A Dual-Mode Intelligent Framework for Monkeypox Detection Using Symptom Analysis and Skin Lesion Imaging

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Abstract

Monkeypox (Mpox) is a viral zoonotic disease that presents clinical symptoms and skin manifestations similar to several other infectious illnesses, making early and accurate diagnosis challenging. Conventional diagnostic approaches such as polymerase chain reaction (PCR) testing and clinical examination are reliable but often time-consuming, costly, and dependent on specialized laboratory infrastructure. To address these limitations, this study proposes a dual-mode automated Monkeypox detection system that supports diagnosis using either clinical symptoms or skin lesion images. The proposed framework integrates two independent models: a Convolutional Neural Network (CNN) for image-based lesion classification and a Random Forest (RF) classifier for symptom-based infection prediction. The CNN model focuses on extracting discriminative visual features from lesion images, while the RF model evaluates structured symptom data to estimate infection risk. Experimental evaluation demonstrates that the image-based CNN achieves an accuracy of 98%, while the symptom-based Random Forest model attains 97% accuracy. By allowing flexible input modalities and maintaining computational efficiency, the proposed system offers a practical and reliable solution for early monkeypox screening, particularly in resource-constrained healthcare environments.

Keywords: Monkeypox detection, Convolutional Neural Network, Random Forest, Symptom-based diagnosis, Image-based classification, Machine learning, Deep learning

1. Introduction

Monkeypox is a viral zoonotic disease caused by the monkeypox virus, which belongs to the Orthopoxvirus family. The infection is primarily transmitted through close contact with infected individuals, exposure to bodily fluids, or interaction with contaminated objects and surfaces. Common clinical manifestations include fever, headache, swollen lymph nodes, fatigue, and characteristic skin lesions. Due to the similarity of these symptoms with other infectious diseases such as measles and chickenpox, accurate clinical differentiation can be difficult, particularly during the early stages of infection. Consequently, timely and dependable detection of monkeypox plays a crucial role in preventing disease spread and enabling prompt medical treatment [1-2].Conventional diagnostic approaches rely heavily on clinical assessment and polymerase chain reaction (PCR) testing. While these methods provide high diagnostic accuracy, they are often expensive, time-intensive, and dependent on advanced laboratory infrastructure and trained personnel. In response to these challenges, recent research has increasingly focused on

the use of machine learning and deep learning techniques to automate infectious disease diagnosis. Existing deep learning approaches for monkeypox detection predominantly utilize Convolutional Neural Networks (CNNs) for image-based classification of skin lesions. However, many of these systems overlook symptom-based diagnosis, which is particularly important when lesion images are unclear or unavailable. Moreover, advanced deep learning architectures, such as Swin Transformer-based models, impose significant computational demands, limiting their feasibility in real-world and resource-limited healthcare environments [3-4].

To address these limitations, this study proposes a dual-mode monkeypox detection framework that supports independent symptom-based and image-based diagnosis. The proposed system incorporates two separate models: a Random Forest (RF) classifier for analyzing clinical symptoms and a Convolutional Neural Network (CNN) for classifying skin lesion images. The CNN architecture is designed for efficient visual feature extraction and includes two max-pooling layers followed by a fully connected layer. In parallel, the Random Forest model evaluates structured symptom information, including fever, sore throat, lymph node enlargement, and fatigue, to estimate the likelihood of monkeypox infection. By allowing users to provide either symptom data or lesion images, the system offers greater diagnostic flexibility compared to traditional single-input approaches [5-6].

The effectiveness of the proposed framework is evaluated using two datasets: a structured clinical symptom dataset for training the Random Forest model and a skin lesion image dataset for training the CNN model. Experimental results demonstrate that the Random Forest classifier achieves an accuracy of 97%, while the CNN-based image classifier reaches 98% accuracy. The complementary operation of these two models enhances diagnostic reliability and efficiency, making the proposed system a practical tool for early monkeypox detection in diverse clinical settings.

