REVOLUTIONISING EPIDEMIOLOGY: A REVIEW OF ARTIFICIAL INTELLIGENCE'S POTENTIAL TO ACCELERATE THE PREDICTION, DIAGNOSIS, AND TREATMENT OF MPOX

TATA, BAVISHYA
Microbiology, College of Medicine, Veterinary and Life Sciences

ABSTRACT

Mpox, formerly referred to as monkeypox, is a viral zoonotic disease characterised by diverse symptoms impacting the respiratory and integumentary systems. It is transmitted via direct or sexual contact, with immunocompromised individuals and pregnant women being especially susceptible. Following the recent breakout in May 2022, the virus has swiftly proliferated to 120 countries, intensifying efforts to mitigate its rapid dissemination. Consequently, to facilitate the prompt identification of mpox for precise diagnosis and treatment, current research endeavours seek to employ artificial intelligence (AI) and machine learning (ML) approaches to enhance epidemiological surveillance and disease management. This review seeks to examine the significant research on various AI and ML models employed or under development to track and regulate the elevated prevalence of mpox. It will evaluate their efficacy, limitations, and future ramifications for research concerning their successful incorporation into mpox studies. This review's results highlight the potential of AI and ML models to enhance comprehensive mpox management, with findings that establish correlations with optimal clinical options for management. Furthermore, this review emphasises the necessity for monitoring a variety of modalities and mutations, given that AI and ML models can potentially revolutionise mpox management. The imminent worldwide threat hence offers a chance to explore AI and ML approaches for implementation in research and healthcare to effectively mitigate the potential severity of the outbreak.

INTRODUCTION

The re-emergence of the neglected emerging zoonotic, mpox orthopoxvirus, raises significant contemporary public health concerns (Ncube et al., 2024). On August 14, 2024, the World Health Organization (WHO) established mpox as an international public health emergency for the second time since 2022 (Parums, 2024). This has reinvigorated mpox as a matter of concern and highlighted the necessity for heightened awareness and preparedness. The viral disease, historically confined to Central and Western Africa and Democratic Republic of Congo, is classified by its clades. Clade Ia from Congo Basin poses an imminent threat with a mortality rate of 11%, whereas Clade IIa from West Africa exhibits a fatality rate of 1% (Moore, 2023). Since its first discovery in 1959, sporadic clusters of the virus have been identified in nations beyond regions of Africa. In 2003, Gambian rats imported from Ghana infected pet prairie dogs in the Midwestern United States (Moore, 2023). This resulted in further transmission to humans, accounting for a total of 53 cases. Recorded cases up to 2021 indicated limited human-to-human transmission and dissemination in regions outside of Africa (Americo et al., 2023).

The 2022 outbreak which first emerged in Europe, documented over 100,000 cases in 122 countries (Centre for Disease Control and Prevention, 2024). This outbreak is classified as Clade IIb, due to its phylogenetic similarities with Clade IIa (Desingu et al., 2024). 99% of cases in non-endemic countries such as Spain and Germany had the highest infectivity among male-to-male sexual intercourse (MSM) subpopulations (Moore, 2023), indicating a human-to-human transmission. Fever, anogenital lesions, and lymphadenopathy are prevalent symptoms of the 2022 outbreak, with increased transmission linked to skin-to-skin contact and exchange of bodily fluids (Liu et al., 2023). Sequence data from 2017 to 2022 suggests that viral evolution and transmission events are ongoing. For instance, the 2024 outbreak of Clade Ib in the Congo Basin and few nations outside Africa (London School of Hygiene & Tropical Medicine, 2024), has prompted an intense focus to inform public health response through surveillance via epidemiological assessments. This includes assessment of disease surveillance, diagnostics and preventative strategies to appropriately alleviate emerging outbreaks (Chukwunweike et al., 2024).

Artificial intelligence (AI), among the oldest domains of computer science, emulates human cognitive intelligence to perform functions such as real-world problem-solving. Machine learning (ML), a subset of AI, creates algorithms to analyse both new and existing data for predictive modelling (Holzinger et al., 2019). The prospects of research into the implementation of AI and ML algorithms in epidemiological assessments have long been in demand (Chukwunweike et al., 2024). Innovations in AI and ML significantly improve public health by assessing risk factors for diseases in vulnerable populations, tracking illness progression real-time, and facilitating access to data from both clinical and non-clinical domains. For example, during the

COVID-19 pandemic, AI-based applications like Geographic Information Systems (GIS) were used as tools to map, evaluate and analyse disease and vaccination trends in affected locations (Hirani et al., 2024), thereby improving oversight and scope of public health initiatives.

