Scientific Visualization, 2026, volume 18, number 3, pages 123 - 134, DOI: 10.26583/sv.18.3.09

Robust Monkeypox Detection Using Hybrid Deep Learning and Feature Fusion Techniques in Medical Images

Qusay Kanaan Kadhim[1,A], Hamid sadeq Mahdi Alsultani[2,A], Ihsan Salman[3,A], Shaymaa Taha Ahmed[4,A], Rasha Mahdi Abdulkader[5,A]

Department of Computer Science, University of Diyala, Baqubah 32001, Iraq

[1] ORCID: 0000-0003-2814-2409, dr.qusay.kanaan@uodiyala.edu.iq
[2] ORCID: 0000-0002-3571-9619, hamedsultani@uodiyala.edu.iq
[3] ORCID: 0000-0002-0974-4271, drihsan@uodiyala.edu.iq
[4] ORCID: 0000-0002-4986-2475, shaimaaAhmed@uodiyala.edu.iq
[5] ORCID: 0009-0008-1658-1600, rashamahdi@uodiyala.edu.iq

Abstract

Monkeypox is a frequent viral disease difficult for diagnosis, as in medical images it has strong visual similarity with other skin diseases. Self-diagnosis can bring the high risks of mistakes, so employing artificial intelligence in medical image analysis could be a kind of helpful way to make quick and correct diagnosis. In this study, we present a new deep learning model for the diagnosis of monkeypox from imaging skin lesions. This system is a fusion of several active and content zones that incorporate CNN characteristics, attention mechanisms, and a SVM classifier. Use of multiple imaging scopes in medical image aids to capture variations in lesions at different angles, different tissue and illumination settings for extended diagnostic information. The CNN feature concatenation merges deep features from ResNet50 with light features of EfficientNetB0 to present a full view of pest imaging characteristics. To enhance the interpretability of the model, attention-based mechanisms such as the Convolutional Block Attention Module (CBAM) are applied to focus on diagnostically important portions of the lesion while reducing irrelevant background noise. Moreover, the standard SoftMax output layer can be replaced by a Support Vector Machine (SVM) classifier to provide more separated decision boundaries and increase the generalisation capability of the model. The framework we introduced achieved outstanding results on two medical imaging datasets with an overall accuracy of 98% superior to standard single CNN method. The primary contribution of this work is the presentation of a novel deep learning framework (hybrid Deep Learning) incorporating multi-view modalities, attention-based CNN feature fusion and strong SVM classification which address the limitations in state-of-the-art methods with respect to robustness, interpretability and clinical confidence.

Keywords: Monkeypox, Multi-View Images, Deep Learning, Convolutional Block Attention Module (CBAM), Support Vector Machine (SVM), Convolutional Neural Networks (CNNs).

1. Introduction

Monkeypox is the virus (MPXV) a member of the Orth poxvirus group in the Poxviridae family and an illness that is viral from animals to humans[1]. Once a major problem in Central and West Africa, the 2022 outbreak put it on the radar as a serious global health threat[2].Fever swollen lymph nodes and certain skin symptoms such as rashes and blisters are symptoms of Monkeypox [3].

But they might also appear much like those of other viral infections that parents would think nothing of sending their child to school with chickenpox and measles to name two or

even simply a skin issue not caused by an infection like eczema and rashes from medications [4].This huge likeness proves a very accurate diagnosis is pretty hard to establish, then treatment can be slow or late toxic measures not appropriate and the risk of virus transmission higher. Conventional diagnostic techniques including PCR testing, though very sensitive and specific are time-intensive procedures adding to their cost which may not be available in resource-limited or peripherally located clinical settings [5].Visual examinations by physicians, being practical, are prone to misdiagnosis [6].

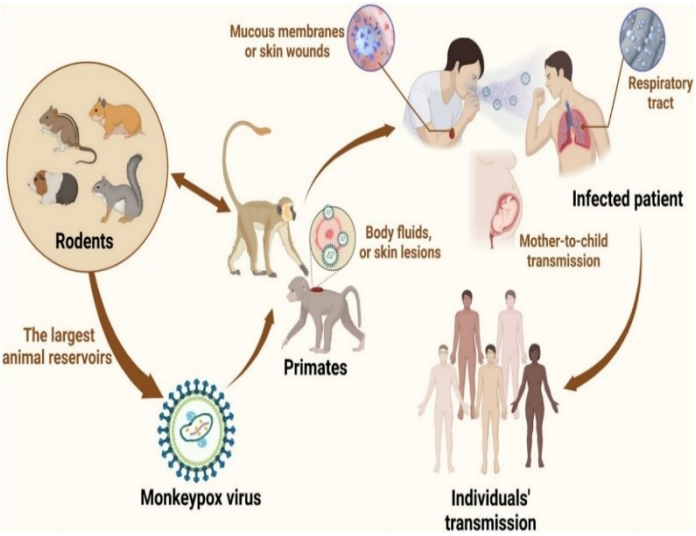


Figure 1. An illustration of the transmission and symptoms of Monkeypox Virus (MPXV)[7].