2. Related Work

The use of machine learning and deep learning techniques in the diagnosis of infectious diseases, particularly monkeypox, has gained considerable research attention. Although polymerase chain reaction testing and clinical evaluation remain the standard diagnostic practices, recent advancements in artificial intelligence–driven systems have demonstrated significant potential to improve the speed, efficiency, and accessibility of monkeypox diagnosis. Automated diagnostic frameworks aim to reduce reliance on specialized laboratory infrastructure while supporting early disease identification.

2.1 Machine Learning Approaches for Monkeypox Detection

Several studies have explored symptom-based monkeypox detection using classical machine learning algorithms. These approaches commonly evaluate models such as Decision Trees, Logistic Regression, Naïve Bayes, Support Vector Machines, and Random Forest classifiers. Among these techniques, ensemble-based models, particularly Random Forest, have consistently demonstrated superior performance in predicting infection probability based on clinical symptoms. Adaptive neural network–based methods combined with optimization strategies have also been investigated and shown to achieve high accuracy and flexibility when compared with conventional machine learning classifiers [3-5].

Further research has emphasized the importance of feature selection techniques, hyperparameter optimization, and balanced datasets to improve classification reliability. These studies indicate that Random Forest models are particularly effective for early monkeypox detection due to their robustness, ability to handle nonlinear relationships, and resistance to overfitting when trained on structured symptom data [6-7].

2.2 Deep Learning Approaches for Image-Based Monkeypox Detection

Deep learning methods have primarily focused on the analysis of skin lesion images for monkeypox diagnosis. Convolutional Neural Networks have been widely adopted for extracting discriminative visual features and performing image-based classification. In addition to image analysis, some studies have integrated machine learning and deep learning techniques to identify biological or molecular patterns associated with monkeypox, further improving detection accuracy through optimized feature selection [8-9].Hybrid diagnostic frameworks that combine deep learning for image analysis with traditional machine learning classifiers have also been explored. These systems demonstrate improved predictive performance by leveraging both visual and statistical features. However, despite their effectiveness, many image-based models exhibit reduced reliability when lesion images are unclear, incomplete, or unavailable [10-11].

Moreover, advanced deep learning architectures, such as transformer-based models, achieve high accuracy at the cost of significant computational complexity. This limits their suitability for real-time deployment in low-resource or remote healthcare environments [12].To address these challenges, a hybrid dual-mode diagnostic approach that integrates Convolutional Neural Networks for image-based detection and Random Forest classifiers for symptom-based prediction offers enhanced diagnostic accuracy and flexibility. By enabling independent analysis of clinical symptoms and skin lesion images, the proposed dual-mode monkeypox detection framework improves adaptability across diverse clinical scenarios while maintaining computational efficiency. This combination of machine learning and deep learning techniques makes the system well-suited for practical implementation in resource-constrained healthcare settings [13-14].

3. Existing System

Advanced deep learning architectures, such as Swin Transformer-based models integrated with Swin–PSO–SVM–based Monkeypox Detection. The Swin-PSO-SVM framework represents a hybrid approach designed for the early identification of monkeypox by integrating transformer-based feature extraction, evolutionary optimization, and margin-based classification. This combined strategy aims to deliver high diagnostic accuracy and reliable performance while maintaining interpretability and reasonable computational efficiency, making it suitable for practical medical applications [15].In this framework, feature extraction is carried out using a Swin Transformer architecture. The model processes images in a hierarchical manner, enabling the capture of both fine-grained local details and broader contextual patterns. Unlike conventional convolutional neural networks, the Swin Transformer divides input images into non-overlapping patches and applies self-attention within localized windows. These attention windows are shifted across layers, allowing the model to learn relationships between neighboring regions and improve contextual understanding. This hierarchical design not only enhances feature representation but also reduces computational complexity compared to global attention mechanisms, enabling the model to adapt to varying image resolutions [16-17].

