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Research Article

Transfer Learning with EfficientNetB3 and ResNet50V2 For MPox Detection

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ABSTRACT

Introduction: Monkeypox (MPox) is a continuing global public health concern for zoonotic disease. Accurate and prompt diagnoses of MPox are key to programmatic disease control. Established key diagnostic modalities are resource intensive, requiring technology and facilities, clinical examination and laboratory testing are thus time-consuming. Conversely, machine learning and deep learning techniques provide fast and automatic diagnostic solutions.

Objectives:To diagnose monkeypox from clinical imagery this work proposes a transfer learning-based method utilizing the EfficientNetB3 and ResNet50V2 models. These models go very well with image classification and prediction. Although this approach is intended to be useful for therapeutic usage in the detection of monkeypox at low resources and inadquate healthcare facilities. This research demonstrates how transfer learning can be utilized to implement pre-trained models for Monkeypox detection with high accuracy thereby reducing the necessity of fully labeled datasets.

Methods: Using transfer learning, this study explores two pre-trained efficient model architectures – EfficientNetB3 and ResNet50V2, to classify skin lesion images exhibited in MPox. Pre-trained on large scale datasets, these models are fine-tuned using the Monkeypox Skin Lesion Dataset (MSLD) v2. 0 to improve prediction accuracy. Simple rotating, scaling, scaling, brightness adjustment, and other methods are used for data augmentation to enrich the dataset and promote generalization. Convolutional neural network is a deep learning architecture which, especially transfer learning based network, significantly improves detection and robustness of MPox with high accuracy and less qualification of the data set labels.

Results: The results of this study demonstrate that deep learning—more especially, transfer learning—can be an effective instrument for managing and detecting outbreaks of monkeypox early on, perhaps leading to better patient outcomes and less strain on healthcare systems. It is essential to combine cutting-edge transfer learning techniques with well-established deep learning algorithms to increase prediction accuracy and clarify the complexities of the ongoing worldwide monkeypox outbreak. Our work presents novel approaches to address this significant health issue while highlighting the ongoing significance of ground-breaking methods. Our proposed models with accuracy of 0.89 and 0.99 have outperformed the existing models in MPox detection.

Conclusions: The suggested transfer learning architecture outperforms the most recent models in terms of MPox detection capabilities. Better early MPox identification, more effective treatment planning, and ultimately better patient care could be the outcomes of these developments.

Keywords: *Monkey Pox (MPox), Transfer Learning(TL), EfficientNetB3, Machine Learning, ResNet50V2, Data Augmentation*

INTRODUCTION

International interest in the zoonosis monkeypox has burgeoned in recent years. A timely and accurate diagnosis is critical for successful management and treatment. Machine learning is one great way to create fast automated MPox detection systems. Machine learning algorithms analyze these large amounts of data to identify specific patterns and features related to the disease, enabling accurate diagnosis. Convolutional neural networks (CNN) have demonstrated efficacy across many clinical tasks and have explored MPox. An improved understanding of the important features of MPox inflammation may be obtained by analyzing the features and patterns learned from these models, facilitating progress in biomarker development approaches through a better understanding of disease pathology and subsequent treatment options. Coupled with the constrained equipment availability and cost in many areas, there is a clear need for value-sensitive scalable solutions.

However, the AI-based systems[2] provide a potential solution to these issues as they can leverage simple data like skin images for the timely and cost-effective detection of MPox. Although machine learning-based MPox detection has shown promise, more research is necessary to ensure the robustness and potential for clinical utility of such techniques, and to further develop and validate them. This require continued efforts to accumulate large datasets, refine architecture, and integrate with the health system. Also, electronic devices can accelerate patient isolation and treatment by reducing diagnosis time, this is especially important during an epidemic.

However, several barriers need to be resolved before an accurate and overall MPox diagnosis model can be established. Those barriers include the disease’s relative rarity, the similarity of skin lesions to other illnesses and the limited availability of educational tools. Supporting findings from contemporaneous research[5] show that machine learning approaches, particularly transfer and deep learning, hold tremendous promise in improving MPox's ability to better identify, control, and treat disease.

Advances in biomedical research have paved the way for a new generation of diagnostic tools based on promising artificial intelligence/machine learning (AI/ML) technology. This type of model, which is often used in software or applications for therapeutic purposes, is trained by maximizing the performance metric on data for a specific task. They include the use of skin imaging to diagnose cancer and optical coherence tomography[7][8][9] to predict visual impairment and clinical observations and test results to predict risk factors of MPox test. At the end of the day, machine learning technology has a lot of potential to improve accuracy in the diagnosis process and make the treatment of all types of diseases more efficient. The fact that computers can sometimes “see” beyond human sight is even more interesting.

This finding piqued people's interest in machine learning, particularly in relation to its potential applications in healthcare. Doctors can interpret clinical results more quickly and more accurately with the use of computer-aided diagnosis and diagnostics that use machine learning algorithms, such as computed tomography angiography. Polyp identification with To build precise and quick diagnostic tools, introduce machine learning (ML) data models for patient information and medical images. Additionally, machine learning techniques can be used to anticipate infections, guide treatment decisions, and improve surveillance and response operations. With all factors considered, there is much potential for bettering outcomes through quicker, more reliable, and helpful decision-making when machine learning is incorporated into MPox diagnosis and therapy.

