POX DISEASE IDENTIFICATION USING DEEP LEARNING

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Abstract: Pox diseases are viral diseases causing serious health and economic and agricultural repercussions in humans, animals, and plants. Therefore, early and accurate identification of these diseases is important for effective management and prevention. The present study proposes an image classification approach based on deep learning to diagnose pox diseases through visual symptoms on the diseased subjects. The model is trained through convolutional neural networks beyond the variations of pox diseases with a diverse dataset of pox disease images that account for variations in species, appearance, and environmental conditions.The developed CNN model shows high accuracy in distinguishing pox diseases from healthy and other diseased states.A detailed performance evaluation asserts the robustness of the system regarding the different measures of precision, recall, and computational efficiency. Performance-wise, the proposed system outdoes all standard machine-learning approaches, thus providing a trustworthy source for automating disease diagnosis. The study indicates the potential of deep learning in aiding the detection and treatment of pox diseases. The results strongly support the integration of the AI-based tool into disease detection workflows to facilitate early detection and decision-making. Furthermore, this research lays the groundwork for the next generation of investigations of deep learning for automated disease management systems.

Keywords: CNN, VGG, Inception V3, DenseNet, NasNet

1 INTRODUCTION

Pox diseases-such as chicken pox, monkeypox, and cowpox-are viral infections where the damages are skin lesions associated with pyrexia and some systemic manifestations. Early and accurate recognition of these diseases is required for timely treatment, thereby preventing outbreaks. The traditional forms of diagnosis, i.e., clinical examination and lab diagnostics, often delay timely intervention and sometimes need extensive specialized expertise.

Deep learning in the past few years has grown into an invaluable potential in the medical image analysis for fully automated and highly accurate disease detection.On the images of the medical, the Convolutional Neural Networks (CNNs) and other deep learning architectures can be trained to detect the patterns or features related to the diseases of pox. Now that a large number of dermal lesion image datasets are accessible, these deep learning algorithms can assist the medical experts in pox diseases in diagnosis speedily.

The work is concerned with deep learning approaches for pox disease diagnosis with the assistance of medical images. The study details various deep learning architectures, the data requirements for training, and the performance evaluation metrics referred to with the view of finding the accuracy of the model. In short, this study proposed a robust and efficient application for the timely diagnosis of diseases due to pox, potentially improving patient outcome and reduction of infection spread.

2 LITERATURE REVIEW

The research "Computer-Aided Detection and Classification of Monkeypox and Chickenpox Lesions in Human Subjects Using Deep Learning Framework" by Dilber Uzun Ozsahin et al. investigates the possibility of employing deep learning (DL) for accurate detection and classification of monkeypox and chickenpox lesions from digital skin images, because the lesions pose the challenge of visual similarity. Exactly describing it, the model was a custom CNN-architecture, comprising a convolution layer with four convolutional layers and three MaxPooling layers. we just gotta mention it: in doing so, the testing accuracy reached 99.60%- much higher than its competitors, AlexNet and VGGNet, which have even lower accuracy values 98% and 80%. Data augmentation was applied to improve model generalization and to help the model avoid over-fitting, showing the feasibility of DL for fast and reliable diagnosis of the two diseases. The research suggests that DL models could be incorporated into the workflows of clinicians for better diagnostic accuracy and to avoid wrong diagnosis. The road is now paved toward further improvements in future works, such as optimization of the model for real-life, real-time deployment in a healthcare setting [1].

The paper "Deep and Transfer Learning Approaches for Automated Early Detection of Monkeypox (Mpox) Alongside Other Similar Skin Lesions and Their Classification," authored by Madhumita Pal et al., has been conducted to prove how deep learning models such as CNN, VGG 19, ResNet 50, Inception v3, and Autoencoder help to find monkeypox at an early stage effectively without delay and correctly differentiate between monkeypox and other similar skin infections like Chickenpox and Measles. Inception v3 was ranked first with a classification accuracy of 96.56%, followed by VGG19 (94.06%) and CNN (93.43%), Autoencoder scored the lowest with an accuracy of 85.62%. Various image augmentation techniques were utilized to build a public dataset to test the deep learning model for robustness. The study substantiates the DL application for real-time clinical diagnostics on account of its superior feature extraction among other models. Future advances are highlighted, including IoT implementation into automated diagnostics, expanding into a form for video-based classification in order to provide better accuracy [2].

