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Effectiveness of Machine Learning algorithms in predicting Monkey Pox (Mpox): A Systematic Literature Review

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Abstract

The re-surfacing of Monkeypox (Mpox) a zoonotic viral disease that causes painful blisters on the skin of the infected, as a global health concern has triggered the rapid and important development of useful and effective diagnostic tools to bolster the existing traditional methods such as contact tracing and timely intervention. Machine learning (ML) algorithms have shown promising results in the early detection and diagnosis of infectious diseases, including Mpox, by leveraging diverse data sources such as electronic health records, clinical images, and laboratory results. This Systematic Literature Review aims to assess the effectiveness of machine learning algorithms in detecting Monkeypox (Mpox). The main question is: 'How well do machine learning algorithms perform in detecting Monkey Pox?"The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines were employed for this review. An in-depth search was done spanning several databases, namely ScienceDirect, IEEE Xplore, ACM Digital Library, and Springer Link. Studies published between 2022 and 2024 were considered. After removing duplicates and screening for relevance and quality, a total of 30 papers were included in the final analysis. The outcomes indicate that ML algorithms, particularly convolutional neural networks (CNNs) and support vector machines (SVMs), have proven to have high accuracy and sensitivity in detecting Mpox. These algorithms perform strongly compared to traditional diagnostic methods like contact tracing, resulting in faster and more reliable results. The integration of ML with imaging techniques, such as dermoscopy and radiography, has further enhanced diagnostic precision. (ML)algorithms present a notable advancement in the detection of Monkeypox. They are very robust in the face of large datasets and give a very high level of accuracy and precision in interpreting the datasets, to this effect however further research is needed to address the challenges of data variability and the need for large, high-quality datasets. The review's findings offer practitioners and policymakers in healthcare important new information. The creation of novel diagnostic procedures and guidelines can be influenced by the proven efficacy of machine learning algorithms in Mpox detection. The results also emphasize the necessity of funding machine learning research and infrastructure to enhance disease surveillance and response tactics.

Keywords
Monkey Pox (Mpox), Machine learning, Epidemiology, Infectious Disease, Predictive Analytics.

1. Introduction
Monkeypox (Mpox), a viral zoonotic disease with recent global outbreaks, has emerged as a major public health concern. The World Health Organisation (WHO) reported a continual rise of Mpox cases globally, the current Mpox

outbreak in South Africa highlights the need for better mechanisms for both diagnosis and control, which calls for investigating other strategies that might be used in addition to established ones (WHO 2024). Early and precise identification is critical for isolating sick people and disrupting transmission pathways. However, standard Mpox diagnosis procedures are time-consuming and resource-intensive such as Polymerase Chain Reaction (Muhammed Kalo Hamdan & Ekmekci 2024). Delays in diagnosis can impede the prompt isolation and execution of appropriate public health treatments, potentially leading to a larger outbreak.

Previous Mpox literature evaluations focused mostly on conventional diagnostic approaches and epidemiological models. Conventional diagnostic procedures, such as Polymerase Chain Reaction testing, are essential in confirming Mpox infection. However, these approaches can take several days to provide findings, causing a considerable delay in the disease's early stages (Nayak et al. 2023). This delay may result in further transmissions while waiting for test findings. Furthermore, while useful for forecasting outbreak trends, epidemiological modelling frequently depends on past data (Alnaji 2024). This depends on historical data, which can restrict the capacity to detect and anticipate developing patterns linked with new infectious illnesses such as Mpox (Mir et al. 2023).

Machine learning (ML) techniques are a viable alternative for improving Mpox prediction. These algorithms can analyse massive volumes of data, such as clinical symptoms, travel history, and contact tracking information. By analysing these varied data sources, ML models can identify persons at high risk of Mpox infection, leading to faster and more accurate predictions than previous techniques (Rampogu 2023a). For example, research by (Martin et al. 2024) highlights using machine learning, especially Artificial Neural Networks (ANNs), to anticipate Mpox cases. This work emphasises the potential of machine learning to anticipate Mpox outbreaks and improve public health policies (Sorayaie Azar et al. 2023).

The potential benefits of utilising ML for Mpox prediction are numerous. ML algorithms can swiftly assess data and detect possible Mpox cases, allowing for early intervention and quarantine. This fast detection can drastically shorten the window of opportunity for transmission (Magsino et al. 2024). ML models can predict Mpox cases more accurately than older techniques that depend purely on clinical signs. This increased precision might result in better-focused actions and resource allocation (Muhammed Kalo Hamdan & Ekmekci 2024). Machine learning can anticipate Mpox outbreaks faster and more accurately, resulting in more effective public health interventions. Early detection of possible cases enables early deployment of treatments including contact tracking, vaccination programmes, and isolation measures (Rahman 2023).