OBJECTIVES

This study introduces a novel approach for Mpox detection by leveraging transfer learning with EfficientNetB3 and ResNet50V2, contributing significantly to the field of medical image analysis and computer-aided diagnosis. Key points of originality and contribution include:

i. **Development of a Transfer Learning-based Model for Mpox Detection:** The study employs EfficientNetB3 and ResNet50V2, pre-trained on large datasets, and fine-tunes them on the Monkeypox Skin Lesion Dataset (MSLD) v2.0. This leveraging of feature representations from ImageNet enriches the model’s detection capacity of Mpox in a highly accurate manner. This effectively utilizes transfer learning, which overcomes the challenges of limited Mpox data, by enabling learning and accurate predictions from a small dataset.

ii. **Comprehensive Data Augmentation Techniques:** To expand the MSLD v2. The study took advantage of MATLAB to conduct data augmentation in order to improve the performance, which incorporates rotation, reflection, scaling, brigthness, and noise addition as advanced samples. This increased the dataset size by around 14x and added variety to the training data resulting into better generalization of the model. Also, this is a good augmentation strategy that we applied, given the inherent data scarcity in Mpox research, which contribute to a robust model training.

iii. **High Performance and Comparative Analysis:** The proposed models also give better performance than far existing models for Mpox detection as shown by the study in the comparison section. Such an improvement, compared to conventional models, would serve to highlight the skill of transfer learning in Mpox diagnosis. Moreover, it presents comparative performance metrics (such as precision, recall, F1-score) against state-of-the-art models to ensure reliability and practicality of the proposed approach.

iv. **Addressing Research Gaps in Mpox Detection:** The study addresses critical research gaps in the field, such as the scarcity of annotated Mpox datasets, challenges in differentiating Mpox from visually similar diseases, and the need for explainable AI methods. By focusing on multi-class classification and the application of transfer learning, this research offers a viable solution to distinguish Mpox lesions from other skin conditions, enhancing diagnostic accuracy.

v. **Potential for Real-world Clinical Application:** The proposed model's architecture is designed for efficient deployment in resource-constrained settings, where rapid and accessible Mpox detection is essential. The compact and highly accurate models, especially EfficientNetB3, allow for deployment on mobile and digital pathology platforms, making it feasible for clinical use in low-resource environments.

vi. **Enhancing Explainability and Usability in AI-based Diagnosis:** Recognizing the importance of explainable AI, the study uses model evaluation techniques like confusion matrices to provide insights into the model's decision-making process. This transparency can increase clinical acceptance and trust in AI-assisted diagnostic tools, fostering integration into healthcare systems for Mpox management.

RELATED WORK

This study[1] assesses the effectiveness of Vision Transformers (ViT) and three learning transitions (M-VGG16, M-ResNet50, and M-ResNet101) across four investigations. The authors were successful in differentiating the virus; in the first, second, and fourth trials, M-VGG16 achieved an accuracy of 88%, 76%, and 77%, while in our course, M-ResNet50 earned an accuracy of 89%. To better understand the causes of monkeypox , they visualized predictions using local-agnostic annotation (LIME). The segmentation of diseased areas by our approach is quite accurate, as demonstrated by the LIME correlation. To calculate total capacity, they also referred to the government's decentralized data study. It will be crucial to combine current deep learning with various learning and interpretation techniques in order to improve forecast accuracy and highlight the seriousness of monkeypox as it spreads globally.

The authors of this study[2] developed a monkeypox diagnosis model using Generalization and Regularization-based Transfer Learning techniques (GRA-TLA) for binary and multiclass classification. They used 10 distinct Convolutional Neural Network (CNN) models to test the proposed approach in three separate trials. Preliminary computational results showed that the proposed technique, when combined with Extreme Inception (Xception), could distinguish between individuals who had and did not have monkeypox with an accuracy range from 77% to 88% in Studies One and Two. With an accuracy ranging from 84% to 99%, Residual Network (ResNet)-101 outperformed the others in Study Three for multiclass categorization.

This study recommends the use of RN-50-ZCA (Residual Network-50-Zero Phase Component Analysis) for feature extraction to enhance classification performance. ZCA-whitening is employed alongside RN-50 to accurately delineate the features associated with the lesions in the image. This method involves linear transformation following data normalization, which has demonstrated a reduction in covariance among the features. This also maintains the concrete variance. Principal component analysis (PCA) is employed to integrate features. The research concludes by proposing MXGBoost (Modified eXtreme Gradient Boosting) as an effective prediction method, utilizing a statistical loss function for the classification of monkeypox and non-monkeypox samples, including other viral samples, chickenpox, and smallpox. Considering specific aspects of the modeled problems, the prediction rate of the model can be enhanced through the use of MXGBoost alongside the loss function. The proposed loss function, by incorporating these features, can reduce overfitting and improve the model's generalizability.

The authors of this study[4] employed deep learning to identify red virus on skin. Using publicly accessible data, they evaluated GoogLeNet, Places365-GoogLeNet, SqueezeNet, AlexNet, and ResNet-18, five pre-existing deep neural networks. The best parameters are chosen by processing the hyperparameters. Performance measures including recall, f1 score, accuracy, precision, and AUC are considered.