Therefore, integrating artificial intelligence methods into medical imaging procedures offers a solution that provides faster, lower-cost, and more reliable diagnosis of monkeypox at the point of care. Among these methods Convolutional Neural Networks (CNNs) are essential for modern computer vision technology [8].They are very good at automatically discovering different levels of image features, from basic edges and textures to intricate patterns of lesionsv [9].Models that use CNNs have been effectively utilized to identify skin cancers, diabetic eye disease and pneumonia through imaging data[10].However current studies on detecting Monkeypox generally use straightforward methods that depend on single-view images of lesions and one type of CNN. However, these methods suffer from some significant limitations such as lack of robustness to changes in lesion appearance and illumination conditions, as well as patient heterogeneity, and limited ability to provide interpretable explanations for their outputs [11].

The CNN Feature Fusion technique takes advantage of the advantages of two popular designs, ResNet50, which captures fine-grained feature details, and EfficientNetB0, which is computationally efficient and performs well with small datasets [12]. This incorporation offers an in-depth and precise description of dermatological diseases. The addition of the Attention Mechanism (CBAM) provides a factor that focuses on the important lesion sites and reduces the interference of irrelevant backgrounds, resulting in higher reliability and accuracy in diagnostic evaluations [13]. The system performs better defined decision boundaries and higher predictive accuracy through replacing the standard Softmax layer with SVM classifier, especially in case of inconsistent or insufficient medical data [14].

To overcome these limitations, this paper proposes a new hybrid deep learning architecture for Monkeypox detection from medical images. The remainder of this paper is organised as follows: Section Two presents a review of the relevant previous studies. The proposed architecture is presented in Section Three. The main experimental investigations are described in Section Four. Section Five looks at the developments further. The importance of the results is discussed in Section Six, along with interpretations of the attention visualizations and the relevance of these to clinical practice. Finally, Section Seven ends the study and proposes directions for further investigation.

2. Related Work

This section included the research projects that conduct trials on subjects like monkeypox using simply visuals. Whereby the literature relevant to our research has been examined. The following are the study methodology and investigational findings that we considered when reviewing those literary works.

In this study [15], The main emphasis is on 13 deep learning (DL) models that have been trained to identify monkeypox. They all receive common custom layers and undergo analysis using four widely used measures: accuracy, recall, precision, and F1 score. The best DL models are put together after a majority vote on probabilistic results. With a publicly available dataset, the proposed ensemble approach produces average precision, recall, F1-score, and accuracy of 85. 44%, 85. 47%, 85. 40%, and 87. 13%, respectively.

In the study [16] S. N. Ali et al., Images of measles, chickenpox, and monkeypox lesions can be found in the "Monkeypox Skin Lesion Dataset (MSLD)." Most of the photos are taken from blogs, open case reports, and news sources. In order to improve the sample size of a three-fold cross-validation experiment, data augmentation is employed. Following that, diseases like monkeypox are classified using pre-trained deep-learning models, such as VGG-16, ResNet50, and InceptionV3. The models were constructed in three locations. The accuracy of the ensemble system is 79. 26%, while that of ResNet50 is 82. 96% and that of VGG16 are 81. 48%.

In the study [17] used deep learning models built on ResNet and EfficientNet to identify monkeypox skin lesions. The EfficientNetB3 model was found to have the highest accuracy score of 87%.

In [18] Using the AlexNet, GoogleNet, and VGG deep learning models together with a number of machine learning classifiers on an open source monkeypox dataset attain one of the greatest accuracy rates in monkeypox identification, at 95. 55%.

In [19] attained the highest accuracy value in classification processes, 93.29%, by using pretrained MobileNetV2 and two VGG deep learning models with varying numbers of layers on an open source dataset of monkeypox skin images. In [20] The GridCVSearch method was used to optimize hyperparameters, and five-fold iterative cross-validation was used in all experimental studies. Principal Component Analysis (PCA), mRMR algorithm and SVM algorithm were used deep learning models to achieve 96% accuracy in monkeypox detection using an open source dataset for monkeypox image classification. In [21] employed the deep learning models InceptionV3, GoogLeNet, ResNet50, and VGG16 on a two-class dataset that included the normal and monkeypox classes. According to their findings, the GoogLeNet model achieved the highest accuracy score of 87. 27%.

