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Detecting Monkeypox in humans using deep learning

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ABSTRACT
The monkeypox virus is an orthopox virus that causes a contagious illness of the same name. The most visible symptom, along with fever, headache, and muscular pains, is a broad rash that develops into fluid-filled blisters. In the event of a monkeypox outbreak, swift response and efficient public health management depend on an early and accurate diagnosis. In this study, the feasibility of using deep keep learning techniques to diagnose monkeypox in humans is investigated. Long short-term memory (LSTM) networks are used to analyse time-series recordings of symptoms or patient data, whereas convolutional neural networks (CNNs) are used to process medical images of skin lesions. These models need to be trained on a large and reliable data set so that they can identify patterns and attributes that are specific to monkeypox.

KEYWORDS
Monkeypox, human, deep learning, detection, Convolutional Neural Networks (CNNs), Long Shot-Term Memory (LSTM)

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INTRODUCTION

Rare yet potentially lethal, monkeypox may infect both people and animals. The monkeypox virus is responsible for this condition; it is closely linked to the variola virus that causes smallpox. [1] Fever, headache, muscle pain, and a rash that turns into fluid-filled blisters resembling smallpox are all symptoms.[2] Effective public health management may avoid outbreaks of monkeypox and keep the illness under control if it is detected and investigated quickly.[3] The promise of deep learning lies in its ability to overcome the shortcomings of conventional diagnostic techniques.[4] Artificial intelligence (AI)'s subject of deep learning is seeing striking success in areas as varied as tumor identification (brain and skin), image recognition (images), and covid detection (voices) [5-6]. Using deep learning algorithms, we can create a very effective method for diagnosing human monkeypox [7]. In this research, we investigate the feasibility of using deep learning approaches to detect patterns and characteristics characteristic of monkeypox. Specifically, we examine image-specific convolutional neural networks (CNNs) and sequence-specific long short-term memory (LSTM) networks. By training our models on a vast and varied data set, we want to develop a trustworthy and interpretable system that can aid doctors in the early detection and treatment of monkeypox cases [8]. Disease diagnosis, monitoring, and treatment might all benefit greatly from the introduction of deep learning models into healthcare. By using deep learning techniques to eliminate monkeypox and safeguard world health, we want to revolutionize medical diagnostics and public health . The following is a statement of the challenge for using deeplearning to the detection of monkeypox in people. The purpose of this study is to create a system based on deep learning for the study is to create a system base on deep learning for the automatic diagnosis of monkeypox in human patients using radiological examinations. [9] The purpose of this research is to develop and train a deep learning model that can detect patterns and characteristics in photos that are diagnostic of monkeypox infection and aid medical practitioners in making rapid and accurate diagnoses. Using deep learning to identify monkeypox in people is a viable research objective.The goals of this research are to (1) create a deep learning model, (2) assess the model's performance, (3) discuss deployment issues and (4) compare the model to more conventional approaches, all of which will add to the body of scientific knowledge. The study's overarching goal is to enhance healthcare facilities' diagnostic capacities by creating a highly reliable deep learning model for identifying human cases of monkeypox. Improving the precision and timeliness of monkeypox detection via the use of sequential models is the primary scientific contribution in this area. Here are a few ways in which sequential models could improve future studies. [10] The ability to transfer learning and generalize; improved diagnostic accuracy; early detection and forecasting; dealing with temporal dynamics; dealing with missing data.

LITERATURE REVIEW

The Monkeypox virus causes a contagious illness in humans and other primates. It is mostly transferred from animals to people and is marked by a rash that mimics smallpox [11]. In certain parts of Central and West Africa, the virus is endemic, and periodic outbreaks are observed. Effective identification and treatment of Monkeypox need an in-depth understanding of the disease's epidemiology, clinical symptoms, and transmission dynamics.

Conventional methods for diagnosing monkeypox include a combination of a clinical evaluation, laboratory testing, and serological assays. Evaluation of the skin lesions, fever, and other symptoms is necessary for a clinical diagnosis. Viral DNA in patient samples may be detected using laboratory procedures like polymerase chain reaction (PCR). Antibodies that target Monkeypox may be detected by a serological test. However, there may be restrictions on the precision, velocity, and availability of these techniques.