The authors[15] suggest DeepSeq2Drug as a solution to the drawbacks of earlier techniques. To increase the number of medications and illnesses and obtain new forecasts, they employ multimodal docking and integration techniques. Four different model types are included in this framework (in addition to extended models): six NLP models, four CV models, four picture models, and two connection models. To be more precise, they first constructed the pipeline and determined how well each condition and medication pairing would predict outcomes. After that, they employed all of the methods for repeatedly using antibiotics and chose the optimal embedding pair. An investigation into the monkeypox virus (MPV) was carried out in order to assess the prediction capacity of the joint model. This framework may be used as a pre-learning technique for deep learning to enhance and rewire the immune system.

The authors of this work[16] examine the application of deep learning in the identification of MPox from skin samples captured by a smartphone camera. This approach addresses the limitations of the MPox image collection through transfer learning. To produce a uniform, clean dataset, data is first hand-picked and preprocessed before being made publicly available for research. Subsequently, they employed the 10x layered cross-validation approach to compare multiple Convolutional neural networks (CNNs) and conducted analysis to assess the model's accuracy for varying skin types.

The authors[19] present, annotate, and make a catalog of transmission electron microscope (TEM) images freely available. Additionally, they offer malware testing and analysis findings using small and large networks that have some of the greatest performance. Additionally, they assess and compare training from scratch with transfer learning; assuming that the latter is necessary for big networks with sparse data to function properly, they get remarkable results while learning tiny networks from scratch.

The unique use of artificial intelligence in the treatment of zoonotic diseases, such as disease prediction, early diagnosis, medication development, and future possibilities, are covered in this comprehensive analysis[22]. Predictive models driven by artificial intelligence leverage extensive data to forecast illness patterns and epidemics, so enabling public health interventions. Artificial intelligence-assisted diagnostic techniques for early diagnosis facilitate disease detection and prevention. The technology also aids in the discovery of new drugs by locating potential targets and improving medication candidates. In addition to discussing these developments, this paper looks at how artificial intelligence might be used to treat zoonotic illnesses. They emphasized the potential of artificial intelligence to safeguard human and animal health globally and the significant role it will play in altering our strategy for controlling zoonotic diseases.

In this study, the distribution units in the original data are unequal. Diverse data augmentation and preprocessing techniques are employed to address this issue. CSPDarkNet, InceptionV4, MnasNet, MobileNetV3, RepVGG, SE-ResNet, and Xception deep learning models were employed for red detection. To enhance the classification outcomes achieved with these models, a novel deep learning model was created for this work by integrating two superior deep learning and long short-term memory (LSTM) models. The proposed hybrid artificial intelligence system for red identification attained an accuracy of 87% and a Cohen kappa value of 0.8222.

In this study[27], a patch-based visual transformer (ViT) model was used to identify scarlet fever and measles from human skin color, representing a significant gain in pain assessment. Using a transformative learning technique, the researchers tested the ViT model's ability to recognize small patterns in spider and measles. The information is important because of well chosen picture enhancement techniques, which improve the model's ability to adapt to various scenarios. Throughout the examination, the patch-based ViT model displayed a high level of intelligence, scoring 93% accuracy, precision, recall, and F1 evaluation.

Research Gaps

Problem: Big, varied datasets are ideal for deep learning models to perform well. Nonetheless, there are still not many annotated datasets of MPox skin lesions that are accessible to the general population.

Research Gap: generating extensive, properly annotated datasets with a variety of lesion presentations, patient demographics, and imaging modalities (e.g., smartphone, dermoscopic, etc.) is essential.

Problem: It can be difficult to distinguish MPox from other dermatological ailments, such as chickenpox and smallpox, because the skin lesions of these illnesses can resemble each other.

Research Gap: Creating reliable models, possibly with the use of multi-class classification or anomaly detection techniques, that can reliably differentiate MPox from diseases that share visual similarities.

Problem: Deep learning models are frequently referred to as "black boxes." Clinical acceptance and trust depend on an understanding of the reasoning behind a model's specific predictions.

Research Gap: By using explainable AI methods to shed light on the model's decision-making process, we can increase the model's credibility and transparency.

Problem: Creating machine learning models is just a portion of the answer. For practical application, seamless integration into current healthcare workflows is necessary.

Research Gap: Developing intuitive user interfaces and decision support tools to help medical practitioners diagnose and treat MPox in real time.

By addressing these research gaps, we can leverage machine learning to create methods for MPox detection that are accurate, dependable, and easily accessible, thereby enhancing the security of global health. The objectives of this work are to eliminate research gaps and overcome challenges related to MPox identification in order to improve the usability of deep learning approaches i.e. Transfer Learning. The epidemic of monkeypox presents a serious threat to public health, making the development of reliable and efficient detection techniques imperative. The main objectives of this study are,

To investigate the red disease identification ability of the transfer learning model with EfficientNetB3 and ResNet50V2 using medical image data. The work strikes a good balance between computing speed and precision, which makes it fascinating. To test the resilience and accuracy of the transfer learning model with EfficientNetB3 and ResNet50V2, their performance was assessed on dataset of monkeypox images, including instances with minor lesions.

To compare the virus detection performance of EfficientNetB3 and ResNet50V2 with different available models. Although deep learning models have shown effective in detecting objects, it is unclear if they can be used to identify small lesions, especially when tissue samples are missing. Through the application of medical expertise, synthetic images containing minute particles can be produced, allowing for data validation, model exposure to difficult situations, and eventual data conversion.