Recent investigations into the mpox outbreak have utilised AI and ML for epidemiological modelling; specifically disease surveillance, diagnostics of mpox lesions, and preventative strategies through research of vaccine and drug formulation (Chadaga et al., 2023). This review examines broader literature by contextualising these applications of AI and ML during the 2022 outbreak, highlighting the strengths and limitations of AI and ML applications in mpox management. An overview of future research on AI and ML cloud-based systems is outlined with the objective to further transformation of AI and ML in disease management and epidemiological research.

HISTORY OF AI AND ML APPLICATIONS IN DISEASE MANAGEMENT

Early applications of AI and ML

Health systems worldwide contend with various challenges. The escalating burden of infectious diseases and the growing demand for health services necessitate a proactive approach to global health concerns (Panch et al., 2018). The incorporation of AI and ML in disease management has evolved over decades, with initial uses of AI in healthcare emerging in the 1970s. *INTERNIST-1* in 1971, transformed clinical diagnosis by utilising a search-based algorithm to determine a patient's diagnosis from the input of symptoms. This aided health care providers, by offering a means of verifying their diagnoses and communicating tailored treatment strategies (Hirani et al., 2024). Contemporary applications of AI have enhanced disease management by generating outputs that are tailored to patient requirements. For instance, the emergence of *Watson*, a question-answering system created by IBM in 2007. This system used DeepQA models to assess inputs with various information sources, producing outputs that extend beyond clinical diagnosis. In 2017, the *Watson* system identified RNA binding proteins linked to amyotrophic lateral sclerosis (ALS) (Hirani et al., 2024), highlighting the accelerating potential of AI and ML in disease management.

AI constitutes a sophisticated network of algorithms that may be utilised to achieve specific results, such as the employment of machine learning algorithms in epidemiological modelling. (Hamilton et al, 2021). Figure 1 delineates this specificity of AI applications, with the innermost box displaying AI subtypes needed to extract complex data, from spatial detection to audio processing (Hirani et al., 2024).

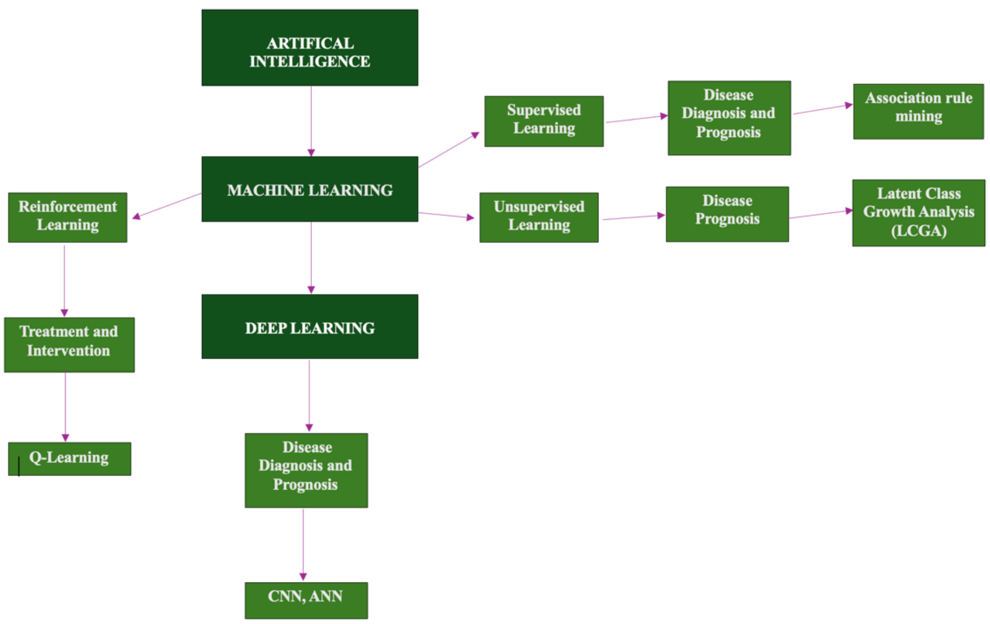

Figure 1: An illustration of the hierarchy of various subtypes of AI and its relevant applications and techniques. The innermost box of ML applications (LCGA and association rule mining) signifies enhanced specificity, including data categorisation into sub-classes and the analysis of intricate audio-visual inputs, such as medical images (Chadaga et al., 2023; Hirani et al., 2024)