1.1 Research Questions

This systematic literature review seeks to answer the following research questions:

- What factors influence the adoption of ML for Mpox prediction in practice?
- Which machine learning techniques have been leveraged in predicting Mpox cases?
- What are the strengths and limitations of different ML algorithms for Mpox prediction?

2. Methodology

A systematic literature review (SLR) methodology was employed to answer the research questions. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) steps included identification, screening, and eligibility and structured the literature analysis of this study (Moher et al. 2009).

2.1. Database and Search Strategy

To evaluate the usefulness of machine learning (ML) methods in identifying monkeypox (Mpox), a thorough search approach was used across four academic databases: ScienceDirect, IEEE Xplore, Springer Link, and ACM Digital Library. These databases include medicine, computer science, and engineering, enabling a comprehensive search for relevant papers. A search term containing "Monkeypox OR Mpox," "Machine Learning," and "Prediction OR Diagnosis OR Prognosis" was tailored to each database's syntax. The initial search turned up 443 publications (ScienceDirect: 178, IEEE Xplore: 113, Springer Link: 121, ACM Digital Library: 31), with ScienceDirect indicating a considerable research interest in this area.

2.2. Inclusion and exclusion criteria

This systematic literature review only considered peer-reviewed journal papers published in English between 2020 and 2024. Studies on the application of machine learning algorithms to predict Mpox cases in people were prioritised, with an emphasis on original research that included performance indicators like accuracy and AUC. Editorials, reviews, case reports, and research on non-human subjects or with a focus other than prediction were eliminated. These criteria enable a targeted selection of studies that directly address the efficiency of machine learning for Mpox prediction.

2.3. Eligibility and Screening

A total of 443 databases were considered and screened for analysis, these were from ScienceDirect (n = 178), IEEE Xplore (n = 113), Springer Link (n = 121), and ACM Digital (n = 31). 335 records were excluded due to misaligned topics and there was little relation to the aims and objectives. This left us with 108 reports for retrieval and the same were assessed for eligibility. A further 78 databases were screened further and 39 were excluded for misalignment with topic a further 23 for not meeting our objectives and 16 did not utilise machine learning algorithms. This in-depth screening was crucial in streamlining only relevant data.

2.4. Included

Following a thorough full-text assessment, only 30 of the initial 443 publications matched the predefined inclusion criteria for this systematic literature review. This included research that offered strong evidence for the efficiency of machine learning algorithms in predicting Monkeypox cases.

3. Results

The (PRISMA) guidelines were used, as proposed by Page et al. (2020). The flow diagram for this study using PRISMA is depicted in Figure 1 and Table 1 presents papers that met the inclusion criteria.

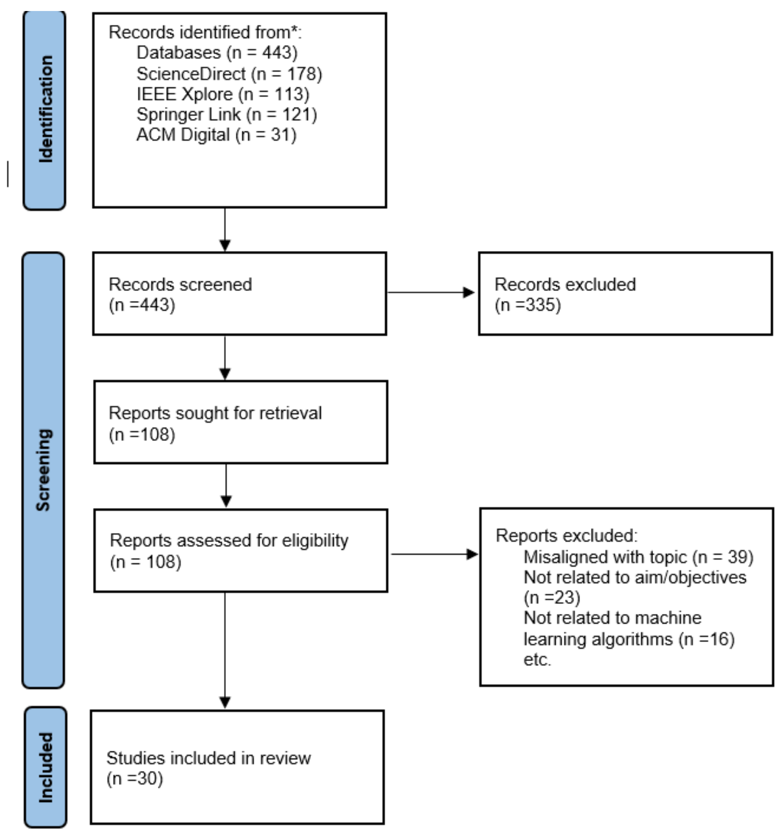

Figure 1. PRISMA Flow Diagram (Page et al. 2020)

Table 1. Papers that met the inclusion criteria.