MATERIAL AND METHODS

Dataset and Data Preparation

Early diagnosis is necessary due to the global healthcare crisis caused by the monkeypox pandemic. The "Monkeypox Skin Lesion Dataset (MSLD)" was developed in order to distinguish instances of monkeypox from non-cases of the disease. Images of measles and chickenpox are included in the dataset, enabling binary classification for early diagnosis. An essential component in the effectiveness of machine learning models is the accessibility and quality of training data. But getting hold of big, varied, and high-quality datasets can be very difficult, particularly in delicate fields like healthcare. A potential answer to this issue is synthetic data generation, which enables scientists and programmers to produce artificial data with properties similar to those of real-world data.

Data Augmentation is used to prepare the data ready for then training the model there by Improving Model Performance with the Creation of Synthetic Data. For the enhancement of data for MPox detection when the dataset is little, data augmentation is a highly helpful method to boost the deep learning model's performance. It entails modifying old data in numerous ways to produce new training models.

The effects that data augmentation produces, increased file size, improving already-existing MPox images may result in the report being larger. Deep learning models frequently require a lot of data to function successfully, therefore this is crucial. Changes in location and image quality that have less impact on the view. As a result, the model is more reliable and capable of handling unknown inputs. By highlighting variations in the training set, data augmentation pushes the model to learn broader knowledge and lessens overfitting. Rotate, flip, crop, and resize MPox lesion photos using the transform tool. Random Delete, Choose rectangles in the image at random and swap them out for random pixels.

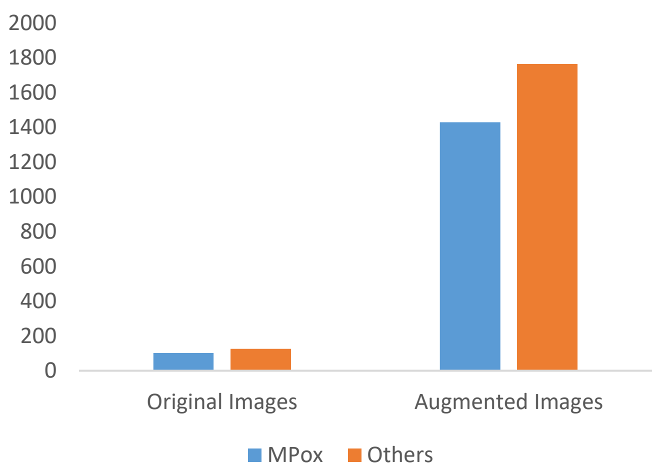
The Mpox Skin Lesion Dataset (MSLD) v2.0[28] is divided into three primary folders—Fold #1, Augmented Images, and Original Images—to facilitate multi-class classification and improve dataset resilience. The Original photographs folder contains 228 photographs that form the dataset's core data. These original photos depict skin lesions from a variety of classes, including Mpox, Chickenpox, Measles, Cowpox, Hand-foot-mouth disease (HFMD), and Healthy, assuring a diverse and representative population.

Extensive data augmentation was employed to address classification problems and the limitations of a small dataset. Multiple techniques including rotation, translation, reflection, clipping, hue and saturation modifications, contrast and brightness modifications, noise injection and rescaling, were performed using MATLAB R2020a. These augmentations greatly increased the number of images that allowed to improve model training by adding more diversity and covering a broader category of visual features represented for each disease category. This method achieved about a 14-time increase for the number of images in the Augmented Images folder, which makes the data set more suitable to train a neural network models.

The Fold #1 folder contains the 5-fold cross-validation image data so that the users are able to evaluate the model performance successfully against as many subsets of data as needed. The Augmented folder maps to the original folder in terms of cross-validation. For each augmented set, the map to the original one, which allows us not to change training and testing.

To make sure the added data was reproducible, the method of augmentation adopted was also to use tools like ImageGenerator and other methods to enhance images. With these augmented photos, the researchers can further boost model generalisation and performance in real-world applications, making it a reliable, computer-assisted solution for detecting Mpox.

Following the update, there were nearly 14 times as many photos. The "MonkeyPox" category contains 1428 photographs, while the "Other" category has 1764 images.



Graph 1 - Dataset Analysis

Transfer Learning

Transferring knowledge from one source (source domain) to another (target domain) for application is the foundation of the transfer learning theory. In general, the destination domain has fewer backup files than the source domain, which contains many backup files. For instance, the classification model[8] lacks universality and has poor classification accuracy when used to classify tasks with minimal training data. Training data at the collecting location can be utilized to address a variety of issues brought on by insufficient samples using transfer learning.

The network model applies the knowledge learned in domain Px and task Tx to target domain Ft and target task Ty, which enhances the performance of the target predictive function fy(•) in the target task Ty. This demonstrates how transfer learning works. The process is different whether the learning goals of the source and target domains are different ($P_x \neq P_y$) or when they share different domains ($T_x \neq T_y$). Figure shows the process of transfer learning, whereby using the information from the source domain improves the network model's performance in generalizing the target task Ty.

Transfer Learning with EfficientNetB3

Digital pathology's introduction has completely changed the field of medical diagnostics by making it possible to identify a wide range of illnesses quickly and accurately. The recent identification of monkey pox, a viral virus that had attracted attention in the past few years due to its ability to create large outbreaks. Previously, the diagnosis of monkey pox was done using standard learning methods — which often require large datasets and computer resources. Modern research on methods such as transfer learning algorithms have opened the doors to better and more effective disease diagnosis.