Contemporary applications of AI and ML

Deep learning, a subset of AI, uses artificial neural networks (ANN) that function like human brain cells to process information. One example is Convolutional Neural Networks (CNN), which are particularly effective at analysing visual data (Hirani et al., 2024). The study by Hirani et al. (2024) on the identification of dermatological conditions by CNN-based image-guided disease classification is notably intriguing. The utilization of CNN was exemplified by the GOOGLE Inception V3 technology. The technology was trained on more than 49,567 photos to accurately identify onychomycosis, a fungal infection of the nails, using images of infected individuals. The results emphasised diagnostic precision relative to the dermatologists included in the project (Hirani et al., 2024). Furthermore, the paper by Shanbehzadeh et al. (2022) on the application of artificial neural networks (ANN) in identifying new COVID-19 cases has proven notably pertinent. The model was developed to identify key predictors of COVID-19 outbreaks, with an accuracy of 94%. This underscores the significant potential for utilising ANN models in prediction and analysis (Shanbehzadeh et al., 2022).

Machine learning, a subtype of AI, makes accurate predictions using three distinct approaches. Supervised learning uses labelled data with an established output. The model is trained to analyse and predict outcomes using structured data (Uddin et al., 2019; Hamilton et al., 2021). The COVID-19 pandemic revitalized ML research. Ilbeigipour and Albadvi (2022) categorised COVID-19 symptoms to enhance patient outcomes. The study used association rule mining, a supervised learning method that examines correlations between variables in large data sets, to classify patient outcomes as recovery or death. The model predicted COVID-19 outcomes with 95.63% accuracy based on symptom categorisation.

Unsupervised learning, the second ML approach, uses unstructured data to uncover correlations between groups without established outputs (Hamilton et al., 2021), (Gupta et al. (2023) evaluated COVID-19-infected healthcare personnel. Depending on self-reported symptoms during clinical visits, unsupervised modelling employing latent class growth analysis (LCGA) investigated disease progression over one year. Implementing statistical techniques, LCGA assessed disease progression and classified COVID-19 symptoms as long-term or short-term. The model was accurate and compatible with COVID-19 patterns found in other research (Gupta et al., 2023).

Finally, the third approach to machine learning, reinforcement learning (RL), is designed to exhibit decision-making within a specific context. The model facilitates a Q-Learning feedback system wherein the agent, who serves as the decision maker, interacts with the unknown environment to gain evaluative outputs in the form of rewards (Khezeli et al., 2023). Zheng et al. (2021) studied reinforcement learning-based oxygen flow control for COVID-19 patients in intensive care units. The study assessed oxygen supply demands based on patient criteria and symptoms and found success, corresponding with Elamari et al. (2020), for diabetic COVID-19 patients. Compared to physician-mediated oxygen flow control therapy's 44% success rate, the RL algorithm reduced critical care unit mortality over seven days (Zheng et al., 2021). Here, the ML-mediated rapid and efficient personalised interventions improved health outcomes. The extensive history of investigations of AI and ML approaches in disease management indicates their potential applicability in mpox management.

