Enhancing Monkeypox Detection: A Fusion of Machine Learning and Transfer Learning

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Abstract—**Monkeypox is a viral disease that affects both animals and humans. Monkeypox can have a substantial negative influence on human health, particularly in areas with a lack of healthcare services. The sickness can produce epidemics, and it might be difficult to stop the spread of the disease. For effective treatment and to stop the disease from spreading further, early identification and detection of monkeypox are essential. Therefore, the healthcare industry may benefit from the development of precise and effective methods for the detection of monkeypox, such as image classification. In this paper, we propose a novel approach for detecting Monkeypox using image classification. The proposed method utilizes a Transfer Learning Model and other machine learning models to classify images of patients with Monkeypox. The system employs a majority voting technique to improve the accuracy of the classification. The proposed system is evaluated using a dataset of images obtained from patients with Monkeypox, and the results show that the proposed approach achieves high accuracy in detecting Monkeypox. The proposed system has the potential to assist healthcare professionals in diagnosing and treating patients with Monkeypox, and it can contribute to the efforts of controlling the spread of the disease.**

Keywords—Classification,Deep Learning,Transfer Learning, ensemble Learning,Monkeypox

I. INTRODUCTION

Monkeypox is a rare viral disease that is similar to human smallpox but less severe. It belongs to the Orthopoxvirus genus and family of Poxviridae. When epidemics hit monkeys maintained for study in 1958, the illness was first recognized. The Democratic Republic of the Congo (formerly Zaire) reported the first human case of monkeypox in 1970. Since then, occasional cases and outbreaks have been documented in various African nations, the United States, the United Kingdom, and Singapore.

Human monkeypox symptoms resemble smallpox symptoms but are less severe. Fever, headache, muscle aches, backache, swollen lymph nodes, chills, and weariness are the first symptoms of the illness. After that, a rash appears, frequently first on the face before moving to other regions of the body. The rash evolves and passes through various stages before developing a scab and eventually falling off. The disease typically lasts 2-4 weeks, and the majority of patients recover completely. However, the illness can occasionally be deadly or seriously debilitating, especially in those with compromised immune systems. For those with low immune systems or those who have not received the smallpox vaccine, monkeypox can be a deadly illness. Monkeypox does not now pose a significant hazard to public health on a par with COVID-19.In the future, it's feasible for a virus like the monkeypox or another infectious agent to start a pandemic like COVID-19. Changes in human behavior, climatic and environmental changes, as well as a rise in international travel and commerce, are just a few of the numerous elements that might lead to the genesis and spread of a new illness.

Viruses may also change and adapt over time, which might increase their virulence or ability to spread. This is why it's crucial to keep an eye on new infectious illnesses, investigate them, and create plans to stop and stop their spread.

AI classification of the monkeypox illness is crucial for a number of reasons. AI can assist in the early identification and categorization of monkeypox cases, which will speed up and increase the precision of diagnosis and treatment. This may be particularly crucial in areas with poor healthcare access or limited resources.

For a variety of reasons, classifying monkeypox using image classification AI can be crucial. Skin lesions and fever are symptoms of the viral illness known as monkeypox, which can be challenging to differentiate from illnesses including chickenpox, smallpox, and measles. Based on clinical and epidemiological information, such as the appearance and location of skin lesions, image classification AI can assist healthcare workers in effectively diagnosing and classifying instances of monkeypox.

To categorize photos of monkeypox skin lesions, we used three machine learning algorithms and transfer learning. A pre-trained neural network is utilized as the foundation for a new neural network that is trained on a particular task in the transfer learning approach. For our model, we started with the Xception pre-trained neural network.

Our research's primary contributions are:

1) Using machine learning and transfer learning techniques to accurately classify monkeypox skin lesions from photos.

2) Analyzing the performance of three machine learning techniques on the monkeypox dataset: support vector machines (SVMs), k-nearest neighbors (KNN), and random forest (RF).

3) Evaluating the three machine learning methods and 1 transfer learning method for categorization

4) Demonstrating how majority voting may be used to combine the predictions of various algorithms, considerably enhancing classification reliability and accuracy.