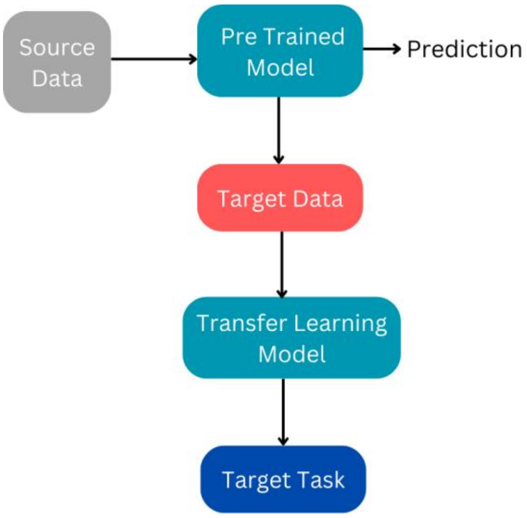


Figure 1 – Architecture of Transfer Learning

Transfer learning, a strategy which incorporates data from models that have already been trained, has been shown to yield encouraging results in the context of medical imaging practices. Over the years, several Convolutional neural networks (CNNs), trained on the ImageNet dataset, have captivated the world with their superior performance, though within application-based limits. The results show that an optimization of the EfficientNet model before training on the MonkeyPox dataset improves performance and accuracy. Thus, transfer learning is able to rapidly design a diagnostic model without having to initially collect and train data.

Transfer Learning with ResNet50V2

Conventional machine learning approaches[15] rely on large data for efficient model training. Transfer learning — a method of leveraging pre-trained models — solves this challenge by allowing a model to quickly learn even from smaller datasets. Fine-tuned version of ResNet50V2, a variant of the ResNet model, can be used for MonkeyPox detection in a limited amount of MonkeyPox skin lesion photos built in our available data. Such an approach can provide improved accessibility and deployment of detection systems, particularly in resource wise challenged settings where healthcare infrastructure is constrained. Transfer learning with ResNet50V2 can be an innovative approach for MonkeyPox detection.

Transfer Learning with EfficientNetB3 and ResNet50V2 has a number of advantages over traditional learning techniques in detection of MPox. The pre-trained model is very quick to adapt the unique properties of MonkeyPox lesions because it has previously learnt a wide range of features from various images.

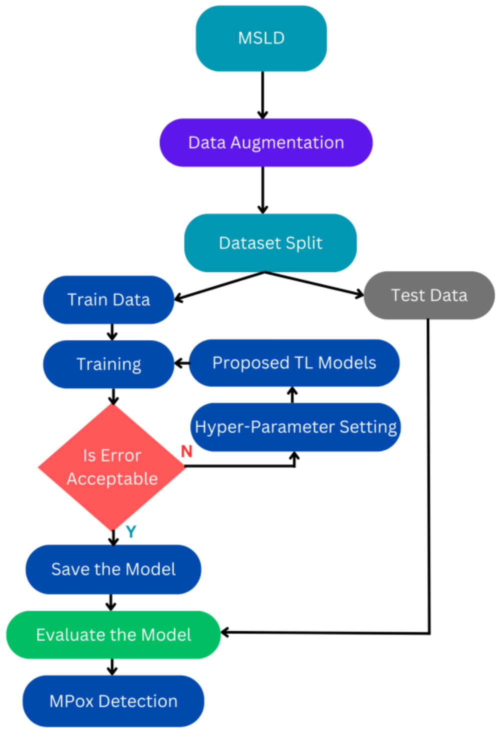


Figure 2 – Architecture of Proposed Transfer Learning Models

The compactness of the EfficientNet architecture allows for faster inference and deployment making it suitable for real-world clinical use. The model can mitigate the issues related to biased and small datasets and improve the detection performance by leveraging the knowledge learned from a large and diverse dataset (like ImageNet).

As a deep network, the ResNet50v2 specializes in identifying complex structures within medical images, allowing for rapid identification of pathologies, while also reducing the issue of the vanishing gradient, which improves performance due to the insufficient amount of data. In conclusion, there is great potential for the accurate and efficient diagnosis of monkeypox when transfer learning is implemented with the EfficientNetB3 and ResNet50V2 architectures.

RESULTS

In this section, we present the results from applying transfer learning to detection of MPox for two state-of-the-art deep learning architectures, EfficientNetB3 and ResNetV2, for image classification tasks. It had further a performance comparison between older and present models also been discussed. We developed the proposed solution using Python. Approach, in fact, transfer learning has been an approach we have been using prominently in Deep Learning, especially where we have constrained dataset. This process allows for the knowledge gained from large datasets like ImageNet to be reused in a target job with the similar features and characteristics as those included in the pre-trained model. Transfer learning has proven to be successful in a number of domains, including medical imaging applications, where a lack of data is frequently an issue.

Transfer learning is a technique that trains a model on a large dataset and fine-tunes it for specific tasks, proving promising in medical imaging. It can use pre-trained models for MPox detection, resulting in faster and more accurate diagnoses. This study considered the factors such as model quality, similarity between source and target domains, and task complexity to enhance the effectiveness of transfer learning using EffivientNetB3 and ResNet50V2. As medical diagnostics evolves, integrating transfer learning and other advanced machine learning techniques will be crucial for timely and accurate detection of emerging infectious diseases.

The suggested model's implementation yields results that are noticeably better than those of the existing cutting models. The new model significantly improves the outcomes across a wide range of metrics. Two Transfer Learning models' outcomes are explained.