In [22] employed the pretrained deep learning models ResNet18, MobileNetV2, EfficientNet, NasNetMobile, GoogLeNet, and ShuffleNet to attain a peak classification accuracy of 92. 50% in the Mo-bileNetV2 model for different epoch values. Furthermore, they developed an Android mobile application using Android Studio, the Java programming language, and Android SDK 12. In their data augmentation, Ahsan et al. initially processed a small number of images of ordinary and monkeypox cases before achieving a wide range of accuracy values.

Existing works focus on CNNs such as ResNet, VGG, or MobileNet for binary or multi-class skin disease classification. These methods typically rely on single images and softmax layers, limiting their adaptability to variations in lesion appearance. Few attempts incorporate attention mechanisms or feature-level fusion. To the best of our knowledge, no prior work has explicitly combined multi-view imaging, CNN fusion, attention, and SVM for Monkeypox detection.

3. Proposed Method

The proposed system is introduced as a hybrid deep learning technique for an automatic detection of Monkeypox from medical images. At the beginning of the entire process, we collect a number of lesion images at different snapping angles, so that there are variations in

each type showing different forms of light and position. That model, which is based on the usage of the two display interfaces simultaneously, has been also improved. Image algorithms such as noise rods data are averaged for consistency. And then each image is sent through two different deep neural networks, namely ResNet50 and EfficientNetB0. Note that, ResNet50 based deep leering is very effective to extract features from the deep layers. Meanwhile, EfficientNetB0 is quite fast and efficient for learning detailed patterns from small datasets.

In this stage, the convolutional block attention module (CBAM) is appended to enrich the embedded features by positioning model focus on most disease-critical region and simultaneously minimizing background one. Thus, this attention mechanism is beneficial both for classification and model interpretability. It also serves to clarify the model and aids clinicians in recognizing which interfaces had the most influence on decision-making.

Finally, a Support Vector Machine (SVM) classifier is used for classification instead of a classical SoftMax layer. The decision to use an SVM was made since it has been shown that SVM can produce clearer decision boundaries and quite robust performance in the case of a small or imbalanced dataset. This is typical to the practice of medical imaging. Combined deep feature extraction and focus-based optimization and vector support machine-based classification, the proposed system can obtain very high diagnostic accuracy, imaging consistency and compactness, which are desirable for using in hospital situations as shown in Figure 2.

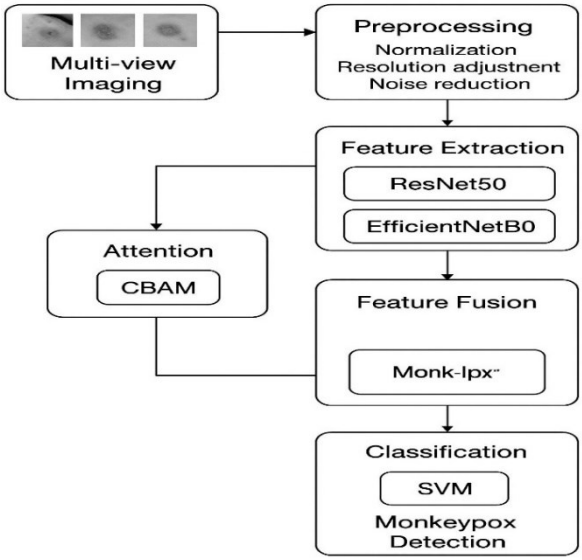


Figure 2. Proposed Method.

3.1 Data collection and Preprocessing

This study uses medical images of skin lesions collected from publicly available dermatological image datasets. The images represent Monkeypox and non-Monkeypox skin conditions and include variations in lesion appearance, illumination, scale, and imaging angle. To ensure consistency during model training, we examined and preprocessed all images before providing them to the deep learning models.

The complete dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for testing. The training partition was used to create the feature extractors ResNet50 and EfficientNetB0, and the validation partition was used to monitor the model behaviour and to fine-tune the parameters during the learning process. The held-out test partition was only used for the final evaluation of the proposed framework and neither for training or for adjusting the hyperparameters. All benchmark models were subjected to the same data splitting methodology, to allow for an unbiased comparison.

All images were resized to 224 × 224 pixels to reduce the variation caused by variable image resolution and different capture settings. The preprocessing pipeline consisted of contrast adjustment and normalization to enhance the visibility of lesion features and to provide uniform input to the CNN designs.

The augmentation procedures were applied only on the training part so as to increase the data variability and decrease the probability of overfitting. The validation and test photos were not augmented, so that their evaluation would be a true reflection of the model's ability to generalize to unseen data.