II. LITERATURE REVIEW

In recent years, advancements in both molecular biology and artificial intelligence have revolutionized the field of medical diagnostics, particularly in the realm of infectious diseases. Among these, Monkeypox, a rare and potentially life-threatening viral infection, has posed unique challenges in terms of rapid and accurate diagnosis. This literature review delves into the multifaceted landscape of Monkeypox diagnosis, ranging from traditional molecular assays to cutting-edge deep learning techniques applied to medical imaging. Within this dynamic spectrum of research, various scholars have contributed to the development of innovative tools and methodologies for the detection and classification of Monkeypox virus. In this context, we explore key studies that have shaped the current understanding of Monkeypox diagnosis. These studies not only elucidate the critical importance of accurate and timely detection but also underscore the diverse approaches employed in addressing this challenge. From real-time PCR assays employed during outbreaks to state-of-the-art deep learning models, this review aims to provide a comprehensive overview of the evolving methodologies in Monkeypox diagnosis, offering insights into their respective contributions and potential implications for public health.

In [1], Yu Li, Victoria A. Olson, Thomas Laue, Miriam T. Laker , Inger K. Damon classified monkeypox virus with real-time PCR assays.There they present two real-time PCR assays critical for laboratory diagnosis of monkeypox during the 2003 US outbreak.

In [2], Md Manjurul Ahsan, Muhammad Ramiz Uddin, Mithila Farjana, Ahmed Nazmus Sakib, Khondhaker Al Momin, Shahana Akter Luna use deep learning model in detecting monkeypox. there they did an image based diagnosis of monkeypox disease with a modified VGG16 deep learning model

In [3], Murat Altun , Hüseyin Gürüler, Osman Özkaraca , Faheem Khan, Jawad Khan and Youngmoon Lee use Convolutional Neural network with transfer Learning for monkeypox detection.

In [4], Ameera S. Jaradat, Rabia Emhamed Al Mamlook, Naif Almakayeel , Nawaf Alharbe , Ali Saeed Almuflih, Ahmad Nasayreh, Hasan Gharaibeh, Mohammad Gharaibeh, Ali Gharaibeh and Hanin Bzizi use a Automated Detection of monkeypox Skin Detection using Deep Learning and Transfer Learning technique.In there they use EfficientNetB3,VGG19,VGG16 and MobileNetV2 to classify the monkeypox using the images.

In [5], Chiranjibi Sitaula, Tej Bahadur Shahi used pre-trained deep Learning model for monkeypox detection.
There they use 13 Deep Learning pre-trained model applied to images to detect the monkeypox.

III. METHODOLOGY

The methodology comprises five key stages: data collection, data preprocessing, model training, majority voting for predictions, and result evaluation. For Monkeypox prediction, a diverse set of models was utilized, including traditional machine learning models like K Nearest Neighbor (KNN), Random Forest Classifier, and Support Vector Classifier, along with deep learning models, namely Xception and ResNet50, via transfer learning. Each model underwent rigorous training using the Monkeypox dataset. Subsequently, predictions from these models were integrated through a majority voting scheme to arrive at a collective decision. The final prediction was thoroughly evaluated using various performance metrics such as accuracy, precision, recall, and F1-score, ensuring a comprehensive assessment of the predictive efficacy of the approach. This methodology not only harnessed the strengths of different modeling techniques but also facilitated robust Monkeypox prediction through ensemble learning.
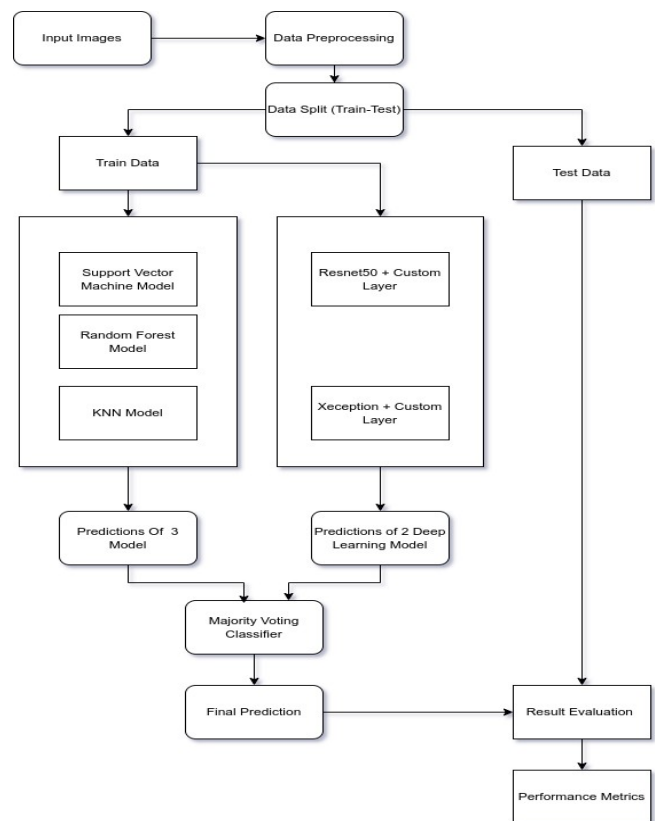