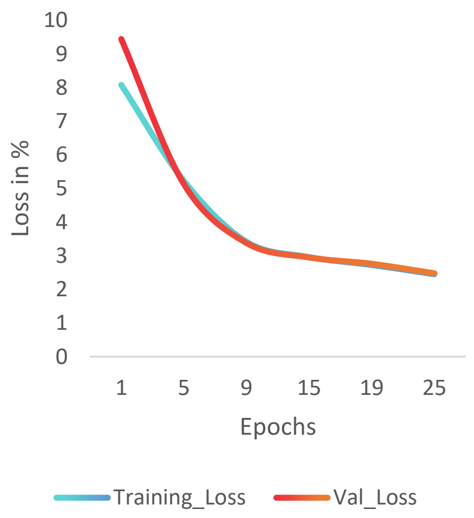
In this work, we evaluated the effectiveness of the ResNet50V2 and EfficientNetB3 models, which had been fine-tuned on a target medical picture dataset after being pre-trained on the MSLD dataset. The outcomes demonstrate the value of transfer learning in this field since both models significantly increased classification accuracy when compared to training from scratch. In this study, the state-of-the-art model ResNet50V2 , which is renowned for its great performance and efficiency, showed especially encouraging results, surpassing the EfficientNetB3 model.

With little training data, the models were able to successfully adapt to the target medical imaging analysis because to the transfer learning strategy, which made use of the rich feature representations they had learnt on the extensive MSLD dataset. The transfer learning models' effectiveness was evaluated and compared to the models that were already in use. The assessment indicators of this model simulation were evaluated and compared. The transfer learning model based on deep learning produces better results with fewer errors than previous models. The suggested transfer learning models enhance the characteristics of the extraction and classification training and analysis procedures.

Transfer Learning Using EfficientNetB3

We documented assessment metrics and assessed the models' performance on the test data in order to do this analysis. We'll apply several well-known classification metrics because this is a categorical classification task.

The Training_loss and val_loss of Transfer Learning Model with EfficientNetB3 is as shown in the graph 2.

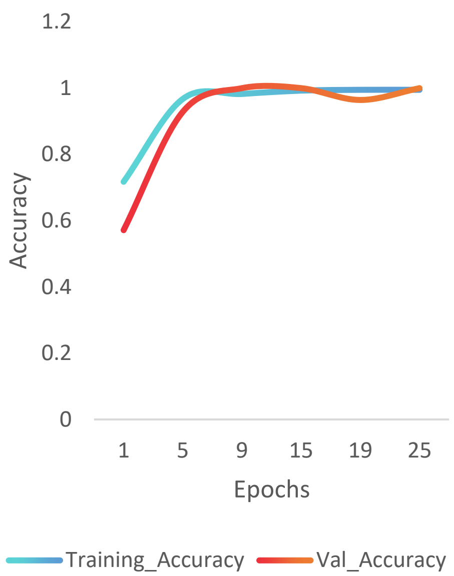


Graph 2 - Training_Loss vs Val_Loss of Transfer learning Model with EfficientNetB3

The training_accuracy and val_accuracy of Transfer Learning Model with EfficientNetB3 is as shown in the graph 3.

The following observation can be drawn based on the results about loss and accuracy

Epoch 25 has the lowest loss
With epoch 18 precision is at its maximum.
The model's loss is 15.21%
The model's accuracy is 89.67%.



Graph 3 - Training_Accuracy vs Val_Accuracy of Transfer learning Model with EfficientNetB3

The confusion matrix seen in the figure -3 can illustrate the classification performance for a multi-class model (EfficientNetB3) that detects monkeypox (MPox) and other skin diseases such as Chickenpox, Measles, Cowpox, Hand-Foot-Mouth Disease (HFMD) and Healthy cases. This led to the correct classification of 254 MPox cases, demonstrating high accuracy for MPox identification. A few cases were incorrectly classified with small numbers being identified and listed as Chickenpox, Measles, Cowpox, HFMD, and Healthy. Again, there were 63 confirmed cases of Chickenpox, and the classifcation was perfect except for a few and were misclassfied as Measles, Cowpox, HFMD, and Healthy. HFMD and Healthy classes were quite well, with 70 and 78-right classifying respectively and little misclassification. Cowpox and Measles were more confused than we expected visually, while the model had a bit of difficult separating Measles from Chickenpox and Cowpox, resulting in misclassifications in those categories. The model performs very well, especially in MPox disease classification, though some cross-over does exist between visually similar diseases. For example, additional features, more diverse training data, or improved augmentation techniques could be used to improve model generalization.

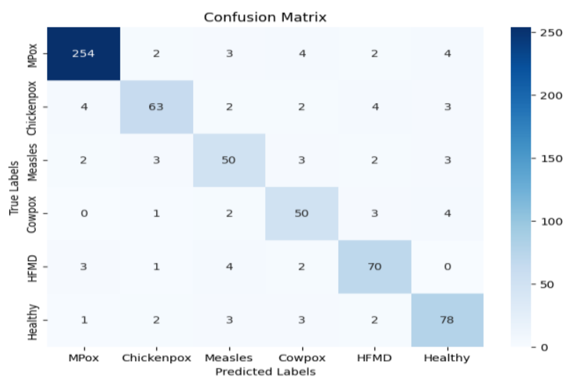


Figure 3 – Confusion Matrix of Proposed Transfer Learning Model using EfficientNetB3

Transfer Learning Using ResNet50V2

Using the ResNet50V2 architecture, this work explores the possibilities of transfer learning to address the problem of monkeypox (MPox) detection. The suggested method makes use of the capabilities of deep learning and the transfer-ability of features discovered on extensive datasets. To be more specific, the ResNet50V2 model—which was previously trained on the ImageNet dataset—is adjusted for the task at hand using a collection of images of MSLD. In many medical imaging applications, where data scarcity is a regular challenge, this method has proven to be effective.

