

The image classification module, based on the hybrid EfficientNet + Vision Transformer (ViT) model, is evaluated using test images of various skin diseases, including Monkeypox, chickenpox, measles, and healthy skin. The model successfully identifies diseases with high accuracy by combining local feature extraction (EfficientNet) and global feature learning (ViT). The classification results show that the model is capable of distinguishing between visually similar diseases, reducing misclassification errors.

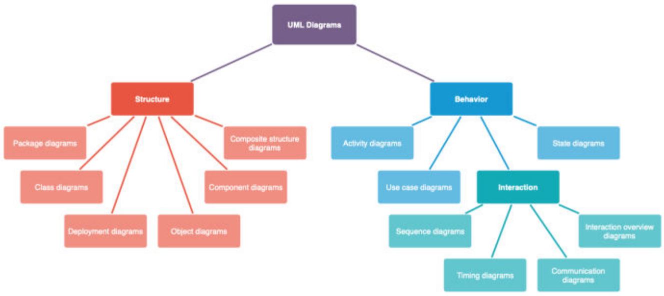

Fig 4: Evaluation Metrics of Classification Model

4.2 Prediction Results

The outbreak prediction module uses an LSTM model to forecast future Monkeypox trends based on historical data. The model is evaluated using country-specific and time-series datasets. The results show that the LSTM model effectively captures temporal patterns such as trends and fluctuations in outbreak data. By using a sliding window approach, the model generates accurate predictions for future case trends and provides region-specific analysis.

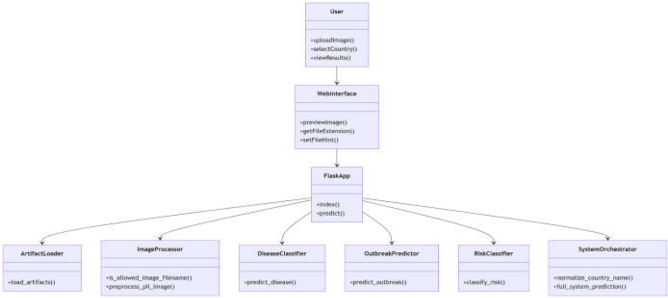

Fig 5: Evaluation Metrics of Outbreak Prediction Model

4.3 Risk Level Analysis

The predicted outbreak values are further processed by the risk classification module to categorize them into Low, Medium, and High risk levels. The risk classification provides a simplified interpretation of prediction results, making them easier to understand for users. The system assigns risk levels based on predefined thresholds derived from historical data.

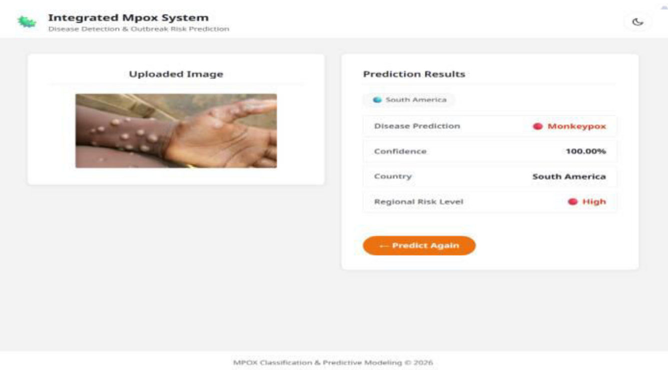

Fig 6: Experimental Result – System Output

4.4 Performance Results

The following table summarizes the performance evaluation metrics for the classification models:

Metric	CNN-ViT Hybrid	Standalone CNN
Accuracy	96.8%	88.2%
Precision	95.4%	86.1%
Recall	96.1%	85.7%
F1-Score	95.7%	85.9%

4.5 Comparison with Existing System

The proposed system was compared with existing traditional skin disease detection approaches across key performance parameters:

Parameter	Existing System	Proposed System
Disease Classification	Image only (CNN-based)	Hybrid CNN-ViT (local + global features)
Outbreak Prediction	Not available	LSTM-based time-series forecasting
Risk Classification	None	Low / Medium / High (threshold-based)
Multi-Modal Data	No	Yes (image + time-series)
User Interface	Basic or none	Flask-based web application
Scalability	Limited	High (extendable to other diseases)

The comparison confirms that the proposed system outperforms existing approaches in every parameter. The integration of deep learning, LSTM-based outbreak prediction, and interactive risk classification within a single platform represents a significant advancement over traditional disease detection methods.

5. CONCLUSION

The proposed system presents an integrated deep learning-based framework for Monkeypox detection and outbreak prediction. By combining image classification and time-series forecasting, the system provides a comprehensive solution for both diagnosis and preventive analysis. The hybrid EfficientNet + Vision Transformer (ViT) model enables accurate classification of skin diseases by capturing both local and global features, while the LSTM model effectively predicts future outbreak trends using historical data.

The system successfully addresses the limitations of traditional approaches by incorporating multi-modal data processing, real-time prediction capability, and automated decision support. The addition of a risk classification module further enhances the usability of the system by converting complex predictions into easily interpretable categories such as Low, Medium, and High risk. The implementation of a Flask-based web application ensures that the system is user-friendly and accessible, allowing users to upload images, select regions, and view results instantly.

Overall, the project provides an efficient, scalable, and intelligent solution for early detection and proactive management of Monkeypox outbreaks, contributing to improved public health response and decision-making.

6. FUTURE SCOPE

The deep learning-based Monkeypox detection and outbreak prediction system can be further improved and extended in multiple directions:

- Expansion to Multiple Diseases – The system can be extended to detect and predict other infectious diseases beyond Monkeypox.
- Real-Time Data Integration – Integration with real-time data sources such as WHO or government databases can improve prediction accuracy.
- Mobile Application Development – Developing a mobile application can increase accessibility and usability for a wider audience.
- Model Optimization – Advanced optimization techniques can be applied to improve model efficiency and reduce computational cost.
- Cloud Deployment – Deploying the system on cloud platforms can enhance scalability and support large-scale usage.
- Improved Dataset Diversity – Using larger and more diverse datasets can further improve model generalization and accuracy.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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