Artificial Intelligence and Image Processing Techniques of Monkeypox Disease Patterns

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Table of Contents

CHAPTER 1

INTRODUCTION TO ANALYSIS OF INFECTIOUS DISEASE USING AI AND IMAGE PROCESSING TECHNIQUES

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Abstract: Infectious diseases, resulting from bacteria, parasites, viruses, and fungus, represent a significant worldwide health issue, particularly in low-income nations and among young children. They disseminate by bodily fluids, contact with infected surfaces, and consumption of contaminated food and beverages. Antimicrobial drugs are often used in treatment, and artificial intelligence has arisen as a mechanism for assessing molecular data. In 2019, lower respiratory infections and diarrheal illnesses were among the 10 leading causes of mortality globally. HIV/AIDS and TB have decreased, although continue to be a major cause of morbidity in low-income nations. Mpox is induced by the monkeypox virus (MPXV), an enclosed double-stranded DNA virus belonging to the Orthopoxvirus genus within the Poxviridae family. This chapter summarizes the latest investigations, expert consensus, and continuing initiatives, providing insights into epidemic containment and enhancing comprehension of the developing infectious illness, along with updated recommendations for prevention, control, and crucial management.

Keywords: disease, infection, drug, monkeypox, virus, health, AI, image, Techniques, genes, mortality.

1. Introduction

Infectious illnesses, resulting from tiny organisms such as bacteria, viruses, fungi, or parasites, are a major cause of mortality globally, particularly in low-income nations and among young children. In 2019, the World Health Organization identified lower respiratory infections and diarrheal disorders as the top 10 causes of mortality. HIV/AIDS and TB have decreased, although continue to be a major cause of morbidity in low-income nations. Malaria is a leading source of morbidity in low-income nations attributable to a single infectious pathogen. In 2020, COVID-19, induced by the SARS-CoV-2 virus, emerged as the leading cause of mortality in the United States.

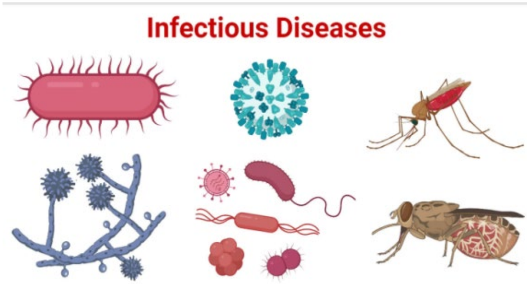

Fig 1: infectious diseases [1]

Widespread immunization has made people less immune to mpox, which has made them more likely to become sick. Changes in the environment, society, and politics in areas where the disease is common may also make people more likely to come into contact with animal reservoirs [2]. Patients who are sick may go to the emergency room or their regular care doctor. An interprofessional team may find and put in place preventative measures and start public health reporting to stop terrible epidemics from happening. Specialty infectious disease pharmacists may help patients get healthier by reconciling their medications and giving them advice.

Infectious illnesses, or diseases that may be spread from one person to another, are a big hazard to health across the world. It is still hard to classify illnesses, and it is very important to stop them from happening in real-time [3]. Artificial intelligence (AI) has made a lot of progress in this sector, and machine learning (ML) is a big part of it. ML models use several ways to find and predict infectious illnesses. Some of the methods utilized include Support Vector Machines (SVM), Decision Tree (DT) algorithms, clustering algorithms, Naive Bayes (NB), Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Long Short-Term Memory (LSTM) networks, Transformers models, and new ones like Transfer Learning. To find the sources of outbreaks and take action to stop them, it is important to know how certain illnesses arise and how they behave. This article talks about how AI might be used to anticipate and stop the spread of infectious illnesses. It focuses on research goals, data analysis, and ways to learn [4].

AI might change several fields, such as healthcare, banking, self-driving vehicles, environmental analysis, natural language processing, production, and learning. It can analyze data [5], process it, and make decisions, which makes it useful in many areas, including disaster response, evaluating forensic evidence, spotting false news, and keeping society safe. AI is also very important for cybersecurity, especially when it comes to protecting against assaults from enemies. This shows how important it is to make the digital world safe [6,7]. AI's capacity to replicate societal issues and enhance the identification and treatment of illnesses, such as Monkeypox (Mpox) in the healthcare business, shows that it might help people be more creative and address big challenges throughout the world. There is no doubt that AI has the power to change industries and spark new ideas.

Digital image processing is a kind of digital signal processing that employs computer algorithms to make picture data better by getting rid of distortions and bringing out important details. This allows more algorithms to be used on input data, which is good for AI-computer vision models. For training and making predictions, images must be the same size as the network's input.

In clinical microbiology laboratory diagnosis, image interpretation is very important since it gives important information such as the presence of microbes, the host's inflammatory response, and the quality of the material. It helps find out whether there is an infection and proposes another diagnosis for treatment [8]. But there aren't enough medical laboratory experts, which makes things harder and opens the door for new artificial intelligence algorithms and automated image-based interpretive duties.

It is becoming more common to utilize AI models to look at medical images to find diseases caused by viruses [9]. For example, Madhavan et al. used a transfer learning method to construct a deep learning model called Res-COvNet that can find the COVID-19 virus. They used characteristics from X-ray scans [10] and added a classification layer to the network. This made it 96.2% accurate for normal, bacterial pneumonia, viral pneumonia, and COVID-19 cases. There have been reports of similar experiments utilizing deep learning to find COVID-19 and face skin diseases [11].

The structure of the study is as follows: Part 2 gives a general summary of the Mpox disease background. Section 3 talks about infectious illnesses and their many forms, as well as how AI and image processing methods were used to investigate Mpox research. Section 4 gives a summary of the uses of AI and image processing techniques. Section 5 goes into further detail regarding the topic throughout the whole chapter. Finally, section 6 presents a summary and some ideas for how AI and image processing may be used in the infectious sector in the future to get the reader thinking.