The Training_loss and val_loss of Transfer Learning Model with ResNet50V2 is as shown in the graph 4.

The training_accuracy and val_accuracy of Transfer Learning Model with ResNet50V2 is as shown in the graph 5.

The following observation can be drawn based on the results about loss and accuracy

Epoch 25 has the lowest loss

With epoch 16 precision is at its maximum.

The model's loss is 0.56%

The model's accuracy is 99%.

The confusion matrix in figure -4 shows classification performance of ResNet50V2 model. 283 discords (5 misclassified cases) in MPox cases were correctly identified by the model. This reflects a high degree of compassionate discrimination between MPox and other conditions. Chickenpox was correctly classified 63 times, with no misclassifications into other categories. Measles and Cowpox had 56 correct classifications each (4 errors in other categories). For HFMD and Healthy categories, the model distinguished perfectly; 78 HFMD cases and 87 Healthy cases were classified without error. Considering the results olf EfficientNetB3, the overall classification accuracy seems to have improved tremendously. Hardly any misclassification is made for any category.

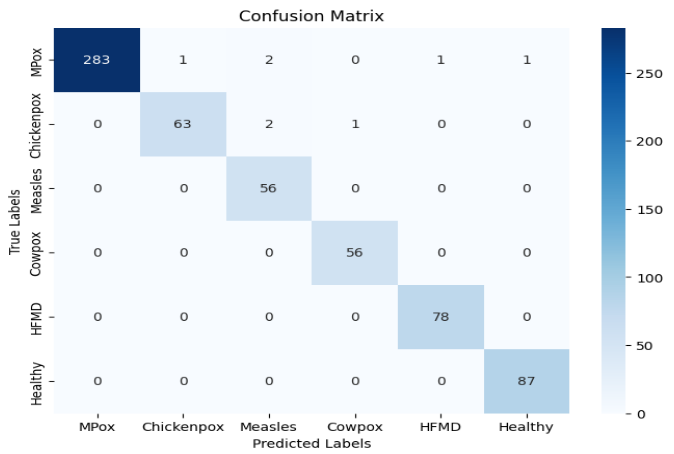
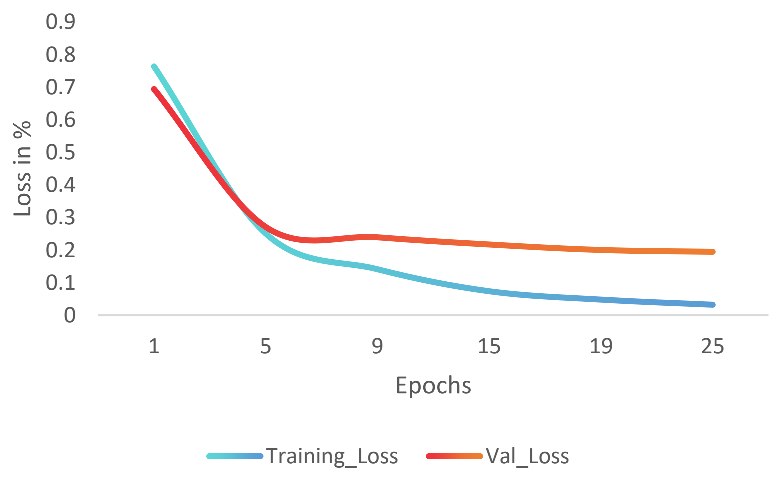


Figure 4 – Confusion Matrix of Proposed Transfer Learning Model using ResNet50V2

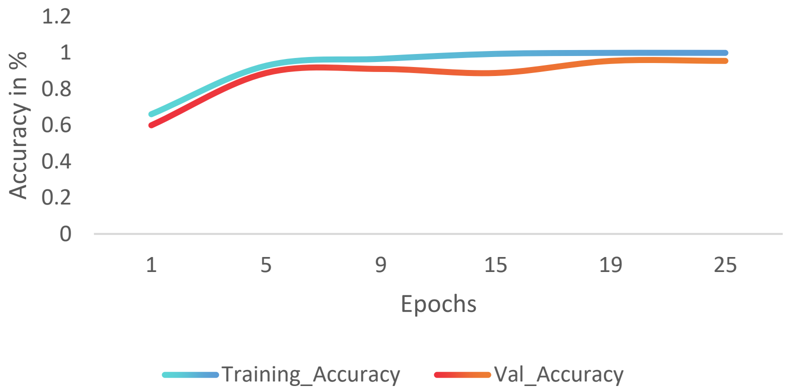
The efficacy of the proposed transfer learning-based technique, which emphasizes the prospect of a rapid and accurate monkeypox diagnosis, is demonstrated by the model's minimal 0.0056 loss and high accuracy of 0.99. This is crucial for early intervention and illness control.



