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REVIEW ARTICLE

Leveraging Advanced Machine Learning for Pioneering Monkeypox Diagnosis: A New Paradigm in Infectious Disease Detection

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ABSTRACT

Artificial intelligence (AI) is revolutionizing medical diagnosis, which continues to face enduring issues including early-stage disease detection, insufficient voluminous data, and ineffective diagnostic processes. This review demonstrates considerable progress in developing machine-learning (ML) technologies for monkeypox detection, tuberculosis diagnosis, cancer diagnosis, and broader infectious-disease assessment. Convolutional neural networks (CNNs) have shown high efficiency in diagnostics; transfer-learning models such as InceptionV3 can reach very high diagnostic accuracy. Privacy-preserving solutions, including federated learning models, improve diagnostic accuracy without increasing exposure of individual data, while synthetic datasets derived from high-resolution techniques such as hierarchical phase-contrast tomography (HiP-CT) help address data scarcity by improving model construction and assessment. Integration of genomic and metabolomic information further enhances diagnostic accuracy, particularly for complex diseases such as COVID-19. However, model generalization remains difficult because of limited data for rare conditions, and the computational demands of many ML models hinder implementation in low-resource environments. Ethical concerns, algorithmic bias, and the black-box nature of advanced models highlight the need for explainable AI (XAI) frameworks that provide visibility and credibility in medical facilities. Future directions include standardized frameworks, improved computational support, and interdisciplinary integration to enable scalable, patient-centered diagnostic technologies.

Keywords: Machine learning ▪ Diagnosis ▪ Deep learning ▪ Privacy-enhancing AI ▪ Synthetic data ▪ Healthcare advancement

1. INTRODUCTION

Monkeypox, a zoonotic viral disease, has gained international attention due to its re-emergence and spread beyond endemic regions. Caused by the monkeypox virus, its symptoms often mimic other diseases, making early and accurate diagnosis vital. Traditional diagnostic methods, such as polymerase chain reaction (PCR), are reliable but are not always feasible in resource-constrained settings. Integrating machine learning into healthcare offers new avenues for efficient and scalable monkeypox diagnosis.

1.1 The Role of Machine Learning in Modern Diagnostics

Machine learning has emerged as an influential factor in contemporary diagnostics by providing tools that improve precision, turnaround time, and scalability. Routine diagnos-

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tic techniques are often based on manual analysis and require substantial resources, which may introduce delays or inaccurate results. In contrast, ML algorithms can handle large and complex databases and produce patterns that practitioners may not easily observe. This incorporation has expanded diagnostic capabilities in medical imaging, predictive analytics, and real-time patient tracking [1, 2].

Deep learning, a subset of ML, has opened a particularly fertile area for diagnostics. Techniques involving convolutional neural networks have led to high-performing image-diagnosis algorithms. Models tested with CNNs have demonstrated improved accuracy in diagnosing cancerous lesions from medical images and may surpass conventional clinical workflows in selected tasks [3, 4]. Predictive diagnostics also extend beyond imaging: by feeding electronic health records, genomics, and other patient data into ML models, practitioners can predict disease development, disease course, and treatment utility.

Nevertheless, the path to integrating ML into diagnostics is not smooth. Important challenges include high-quality data availability, interpretability of complex algorithms, ethical concerns, and data privacy. These problems must be addressed to enable better exploitation of ML opportunities in healthcare [5].

1.2 Image-Based Monkeypox Detection

Image-based ML has proved useful in detecting characteristic skin lesions of monkeypox through practical applications in automated triage and decision support. CNNs and transfer-learning architectures can identify lesion morphology and distinguish monkeypox from clinically similar conditions such as chickenpox, measles, and other pox-like eruptions. Such models are particularly attractive where PCR confirmation is delayed or unavailable.

Recent computer-aided diagnosis systems combine contrast enhancement, feature extraction, and optimized deep-learning classifiers to improve lesion detection. However, image-based models require diverse training datasets, robust annotation, and validation across skin tones, camera conditions, and clinical settings to ensure fairness and generalizability.

1.3 Challenges in Implementing ML for Monkeypox Diagnosis

The main implementation challenges are data scarcity, dataset bias, insufficient external validation, high computational requirements, and regulatory uncertainty. Monkeypox datasets are often limited in size compared with datasets for more common diseases, while public images may vary widely in quality and labeling. These limitations can produce overfitting and reduce model reliability in real clinical settings.