The study "Monkeypox Virus Detection via Pre-trained Deep Learning Approaches" compares 13 pre-trained deep learning models for monkeypox detection, augmented with some custom layers for better accuracy and performance. The tests followed techniques of ensemble learning, furnishing an effective mean accuracy value of 87%, spread across majority voting, joining the Xception and DenseNet-169 models into a single unit, doing quite better than each model run separately. The dataset contained augmented images classified into Monkeypox, Chickenpox, Measles, and Normal. The experiment has shown the possibility and accomplishment of ensemble-based DL models for accurate and early detection, which leaves room for other future avenues of research, such as introducing techniques to improve model interpretability using Grad-CAM and LIME and applying advanced ensemble methods for greater diagnostic accuracy [3].

This paper by Muhammed Çelik and Özkan İnik focuses on the study entitled "Detection of Monkeypox Among Different Pox Diseases with Different Pre-Trained Deep Learning Models", in which they investigate the specificity of deep learning models in differentiating monkeypox from other similar smallpox and chickenpox. The study employs the Monkeypox 2022 Remastered dataset (Kaggle), comprising original and augmented images of various pox diseases. Several CNN architectures were employed, including VGG-16, VGG-19, MobileNet V2, GoogLeNet, and EfficientNet-B0. The MobileNet V2 attained the highest accuracy (99.25%) on the augmented dataset and that of VGG-19 was the best one (78.82%) on the original dataset.It emphasizes on presenting the necessity of diverse very big datasets when deploying deep learning onto dataset augmentation effect on the performance of deep learning. Possible improvement is associated with the diagnostics tools to be developed in real time, alongside better standardization towards increasing generalization of the models. [4].

The research paper entitled "Monkeypox Skin Lesion Detection Using Deep Learning Models: A Feasibility Study" has been written by Shams Nafisa Ali, Md. Tazuddin Ahmed, Joydip Paul, Tasnim Jahan, S. M. Sakeef Sani, Nawsabah Noor, and Taufiq Hasan. The aim of the work was to investigate monkeypox using AI. The research also proposed the Monkeypox Skin Lesion Dataset (MSLD), which is a collection of images of different skin lesions of monkeypox, chickenpox, and measles, gathered from several online sources. The classifiers were VGG-16, ResNet50, and InceptionV3, which achieved the best accuracy of 82.96% with ResNet50, followed by VGG-16 with 81.48% and an ensemble model with 79.26%. A prototype web application was created to allow rapid monkeypox screening. The study comments on the need for a larger set of datasets with a diverse demographic to improve generalizability and intends to improve model performance with better feature extraction and clinical validation [5].

In the paper "Reservoir Computing in Epidemiological Forecasting: Predicting

Chickenpox Incidence," Kaushal Kumar performs a time-series forecast aimed at predicting chickenpox incidence rates. Using publicly available epidemiological data released by Rozemberczki et al., it compares many deep learning models like ARIMA, LSTM, Bidirectional LSTM (BLSTM), GRU, Bidirectional GRU (BGRU), and Reservoir Computing.Results indicate that Reservoir Computing, which is considered highly valuable, has produced the least RMSE in several cases. The paper states that Reservoir Computing is, indeed, effective and flexible, further suggesting enhancements to its models for real-time predictions within epidemiology [6].

The research conducted by Othman A. Alrusaini "Deep Learning Models for the Detection of Monkeypox Skin Lesion on Digital Skin Images" investigates the applications of deep learning (DL) in the detection of Monkeypox from digital skin images. The dataset was created through web scraping (Google) employing the BeautifulSoup, SERP API, and requests libraries in Python, with the images validated by medical physician experts.Different architectures of CNNs, such as VGG-16, ResNet50, SqueezeNet, InceptionV3, and SVM classifiers, were applied to classify skin lesions. VGG-16 attained the highest accuracy of 96% with an F1-score of 0.92, compared to SVM (90%), ResNet50 (90%), SqueezeNet (86%), and InceptionV3 (89%). Therefore, AI is to be used in future studies to improve Monkeypox diagnosis, reduce diagnostic error, and foster early detection. Future work on the enhancement of these models should concentrate on data expansion by incorporating other skin lesions for testing and validation and the establishment of mobile applications that use these models as real-time and convenient diagnosis solutions [7].