Figure 1: Workflow of detecting Monkeypox

3.1 Data Collection:

The data collection phase commenced with the acquisition of a comprehensive dataset specifically obtained from Kaggle, a reputable platform for datasets and machine learning competitions. This Kaggle dataset was meticulously selected for its relevance to Monkeypox prediction and its alignment with the research objectives. It encompassed a total of 300 Monkeypox cases, represented by a diverse set of image samples, spanning various demographics, geographic regions, and clinical presentations.
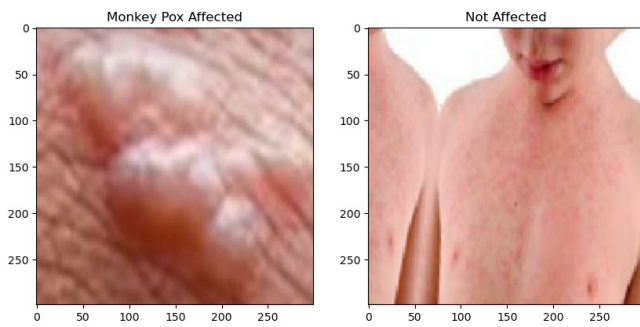
Figure 2 :Image of Monkeypox affected and non affected skin

To maintain transparency and traceability, detailed documentation of the Kaggle dataset source, version, and licensing was recorded, ensuring compliance with all terms of data usage and attribution as specified by Kaggle and the dataset contributors. Ethical considerations and privacy standards were consistently upheld throughout the data collection process.

3.2 Data Preprocessing:

Data preprocessing played a pivotal role in readying the dataset for model training. For deep learning models, specifically Xception and ResNet50, all images were resized to a standardized dimension of (299, 299, 3) to align with model architecture requirements. In contrast, for traditional machine learning models, a distinct preprocessing strategy was applied. Images were flattened into one-dimensional arrays, facilitating compatibility with these models, and subsequently, the data was normalized to a standardized range, enhancing convergence and stability during model optimization. This dual approach ensured that the dataset was prepared optimally, catering to the specific needs of both deep learning and traditional ML models, contributing to the overall robustness of the Monkeypox prediction framework.

3. 3 Model Training:

Model training constituted the heart of the methodology, where a diverse set of models was meticulously cultivated. Traditional machine learning models, including K Nearest Neighbor (KNN), Random Forest Classifier, and Support Vector Classifier, were imbued with domain knowledge through extensive hyper-parameter tuning. Deep learning models, such as Xception and ResNet50, were integrated through transfer learning, leveraging pre-trained weights from vast image datasets.

- ResNet50 : A key member of the ResNet family known for its efficiency in image classification tasks is ResNet-50, a deep convolutional neural network design. This technique, developed by Kaiming He et al. in 2015, uses skip

connections, also known as residual connections, to address the vanishing gradient problem and enable the training of extraordinarily deep networks. ResNet-50 has established itself as a cornerstone in computer vision thanks to its 50-layer design and pre-training on datasets like ImageNet. It provides cutting-edge results for a variety of picture identification applications.

- Xception : A powerful tool for feature extraction and picture classification, the Xception model was pretrained on the enormous and varied ImageNet dataset. François Chollet created Xception in 2016. Its design, which uses depth wise separable convolutions, enhances its computing effectiveness and adaptability. Xception is a great tool for transfer learning tasks since it encodes rich and generalized feature representations using the information it gained from its original training on ImageNet. This pre-trained model provides a solid basis for many computer vision applications, making it possible for researchers and professionals to use it to tackle unique picture identification problems with a high degree of efficiency and accuracy.
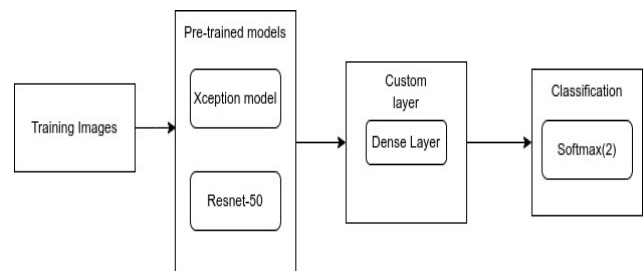

Figure 3 : High level workflow to train the pre- trained DL models with custom layers

The training process involved exhaustive experimentation with various hyper-parameters, encompassing learning rates, batch sizes, and optimization techniques. Extensive model validation, including k-fold cross-validation, ensured robustness and minimized over fitting. Furthermore, convergence analysis and early stopping mechanisms were employed to enhance model stability and efficiency.