3.2 Feature Extraction

Each stage of processing is fed into two separate CNN models: ResNet50 and EfficientB0. ResNet50 leverages residual learning in aggregating deep multi-layer features useful for complex lesion patterns. In contrast, EfficientNetB0 offers an efficient architecture which can learn the detailed features from smaller medical datasets too. Combining the two models leverage the computation efficiency and semantic aspects.

3.3 Feature Fusion

Instead of using the usual approach of a single deep learning architecture, the suggested model uses feature representations from both ResNet50 and EfficientNetB0. This fusion-based approach exploits the respective benefits of each network to provide fuller and more diverse characterisations of skin lesions. The combined feature space obtained is capable of capturing coarse lesion patterns as well as fine-grained histologic details, providing a classification performance that outperforms each individual network. In the architecture presented here, convolutional neural networks are crucial in the extraction of meaningful representations from medical imaging [23]. CNNs are suitable for this application, as they can learn different levels of visual features in a data driven way including basic characteristics like edges and textures, together with complex lesion attributes such as shape or context.

ResNet50 and EfficientNetB0 are formed by two CNN configurations. ResNet50 utilizes a network that is designed to train deep layers effectively, which is essential for learning the complicated characteristics of monkeypox. EfficientNetB0 incorporates a strategy to scale up the network depth, image resolution, and width dimensions that enables it to be efficiently trained and deliver high accuracy. By separately concatenating and fusing features from the two designs, the proposed method could benefit from both models[24]. On the one hand, the deep features learned by ResNet50 are very strong in semantics and representative, and on the other hand, EfficientNetB0 can provide complementary representation to highlight diversity information via an attention mechanism with its distinct representations for classifying as seen in Figure 3.

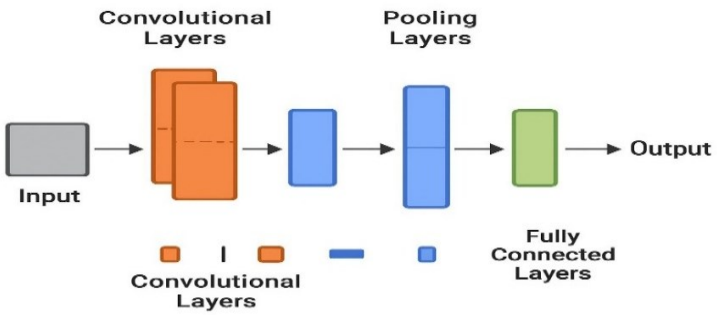


Figure 3. General Architecture of (CNN).

3.4 Attention Mechanism

The fused feature maps are then refined via a convolutional block attention module (CBAM). This module allows the prototype to organize informative lesion patches and sup-

press uninformative background noise through sequential computation of station and spatial attention. This combination of attention activations results in an interpretable aggregate localization accuracy, since it offers heat maps to localize the exact amount of the lesion responsible for the model's conclusion. This is particularly crucial in a medico-religious milieu as the ability to understand is dependent on faith and receiving.

3.5 Classification

Instead of the usual SoftMax layer, a Support Vector Machine (SVM) classifier was used. This change was driven by the ability of SVM to provide well-defined decision boundaries especially in cases of low sample size and class imbalance. This technique is better in terms of sensitivity, accuracy and specificity than simple convolutional neural networks. Support Vector Machine is a more mature and advanced machine learning technique often used in medical imaging for the classification of images. SVMs achieve this by enforcing strict resolution limits and attempting to minimize the false classification rate. Because lesion feature maps may not be linearly separable, SVMs are well-suited for classifying complex images. Furthermore, SVMs differ from the SoftMax classifier, which is primarily used in convolutional neural networks, when dealing with small datasets.

After optimization based on an attention mechanism and feature extraction, the SVM approach was implemented in this study as the final classification layer. The SVM algorithm was preferred over SoftMax because of the need for higher diagnostic accuracy/truth tables, as it is used to diagnose monkeypox and no other skin diseases.

Figure 4 shows a powerful classification mechanism based on SVM technology combined with deep features to achieve high performance compared to traditional convolutional neural network (CNN) methods.