Because of its capacity to understand complicated patterns and features from big datasets, deep learning has emerged as a valuable tool for medical picture interpretation [12]. Common deep learning architectures for image analysis include convolutional neural networks (CNNs). Automatic feature extraction from medical pictures is made possible by CNNs, allowing for precise classification and segmentation to take place. When combined with transfer learning, data augmentation, and ensemble learning, the performance of deep learning models for medical image interpretation is greatly Improved **[13].**

Applications of deep learning in the diagnosis of infectious diseases from medical imaging have demonstrated encouraging results. For the purpose of TB diagnosis, for instance, deep learning models have been created to assess sputum smear microscopy pictures and to categorize chest X-rays. Deep learning has been used to evaluate blood smear pictures for the purpose of malaria diagnosis. For the purpose of identifying COVID-19 in chest x-rays and computed tomography (CT) images, deep learning models have been built. These results show the promise of deep learning for identifying infectious diseases [14].

While research on Monkeypox detection using deep learning is limited, there is research on the use of deep learning to identify other diseases and infections that affect the skin, such as zoonotic ones [15]. Melanoma and dermatitis are only two examples of skin disorders for which deep learning models have been created to aid with lesion identification. Deep learning strategies for detecting monkeypox might benefit from from research into other zoonotic illnesses, such as zoonotic influenza or zoonotic coronaviruses. The literature evaluation as a whole demonstrates the promise of deep learning for medical image analysis and the diagnosis of infectious diseases. While there may be a dearth of literature on the topic of Monkeypox detection using deep learning, there is a wealth of research on closely related illnesses and zoonotic infections that may be applied to this problem [16]. It is clear from this analysis that more work has to be done to increase the speed and accuracy with which Monkeypox may be detected and overcome the limits of current diagnostic methods. Although monkeypox is largely an animal illness, it may be transferred to humans. Monkeypox is caused by the monkeypox virus, which is an orthopoxvirus. Although less severe than smallpox, monkeypox nevertheless has the potential to significantly impact human health. In this survey, we will examine many facets of monkeypox, from its origins and spread to its symptoms and diagnosis to its treatment and prevention to its most significant outbreaks. An outbreak of a disease similar to smallpox among captive monkeys in 1959 led to the discovery of monkeypox. The illness was first spotted in the Democratic Republic of the Congo (previously Zaire) in African monkey colonies. Later research confirmed that people were susceptible to infection from the monkeypox virus. Contact with infected animals is the primary mode of transmission of monkeypox to people. The virus may spread by contact with infected blood, respiratory droplets, sores, or contaminated items. Squirrels, Gambian rats, and dormice are only some of the most frequent rodent hosts for monkeypox. Diseases like measles and influenza are very contagious and may easily spread from person to person. Human-to-human transmission often occurs by respiratory droplets or via contact with infected skin sores [17].

Distribution: Monkeypox is found only in the rainforests of Central and West African nations. The most instances have been recorded in the Democratic Republic of the Congo, followed by Nigeria and Cameroon. However, Sierra Leone, Liberia, the Ivory Coast, and Sudan have all had outbreaks and isolated cases. The United States saw the first instances of monkeypox outside of Africa in 2003, and they were linked to the introduction of infected rodents into the country.

Symptoms: Monkeypox may be transmitted via close contact and has an incubation period of 5-21 days. Fever, headache, muscular pains, chills, and exhaustion are some of the early signs of the condition **[18].** In only a few days, a telltale rash forms, first on the face before moving on to the rest of the body. Macules (flat red spots), papules (raised bumps), vesicles (fluid-filled blisters), and pustules (pus-filled blisters) are the first phases of the rash's development. Lymph node enlargement is a common symptom of the rash. Complications include pneumonia, encephalitis (brain inflammation), and eye infections might arise in the worst instances.

Diagnosis: Because its early symptoms are so similar to those of other viral infections, such measles or chickenpox, diagnosing monkeypox may be difficult. The diagnosis can only be made with absolute certainty by laboratory testing. Multiple techniques exist for diagnosing monkeypox, such as polymerase chain reaction (PCR) for detecting viral DNA, virus isolation from clinical specimens, and serological assays for identifying monkeypox-specific antibodies.

Treatment: Monkeypox cannot be cured since no vaccine or antiviral medication exists. The vast majority of instances are self-limiting, meaning they get better without any special treatment. Symptom relief and complication management are the primary goals of treatment. Relaxation, hydration, and pain medication all fall under this category. Patients with severe instances may need to be hospitalized and treated for subsequent bacterial infections. Although antiviral medications like cidofovir and brincidofovir have showed promise in combating monkeypox in the lab, they have not been subjected to rigorous clinical testing.