HOW AI AND ML ARE CHANGING MPOX DETECTION AND TREATMENT

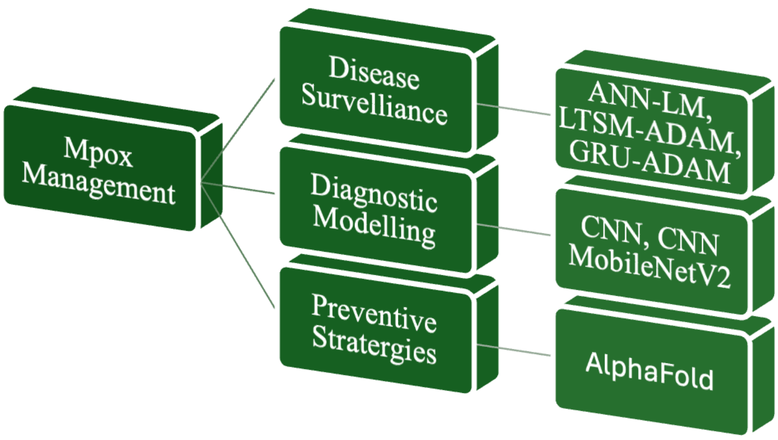

Figure 2: An overview of the AI and ML models detailed in the research findings concerning mpox management. The three areas of epidemiologic epidemiological assessment have utilised various subtypes of AI and ML according to their mpox management outcomes (Chadaga et al., 2023)

Disease surveillance of mpox

Active mpox surveillance is necessary to determine its transmission mechanisms. Serological investigation in Autumn 2022 by the US Centers for Disease Control and Prevention found three undetected mpox cases in sample of 74 homeless individuals (Roper et al., 2023). Local surveillance is required to discover outbreak patterns that could affect global disease surveillance. With the global outbreak continuing beyond 2024, improved indicators must be developed to predict future outbreaks.

Alnaji (2024) conducted a study assessing the efficacy of ANN models in predicting future mpox outbreaks. The model's efficacy was evaluated against two other computational models, including the Long Short-Term Memory (LSTM) model and the Gated Recurrent Unit (GRU) model. The model was trained with a time series dataset and examined in six countries (Argentina, Brazil, Chile, France, Germany, and Mexico) to evaluate the intensity of the spread. The results indicated that the ANN-LM (Levenberg-Marquardt Algorithm) model had superior performance, achieving an R value of 0.99 (99%,) compared to 0.98 (98%) for the LSTM and GRU models. This indicates that the predicting accuracy of ANN-LM models was more precise and robust in evaluating the 2022 mpox outbreaks. Similar findings were also delineated in the study by Manohar and Das (2022). This study evaluated the 2022 mpox outbreak in five countries which reported the highest rates of mpox: the USA, Germany, the UK, France, and Canada. This study compares the same models as Alnaji (2024): ANN-LM, LSTM-ADAM, GRU-ADAM. Findings indicated an R-value of 0.99 (99%) across all five nations, demonstrating that the ANN-LM model is well-suited for predictive modelling of mpox. The R value of LTSM-ADAM and GRU-ADAM reported was 0.98 (98%), as indicated by Alnaji (2024). The findings from both experiments indicate that the ANN-LM is optimally designed for precise widespread forecasting across nations.

Diagnostic modelling of mpox

Mpox is defined by its characteristic skin lesions, with its recognition being synonymous with the disease. According to WHO case definitions, a considerable percentage of cases exhibiting the distinctive pustular lesion remain undiagnosed, primarily due to a lack of contact history with a mpox-infected population (Thieme et al., 2023). Consequently, it is essential to implement several case definitions in relation to mpox to determine diagnosis. Thieme et al. (2023) tested CNN models for mpox lesion identification. The model's performance was assessed using large image datasets of varied skin tones and lesion sites. To combat healthcare bias, models included varied skin tones and lesion kinds. Models trained on homogeneous datasets may not recognise lesions on darker skin tones. This causes misdiagnosis, delayed response, and new transmission chains that effect public health response. To reduce evaluation bias, mpox skin lesions (n=676) were compared to other acute dermatological disorders (n=138,522) with similar appearances. Stanford University Medical Centre patients provided mpox skin lesion photos, while public dermatological repositories provided non-mpox photographs. The model was trained to classify skin lesions as acute or chronic to improve suitability evaluation. The model's mpox detection sensitivity was 0.89 (89%) in Stanford University Medical Centre images, with an overall sensitivity of 0.91 (91%). The model detected mpox extensively in lesions present for less than 7 days. The CNN model detected 100% of anogenital lesions, 85.7% of lower extremities, and images spanning several regions of the body.