Author and Year	**Country**	**Factors**	**Machine Learning Techniques**	**Strengths**	**Limitations**
(Rabaan, Alwashmi, et al. 2023)	Pakistan	• Accuracy and effectiveness	• Cheminformatics, • Machine learning models	• Potential to identify existing antiviral drugs effective against monkeypox	• Not tested on real-world data, • Relies on existing antiviral compounds
(Kakulapati 2023)	India	• Cost-effectiveness	• UNETs, • VGG16	• Automated skin lesion classification, Potential for rapid diagnosis	• Limited dataset, • Performance on diverse skin tones not evaluated
(Jain et al. 2024)	Latvia	• Cost-effectiveness	• Naïve Bayes	• A comprehensive review of diagnostic techniques, • Guidelines for Clinical Settings	• Focuses on traditional diagnostic methods, • Limited discussion of emerging technologies
(Muhammed Kalo Hamdan & Ekmekci 2024)	Turkey	• Comprehensive data utilization	• Adaptive artificial bee colony algorithm, • Artificial neural network	• Ability to predict infection from symptoms, • Adaptable to changing disease patterns	• Requires further validation on larger datasets
(Thorat & Gupta 2024)	India	• Accuracy and effectiveness	• Transfer learning, • Skin disease classification	• Leverages pre-trained models, • Potential for generalization to other skin diseases	• Dataset limitations, • Performance on diverse skin types not assessed
(Mohbey et al. 2024)	India	• Public perception and communication.	• Convolutional neural network (CNN), • Long short-term memory (LSTM)	• Insights into public perception and concerns, • Potential for early warning systems	• Limited to social media data, • Susceptible to biases in user-generated content
(Vega et al. 2023)	Luxembourg	• Cost-effectiveness	• CNN, • SNM	• Critical analysis of dataset limitations, • Highlights the need for high-quality data	• Focuses on dataset quality, • Does not propose solutions for dataset improvement

(Kulkarni et al. 2024)	India	• Automation and workflow integration	• Histogram of Oriented Gradients (HOG), • Support Vector Machine (SVM)	• Effective disease classification from images, • Potential for deployment in clinical settings	• Requires further validation on larger and more diverse datasets
(Chunhapran et al. 2024)	Thailand	• Accuracy and effectiveness	• Deep learning techniques	• Ability to accurately assess disease progression, • Potential for automated monitoring	• Performance may vary across different patient populations and clinical settings
(Gupta et al. 2023)	India	• Early detection and intervention	• Blockchain technology, • IoT integration	• Decentralised and secure disease surveillance, • Potential for early warning systems	• Reliance on widespread IoT adoption, • Regulatory and privacy considerations
(Yolcu Oztel 2024)	Turkey	• Standardization and best practices	• Vision transformer, • Convolutional neural networks	• Robust skin lesion analysis, • Potential for generalization to other skin diseases	• Limited to visual analysis, • May require complementary diagnostic techniques
(Dhapola & Kumar 2024)	India	• Accuracy and effectiveness	• Internet of Things (IoT)	• Enhance disease surveillance and monitoring, • Potential for early detection and response	• Requires widespread IoT infrastructure, • Privacy and security concerns
(Eliwa et al. 2023)	Egypt	• Comprehensive data utilization	• Convolutional neural networks	• Automated and accurate skin lesion classification, • Potential for rapid diagnosis	• Dataset limitations, • Performance on diverse skin types not evaluated
(Pikulkaew et al. 2024)	Thailand	• Cost-effectiveness	• Deep learning, • Image processing	• Improved accuracy in skin lesion classification, • Potential for integration with clinical workflow	• Limited to visual analysis, • May require complementary diagnostic techniques
(Ren et al. 2023)	China	• Data security and privacy	• Multimodal machine learning	• Improved diagnostic accuracy by leveraging diverse data sources	• Requires access to both clinical and imaging data,