2. Background of the Study

Infectious illnesses, induced by pathogens such as bacteria, viruses, fungi, or parasites, have historically affected human populations. Historical records and archeological discoveries provide evidence of outbreaks and epidemics. Significant epidemics, such as the Antonine Plague, the Black Death, and the 1918 Spanish Flu pandemic, have resulted in catastrophic repercussions throughout history. Global dissemination has been enabled by colonization, slavery, warfare, enhanced international travel, and urbanization. Pathogens may be transferred by several channels, including direct contact between individuals, contaminated food or drink, insect bites, and exposure to diseased animals or habitats. Medical discoveries, including the germ theory of illness, vaccines, antibiotics, public health initiatives, and zoonotic diseases, have transformed our comprehension of infectious diseases. The rise of antibiotic-resistant microorganisms presents an escalating danger to world health. Public health interventions, including sanitation, potable water, and quarantine, have been crucial in avoiding and managing the spread of infectious illnesses [12].

One of the main causes of mortality globally, particularly in low-income nations, is infectious diseases, which are brought on by tiny organisms like bacteria, viruses, fungi, or parasites. These infections are especially harmful to young children. In 2019, the World Health Organization identified lower respiratory infections and diarrheal disorders as the top 10 causes of mortality. Malaria is a leading cause of mortality attributable to individual infectious pathogens. In 2020, COVID-19, induced by the SARS-CoV-2 virus, emerged as the third predominant cause of mortality in the United States, behind heart disease and cancer [13].

Leprosy, a chronic infectious disease, has posed a considerable worldwide health challenge since the 11th century. The Black Death of the 14th century, the second greatest epidemic, resulted in the deaths of 30-60% of the European population. In 1665, the Great Plague of London resulted in the death of 20% of the city's inhabitants. Since 1817, seven cholera pandemics have occurred, and a cholera vaccine was developed in the late 1800s. The 1800s saw the third epidemic of the bubonic plague, resulting in nearly 15 million fatalities. The 1875 Fiji Measles Pandemic caused 40,000 fatalities. Influenza pandemics increased in frequency throughout the 20th century, with the Russian Flu resulting in 360,000 fatalities from 1889 to 1890. The Spanish Flu pandemic caused 50 million fatalities, followed by the Asian Flu epidemic in the 1950s. The last pandemic of the 20th century was the human immunodeficiency virus (HIV)/acquired immunodeficiency syndrome (AIDS) pandemic, first recognized in 1981. In the previous four decades, this illness has claimed approximately 32 million lives [14].

Mpox is an infectious disease caused by the MPXV virus, initially identified in 1958 and documented in many African nations, mostly in the DRC and Nigeria. In 2003, mpox was documented in the United States after an epidemic resulting from the introduction of rats from Africa. MPXV has two major genetic clades: clade I (formerly referred to as the Central African or Congo Basin clade) and clade II (formerly known as the West African clade). Clade I MPXV has previously been transferred from animals to humans, with small mammals and primates serving as hosts. In March 2023, illnesses associated with sexual contact and foreign travel were documented in the DRC. In 2024, instances emerged from nations beyond the five Central African Region countries, perhaps attributable to diminishing population immunity from the halted smallpox vaccination and evolving environmental and socioeconomic dynamics [15].

Fig 2: Human Monkeypox Virus (hMPXV)[16]

Microbiologists possess expertise in image analysis, discerning infections, and inflammatory conditions in diverse samples. They categorize colony development on agar plates for triage and evaluation. Advancements in artificial intelligence possess the capacity to automate these procedures, facilitating more precise diagnosis. AI methodologies used in infectious disease imaging vary from basic algorithms for organized datasets to sophisticated deep-learning algorithms for predictions derived from unstructured datasets, including extensive imaging data.

3. Related Works

Researchers in medical image processing try to improve the quality and amount of information in images by integrating several imaging methods, such as averaging and extreme value selection. Averaging, on the other hand, lowers contrast, extreme value procedures don't do much to improve things, and the Brovey technique may mess with colors [17]. Researchers are utilizing machine learning and deep learning to find the monkeypox virus early and correctly classify it. This virus is less lethal than COVID-19. This joint approach might lead to quick, automated diagnosis in places where traditional diagnostic procedures are restricted or expensive. This could help solve the worldwide monkeypox problem.

The research [18] shows that the monkeypox epidemic is the new zoonotic warning following the COVID-19 pandemic. As of July 2022, there were more than 15,000 verified cases throughout the globe. This was a 383.94% rise in only one month. The US, South America, and Europe are the most impacted. The research shows that Tecovirimat-based medication may be given by mouth or via an IV.

The number of monkeypox cases throughout the world is rising, and the illness has spread to over twenty nations and continents. Experts consider it a possible pandemic, and although there are no therapies, providing antiviral medications and immunizations might help prevent and cure the sickness. We employ machine learning methods including linear regression, decision trees, random forests, elastic net regression, artificial neural networks, and convolutional neural networks (CNN) to look at how the virus spreads. Knowing how the virus spreads may assist stop it from spreading further and make sure that treatment is given quickly and effectively [19].

Researchers have looked at using artificial intelligence (AI) to find monkeypox sickness. Researchers have devised several strategies to improve deep neural networks, obtaining great classification accuracy. Abdelhamid et al. created a hybrid technique to improve deep neural networks on a dataset relevant to monkeypox. It got a classification accuracy of 98.8% [20]. Using the Harris Hawks optimizer method, Almutairi improved the hyperparameters of the VGG, Xception, and MobileNet deep learning models. Dwivedi et al. employed deep learning models based on ResNet and EfficientNet to discover monkeypox skin lesions. They found that the EfficientNetB3 model had the greatest accuracy value of 87% [21]. Using AlexNet, GoogleNet, and VGG deep learning models and other machine learning classifiers, Gairola and Kumar got an accuracy of 95.55%. Irmak et al. used pre-trained MobileNetV2 and two VGG deep learning models with varied numbers of layers on an open-source monkeypox skin picture dataset to achieve 91.38% accuracy in classification procedures.

