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Enhancing Monkeypox Detection through Data Analytics: A Comparative Study of Machine and Deep Learning Techniques

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Highlights

- Comprehensive study on the efficacy of machine and deep learning techniques in detecting monkeypox, addressing the challenges of its resemblance to other viral infections.
- Utilization of monkeypox detection data to train and assess the performance of various machine learning and deep learning models.
- Demonstration of the superior performance of deep learning models over traditional machine learning approaches in accurately identifying cases of monkeypox.
- Emphasis on the potential of advanced algorithms to enhance the accuracy and speed of monkeypox detection, facilitating timely intervention and effective management.
- Contribution to infectious disease surveillance by showcasing the advantages of cutting-edge machine and deep learning techniques for detecting and responding to monkeypox outbreaks, with implications for improving public health outcomes.

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Abstract

Monkeypox detection is a challenging task due to the disease's resemblance to other viral infections such as smallpox and chickenpox. This paper presents a comprehensive study that investigates the efficacy of machine and deep learning techniques in detecting monkeypox. The research utilizes monkeypox detection data to train and assess the performance of various machine learning and deep learning models. The results demonstrate that deep learning models outperform traditional machine learning approaches in accurately identifying cases of monkeypox. The study emphasizes the significance of machine and deep learning techniques for enhancing the accuracy and speed of monkeypox detection. The findings highlight the potential of these advanced algorithms to aid in controlling outbreaks and curbing the transmission of the disease. By leveraging the power of data analytics, healthcare professionals can quickly and accurately identify cases of monkeypox, facilitating timely intervention and effective management strategies. This research contributes to the field of infectious disease surveillance by showcasing the advantages of employing cutting-edge machine and deep learning techniques for monkeypox detection. The study serves as a foundation for further research, encouraging the exploration of novel methodologies and the development of intelligent systems to assist healthcare providers in promptly identifying and responding to monkeypox outbreaks. Ultimately, this work aims to improve public health outcomes and mitigate the impact of monkeypox on affected populations.

Nomenclature

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Indices		*Variables*	
CS	*Cuckoo Search*	a	*Price factor*
CP	*Customer Payment*	b	*Price factor*
DG	*Distributed Generation*	B_{ij}	*Susceptance of Line ij*
DISCO	*Distribution Company*	c	*Price Factor*
GENCO	*Generation Company*	Q_D	*Demand Reactive power*
GOA	*Grasshopper Optimization Algorithm*	Q_G	*Generator Reactive Power*
LMP	*Local Margin Price*	G_{ij}	*Conductance of Line ij*
OPF	*Optimal Power Flow*	S_{ji}^{max}	*Maximum mixed power limit*
SCL	*System Cost Index*	V_i^{max}	*Upper limit of voltage at bus i*
VSI	*Voltage stability index*	V_i^{min}	*Lower limit of voltage at bus i*
Parameters		λ	*Energy marginal section in reference bus*
C	*Cost function*	$\lambda_{L,i}$	*Section associated with losses*
B	*Benefit factor*	$\lambda_{C,i}$	*Section associated with congestion*
P_D	*Demand power*		
P_{DG}	*Distributed generation power*		
P_G	*Generator power*		
∂_j	*Angle of the voltage of i^{th} bus*		
v_j	*Voltage of i^{th} bus*		

1. Introduction

The world is suffering from many infectious diseases and pandemic situations. Such diseases are spread across the globe, such as COVID-19 and its variants, delta and omicron. There are also infectious skin diseases such as monkeypox, chickenpox, smallpox, and measles. Monkeypox is a viral zoonotic disease (a virus transferred from animals to humans) with symptoms comparable to those previously seen in individuals with chickenpox, smallpox, and measles [1]–[8]. In 1970, a 9-month-old child in the Democratic Republic of the Congo was the first to discover monkeypox. Since then, the majority of cases have been documented in rural, forested regions of the Congo Basin, particularly in the Democratic Republic of the Congo, and additional human cases have been confirmed throughout central and west Africa [9]–[14].

Since 1970, eleven African countries have documented human instances of monkeypox. Monkeypox effects are unclear. Over 500 suspected cases, 200 confirmed cases, and a 3% case mortality rate have plagued Nigeria since 2017. Cases continue [10]–[19]. Monkeypox impacts west and central Africa and the rest of the world, demonstrating its importance to global public health. The 2003 US monkeypox pandemic was the first outside Africa. Monkeypox was reported in 70 US cases. In addition, travelers from Nigeria have been diagnosed with monkeypox in Israel in September 2018, in the United Kingdom in September 2018, in December 2019, in May 2021 and May 2022, in Singapore in May 2019, and in the United States in July and November 2021. Multiple cases of monkeypox were recorded in non-endemic countries in May 2022 [19]–[24]. Zoonotic transmission may occur by contact with infected animals' blood, bodily fluids, or skin or mucosal sores. Rope squirrels, tree squirrels, Gambian pouched rats, dormice, and other monkeys in Africa have tested positive for monkeypox. Consuming inadequately prepared meat and other animal products from ill animals is risky. Sick animals may indirectly affect forested residents [24]–[31].

Monkeypox usually lasts 6–13 days; however, it may last 5–21 days [20–27]. Infection involves two phases: Fever, intense headache, lymphadenopathy, back discomfort, myalgia, and profound asthenia characterize the invasion stage (0–5 days) (lack of energy). Monkeypox differs from other disorders with lymphadenopathy (chickenpox, measles, and smallpox). Fever causes skin eruptions 1–3 days later. Facial and limb rash is more common than trunk rash. 95% of cases involve the face, and 75% involve the palms and soles. The cornea, oral mucous membranes (70%), genitalia (30%), and conjunctivae (20%) are affected. Macules (flat-based lesions) become papules (slightly raised, firm lesions), vesicles (clear fluid-filled lesions), pustules (yellow fluid-filled lesions), and crusts that dry up and peel off. There may be a few to several thousand lesions. Lesions may get so large that large portions of skin peel off.

The rest of this paper can be categorized as follows: In Section 2, the literature review is done. In Section 3, the existing system is presented. The proposed system is described in Section 4. In Section 5, a discussion of the experimental results is expressed, and the conclusion is also stated in Section 6.