					• May not be feasible in all healthcare settings
(Guo et al. 2023)	China	• Accuracy and effectiveness	• Explainable AI, • Outbreak modelling	• Provides interpretable insights into key drivers of monkeypox outbreaks	• Relies on the availability of comprehensive demographic and environmental data
(Ahsan et al. 2024)	USA	• Scalability and flexibility	• Federated learning, • Privacy-preserving techniques	• Enables collaborative disease monitoring while protecting patient privacy	• Requires widespread adoption of federated learning infrastructure
(Shah 2022)	India	• Automation and workflow integration	• Convolutional neural networks, • Semantic segmentation	• Precise localization of monkeypox skin lesions, • Potential for automated monitoring	• Performance may vary across diverse dermatoscopic image datasets
(Gairola & Kumar 2022)	India	• Cost-effectiveness	• Multitask learning, • Deep neural networks	• Comprehensive assessment of monkeypox status, • Potential to guide clinical decision-making	• Requires access to diverse clinical data, • May not generalise well to new patient populations
(Alnaji 2024)	Saudi Arabia	• Early detection and intervention	• Reinforcement learning, • Simulation-based optimization	• Identifies effective contact tracing policies to minimize disease spread	• Relies on the availability of detailed contact tracing data, • May require extensive computational resources
(Singh et al. 2024)	India	• Accuracy and effectiveness	• Graph neural networks, • Epidemiological modelling	• Leverages structural and temporal information to predict disease spread	• Requires access to comprehensive mobility and contact data, • May not capture all transmission dynamics
(Ajmal et al. 2023)	Egypt	• Scalability and flexibility	• Natural language processing,	• Enables remote and scalable symptom tracking,	• Dependent on user engagement and

			• Dialogue systems	• Potential for early detection of outbreaks	willingness to report symptoms
(Kundu et al. 2024)	Banglade sh	• Cost-effectiveness	• Generative adversarial networks (GANs)	• Expands limited skin lesion datasets, • Improves performance of lesion classification models	• Potential for generating unrealistic or biased synthetic data
(Pramanik et al. 2022)	Banglade sh	• Scalability and flexibility	• Multivariate time series models, • Forecasting	• Ability to forecast future outbreak trends and hotspots	• Requires access to comprehensive surveillance data, • Performance may vary across different regions
(Molla et al. 2023)	Canada	• Comprehensiv e data utilization	• Epidemiologica l models, • Climate data integration	• Provides insights into the role of environmental factors on disease spread	• Complexity in modelling the interactions between multiple environmental variables
(Maqsood et al. 2024)	Canada	• Data security and privacy	• Multimodal machine learning, • Risk prediction	• Comprehensive evaluation of individual and community-level risk factors	• Requires access to diverse data sources, • May face challenges in real-world deployment
(Demir et al. 2024)	Turkey	• Cost-effectiveness	• Object detection, • Tracking algorithms	• Enables continuous monitoring of lesion progression, • Potential for remote patient care	• Dependent on high-quality image data, • May face challenges in diverse clinical settings
(Tripathi & Kumar 2023)	India	• Standardizatio n and best practices	• Interpretable machine learning, • Simulation-based optimization	• Provides actionable insights to inform outbreak response strategies	• Requires collaboration between domain experts and AI researchers
(Rampogu 2023b)	India	• Accuracy and effectiveness	• Graph neural networks, • Community detection	• Identifies key transmission hubs and clusters to	• Dependent on the availability of comprehensive

				guide targeted interventions	contact tracing data
(H S et al. 2023)	India	• Early detection and intervention	• Bayesian statistical models, • Causal inference	• Quantifies the impact of various factors	• Requires access to detailed vaccine,

3.1 Publication characteristics
Machine Learning algorithms have witnessed a rise in use throughout the world because of collaborative action to enhance public health and better prevent and prepare for highly contagious and communicable illnesses. 3 papers were published in 2022, 12 papers in 2023, and 15 papers in 2024 asserting the increase in publications by the year (Figure 2). Continents with superior research facilities and funds, such as Asia (19 papers) and Europe (5 papers), generate more publications in this discipline than other regions. Africa had 3 publications and North America also recorded 3 from our screened papers other continents such as Antarctica, Australia and South America had 0 papers.