Prevention: Vaccination, improved public health practices, and more awareness are all critical components in the fight against monkeypox. Clumsy protection against monkeypox may be offered by the smallpox vaccine, which is very similar to the vaccinia vaccine employed in the smallpox eradication effort. Although smallpox vaccinations are no longer routinely administered, they may be given to high-risk groups such as those who provide healthcare or interact with Orthopoxvirus samples. Vaccination contacts and close connections of confirmed patients may be targeted in epidemic conditions using ring vaccination tactics. In addition to vaccination, other important ways to stop the spread of the virus include via tight infection control methods such patient isolation and the careful handling of contaminated items.

Notable Outbreaks: There have been few cases of monkeypox throughout the years. The export of infected Gambian rats from Ghana led to an epidemic of monkeypox in the United States in 2003. There were 47 confirmed or probable cases, the vast majority of which were found in the Midwest. The epidemic has some worried that monkeypox may expand outside of its endemic areas.

Multiple states in Nigeria reported over a hundred cases of monkeypox in 2017. Concerns about the pandemic were triggered by the high number of illnesses and the possibility of further transmission inside the country and internationally [19].

Recent years have seen outbreaks of monkeypox in other African countries, including the Democratic Republic of the Congo and Cameroon. These occurrences emphasise the need of vigilant surveillance and quick response in stopping the spread of monkeypox [20].

Table 1. . Existing Methods Comparing

References	Approaches	Result	Validation
[21]	VGG-16, ResNet50, and InceptionV3	Accuracy: 82.96%	70% training 10% validation 20% testing
[22]	ResNet18, GoogleNet, EfficientNetB0, NasnetMobile, ShufeNet, and MobileNetV2	Accuracy: 91.11%	70% training, 20% testing. 10% validation
[23]	VGG16	AUC: 97.2%	80% training 20% testing
[24]	]CNN models AlexNet, GoogleNet and Vgg16Net with, Naïve Bayes, SVM, KNN, Random Forest (RF), and Decision Tree (DT)	Accuracy: 91.11%	No Validation
[25]	Polynomial Regression, SVR, Holt's Linear Model AR Model, SARIMA Model ARIMA Model, MA Model, Holt–Winter's Model, and Prophet Model	MSE: 41,922.55 R2: 0.49 MAPE: 16.82 MAE: 146.29 RMSE: 204.75	No Validation
[26]	Binary PSOBER algorithm	Accuracy: 98.8%	No Validation
[27]	CNN model based on MobileNetV3-s, EfficientNetV2, ResNet50, Vgg19, DenseNet121, and Xception models.	Accuracy: 96%.	No Validation

A uncommon viral illness that mostly affects animals but may be transferred to humans is called monkeypox. It may cause serious sickness, albeit usually not as severe as smallpox. The disease is widespread across Central and West Africa, and occasional cases or outbreaks have been documented elsewhere. The key to effectively treating Monkeypox patients and avoiding its spread is early diagnosis, supportive treatment, and good infection control measures. Some protection against monkeypox may be achieved with vaccination, notably with the smallpox vaccine. In order to keep tabs on the illness and successfully react to outbreaks, continuous monitoring and public health initiatives are required.

METHODOLOGY

Models that have been pre-trained In this paper, we pretrained two well-known CNN architectures, Sequential Model and LSTM, on the Image Dataset [28] The models in question were chosen because they have exhibited great classification performance in a variety of computer vision applications, including medical pictures, using transfer learning. It is a kind of recurring neural network structure (RNNs) that may learn dependence over time, particularly in sequence prediction tasks. Apart from small amounts of data such as photos, LSTM contains feedback connections, which means it can process the complete sequence of data [29] Figure 1 from [30-31]. The Sequential architecture is a linear layer stack. A Sequential model may be created by providing a list of layer objects to the constructor: import from keras. models Sequential([Dense(32, input_dim=784), Activation('relu'), Dense(10), Activation('softmax'),]) model