This coincides with the 2022 outbreaks transmission mechanism of sexual contact resulting in anogenital lesions. The detection sensitivity ranged from 85.7% to 100% across all skin tones. Acute and chronic classification performed well with specificities of 0.886 and 0.900. In their study of five CNN models (ResNet50, VGG16, MobileNetV2, VGG19, and EfficientNetB3) Jaradat et al. (2023) revealed commonalities. The model included 45 mpox lesions and 74 non-mpox lesions. These images were carefully chosen from many web repositories. In contrast to Thieme et al. (2023), this study scaled or standardized images to 224x224 to reduce model biases during image analysis. Data augmentation approaches were used to train the model on image orientation, zoom, height, and width to improve generalisability and expose it to image variances. CNN MobileNetV2 had the highest accuracy at 0.9890 (98.90%), followed by VGG19 at 0.9779 and VGG16 at 0.9669. CNN models have sensitivity or accuracy between 90%, matching Thieme et al. (2023). This demonstrates that the models can recognise mpox lesions in real time, enabling rapid and precise diagnosis in clinical and non-clinical settings.

Preventative strategies of mpox

Drug repurposing presents a viable way to tackle the mpox crisis, given the absence of FDA-approved treatments. The drug development process can be extensive and expensive; hence, drug repurposing can significantly reduce disease complications due to its accessibility, cost efficiency, and comprehensive safety and efficacy evaluations that have secured regulatory authorisation for use. Furthermore, research on personalised treatment for immunocompromised individuals, such as pregnant women, can be achieved through the application of deep learning algorithms identifying target-specific therapy sites (Lam et al., 2022).

The study by Lam et al. (2022) utilises a deep learning methodology to formulate a drug repurposing strategy. A homology model of the mpox E8 protein, a transmembrane glycoprotein, was developed that facilitates viral attachment and entrance into host cells. The homology was established utilising two domains. Domain I was found to be homologous to VACV D8 (vaccinia virus transmembrane glycoprotein), which is structurally similar to E8. While two antiparallel alpha helices formed the transmembrane structure of Domain II. AlphaFold deep learning technology was used to model these domains and determine the protein structures for drug candidate identification. The study found that Domain I is the best drug screening target with 94.85% confidence, proposing use of the VACV D8 target to create mpox therapies. Although mpox treatment research is limited, this study is one of the first AI-based applications to generate cutting-edge therapies.

LIMITATIONS OF AI AND ML APPLICATIONS

Alongside the merits of the reported findings, the results must be assessed for their limitations to assure the generalisability of the applications to epidemiological assessments (Asif et al., 2024). Research by Alnaji (2024) and Manohar and Das (2022) emphasised the efficacy of ANN-LTM models in the surveillance and management of mpox. Both studies investigated the 2022 outbreak in different nations; however, clade-specific analysis was not published in either study. Therefore, classification of subpopulations impacting disease spread could not be measured. Furthermore, multiple countries were examined in each study, where differing climatic conditions and population density complicate the prediction of future disease outbreaks. The studies did not report these aspects, primarily concentrating on historical case data to evaluate long-term trends (Alnaji, 2024). Including these factors will address geographic disparities in disease prevalence. The findings do not consider socio-economic factors, such as financial stability, education, and cultural norms and practices, which may indirectly influence the dynamics of disease progression across nations. In summary, the constraint of ANN models lies in their limited capacity to manage contextual information (Alnaji, 2024).

Thieme et al. (2023) and Jaradat et al. (2023) elucidate the efficacy of CNN models in diagnosing mpox lesions. A significant limitation of both studies is the lack of images depicting mpox lesions. The study by Thieme et al. (2023b) acknowledges potential bias, as images sourced from repositories may disproportionately represent severe mpox lesions rather than early-stage lesions, which correlates with the limited sample size of mpox lesion photographs (n=676). Jaradat et al.'s 2023 study with a limited sample size (n=45), suggests reduced generalisability to populations infected with mpox across different nations. Therefore, validation of the models must be conducted using varied datasets to augment their reliability. The limitation of CNN algorithms in recognising mpox lesions is attributed to datasets. Therefore, it is essential to gather datasets from various repositories, both online and offline, together with real-time testing to enhance mpox diagnosis modelling.

Research by Lam et al. (2022) outlines the effectiveness of deep learning algorithms in drug repurposing. A major constraint of the study is the lack of research on novel therapies for mpox. The identification of E8 as a possible target necessitates that future studies employ AI and ML methodologies to discover potential therapeutic targets.