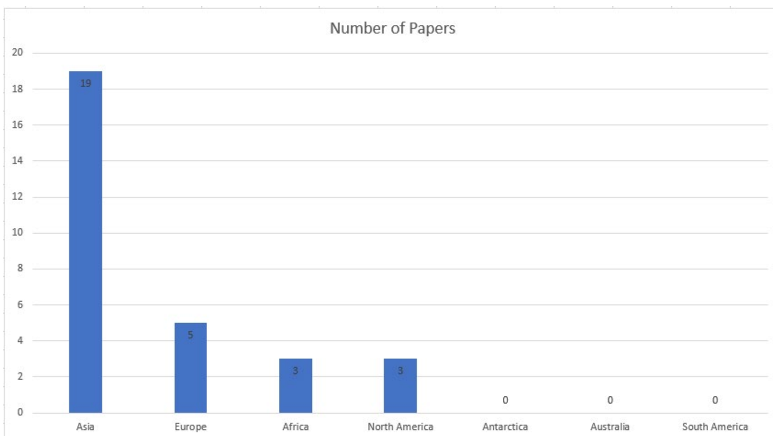

Figure 2. Number of papers per continent

3.2 Factors influencing the adoption of ML for Mpox prediction in practice
The study identified 9 major factors that influence the adoption of machine learning for Mpox prediction in practice. The leading factor is accuracy and efficiency (7 studies) in diagnosing skin lesions as the deep learning techniques significantly reduce diagnostic time and give improved outcomes. The studies reviewed highlight that cost-effectiveness (7 studies) greatly affects the adoption as machine learning can potentially reduce the costs associated with manual diagnostics and interventions. The studies showed that early detection and intervention (3 studies), standardization and best practices (2 studies), data security and privacy (2 studies), and comprehensive data utilization (3 studies) are also the leading factors influencing the adoption of ML for Mpoc prediction. Public perception and communication (1 study) and automation and workflow integration (2 studies) have been proven to improve communication and reduce the burden on healthcare professionals. Scalability and flexibility (4 studies) also influence the adoption rate as ML models that can scale and adapt to different settings and data types are more versatile.

3.3 Machine learning Techniques for Mpox prediction
The studies reviewed showed that Convolutional Neural Networks (CNNs) (6 studies) were the most prominent with 20% of the studies using them for skin lesion classification and segmentation, due to their high efficiency in analyzing medical images (Figure 3). The other prominent techniques were Support Vector Machines (4 studies), Blockchain Technology and the Internet of Things (4 studies), deep learning techniques (3 studies), naïve Bayes classifier (3 studies), and Artificial Neural Networks (2 studies). Transfer learning with pre-trained models (2 studies), Long Short-Term Memory (LSTM) with CNNs (2 studies), explainable AI and outbreak modelling (2 studies), and federated learning (2 studies) gave efficient results in the Mpox prediction.

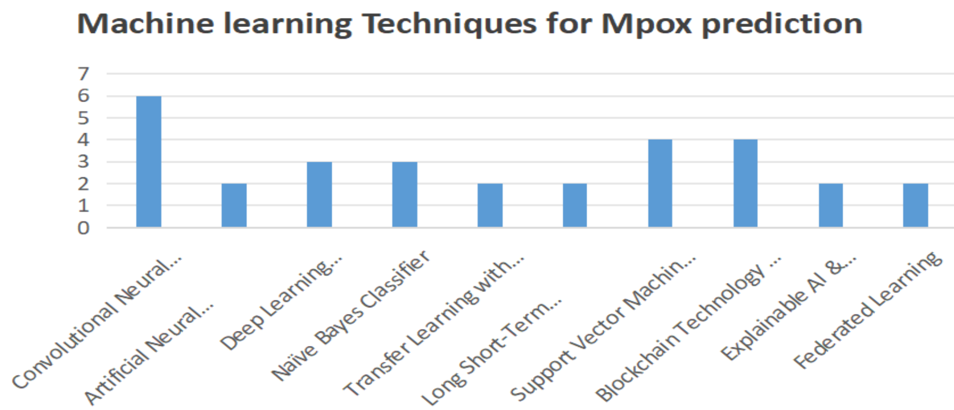

Figure 3. Number of studies per technique

3.4 Strengths of Machine learning Techniques for Mpox prediction

The studies reviewed showed 6 strengths of machine learning techniques for Mpox prediction. The studies highlighted that improved diagnostic accuracy (8 studies) is the major strength of the machine learning techniques as it results in a more accurate diagnosis, particularly in the early stages of the disease. The studies indicated that early detection of outbreaks (6 studies), the ability to predict infection risk (5 studies), and automated analysis of medical images (4 studies) are the leading strengths of machine learning. Four studies indicated that continuous monitoring of disease progression is one of the leading strengths of machine learning, and three studies mentioned that potential for drug discovery is one of the strengths.

3.5 Limitations of Machine learning Techniques for Mpox prediction

The studies reviewed revealed four major limitations of machine learning techniques for Mpox prediction. Dataset limitation (10 studies) is the major limitation as 6 of the studies required larger datasets and 4 required various datasets. Two of the major limitations are real-world data and validation (9 studies) and data accessibility and quality (9 studies) (Figure 4). Two studies highlighted that infrastructure and practical implementation are also limitations of machine learning techniques for Mpox prediction.