Following feature extraction, Particle Swarm Optimization is applied to select the most informative features and reduce dimensionality. In this optimization process, each particle represents a candidate subset of extracted features and navigates the solution space by updating its position and velocity based on individual and collective performance. The quality of each feature subset is evaluated using the classification accuracy achieved by the downstream classifier. Through this optimization process, only the most discriminative features are retained, which improves generalization performance and helps mitigate overfitting [18-19].The optimized feature set is then passed to a Support Vector Machine classifier, which assigns each input sample to one of several classes, including normal cases, measles, chickenpox, and monkeypox. The SVM constructs an optimal decision boundary by maximizing the margin between classes, ensuring robust separation even in high-dimensional feature spaces. Particle Swarm Optimization is also employed to fine-tune the SVM hyper-parameters, such as kernel selection and regularization strength, further enhancing classification performance and stability [20].

Overall, the Swin-PSO-SVM framework provides a reliable solution for automated monkeypox detection by combining the representational strength of transformer-based models, the efficiency of evolutionary optimization, and the robustness of margin-based classification. The approach demonstrates strong accuracy and balanced performance across multiple disease categories while effectively controlling overfitting. Although more efficient than traditional transformer models, the Swin Transformer still introduces notable computational overhead. Despite this limitation, the framework achieves high diagnostic accuracy across different datasets, making it a promising candidate for automated monkeypox diagnosis, with potential for further optimization to improve cost-effectiveness and real-world applicability [21].

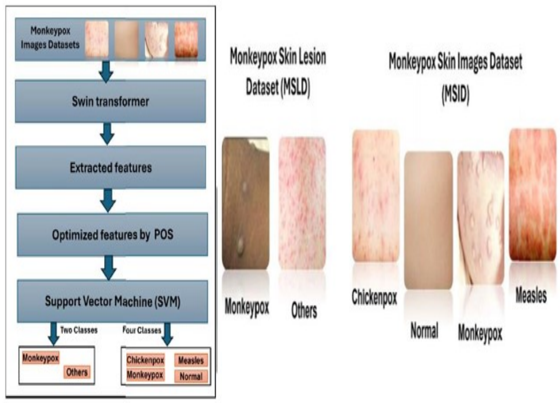

Figure 1: Process flow of Swin-PSO-SVM model for Monkeypox detection

4. Introduction to the Proposed System

The proposed methodology introduces a dual-model classification framework designed to provide an automated, accurate, and efficient solution for monkeypox detection. The system integrates image-based analysis using Convolutional Neural Networks and symptom-based assessment using a Random Forest classifier to ensure a comprehensive diagnostic process. By combining these two complementary approaches, the framework enables rapid and reliable identification of monkeypox, supporting early medical intervention and improved patient management.

4.1 Architecture of the System

The overall architecture of the proposed system consists of two primary diagnostic components that operate independently based on the type of input provided. The first component focuses on symptom-based prediction, while the second component performs image-based classification of skin lesions. This modular design allows users to obtain diagnostic results using either clinical symptoms or lesion images, thereby increasing flexibility and usability in real-world healthcare scenarios [22].The symptom-based module is designed to analyze user-reported clinical features associated with monkeypox and related conditions. A Random Forest classifier is trained using a structured dataset that includes symptoms such as systemic illness, rectal pain, sore throat, penile oedema, oral lesions, solitary lesions, swollen tonsils, HIV infection, and sexually transmitted infections. The model employs an ensemble of decision trees along with feature selection mechanisms to identify the most significant symptom patterns for classification. This approach enables the system to distinguish monkeypox cases from other illnesses with an accuracy of 97%, providing users with a preliminary diagnostic assessment before proceeding to image-based analysis [22-23].

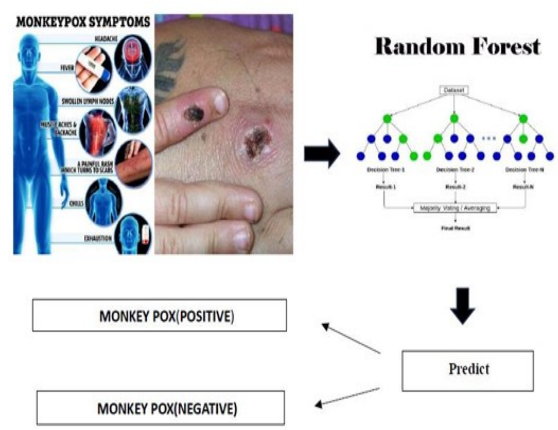

Figure 2: Basic architecture of Random Forest (RF)

The image-based diagnostic module focuses on the classification of skin lesion images to accurately identify monkeypox-related rashes. A deep Convolutional Neural Network is trained using images of monkeypox lesions as well as other dermatological conditions. The network architecture includes multiple convolutional and max-pooling layers that facilitate the extraction of complex visual features from the input images, followed by fully connected layers for classification. The model achieves an accuracy of 98% in detecting monkeypox lesions and provides real-time prediction results along with probability scores to users who upload lesion images [23].