CONCLUSION: FUTURE RESEARCH ON MPOX MANAGEMENT

This review aims to elucidate the strengths and limitations of AI and ML applications to advance their transformation in disease management and epidemiological surveillance. By highlighting the vast potential of AI and ML techniques, further insight into their effective integration in research on underexplored rare emerging diseases was established. The conclusion based on the findings suggests that AI and ML applications significantly enhance disease surveillance, diagnosis, and treatment, particularly when integrated with deep learning models such as ANN and CNN. Although, this review focused on deep learning in mpox management, excluding other AI applications. Subsequent, analyses on this topic could involve examination of literature that details the implementation of ML approaches in mpox management.

AI and ML integrated in cloud-based systems represent the future (Chadaga et al., 2023). Uploading images to AI-powered smartphone apps might accelerate and enhance mpox diagnosis, especially in remote locations. Application customisation can benefit clinicians and local and international organizations, supplying clinical data from various locations for system-wide analysis to inform public health strategy. Although valuable, such apps exhibit limitations. These include lack of technical literacy and internet access in low-income and rural areas, hindering adoption. The application must also comply with the General Data Protection Regulation (GDPR) in several jurisdictions to protect data breaches (Thieme et al., 2023). There are also false positive risks. Due to region-specific databases, AI and ML can be biased during training, under-representing afflicted groups (Chadaga et al., 2023), therefore hindering mpox diagnosis and triggering unwarranted anxiety. Thus, this approach may minimize mpox transmission but should not replace laboratory testing or direct medical examination and care. Finally, utilising AI and ML-based predictions and diagnostics to map effected zones within the application might further enable effective disease management and epidemiological surveillance.

REFERENCES

Americo, J.L., Earl, P.L. and Moss, B. (2023). Virulence differences of mpox (monkeypox) virus clades I, IIa, and IIb.1 in a small animal model. *Proceedings of the National Academy of Sciences*, **120**(8). doi: https://doi.org/10.1073/pnas.2220415120.

Asif, S., Zhao, M., Li, Y., Tang, F., Saif and Zhu, Y. (2024). AI-Based Approaches for the Diagnosis of Mpox: Challenges and Future Prospects. *Archives of computational methods in engineering*, **31**, pp.3585–3617. doi: https://doi.org/10.1007/s11831-024-10091-w.

CDC (2024). *Mpox in the United States and around the world: current situation*. [online]. [Accessed 30 Oct. 2024]. Available at: https://www.cdc.gov/mpox/situation-summary/index.html.

Desingu, P.A., Rubeni, T.P., Nagarajan, K. and Sundaresan, N.R. (2024). Molecular evolution of 2022 multi-country outbreak-causing Monkeypox virus Clade IIb. *iScience*, **27**(1), pp.108601. doi: https://doi.org/10.1016/j.isci.2023.108601.

Chadaga, K., Prabhu, S., Sampathila, N., Nireshwalya, S., Katta, S.S., Tan, R.-S. and Acharya, U.R. (2023). Application of Artificial Intelligence Techniques for Monkeypox: A Systematic Review. *Diagnositics*, **13**(5), pp.824. doi: https://doi.org/10.3390/diagnostics13050824.

Chukwunweike, J., Oladokun, P., Abubakar, I.O. and Afolabi, S. (2024). Leveraging AI and Deep Learning in Predictive Genomics for MPOX Virus Research using MATLAB. *International Journal of Computer Applications Technology and Research*, [online] **13**(9). doi: https://doi.org/10.7753/ijcatr1309.1001.

Elamari, S., Motaib, I., Zbiri, S., Elaidaoui, K., Chadli, A. and Elkettani, C. (2020). Characteristics and outcomes of diabetic patients infected by the SARS-CoV-2. *Pan African Medical Journal*, **37**. doi: https://doi.org/10.11604/pamj.2020.37.32.25192.