Privacy is another important concern. Medical images and clinical records contain sensitive personal information, and centralized training can expose patient data. Privacy-enhancing approaches such as federated learning and cancelable biometric representations can reduce this risk, but they add complexity to model development, deployment, and evaluation [6, 7].

1.4 Prospects of ML in Disease Diagnostics

Future ML-based diagnostic systems will likely integrate multiple modalities, including images, clinical metadata, genomics, metabolomics, and environmental surveillance. Multimodal systems can improve robustness by combining complementary evidence. Explainable AI techniques can also help clinicians understand why a model assigns a diagnosis, increasing trust and supporting adoption.

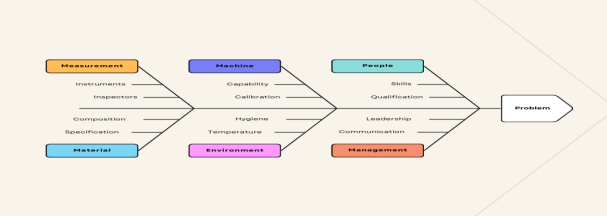


Figure 1. Flow diagram for diagnosis using machine learning.

Figure 1 summarizes a cause-and-effect style diagnostic workflow in which measurement, material, machine, environment, people, and management factors converge toward problem identification and clinical decision-making.

2. LITERATURE REVIEW

The rapid development of ML has transformed medical diagnostics by providing scalable, efficient, and accurate tools for detecting diseases such as monkeypox, tuberculosis, breast cancer, bacteremia, sepsis, COVID-19, and knee osteoarthritis. This section synthesizes representative studies ranging from advanced deep-learning architectures to privacy-preserving diagnostic tools. These approaches address resource constraints and data variability while offering scalable solutions for global healthcare needs.

The monkeypox virus has crossed national boundaries rapidly, highlighting the need for early detection to curtail transmission and support timely therapy. Computer-aided diagnostic systems that employ advanced deep-learning frameworks such as Vision Transformers, ResNet-50, and EfficientNetV2 have demonstrated strong accuracy. Fusion-based contrast enhancement and sparse image decomposition have improved feature extraction for low-contrast lesion images [8].

Transfer learning has also been widely explored. InceptionV3-based systems trained on publicly available monkeypox datasets report strong results in differentiating monkeypox from other dermatological conditions, emphasizing their potential in resource-poor settings [9]. Optimization strategies such as the Sparrow Search Algorithm have been used to tune pretrained CNNs, improving speed, reliability, and accuracy for medical imaging [10].

Privacy-preserving models are another important direction. CanDark combines DarkNet-53 feature extraction with cancelable biometric methods to detect monkeypox while protecting patient identity [6]. Federated learning approaches similarly allow institutions to collaborate without directly sharing raw patient data [7, 11]. Beyond monkeypox, synthetic-data generation, capsule networks, molecular informatics, wastewater surveillance, and metabolomics-based ML demonstrate the expanding scope of AI-driven diagnostics.

Findings from the literature show that machine learning has a

Table 1. Summary of literature review

Ref.	Methodology	Key findings	Applications	Limitations
[8]	Deep learning using ViT, ResNet-50, EfficientNetV2, contrast enhancement, and sparse image decomposition	98.64% accuracy, surpassing traditional methods	Monkeypox lesion diagnosis in clinical settings	Data scarcity and ethical concerns
[9]	Transfer learning using InceptionV3	98% accuracy in resource-limited settings	Early detection in low-resource environments	Limited dataset dependency
[10]	Sparrow Search Algorithm optimizing pretrained CNNs	99.87% accuracy with improved speed and reliability	Optimized lesion detection with computational imaging	High GPU dependency and infrastructure challenges
[6]	Cancelable biometric-based deep learning using DarkNet-53	98.81% accuracy with privacy-aware performance	Secure scalable diagnostics for infectious diseases	Interpretability challenges
[12]	Wearable plantar pressure analysis with regression models	MAE of 2.686 s for gait analysis	Functional assessment for knee osteoarthritis	Specialized hardware dependency
[13]	Ensemble transfer learning with data augmentation	90.615% accuracy for lesion identification	Enhanced clinical lesion diagnostics	Annotated data scarcity
[14]	Efficient transfer and self-supervised ensemble framework	Up to 14.4% improvement over state-of-the-art methods	Versatile framework for medical applications	Scalability across diverse applications
[7]	Federated learning for privacy-preserving diagnostics	87.50% accuracy while maintaining data privacy	Privacy-focused public-health diagnostics	Framework complexity
[11]	Federated learning for mammographic breast-cancer diagnostics	72.46% accuracy with mammographic feature extraction	Personalized breast-cancer screening	Moderate accuracy for selected clinical features
[15]	Synthetic datasets using HiP-CT scans and ML	Improved ML models for diverse tuberculosis presentations	Advanced diagnostics for pulmonary tuberculosis	Need for high-quality diverse datasets
[16]	AI-CDSS integrating ML with MALDI-TOF MS	AUC of 0.95 for drug-resistance prediction	Precision treatment for resistant infections	Data quality issues in low-resource regions
[17]	Capsule networks for audio-based tuberculosis detection	0.97 accuracy through cough analysis	Low-cost tuberculosis screening	Need for robust architectures
[18]	Metabolomics with ML for COVID-19 prognosis	AUC of 0.92, improving over clinical parameters	COVID-19 prognosis and resource optimization	Scalability of metabolomics workflows
[19]	Feature engineering with SVM for monkeypox detection	91.87% accuracy with deep-feature engineering	Automated outbreak-control diagnostics	Dataset variability and annotation issues
[20]	Systematic review of ML applications for monkeypox	High potential, but data limitations persist	Strategic development for monkeypox management	Data quality and variability challenges