4.2 Data Preprocessing

To enhance model performance and ensure consistent input quality, appropriate data preprocessing techniques are applied to both symptom and image datasets. The structured symptom data is collected from academic sources, public health repositories, and medical records. This data includes clinical indicators such as systemic illness, rectal pain, sore throat, penile oedema, oral lesions, solitary lesions, swollen tonsils, HIV infection, and sexually transmitted infections. The dataset undergoes cleaning, normalization, and encoding to maintain consistency and reliability. For model development and evaluation, the data is divided into training and testing subsets using an 80:20 ratio [21].

The image dataset consists of high-resolution photographs of monkeypox lesions. To ensure uniformity, all images are resized to a fixed resolution, such as 128 × 128 or 120 × 120 pixels. Depending on the model requirements, images are converted into RGB or grayscale format. Pixel values are normalized to a range between 0 and 1 to facilitate faster convergence during training. Additionally, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied to increase dataset diversity and improve the generalization capability of the CNN model [22].

4.3 Training and Development of Models

The Random Forest classifier is selected for symptom-based detection due to its strong classification performance and ability to handle large and complex datasets. The model consists of multiple decision trees, each trained on different subsets of the data to enhance robustness. Feature importance analysis is used to identify the most influential symptoms contributing to monkeypox detection. Hyper-parameters such as the number of trees, maximum tree depth, and minimum samples required for splitting are optimized to achieve optimal performance. Cross-validation techniques are employed to reduce overfitting, resulting in a classification accuracy of 97% with high precision and recall.For image-based detection, the CNN model employs a deep learning architecture designed to accurately classify monkeypox skin lesions. The network includes several convolutional layers for feature extraction, followed by max-pooling layers to reduce spatial dimensions and computational complexity. The extracted features are combined using fully connected layers, with non-linearity introduced through the ReLU activation function. A Softmax activation function is used in the final layer to perform multi-class classification. The model is trained using the Adam optimizer with a learning rate of 0.0005. The dataset is split into training and validation sets using an 80:20 ratio, and the model achieves an accuracy of 98%, demonstrating high reliability for practical deployment [19].

4.4 Performance Evaluation

The effectiveness of the proposed system is evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correct predictions made by the model, while precision indicates the percentage of correctly identified positive cases. Recall, also known as sensitivity, reflects the model's ability to identify actual monkeypox cases. The F1-score provides a balanced evaluation by computing the harmonic mean of precision and recall. Confusion matrices are used to analyze true positives, false positives, true negatives, and false negatives. Training loss and accuracy trends are visualized using graphical plots generated with Matplotlib to illustrate model convergence and performance improvement over time.

4.5 System Implementation and User Interface

The proposed system is implemented as a web-based application that provides users with an interactive interface for monkeypox detection. The interface includes a symptom input section where users can enter clinical symptoms to obtain a preliminary diagnosis using the Random Forest model. An image upload section allows users to submit photographs of skin lesions, which are analyzed in real time using the CNN model. The results section displays prediction outcomes along with classification probabilities for both symptom-based and image-based diagnosis, enabling users to make informed decisions [13-15].