Graph 4 - Training_Loss vs Val_Loss of Transfer learning Model with ResNet50V2

Comparative Analysis

This section presents a comparison between the proposed model and the existing conventional system[16]. The performance of these models on diverse data sets, computational effectiveness, and task generalization will all be compared. When this model is compared to the previous way, the performance of this tool is superior. This comparative analysis compares the proposed model with the state-of-the-art deep learning methods, as illustrated in Table 1. with metrics like Accuracy,Precision, Recall and F1-Score



Graph 5 - Training_Accuracy vs Val_Accuracy of Transfer learning Model with ResNet50V2

The accuracy of the results was great, ranging between 0.89 and 0.99. Compared to the current models, the accuracy of the transfer learning models is higher. As a result, the suggested strategies outperform the methods and strategies now in use.

The drive for more precise and effective models among the deep learning community has led to the development of several designs. Transfer learning models also appear to have the ability to improve model performance. This section compares the current models and discusses their advantages, disadvantages, and practical applications.

Comparing performance metrics, we find that transfer learning using the ResNet50V2 model outperformed transfer learning using the EfficientNetB3 model. The ResNet50V2 outperformed the EfficientNetB3 and the other MPox detection studies shown in Table 1 in terms of performance metrics. Numerous findings from past studies attest to the advantages of using transfer learning techniques. Additionally, our work correlates with past data with little loss and improved accuracy.

Transfer learning and conventional learning are two learning paradigms that enhance model performance in Monkeypox detection. Transfer learning leverages knowledge from previous tasks to improve performance on related tasks, while conventional learning relies on scratch training. Transfer learning models can achieve superior performance with limited training data and generalize better to unseen Monkeypox virus variations.

The recommended transfer learning model employing ResNet50V2 outperforms the previous works[23] in terms of accuracy when it comes to MPox identification. When compared to traditional learning models trained exclusively on the restricted MPox dataset, the transfer learning strategy improves performance by enabling the model to utilize pertinent features learnt from prior tasks.

Table 1 - Comparison of Existing Models with Proposed Models

Method(s) Used	Accuracy	Precision	Recall	F1-Score
Xception[1]	0.84	-	-	-
VGG16[1]	0.82	0.85	0.81	0.83
InceptionV3[1]	0.74	0.74	0.81	0.78
Ensemble[1]	0.80	0.84	0.79	0.81
ResNet50[1]	0.80	0.87	0.83	0.84
M-VGG16[1]	0.88	0.90	0.88	0.87

M-ResNet50[1]	0.89	0.83	0.84	0.82
Proposed TL Model with EfficientNetB3	0.89	0.88	0.86	0.85
Proposed TL Model with ResNet50V2	0.99	0.98	0.99	0.98

The ability to quickly and accurately detect new infectious diseases is critical in the fast developing field of medical diagnostics. One such illness that has attracted a lot of interest is MPox, a viral infection that can have detrimental effects if it is not treated and recognized in a timely manner.

Medical personnel have historically diagnosed MPox using traditional learning methods, such as physical examination of clinical symptoms and laboratory testing. But new methods for analyzing medical imaging have emerged with the introduction of deep neural networks and machine learning, which could completely change the way diseases are identified.

DISCUSSION

Maps, navigations and computer-aided diagnosis (CAD) technology has immensely been transformed with deep learning techniques, and MPox detection is no exception. These advancements offer an automated and effective method for diagnosing MPox, especially using skin lesion imagery, which is indispensable for early treatment and containment. Conventional diagnosis relies on clinical examination and laboratory testing, which, although effective, is limited by time, access, and cost and may be an impossibility in resource-limited environments. Timely diagnosis also rests upon trained healthcare professionals and specialized equipment.

This study sheds light on traditional methods' limitations and shows the improvement in MPox detection by using transfer learning based deep learning models. The study leverage on EfficientNetB3 and ResNet50V2, which are fine-tuned state-of-the-art Convolutional Neural Networks (CNNs) trained to deliver optimum performance on large scale datasets but now fine-tuned on the Monkeypox Skin Lesion Dataset (MSLD) v2. 0. This transfer learning through fine-tuning helps models take advantage of prior knowledge, identifying fine-grain correlations among pixel values and important feature(s) in skin lesions.

As mentioned earlier, the performance of the model was evaluated from different classification metrics including accuracy, precise values, recall, and F1. Results showed that both models worked remarkably well, achieving 89% accuracy for EfficientNetB3 and 99% accuracy for ResNet50V2. These results validate the advantages of transfer learning-based architectures over classical methods; they indeed tackled the problems of limited number of samples and diverse presentation of skin lesions.

Overall, ResNet50V2 was the best-performing model, outcompeting all other techniques in MPox classification. ResNet50V2 has a built-in feature extraction architecture which facilitates the extraction of deeper features enabling highly accurate differentiation of MPox lesions from other similar rashes like chickenpox and measles. This property enables cross-dataset generalization, which benefits deployment of an AI-based diagnostic tool in real-world settings.

The transfer learning-based method proposed in this study outperforms recent models in terms of detection accuracy, efficiency, and adaptability, providing a valuable addition to MPox diagnostic approaches. This is making significant contributions to public health and clinical care, especially enabling rapid, cost-effective, and scalable detection of MPox. This research highlights that deep learning-based transfer learning models offer a strong and reliable approach for effective MPox detection, paving the way for enhanced disease monitoring, rapid outbreak control efforts, and improved healthcare accessibility. With the incorporation of AI-induced models on clinical work process, real-time detection, signaling and early intervention are feasible, that result in quicker disease management and control within global healthcare settings.

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