Using the AL-Biruni Earth radius stochastic fractal search strategy to improve a deep convolutional neural network, Khafaga et al. found monkeypox with 98.83% accuracy. Singh and Songare employed the deep learning models InceptionV3, GoogLeNet, ResNet50, and VGG16. They found that the GoogLeNet model had the greatest accuracy value of 88.27%. Using three different optimizers, Ahsan et al. found a broad range of accuracy values for classification tasks using the ResNet, VGG, Xception, NasNet, and EfficientNet deep learning models [22]. The hybrid MobileNetV3 worked best for Altun et al. It had a f1 score of 0.98 and an accuracy of 96%. [23] Saleh and Rabie employed the binary chimp optimization method on data from the internet and got a 98.48% accuracy rate for classifying monkeypox operations [24].

The research [25] used a Siamese deep learning model to sort things, and it worked quite well. The model's performance was affected by the amount of data, and more data made it work better. The categorization technique worked even if there were not many data points. There was no feature extraction, which suggests that other methods are needed. Ensemble approaches worked better than the Siamese deep learning model. It took an average of 17 seconds for each iteration of the training procedure, which added up to 28.3 minutes.

Used machine learning techniques [26] including NB, SVM, KNN, DT, and RF to predict monkeypox using CNN structures and skin pictures. The performance was measured by its accuracy, F1 score, precision, and recall. Researchers showed that transfer learning worked, and ensemble classifiers including ResNet, EfficientNet, and MobileNet models had the best accuracy score of 98.33%.

The research [27] utilizes a database that has pictures of skin lesions and rashes from five distinct diseases: Monkeypox, Chickenpox, Smallpox, Cowpox, and Measles. It also has pictures of healthy skin. The database has more information on pox, measles, and healthy photos that were taken from the Web than previous databases like it [28]. We evaluated seven cutting-edge deep models on digitized skin photos to see how well they could classify diseases. These models were ResNet50, DenseNet121, Inception-V3, SqueezeNet, MnasNet-A1, MobileNet-V2, and ShuffleNet-V2. We did five-fold cross-validation tests on each AI deep model to get a full picture of the results, which is different from earlier research that used smaller datasets [29].

Zhang et al.'s dataset has a big problem with not having enough image classifications, such as not having a "Healthy" class. This might present problems when testing the classifier with healthy tissue pictures, which could mean that a lot of data is thrown away that could have been used for training [30]. The datasets utilized to train the classifiers don't have a pattern of resemblance, such as full-body photos or images of only one body component. To fix the training, a lot of the photographs may need to be thrown out because they are not good enough or because they overlap with other images [31].

Research [32] that investigated how to find skin lesions in dermoscopy pictures used the best feature set selection for diagnosing melanoma in skin cancer. Different researchers effectively tackled the problems of feature extraction dependent on the quantity of the dataset they had.

4. About Infectious Disease

Microorganisms generate infectious illnesses, which may afflict individuals of different ages, genders, and socioeconomic classes. They may spread by intimate contact, contaminated food, bug bites, or droplets from the nose or mouth. Hand cleanliness, vaccinations, and infection control methods are some of the ways to lower the chance of transmission. To make good decisions in healthcare, professionals, patients, and families need to work together, communicate clearly, and keep researching to make patient care better [33].

Animal models of infectious illnesses are less complicated and noisy than human imaging data because of uncontrolled and confusing circumstances. These things may change how the body reacts to an illness and make the model work less well. This may be risky for therapeutic use since patients who don't get treatment are the most at risk. It is important to make sure that AI models do not have fake correlations with response variables and to use explainable AI methods to make accurate predictions [34, 35].

There are several ways that infectious illnesses might spread, such as touching something that is infected or breathing in the air. The way an infectious agent spreads is very important for how quickly it spreads. For example, an agent that can move via the air has a better chance of infecting more individuals. The amount of time the infectious agent may live in the environment is also crucial since it can infect additional individuals [36].

Pathogens produce infectious illnesses, whereas genetics, lifestyle, or the environment are the main causes of non-infectious diseases including cancer, diabetes, and heart disease. People may get infectious illnesses from other people or the environment, but non-infectious diseases cannot be shared [37].

There are many kinds of infectious illnesses, and each one is caused by a distinct kind of bacteria. These are some of the most prevalent types:

- Infections caused by viruses
- Infections caused by bacteria
- Infections caused by fungi
- Infections caused by parasites
- Diseases caused by prions

A study team from the University of Helsinki employed Aiforia to look at kidney biopsy samples from patients with acute hemorrhagic fever with renal syndrome (HFRS) who had the puumalavirus. The AI training method has 2500 iterations and 500 annotations. It found that HFRS patients' kidneys had more monocyte and macrophage markers [38].

Hantaviruses are human diseases that are coming back and may cause serious illness, usually in the lungs or kidneys. They mostly infect endothelial cells, which causes blood vessels to leak and hemorrhagic fever with renal syndrome (HFRS). Researchers looked at PUUV-infected individuals with acute HFRS and discovered that the number of nonclassical monocytes dropped significantly, while the number of classical and intermediate monocytes rose [39]. Patients with HFRS have more monocyte and macrophage markers in their kidneys. Monocyte subsets respond differently to hantavirus exposure that is cell-free or cell-associated.

Orthohantaviruses are zoonotic infections that cause hantavirus pulmonary syndrome and hemorrhagic fever with renal syndrome, both of which are very bad for health. We don't know all about how these illnesses start, but an overactive immune system could play a role. Researchers showed that individuals with acute HFRS and HPS had freer immunoglobulin light chains, which suggests that aberrant antibody responses may be involved [40].

The varicella-zoster virus causes chickenpox, which is an infectious illness that causes an itchy red rash and blisters filled with fluid. Symptoms generally show up two weeks after being exposed and may persist anywhere from ten days to three weeks. Kids are more likely to have chickenpox, but adults may get a worse case and take longer to get well. Getting vaccinated is the greatest method to stay safe against chickenpox [41].

The SARS-CoV-2 virus causes COVID-19, which is an infectious illness that may afflict anybody. People who are older or have other health problems are more likely to have it. To stop the spread, remain at least 1 meter away from other people, wear masks, wash your hands often, get vaccinated, and follow local advice. Small droplets of fluids from an infected person's lips or nose may transmit the virus [42].