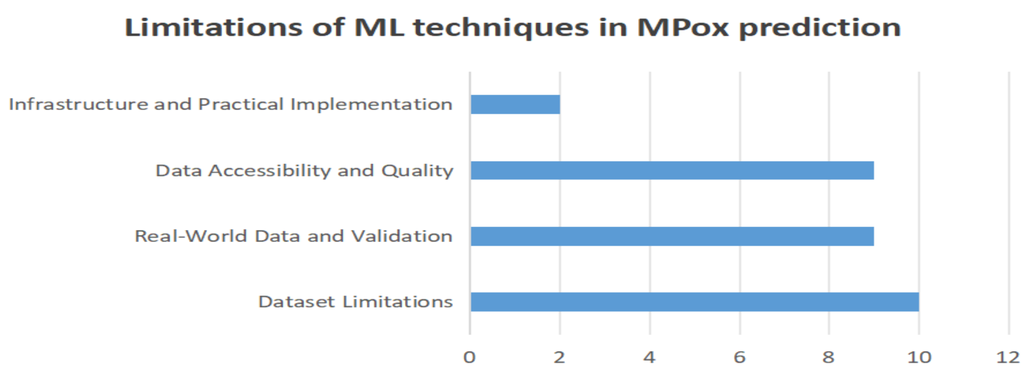

Figure 4. Number of papers per limitation.

4. Discussion

This section will provide a detailed analysis of the research findings and identify research gaps for future research.

4.1 Factors influencing the adoption of ML

This study identified 9 factors that influence the adoption of machine learning algorithms in detecting monkeypox. Maqsoad et al. (2024) noted that data security and privacy are a major influencing factor with blockchain technology and federated learning ensuring data security and privacy, which are critical in healthcare settings. Organisations are more likely to adopt machine learning solutions that guarantee the security and privacy of patient data, therefore being compliant with regulatory standards Demir et al. (2024). Thorat and Gupta (2024); Rabaan et al. (2023); Rampogu (2023b) concur that accuracy and efficiency can significantly reduce diagnostic time and improve patient outcomes. Machine learning algorithms that demonstrate high accuracy and efficiency are more likely to be adopted by organizations (Singh et al. 2024; Guo et al. 2023; Dhapola and Kumar 2024; Chunhapran et al. 2024). H S et al. (2024); Alnaji (2024) highlighted that early detection and intervention of infection through predictive models can lead to timely interventions and better management of outbreaks. Gupta et al. (2023) noted that detecting infections early and intervening promptly encourages clinics to implement these technologies to enhance their public health response. Demir et al. (2024); Kakulapati (2023); Kundu et al. (2024); Gairola and Kumar (2022) mentioned that cost-effectiveness is one of the major factors as machine learning can potentially reduce the cost associated with manual diagnostics and intervention. Cost savings and improved resource allocation drive the adoption of machine learning in resource-constrained settings (Pikulkaew et al. 2024; Vega et al. 2024; Jain et al. 2024). Tripat and Kumar (2023) mentioned that standardization of diagnostic techniques provides a framework for consistent and reliable diagnosis. Adopting standardized ML algorithms ensures that clinics follow best practices, improving the reliability of diagnostic outcomes Yoleu Oztel (2024). Muhammed Kalo Hamdan and Ekmekci (2024). Eliwa et al. (2023) concur that comprehensive data utilization provides a comprehensive approach to diagnostics and outbreak modeling. Mola et al. (2023) noted that the ability to utilize diverse data sources and provide transparent, interpretable results encourages adoption by providing a holistic view of patient health and outbreak dynamics. The ability to scale and customize ML solutions according to the specific needs of an organization makes them more appealing for widespread adoption (Ajmal et al. 2023; Pramanik et al. 2022). Ahson et al. (2024) highlighted that ML models that can scale and adapt to different settings and data types are more versatile. Shah (2022) stated that automated systems for lesion and rash stage classification can streamline workflows and reduce the burden on healthcare professionals. Kulkarni et al. (2024) concurred that automation of routine diagnostic tasks frees up healthcare professionals to focus on more complex cases, making ML algorithms attractive for integration into clinical workflows. Mohbey et al. (2024) mentioned that by understanding public sentiment, through sentiment analysis, healthcare organizations can tailor their communication and intervention strategies, improving public trust and compliance.