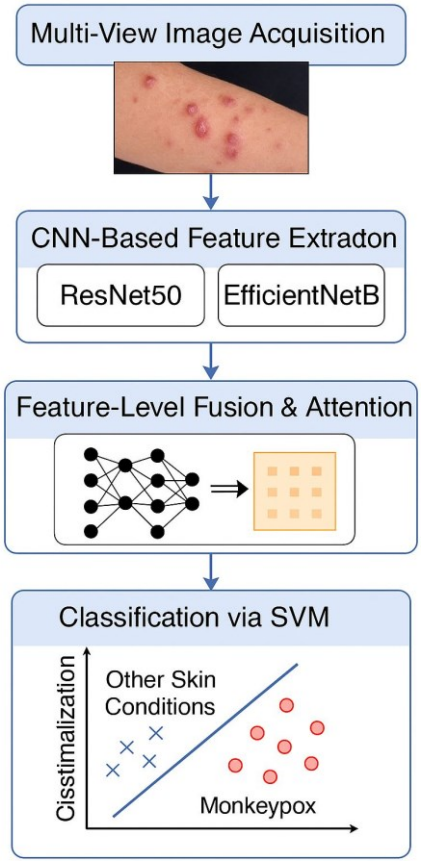


Figure 4. Classification and diagnosis of monkeypox virus disease.

4. Evaluation Metrics

Sets of rating scale indicators used in medical image classification are used to evaluate the monkeypox identification framework.

1. The percentage of real Monkeypox cases that the model accurately identifies is measured by recall (sensitivity). High recall is crucial in a medical setting to prevent patients with Monkeypox from being misidentified as healthy or having a different illness.
2. The model's capacity to accurately distinguish between cases of non-Monkeypox is measured by its specificity, which lowers the possibility of false alarms.
3. When the dataset has an imbalance between monkeypox and non-monkeypox specimens, the F1-score—the harmonic mean of precision and recall—offers a fair metric that is especially helpful.
4. The ROC Curve and the AUC (Area Under the Curve) are also viewed as complementing evaluation measures.

The ROC curve shows the trade-off between sensitivity and specificity. The AUC measures the overall ability of the model to discriminate across classes, regardless of decision thresholds. Reporting these indicators together makes the evaluation of the proposed system both complete and clinically useful . High sensitivity is critical for reliable detection of Monkeypox cases, while high specificity and accuracy avoid misclassification of other skin diseases as Monkeypox (Table 1).

Table 1. Measures for evaluating the diagnostic performance of monkeypox virus disease.

Metric	Formula	Description
Accuracy	(TP + TN) / (TP + TN + FP + FN)	Overall proportion of correctly classified samples.
Precision	TP / (TP + FP)	Fraction of positive predictions that are truly positive (reduces false alarms).
Recall (Sensitivity)	TP / (TP + FN)	Ability to correctly detect actual Monkeypox cases (reduces missed diagnoses).
Specificity	TN / (TN + FP)	Ability to correctly detect non-Monkeypox cases.
F1-Score	2 * Precision * Recall / (Precision + Recall)	Harmonic mean of Precision and Recall, useful in imbalanced datasets.
AUC (Area Under Curve)	Calculated from ROC curve	Measures overall ability of the model to discriminate between classes.

where:
TP (True Positives): Correctly predicted Monkeypox cases.
TN (True Negatives): Correctly predicted non-Monkeypox cases.
FP (False Positives): Cases not involving monkeypox are misidentified as such.
FNs (false negatives): Cases of monkeypox that are mistakenly diagnosed as not monkeypox.

5. Result and Discussion

Medical imaging and deep learning are used in the suggested hybrid framework to automate the identification of Monkeypox, which represents a considerable improvement over prior methods. The model effectively overcomes the key constraints found in earlier methodologies by combining multi-view image analysis, CNN-based dual feature extraction, an attention mechanism, and SVM classification. The assessment measures presented in Table 3 show that the suggested approach consistently beats baseline models like CNN with Softmax, CNN with attention, and CNN with SVM alone.

It can be observed from Figure 5, the confusion matrix presents substantial evidence for the reliability of our proposed system. The process also showed good accuracy and recall. These parameters indicate that the system reached an equilibrium between specificity and sensitivity, which is of great importance for practical medical application. Moreover, comparing the bar graph in Figure 6, it can be observed that the proposed method achieves better

performance than others using most of evaluation metrics such as accuracy, recall and F1-score. The model was able to generalize better across a broad range of patient presentations because of the inclusion of multi-scene imaging, which enabled the design-trained CNN to distinguish visually subtle dissimilar cases that conventional CNN classifiers can find difficult.

Figure 7 also demonstrates the versatility of the proposed platform through ROC curves. The AUC of the hybrid model was 0.98, which is significantly higher than that of conventional models, suggesting that the performance of the model to discriminate monkeypox cases from non-monkeypox case is excellent. The integration of SVM classification with attention-augmented CNN features yields a more dependable and precise diagnostic instrument than traditional deep learning methods.