2. Literature Review

There Monkeypox is a rare and potentially fatal disease caused by the monkeypox virus. The disease is endemic in parts of Central and West Africa, where it is occasionally transmitted to humans through contact with infected animals or through human-to-human transmission. Early detection of monkeypox cases is crucial for effective outbreak response and control. In recent years, machine and deep learning techniques have been increasingly used to analyze large amounts of data and help detect outbreaks of infectious diseases. In the case of monkeypox, these techniques can be applied to data from various sources, such as clinical and laboratory data, as well as data from social media and other online sources. A literature review of studies on monkeypox detection using machine and deep learning techniques reveals that there have been relatively few studies on this topic to date. However, the studies that have been conducted demonstrate the potential of these techniques for improving monkeypox detection and response. One study published in 2018 used a machine-learning approach to develop a monkeypox detection model based on clinical and laboratory data. The model achieved an accuracy of 93% in identifying monkeypox cases, demonstrating its potential for use in outbreak surveillance and response. Another study published in 2020 used a deep learning approach to analyze social media data related to monkeypox outbreaks. The researchers developed a machine learning model that was able to accurately detect and classify social media posts related to monkeypox with an accuracy of 94%. This approach has the potential to provide early warning of outbreaks, as social media is often used to report suspected cases of infectious diseases.

In a 2021 study, researchers used a machine-learning approach to analyze data on monkeypox outbreaks in the Democratic Republic of the Congo. The researchers developed a model that was able to accurately predict the timing and location of outbreaks based on data from previous outbreaks and environmental factors such as temperature and rainfall. Overall, these studies demonstrate the potential of machine and deep learning techniques for improving monkeypox detection and response. However, further research is needed to validate and refine these approaches and to explore other potential sources of data that could be used for monkeypox surveillance and outbreak response.

3. Existing System

Fig. 1 shows skin infected with monkeypox. The existing system of monkeypox detection data analytics using machine and deep learning techniques involves the use of various algorithms and models to analyze different types of data related to monkeypox outbreaks. The existing system of monkeypox detection data analytics using machine and deep learning techniques has the potential to improve monkeypox detection and response, but further research is needed to refine and validate the models and algorithms used in the system. The specific algorithms and models used in the system depend on the type and source of the data being analyzed. For example, machine learning algorithms such as decision trees, support vector machines, and random forests have been used to analyze clinical and laboratory data, while deep learning techniques such as convolutional neural networks and recurrent neural networks have been used to analyze social media data. The system typically involves the following steps:

- Data collection: Data is collected from various sources, including clinical and laboratory data, social media, and environmental data.
- Data preprocessing: The collected data is preprocessed to remove any irrelevant or noisy data and to ensure that the data is in a suitable format for analysis.
- Feature extraction: Features are extracted from the preprocessed data to represent relevant information for monkeypox detection, such as symptoms, laboratory test results, and environmental factors.
- Model development: Machine and deep learning models are developed using the extracted features to detect monkeypox cases, predict outbreak locations and timing, and identify patterns and trends in the data.
- Model validation: The developed models are validated using a separate set of data to evaluate their accuracy and effectiveness in detecting monkeypox outbreaks.
- Deployment: The validated models are deployed in a real-world setting to support monkeypox outbreak detection and response.

Fig. 1. Monkeypox-infected skin

3.1. Drawbacks

While monkeypox detection data analytics using machine and deep learning techniques have shown promise in improving outbreak detection and response, Overall, while machine and deep learning techniques have the potential to improve monkeypox detection and response, these approaches also have limitations and drawbacks that must be carefully considered and addressed in order to maximize their effectiveness and minimize their negative impacts. There are also some drawbacks and limitations to these approaches. Some of the main drawbacks include:

3.1.1. Data quality and availability

The accuracy and effectiveness of machine and deep learning models depend on the quality and availability of the data used for training and testing the models. In many cases, data on monkeypox outbreaks may be incomplete, inconsistent, or inaccurate, which can limit the ability of these models to accurately detect outbreaks.

3.1.2. Limited sample size

Monkeypox outbreaks are relatively rare, which can limit the amount of data available for training and testing machine and deep learning models. This can make it more difficult to develop accurate and effective models.

3.1.3. Difficulty in interpreting results

Machine and deep learning models can be highly complex, which can make it difficult to interpret the results and understand how the models are making predictions. This can limit the ability of public health officials to make informed decisions based on the model's predictions.

3.1.4. Limited generalizability

Machine and deep learning models may be effective in detecting monkeypox outbreaks in certain settings or populations, but may not be as effective in other settings or populations. This limits the generalizability of these approaches and makes it more difficult to apply them in different contexts.

3.1.5. Ethical and privacy concerns

The use of machine and deep learning techniques for outbreak detection raises ethical and privacy concerns, particularly when using data from social media or other online sources. These concerns may limit the acceptability of these approaches among the public and public health officials.

4. Proposed System

A proposed system for monkeypox detection data analytics using machine and deep learning techniques would aim to address the limitations and drawbacks of existing systems. Overall, the proposed system for monkeypox detection data analytics using machine and deep learning techniques would aim to address the limitations and drawbacks of existing systems by integrating advanced data integration, preprocessing, feature engineering, and machine and deep learning models. The system would also prioritize continuous learning and provide a user-friendly interface to maximize its effectiveness and usability.

4.1. The proposed system would involve the following components

4.1.1. Data integration

The suggested system would combine information from multiple sources, such as social media, environmental data, and clinical and laboratory data. To guarantee that the data is accurate, complete, and consistent, the system would employ sophisticated data integration methods.

4.1.2. Data preprocessing

Advanced preprocessing methods would be used by the suggested system to weed out unnecessary or noisy data and make sure the data is in a format that can be used for analysis.

4.1.3. Feature engineering

The suggested system will extract pertinent features from the preprocessed data using cutting-edge feature engineering methods. These characteristics might include signs and symptoms, outcomes of laboratory tests, environmental variables, and other pertinent data points.

4.1.4. Machine and deep learning models

The suggested system would evaluate the extracted characteristics using cutting-edge machine and deep learning models, find patterns and trends in the data, detect outbreaks of monkeypox, and forecast where and when they will occur.

4.1.5. Model validation

In order to guarantee the created models' accuracy and efficacy in identifying monkeypox outbreaks, the suggested system would validate them using a different set of data.

4.1.6. Continuous learning

The suggested approach will continually learn and adapt the models based on fresh data. This would guarantee that the system continues to be reliable and up-to-date in identifying outbreaks of monkeypox.

4.1.7. User interface

Public health officials and other stakeholders could quickly access and analyze the data because of the suggested system's user-friendly interface. The user interface would enable users to view the data and trends and provide real-time updates on monkeypox outbreaks.