4.2 Machine learning Techniques for Mpox prediction

a. Convolutional Neural Networks (CNNs)

Eliwa et al. (2023) used CNN for Monkeypox skin lesion classification and the study resulted in an automated and accurate skin lesion classification with the potential for rapid diagnosis. However, there are dataset limitations and performance on diverse skin types has not been evaluated. Shah (2022) used CNN for Monkeypox skin lesion segmentation using dermatoscopic imaging. The study resulted in the precise localization of monkeypox skin lesions with the potential for automated monitoring. Performance may vary across diverse dermatoscopic image datasets. Mohbey et al. (2024) used CNN for Monkeypox-related sentiment analysis using social media data. The study provides insights into public perception and concerns with the potential for early warning systems, however, the study is limited to social media data and susceptible to biases in user-generated content. Yolcu Oztel (2024) leverages CNN and vision transformers for Monkeypox skin lesion classification using vision transformers and CNNs. The study resulted in a robust skin lesion analysis with potential for generalization to other skin diseases, however, it is limited to visual analysis and may require complementary diagnostic techniques. Kakulapati (2023) used UNETs and VGG16 for Monkeypox skin lesion detection diagnosis. The study had a limited dataset and performance on diverse skin tones was not evaluated.

b. Deep Learning Techniques

Chunhapran et al. (2024) employed deep learning techniques for Monkeypox lesion and rash stage classification and the study accurately assesses disease progression with potential for automated monitoring. Performance may vary across different patient populations and clinical settings. Pikulkaew et al. (2024) developed a study on Monkeypox skin lesion classification using deep learning and image processing. It resulted in improved accuracy in skin lesion classification with the potential for integration with clinical workflow. Gairola and Kumar (2022) worked on Monkeypox diagnosis, symptom prediction, lesion detection, and transmission risk using multitask learning and deep neural networks and the study resulted in a comprehensive assessment of monkeypox status with potential to guide clinical decision-making. This requires access to diverse clinical data and may not generalize well to new patient populations.

c. Multimodal Machine Learning

Ren et al. (2023) used multimodal data fusion for Monkeypox diagnosis and the study resulted in improved diagnostic accuracy by leveraging diverse data sources. However, this requires access to both clinical and imaging data and may not be feasible in all healthcare settings. Maqsood et al. (2024) employed multimodal data for Monkeypox risk assessment and the outcome was a comprehensive evaluation of individual and community-level risk factors. However, the study requires access to diverse data sources and may face challenges in real-world deployment.

d. Reinforcement Learning
Alnaji (2024) focused on Monkeypox contact tracing and outbreak management. The study identifies effective contact tracing policies to minimize disease spread. The study relies on the availability of detailed contact tracing data and may require extensive computational resources.

e. Graph Neural Networks
Singh et al. (2024); Demir et al. (2024) focused on Monkeypox spread modelling using mobility data. The studies leverage structural and temporal information to predict disease spread, however, they require access to comprehensive mobility and contact data and may not capture all transmission dynamics. Rampogu (2023b) worked on Monkeypox transmission networks using graph-based analysis, the study identifies key transmission hubs and clusters to guide targeted interventions and it is dependent on the availability of comprehensive contact tracing data.

f. Natural Language Processing (NLP)
Ajmal et al. (2023) use NLP for monkeypox symptom monitoring using conversational AI. The study enables remote and scalable symptom tracking with potential for early detection of outbreaks and it is dependent on user engagement and willingness to report symptoms.

g. Generative Adversarial Networks (GANs)
Kundu et al. (2024) worked on monkeypox skin lesion data augmentation using image synthesis. The study expands limited skin lesion datasets and improves the performance of lesion classification models however it has the potential for generating unrealistic or biased synthetic data.

h. Bayesian Modeling
H S et al. (2023) developed a study on monkeypox vaccine effectiveness using Bayesian statistical models and causal inference. The study quantifies the impact of various factors on vaccine effectiveness, however, it requires access to detailed vaccine and epidemiological data.

i. Internet of Things (IoT)
Gupta et al. (2023) worked on monkeypox early detection and healthcare monitoring using blockchain technology and IoT integration. It resulted in decentralized and secure disease surveillance with the potential for early warning systems. Dhapola and Kumar (2024) investigated the monkeypox virus spread using IoT applications. It resulted in enhanced disease surveillance and monitoring with the potential for early detection and response, however, it requires widespread IoT infrastructure and has privacy and security concerns.

j. Support Vector Machine (SVM)
Kulkarni et al. (2024) investigated monkeypox disease classification using a Histogram of Oriented Gradients (HOG) and SVM and resulted in effective disease classification from images with potential for deployment in clinical settings, however, the study requires further validation on larger and more diverse datasets.

4.3 Strengths of Machine Learning Algorithms for Mpox Prediction

a) High accuracy and sensitivity.

