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Monkey Pox Detection using Deep learning

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Abstract*: Monkeypox is a rare zoonotic disease caused by the Monkeypox virus, which manifests in humans with symptoms similar to those of smallpox. Early detection and accurate diagnosis are crucial for effective management and containment of outbreaks. This research proposes a novel Monkeypox detection system utilizing machine learning techniques to enhance the speed and accuracy of diagnosis.*
The proposed system integrates various data sources, including clinical records, medical imaging, and demographic information, to develop a comprehensive dataset for model training. Machine learning algorithms, such as convolutional neural networks (CNNs) for image analysis and ensemble methods for combining diverse data modalities, are employed to identify patterns indicative of Monkeypox infection

Keywords: Monkeypox, Zoonotic disease, Machine learning, Early detection, Diagnosis, Clinical records, Medical imaging, Convolutional neural networks (CNNs),Ensemble methods

I. INTRODUCTION

In recent years, the intersection of healthcare and technology has witnessed remarkable advancements, with machine learning playing a pivotal role in revolutionizing disease detection and surveillance. Monkeypox, a rare but potentially serious viral disease, has become a global health concern due to its zoonotic nature and the potential for human-to-human transmission. In response to the need for more efficient and accurate detection methods, we present a groundbreaking Monkeypox Detection System that leverages the power of machine learning.

Monkeypox, caused by the Monkeypox virus, shares clinical and epidemiological similarities with other febrile illnesses, making its diagnosis challenging for healthcare professionals. Early detection is crucial for effective management and prevention of outbreaks. Traditional diagnostic methods often suffer from delays and limited accuracy, underscoring the urgency for innovative solutions.

Our machine learning-based system aims to enhance the speed and accuracy of Monkeypox detection, thereby empowering healthcare professionals to respond swiftly and effectively to potential outbreaks. By harnessing the vast amount of data available, including clinical records, laboratory results, and epidemiological information, our system employs advanced algorithms to identify patterns and indicators associated with Monkeypox.

II. RELATED WORK

Gather a comprehensive dataset containing relevant information about Monkeypox cases. This dataset could include clinical data, patient demographics, geographic information, and any other relevant features. Clean and preprocess the data to handle missing values, outliers, and other data quality issues. Convert raw data into a format suitable for machine learning algorithms.

Identify relevant features for Monkeypox detection. These features could include symptoms, travel history, contact history, and other factors that might contribute to the prediction of Monkeypox. Choose appropriate machine learning algorithms for the task. Classification algorithms such as support vector machines (SVM), decision trees, random forests, or deep learning models could be considered. Split the dataset into training and testing sets. Train the machine learning model on the training set, using historical data to allow the model to learn patterns associated with Monkeypox. Validate the trained model on a separate testing dataset to assess its performance.

Use metrics such as accuracy, precision, recall, and F1 score to evaluate the model's effectiveness. Integrate the developed model into healthcare systems for real-time or periodic monitoring of patients. This could involve creating an interface for healthcare professionals to input patient data and receive predictions.