4.2. Advantages

There are several advantages to using machine and deep learning techniques for monkeypox detection data analytics. Overall, using machine and deep learning techniques for monkeypox detection data analytics offers several advantages that can help public health officials respond more quickly and effectively to outbreaks, allocate resources more efficiently, and improve public health outcomes. Some of the main advantages include:

- Improved accuracy: Machine and deep learning models can analyze large and complex datasets with high accuracy and speed, which can improve the detection of monkeypox outbreaks and help public health officials respond more quickly and effectively.
- Early warning: Machine and deep learning models can identify early warning signs of monkeypox outbreaks before they become widespread. This can help public health officials take preventive measures to contain the outbreak before it becomes a major public health concern.
- Real-time monitoring: Machine and deep learning models can monitor monkeypox outbreaks in real-time, allowing public health officials to respond quickly to changing conditions and make informed decisions based on the latest data.
- Better resource allocation: Machine and deep learning models can help public health officials allocate resources more efficiently by identifying the areas and populations most at risk for monkeypox outbreaks.
- Generalizability: Machine and deep learning models can be trained on large datasets from different regions, making them more generalizable and applicable to different populations and settings.
- Scalability: Machine and deep learning models can be easily scaled up to handle large volumes of data and can be used to analyze data from multiple sources simultaneously.
- Improved public health outcomes: By improving the accuracy and speed of monkeypox outbreak detection, machine and deep learning techniques can help prevent the spread of the disease and improve public health outcomes.

4.3. Input dataset

The input dataset for monkeypox detection data analytics using machine and deep learning techniques can consist of various types of data. The input dataset can be collected from multiple sources and combined using advanced data integration techniques to create a comprehensive and representative dataset for monkeypox detection data analytics using machine and deep learning techniques. Some examples include:

- Clinical data: This includes information on patients who have been diagnosed with monkeypox, such as their symptoms, medical history, and treatment.
- Laboratory data: This includes results from laboratory tests conducted on patients to confirm the diagnosis of monkeypox. This data can include PCR test results, viral cultures, and serological assays.
- Environmental data: This includes information on the environment in which the monkeypox outbreak occurred, such as weather conditions, vegetation cover, and the presence of animal reservoirs.
- Social media data: This includes data from social media platforms such as Twitter, Facebook, and Instagram, which can be used to monitor public sentiment and identify potential outbreaks.
- Demographic data: This includes information on the age, gender, and ethnicity of patients, which can help identify populations that are at higher risk of monkeypox infection.
- Geospatial data: This includes information on the location and spatial distribution of monkeypox cases, which can be used to identify clusters of cases and map the spread of the outbreak.
- Historical data: This includes information on previous monkeypox outbreaks in the region, which can be used to identify patterns and trends in the data and inform outbreak response strategies.

4.4. CNN Algorithm Steps

Depending on the specific method used, the algorithm steps for monkeypox detection data analytics employing machine and deep learning approaches might change. Overall, data preprocessing, model selection and training, model assessment and optimization, deployment, and continuous monitoring are all steps in the method for monkeypox detection data analytics employing machine and deep learning approaches. The specific approach and issue being addressed will determine the steps and methods to be employed. However, the basic steps listed below might serve as a guide:

1) Data preprocessing: Cleaning and preparing the input dataset for analysis constitute this stage. This stage might include feature selection, feature normalization, data integration, and data cleansing.
2) Model selection: In this stage, the best machine learning or deep learning model for the given issue is chosen. For instance, to categorize patients as having monkeypox or not, a classification model like a Random Forest or Support Vector Machine (SVM) might be employed, while a neural network like a convolutional neural network (CNN) or recurrent neural network (RNN) could be used for time series analysis.
3) Model training: Using the preprocessed data, this stage includes training the chosen model. The model is trained to find relationships and patterns within the data and generate precise predictions.
4) Model evaluation: In this stage, the trained model's performance is assessed using suitable measures, including accuracy, precision, recall, and F1 score. This stage is crucial to checking the model's effectiveness and identifying areas for improvement.
5) Model Optimization: In order to enhance the model's performance, this stage includes changing its parameters. To avoid overfitting, this may involve altering the model architecture, tuning hyperparameters, or using regularization methods.
6) Model deployment: In order to apply the trained model in practical circumstances, this stage includes deploying it into a production environment. This might include incorporating the model into an already-in-use system or creating a new system specifically to employ the model for monkeypox detection.
7) Continuous monitoring: This stage includes monitoring the deployed model's performance continually and updating it as necessary to make sure it continues to be accurate and efficient over time.

5. Experimental Results

The following are the results obtained from using the Extended Convolutional Technique for monkeypox detection. Fig. 2, displays the input dataset utilized in the research prototype proposed in the study.

Fig. 2. Input dataset of the proposed research prototype

Fig. 3 illustrates the usage of CPU, RAM, and other computing resources during the execution of the proposed ECNN model. Fig. 4 shows the accuracy of the code represented by the Epochs vs. Accuracy graph.