The research paper states by Ghazi Mauer Idroes et al. "Explainable Deep Learning Approach for Mpox Skin Lesion Detection with Grad-CAM". This paper presents deep learning models for Mpox skin lesions classification using explainable artificial intelligence methods such as Grad-CAM for making it interpretable. The dataset used for this experiment consisted of 1,594 images of six skin conditions; Mpox, chickenpox, cowpox, HFMD, healthy, and measles. The different architectures that were used for classification included ResNet50v2, EfficientNetB4, and DenseNet169. ResNet50v2 was found to have the highest accuracy of 99.33% and the highest F1-score of 99.32%, quite above DenseNet169 (93.94%) and EfficientNetB4 (62.63%). This study has asserted that AI-based diagnostic tools are quite efficient in differentiating Mpox from almost identical maladies and emphasizes how more data sets, as well as modeling enhancements, would add up to accuracy and reliability [8].

The research work entitled "Image Data Collection and Implementation of Deep Learning-Based Model in Detecting Monkeypox Disease Using Modified VGG16" is conducted by Md Manjurul Ahsan and his co-authors on their papers presenting a deep learning technique on detection of Monkeypox using modified VGG16. The authors created "Monkeypox2022," a collection of 1,915 images, mainly from open-access sources, and augmented them so that the model performance could be boosted. The research experiment was carried out in two formats: experiment one scored 97% (AUC = 97.2), and experiment two scored 88% (AUC = 86.7). The authors concluded that deep learning model effectiveness is best as regards medical image classification and made suggestions on improvement by extending the dataset and including explainable AI techniques such as LIME for improving interpretability and trustworthiness of the model [9].

The article "Diagnosis of Monkeypox Disease using Machine Learning Approach" by Ajay Krishan Gairola and Vidit Kumar describes the usage of ML for the diagnosis of monkeypox through RGB skin images, which is really very difficult owing to its visual similarity to other pox diseases. In an open-source dataset of 2,187 images, evaluation has been performed using three convolutional neural networks, which are AlexNet, GoogleNet, and VGG16, along with applications of six ML classifiers like Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), and Naïve Bayes (NB). The highest accuracy of 91.11% has been achieved using the VGG16 model combined with Naïve Bayes and Random Forest classifiers, with an improved using a sort of fusion strategy with CNNs giving an improved accuracy of 95.55%. This research demonstrates ML and deep learning (DL) potential for automating the fold of monkeypox diagnosis to avoid excess reliance on confirmatory PCR tests and to assist with early detection. Suggested future improvements include further diversification of the dataset, development of mobile-based applications for real-time diagnostics, and enhancement of the fusion scheme for better generalizability [10].

The paper "Early Detection of Monkeypox Skin Disease Using Patch-Based DL Model and Transfer Learning Techniques" is by Abbaraju Sai Sathwik et al. and describes working with the evaluation of various deep learning models for monkeypox classification with some dataset obtained from Kaggle.The authors analyzed several CNN architectures namely VGG16, VGG19, ResNet50, ResNet101, and EfficientNet in comparison with transfer learning techniques. VGG19 and ResNet50 results scored the highest accuracies of 92%. The approach also employed data augmentation techniques for better training performance and to address limited medical image data. The authors showcase the use of the patch-based classification in proving the efficacy of the CNNs in the detection of monkeypox skin lesions. Future work involves making it more real-time-workable by increasing dataset size, studying ensemble learning techniques, and working on mobile-based diagnostic applications for broad accessibility [11].