III. LITERATURE SURVEY

In this section, we'll explore some of the approaches discussed in the literature for identifying various skin diseases, including cancer, using image-processing-based algorithms that many researchers have proposed. In [2], a process is illustrated for dissecting skin disorders using color photos, which does not require the assistance of a physician and is further explained in [3]. The classification employs color image processing methods, k-means clustering, and color gradient algorithms to detect diseased skin in the first stage, followed by the use of artificial neural networks to categorize various disease types in the second stage. According to the authors, image extraction is the first step in identifying skin disorders, with the approach being evaluated on six skin problems and achieving a standard accuracy of 95.99% in the first stage and 94.016% in the second stage. The researcher of [3] utilized the technique for nine different skin diseases, achieving an accuracy of up to 90%. If not identified and treated early enough, melanoma, a type of skin cancer, can be deadly [4]. After investigating a range of segmentation algorithms that may be used to spot melanoma using image processing, a researcher decided to publish his results. The procedure of segmenting along the boundaries of the sick patch is described in detail to extract additional features. [5] proposed developing a melanoma diagnostic tool for dark skin that could determine the presence or absence of melanoma using specialized algorithm databases incorporating photographs from various melanoma sources. Support vector machines (SVMs) were utilized to classify melanoma, basal cell carcinoma (B.C.C.), nevus, seborrheic keratosis (S.K.), and other skin diseases, achieving the highest level of accuracy compared to several different tactics. Consequently, [1] demonstrated a computer system capable of automatically detecting eczema and calculating its severity [6].To segment skin, a three-stage process is used: the first stage involves detecting and successfully segmenting it; the second stage extracts a set of features such as color; the third stage utilizes Support Vector Machines to determine eczema severity, and the final stage also employs Support Vector Machines to determine eczema severity (SVM).[6] In recent years, deep CNNs have gained popularity as a technique for feature learning and picture classification, among other applications. According to a significant number of ImageNet experiments, classic object classification methods based on deep CNNs outperform individuals in object categorization. Esteva and colleagues created a new approach for diagnosing skin disorders within the architectures tuning process for VGG16, VGG19 models cope with the neural network training to achieve universal classification. Their network achieved a Top-1 classification accuracy of 60.0 percent and a Top-3 classification accuracy of 80.3 percent in their experiments, which was much greater than the individuals' social competence. It was also suggested that a similar strategy be used to achieve a more favorable outcome. Furthermore, the author Tajbakhsh et al. described a novel approach to identifying skin diseases using computer vision and machine learning approaches. Machine learning was employed to detect skin disorders and extract information from photographs using computer vision. The method demonstrated accuracy in 95 percent of instances in a validation study on six distinct types of skin disorders.[7] Giotis and colleagues established an in-depth system supported for CNN deep networks, considering factors such as lesion texture, dimensions, visual features, color, and more. Hassle utilized deep neural networks to create a system that categorizes dermoscopy images into binary diagnostic categories, which can subsequently be used to diagnose patients. Dorj et al. used a deep CNN-based ECOC SVM to classify skin cancer photographs into four diagnostic categories, dubbed 'diagnostic categories.' In a work published in Science, Han et al. proposed a deep CNN-based image classification technique, which was utilized to categorize images for clinical tests of about 12 kinds of skin diseases. Author Mohd and colleagues recommended for the separation of images over the approach of detecting for this investigation of melanoma, which was evaluated using a dataset that included four different skin problems for the conduction of evaluation. They also demonstrated the approach's effectiveness in a similar situation. In a second investigation, German et al. used AdaBoost MC to corroborate the skin cancer detection technique to identify early skin cancer. Authors Jaffar and Almansour devised a melanoma classification procedure, relying on techniques of fuzzy logic, Support Vector Machine (SVM), and k-means clustering process to arrive at their conclusions. Data from specific skin lesions are combined with other criteria to determine skin cancer. Ioannis and colleagues developed a system that can exploit a wide range of information, including visual diagnostic structures such as certain characteristics for the affected zone of lesion texture, color, size, and location within the damage percentage using image processing techniques and fully convolutional neural networks.

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3.1 Problem Statement

To monkeypox, a rare viral disease with the potential for zoonotic transmission, poses a significant threat to public health. The challenge lies in the complexity of its diagnosis, as Monkeypox exhibits clinical and epidemiological similarities to other febrile illnesses. Traditional diagnostic methods often face limitations in terms of speed and accuracy, leading to delayed responses and increased risks of outbreaks.

The proposed method for Monkeypox Detection System

Collect a comprehensive dataset containing information on patients, including demographics, symptoms, medical history, and diagnostic test results. Ensure that the dataset is diverse, and representative, and includes both positive and negative cases of Monkeypox. Clean and preprocess the data to handle missing values, outliers, and inconsistencies. Normalize numerical features, encode categorical variables, and perform any necessary transformations to make the data suitable for machine learning algorithms