There are many other infectious diseases are exist, this chapter, mainly focuses on monkeypox infectious disease analysis using different applications using emerging technologies. The Monkeypox virus, which is prevalent in rodents, monkeys, and other animals, causes the zoonotic illness mpox. People found it in 1958, but they do not know where it came from. The first instance of this disease in a person was reported in the Democratic Republic of the Congo in 1970. Mpox spread over the globe in 2022, largely because people traveled or brought animals from areas where it was common. In 2022, the World Health Organization changed the name of the illness, although it still goes by its old name. There are two types: clade I, which is driving the present spike in cases in Central and Eastern Africa, and clade II, which is less severe and causes more than 99.9% of individuals to survive [43].

Fig 3: sample images of monkeypox

Artificial intelligence and image processing methodologies are used to examine infectious illness patterns, facilitating swifter and more precise diagnoses than conventional approaches. Deep learning techniques, such as convolutional neural networks, identify intricate patterns in complicated pictures, facilitating early identification, illness monitoring, and enhanced treatment planning. Prevalent image processing methodologies including deep learning, transfer learning, picture augmentation, and feature extraction. Studied infectious illnesses include TB, pneumonia, malaria, COVID-19, monkey fox, and Ebola. Nonetheless, significant factors include data integrity, clinical validation, and ethical ramifications. Dependable and extensive datasets with precise annotations are essential for developing resilient AI models, while ethical considerations include data protection and openness in decision-making. Employing AI in infectious disease imaging enables researchers to enhance early identification, illness surveillance, and therapeutic strategizing.

5. Application of Infectious Diseases using AI and Image Processing

AI-based diagnostics in microbiological labs are free and may be conducted on low-cost PCs. AI algorithms can only make predictions about data sets that are identical to the ones used for training. This means that models trained to look at colonies on certain types of media or stains could not work if you use other brands. AI-assisted image analysis from a distance if you have a microscope and a method to send photos via the internet or a mobile phone. AI-based image analysis for diagnosing infectious diseases could find a place in healthcare systems.

PCR is the current way to find Human Monkeypox, however, it doesn't always work since the virus stays in the blood and further information is needed [44]. This approach costs a lot and does not work well in remote locations. A system that uses AI and real-time data might provide almost flawless diagnoses [45]. You can utilize deep neural networks to teach convolutional neural networks how to solve new issues using old hardware [46]. This method is being worked on to find Monkeypox using RBG photos taken with smartphone cameras.

The monkeypox virus is a big worry since it may cause pneumonia, eye difficulties, and infections on the skin. AI has made detection techniques better, but they still are not very accurate. This research suggests using RN-50-ZCA to extract features to enhance the performance of classification. Data normalization and linear transformation lower co-variance, whereas ZCA-whitening finds features that match up with picture lesions. PCA combines features, and MXGBoost sorts monkeypox and non-monkeypox pictures such that predictions are more accurate. The suggested loss function speeds up prediction rates by considering certain characteristics, which lowers overfitting and makes the model more generalizable. It was found that the research had a superior prediction rate than the three previous studies [47].

AI algorithms like CNN and its variants are widely used for detecting mpox, while conventional machine learning algorithms like support vector machine, K nearest neighbor, decision tree, and random forest are also used. Deep learning models are highly effective in distinguishing between mpox and similar diseases and can be used in parallel to PCR tests to prevent false negative results. The most promising drugs for mpox detection include diosmin, flavin adenine dinucleotide, and fludarabine. Explainable artificial intelligence (XAI) is often used for mpox detection, and LIME and gradient-weighted class activation maps (Grad-CAM) can be used to visualize lesions in images [48].

This study [49] looks into Information Expansion, a way to add more information to Deep Convolutional Neural Networks (DCNs) that don't have enough of it. It talks about new ideas including changing arithmetic, adding more variation space, piece channels, combining images, deleting things at random, preparing for conflict, generating ill-disposed networks, brain style moves, and meta-learning. The paper also talks about how GAN-based expansion techniques may be used and how they affect test-time expansion, goal effect, final dataset size, and learning in the educational plan. It talks about present processes, possible new events, and conversations at the meta-level about how to carry them out.

AI computer vision methods have made imaging for infectious diseases much better by automating tasks like segmentation and classification. This is very important for looking at 3D pictures with a wide field of view and high resolution that are generated by medical imaging methods like CT and MR imaging. Research and clinical practice in infectious disease imaging need to go forward so that accurate automated segmentation techniques be developed [50].

CNNs want their interpretations to be more than 99% accurate, but the more pictures they train on, the more accurate they become. To get around this, data augmentation methods like rotation, inversion, displacement, or distortion are used. This approach, on the other hand, takes a lot of computing power since each picture must be changed separately. Using a powerful computer, Smith and Kirby were able to effectively add more data [51]. After a lot of training, testing, and putting into use, AI-based diagnosis is now free. Microbiology labs can do image analysis on computers that are not very powerful. AI algorithms can only make predictions about data sets that are like the training set, hence they need to be retrained. You can do AI-assisted image analysis from a distance if you have a microscope and can send images.

AI programs compare the proteome fingerprints of unknown samples to those in known databases using mass spectra. Traditional software, on the other hand, utilizes set criteria to check for similarities. To make predictions about antimicrobial resistance, machine learning approaches look for trends in the data itself [52]. Weis et al. produced the DRIAMS collection, which has resistance information for more than 70 antimicrobials and 300,000 clinical strains from 803 diseases. We used this dataset to train three machine learning algorithms: logistic regression, deep neural network classifier (MLP), and gradient-boosted decision trees (LightGBM) [53]. AI and ML approaches also look at bacterial DNA sequences together with their antimicrobial susceptibility phenotype. These models can successfully predict how susceptible fresh isolates will be during sequencing [54].