The paper titled 'Comparison of Monkeypox and Wart DNA Sequences with Deep Learning Model' by Talha Burak Alakus and Muhammet Baykara illustrates how deep learning is capable of classifying viruses set forth by the DNA sequences of both monkeypox and wart. It produced an accuracy of 96.08% for the model, employing BiLSTM (Bidirectional Long Short-Term Memory) with various DNA mapping techniques, and an F1 score of 99.83%. It proves to be a better approach compared with visual examination concerning classification of sequences. The technical potential of bioinformatics and deep learning in disease differentiation and misdiagnosis reduction, thus allowing the rapid-accurate detection, is signaled in the study. Future work will also be laid out by this for future data sets enhancement, researching better classifiers, and integrated genomic analysis towards automated medical diagnostics [12].

In the study titled "Optimized Deep Learning-Based Monkeypox Diagnostic Framework Using the Metaheuristic Harris Hawks Optimizer Algorithm," Saleh Ateeq Almutairi proposes an integrated deep learning and machine learning approach to monkeypox diagnosis at an incipient stage. Applying pre-trained CNNs (VGG16, VGG19, Xception, MobileNet, MobileNetV2) with an optimizing step based on the Harris Hawks Optimizer (HHO) and with classification through seven machine learning models, the framework achieved accuracies of 97.67% on the MSID dataset and 97.51% on the MPID dataset. This deeply highlights the role of feature optimization and the role of majority voting toward improving classification accuracy; future work will focus on expanding the dataset, optimizing techniques, and deployment in real life [13].

The research "Deep Learning Model for Recognizing Monkeypox Based on DenseNet-121 Algorithm" by Mohamed Torky, Ali Bakheit, Mohamed Bakry, and Aboul Ella Hassanien looks at deep learning's ability to detect monkeypox from images of skin lesions. It compares the two models, DenseNet-121 and CNN, with the former performing better in testing accuracy with 93%. The study stresses the importance of deep learning in automating the diagnosis of infectious diseases and suggests enhancing future work through the use of larger datasets and better-performing AI models for improved detection accuracy and reliability [14].

The researchers Mohd. Coşkun Irmak and Mete Yağanoğlu, along with Tolga Aydın, conduct the study titled "Monkeypox Skin Lesion Detection with MobileNetV2 and VGGNet Models," applying deep learning models to monkeypox skin lesions, whose similarity makes it easy to confuse them with other diseases like chickenpox and measles. So they used pre-trained CN models using MobileNetV2, VGG16, and VGG19 on Kaggle Monkeypox Skin Image Dataset containing 770 images belonging to 4 classes (Chickenpox, Measles, Monkeypox, and Normal). The highest accuracy, 91.37%, was achieved by MobileNetV2, followed by VGG16 at 83.62% and VGG19 at 77.58%. Data augmentation was adopted to remedy the small size of the dataset to enhance the generalization of the models. The study suggested that MobileNetV2 may be effectively applied to accurate classification and could encourage future work on different deep learning architectures and ensemble learning methods toward improving detection performance [15].

3 METHODOLOGY

CNN:

A convolutional neural network (CNN) is a specialized algorithm that quickly comes in as an example of deep learning models. Their common end applications may be image classification, object detection, or image segmentation. In such architectures, a multitude of specific CNNs learn automatically and adaptively the spatial hierarchies of features from the images taken in by input. The architecture of the typical CNN consists of convolutional, pooling, fully connected layers, and activation functions. The convolutional layers extract features using filters or kernels, while pooling layers maintain a smaller spatial size in order to decrease computational load. Classification of the features comes at the end, whereas activation functions are introduced at various points in the model to introduce non-linearity, such as ReLU.

VGG:

The VGG networks is a set of deep CNN architectures noted for their simplicity and efficiency in the image classification domain. There are several instances of VGG, namely VGG16 and VGG19, which denote the layers in the network. The architecture uniformly applies small 3x3 filters to all convolutional layers. This allows for the learning of more complex features and yet retains a uniform architecture. Downsampling is performed using max pooling, and at the very end, a couple of fully connected layers are employed for classification. Even though the accuracy is increasing with increasing depth of architecture, its computation cost is also drastically increasing.