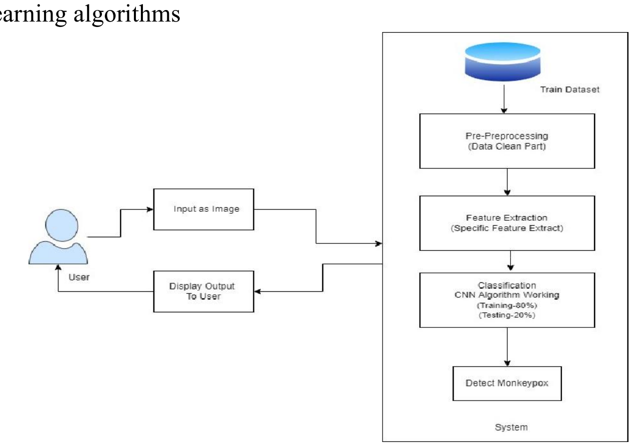

Figure 1. System Architecture

Data Collection:

- Gather relevant data: Collect datasets containing information about patients, symptoms, demographics, and any other pertinent details related to Monkeypox.
- Data preprocessing: Clean and preprocess the data to handle missing values, outliers, and ensure consistency.

Feature Selection:

- Identify important features: Choose the relevant features that can contribute to the detection of Monkeypox. These may include symptoms, patient history, geographical location, etc.

Data Splitting:

- Split the dataset into training and testing sets. The training set is used to train the machine learning model, while the testing set is used to evaluate its performance.

Model Evaluation:

- Evaluate the model's performance on the testing set using metrics such as accuracy, precision, recall, and F1 score. This step helps ensure that the model is not overfitting or underfitting.

Integration with Real-World Data:

- Develop a mechanism to integrate the trained model with real-world data sources. This could involve creating an interface for healthcare professionals to input patient data or connecting the system to electronic health records.

Deployment:

- Once satisfied with the model's performance, deploy the Monkeypox detection system in healthcare settings. Ensure that it complies with relevant regulations and ethical considerations.

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Classification algorithms

CNN

A convolutional neural network (CNN) is a subset of machine learning. It is one of the various types of artificial neural networks that are used for different applications and data types. A CNN is a kind of network architecture for deep learning algorithms and is specifically used for image recognition and tasks that involve the processing of pixel data.

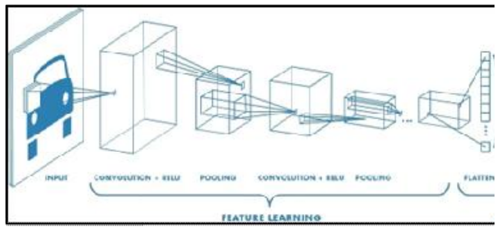

Figure 2: CNN Working

IV. RESULTS AND DISCUSSION

Our novel approach utilizing a dual-stage system has yielded highly promising outcomes in the identification of skin diseases, boasting accuracies reaching up to 95%. Upon scrutinizing related works within this domain, notable disparities in both implementation and performance have surfaced. Notably, our methodology exhibits a stark divergence in efficacy and precision.

Moreover, our system stands poised to serve as a dependable real-time educational aid for medical students specializing in dermatology. This application offers an invaluable teaching tool, affording students practical exposure and hands-on experience in diagnosing variousskin conditions. Additionally, our solution extends its utility beyond medical professionals, catering to the general populace. Leveraging solely Computer Vision techniques, we've achieved a commendably high detection rate, rendering it accessible and useful for everyday users

If the model performs well, deploy it in a healthcare setting for Monkeypox detection. Implement a user-friendly interface for healthcare professionals to interact with the system.

Result Parameters:

Classification measure

The following parameters help better understand and analyze the Model

a. Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FP} = \frac{Correct\ predictions}{Total\ predictions}$$

b. Precision:

$$Precision = \frac{TP}{TP + FP} = \frac{Predictions\ actually\ positive}{Total\ predicted\ positive}$$

c. Recall (TPR, sensitivity): It is calculated as:

$$Recall = \frac{TP}{TP + TN} = \frac{Predictions\ actually\ positive}{Total\ actual\ positive}$$