AI can use machine learning and ontology-based prediction frameworks to sort Monkeypox genomes, but we need to make quick progress in monitoring, surveillance, prevention, and therapy. It is important to know how Monkeypox works on a molecular level since it's the second epidemic after Coronavirus. AI has been able to accurately diagnose COVID-19 and find new drugs, but it needs more varied datasets, a legal framework, and ethical issues to be fully useful. To stop outbreaks and beat Monkeypox, we need to work together, follow government rules, and get vaccinated [55].

The goal of this work [56] is to use Explainable Artificial Intelligence (XAI) to create a machine-learning model that can predict monkeypox based on clinical symptoms. Using XAI, the strong model correctly predicts human monkeypox infection and finds important clinical aspects. It also has artifacts that help people make judgments about monkeypox cases early on and manage them, showing how important it is to trust AI-driven decisions in healthcare.

The work [57] combines a numerical dataset of monkeypox symptoms and artificial intelligence to find the illness. They suggest employing artificial neural networks and the ABC method for network training to construct a predictive model. We picked the adaptive model (an ABC) since it converged quickly. We evaluated the approach using clinical data from the BMJ center and compared it to other algorithms. This showed that it may be used to detect monkeypox early.

6. Discussion

AI and image processing are being used to find, diagnose, and forecast monkeypox infections. You may use these methods on digital pictures of skin to find patterns that show the illness and tell it apart from other skin problems. This method helps with early detection, keeping patients apart, and tracking down those who have been in touch with them to stop the illness from spreading. Monkeypox lesions may be used to train deep-learning models like ResNet-18 to find patterns that are typical of the disease [58]. This makes it easy to find suspicious cases quickly. AI can also predict how monkeypox will spread, which lets people prepare ahead and use their resources wisely. AI can also look at big collections of medication and vaccine candidates, which speeds up the process of finding possible treatments.

Mpox, a global virus, is diagnosed using polymerase chain reaction (PCR), but this method is prone to false-negative results and requires trained medical professionals. This review explores machine learning and deep learning techniques for diagnosing mpox, focusing on skin lesion images and deep learning models. Similar diseases like measles, chickenpox, and smallpox are present in the datasets.

Monkeypox is a double-stranded DNA virus that is different from other orthopoxviruses. Transmission happens when big drops fall on someone or when they touch someone directly. Monkeypox spreads less easily than smallpox. But when more people do not get vaccinated, the frequency of secondary transmission occurrences likewise goes up. Most of what we know about human illness and epidemiology comes from descriptive studies done in Africa since 1986 [59, 60].

Using data from social media, hospital records, and blood tests, AI integration in predicting infectious diseases has shown potential. However there are still problems with privacy, data quality, and model variability, and since infectious illnesses change so quickly, deployment must be done carefully.

7. Conclusion

This study looks at how AI, especially machine learning and deep learning, may be used to find and forecast illnesses that can be spread. It shows how important it is to have different sorts of data to speed up the growth of ML. AI's ability to analyze images may help doctors find diseases earlier, diagnose them more accurately, and treat them more effectively. This might stop the spread of diseases and stop future epidemics and pandemics by finding early indicators of sickness.

8. Future Enhancement

In the future, machine learning techniques like deep learning and hybrid models might be utilized to find monkeypox disease. Using AI and image processing together and in real-time might make predictions better. Future studies should investigate other metaheuristic optimization algorithms, ensemble methods, and making skin lesion identification for monkeypox detection during pandemics easier to understand and explain.

References

1. https://microbenotes.com/infectious-diseases/.
2. Rimoin AW, Mulembakani PM, Johnston SC, Lloyd Smith JO, Kisalu NK, Kinkela TL, Blumberg S, Thomassen HA, Pike BL, Fair JN, Wolfe ND, Shongo RL, Graham BS, Formenty P, Okitolonda E, Hensley LE, Meyer H, Wright LL, Muyembe JJ. Major increase in human monkeypox incidence 30 years after smallpox vaccination campaigns cease in the Democratic Republic of Congo. Proc Natl Acad Sci U S A. 2010 Sep 14;107(37):16262-7.
3. Medical Reports & Case Studies," https://www.iomcworld.org/medical-journals/diseases-online-journals-55099.html, 2023.
4. N. K. Kumar and K. T. Sikamani, "Prediction of chronic and infectious diseases using machine learning classifiers-a systematic approach," Int J Intell Eng Syst, vol. 13, no. 4, pp. 11–20, 2020.
5. M. Javaid, A. Haleem, R. P. Singh, and R. Suman, "Artificial Intelligence Applications for Industry 4.0: A Literature-Based Study," J. Ind. Integr. Manag., vol. 07, no. 01, pp. 83–111, 2022, doi: 10.1142/S2424862221300040.
6. Y. L. Khaleel, H. M. Abdulfattah, and H. Alnabulsi, "Adversarial Attacks in Machine Learning: Key Insights and Defense Approaches," Appl. Data Sci. Anal., vol. 2024, pp. 121–147, 2024, doi: 10.58496/ADSA/2024/011.
7. A. S. Albahri, Y. L. Khaleel, and M. A. Habeeb, "The Considerations of Trustworthy AI Components in Generative AI; A Letter to Editor," Appl. Data Sci. Anal., vol. 2023, pp. 108–109, 2023, doi: 10.58496/adsa/2023/009.
8. Garcia E, Kundu I, Ali A, Soles R, The American Society for Clinical Pathology's 20162017 Vacancy Survey of Medical Laboratories in the United States, Am J Clin Pathol 149(5) (2018) 387–400.
9. Unnikrishnan M, Gontu HL, Khwairakpam BS, Sagar P (2022) Detection of covid from chest X-rays using gan. EPRA International Journal of Research and Development (IJRD) 7:166–175, http://www.eprajournals.net/index.php/IJRD/article/view/453.