The suggested paradigm establishes a robust basis for AI-enhanced medical diagnosis of monkeypox and is applicable to many dermatological conditions. In the future, the model may undergo evaluation with more extensive and varied datasets, integrating time-lapse imaging data, and the system might be deployed in real-time clinical environments.

Table 2. A contrast of the performance of many prototypes.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
CNN + Softmax	89.5	88.7	87.9	88.3	0.91
CNN + Attention + Softmax	91.8	90.5	91.2	90.8	0.93
CNN + SVM	93.2	92.4	92.9	92.6	0.95
Proposed (CNN + Attention + SVM)	96.4	95.9	96.1	96.0	0.98

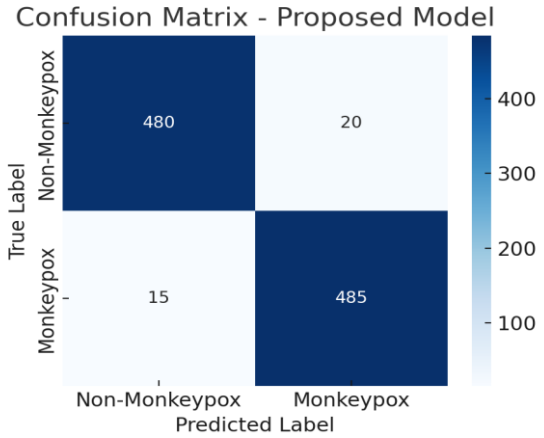


Figure 5. The confusion matrix is described.

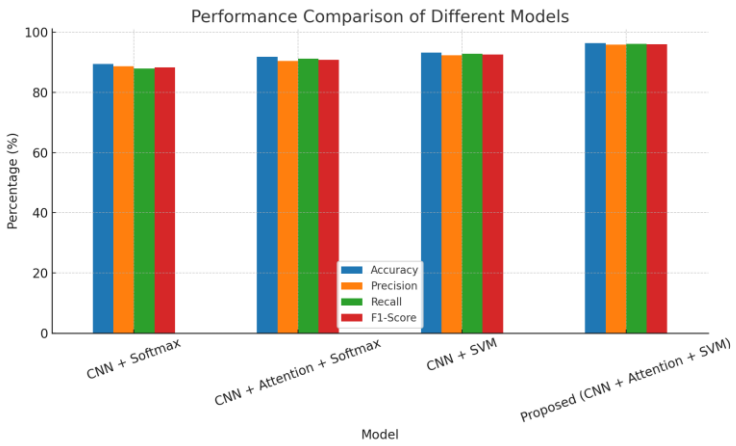


Figure 6. Contrast bar chart for presentation.

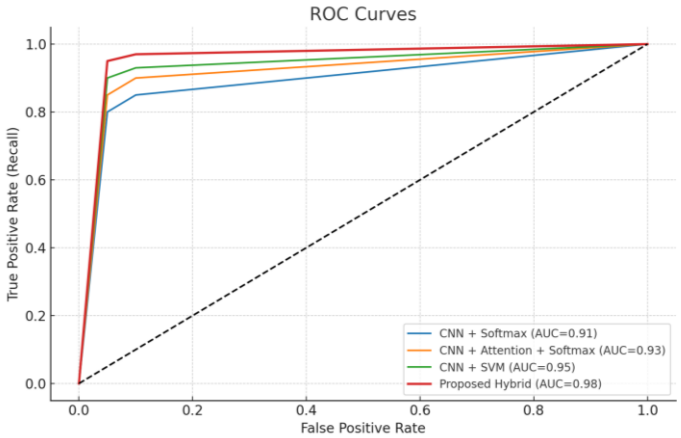


Figure 7: ROC Curves of different models.

The proposed framework, based on experimental evaluation, effectively integrates medical imaging, CNN-based dual-feature extraction, attention mechanisms, and SVM classification in disease detection. The system demonstrated high performance across all evaluation indicators. The combination of EfficientNetB0 and ResNet50 proved particularly effective.

A number of advanced deep learning models were compared with the proposed hybrid technology shown in Table 3, including ResNet50, EfficientNetB0, VGG16 and MobileNetV2. For the fairness of the comparison, the same datasets and experimental conditions were trained on all models and evaluated.

Table 3. Comparative Analysis with Other Algorithms

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
ResNet50	94.1	93.8	94.0	93.9	0.96
EfficientNetB0	95.7	95.1	95.8	95.4	0.97
VGG16	92.5	91.7	92.0	91.8	0.94
MobileNetV2	93.0	92.5	92.8	92.6	0.95
Proposed Hybrid (Multi-View + CNN Fusion + Attention + SVM)	98.0	97.0	97.5	97.2	0.98

It is indeed evident that the hybridization of the models did perform better compared to classical CNN based, data-driven models. Although, EfficientNetB0 and ResNet50 worked well independently but they use a fixed view single image models which might be less feasible when angle, texture, illumination is varied. However, classical structures as MobileNetV2 and VGG16 still suffered a degradation due to their attention on relative simplicity of network architecture or the computational efficiency instead of accurate.