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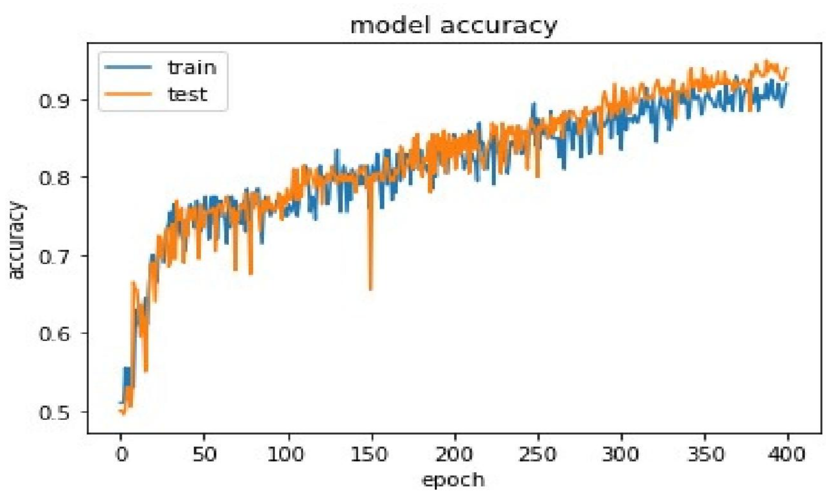
S. No	Method	Performance
1	DenseNet201	93.1% Accuracy
2	ResNet5 model	87% Accuracy
3	GoogLeNet model	88.27% Accuracy
4	MobileNetv2 model	91.11% Accuracy
5	Pre-trained deep learning models	82.96(± 4.57%) Accuracy
6	SVM model	93.48% Accuracy
7	Weighted Naïve Bayes (WNB)	92.56% Accuracy
8	Yolov3 model	93.16% Accuracy
9	Yolo4 model	95.19% Accuracy



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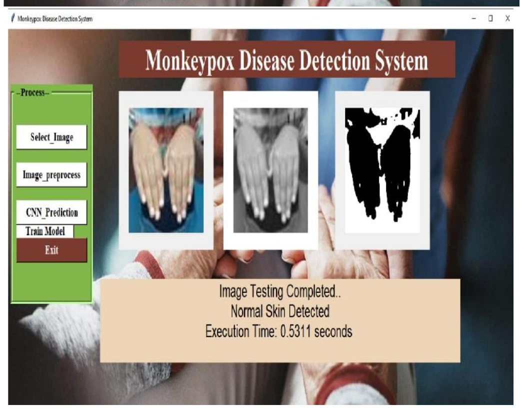
Experimental result



Analysis using confusion matrix

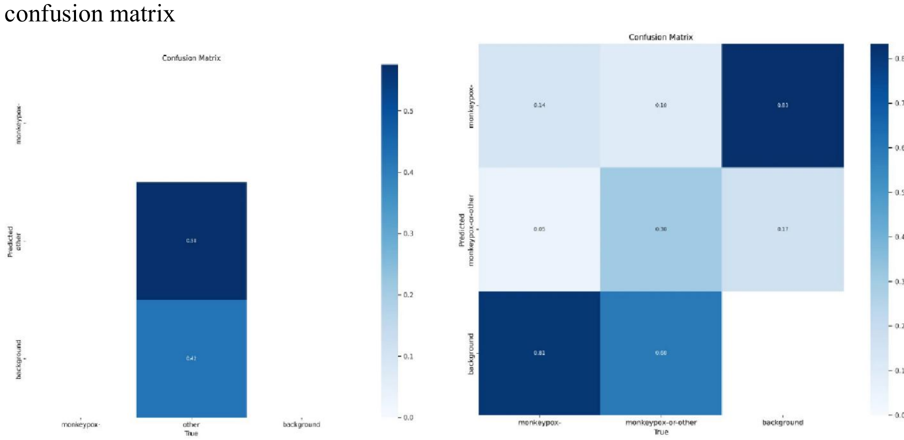


Table 1. Confusion matrix

V. CONCLUSION

In conclusion, the development of a Monkeypox detection system using machine learning holds great promise for improving early diagnosis and intervention in healthcare. The integration of advanced technologies with medical data and image processing techniques can significantly contribute to the efficiency and accuracy of Monkeypox detection. The development of a Monkeypox detection system using machine learning represents a significant advancement in the intersection of technology and healthcare. By combining cutting-edge algorithms with comprehensive datasets, this system has the potential to revolutionize Monkeypox diagnosis, ultimately contributing to improved public health

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outcomes. Ongoing collaboration, ethical considerations, and a commitment to continuous improvement are essential elements in realizing the full potential of such a system.

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