10. Sitaula C, Shahi TB, Aryal S, Marzbanrad F (2021b) Fusion of multi-scale bag of deep visual words features of chest x-ray images to detect COVID-19 infection. Scientific reports 11(1):1–12.
11. Yadav N, Alfayeed SM, Khamparia A, Pandey B, Thanh DN, Pande S (2022) Hsv model-based segmentation driven facial acne detection using deep learning. Expert Systems 39(3): e12760.
12. https://www.mayoclinic.org/diseases-conditions/infectious-diseases/symptoms-causes/syc-20351173.
13. https://www.bcm.edu/departments/molecular-virology-and-micro biology/emerging-infections-and-biodefense/introduction-to-infectious-diseases#:~:text=Infectious%20diseases%20have%20 plagued%20humans,are%20but%20a%20few%20examples.
14. https://www.news-medical.net/health/History-of-Infectious-Diseases.aspx.
15. https://www.gov.uk/guidance/monkeypox
16. https://www.news-medical.net/news/20220921/Virology-of-the-human-monkeypox-virus.aspx
17. WangZ.; ZiouD.; ArmenakisC.; LiD.; LiQ.AComparativeAnalysisof ImageFusionMethods. IEEE Trans. Geosci. RemoteSens. 2005, 43,1391–1402.https://doi.org/10.1109/TGRS.2005.846874.
18. Sharma, A.; Priyanka; Fahrni, M.L.; Choudhary, O.P. Monkeypox outbreak: New zoonotic alert after the COVID-19 pandemic. *Int. J. Surg.* **2022**, *104*, 106812.
19. Priyadarshini, I., Mohanty, P., Kumar, R., & Taniar, D. (2023). Monkeypox Outbreak Analysis: An Extensive Study Using Machine Learning Models and Time Series Analysis. *Computers*, *12*(2), 36. https://doi.org/10.3390/computers12020036.
20. Abdelhamid, A.A.; El-Kenawy, E.-S.M.; Khodadadi, N.; Mirjalili, S.; Khafaga, D.S.; Alharbi, A.H.; Ibrahim, A.; Eid, M.M.; Saber, M. Classification of Monkeypox Images Based on Transfer Learning and the Al-Biruni Earth Radius Optimization Algorithm. *Mathematics* **2022**, *10*, 3614.]
21. Dwivedi, M.; Tiwari, R.G.; Ujjwal, N. Deep Learning Methods for Early Detection of Monkeypox Skin Lesion. In Proceedings of the 8th International Conference on Signal Processing and Communication (ICSC), Noida, India, 1–3 December 2022
22. Singh, U.; Songare, L.S. Analysis and Detection of Monkeypox using the GoogLeNet Model. In Proceedings of the 2022 International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, 13–15 December 2022.

23. Altun, M.; Gürüler, H.; Özkaraca, O.; Khan, F.; Khan, J.; Lee, Y. Monkeypox Detection Using CNN with Transfer Learning. *Sensors* **2023**, *23*, 1783.
24. Saleh, A.I.; Rabie, A.H. Human monkeypox diagnosis (HMD) strategy based on data mining and artificial intelligence techniques. *Comput. Biol. Med.* **2023**, *152*, 106383.
25. Alakuş, Talha. (2023). Prediction of Monkeypox on the Skin Lesion with the Siamese Deep Learning Model. Balkan Journal of Electrical and Computer Engineering. 11. 225-231. 10.17694/bajece.1255798.
26. S.L. Munoz, L.E. Escobar, M.J. Civit, P.F. Luna, A. Civit, et al. "Monkeypox diagnostic-aid system with skin images using convolutional neural networks." SSRN, 2022.
27. M. M. Ahsan, M. R. Uddin, and S. A. Luna, "Monkeypox image data collection," arXiv preprint arXiv:2206.01774, 2022.
28. S. N. Ali, M. Ahmed, J. Paul, T. Jahan, S. Sani, N. Noor, T. Hasan, et al., "Monkeypox skin lesion detection using deep learning models: A feasibility study," arXiv preprint arXiv:2207.03342, 2022.
29. Hussain, Mohammad Arafat & Islam, Towhidul & Chowdhury, Forhad & Islam, B. (2022). Can Artificial Intelligence Detect Monkeypox from Digital Skin Images? 10.1101/2022.08.08.503193.
30. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770–778).
31. Thomas, S. M. et al. (2021). Interpretable deep learning systems for multiclass segmentation and classification of non-melanoma skin cancer. Medical Image Analysis, 68, 101915.
32. Javed, R., Rahim, M.S.M., Saba, T. and Rehman, A., 2020. A comparative study of feature selection for skin lesion detection from dermoscopic images. Network Modeling Analysis in Health Informatics and Bioinformatics, 9, pp.1-13.
33. Muhammad Ahsan, Robertas Damaševičius, Artificial intelligence-powered image analysis: A paradigm shift in infectious disease detection, Artificial Intelligence in Medicine, Volume 159,2025,103025, ISSN 0933-3657, Doi: 10.1016/j.artmed.2024.103025.
34. Oakden-Rayner L. Exploring large-scale public medical image datasets. Acad Radiol 2020; 27:106–12.
35. Winkler JK, Fink C, Toberer F, et al. Association between surgical skin markings in dermoscopic images and diagnostic performance of a deep learning convolutional neural network for melanoma recognition. JAMA Dermatol 2019; 155:1135–41