3.4 Majority Voting for Predictions:

The majority voting mechanism served as the linchpin for aggregating model predictions into a unified decision. It was a principled approach wherein each model's prediction held equal weight. In the case of binary classification, the majority vote determined the final ensemble prediction, offering a democratic means of reconciling diverse model

perspectives. The process was transparent and easily interpretable, ensuring that the combined decision was equitable and unbiased. The majority voting approach effectively harnessed the ensemble's collective intelligence, mitigating the impact of individual model idiosyncrasies and uncertainties.

3.5 Performance Evaluation :

The comprehensive assessment of experimental outcomes is conducted and communicated through the application of prevalent statistical methodologies. These encompass well-established metrics, including, precision (1), recall (2), F1-score (3) , accuracy (4) which collectively offer a robust and nuanced evaluation of the models' performance.

$$P = TP/(TP+FP) \qquad (1)$$

$$R = TP/(TP+FN) \qquad (2)$$

$$F = 2*(P*R)/(P+R) \qquad (3)$$

$$A = (TP+TN)/(TP+TN+FP+FN) \qquad (4)$$

Here TP,TN,FP and FN represent true positive,true negative,false positive and false negative respectively. P,RF and A represents Precision,Recall,F1-score and Accuracy respectively.

IV. RESULTS

Based on the common assessment metrics on this dataset, we compare the proposed technique with the pre-trained DL models that are available off-the-shelf. The outcomes are shown in Table 1.
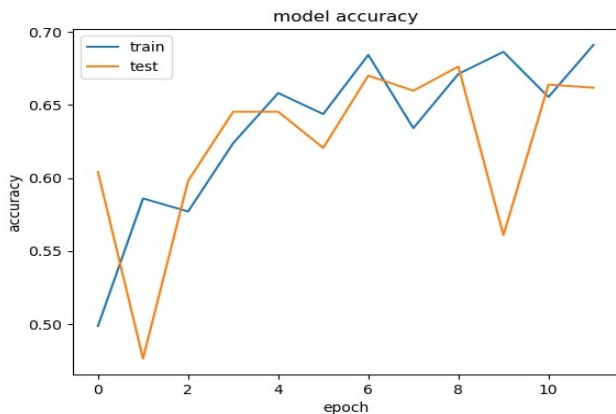

Figure 4: Sample Train Test plot for accuracy obtained from fine tuned Resnet-50 Model
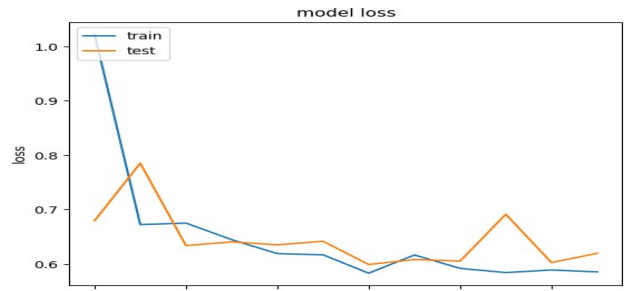

Figure 5: Sample Train Test plot for loss obtained from fine tuned Resnet-50 Model

Table 1: Comparison of ML & DL model and ensemble approach using Precision,Recall,F1-score and Accuracy

Methods	P(%)	R(%)	F(%)	A(%)
SVM	74.23	83.5	78.6	78.3
KNN	63.7	69.2	66.3	66.5
Random Forest	76.59	77.9	77.25	78.14
Xception	85.01	85.14	85.02	86.51
Resnet-50	82.81	82.94	82.82	84.87
Ensemble Approach	**91.61**	**91.6**	**91.7**	**91.51**

V. CONCLUSION

In this Paper Majority Voting is performed with 3 Machine Learning model and 2 Deep Learning model. Our ensemble method perform better then the standalone method. Our models offer a competitive prediction of monkeypox detection even with the smaller dataset. Our contribution give valuable insights into the primary screening of monkeypox detection.

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