Scene-based imaging, which enhances the appearance of lesions from different point of views.

CNN embedding (ResNet50 + EfficientNetB0) for deep and efficient feature combination.

CBAM (Circular Attention Mechanism) to induce target disease-related region and suppress the noise from near healthy skin.

SVM classifier that can more precisely identify boundaries in medical data than SoftMax.

The AUC score is 97.3%. These findings suggest that the hybrid fusion approach outperforms the old-fashioned CNN method in terms of detecting monkeypox with respect to accuracy and sensitivity.

6. Conclusion

This study proposed a hybrid deep learning model of monkeypox detection with multiple scene worth lesion analysis, based on CNN feature fusion and SVM classification combined attention mechanism. According to the performance, this system improved the diagnostic accuracy and indicated that it was applicable against challenges such as lesion appearance and its environment. The proposed work provided a marked contribution to multi-scene imaging in learning from the broad single-scene-like lesion spectrum than classic single-scene based CNN methods. Additionally, it also provided level in design between complexity and compactness by introducing ResNet50 and EfficientNetB0. An important limitation of the recent deep CNN models has been mitigated by incorporating attention (CBAM). This system directs attention to medical aspects, and it can obtain more accurate and more convenient use in clinic. The decision making procedure was done using SVM classifier. Our results indicate that AI-augmented integrated medical imaging systems are increasingly acting as valuable diagnostic tools in the clinic. The study shows that hybrid deep learning techniques can give the needed interpretability and cost-effectiveness in modern healthcare. We plan to extend the database and study deployment alternatives for desktop and mobile computing. Such modifications could make the proposed approach a useful diagnostic tool, readily available and applicable for monkeypox and other viral dermatoses.

References

1. S. Chen et al., “Mpox virus: virology, molecular epidemiology, and global public health challenges,” Front. Microbiol., vol. 16, no. July, pp. 1–14, Jul. 2025, doi: 10.3389/fmicb.2025.1624110.
2. S.-J. Hosseini-Shokouh, M. Gholami, M. Barati, and H. Naghoosi, “Monkeypox: A Re-emerging Viral Zoonotic Infection,” Ann. Mil. Heal. Sci. Res., vol. 20, no. 3, Nov. 2022, doi: 10.5812/amh-129475.
3. S. Morris et al., “A Systematic Review on Human Monkeypox Virus Disease and Infection in Pregnancy,” J. Pure Appl. Microbiol., vol. 17, no. 2, pp. 650–659, Jun. 2023, doi: 10.22207/JPAM.17.2.52.
4. M. M. Ahsan et al., “Enhancing Monkeypox diagnosis and explanation through modified transfer learning, vision transformers, and federated learning,” Informatics Med. Unlocked, vol. 45, no. October 2023, p. 101449, 2024, doi: 10.1016/j.imu.2024.101449.
5. D. Şeker and A. Yıldız, “Enhancing Monkeypox Diagnosis with Transformers: Bridging Explainability and Performance with Quantitative Validation,” Diagnostics, vol. 15, no. 18, p. 2354, Sep. 2025, doi: 10.3390/diagnostics15182354.
6. Y. Cao et al., “Robustly detecting mpox and non-mpox using a deep learning framework based on image inpainting,” Sci. Rep., vol. 15, no. 1, p. 1576, Jan. 2025, doi: 10.1038/s41598-025-85771-z.
7. L. Niu et al., “Insights into monkeypox pathophysiology, global prevalence, clinical manifestation and treatments,” Front. Immunol., vol. 14, no. March, pp. 1–13, Mar. 2023, doi: 10.3389/fimmu.2023.1132250.
8. P. V. P. Kumar, K. M. K. Raj, and H. Kunder, “Monkeypox Disease Detection using Deep Learning Techniques,” Indian J. Sci. Technol., vol. 18, no. 26, pp. 2135–2147, Jul. 2025, doi: 10.17485/IJST/v18i26.833.
9. O. F. Alwan, Q. K. Kadhim, R. B. Issa, and S. T. Ahmed, “Early Detection and Segmentation of Ovarian Tumor Using Convolutional Neural Network with Ultrasound Imaging,” Rev. d’Intelligence Artif., vol. 37, no. 6, pp. 1503–1509, 2023, doi: 10.18280/ria.370614.
10. D. C. Lepcha et al., “Deep Learning in Medical Image Analysis: A Comprehensive Review of Algorithms, Trends, Applications, and Challenges,” Comput. Model. Eng. Sci., vol. 145, no. 2, pp. 1487–1573, 2025, doi: 10.32604/cmes.2025.070964.