36. https://www.bcm.edu/departments/molecular-virology-and-microbiology/emerging-infections-and-biodefense/introduction-to-infectious-diseases.
37. https://www.sparshhospital.com/blog/infectious-disease/.
38. https://www.aiforia.com/resource-library/infectious-diseases-and-ai.
39. Vangeti S, Strandin T, Liu S, Tauriainen J, Räisänen-Sokolowski A, et al. (2021) Correction: Monocyte subset redistribution from blood to kidneys in patients with Puumala virus-caused hemorrhagic fever with renal syndrome. PLOS Pathogens 17(8): e1009876. https://doi.org/10.1371/journal.ppat.1009876.
40. Hepojoki J, Cabrera LE, Hepojoki S, Bellomo C, Kareinen L, Andersson LC, et al. (2021) Hantavirus infection-induced B cell activation elevates free light chain levels in circulation. PLoS Pathog 17(8): e1009843, Doi: 10.1371/journal.ppat.1009843.
41. https://www.healthdirect.gov.au/chickenpox#what-is.
42. https://www.who.int/health-topics/coronavirus#tab=tab_1.
43. https://www.cdc.gov/mpox/about/index.html.
44. A.P. Mondolfi, S. Guerra, M. Muñoz, N. Luna, M.M. Hernandez, L.H. Pat ino, J. Reidy, R. Banu, P. Shrestha, B. Liggayu, A. Umeaku, Evaluation and validation of an RT-PCR assay for specific detection of Monkeypox virus (MPXV), J Med Virol (2022 Oct 21), 10.1002/jmv.28247.
45. K. Chadaga, S. Prabhu, N. Sampathila, S. Nireshwalya, S.S. Katta, R.S . Tan, U.R. Acharya. Application of artificial intelligence techniques for monkeypox: a systematic review, Diagnostics, 13 (5) (2023 Feb 21), p. 824, 10.3390/diagnostics13050824.
46. B. Norgeot, B.S. Glicksberg, A.J. Butte, A call for deep-learning healthcare, Nat Med, 25 (1) (2019 Jan), pp. 14-15, 10.1038/s41591-018-0320-3.
47. Sonam Yadav, Tabish Qidwai, Machine learning-based monkeypox virus image prognosis with feature selection and advanced statistical loss function, Medicine in Microecology, Volume 19, 2024, 100098, ISSN 2590-0978, Doi.org/10.1016/j.medmic.2024.100098.
48. Jahmunah V., Ng E.Y., Tan R.S., Oh S.L., Acharya U.R. Explainable detection of myocardial infarction using deep learning models with Grad-CAM technique on ECG signals. Comput. Biol. Med. 2022; 146:105550. Doi: 10.1016/j.compbiomed.2022.105550.
49. V.Kakulapati et al., Monkeypox Detection using Transfer learning, ResNet50, Alex Net, ResNet18 & Custom CNN Model "Asian Journal of Advanced Research and Reports, Volume 17, Issue 5, Page 7-13, 2023; Article no. AJARR.98548 ISSN: 2582-3248.

50. Chu WT, Reza SMS, Anibal JT, Landa A, Crozier I, Bağci U, Wood BJ, Solomon J. Artificial Intelligence, and Infectious Disease Imaging. J Infect Dis. 2023 Oct 3;228(Suppl 4): S322-S336. Doi: 10.1093/infdis/jiad158.
51. Smith KP, Kirby JE. Image analysis and artificial intelligence in infectious disease diagnostics. Clin Microbiol Infect. 2020 Oct;26(10):1318-1323. doi: 10.1016/j.cmi.2020.03.012.
52. Mather, C. A. et al. Rapid detection of vancomycin-intermediate staphylococcus aureus by matrix-assisted laser desorption ionization-time of flight mass spectrometry. *J. Clin. Microbiol.* **54**, 883–890 (2016).
53. Weis, C. et al. Direct antimicrobial resistance prediction from clinical MALDI-TOF mass spectra using machine learning. *Nat. Med.* **28**, 164–174 (2022).
54. Ali, T. et al. Artificial intelligence for antimicrobial resistance prediction: challenges and opportunities towards practical implementation. *Antibiotics* **12**, 523 (2023).
55. Patel M, Surti M, Adnan M. Artificial intelligence (AI) in Monkeypox infection prevention. J Biomol Struct Dyn. 2023 Oct-Nov;41(17):8629-8633. doi: 10.1080/07391102.2022.2134214.
56. Setegn, G.M., Dejene, B.E. Explainable AI for Symptom-Based Detection of Monkeypox: a machine learning approach. *BMC Infect Dis* **25**, 419 (2025). https://doi.org/10.1186/s12879-025-10738-4.
57. Patel A, Bilinska J, Tam JCH, Da Silva Fontoura D, Mason CY, Daunt A, Snell LB, Murphy J, Potter J, Tuudah C, Sundramoorthi R, Abeywickrema M, Pley C, Naidu V, Nebbia G, Aarons E, Botgros A, Douthwaite ST, Pannerden VNT (2022) Clinical features and novel presentations of human monkeypox in a central London center during the 2022 outbreak: descriptive case series. The BMJ. https://doi.org/10.1136/bmj-2022-072410.
58. Chadaga K, Prabhu S, Sampathila N, Nireshwalya S, Katta SS, Tan RS, Acharya UR. Application of Artificial Intelligence Techniques for Monkeypox: A Systematic Review. Diagnostics (Basel). 2023 Feb 21;13(5):824. doi: 10.3390/diagnostics13050824.
59. Breman J. Monkeypox: an emerging infection for humans? In: Scheld W, Craig W, Hughes J, eds. Emerging infections 4. Washington, DC: ASM Press, 2000:45–67.
60. Jezek Z, Marennikova S, Mutumbo M, Nakano J, Paluku K, Szczen iowski M. Human monkeypox: a study of 2,510 contacts of 214 patients. J Infect Dis 1986; 154:551–5.

CHAPTER 2

IMPETUS FOR MACHINE LEARNING IN INFECTIOUS DISEASE DIAGNOSIS

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Abstract: The rise of machine learning has significantly transformed the way infectious diseases are diagnosed, offering new ways to analyze and interpret complex medical data for better outcomes. This chapter explores the role and potential of machine learning in the future of infectious disease diagnostics, accentuating its ability to process enormous amounts of data and leverage artificial intelligence to refine decision-making beyond human capabilities. Infectious diseases can be erratic and progress quickly, making timely and accurate diagnosis critical to prevent severe repercussions. Machine learning distinguishes itself here, as it uses advanced algorithms that can learn from data, automate decision-making, and improve diagnostic accuracy. The chapter discusses key machine learning techniques such as supervised learning for disease classification, anomaly detection, and deep learning applications in image and genomic analysis. Practical case studies illustrate how machine learning has been successfully applied in diagnosing diseases like tuberculosis, sepsis, and COVID-19—showing improvements in sensitivity, specificity, and diagnosis speed. The prospect of machine learning extends beyond standalone diagnostics. By integrating with electronic health records and wearable devices, machine learning can provide a more comprehensive view of patient's health while enabling real-time alert systems. However, several challenges must be addressed for machine learning to be widely adopted in clinical settings. Issues such as data privacy, algorithm transparency, and patient confidentiality remain key concerns. The chapter highlights promising solutions like federated learning and explainable AI,

which can help mitigate these risks. Finally, machine learning is set to transform infectious disease diagnostics by enhancing efficiency, accuracy, and accessibility in healthcare. By replacing traditional methods with intelligent, data-driven solutions, it holds the power to redefine global healthcare and bolster efforts to combat infectious diseases.