Gao, L., Shi, Q., Dong, X., Wang, M., Liu, Z. and Li, Z. (2023). Mpox, Caused by the MPXV of the Clade IIb Lineage, Goes Global. *Tropical Medicine and Infectious Disease*, **8**(2), pp.76. doi: https://doi.org/10.3390/tropicalmed8020076

Gupta, V., Kariotis, S., Rajab, M.D., Errington, N., Elham Alhathli, Jammeh, E., Brook, M., Meardon, N., Collini, P., Cole, J., Wild, J.M., Hershman, S., Javed, A., Thompson, R., Silva, T. de, Ashley, E.A., Wang, D. and Lawrie, A. (2023). Unsupervised machine learning to investigate trajectory patterns of COVID-19 symptoms and physical activity measured via the MyHeart Counts App and smart devices. *npj Digital Medicine*, [online] **6**(1). doi: https://doi.org/10.1038/s41746-023-00974-w.

Hamilton, A.J., Strauss, A.T., Martinez, D.A., Hinson, J.S., Levin, S., Lin, G. and Klein, E.Y. (2021). Machine learning and artificial intelligence: applications in healthcare epidemiology. *Antimicrobial Stewardship & Healthcare Epidemiology*, [online] **1**(1). doi: https://doi.org/10.1017/ash.2021.192.

Hirani, R., Noruzi, K., Khuram, H., Hussaini, A.S., Aifuwa, E.I., Ely, K.E., Lewis, J.M., Gabr, A.E., Smiley, A., Tiwari, R.K. and Etienne, M. (2024). Artificial Intelligence and Healthcare: A Journey through History, Present Innovations, and Future Possibilities. *Life*, [online], **14**(5), pp.557. doi: https://doi.org/10.3390/life14050557.

Holzinger, A., Langs, G., Denk, H., Zatloukal, K. and Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. *WIREs Data Mining and Knowledge Discovery*, [online], **9**(4). doi: https://doi.org/10.1002/widm.1312.

Ilbeigipour, S. and Albadvi, A. (2022). Supervised learning of COVID-19 patients' characteristics to discover symptom patterns and improve patient outcome prediction. *Informatics in Medicine Unlocked*, **30**, pp.100933. doi: https://doi.org/10.1016/j.imu.2022.100933.

Jaradat, A.S., Al Mamlook, R.E., Almakayeel, N., Alharbe, N., Almuflih, A.S., Nasayreh, A., Gharaibeh, H., Gharaibeh, M., Gharaibeh, A. and Bzizi, H. (2023). Automated Monkeypox Skin Lesion Detection Using Deep Learning and Transfer Learning Techniques. *International Journal of Environmental Research and Public Health*, **20**(5), pp.4422. doi: https://doi.org/10.3390/ijerph20054422.

Khezeli, K., Siegel, S., Shickel, B., Ozrazgat-Baslanti, T., Bihorac, A. and Rashidi, P. (2023). Reinforcement Learning for Clinical Applications. *Clinical Journal of the American Society of Nephrology*, Publish Ahead of Print, **18**(4), pp.521-523 doi: https://doi.org/10.2215/cjn.0000000000000084.

Lam, T.-P., Tran, V.-H., Mai, T.T., Lai, N.V.-T., Dang, B.-T.N., Le, M.-T., Tran, T.-D., Trinh, D.-T.T. and Thai, K.-M. (2022). Identification of Diosmin and Flavin Adenine Dinucleotide as Repurposing Treatments for Monkeypox Virus: A Computational Study. *International Journal of Molecular Sciences*, **23(19)**, pp.11570. doi: https://doi.org/10.3390/ijms231911570.

Liu, Q., Fu, L., Wang, B., Sun, Y., Wu, X., Peng, X., Li, Y., Lin, Y.-F., Fitzpatrick, T., Vermund, S.H. and Zou, H. (2023a). Clinical Characteristics of Human Mpox (Monkeypox) in 2022: A Systematic Review and Meta-Analysis. *Pathogens*, **12**(1), pp.146. doi: https://doi.org/10.3390/pathogens12010146.

Alnaji, L. (2024). A Comprehensive Analysis of the Artificial Neural Networks Model for Predicting Monkeypox Outbreaks. *Heliyon*, [online] **10**(17). doi: https://doi.org/10.1016/j.heliyon.2024.e37274.

Manohar, B. and Das, R. (2022). Artificial Neural Networks for the Prediction of Monkeypox Outbreak. *Tropical Medicine and Infectious Disease*, **7**(12), pp.424. doi: https://doi.org/10.3390/tropicalmed7120424.