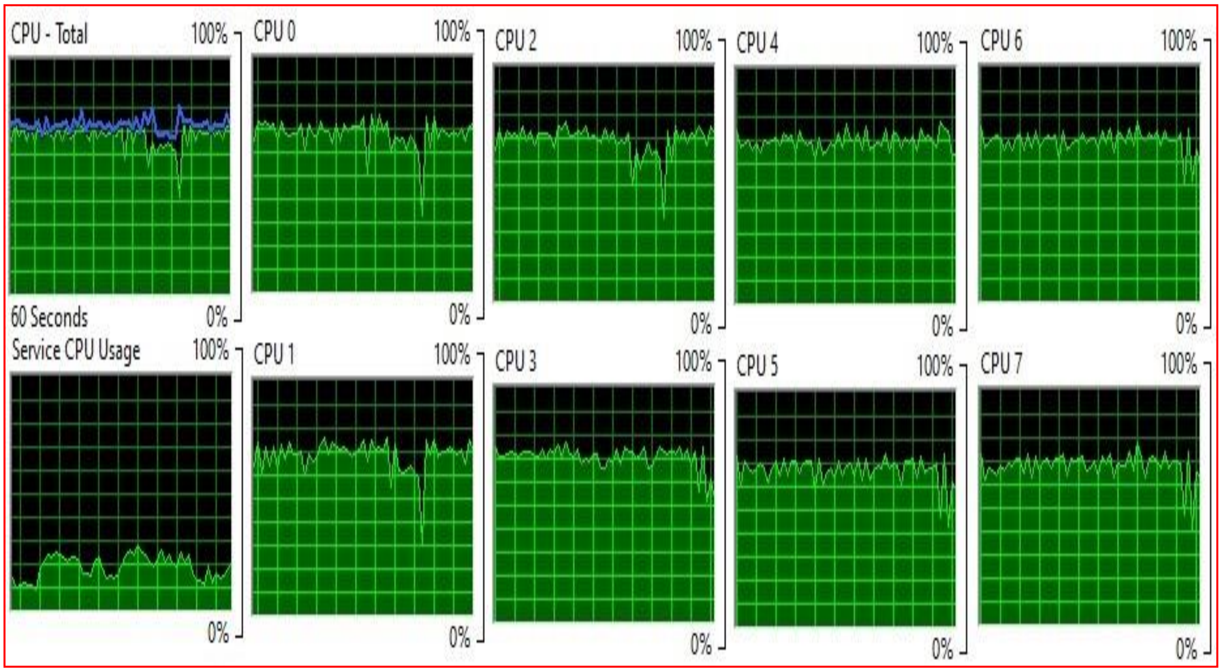

Fig. 3. Computer hardware utilization during the testing phase of the model

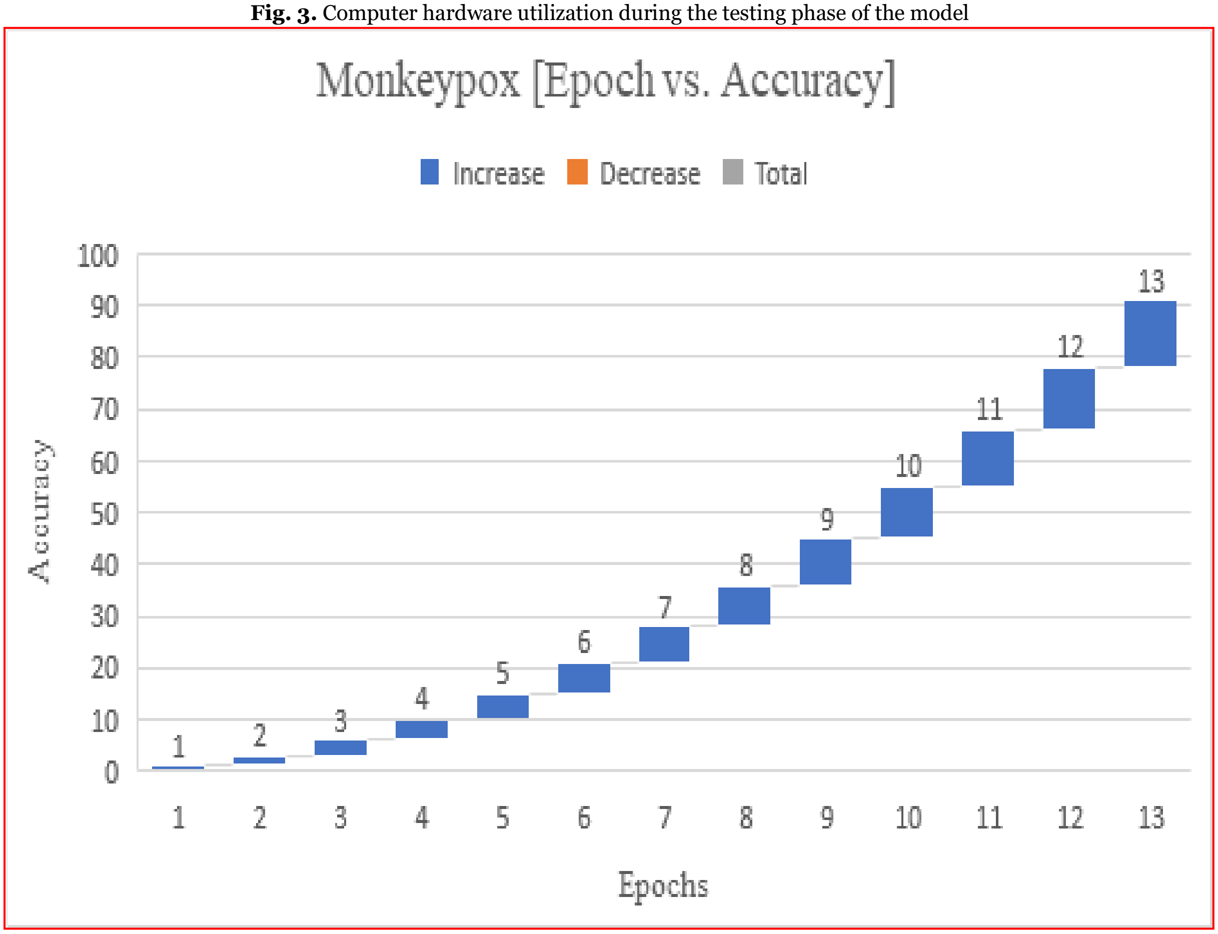

Fig. 4. Monkeypox ECNN model's Epochs vs. Accuracy comparison

Fig. 5 illustrates the decrease in the loss ratio compared to the time consumption during the execution of ECNN code on the Monkeypox dataset acquired from Kaggle. The above Fig. 6 illustrates the duration of each iteration during the execution of the Monkeypox ECNN code for each epoch.