InceptionV3:

The InceptionV3 network, part of the Inception family (or GoogleNet), consists of the Inception modules that process multiple filter sizes (1x1, 3x3, and 5x5) in parallel such that the network can learn from a variety of spatial scales. The architecture employs factored convolutions whereby a larger convolution is decomposed into smaller and more efficient convolutions, e.g. a 3x3 convolution is split into 1x3 and 3x1. Auxiliary classifiers are also involved during training in order to improve gradient flow. The integration of all these features permits fewer traditional CNN parameters for a deeper network.

DenseNet:

DenseNet architecture promotes dense connections, where every layer receives input feed from all previous layers. It enhances the reuse of features and gradient flow improvement, which minimizes the vanishing gradient problem. While 1x1 convolutions are used as bottleneck layers to reduce the computation and then have an immediate 3x3 convolution, transition layers are put in place to control the complexity of deep learning models by downsampling with the use of 1x1 convolution and average pooling. The highly accurate dense network produces fewer parameters than other deep networks like ResNet and VGG because of its efficient feature reuse.

NasNet:

NASNet is an advanced deep-learning architecture designed using Neural Architecture Search (NAS). It builds on reinforcement learning to find optimal convolutional cells, i.e., normal cells for feature extraction, and reduction cells for downsampling. These cells are repeated across the architecture to build the entire model. NASNet offers two variants: NASNet-A (large), for high accuracy, and NASNet-Mobile, for mobile devices. It is state-of-the-art in terms of image classification.

4 WORKFLOW

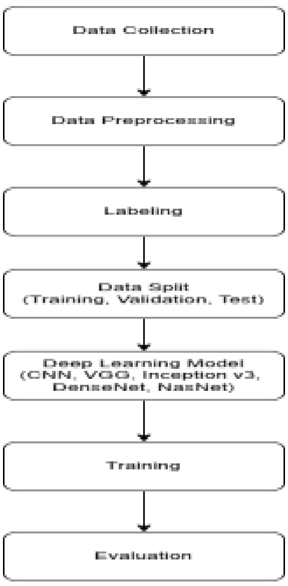

Figure 1: Workflow.

Explanation for workflow

Data Collection:

- Collect relevant images of chickenpox, cowpox, monkeypox, and healthy skin. Organize them into folders for easy processing.

Data Preprocessing:

- Resize images to the model's input size and normalize pixel values. Optionally, apply data augmentation to improve generalization.

Labeling:

- Assign class labels automatically using folder names. Ensure labels are one-hot encoded for multi-class classification.

Data Split (test, train):

- Divide the dataset into training, validation, and test sets. Maintain class balance for fair evaluation.

Deep Learning Model:

- Select a pretrained model and adapt the output layer for four classes. Fine-tune specific layers to learn domain-specific features.

Training:

- Train the model using the training set and validate with the validation set. Monitor accuracy and loss to avoid overfitting.

Evaluation:

- Evaluate the model on the test set using metrics like Accuracy, Precision, Recall, and F1-Score. Analyze misclassifications using a Confusion Matrix.

5 RESULTS

Table 1: Output values.

Algorithm Used	Accuracy	Precision	Recall	F1-Score
CNN	0.82	0.85	0.82	0.82
VGG	0.81	0.86	0.81	0.81
Inception V3	0.85	0.81	0.93	0.85
DenseNet	0.92	0.93	0.92	0.92
NasNet	0.86	0.85	0.86	0.82

Diagrammatic representation of outputs

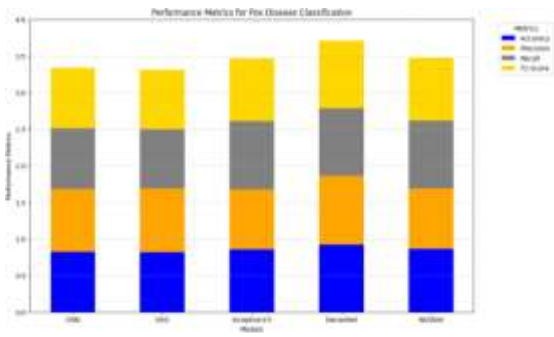

Figure 2: Performance Metrics.