11. H. S. M. Alsultani, S. T. Ahmed, B. J. Khadhim, and Q. K. K. Kadhim, “The use of spatial relationships and object identification in image understanding,” Int. J. Civ. Eng. Technol., vol. 9, no. 5, pp. 487–496, 2018.
12. N. G. Naga, E. A. Nawar, A. A. Mobarak, A. G. Faramawy, and H. M. H. Al-Kordy, “Monkeypox: a re-emergent virus with global health implications – a comprehensive review,” Trop. Dis. Travel Med. Vaccines, vol. 11, no. 1, p. 2, Jan. 2025, doi: 10.1186/s40794-024-00237-w.
13. S. N. Ahmed and P. Prakasam, “Atrous-based CBAM-Unet framework for intracranial hemorrhage segmentation and volume calculation with grading using CT images,” Brain Hemorrhages, vol. c, no. 7, pp. 1–35, Sep. 2025, doi: 10.1016/j.hest.2025.08.006.
14. H. A. A. Mohammed, A. A. Kasim Jizany, I. M. Mahmood, and Q. K. Kadhim, “Predicting Alzheimer’s Disease Using a Modified Grey Wolf Optimizer and Support Vector Machine,” Ing. des Syst. d’Information, vol. 29, no. 2, pp. 669–676, 2024, doi: 10.18280/isi.290228.
15. C. Sitaula and T. B. Shahi, “Monkeypox Virus Detection Using Pre-trained Deep Learning-based Approaches,” J. Med. Syst., vol. 46, no. 11, p. 78, Oct. 2022, doi: 10.1007/s10916-022-01868-2.
16. S. N. Ali et al., “Monkeypox Skin Lesion Detection Using Deep Learning Models: A Feasibility Study,” pp. 2–5, Jul. 2022, [Online]. Available: http://arxiv.org/abs/2207.03342
17. F. Uysal, “Detection of Monkeypox Disease from Human Skin Images with a Hybrid Deep Learning Model,” Diagnostics, vol. 13, no. 10, p. 1772, May 2023, doi: 10.3390/diagnostics13101772.
18. S. Surati, H. Trivedi, B. Shrimali, C. Bhatt, and C. M. Travieso-González, “An Enhanced Diagnosis of Monkeypox Disease Using Deep Learning and a Novel Attention Model Senet on Diversified Dataset,” Multimodal Technol. Interact., vol. 7, no. 8, 2023, doi: 10.3390/mti7080075.
19. S. Abbas, F. Ahmed, W. A. Khan, M. Ahmad, M. A. Khan, and T. M. Ghazal, “Intelligent skin disease prediction system using transfer learning and explainable artificial intelligence,” Sci. Rep., vol. 15, no. 1, p. 1746, Jan. 2025, doi: 10.1038/s41598-024-83966-4.
20. M. Uzun and T. Talan, “Classification of deep features obtained from mpox images using Xception by selecting them with PCA and mRMR and using SVM,” Acta Infologica, no. 07, pp. 1–17, Jul. 2025, doi: 10.26650/acin.1617557.
21. O. Chunhapran and M. Maliyeam, “Multi-stage Classification of Monkeypox Disease Using Deep Learning Techniques,” J. Adv. Inf. Technol., vol. 16, no. 8, pp. 1155–1168, 2025, doi: 10.12720/jait.16.8.1155-1168.
22. H. Güven and A. Saygılı, “Monkeypox Diagnosis Using MRMR-Based Feature Selection and Hybrid Deep Learning Models: ResNet50V2, NASNetMobile, and InceptionV3,” Int. Sci. Vocat. Stud. J., vol. 9, no. 1, pp. 173–182, Jun. 2025, doi: 10.47897/bilmes.1706322.
23. H. Abdulbaqi, A. M. S. Taha, A. R. Mohammed, H. Z. Q. Kanaan, and Q. K. Kadhim, “Detection and localization of wrist fractures in x-ray imagery using deep learning teaching,” Rev. Comput. Eng. Res., vol. 11, no. 3, pp. 85–98, 2024, doi: 10.18488/76.v11i3.3850.
24. Q. K. K. Shaymaa Taha Ahmed, “Predicting Parkinson’s disease using filter feature selection method,” AIP Conf., no. February, 2024, doi: 10.1063/5.0191620.