promising future in medical diagnostics. Many ML applications improve accuracy, reduce evaluation time, and provide scalable solutions for low-resource environments. However, data availability, hardware limitations, and ethical issues remain unresolved. Continued research and standardization are therefore necessary for AI-based systems to redefine diagnostic standards and improve health outcomes worldwide.

3. DISCUSSION

3.1 The Role of Advanced ML Architectures in Diagnostic Accuracy

Advanced architectures such as CNNs, Vision Transformers, ensemble transfer-learning systems, and optimized hybrid models have improved diagnostic accuracy across medical-imaging tasks. For monkeypox diagnosis, these architectures extract discriminative lesion features and can differentiate visually similar diseases. Their performance is strengthened by preprocessing, contrast enhancement, and hyperparameter optimization.

A simplified diagnostic decision function can be represented as:

$$\hat{y} = \arg\max_{c \in C} P(c \mid \mathbf{x}; \theta), \tag{1}$$

where $\mathbf{x}$ denotes patient data or lesion images, θ denotes learned model parameters, and C is the set of diagnostic classes. In practice, the reliability of $\hat{y}$ depends on dataset representativeness, model calibration, and clinical validation.

3.2 Ethical Considerations and Challenges in Deployment

AI systems in healthcare must address patient privacy, bias, accountability, and transparency. Privacy-preserving methods such as federated learning can train models across multiple institutions without transferring raw data. A general federated update can be expressed as:

$$\theta_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} \theta_t^{(k)}, \tag{2}$$

where $\theta_t^{(k)}$ is the local model from institution k, n_k is the local sample size, and n is the total sample size. Although useful, federated systems require secure communication, governance, and careful auditing.

Explainability is also essential. Clinicians need insight into which image regions or clinical features influence predictions. XAI approaches can reduce black-box concerns, support error analysis, and improve clinical trust.

3.3 Emerging Trends and Future Directions

Emerging trends include multimodal learning, self-supervised learning, synthetic-data generation, privacy-preserving collaboration, and deployment on edge devices. Multimodal learning can combine lesion images with clinical symptoms and laboratory results. Self-supervised learning can reduce dependence on expensive annotations. Synthetic data can expand rare-disease datasets while preserving privacy, provided that generated data are clinically plausible and carefully validated.

For low-resource environments, lightweight architectures and mobile deployment will be important. These systems should be optimized for inference efficiency, interoperability, and usability by frontline health workers.

4. CONCLUSION

This review highlights the transformative role of advanced machine learning in monkeypox diagnosis and infectious-disease detection. Deep-learning systems, transfer learning, optimiza-

tion algorithms, federated learning, synthetic datasets, and multimodal analytics have all contributed to improved diagnostic accuracy and scalability. Monkeypox diagnosis is a particularly important use case because clinical similarity to chickenpox, measles, and other skin diseases can delay treatment and public-health response.

Despite promising results, major obstacles remain. Limited datasets, biases, privacy risks, computational demands, and lack of interpretability can restrict real-world deployment. Addressing these challenges requires standardized validation, explainable AI frameworks, privacy-preserving infrastructures, and interdisciplinary collaboration among clinicians, computer scientists, epidemiologists, and policymakers.

When these barriers are addressed, ML-based diagnostic systems can support early detection, reduce diagnostic burden, and improve patient-centered healthcare outcomes globally.

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