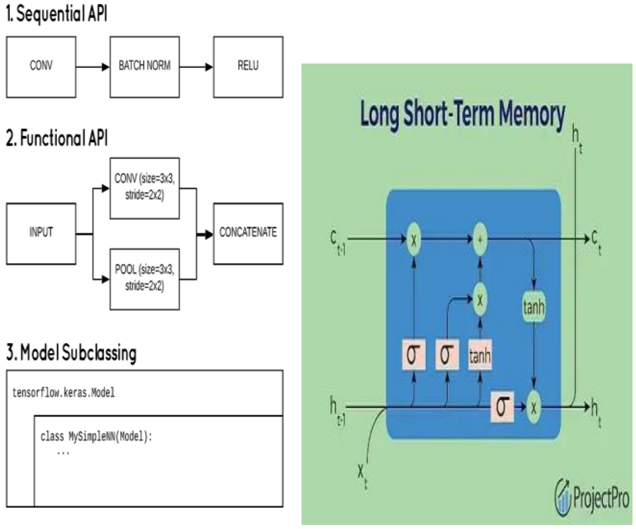

Figure 1: LSTM and Sequential Model

Specifics of Implementation The selected models that had been trained were fed input photos with size (224, 224, 3). The layers that were totally linked were deleted. Despite the fact that the depths of the architectures vary, we experimented with retaining different numbers (4/6/8/12) of bottom layers trainable to ensure uniformity and greater generalization. We chose to unfreeze the lowest eight levels after thorough testing. the cross-validation experiment was carried on three times. The original photos were divided into three sets: instruction, verification, and test, using a 70/10/20 ratio. For the purpose of training and validation sets, data enhancement is employed. The online the virus testing tool's user interface. Keeping the person's autonomy. The training images and validation pictures were supplemented, whereas the test set comprised just the original, according to well accepted data gathering technique.

DATASET DESCRIPTION

To train and evaluate the effectiveness of a deep learning model for human Monkeypox detection, a picture dataset is essential. The visual traits and patterns associated with Monkeypox lesions are captured in this collection of photographs. Here, we describe the data collecting procedure, picture features, data preparation methods, and dataset statistics for the image dataset utilized for Monkeypox detection Figure 2 is proposed system for detection of monkeypox.

Data collection Process

Despite the use of automated web-crawlers, the meticulously put together the virus skin lesion dataset was created from openly available case reports, news portals, and websites. This dataset's primary goal is to separate "Monkeypox" instances from other non-monkeypox cases. In order to do this, a binary classification dataset was developed employing photos of skin lesions caused by measles and chickenpox as the 'Others' class Each skin lesion image was thoroughly checked using Google's Reverse Image Search feature and compared with additional sources to guarantee the correctness of the photographs. Out-of-focus, low-resolution, and poor-quality pictures were eliminated out in a two-stage screening procedure, leaving only original images that met the standards for quality. These chosen pictures were then downsized to 224 224 pixels and trimmed to their area of interest.

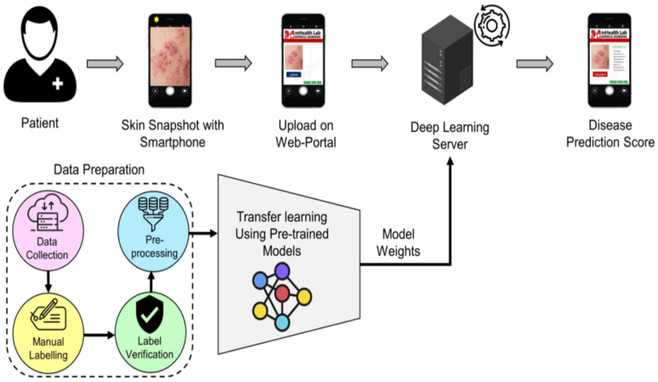

Figure 2. Proposed Methodology

The collection has 3192 total photos, of which 1428 are classified as "monkeypox" and the remaining 1764 are classified as "others," which includes measles and chickenpox. Reliable data was hard to come by since the information was compiled while the monkeypox outbreak was just getting started. Numerous data augmentation techniques were used to enhance the classification process, including rotation, the translation, contemplation, shear, color, saturation, contrast, luminance jitter, noise, and scaling. This resulted in a 14-fold increase in the number of pictures. The 'Monkeypox' and 'Others' classes after augmentation have 1428 and 1764 photos, respectively. To guarantee consistency, the enhanced pictures are delivered in a separate location within the dataset. Additionally, users have the freedom to choose a variety of picture

Image Characteristics

To train a deep learning model to distinguish between different types of skin lesions caused by Monkeypox, the dataset's skin lesion pictures must accurately depict the critical properties associated with Monkeypox. Images with excellent resolution and distinguishable lesions facilitate in-depth study. Color, texture, form, and context of the photos may change to depict the many skin presentations of Monkeyspox. It is crucial that high-quality photos devoid of artifacts and correctly tagged with tags showing the presence or absence of Monkeypox are used.