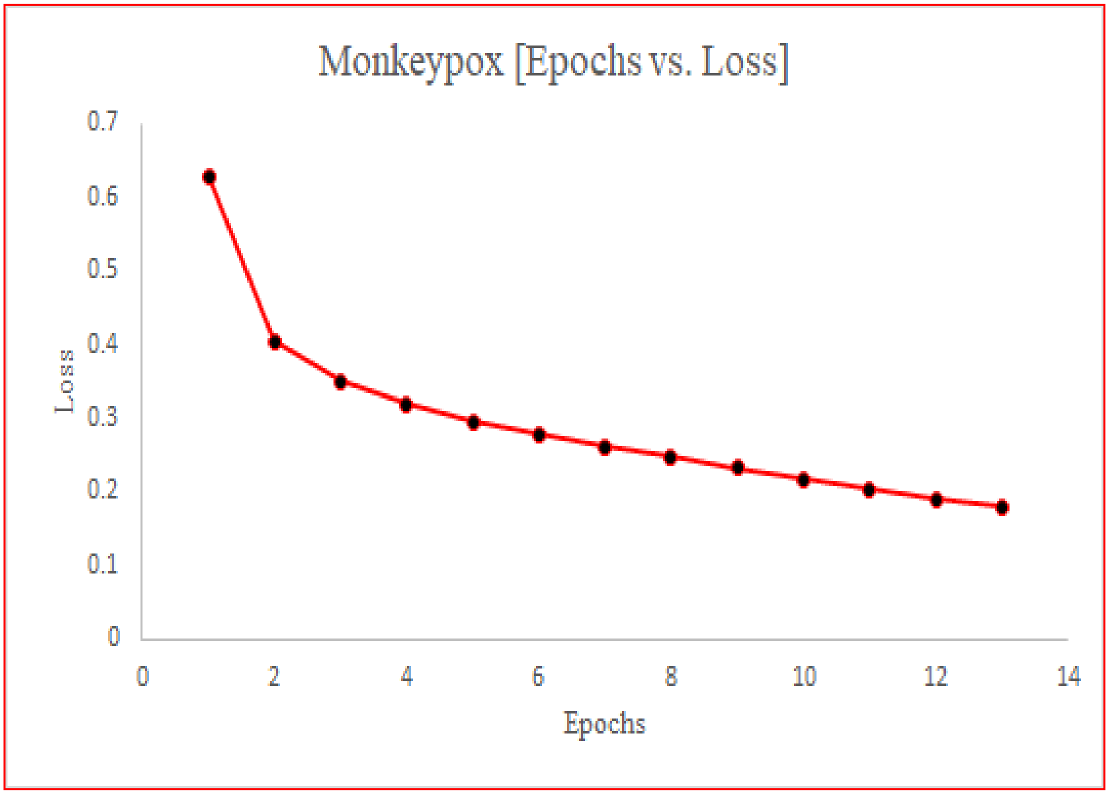

Fig. 5. Monkeypox ECNN model's Epochs vs. Loss comparison

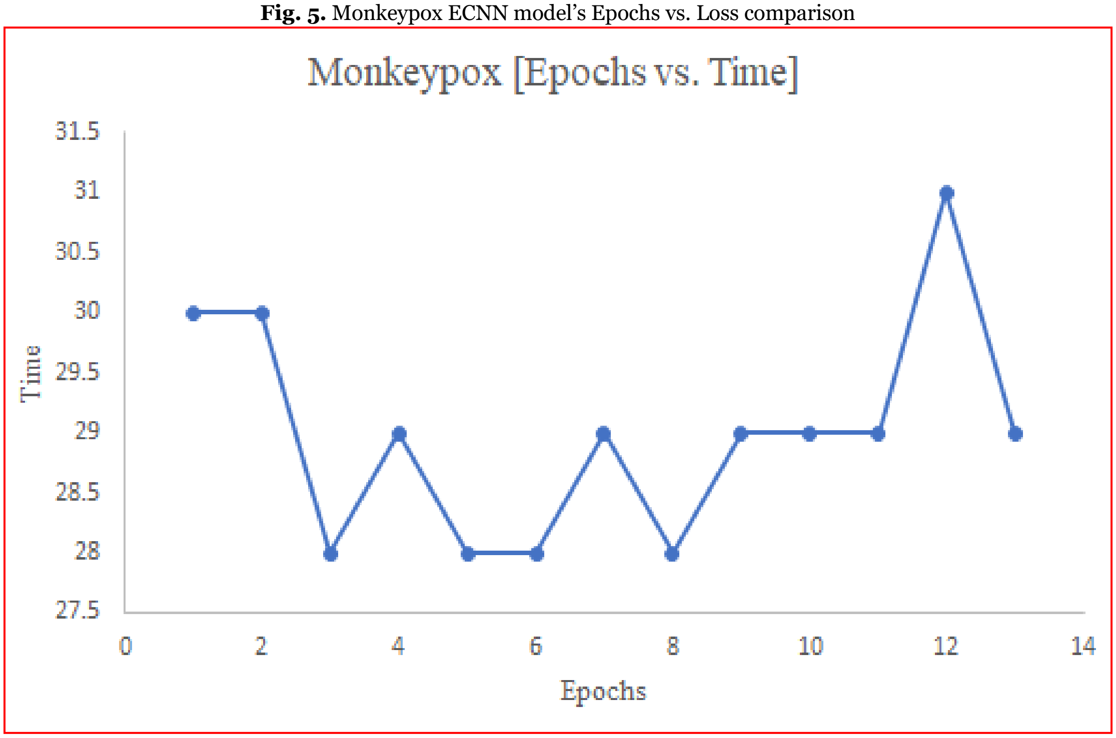

Fig. 6. The time taken for each iteration of Monkeypox ECNN code execution per epoch

The graph in Fig. 7 illustrates and compares the degree of loss to the accuracy of the Monkeypox ECNN code executed on the database. Fig. 8 illustrates how the proposed model reduces loss over time and improves accuracy at each epoch.