CNNs have shown exceptional effectiveness in automated Monkeypox skin lesion categorization, with excellent accuracy and sensitivity in identifying Mpox cases (Eliwa et al. 2023). This indicates their capability for accurate and efficient diagnosis.

b) Accurate disease progression assessment.
Deep learning approaches have been proven to properly categorise monkeypox lesions and rash phases (Chunhapran et al. 2024). This allows for close monitoring of disease development, resulting in prompt interventions.

c) Improved diagnostic accuracy.
Multimodal machine learning algorithms can increase Mpox diagnosis accuracy by using many data sources, including clinical and imaging data (Ren et al. 2023). This extensive examination gives a stronger foundation for diagnosis.

d) Potential for early detection and intervention.

Several machine learning algorithms, including those listed above, show promise for early diagnosis of Mpox infections. This can result in earlier interventions and improved epidemic management (H S et al. 2024; Alnaji 2024; Gupta et al. 2023).

e) Scalability and customisation.
Machine learning solutions may be modified and scaled to the unique demands of healthcare organisations, making them suitable for general adoption (Ajmal et al. 2023; Pramanik et al. 2022).

f) Automation of tasks
Machine learning may automate common processes such as lesion categorization, speeding workflows and lowering the strain on healthcare workers (Shah 2022; Kulkarni et al. 2024).

4.4 Limitations of Machine learning Techniques for Mpox prediction

a) Dataset Limitations
Kakulapati (2023); Eliwa et al. (2023) had limited datasets and performance on diverse skin tones was not evaluated. Muhammed Kalo Hamdan and Ekmekci (2024) require further validation on larger datasets. Thorat and Gupta (2024) faced challenges with dataset limitations and performance on diverse skin types was not assessed. Kulkarni et al. 2024 required further validation on larger and more diverse datasets. Ren et al. (2023); Gairola and Kumar (2022) required access to both clinical and imaging data and the results may not be feasible in all healthcare settings. The performance of the model developed by Shah (2022) may vary across diverse dermatoscopic image datasets. Maqsood et al. (2024) required access to diverse data sources and the results faced challenges in real-world deployment.

b) Real-world data and Validation
Rabaan et al. (2023) had results that were not tested on real-world data and relied on existing antiviral compounds. Jain et al. (2024) Focused on traditional diagnostic methods and had limited discussion of emerging technologies. Yolcu Oztel (2024); Pikulkaew et al. (2024) were limited to visual analysis and required complementary diagnostic techniques. The research by Ajmal et al. (2023) was dependent on user engagement and willingness to report symptoms. Pramanik et al. (2022) required access to comprehensive surveillance data and performance may vary across different regions. Tripathi and Kumar (2023) required collaboration between domain experts and AI researchers. The study by Demir et al. (2024) was dependent on high-quality image data and may face challenges in diverse clinical settings.

c) Data Accessibility and Quality
The study by Mohbey et al. (2024) was limited to social media data and it was susceptible to biases in user-generated content. Vega et al. (2023) focused on dataset quality and did not propose solutions for dataset improvement. Guo et al. (2023) relied on the availability of comprehensive demographic and environmental data. Ahsan et al. (2024) required widespread adoption of federated learning infrastructure. Alnaji (2024) relied on the availability of detailed contact tracing data and required extensive computational resources. Singh et al. (2024) required access to comprehensive mobility and contact data and did not capture all transmission dynamics. Rampogu (2023) was dependent on the availability of comprehensive contact tracing data. H S et al. (2023) required access to detailed vaccine and epidemiological data.

d) Infrastructure and Practical Implementation

The study by Gupta et al. (2023) was reliant on widespread IoT adoption and regulatory and privacy considerations. Dhapola and Kumar (2024) required widespread IoT infrastructure and privacy and security concerns.

5. Conclusion Recommendations and Future Works

This systematic literature review (SLR) examined the utility of machine learning (ML) methods in identifying monkeypox and found that ML has tremendous promise for improved Mpox detection. Convolutional neural networks (CNNs) have emerged as particularly effective methods for detecting Mpox cases with high accuracy and sensitivity. The accuracy of diagnosis can be increased by combining machine learning (ML) with imaging modalities like radiography and dermoscopy. Additionally, ML algorithms can process vast datasets that include clinical symptoms, travel history, and contact monitoring information, enabling more rapid and targeted responses. The SLR identifies areas for additional research despite these encouraging results. These include data quality and standardization, the explainability and generalizability of algorithms, integration with current healthcare workflows, ethical considerations, a focus on the early stages of Mpox, comparison research with traditional methods, and cost-effectiveness analysis. A more effective global response to this emerging public health concern can be achieved by addressing the limitations of machine learning techniques and suggesting future research directions. This SLR acknowledges that it has certain limitations, including publication date and language restrictions. Overall, however, it concludes that machine learning techniques are an effective way to improve monkeypox detection.

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