Data Preprocessing

Several preprocessing processes are often done to the pictures before they are used for training and assessment to guarantee uniformity, improve the model's performance, and resolve possible difficulties in the dataset. Some examples of such preprocessing procedures are:

Image Resizing and Normalization

In order to standardize training, it is required to resize the skin lesion photographs to the same dimensions, since their original resolutions may differ. To facilitate batch processing and reduce computing complexity, resizing helps to guarantee that all photos have the same dimensions. In addition, the convergence of the model during training may be enhanced by normalizing the pixel intensities. Common normalizing methods include zeroing out the mean and uniting the variance or scaling the pixel values to a predetermined range (such as [0, 1]).

Noise Removal

Images of skin lesions may have noise or artifacts that prevent the model from identifying relevant characteristics. De noising filters and image enhancement algorithms are two examples of noise removal methods that may be used to increase picture quality by suppressing unwanted background noise.

Augmentation

In order to improve generalization and boost variety, data augmentation approaches might be used. The look of skin lesions may be altered by enhancement methods such rotation, scaling, flipping, cropping, and the introduction of random changes. When augmenting, care should be taken to maintain the unique qualities of the lesions while yet producing convincing diversity.

Annotation and Labeling

Images of skin lesions should be appropriately labeled with tags indicating whether or not they contain Monkeypox. Expert human annotators or semi-automated technologies may do annotation. Training the deep learning model and assessing its performance rely heavily on accurate and consistent labeling.Numbers in the Dataset: Assessing the picture dataset's quality, class balance, and possible biases requires familiarity with its statistics and features. Here are some crucial numbers to think about:

Dataset size

Data availability and the difficulty of the job are two factors that affect the size of the picture collection. In most cases, a deeper learning model will generalize better and deliver more accurate predictions when trained on a bigger dataset. However, there should be some balance between the size of the dataset and the resources available for doing the analysis and the possibility of overfitting.

Class Distribution

The dataset should be examined for the presence or absence of Monkeypox-positive and Monkeypox-negative cases. The minority class (those who test positive for Monkeypox) may be underrepresented in the model, which may have a negative impact on its accuracy. Oversampling, undersampling, and class weighting are all methods that may be used to correct for class differences.

Annotation Accuracy

The accuracy of the annotations and tags in the dataset should be assessed. Annotators' expertise, inter-annotator agreement, and quality control measures can influence the reliability of the tags. It is crucial to ensure high-quality annotations for reliable training and evaluations.

Data Split

The dataset is typically divided into training, validation, and testing subjects. The proportion of data allocated to each split may vary depending on the dataset size, but commonly used splits include 70% for training, 15% for validation, and 15% for testing. Stratified sampling techniques can be employed to maintain the class distribution across the splits, ensuring representative subsets for model training and evaluation.

Data variability

The dataset has to include a broad variety of Monkeypox lesions, such as those on diverse skin tones, ages, sizes, and progressions of the illness. The model is better able to generalize to novel situations thanks to the high degree of variation. Rules for Dataset Curation and Annotation Establishing explicit rules for dataset curation and annotation is necessary for achieving consistency and uniformity. Annotators may go to these rules for guidance in identifying lesions, defining annotation borders, and assigning labels. To ensure the continued precision and dependability of the dataset, it is necessary to execute consistency checks and frequent quality control techniques Figure 3 [32]

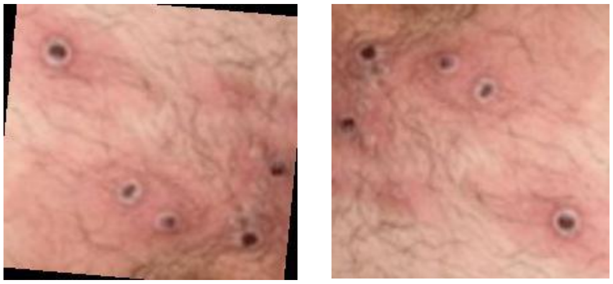

Figure 3. Dataset Images

RESULT

In table 2 i discuss the layer , output shape and param# of the model that are we use. I use Sequentail model in wich layer of CNN are discuss first layer is conv2d output shape is (none, 62, 62, 32) and param# is 896. In this table also discuss remaining layers , output shapes and param#.