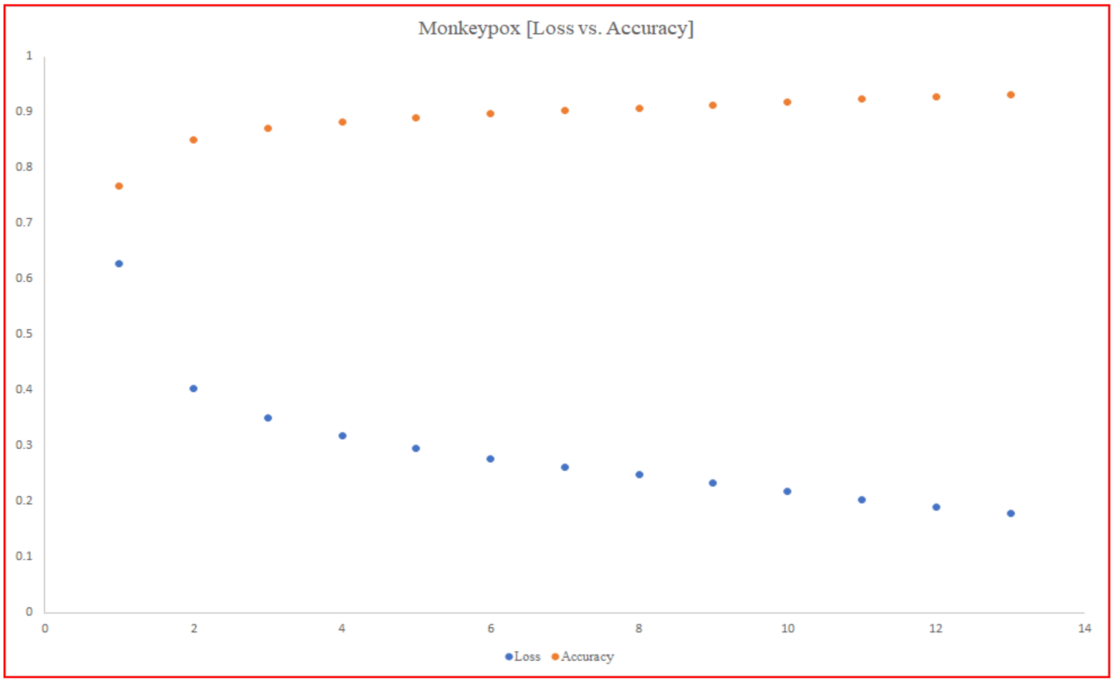

Fig. 7. The Monkeypox ECNN model's accuracy and execution loss.

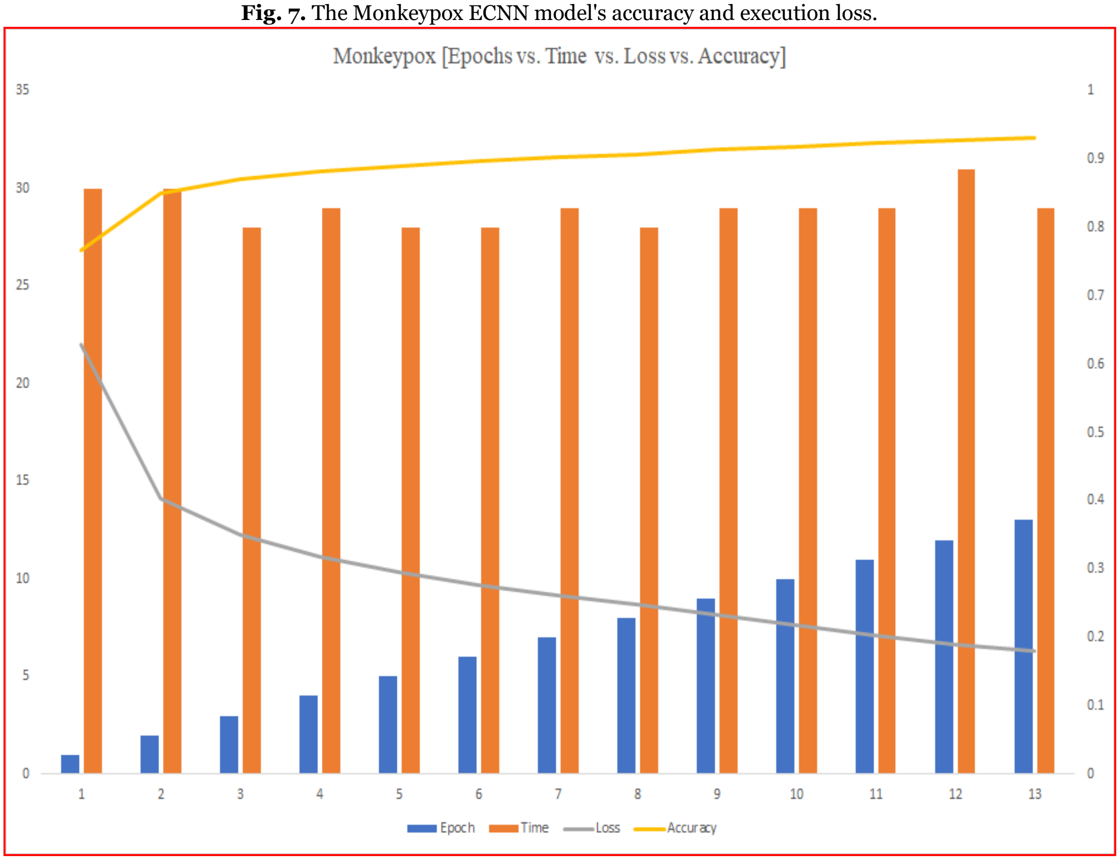

Fig. 8. Epochs, Time, Loss, and Accuracy in Monkeypox ECNN model

Fig. 9 illustrates the Val_Loss of the dataset compared to the loss on the provided dataset in the Monkeypox ECNN model. Fig. 10 elucidates the improvement of accuracy and Val_accuracy on the provided dataset in the Monkeypox ECNN model.