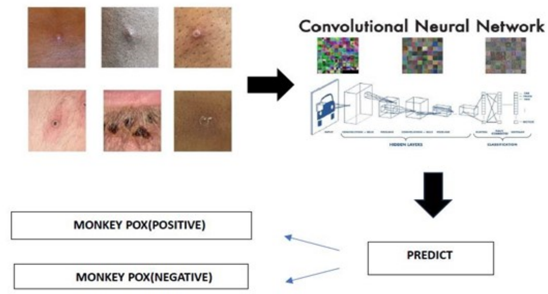

Figure 3: Basic architecture of CNN

4.6 Advantages of the Proposed System

The proposed framework offers several advantages, including high diagnostic accuracy, achieving 98% accuracy for image-based classification and 97% accuracy for symptom-based detection. The dual-model approach enhances diagnostic reliability by combining visual and clinical analysis. The automated nature of the system enables rapid predictions, significantly reducing the time required for disease identification. The architecture is scalable and can be extended in the future to detect additional skin-related or infectious diseases. Furthermore, the user-friendly web interface ensures ease of use for both healthcare professionals and individuals, supporting wider adoption in clinical and remote healthcare environments.

5. Results

The experimental results obtained from the image-based and symptom-based models demonstrate strong performance for monkeypox detection. The evaluation graphs illustrate that the image-based model achieves an accuracy of 98%, while the symptom-based model attains a slightly lower accuracy of 97%. These results indicate that both models provide highly accurate and reliable predictions.Across all evaluation metrics, including accuracy, precision, recall, and F1-score, the image-based model consistently outperforms the symptom-based model. Its higher precision and recall values reflect an improved ability to correctly classify monkeypox cases from skin lesion images, as well as a strong sensitivity in identifying true positive instances. This performance advantage can be attributed to the model's capability to capture detailed visual features that enhance classification effectiveness.

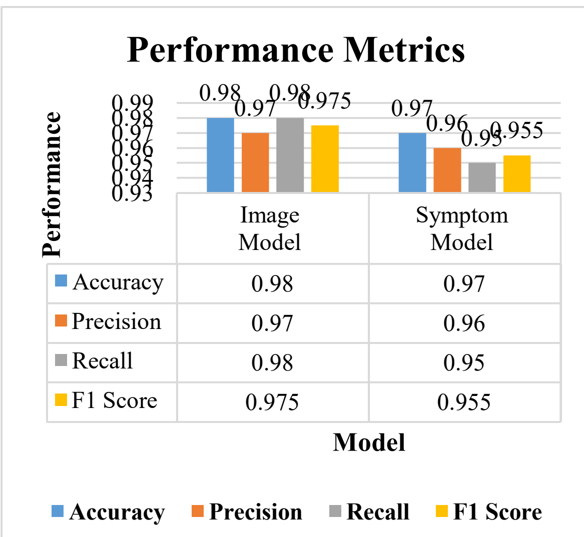

Figure 4: Evaluating performance metrics for models of Monkeypox detection.

Although the symptom-based model exhibits marginally lower performance, it remains a dependable diagnostic alternative. Its strong results highlight the effectiveness of symptom-driven analysis, particularly in scenarios where image data is unavailable or difficult to obtain. Such situations are common in remote or resource-limited healthcare settings, where access to imaging facilities may be restricted. Overall, the complementary strengths of both models contribute to a flexible and robust diagnostic framework for monkeypox detection.

6. Conclusion

This study presents an automated dual-mode framework for monkeypox detection that combines image-based analysis using a Convolutional Neural Network with symptom-based prediction through a Random Forest classifier. By integrating deep learning and machine learning techniques, the proposed system delivers reliable diagnostic performance while maintaining computational efficiency. The high accuracy achieved by both models, along with their ability to operate independently, makes the framework well suited for early screening and preliminary diagnosis of monkeypox.The proposed approach enables rapid prediction and reduces dependence on time-consuming laboratory procedures, thereby supporting timely clinical decision-making. Its user-friendly design further enhances accessibility, allowing both healthcare professionals and individuals to utilize the system with minimal technical expertise. The flexibility of accepting either symptom data or skin lesion images ensures effective diagnosis even in scenarios where one form of input is unavailable.

Future work may focus on extending the framework to support the detection of additional infectious and dermatological diseases, incorporating larger and more diverse datasets to improve generalization, and deploying the system as a mobile or cloud-based application for wider reach. Such enhancements would further strengthen the system's applicability in real-world healthcare environments, particularly in remote and resource-constrained settings.

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