Moore, M., Zahra, F. and Rathish, B. (2022). *Monkeypox*. [online] PubMed. Available at: https://www.ncbi.nlm.nih.gov/books/NBK574519 / [Accessed 30 Oct. 2024].

Ncube, B., Maybin Dzikiti, Akim Nyoni, Mthandazo Ncube and Ndlovu, B.M. (2024). Effectiveness of Machine Learning algorithms in predicting Monkey Pox (Mpox): A Systematic Literature Review. *7th European Conference on Industrial Engineering and Operations Management*. [online] doi: https://doi.org/10.46254/EU07.20240072.

Okoli, G.N., Paul Van Caeseele, Askin, N. and Abou-Setta, A.M. (2023). A global systematic evidence review with meta-analysis of the epidemiological characteristics of the 2022 Mpox outbreaks. *Infection*, **52**(3), pp.901–921. doi: https://doi.org/10.1007/s15010-023-02133-5.

Panch, T., Szolovits, P. and Atun, R. (2018). Artificial intelligence, machine learning and health systems. *Journal of Global Health*, 8(2). doi: https://doi.org/10.7189/jogh.08.020303.

Parums, D.V. (2024). Editorial: Reasons for Increasing Global Concerns for the Spread of Mpox. *Medical Science Monitor*, [online], **30**. doi: https://doi.org/10.12659/msm.946343.

Patel, M., Surti, M. and Adnan, M. (2022). Artificial intelligence (AI) in Monkeypox infection prevention. *Journal of Biomolecular Structure and Dynamics*, **41**, pp.8629-8633. doi: https://doi.org/10.1080/07391102.2022.2134214.

Ranjan, S., Vashishth, K., Sak, K., and Tuli, H.S. (2023). The Emergence of Mpox: Epidemiology and Current Therapeutic Options. *Springer Nature Link*, **9**(3), pp.144–153. doi: https://doi.org/10.1007/s40495-023-00318-y.

Roper, R.L., Garzino-Demo, A., Del Rio, C., Bréchot, C., Gallo, R., Hall, W., Esparza, J., Reitz, M., Schinazi, R.F., Parrington, M., Tartaglia, J., Koopmans, M., Osorio, J., Nitsche, A., Huan, T.B., LeDuc, J., Gessain, A., Weaver, S., Mahalingam, S. and Abimiku, A. (2023). Monkeypox (Mpox) requires continued surveillance, vaccines, therapeutics and mitigating strategies. *Vaccine*, [online] **41(20),** pp.3171-3177. doi: https://doi.org/10.1016/j.vaccine.2023.04.010.

Shanbehzadeh, M., Nopour, R. and Kazemi-Arpanahi, H. (2022). Developing an artificial neural network for detecting COVID-19 disease. *Journal of education and health promotion*, [online] **11**, pp.2. doi: https://doi.org/10.4103/jehp.jehp_387_21.

Thieme, A.H., Zheng, Y., Machiraju, G., Sadee, C., Mittermaier, M., Gertler, M., Salinas, J.L., Srinivasan, K., Gyawali, P., Carrillo-Perez, F., Capodici, A., Uhlig, M., Habenicht, D., Löser, A., Kohler, M., Schuessler, M., Kaul, D., Gollrad, J., Ma, J. and Lippert, C. (2023). A deep-learning algorithm to classify skin lesions from mpox virus infection. *Nature Medicine*, [online] **29**(3), pp.738–747. doi: https://doi.org/10.1038/s41591-023-02225-7.

Uddin, S., Khan, A., Hossain, M.E. and Moni, M.A. (2019). Comparing different supervised machine learning algorithms for disease prediction. *BMC Medical Informatics and Decision Making*, [online] **19**(1). doi: https://doi.org/10.1186/s12911-019-1004-8.

UK, in (2024). *Expert Comment – First case of Clade Ib mpox detected in UK | LSHTM*. [online]. [Accessed 13 Nov. 2024].Available at: https://www.lshtm.ac.uk/newsevents/news/2024/expert-comment-first-case-clade-ib-mpox-detected-uk

Zheng, H., Zhu, J., Xie, W. and Zhong, J. (2021). Reinforcement learning assisted oxygen therapy for COVID-19 patients under intensive care. *BMC Medical Informatics and Decision Making*, **21(1).** doi: https://doi.org/10.1186/s12911-021-01712-6.