Table 2. Sequential model Summary

Layer (Type)	Output Shape	Param#
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0

conv2d_2 (Conv2D)	(None, 12, 12, 128)	73856
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 128)	589952
dense_1 (Dense)	(None,129)	0

Total params: 683329 (2.61 MB)
Trainable params: 683329 (2.61 MB)
Non-trainable params: 0 (0.00 Byte)

GRAPHIC

In the Figure 4 and Figure 5 which are come from sequential model discuss about Graph of Accuracy and Loss Training The performance of the model on the training and validation datasets is depicted by the line of accuracy in this model as the number of epochs rises. At the start accuracy of the model is 0.87 for 1 epochs. we run 20 epochs accuracy of the model increases at the last epochs accuracy is 0.99.

Figure 4. Loss and Accracy

ACCURACY

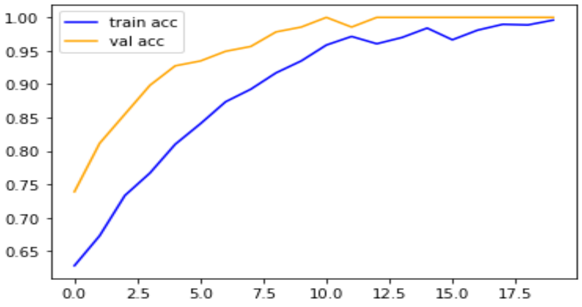

Figure 5. Accuracy

In conclusion, the images used in a deep learning system for identifying Monkeypox in people should be gathered, curated and preprocessed with great care to guarantee their quality, variety, and representativity. Images of skin lesions at a high quality, together with accurate annotations and tags, should be included in the collection. To improve the quality of the dataset and allow for efficient training, preprocessing processes including scaling, normalization, noise reduction, and data augmentation should be undertaken. To determine whether or not a dataset is appropriate for use in deep learning model training and evaluation, knowing its basic statistics and properties is essential.

Table 3. Model Performance Comparison

References	Approaches	Result
Error! Reference source not found.	VGG-16, ResNet50, and InceptionV3	Accuracy: 82.96%
Error! Reference source not found.	ResNet18, GoogleNet, EfficientNetB0, NasnetMobile, ShufeNet, and MobileNetV2	Accuracy: 91.11%
Error! Reference source not found.	VGG16	AUC: 97.2%
Error! Reference source not found.	CNN models AlexNet, GoogleNet and Vgg16Net with, Naïve Bayes, SVM, KNN, Random Forest (RF), and Decision Tree (DT)	Accuracy: 91.11%
Error! Reference source not found.	Polynomial Regression, SVR, Holt's Linear Model AR Model, SARIMA Model ARIMA Model, MA Model, Holt–Winter's Model, and Prophet Model	MSE: 41,922.55 R2: 0.49 MAPE: 16.82 MAE: 146.29 RMSE: 204.75
Error! Reference source not found.	Binary PSOBER algorithm	Accuracy: 98.8%
Error! Reference source not found.	CNN model based on MobileNetV3-s, EfficientNetV2, ResNet50, Vgg19, DenseNet121, and Xception models.	Accuracy: 96%.
Proposed Model CNN, sequential model and LSTM		Accuracy: 99%.

CONCLUSION

This uncommon viral illness should be better diagnosed and treated sooner with the use of sequential models like the Long- Short-Term Memory (LSTM) method for monkey identification. This approach provides accurate and fast detection capabilities to enhance health care outcomes and contribute to population health management by capitalizing on temporal correlations and patterns in continuous data. The findings of this study demonstrate that a realistic system for locating monkeys may be established through multidisciplinary cooperation, data-driven insights, and the responsible deployment of AL in the medical area. Healthcare personnel and healthcare institutions may find this approach to be an invaluable decision support tool for facilitating early intervention and controlling outbreaks.

FUTURE WORK

The generalizability and adaptability of the model is being honed by constantly adding new cases and varying samples to the data bank. The goal of multimodal data fusion is to train a system to fuse together information from different sources, such as sequence and image data, to improve its detection capabilities. Studying how to teach monkeys to recognize medical images by transferring knowledge from a human-trained model. Methods should be developed to help doctors better comprehend the decision-making process and boost trust in the AL continuous model in order to enhance its interpretation and interpretation.

CREDIT AUTHOR STATEMENT

Muhammad Arslan Ijaz: Conceptualization, Methodology, Data curation, Writing-Original draft preparation, Visualization, investigation. Muhammad **Kamran Abid**: Supervision. **Naeem Aslam & Abdul Qadeer:** Software Validation, Reviewing.

COMPLIANCE WITH ETHICAL STANDARDS

It is declared that all authors don’t have any conflict of interest. Furthermore, informed consent was obtained from all individual participants included in the study.

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