Keywords: Machine Learning, Infectious Disease Diagnostics, Medical Data Analysis.

1. Introduction

Infectious diseases remain a crucial global health challenge, affecting millions of people each year and contributing to high rates of illness and death. These diseases, caused by bacteria, viruses, fungi, and parasites, spread rapidly and pose serious threats to public health. Despite significant advancements in medical research and technology, diagnosing infectious diseases accurately and promptly is still a challenge. Traditional diagnostic methods, such as culture tests, serology, and molecular techniques, often have drawbacks, including slow processing times, inconsistent accuracy, and the need for specialized laboratories and trained professionals. These limitations can delay treatment and hinder efforts to control outbreaks, making early and precise diagnosis more crucial than ever.

Machine learning (ML), a branch of artificial intelligence (AI), is reshaping the way infectious diseases are diagnosed. By analyzing large amounts of data, machine learning algorithms can identify patterns that might not be immediately apparent to human experts. This capability allows for improved diagnostic accuracy and faster decision-making. Machine learning is already being applied in areas such as medical imaging, genomic sequencing, and electronic health records, enabling real-time analysis and early detection of infections. Moreover, machine learning-powered diagnostic tools can automate tasks that traditionally require significant manual effort, making healthcare more efficient and accessible.

Timely and accurate diagnosis is essential for preventing the spread of infectious diseases, improving treatment strategies, and ensuring better patient outcomes. Delayed or incorrect diagnoses can lead to severe complications, increased medical costs, and difficulties in controlling outbreaks. Integrating machine learning into diagnostic processes helps healthcare providers detect diseases earlier, make informed treatment decisions, and enhance overall patient care. By addressing gaps in current diagnostic methods, machine learning has the potential to revolutionize healthcare, making it more precise, efficient, and responsive to new and emerging health threats. As technology advances, ML is expected to play an even greater role in combating infectious diseases, shaping the future of medicine and public health.

Beyond diagnostics, machine learning is also being used to track disease outbreaks and predict potential health crises. By analyzing real-time data from multiple sources—such as social media trends, travel patterns, and environmental factors— machine learning models can detect early warning signs of outbreaks. This predictive capability allows health organizations to take preventive measures, allocate resources more efficiently, and control disease spread before it becomes widespread. The ability to anticipate outbreaks with greater accuracy can significantly improve global health preparedness and response efforts.

Despite its potential, implementing machine learning in healthcare comes with challenges. Concerns about data privacy, biases in algorithms, and the need for transparency in AI-driven models must be addressed to ensure ethical and effective use. Additionally, integrating machine learning into medical workflows requires close collaboration between healthcare professionals, data scientists, and policymakers. As research continues and technology evolves, tackling these challenges will be key to fully harnessing the benefits of machine learning in infectious disease management and advancing AI-driven diagnostics responsibly and sustainably.

The growing use of machine learning in diagnosing infectious diseases is not just changing how doctors detect illnesses—it's also opening new doors in global health research. Breakthroughs in fields like language processing, deep learning, and collaborative AI systems are making medical tools smarter, more accurate, and more accessible. Scientists, healthcare professionals, and tech innovators are working together to create AI models that can spot new disease threats, track outbreaks, and improve public health responses. As this technology advances, its impact will go beyond diagnosis, helping to develop better treatments, refine vaccine strategies, and monitor drug resistance in real time. With these innovations, we are stepping into a future where medicine is not only faster and more efficient but also better equipped to tackle emerging health challenges.

As machine learning advances, it's joining forces with other cutting-edge technologies like the Internet of Things (IoT) and blockchain to improve how we manage infectious diseases. Smart biosensors and wearable devices can track vital signs around the clock, sending real-time data for AI analysis to detect infections before symptoms even appear. At the same time, blockchain can help keep patient records secure and ensure seamless data sharing across healthcare systems without risking privacy. By bringing these technologies together, we're building a smarter, more connected healthcare system—one that gives doctors real-time insights, leads to better patient outcomes, and reshapes the way we diagnose and prevent infectious diseases.

2. Importance of Machine Learning in Infectious Disease Diagnostics

Machine learning is making infectious disease diagnosis faster, more accurate, and more accessible. Traditional diagnostic techniques—such as culture-based tests, polymerase chain reaction (PCR), and serological assays—often require specialized labs and skilled personnel, leading to treatment delays. ML-powered diagnostic tools, on the other hand, can quickly analyze large datasets, providing real-time insights that enhance decision-making and improve patient care.

One of the biggest advantages of ML is its ability to handle diverse types of data, including medical imaging, genomic sequencing, electronic health records, and data from wearable devices. For example, deep learning models can analyze X-ray images to detect lung infections with high accuracy, while ML algorithms can classify pathogens based on genetic sequencing data. These capabilities reduce diagnostic errors and enable early detection, preventing disease progression and transmission.

ML-driven diagnostics also improve healthcare accessibility, particularly in remote or resource-limited settings. AI-powered smartphone applications and portable biosensors allow for early and remote disease detection, reducing reliance on centralized laboratories, and making diagnostics more available to underserved communities.

Additionally, ML aids in outbreak prediction and management. By analyzing epidemiological data, social media trends, and global travel patterns, ML models can identify potential disease outbreaks before they escalate. This predictive ability is essential for controlling emerging infectious diseases like COVID-19, tuberculosis, and antimicrobial-resistant infections.