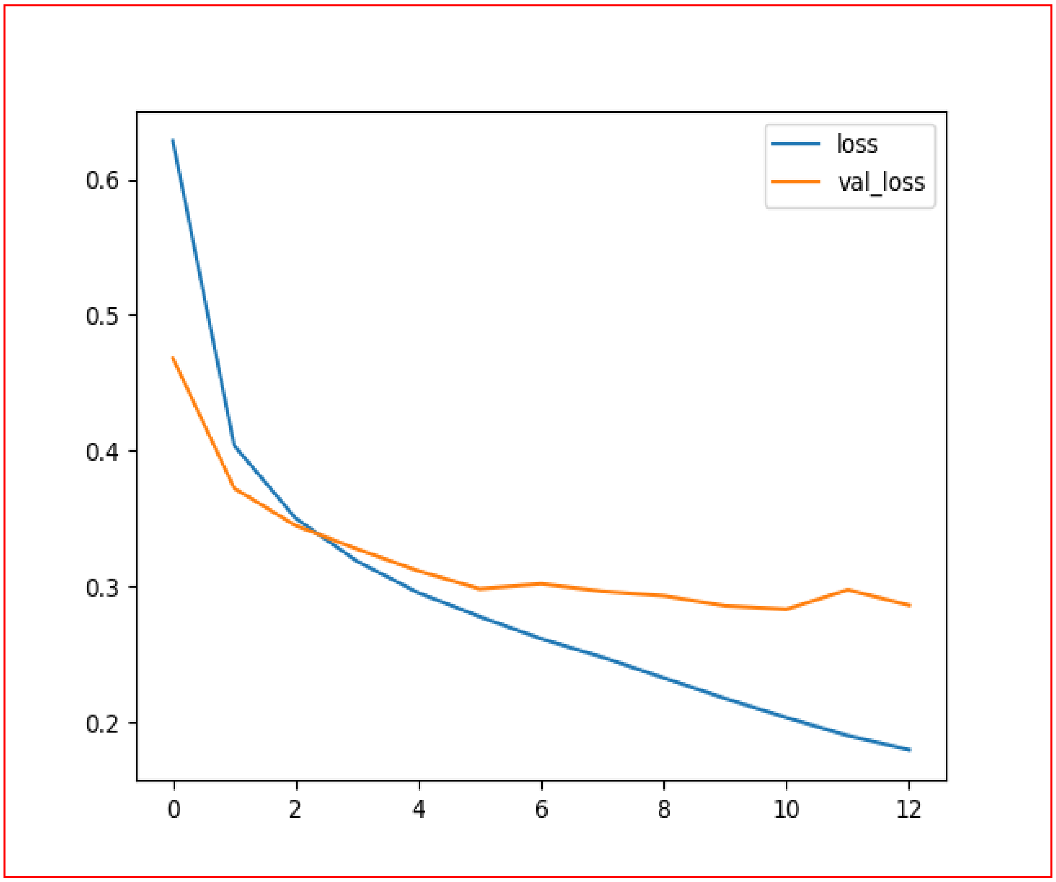

Fig. 9. Loss vs. Val_Loss during Monkeypox ECNN training and testing

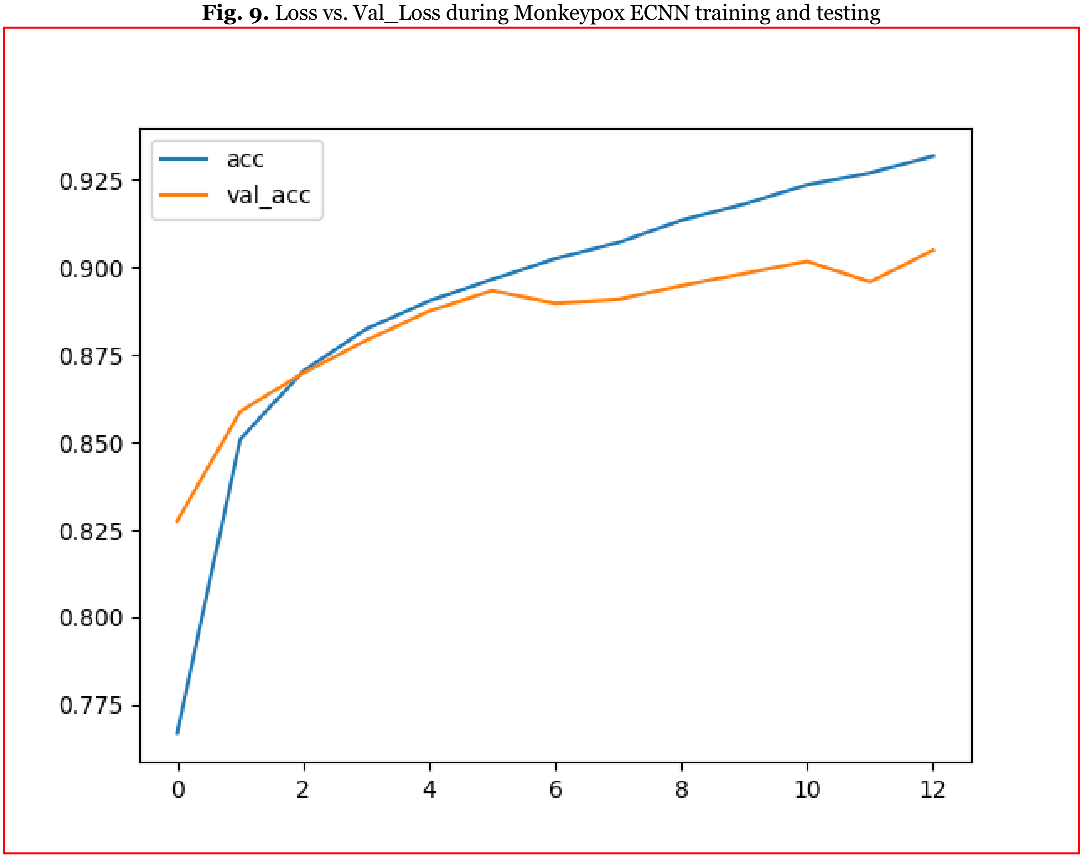

Fig. 10. Analyzing Accuracy vs. Val_Accuracy for the Monkeypox ECNN prototype in training and testing.

Fig. 11 illustrates the ultimate implementation of the prototype, which attained an accuracy of 88.10% during the module's training.