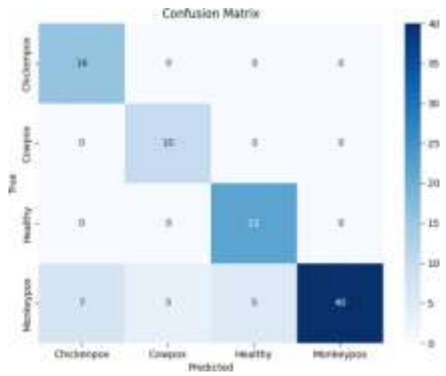

Figure 3: Confusion matrix of Inception V3.

The InceptionV3 architecture is based on Inception modules that act in parallel with convolutional filters of different sizes (1x1, 3x3, and 5x5) in order to allow for simultaneous learning of features at various scales by the network. This becomes even more pertinent for medical images, such as the pox disease images that have many different aspect ratios visualized at an array of scales. Another feature present in InceptionV3 is the use of factorized convolutions where the computation cost is reduced while using high-quality computations. Also defined are the auxiliary classifiers, otherwise referred to as pseudo-outputs, to improve the gradient flow during training thereby improving efficiency and accuracy in learning. These traits qualify InceptionV3 to be a strong candidate in the arena of classification tasks for medical images since its intricate details will render fine images required for differentiating diseases like chickenpox, cowpox, and monkeypox.

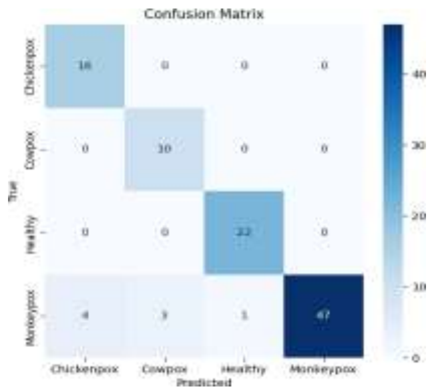

Figure 4: Confusion Matrix of DenseNet.

DenseNet's design has led to reasonable performance since it connects every layer to all previous layers in the network. Such dense connections enable the model to proceed with feature reuse from the prior layers and efficiently learn. Another significant aspect is that connecting all layers with those that precede them would assure better gradient flow and feature reuse for the network, which in turn are essential for learning complex patterns while not requiring a vast number of parameters. Loosely translated, the design is intended to prevent any verging on a vanishing gradient scenario, and this somewhat explains the model's cherished reputation in training deep neural networks using datasets that are huge but not terribly huge. This means that by virtue of its small model design, DenseNet can learn quite well even on small datasets without falling prey to overfitting, while also learning rich and expressive image features of your dataset.

6 CONCLUSION

The present work classifies and identifies different pox diseases (monkeypox, cowpox, or chickenpox) and healthy states using five different deep learning models, i.e., Convolutional Neural Network (CNN), VGG, InceptionV3, DenseNet, and NASNet. Of these algorithms, the findings suggested that the most effective model was DenseNet with an accuracy of 92.23% compared to the other models. This high classification accuracy is due to its better feature extraction and layer connectivity efficiency. NASNet and InceptionV3 were noted to perform with high performance as they achieved 86.41% and 85.43% accuracies, respectively, while CNN and VGG were less performing at 82.54% and 81.55% accuracies. In addition, based on the study, the use of sophisticated deep learning models would be important in the right classification of the pox diseases to enable proper early diagnosis and intervention.

7 FUTURE SCOPE

For future work, it will be interesting to explore higher-order models such as EfficientNet and the Vision Transformers to improve accuracy and robustness. Transfer learning and fine-tuning on larger datasets of medical images can help in performance enhancement. Explainable AI methods such as Grad-CAM will also help improve interpretability and trust in the decisions of the model. The prospect of developing a mobile or web-based application for real-time diagnosis and clinical validation in the collaboration of healthcare institutions looks bright. With such approaches, there is immense potential for diagnosis of pox diseases to improve accuracy, accessibility, and reliability via automation.

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