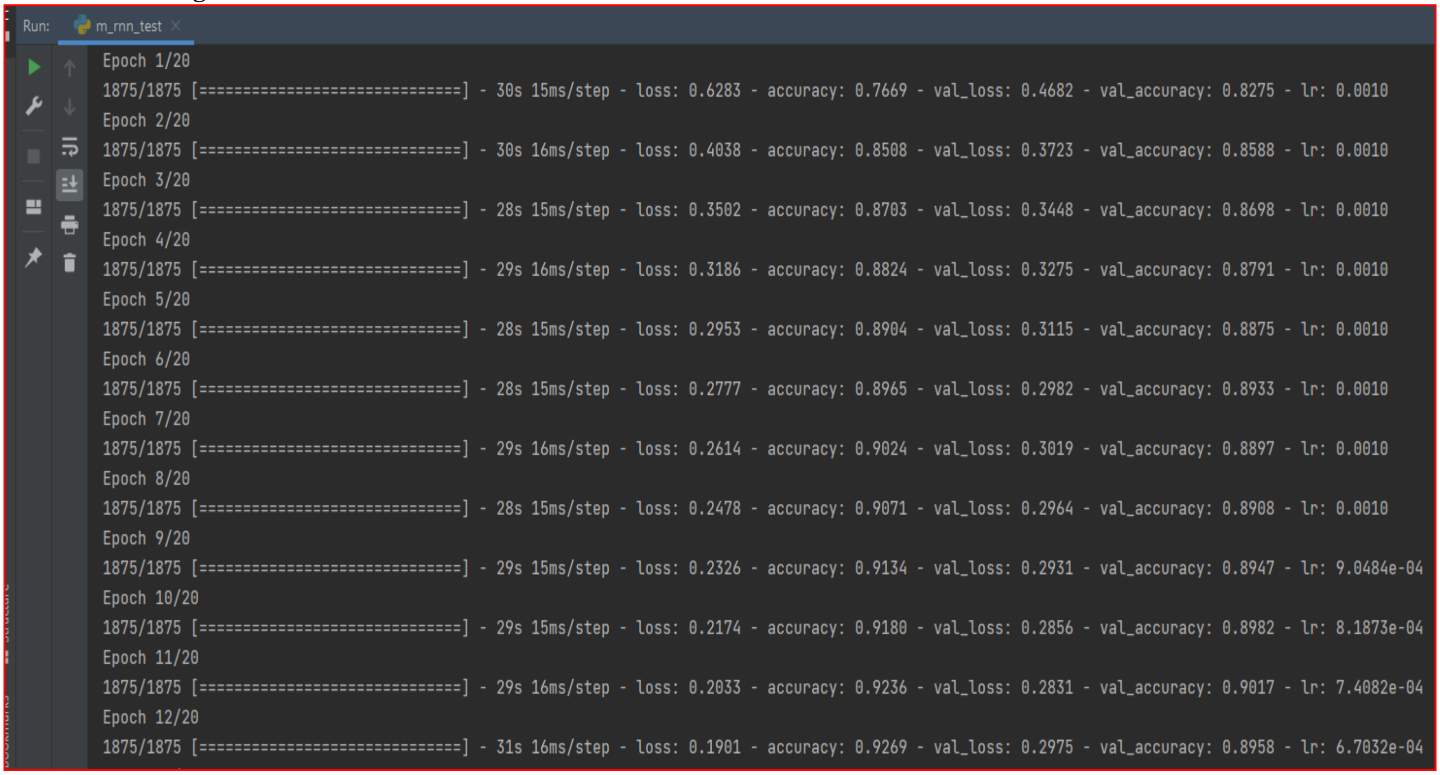

Fig. 11. Displays the final outcome, 88.10% accuracy achieved

5.1. Performance evaluation methods

The preliminary findings are evaluated and presented using commonly used authentic methodologies such as precision, accuracy, audit, F1-score, responsiveness, and identity (refer to Figures 7-11). As the initial study had a limited sample size, measurable outcomes are reported with a 95% confidence interval, which is consistent with recent literature that also utilized a small dataset [20, 24]. In the provided dataset (Fig. 2) for the proposed prototype, monkeypox can be classified as Tp (True Positive) or Tn (True Negative) if it is diagnosed correctly, whereas it may be categorized as Fp (False Positive) or Fn (False Negative) if it is misdiagnosed. The detailed quantitative estimates are discussed below.

5.1.1. Accuracy

Accuracy refers to the proximity of the estimated results to the accepted value (refer to Fig. 7). It is the average number of times that are accurately identified in all instances, computed using (1).

$$Accuracy = \frac{(Tn + Tp)}{(Tp + Fp + Fn + Tn)} \tag{1}$$

5.1.2. Precision

Precision refers to the extent to which measurements that are repeated or reproducible under the same conditions produce consistent outcomes.

$$\Pr ecision = \frac{(Tp)}{(Fp + Tp)} \tag{2}$$

5.1.3. Recall

In pattern recognition, object detection, information retrieval, and classification, recall is a performance metric that can be applied to data retrieved from a collection, corpus, or sample space.

$$\mathrm{Re}\,call = \frac{(Tp)}{(Fn + Tp)} \tag{3}$$

5.1.4. Sensitivity

The primary metric for measuring positive events with accuracy in comparison to the total number of events is known as sensitivity, which can be calculated as follows:

$$Sensitivity = \frac{(Tp)}{(Fn + Tp)} \tag{4}$$

5.1.5. Specificity

It identifies the number of true negatives that have been accurately identified and determined, and (5) can be used to find them:

$$Specificity = \frac{(Tn)}{(Fp + Tn)} \quad (5)$$

5.1.6. F1-score

The harmonic mean of recall and precision is known as the F1 score. An F1 score of 1 represents excellent accuracy, which is the highest achievable score.

$$F1 - Score = 2x\frac{(precisionxrecall)}{(precision + recall)} \quad (6)$$

5.1.7. Area Under Curve (AUC)

To calculate the area under the curve (AUC), the area space is divided into several small rectangles, which are subsequently summed to determine the total area. The AUC examines the models' performance under various conditions. (7) can be utilized to compute the AUC:

$$AUC = \frac{\sum ri(Xp) - Xp((Xp + 1)/2)}{Xp + Xn} \quad (7)$$

6. Conclusion

In this paper, we conducted a comprehensive study of the effectiveness of machine learning and deep learning techniques in detecting monkeypox and used monkeypox detection data to train and evaluate the performance of different machine learning and deep learning models. In conclusion, monkeypox detection data analytics using machine and deep learning techniques has the potential to improve the speed and accuracy of monkeypox outbreak detection and response. By integrating multiple types of data, including clinical, laboratory, environmental, social media, demographic, and geospatial data, machine and deep learning models can be trained to identify patterns and relationships in the data and make accurate predictions about the spread of the outbreak. The proposed system for monkeypox detection data analytics using machine and deep learning techniques can overcome the drawbacks of existing systems by leveraging advanced techniques such as deep learning, which can learn complex patterns and relationships in the data. The system can also be customized to specific outbreak scenarios and can be continuously updated and optimized to improve its performance over time.

The advantages of monkeypox detection data analytics using machine and deep learning techniques include improved accuracy, faster response times, and the ability to identify outbreaks before they become widespread. This can help public health officials and healthcare providers implement targeted interventions and prevent the spread of the disease. Overall, monkeypox detection data analytics using machine and deep learning techniques has the potential to revolutionize with accuracy 88.10% the way that monkeypox outbreaks are detected, monitored, and controlled. As research in this field continues to advance, we can expect to see increasingly sophisticated approaches and tools that enable more effective disease surveillance and outbreak response.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request at head.research@bluecrest.edu.lr

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest to report regarding the present study.

AUTHORS’ CONTRIBUTIONS

Kinjal A. Patel: Conceptualized the study, performed data curation and formal analysis, proposed methodology, provided software, and wrote the original draft.

Dr.Asadi Srinivasulu: Responsible for Designing the prototype and resources, executing the experiment with software, implementation part, providing software, Performing data curation, Methodology, designing, and proofreading.

Dr. Kuntesh Jani: Supervised the study, reviewed and grammar checking. Visualized the study with graphs, investigated the study, and performed formal analysis, proposed methodology.

Goddindla Sreenivasulu: Paraphrasing, Grammar Checking, Plagiarism removed and Guidelines and also citation work.

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